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Benchmark electronics

INDUSTRIAL ENGINEERING & MANAGEMENT

IMPROVING PRODUCTION TIME ESTIMATION FOR A PCBA MANUFACTURER

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Improving production time estimation for a PCBA manufacturer

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Management Summary

Benchmark Almelo specializes in printed circuit board assembly (PCBA) manufacturing and development for industries like aerospace, semiconductor, and defense. The company has grown in revenue in recent years, increasing capacity and driving the integration of new machinery and manufacturing techniques to enhance efficiency. However, these positive changes have introduced operational challenges, particularly in production time estimations used for the quotations of their products. As Benchmark's production processes have become more complex and varied, the existing Labor Quote Tool (LQT) that is used for determining a quote by estimating the production times of all new product processes, struggles to provide accurate production time estimates.

An analysis was performed to identify the capabilities and limitations of the existing LQT and its accuracy was determined. The existing tool uses production parameters to determine production times, which are quantified with input data from the specific PCBA. Interviews with users showed that the structure of the tool is considered complex and user-unfriendly because it contains a complicated web of interlinked formulas which can be referred to as a 'black box'. To determine the accuracy of the existing LQT, the Mean Absolute Percentage Error (MAPE) is calculated. The MAPE is commonly used as a measure for accuracy and calculates the under- or overestimation of the existing tool. The MAPE was calculated for three out of four manual labor processes that are studied for this thesis. These are Pre-wave Assembly, Hand Solder, and Final Assembly and have a MAPE of 44.8%, 43.3%, and 53.1% for 16 products, respectively. Press-fit—the fourth manual labor process— could not be included within this verification, because of data collection issues. This accuracy data analysis also showed deviations as large as 204,0%, showing that the existing tool sometimes severely overestimates the actual required time that the product takes to produce. It can be concluded that inaccuracies are likely due to outdated production parameters, as the existing tool lacks a framework to enable regular updates, and because it includes an insufficient number of parameters, as more parameters typically improve accuracy according to the literature. However, accurate estimations are important for cost estimation and production scheduling, as they both depend on these production times. The current inaccuracies lead to the failure to meet customers' targets and inaccurate quotations. To address these challenges, the main research question is stated:

How can Benchmark's LQT be enhanced to improve the accuracy of the quoted production times?

The research for enhancing the accuracy of the LQT was conducted in two phases: determining new parameters and developing an enhanced tool. In the first phase, input parameters were identified for processes including the pick-and-place machine of the Surface Mount Technology (SMT) line and the four manual processes: Pre-wave Assembly, Hand solder, Final Assembly and Pressfit. Additional parameters include productivity levels for manual labor and the learning curve for operators handling new products. In the second phase, a new framework for an enhanced tool was designed and included the parameters that were determined in the first phase.

The literature presents multiple estimation methods for determining production times, each having its own advantages depending on the product phase. An analogical estimation method can interpolate and extrapolate between similar products, yielding the most precise estimates as it uses available record data, providing that extensive and reliable data is present. Benchmark does store production records of all their production processes. However, data analysis has proven that the production data is inaccurate. Therefore, a parametric model is used as a suitable approach for Benchmark, estimating production times based on available input data that quantifies the parameters. Additionally, analytical techniques, characterized by breaking down the work into tasks or activities, have also been applied to enhance the accuracy of the parameters. Other methods for collecting data were found in the literature, including work sampling and time study, both recognized as reliable approaches for collecting data. Work sampling is useful for determing the proportion of time spent on various tasks, while time study offers precise measurements of task durations. Additionally, multiple linear regression was identified as a valuable analysis method, for its potential to uncover relationships between variables and their impact on performance outcomes.

For the four manual processes, production parameters were derived by a performed time study, which is a technique that breaks down processes into tasks and quantifies the time spent on all these tasks by observing. This is essential for analyzing the current reality collecting reliable production data and providing an overview of the time spent per production element. Furthermore, work sampling is performed to determine the proportion of time that workers actively spend on the defined tasks. This is an observation method that can quantify the productivity level of the workers. The work sampling showed a productivity level of on average 80.8%. Both time study and work sampling deliver reliable data, crucial for accurate production time estimations. In addition, a regression analysis model was made that determines the relationship between variables and cycle times for the productive time of the SMT line, excluding downtime as this should not be quoted. This was possible since the SMT line does provide reliable simulation times of its products. For the development of the regression model, the consideration was made that the full production times for the line can be determined by focusing on the bottleneck since the bottleneck determines the maximum throughput of the entire line. This approach proved to be effective, as it resulted in a MAPE of 10,6% for the productive time of the SMT line. In comparison, the existing LQT gave a MAPE of 211,3%, and even after excluding an outlier, it was still 128,1%. Notably, this outlier is not considered an outlier in the new LQT making the results more significant.

The regression analysis model functions as a predictive model and achieves a high accuracy. Altogether, these approaches are combined and form a methodology for improving production time estimation, as shown in table 1.

Table 1: Comparison of the MAPE for the estimation of the production times between existing and new LQT to show the accuracy for the different processes

Process time estimation	**Pre-wave Assembly**	**Hand Solder**	**Final Assembly**	**SMT Line**
MAPE Existing LQT	44.8%	43.3%	53.2%	211.3%
MAPE New LQT	34.3%	14.2%	19.7%	10.6%

In the second phase, a new framework for estimating production times was developed and incorporated the determined parameters from phase one. The new framework consists of using the available input data of products and components to categorize all components into a process. Then for each process, the determined production parameters can be quantified with the available information of the product and input from the engineer. The new framework will estimate the production times based on this information multiplied with the parameter and output them in an overview per process.

Before the new LQT could be implemented, it was necessary to validate the new LQT, to determine if the accuracy improved compared to the existing LQT. The validation was done for three out of four manual processes, the SMT line, and the work sampling study. The processes were studied to assess the accuracy of the new framework for determining parameters and validated with secondary operator data. An improvement in accuracy was observed for each process, as illustrated in table 1.

Data recommendations:
Reviewing the data collection methods is important since the current data reliability makes it unusable for analysis. The data collection software should be redesigned in a way that prevents inaccuracies caused by the design, ensuring that errors in data entry are not possible. The system is already present and given its cost, it would be wasteful not to fully utilize it, requiring only an update to maximize its potential. In this age, where data becomes increasingly important accurate measurement, monitoring, and processing of the data from all the operations is essential to gain better insights into the manufacturing department. Several recommendations for improving the data logging are listed below:

- A PFS software update should change the option the operators have to either record their production times or view the order without logging the production data. This second option often leads to incomplete data collection, as workers may avoid recording to prevent being monitored for speed. Changing the PFS system to remove this choice can ensure the production data is logged reliably. This should be changed in the software and implemented as soon as possible, ensuring more reliable data for future analysis.

- Another important feature for an update should be, that the cycle times for each single product in an order should be logged. This way more data on the cycle times can be collected. Currently, the time is logged for a full order with only one starting time and end time for multiple products produced, this reduces the level of detail in the data.
- The PFS software must prevent operators from working on a new order before completing the previous one. Sometimes operators may finish an order but forget to stop recording, continuing with a new order while the system still records the old one. At the end of the day, they might stop recording the old order, completing the new ones in just a few seconds, leading again to inaccurate data.

Tool recommendations:
Besides improving the data reliability we also provided recommendations for the new tool, which are as follows:

- If the data logging can not be improved shortly then there must be a focus on continuously updating the parameters to estimate the production times.
- Another critical aspect is the IEs should continuously adjust the production times based on feedback from the operators. The new LQT is not yet data-driven and there is no feedback on production times once the products are in production. It is important to adjust the production times when products prove to be more complex than expected. Exceptions occur and the new LQT can not take into account every. The LQT is designed so that IEs can add remarks to their input explaining the discrepancies. These remarks are essential for understanding why certain processes take longer than expected and should later be analyzed to identify potential parameter changes that could improve time estimates.
- Currently the new learning curve is not implemented in the tool since its analysis is based on limited data. Additionally, the learning curves are applied to batches instead of across the entire product lifecycle as described in the literature. Nevertheless, the existing learning curve that is implemented as discussed, substantially impacts the production time estimates and should therefore be re-evaluated with more data to determine a more accurate result.
- As already mentioned in the future research, the current proto allowances have to be re-evaluated. In Almelo many prototypes are tested with smaller batch sizes, requiring more support from other departments, which are accounted for with a proto allowance. A focus should be on a comprehensive analysis of determining accurate values for these allowances and a justification for these values.

Preface

This thesis presents my final result of my master's thesis "Improving production time estimation for a PCBA manufacturer" performed at Benchmark Almelo for the study of Industrial Engineering & Management with a specialization in Production, Logistics, and Management at the University of Twente.

As I reflect on my time at Benchmark Almelo, I am grateful for the opportunity and assignment I received. I learned many things and gained new insights into PCBA manufacturing and manufacturing in general, seeing it as an invaluable experience.

I am grateful to those who have supported and encouraged me throughout this process. I would like to express my gratitude to Arnaud, my company supervisor, for his support. Our weekly discussions were both helpful and crucial for the progress and successful completion of this assignment, as well as keeping me on track within the timeframe of this research. I enjoyed working with the team and am looking forward to our continued cooperation.

This thesis would have been much more difficult without the help of others. I want to extend my heartfelt thanks to my girlfriend for her unwavering support throughout this period. I am also deeply thankful to my family and friends, for their encouragement. And also, to my housemates for the enjoyable moments while working together in the living room.

I also want to thank Engin for his invaluable guidance and insightful feedback as my first supervisor. I want to thank Ipek Seyran Topan as well for the constructive feedback in the later stages of this research. Finally, as I conclude this chapter of my academic life, and begin my new role at Benchmark. I invite you to read my thesis, and I hope it provides new insights.

Jasper Scholten
Enschede, October 2024

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Acronyms

ABC	Activity Based Costing.
AOI	Automated Optical Inspection.
BOM	Bill of Materials.
ETO	Engineer-To-Order.
IEs	Industrialization Engineers.
ITAR	International Trade and Arms Regulations.
LQT	Labor Quote Tool.
MAD	Mean Absolute Deviation.
MAPE	Mean Absolute Percentage Error.
MSE	Mean Squared Error.
MTO	Make-To-Order.
NN	Neural Network.
ODB	Open DataBase.
OEM	Original Equipment Manufacturer.
PCBA	Printed Circuit Board Assembly.
PFS	Process Feedback System.
SMT	Surface Mount Technology.
THMT	Through Hole Mounted Technology.
TMU	Time Measurement Unit.
VBA	Visual Basic for Applications.
VIF	Variance Inflation Factor.
WPI	Work Place Instructions.

Chapter 1

Introduction

This report presents the outcomes of an Industrial Engineering master's assignment conducted at Benchmark Electronics in Almelo.

1.1 Company description

Benchmark Electronics Inc. is a leading provider in developing and manufacturing electronic products, as well as providing services to Original Equipment Manufacturer (OEM) with locations worldwide. They serve aerospace, medical technology, semiconductor, and defense industries. Initially, Benchmark was a Philip's company, which had two locations in Enschede and Almelo. After several collaborations and takeovers, it was taken over by Benchmark in 2005 (Benchmark Electronics, 2024). The headquarters are US-based in Tempe, Arizona, from where they operate in eight countries with 24 sites. Benchmark Almelo serves as the European headquarters and is divided into three main parts: Operations, Design Engineering, and the staff departments.

Figure 1.1: Locations of Benchmark worldwide.

Benchmark offers the customer a package from an initial phase to a final phase of a product. This includes the design, development, testing, production, and delivery of a product. The company offers products that range from PCBA to electronic cabinets. The production department in Almelo consists of the PCBA production, box build (for aerospace or medical), and racks and cabinets that are mainly produced for a key customer of Benchmark.

For this thesis, the research is conducted at the PCBA production facility in Almelo. In this department, they produce a variety of more than 1000 different PCBAs specialized and individualized for their customers. Their products are either Engineer-To-Order (ETO) or Make-To-Order (MTO). For ETO the Design Engineering department collaborates with the customer for the Bill of Materials (BOM) design and production process design, starting the order once it is received. The key customer mostly does MTO for their products, whereas Benchmark Almelo produces and assembles the products. Order sizes range widely from single products (such as prototypes of just one) to batches of 500 products. For some products, Benchmark must comply with International Trade and Arms Regulations (ITAR) regulations which are related to the export and import of defense and military-related technologies and are meant to limit access to these specific technologies. Other regulations Benchmark Almelo complies with are AS9100:2016, ISO 13485:2016, ISO 14001:2015, and ISO 9001:2015.

1.2 Problem description

In recent years, the production facility of Benchmark Almelo has grown in both scale and product variety. This growth has allowed Benchmark to expand its customers and increase its production capacity. As a result, new machinery and advanced manufacturing techniques have been integrated into production processes to increase their production efficiency. However, as a result of these positive developments, Benchmark Almelo now experiences some operational challenges considering their production time estimations and quotations.

As Benchmark has grown over the past few years, the complexity and capacity of its production processes have increased. The current workflow of the production facility now has more variables and a wider variety of products, compared to the old workflow. These changes are therefore not integrated in the existing production time estimation framework. In addition, the adoption of new machinery and workflow adjustments also made it difficult to maintain an accurate production cost estimation framework. As a result, the current labor time estimation framework also called the Labor Quote Tool (LQT), no longer reflects the true production times and costs. To solve this issue provisionally, the IEs of Benchmark are tasked with the complex challenge of estimating the production time required for the processes of the manufacturing department.

Accurate estimations of production times are essential as they directly impact cost estimation and production scheduling. The existing LQT has been developed to support the IEs and simplify the production time estimations. Even though the existing LQT is outdated, it is still an indispensable asset for this department. In addition, the existing LQT is also indispensable for the planning department, which uses the LQT to estimate the production capacity of the facility and for their planning to get an estimate of the remaining time. It is therefore important that the existing LQT must be assessed because if the production time estimates do not align with the actual times, it potentially impacts the margins of Benchmark. For example, miscalculations lead to disruptions in the factory, increasing the lead time. Furthermore, unfeasible planning will result in not meeting the targets of the customers, and losing credibility and trust.

The concern about the inaccuracy of the existing LQT has been addressed by the IEs, since they observed inaccurate estimations, particularly for the products that involve manual labor tasks. Challenging manual labor tasks to estimate are Pressfit, Pre-wave Assembly, Hand Soldering, and the Sub/Final Assembly. The IEs also observed that the existing LQT does not apply to newer products, indicating that the LQT is outdated. Besides the observed inaccuracies, the IEs also addressed the not user-friendly structure of the LQT, as it is difficult to trace down the estimations and, consequently, the origins of the inaccuracies. It lacks a clear overview of how it is built up and is often referred to as a 'black box'.

A problem cluster of the situation at Benchmark is composed and presented in figure 1.2. All different problems are mapped with their mutual relationships. This is used to structure the problem context, which allows for the identification of the core problem and to make it manageable (Heerkens & Van Winden, 2016). The core problem is identified as the 'Lack of an accurate production time estimation framework'. It is important to identify a core problem because then the improvement can be quantified and measured after solutions have been implemented (Heerkens & Van Winden, 2016). Another requirement of a core problem should be that the core problem must be impressionable. As can be seen in figure 1.2, the core problem is indeed impressionable in several aspects.

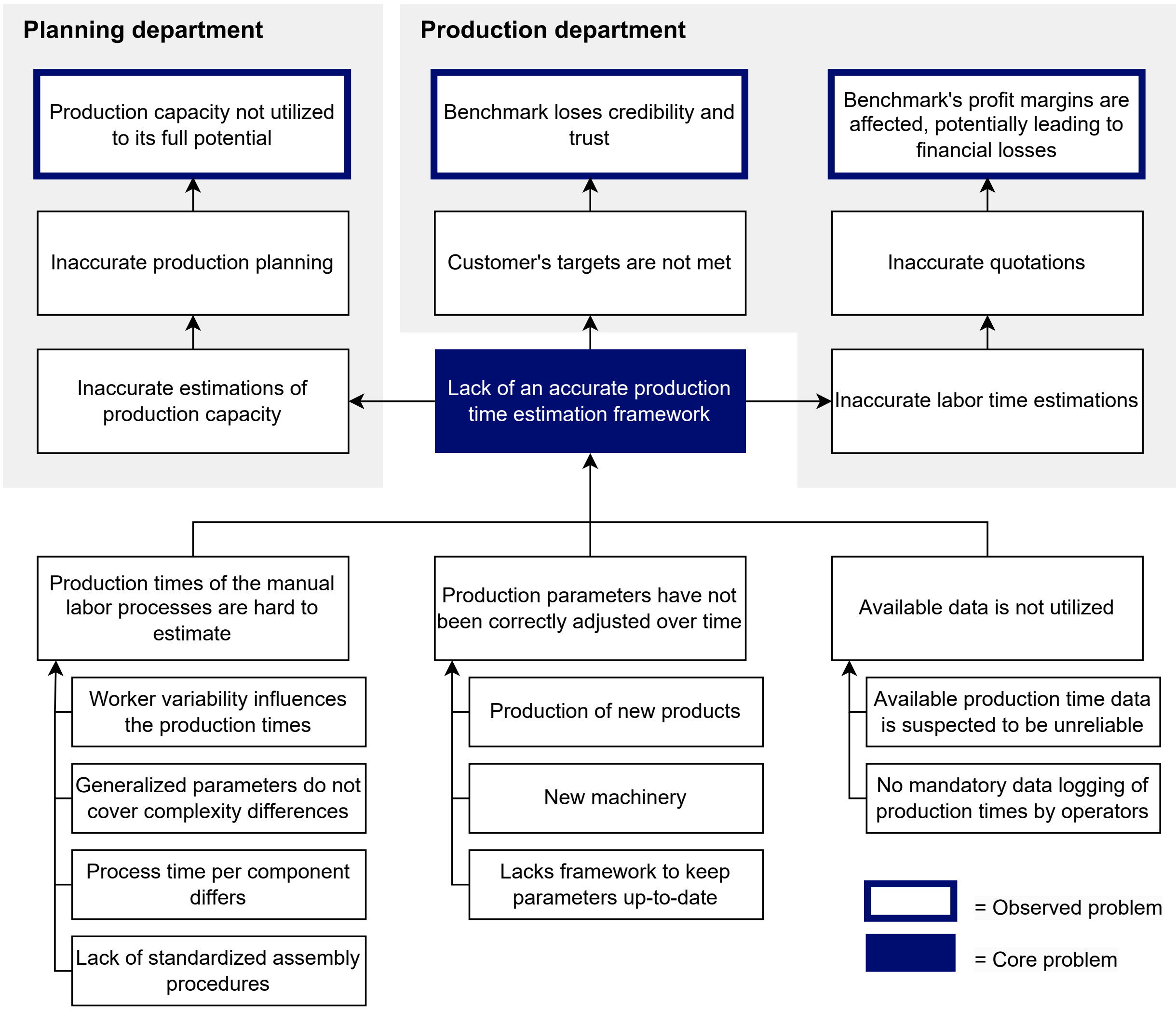


Figure 1.2: Problem cluster of inaccurate estimation of production times

The discrepancy between the tool and reality can be attributed to various factors, and this issue, which is essentially a deviation from the norm, represents an action problem. The action problem is quantifiable in terms of the accuracy. These action problems never occur on their own, as described in (Heerkens & Van Winden, 2016). Three factors that contribute to the inaccuracy are analyzed below:

1. Production times of manual labor processes are hard to estimate:

- ***Operator variability influences the production times:*** Operators have different levels of experience, which influences the processing time. Experienced operators tend to be more productive and efficient because they have trained their skills. On the other hand, inexperienced operators take longer, are still in a steep learning curve, and make more mistakes. In addition, inexperienced operators require more time for quality checks or corrections, impacting production times. As the growth of Benchmark has led to many new hires, a high level of inter-operator variability is expected.

- ***Generalized parameters do not cover complexity differences:*** The complexity of manual operations varies among products, and is challenging to quantify. Tedious tasks such as handling minuscule wires or fastening screws in confined places in the assembly take more time than a standard component. In addition, tasks like hand soldering a bridge component on a very small area often require a few attempts for successful completion. The existing LQT does not acknowledge these complexity differences, which results in deviations from the estimated production times.

- ***Process time per component differs:*** Certain manually assembled components significantly vary in assembly time per assembly task, which is often disregarded in the existing LQT. An example is a specific type of LEMO connector utilized in many products manufactured for a key customer of Benchmark. This LEMO connecter can take up to four minutes in the Pre-wave Assembly, while other components might take 30 seconds. The existing LQT does not acknowledge these differences and is set at only 30 seconds. Consequently, multiple instances of these LEMO connector components on one PCBA, increase the error in the production time estimate significantly for this product.

- ***Lack of standardized procedures:*** Logging of production times can provide valuable insights into the actual time spent on the manual labor per process. However, without standardized and well-executed time-logging procedures, the collected data gets contaminated easily and does not represent the actual time spent on the process. Currently, no rules are applied for logging production times at Benchmark. This probably results in unreliable data, so a data analysis will be conducted within this thesis. Furthermore, a standardized execution method would be beneficial for the determination of required times of manual labor tasks. At Benchmark, each process does have a Work Place Instructions (WPI), but this does not describe the optimal order of the method. Consequently, operators are using a wide range of approaches. Some of these approaches are less efficient techniques than others, increasing the variability of the production times of a product.

2. Production processes have not been correctly adjusted over time:

- ***Production of new products:*** In recent years, Benchmark has grown and expanded its product variety. As the existing LQT is based on aggregated parameters, it does not distinguish different manual assembly tasks. These aggregated parameters make it hard to include time estimations of new products in the existing LQT. New products are therefore often not added or are based on aggregated parameters that were never specified for these new products.

- ***New machinery:*** With the growth of Benchmark, new machinery has been installed since the introduction of the existing LQT. For example, a new Surface Mount Technology (SMT) line, explained in section 2.2.1, has been introduced in the manufacturing department of Benchmark, working twice as fast as the previous one. Furthermore, new tools have been introduced that can increase the speed of a process. For example, a faster screw fastening tool has been introduced that allows for easy fastening and is always fastening with the right torque. All these new developments are not taken into account in the current parameters of the existing LQT.

- ***Lack of framework to keep parameters up-to-date:*** The existing LQT descriptions of the processes are no longer as clear since these descriptions have been renamed and redefined more precisely. However, the parameters are determined for the various grouped processes that cover the older process descriptions. As production processes changed over time, it was difficult to keep the parameters up-to-date, because there is no framework for adjusting the parameters. Consequently, adjusting the parameters was often neglected, which resulted in an increased deviation between the production time estimates and reality.

3. Available manufacturing data is not utilized:

- ***Available production time data is suspected to be unreliable:*** The data logging process remains susceptible to contamination. Upon finishing a product, operators scan the serial number, which increments the production quantity of the production order by one. Sometimes operators will work on some products and not finish them or scan them in the end. However, instances occur where operators work on products but fail to complete and scan them. The following day, another operator, who does not log their labor, may quickly complete and sign off these products, logging inaccuracies into the data. Because the majority of all the work performed is not logged and cross-contamination can happen in the data that is available, it is hard to get a good estimate. Determining the reliability of data points is challenging without a reference against which they can be evaluated. Determining references for all the products and processes is very labor-intensive.
- ***No mandatory data logging of production times by operators:*** When operators commence an order, they are presented with two options: "record labor" and "viewing only". The first option allows them to work on the order and log their labor while selecting the second enables them to only view the order without logging labor. Analysis of the logged data over a specific period has revealed that approximately 15% of the total worked hours are logged, assuming all the persons work full-time. Despite the existence of a logging system, this amount of logging is remarkably low, indicating considerable room for improvement. Supervisors could check if workers are not recording the labor and could in this way enforce it. However, this is neglected, because this was not necessary in the past. Introducing it now will cause resistance from operators who fear it may be used against them to evaluate their pace of work.

All these problems contribute to deviation from the norm stated in the existing LQT. The IEs fine-tune the labor sheet in the end to account for the error, but this is usually done arbitrarily and based on experience, lacking any standardized methodology. This method is therefore also contributing to the inaccuracy of the production time estimates.

1.2.1 Research objective

This research aims to investigate the existing LQT and to develop a new comprehensive LQT to accurately determine the production time estimates of products of the manufacturing department of Benchmark. Given the complex nature of the products, which differ in characteristics such as assembly difficulty and requiring different components and tooling, generalized parameters may not provide a perfect estimate for every product. With the number of production processes and products at Benchmark, accurate production time estimates are essential for cost estimation and scheduling. By integrating existing aspects of the LQT, detailed production time assessments, and new findings, this new tool must improve the overall accuracy of the production time estimates.

By integrating elements of the existing LQT with the new findings, this study will aim to improve the overall accuracy of the estimations and design an alternative tool that ensures more accurate quotation times for the PCBA manufacturing department and its supporting departments.

1.3 Research approach

A well-structured research approach has been conducted to develop an accurate LQT for the manufacturing department of Benchmark. The main question of this research will answer:

> *'How can Benchmarks LQT be enhanced to improve the accuracy of the quoted production times?'*

The research is furthermore divided into several phases, supported with sub-questions that relate to that phase of the assignment. The research sub-questions are as follows:

1.3.1 Research sub-questions

1. **How are the current quoted production times estimated with the existing LQT of Benchmark?**

    a. *How does the current LQT of Benchmark work and what are the main components?*
    b. *What is the deviation in the actual and estimated production times in the current LQT?*
    c. *Which data is available and which data is currently used as input for the LQT?*
    d. *What are the improvement points of the LQT?*

2. **Which methods are present in the literature for estimating the production times for the assembly processes?**

    a. *Which problems are known to be present in estimating the production times in assembly processes, and what applies to Benchmark?*
    b. *What methodologies or technologies are present in the literature to estimate and improve the accuracy of the quoted production times?*
    c. *What is a suitable solution approach for the manufacturing department of Benchmark?*

    With the answers to these sub-questions, the development of a new framework for the tool can start. The research will be split into two phases, in which the first phase will consist of determining the production times of the complex manual processes. The second phase will consist of the development of the framework and model of the to-be-developed tool. A newly determined estimation model will be integrated making a new, more accurate, and to-be-developed labor quote tool for the manufacturing department of Benchmark.

3. **How can the production times for the processes be determined?**

    a. *What data is required and can be used for production time estimation?*
    b. *Which assumptions are made to determine the production times?*
    c. *How can we construct a method for accurately estimating the production times?*

4. **How can a tool be developed to integrate and summarize the new production time estimation framework?**

    a. *What data is required as input for the tool?*
    b. *How will the input be processed and applied within the tool?*
    c. *What are the key features and functionalities required for the tool to estimate the production time?*
    d. *How can we design a tool to ensure improved production time estimations, with a user-friendly experience for end-users?*

When the tool is developed, it must be tested and validated to see how it performs in practice. Therefore, the following sub-questions need to be answered as well:

4. **How accurate is the new tool for all products for a key customer of Benchmark?**

    a. *Which testing and validation methods are most suitable according to the literature?*
    b. *What is the accuracy of the tool?*
    c. *Can patterns of overestimation or underestimation be identified?*
    d. *What factors contribute to estimation errors?*
    e. *What is the overall user satisfaction with the new tool?*

5. **Are there ways to improve the new tool's quotation capabilities and make it accurate across the products for all customers?**

1.4 Scope of the research

The research scope is delimited to four specific manual processes within the PCBA assembly process. The focus will be on four manual operations with production times that are the hardest to estimate namely, Pressfit, Pre-wave Assembly, Hand Soldering, and the Sub/Final Assembly. The accuracy of the current LQT will be assessed, new solutions will be explored and recommendations will be derived. A new labor quotation tool will be developed and validated on this selection based on the assessment. This ensures an accurate representation of the quotation times of the processes.

The final result of this research will be a new LQT that can calculate/estimate production times for the SMT-line, the Pre-wave Assembly, Hand Soldering, Pressfit, and the Sub and Final Assembly. With the help of other process engineers parameters for other processes will also be defined but not validated. Their expert knowledge should be sufficient and a not validated estimate is better than no estimate. The tool should contain history-based estimations that use previous working orders of the same product to find an accurate estimation of the production times. Also, the tool should be able to predict the amount of labor of a new product, where both must follow a standardized methodology.

Chapter 2

Context Analysis

This chapter presents the context analysis conducted on the existing LQT. The analysis aims to address the following sub-research question:

> *How are the current quoted production times estimated with the existing LQT of Benchmark?*

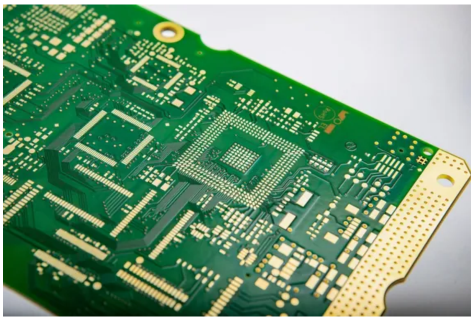
In section 2.1, an introduction to the LQT is provided. The next section 2.2 follows with an explanation of PCBAs and their assembly processes. Section 2.3 offers an overview of the existing LQT and its functions, while section 2.4 evaluates the accuracy of the existing LQT. In section 2.5 the

2.1 Introduction

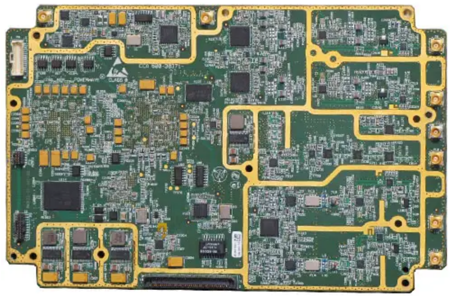
To gain insights into the context, literature research is done and users of the LQT are interviewed. Currently, the tool is used by most IEs in the manufacturing department. They fill in the LQT according to the product specifications, from which the tool produces an estimate of the production time used for the final quotation. The quotation department uses the output of the tool for the quotations of the customers. These quotations are based on the input of the IEs, who know the products the best. In addition, the planning department, which utilizes the labor times of the tool for their daily operations is interviewed. The planning department uses the tool to get an indication of the product processing times and lead times, creating the planning and forecasts for the manufacturing department. Wrong output in the tool directly leads to inaccurate calculations for these departments. Performance of the tool directly affects the profitability, because these departments use the tool for their processes. An effective tool should represent the real situation and give accurate estimates about the processing times and the amount of labor necessary.

2.2 Printed Circuit Board Assemblies

This thesis presents the development of a tool specifically designed to estimate the production times to be quoted for the assembly of PCBAs. PCBAs are important for electronic devices, serving crucial functions, and enabling the execution of specific tasks through the integration of various electronic components. Components, such as resistors, capacitors, integrated circuits, and transistors, are mounted onto a PCB substrate to create functional circuits. The difference between PCBs and PCBAs is that a PCB is the circuit board, while the PCBA refers to the circuit board assembly see figure 2.1. PCBA technology is continuously evolving and currently there are also flexible circuit designs available (Coombs & Holden, 2016).



(a) A bare PCB



(b) A fully assembled PCBA

Figure 2.1: Difference between a PCB and a PCBA

The process of PCBA is for a large part heavily automated by processes. However, some components need to be manually assembled by operators. An important part of the assembly process is also testing procedures and assuring high quality and yield. Examples of processes are the flying probe tester, in-circuit testing, and quality control measures. An overview of all automated and manual processes are visualized in figure 2.2. The processes that this study will focus on are marked in blue.

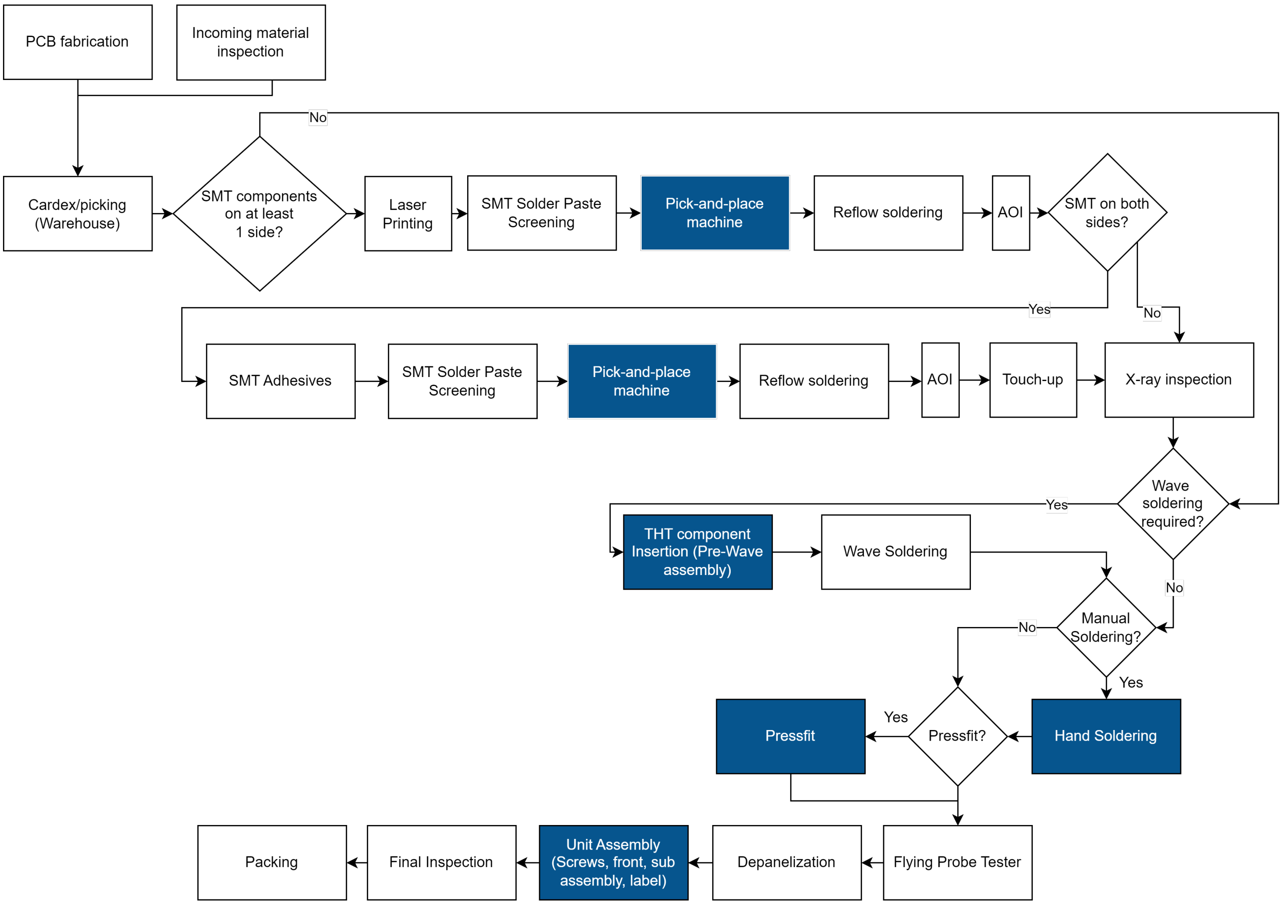


Figure 2.2: Visualisation of a schematic overview of the PCB Assembly process, with the processes that will be analyzed in this study marked in blue

2.2.1 SMT Assembly process

The SMT line is the first part of the assembly process and consists of several production processes that automatically mount electrical components onto the PCB. By using the SMT line, manual labor is minimized, which improves production efficiency. Additionally, this approach reduces the need to store semi-finished products. For a PCBA that requires a top and bottom side, the line is utilized twice. Benchmark has two SMT lines, with one being newer and almost twice as fast. A typical line is shown in figure 2.3 and consists of several steps (see Noble, 1989, for example):

- **Material preparation and examination:** This step examines PCBs and SMT components for any flaws.
- **Stencil preparation:** This provides a fixed position for solder paste to be printed on according to the design positions of the solder pads.
- **Solder paste printer:** A mixture of flux and tin is applied to connect SMC and solder pads on the PCB.
- **Pick-and-place (SMT) machines:** These multiple gantry SMT machines pick and place the components onto the PCB. As the bottleneck in the line, they determine the cycle time of the SMT process (Vainio et al., 2015). No leads have to be bent or preformed and it only requires placing it in the correct position. It is held in position temporarily with solder paste until the subsequent soldering process of the SMT line is finished.
- **Reflow soldering oven:** After placement the boards will go into a reflow soldering oven. Boards are slowly heated to the reflow zone where the solder paste melts bonding the components to the pads.
- **Buffer:** Used to keep the pick-and-place (bottleneck) of the line running in case anything breaks down in the back of the line.
- **Automated Optical Inspection (AOI):** This machine inspects the components for defects in the soldering, placement, or if any components are missing.
- **Unloader:** Automatically unloads the PCBs.
- **Storage rack:** Unlaoded PDBs are stored and depending of the height of the highest component 50 PCBs can be stored here.
- **Cleaning and inspection or touch-up :** Afterwards, the boards are cleaned and inspected for any flaws determined by the AOI. This part is the end of the process and all products that had an error in the machine will be manually fixed and finished.

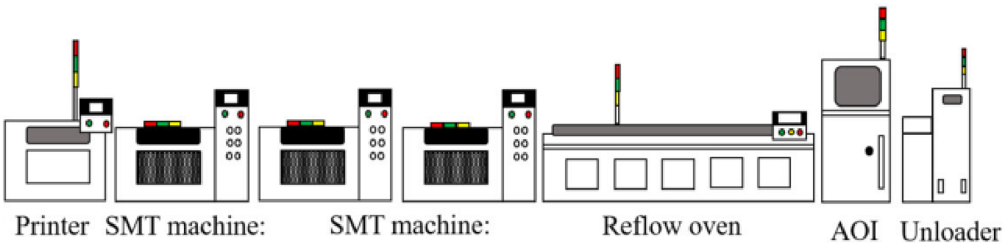


Figure 2.3: Example illustration of an SMT line (Vainio et al., 2015)

The advantages of the SMT line are that it is highly adaptable to different designs. Another advantage is smaller components can be placed quickly allowing for more components in a smaller area.

2.2.2 Manual PCB Assembly processes

The research will primarily concentrate on four manual processes: Pre-wave Assembly, Pressfit, Hand Soldering, and Final Assembly. These four were selected because they are the most challenging to accurately estimate, making them the most interesting to improve. The manual processes are explained in detail below.

- **Pre-Wave Assembly:** Before a product can undergo wave soldering, the PCBs go through a pre-wave assembly phase, which involves the manual placement of components. Some components are mounted with screws, some will have their leads cut, and most are clicked onto the PCB. After all necessary components are inserted, the PCB can be wave-soldered. With wave-soldering, components mounted on the upper side, move over a container of molten solder, where a pump creates a standing wave. The combination of heat, flux, and capillary action creates a precise solder joint, as described in (Noble, 1989). This method is used for components that are not suitable for placement by the SMT line.

- **Pressfit:** Pressfit involves securing through-hole components in the PCB by pressing them into place without the use of glue or solder. The method relies on pressing pins through the holes of a PCB by which the components are kept in place with a mechanical force. The connection is solder-free and no heat is involved, which reduces thermal stress on the PCB. This process is supported with a machine that does the pressing after components are properly positioned.
- **Hand Soldering:** Hand soldering is highly labor intensive. Therefore, Benchmark attempts to minimize its application whenever possible. It is only applied when other methods are not possible, usually due to factors such as the thickness of PCBs, components that can not withstand heat, or components that are considered difficult to solder.
- **Final Manual Assembly:** The last manual labor operation in the production process is Final assembly. It often consists of many manual tasks and here the last components are assembled. Examples are: turning screws, mounting a back or front plate, connecting wires, adding LEDs to the front, and assembling protective parts around the PCBAs. After this process, the product is ready for a final inspection, from where it will go to packaging and be sent to the customer.

These manual labor processes are incorporated within the existing LQT. An overview of the corresponding production parameters are shown in table 2.1. Remarkably, all production parameters are rounded and suspected to deviate from reality. Furthermore, these production parameters are currently not covering all aspects of the processes.

Table 2.1: Production parameters for the existing LQT

Description	Production Parameter (sec)
Pressfit	
Pressfit component	60
Setup time	600
Pre-wave Assembly	
Inserting a THT component	10
Hand Soldering	
Soldering one component	15
Soldering one lead	5
Setup time	300
Assembly	
CAD	30
Electrical component	30
Glue	30
Large mechanical part	30
Small/medium mechanical part	30
Screws	30
Washers	30
Nuts	30
Other assembly component	30
Labels	20
Setup time	300

2.3 Overview of the Existing Labour Quote Tool

The manufacturing department of Benchmark has an LQT, which is supposed to support them with determining the production times to be quoted. However, the department suspects the existing tool to be inaccurate. An overview of the existing LQT has been made and is further described within this section.

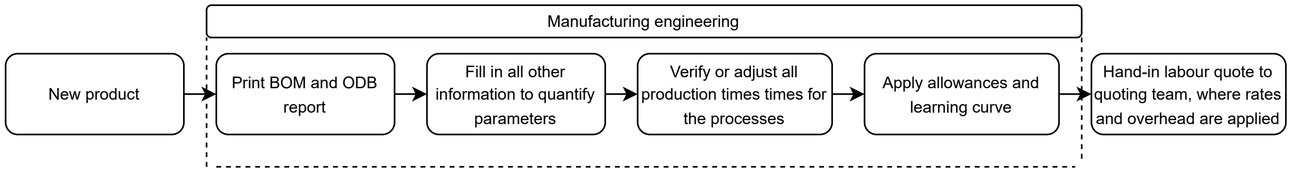


Figure 2.4: Overview of the existing tool

The existing LQT is built in Excel and contains several worksheets, each with its function. It uses input data of the BOM and Open DataBase (ODB) which is a CAD-CAM data exchange format and is often used in the electronic industry for all the components. The IEs add additional information to each of the processes. The workflow of the quotation process for the production times with the existing labor quote tool is visualized in figure 2.5. The function of each worksheet in Excel is as follows:

Info fill in sheet: When a new quote has to be made, the IEs fill in this worksheet. Blue rows represent separate processes that a product can pass within its routing. Each process has distinct parameters that are used to estimate production hours, such as a screw or bolt is set to 30 seconds. Light orange cells are used to manually overwrite values when needed and is used to adjust or fine-tune the values. All characteristics of the processes are presented here and can be filled in accordingly.

BOM Analysis: The manufacturer provides the BOM that is accessible in Agile. Agile is a software that stores all quality and product-related information. The BOM contains information such as the reference of the components (coordinate), quantity, part description, and part number. The stored product BOM in Agile must be directly copied into the BOM Analysis worksheet of the tool. This worksheet, therefore, contains the assembly information about the components such as the number of components, glue, screws, and washers. The BOM serves as a list for the assembly process, ensuring that the correct components are procured, picked, and assembled.

ODB Analysis: Its function is to improve the communication between the design and manufacturing of a PCB assembly (Sai & Ravindra, 2024). In this tool, the ODB script outputs a report with all design information, such as the component reference (coordinate), number of pins, quantity, SMT or Through Hole Mounted Technology (THMT) component, top or bottom placement, part name, and part description, which is all pasted into the worksheet. Subsequently, the worksheet uses the output to determine the number of pins for processes such as the selective wave and which components should be assembled on the SMT line. When the analysis button is pressed, it results in an analysis, showing the SMT or THMT components. It also has the option to change the type to pressfit or assembly although this functionality does not work correctly for the assembly components. Information about the components such as the part numbers, placement on the top or bottom side of the PCB, location, and class is also shown.

Process Parameters: The process parameters worksheet contains all the production parameters, such as label scanning, label printing, paste jet applying, etc. These are used as input in other worksheets of the tool. The reliability of the labor quote tool lies in the values and types of process parameters, as they determine the assembly duration for each component listed in the BOM. Each type of process has a specified time, either in seconds or in sec/lead. Failure rates in PPM are also specified for some processes.

Production Timing: This worksheet contains all descriptions routings/operations with the calculated setup and cycle times per PCBA and is generally used for all customers, except Customer X. All production times are calculated here

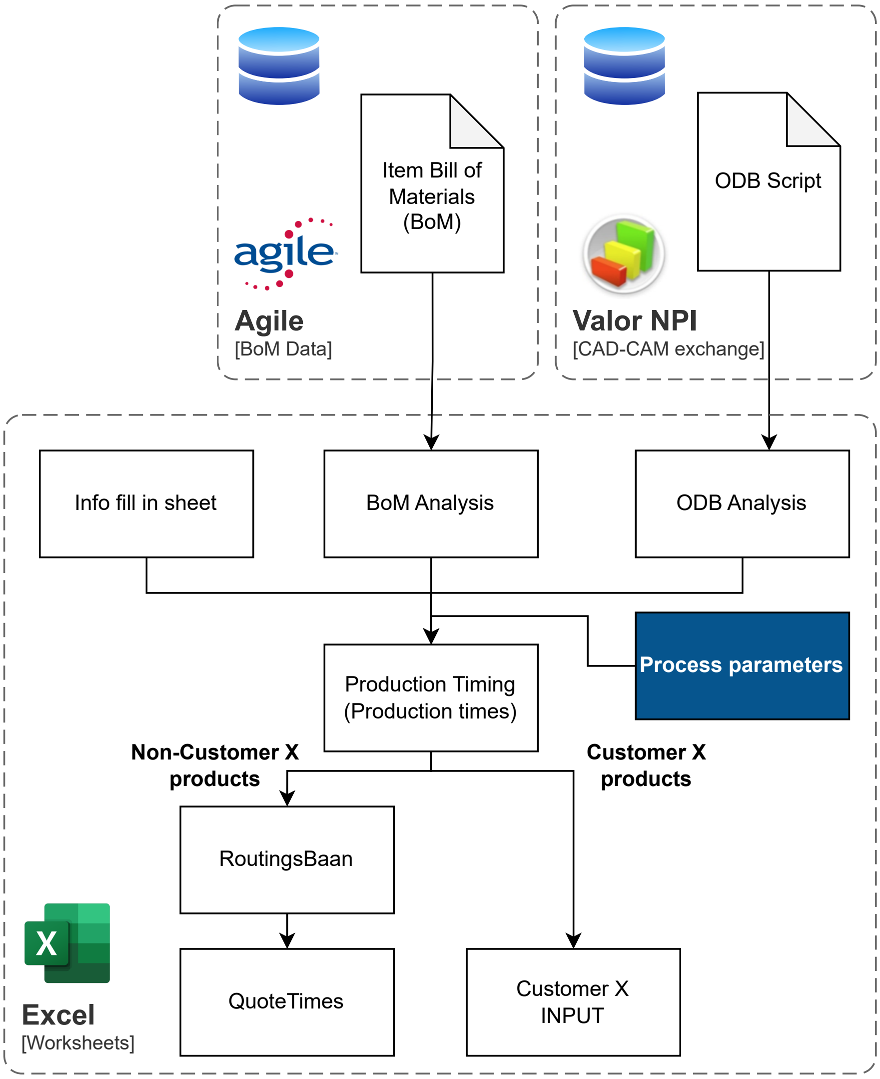


Figure 2.5: Overview of the programs and worksheets in the existing tool

according to the components from the BOM List, ODB Analysis, and process parameters worksheets. The descriptions of the processes are not the same as the processes in the factory. It will for example group multiple processes together, making interpretation more difficult, which process is costing more time. The output is separated into the production times (set-up + cycle time), test cover rate, and the processes' respective failure rates.

RoutingsBaan: This worksheet is used for all non-Customer X products. In 'RoutingsBaan' all routings are shown with their corresponding routing number, and their determined production times from the worksheet *Production Timing*. The function of this worksheet is to be able to fill in multiple batch sizes and compare them to aid in determining an optimal batch size. In the worksheet, the setup and cycle times are provided in minutes per batch including the allowances added in the Customer X INPUT worksheet.

Customer X INPUT: This sheet summarizes the production times for the quoting team for all Customer X products. The function of this worksheet is to summarize the output in gross and net hours and to fill in a batch size. It contains all information that is directly copied by the quotation team for all their quotes. The production times come from 'production Timing', on which allowances are applied in this worksheet. It is divided into two sections, the gross and net hours, where the net hours are without the allowances, and gross is the estimated hours with allowances that will be quoted for a product. The allowances consist of personal care, repair, and preparations. The gross hours are the estimated hours that the quoting department uses. The production times in this worksheet are the sum of the setup and cycle times divided by the batch size, which is different from 'Production Timing' which does not take a batch size into account. This worksheet therefore also serves to see what effects a certain batch size has on the production times for a process per PCBA.

QuoteTimes: This worksheet is very similar to the Customer X INPUT, but is used for all other customers. The estimated production times are summarized in this worksheet and give insight into which batch size to use. No allowances are yet applied here and will be applied later by the quoting team in a different tool. In this worksheet, different batch sizes can be tested to see how the set-up times influence the batch and times per product. The labor is summarized and divided into categories on the bottom.

2.4 Tool accuracy

To investigate the reliability of the existing tool an evaluation process is undertaken. This evaluation involved comparing the tool's time estimates with estimates from experienced operators familiar with the products for three manual processes and 16 products. The estimates from experienced operators are referred as *secondary operator data*. The three processes are Pre-wave Assembly, Hand Solder and Final Assembly. Pressfit could not be included, due to data collection issues. Two products were specifically selected because these are often produced. The other 14 were picked at random.

In table 2.3, the comparison can be found between the estimates of the existing tool and the estimates by the operators. We gathered the data in collaboration with the supervisor and operators for this research. The percentage error and deviation are calculated for each analyzed product. The reason for the blank cells is that not all products have a hand solder or assembly stage.

The estimated times for the tool were not easy to determine it requires back-tracking to find the values since some processes are grouped under a larger process name. The total accuracy is determined for each part, and the production times are taken from the gross hours. This includes the allowances for Customer X products determined in the worksheet 'Customer X Parameters'. In table 2.2, the allowances in the existing LQT for the products are presented. The allowances consist of 16% personal care, 5% for repair, and 10% for preparations, which adds up to a total allowance of 31%. The allowances are applied to the estimated production times by multiplying them with the allowance, which is compared to the expected times of the operators.

Table 2.2: Allowances in the existing LQT

Allowance	**Percentage**
Personal care	16 %
Repair	5 %
Preparations	10 %
Total	31 %

All the production times calculated by the existing tool are derived from the 'Production Timing' worksheet, which divides the production times per certain tasks instead of processes. Pre-wave Assembly is determined by the process tracing, the time required for adding batch lot information, the time required for linking serial numbers, the manual insertion of the components, labor preparation such as panel adjustments, and pre-programming of parts. Hand soldering is calculated by adding the wiring, potting, and manual soldering times. The assembly process is derived from the calculation for the non-soldering items, labels, front plates, and other mechanical parts.

Table 2.3: Comparison for three processes between the existing tool and the estimated actual times given by the operators for a single product

	Pre-wave Assembly			**Hand Solder**			**Final Assembly**		
Description	Tool	Avg time	Deviation	Tool	Avg time	Deviation	Tool	Avg time	Deviation
PCBA 1	8,0	15	-46,5%				9,3	11	-15%
PCBA 2	1,6	3	-47,2%						
PCBA 3	10,8	14	-22,8%				8,9	4	122%
PCBA 4	10,3	13	-21,1%				8,5	8	6%
PCBA 5	19,6	15	30,6%	13,3	19,0	-30%	24,4	20	22%
PCBA 6	5,9	15	-60,7%				15,2	5	204%
PCBA 7	2,7	4	-31,8%				14,8	5	196%
PCBA 8	7,3	12	-39,5%				39,5	35	13%
PCBA 9	1,5	3	-49,1%				14,6	15	-3%
PCBA 10	5,8	10	-41,6%	39,5	30,0	32%	10,6	10	6%
PCBA 11	4,5	10	-54,7%	5,4	10,0	-46%	20,7	19	9%
PCBA 12	4,2	6	-30,0%	13,3	15,0	-12%	16,1	28	-42%
PCBA 13	1,9	5	-61,8%	4,1	10,0	-59%			
PCBA 14	6,9	15	-53,8%				119,8	75	60%
PCBA 15	1,5	8	-80,9%				14,6	15	-3%
PCBA 16				16,5	88	-81%	90,0	63,00	42,9%
Mean Absolute Deviation			**4,3**			**16,5**			**8,8**
Mean Absolute Percentage Error			**44,8%**			**43,3%**			**53,1%**

The tool demonstrated concerning results compared to the average times estimated by the operators, with different degrees of accuracy for each of the three processes investigated. This confirms that the production times are not accurate since only 8 samples out of the total 35 tested have a deviation smaller than 15%. Benchmark has established this 15% as an accuracy target. This will also be used throughout this research for verification and validation purposes. To the determine the accuracy of the existing LQT, the Mean Absolute Percentage Error (MAPE) (shown in equation 2.1) and Mean Absolute Deviation (MAD) (shown in equation 2.2) are calculated. These metrics are commonly used as a measure for accuracy and calculate the under- or overestimation as an absolute value of the existing tool. After analysis, a MAPE was found of 44,8%, 43,3%, and 53,1% for the Pre-wave Assembly, Hand Solder, and Final Assembly, respectively. Additionally, a MAD of 4,3, 16,5, and 8,8 minutes was found for the Pre-wave Assembly, Hand Solder, and Final Assembly, respectively. These values can be found in table 2.3. Notice that the deviations are not absolute values, as they provide insights into whether the product was under- or overestimated.

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|A_i - F_i|}{A_i} \tag{2.1}$$

$$\text{MAD} = \sum_{i=1}^{n}\frac{|x_i - \bar{x}|}{n} \tag{2.2}$$

The maximum deviation was found of 204% and a minimum of -3,0% is found for a process. Consequently, the tool's performance underestimates the quoted production times for the Pre-wave Assembly and Hand Solder and overestimates the production time required for the Final Assembly. A significant discrepancy between the actual and projected production times is observed.

2.5 Challenges in production data

Benchmark has software, called PFS, that contains a database of production records that stores the duration of various production processes. This data could have been valuable for making informed decisions and quotations, so we analyzed the data by comparing the production records with the validation data (this analysis will be further discussed in section 4.2). It was observed that the data was not accurate at all. For example, a production process that usually take approximately an hour per PCBA will sometimes be logged as seven hours, even though operators explain that slower than 2 hours is not possible. The data contains significant outliers of the recorded times, and the lack of a standardized logging protocol leads to inconsistencies in how the data is logged. Some specific causes that contribute to unreliability are:

1. Not all the operators record the manual labor in the system. This is possible because operators have an option to either view or appropriately record the time spend to complete the task. Conversations with operators revealed that some fear that the data might be used against them, making them choose not to record it.

2. Another problem occurs when operators finish an order but forget to stop the time recording before starting a new task. At the end of the day, operators will stop the recording of the first order with significantly longer times and then finish the new products shortly after. This will make the first order have significantly longer production times and the second order significantly shorter production times.

3. A similar situation occurs when operators work on a large order over multiple days. They may not sign off any products during the initial days and then sign off all products on the last day. This will appear in the data as operators working several hours without completing any products, while the production record of another operator will show an unrealistic completion time for the products.

4. Furthermore, some operators multitask on orders simultaneously because they are instructed to work on the

same product the whole day. This makes it difficult to attribute the time to that specific process and contaminates the data.

5. Cycle times of single products are also not logged, which makes it impossible to find cycle times for a single product. If an issue occurs to just one of the few products produced, it will contaminate all the data for the other parts that were correctly produced.

As a result, the data lacks accuracy and can not be used effectively for any meaningful insights or new quotation tool.

2.6 Conclusion

This chapter explains the assembly process of a PCBA, shows an overview of the existing LQT, and answers the following research question: *How are the current quoted production times estimated with the existing LQT of Benchmark?* Furthermore, insights are given into the products, studied processes, and accuracy of the existing LQT.

The study focuses on the assembly processes, the surface mount technology (SMT) line, and four challenging manual processes, which have been selected for a more detailed examination. The existing LQT is examined to understand the estimation techniques currently in use, and an analysis for each of the worksheets is given explaining the function with its input and output. It was found that a parametric approach is used with the production parameters for each of the four manual processes shown in table 2.1.

After analyzing the parametric estimation method used in the existing LQT, the accuracy of the existing tool is analyzed with a MAPE of 44,8%, 43,3%, and 53,1% for the Pre-wave Assembly, Hand Solder, and Final Assembly, respectively, with deviations as large as 204% and 196%. In section 2.5 the logging of the production data at Benchmark was studied and found to contain significant outliers due to inconsistent recording practices described, such as operators choosing to not log their production orders. Additionally, some operators will work on a large order over multiple days and not sign off any products during the initial days and then sign off all products on the last day. This will appear in the data as operators working several hours without completing any products, while the production record of another operator will show an unrealistic completion time for the products. These practices are inherent to the software, which contaminate the dataset, making it challenging to derive reliable insights in the manufacturing department for future analysis.

The next step in this research is conducting a literature review to find solutions for which type of estimation method is most suitable for the development of a new LQT.

Chapter 3

Literature Review

The context analysis revealed inaccuracies in estimating the production times in the existing LQT, highlighting the need for improving the framework to a more precise method. Therefore a better understanding is required of existing literature. In the following chapter, we will review several studies and methods to research the problem, aiming to answer the second research question:

> *Which methods are present in the literature for estimating the quoted production times for assembly processes?*

Section 3.1 will explain various cost estimation methods. Section 3.2 provides a method for measuring production times and gathering data about the assembly activities by breaking it down into elements. Section 3.2 another method is explored for measuring the proportion of time spent by the operators on certain tasks, this also includes learning curves and allowances. Section 3.3 will describe work sampling another statistical technique for determining proportions for the time workers spend on tasks. Finally in section 3.5 multiple linear regression is explained.

3.1 Product time estimation methods

There is a diverse range of cost estimation methods in the manufacturing environment known in the literature. Considering the close relationship between cost and labor within this thesis. This section reviews several cost estimation techniques described by two papers that can be applied for estimating labor. The first, (Haberle & Graves, 2001), describes several common methods for estimating labor in the development phase suitable for the manufacturing department of Benchmark. The first method, time study, documents the time required for motions and assumes tasks are performed sequentially and defined in detail. Standard times for tasks are used to estimate the total production time for a process, and a database can be constructed with these standard times. The second method involves linear regression to estimate labor times, which will be explained. The third method uses a knowledge-based approach, where experts provide insights into key drivers of cycle times. These experts can quantify the impact of different drivers and indicate how they affect cycle times. However, it's crucial to balance expert input with empirical data. Understanding labor times for individual components has significant implications beyond cost estimation. For example, Design for Manufacturability can model the relationship between a part's geometric features and production costs. This approach allows for cycle time estimation in the early design stages. It also helps uncover design issues that may increase production time.

The second paper of (Qian & Ben-Arieh, 2008) describes four types of product cost estimation approaches: intuitive, analogical, parametric, and analytical. The first relies on pure experience and uses historical data and personal judgment to estimate costs. This approach can be valuable when data is scarce or when a quick estimate is useful. Another approach by (Duverlie & Castelain, 1999) presents a method for picking the right estimation method from the four in Figure 3.1. Throughout the life cycle, certain methods prove more effective than others, depending upon the specific context. In the subsequent sections, these methods will be explored.

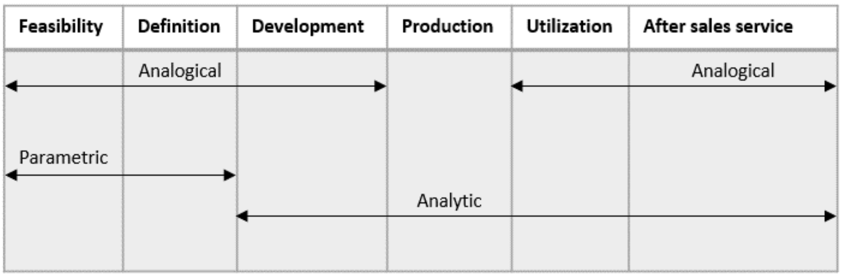


Figure 3.1: Suitable estimation methods for lifecycle phase of the product (Duverlie & Castelain, 1999)
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3.1.1 Parametric methods

The parametric method bases the costs on parameters associated with the product. This is usually represented by a simple equation. (Duverlie & Castelain, 1999) talks about how the parametric method can be useful and rapid, but criticizes that it can function as a 'black box', in which it can be difficult to comprehend the important elements of the manufacturing process and justify the results. Also, it is necessary for this method that when the workshop has been modified the parameters should be re-evaluated. A parametric model will consist of three data types: technical specifications, relationships connecting data to some intermediate or final variable, and the constant. A cost estimation formula is generally used for a parametric model. It is limited to a product type, process type/manufacturing technology, or a step in the life cycle of the product. A multiple linear regression model can set up the formula. One of the advantages of this method is that it becomes clear what influence the different parameters is on the labor times or cost. As an example, they use data for pistons to apply the model to, in which they use parameters such as the diameter, height, axis diameter, no. of holes, no. of grooves, and quantity. After several regressions namely, logarithmic, polynomial, and linear, they conclude that the best results were obtained with linear regression. This regression shows an interval of confidence of zero on either side, resulting in a reliable and accurate method. Consequently, this is the most reliable and was the lowest in terms of average error, rate of error, and maximum error. (Wierda, 1988), describes a method for developing a cost function. First, a substantial number of products should be considered, which can be grouped if necessary. Then the variables that influence the cost are identified. These features can consist of characteristics of the product and are ideally quantifiable. The influence of these variables is investigated by plotting the costs of the product against a variable and applying regression analysis to determine the magnitude of their impact. Then the costs can be modeled as a function and the accuracy of the model can be evaluated, by comparing the prediction with the actual costs of the existing products to ensure alignment with the real-world data.

3.1.2 Analogical methods

The analogical methods compare the costs of products to similar products from which the costs are known. This is done by identifying the variables and extrapolating these. This approach uses historical data knowledge and can be very useful when comparable products have to be Benchmarked. This technique is established by using a similarity index to find a linear relationship between the products and predict a cost for the product (Niazi et al., 2006). The variables are usually deducted from linear regression analysis as mentioned already. Another analogical technique is

Backpropagation neural network models (BPNN), which is a form of deep learning. These models leverage Neural Network (NN) that can be trained to store knowledge and find answers to questions that they have not encountered before. Several advantages of BPNN over traditional regression models are that regression models assume linear relationships between costs and variables. BPNN overcomes this by capturing nonlinear dependencies (Weckman et al., 2010). An example is also given in (Weckman et al., 2010), who use a NN to estimate the costs of jet engine components specifically shafts and cases, and compare this to a regression-based method. Since NNs require a lot of data, it often occurs that the available data is not sufficient enough to train the model. In these cases, data expansion techniques can be applied, such as data doubling and data creation. Even after using data expansion techniques, the resulting cost estimations with the use of NNs still show superior results compared to linear regression without NNs. The drawbacks of neural networks are that the black box nature can make the reasoning behind the estimate less understandable because they do not display the underlying process and cost drivers. If transparency is necessary the NNs can be used as a starting point for the creation of cost estimate relationships in the current estimation method (Weckman et al., 2010).

3.1.3 Analytical methods

Moreover, analytical methods can be used, which breaks down the work required into elementary tasks, operations, or activities. Subsequently, each activity or task is assigned a known cost. This method provides a detailed understanding of the cost drivers.

One example of an analytical approach is the Activity Based Costing (ABC), introduced in the mid-1980s through cases and articles at the Harvard Business School. It assigns costs to activities rather than directly to products or services. Costs will be related to activities like packing, receiving, inspecting, and picking. It identifies all activities using activity charts, worksheets and cost build-up tables to find activity cost drivers. These cost driver rates are calculated by dividing the activity costs by the quantifiable outputs of each activity. (Ong, 1995) gives an example, which presents an ABC estimating system for the costs of PCB assembly during the design phase, in this case, it provides valuable information for design improvement. The ABC method highlights which activities incur substantial costs so that designers can reduce these costs by minimizing these activities.

3.1.4 Intuitive methods

These types of methods rely on the expertise of an experienced person who estimates the production cost based on their knowledge and experience. However, because this is subjective and based on personal judgment, the results can be uncertain and sometimes inaccurate. Despite this, these methods are cost-effective to use.

3.2 Time Study

Time study is a work measurement technique for recording the working rate for all execution steps, which are called elements, within a specified job at a defined performance. Time study aims to observe the execution of tasks by using a stopwatch, camera, or any other measurement device, and analyzing the elements of the task at a defined level of performance (Taylor, 1911). Time study is a scientific management theory and formulated by Frederick Winslow Taylor, who is regarded as the father of this theory. His theory now belongs to one of the most important theories in the field of Industrial Engineering. Frederick Winslow Taylor was an engineer in the previous century and had a strong interest in increasing the efficiency of workers by increasing their productivity using the least possible time and resources. The basic principles of Taylor's scientific management are:

- Standardisation of tasks
- Equal division of workload and responsibility between worker and management

- Collaboration between management and workers

To conduct a time-study several steps should be taken. Firstly, all necessary information should be collected, such as the working order, serial number, quantity, and also all operator variables as described in. Other information such as the type of measurement tool is important that is also precise and easy to use. After collecting all the information, the execution of the job should be recorded and the operation should be broken down into smaller observable elements. Each element has to be distinct and measurable. This allows for the analysis of all elements individually and combined, to ensure the most effective outcome. The next step is to conduct the time study and record the observations, which should be repeated to improve the accuracy. The time units in time study are given in Time Measurement Unit (TMU), in which one TMU equals 0,00001 hours. Afterward, average times can be calculated and the performance rating is applied, depending on the pace of the worker. For each element, a normal time is now calculated to which allowances can be added to determine the final standard time. It is crucial to consider factors like operator variability, learning curves, and allowances. The following sections will delve into these aspects, exploring how they influence time estimation and process improvement in time study.

3.2.1 Operator variability

In operations where manual labor plays a significant role, the outcomes of the same specific production process can differ due to a difference in individuals performing a specific task. In the early 20th century (Gilbreth & Gilbreth, 1916), the founder of motion study, and (International labour office, 1979) have described variables that cause those differences. They state that the variables can be grouped into three types: Worker variables, environmental variables, and motion variables. Worker variables relate to the operator such as the level of experience of an operator. Other factors can include training, skill, health, habits, and fatigue. Secondly, some variables are related to the surroundings (environment) and the equipment and tools the operators are using. These variables could be the appliances, clothes, heating, cooling, lighting, tools, or entertainment such as music available in their environment. Thirdly, there are variables in the motions individuals perform. These range from the weight, acceleration, length, and speed all affect the degree of fatigue of the operator. Understanding this operator variability is crucial for determining accurate quotation times.

Most of these factors are also extensively described in psychological literature. One of them is operator experience, which can have a big influence on the processing time for a given operation. (Johnson, 1981) concludes that from a variety of studies in many different environments, the outcomes are very similar. A common measure is the ratio of the fastest (shortest time) and the slowest (longest time) is generally in the range of 1:2,0 or 1:2,5. This creates the problem of how much should be allocated to the assembly line. Time study engineers say: that the 'normal' operator should be picked, the definition of a normal operator is usually referred to as the average.

3.2.2 Allowances

A tedious task in time study is determining the allowances for the standard times. Since variability could occur from person to person, product to product, and even day-to-day, and because of the number of variables present, allowance determination is seen as one of the most difficult jobs in time study. However, standardized norms are available and used in regular practice by engineers. According to (Niebel & Irwin, 1960) allowances need to cover three different categories: personal delays, unavoidable delays, and fatigue. Allowances must be determined as accurately as possible, otherwise all precision used during the rest of the time study is wasted. Three theories, (Groover, 2007), (Maynard & Zandin, 2023), and (International labour office, 1979), that provide valuable insights into the topic of allowances are explored. A brief overview can be seen in Table 3.1.

(Groover, 2007) talks about several types of allowances. The first is the (PFD) allowance for personal time, fatigue, and Delay. Typically a 5% allowance is applied and encompasses activities such as restroom breaks, phone calls, water fountain visits, and similar interruptions. The fatigue or rest allowance compensates workers for the time needed to recover from work-related stresses and conditions. Delays are unpredictable interruptions during the workday, often arising from work-related events. Contingency allowances address potential issues with tasks or production equipment. Additionally, training allowances are assigned to workers responsible for teaching their job duties to others, while learning allowances support employees undergoing training for new roles or those new to the job.

(Maynard & Zandin, 2023) have a different approach for certain allowances. For personal rest and delay allowances, they recommend the use of specified break and washup periods as the basis for this compensation. They also describe contingency allowances, which should ideally be derived from either work sampling studies or full production studies to ensure accuracy. Policy allowances should not be utilized as often and well documented. In addition, they also name interference allowances, which can be calculated using available formulas, tables, and charts, and are used when an operator uses multiple machines and there is unoccupied time.

Table 3.1: Overview of the allowances

Groover	**Maynard and Zandin**	**International labour office**
Overall Personal Rest, Delay (PRD)	Personal time	Relaxation: personal needs
Fatigue	Fatigue	Relaxation: basic fatigue
Delay	Delay	Variable
Policy	Contingency	Contingency
Interference	Training	Special
	Learning	

The (International labour office, 1979) also discusses various allowances. Relaxation allowances comprise fixed and variable components. Fixed allowances include time for personal needs, such as personal hygiene and refreshment breaks, often ranging from 5 to 7 percent, and allowances for basic fatigue, generally set at 4 percent. This allowance is for resting from energy expended during work and dealing with monotony. Variable allowances supplement the fixed ones when working conditions deviate significantly from the norm due to environmental conditions or job-related stress. Contingency allowances, usually not exceeding 5 percent, cover minor delays and unforeseen extra work. Special allowances may be allocated for activities essential to work performance but ae not part of the operation cycle.

3.2.3 Learning curves

In Industrial Engineering, learning curves play a crucial role in estimating initial production costs. It e is a valuable methodology and tool for management. It enables them to predict future manufacturing costs, assess workforce needs, and evaluate equipment and labor capacity. As operators become more familiar with a product or process, their efficiency increases. In a factory where operators are just starting or where the product variety is large, the operators need additional time to reach the established standard time. (Maynard & Zandin, 2023), defines a learning curve as: "A plot of productive output or unit work times of an individual or group as a function of time or output per unit time; used to predict the learning rate in starting up a new job or project. A learning curve is usually exponential and flattens out with time.".

The most common and useful model describing the effects of the learning curve was discovered by T.P. Wright. He delved into the production of airplanes and noticed an exponential trend between the cumulative unit cost of producing each airplane and the total quantity produced, see equation 3.1. This relation became known as the

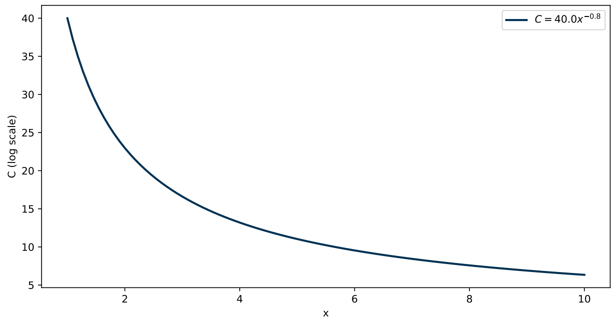


Figure 3.2: Learning curve Wright.

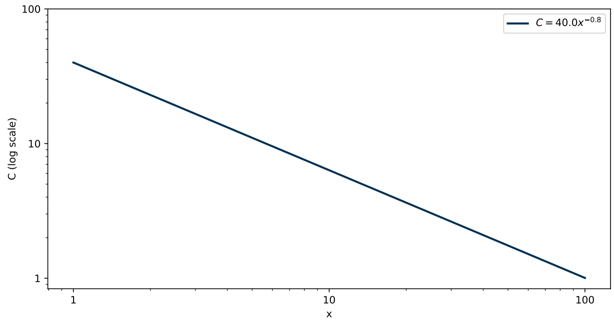


Figure 3.3: Learning curve Wright logarithmic scale.

Wright curve and is plotted in Figure 3.2. His curve is also often plotted on a logarithmic scale, see Figure 3.3, for an easier interpretation and analysis. Such learning curves can be made for individual performances, process-specific learning performances or performance in general.

$$\text{Cumulative average time per unit} = Fx^{\frac{n}{x}} \tag{3.1}$$

where: F = Theoretical time of the first unit
x = Cumulative quantity of units produced
n = Wright's learning curve constant

Other models were also studied such as Boone's model, which addresses the nonconstant rate of learning, leading to a flattening effect towards the end of production cycles, with its learning rate estimated as a decreasing function over time. This model incorporates a decay factor (c) that reflects the diminishing learning effects, ensuring the learning rate decreases with each additional unit produced, making it more accurate for processes with minimal automation and high manual labor. In contrast, Wright's model is more precise for other values of incompressibility, as evidenced by significant reductions in MAPE and SSE, demonstrating the effectiveness of Boone's learning curve equation.

$$\text{Cumulative average time per unit} = Fx^{n/(1+\frac{x}{c})} \tag{3.2}$$

The learning curve of operators depends on several factors that can be challenging to quantify. These factors as described by (Maynard & Zandin, 2023) include operator proficiency, product and process familiarity, and loss of learning.

- **Operator Proficiency:** This depends on factors like task complexity, job cycle duration, and repetition of similar motions. Each proficiency level requires different skills and efficiencies to meet the standard time. In the aerospace industry, proficiency is often achieved after producing 1,000 units, a process that can take weeks to months (Maynard & Zandin, 2023).
- **Product and Process Familiarity:** Familiarity with the product and processes significantly impacts the learning curve, as operators who understand product requirements and master basic skills perform more efficiently. As they gain experience, their familiarity enhances their efficiency and initial performance in production.
- **Loss of Learning:** Over time, natural learning loss can occur for various reasons, such as the wide variety of products and new prototypes produced in Almelo, which disrupt production continuity. Additional factors include operator turnover and irregular product demand, leading to infrequent production.

3.2.4 Normal and standard time

Normal time represents the average time that is required to perform a specific motion or task under certain conditions. It is the sum of manual time, which is the duration of completing a defined element of work by hand or with tools, and process time, managed by machines. The time study analyst records the worker's pace as a performance rating, and normal time is calculated by multiplying the observed time by this rating, with multiple cycles averaged for accuracy.

As described in section 3.2.2, adding all allowances to the normal time results in the standard time as described in equation 3.3, which is used to define "A fair day's work" (Niebel & Irwin, 1960). This refers to the amount of work that a qualified employee can produce at a normal pace while utilizing time efficiently. Conducting a time study requires that the operator fully understands the process and should not be learning new techniques during the study, as this would amplify the learning curve effects, especially in the initial phase, where it follows an exponential trend, as shown in figure 3.2. The operator must already know the process to minimize these effects. Additionally, each element of the process must be standardized to reduce variability, ensuring reliable observations. Without standardization, the results of the study could be questioned, leading to mistrust or friction in the outcomes (Niebel & Irwin, 1960).

$$\text{Standard Time} = \text{Normal Time}\left(\frac{100}{100 - \text{Allowance (\%)}}\right) \tag{3.3}$$

When time study is done extensively a Standard Data System (SDS) can be created. This is a comprehensive database that contains normal times for all work elements performed in the facility. After analyzing all work elements with their inherent variability, an organization can establish precise standard times.

3.3 Work sampling

Work sampling is yet another technique for measuring the fair day's work. It is possible to measure the delays and activities of an operator and see which proportion of time the operator is performing each task. It also helps in establishing the time standards for a certain job at a certain condition.

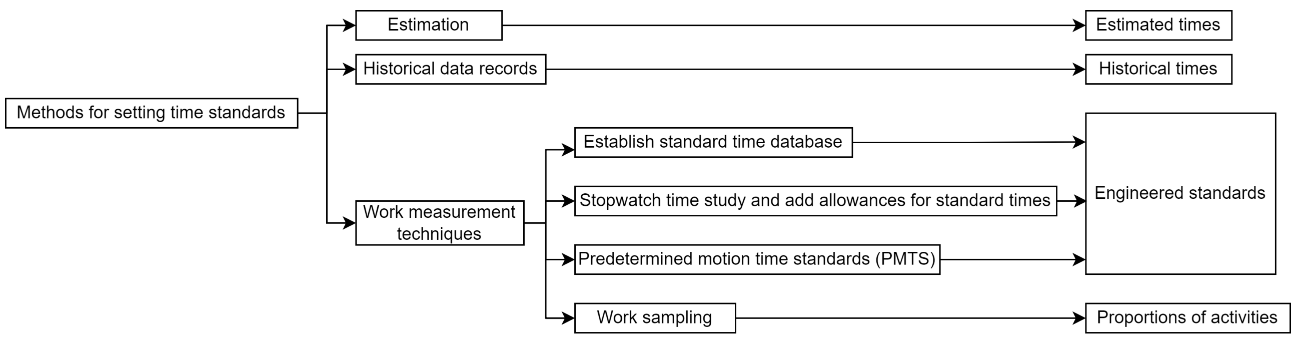


Figure 3.4: Time measurement techniques summarised (Groover, 2007)

A work sampling study involves numerous random observations, during which the state of the subject is recorded and categorized into predefined activity categories. By analyzing the proportions of observations in each category, conclusions are drawn about the overall work activity. Work sampling relies on the binomial distribution, where "p" represents the proportion of time spent on a specific activity (Groover, 2007), and this is often approximated by the normal distribution for ease of calculation. The accuracy of the normal approximation improves with the large number of observations made in a work sampling study. Although average task times and standard times can be determined, work sampling is less precise than direct time studies or predetermined time systems. However, work sampling serves as a practical alternative in case more accurate measurement techniques are impractical due to time constraints. In these cases, work sampling provides a useful estimate of average task time, which is calculated by dividing the total time for a specific category by the number of completed work units, see equation 3.4. Moreover, setting a standard through work sampling requires precise categorization of activities and an evaluation of the worker's performance. Accurate calculation also depends on tallying the number of work units completed during the study.

$$T_{ci} = \frac{p_i(TT))}{Q_i} \tag{3.4}$$

where: Tci = the average time for task I
pi = the proportion of observations associated with this category
TT = the total time of work sampling study
Qi = total quantity of work units produced

In (Groover, 2007), an example shows how average task times are determined using work sampling, although the data has limitations since work units likely include different types of parts with varying setup and machining times. Despite teh limitations, the study can offer valuable insights. For instance, it reveals the average setup time per batch and cycle time per part. However, these findings should be evaluated by an expert familiar with the process to ensure the setup and cycle times align with expactations. A confidence interval used for proportions to assess the data is as follows:

$$\hat{p} \pm c\sqrt{\frac{\hat{p}(1-\hat{p})}{n}}, \text{ where } \Phi(c) = 1 - \frac{1}{2}\alpha \tag{3.5}$$

For convenience is it possible to determine the number of observations required for a confidence interval of alpha, the formula is presented below:

$$n = \frac{z^2 p(1-p)}{\sigma^2} \tag{3.6}$$

where: σ = standard deviation
n = number of observations required
z = standard score

Establishing category definitions requires precision, ensuring alignment with the study's objectives. These definitions should be easily recognizable by observers and must not overlap, ensuring each category is distinct. Assessing performance in work sampling can be challenging due to the limited time available for judgment. Even though it is challenging, it is important to evaluate how fast or how hard the worker is working to make sure the time standard matches what the company considers normal performance. However, if the activity falls under non-work categories (e.g., idle time, away from workstation), performance rating is unnecessary (Groover, 2007). To conclude, work sampling could be valuable in offering management information about the average time needed for each work task.

3.4 Data-driven methods

In this section, we explore data-driven estimation methods for unknown processing times, focusing on their integration within Industry 4.0 frameworks. Industry 4.0 introduces a wide range of innovations through various digital technologies, it leverages real-time data and advanced analytics, these methods aim to enhance decision-making and help with the transition toward smart manufacturing. This methodology emphasizes real-time data collection, monitoring, and analysis, using big data analytics (Koh et al., 2019). Big data analytics enhances data collection from multiple sources and enables comprehensive analysis, real-time decision-making, and failure detection, supporting predictive analytics. However, achieving the full potential of big data requires overcoming challenges related to data quality and analysis capabilities.

(Yamashiro & Nonaka, 2021) proposes a machine learning approach to accurately estimate unknown processing times in manufacturing environments, where traditional methods often rely on simple distribution assumptions. They use models such as LightGBM and Gaussian process regression. The authors demonstrate that their method can effectively estimate complex processing times from real factory data, resulting in an average reduction of approximately 30% in makespan during scheduling optimization.

The paper of (Hajj Chehade et al., 2024) addresses the challenge of estimating manufacturing time for offer pricing in the metallurgy industry, particularly in MTO and ETO contexts similar to Benchmark where product diversity complicates pricing due to reliance on expert experience. The new approach introduces a machine learning framework that integrates structured and unstructured data, using CatBoost to optimize estimation accuracy. Tested in a real industrial case, CatBoost emerged as the top-performing model, demonstrating the method's effectiveness.

3.5 Multiple linear regression

A practical for predicting the response of a predictor variable is linear regression. When the outcome depends on multiple predictors, multiple linear regression is a more suitable option to use, as it allows multiple predictors in the same algorithm. To achieve this, slope coefficients are assigned to each predictor within the model. In a general scenario with (p) unique predictors, the multiple linear regression model is formulated as follows in equation 3.7.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p + \varepsilon \tag{3.7}$$

Where X_j represents the jth predictor, and β measures the relationship between that variable and the response.

(Haberle & Graves, 2001) discuss how to determine production times using regression involves modeling the cycle time (considered the dependent variable) as a function based on several predictor variables (independent variables). By using data from previously manufactured products, a dataset is constructed to build a regression model. Consequently, the model will be able to predict production times for new products based on the specific predictor variables or features.

When building reliable regression models, it is crucial to address collinearity, which occurs when two or more independent variables are highly correlated. This can be identified by determining the correlation matrix, which indicates potential issues in the data. However, collinearity can exist between more than two variables without showing a high correlation, this is known as multicollinearity. Depending on the specific regression model this issue will need attention when detected. There are methods to handle collinearity, such as combining correlated variables into a single variable or removing the highly correlated variables altogether. To mitigate the multicollinearity it is possible to calculate the VIF. The VIF shows how much the variance β_j of a regression coefficient is inflated due to collinearity with other predictors. The VIF is determined by of fitting the full model divided by the variance β_j of its own. the smallest value the VIF can have is 1, and above 5 or 10 is considered problematic (James et al., 2021).

In addition, it is important to check if the model contains a systematic error, also called bias. Bias influences the outcome and can lead to an over- or underestimation by the model. There are multiple causes for bias, such as when a linear relationship is assumed when the data is non-linear or when not enough variables are used and the model is too simple to capture all patterns in the data. A technique to address this is to look at the residual plot. If a pattern is present, it identifies the presence of bias. Another indicator is a high mean squared error.

3.6 Conlusion

To conclude, this chapter offers a review of the existing literature concerning the research question: "*Which methods are present in the literature for estimating the quoted production times for assembly processes?*". The literature presents multiple estimation methods for determining the production times. Each method has its advantages in each product phase as shown in figure 3.1. The analogical method results in the most precise estimates by using available data on similar products. However, this method is complex and requires a lot of data, which is not always available. The parametric method is easier to apply since it does not require a lot of data and is also suitable for the feasibility phase of a product. In addition, the analytical method breaks down costs or time into smaller elements or tasks and is suitable for any other phase than the first and second phases. However, this method is resource-intensive, since more specific data has to be gathered and requires breaking down the tasks into smaller and more detailed tasks, which takes longer than an analogical method that simply compares a product with other similar products. Furthermore, the intuitive method uses the knowledge and experience of experts. However, this is generally only used when data is unavailable.

Time study will provide an overview of the elements in the processes, which is essential for analyzing and understanding the current reality. Simultaneously, the time study serves as data collection that can be used for other purposes, such as data reliability analyses. Therefore, analysis in the solution design to verify the suspected unreliability of the existing production data.

To relate to the production time estimation problem experienced by Benchmark, the most ideal estimation method would be the analogical method. However, as stated in section 3.1.2, a lot of usable data must be available. Therefore, a thorough analysis of the available data at Benchmark must be conducted before choosing a certain estimation method. Another suitable estimation approach for Benchmark would be the parametric method. This is because the LQT is mainly used for products in the early product phase.

Chapter 4

Methodology

Based on insights gathered from both the context analysis and literature review, this chapter begins with a study on the accuracy of production records, followed by the methodology for the estimation of the production times. Section 4.2 reveals that the production records are unreliable to use for a new tool, making an analogical estimation method unfeasible. Therefore a parametric estimation method is picked as the next best alternative.

The design for this research is split into two phases. The first phase focuses on determining key parameters necessary for the estimation of the production times, which is structured over the next two chapters. In this chapter, the methodology used to determine each of the parameters for each process is outlined. It provides a detailed explanation of the techniques and procedures that will be used for the data collection and analysis. In this chapter, the following research question will be answered:

How can the production times for the processes be estimated?

Chapter 5 presents the results obtained from applying the outlined methodologies in this chapter, where each subsection concludes by summarizing the parameters that will be used as input for the new tool.

Finally, the second phase is presented in Chapter 6 and will consist of developing and validating the new tool that supports the making of accurate production time estimations for each of the processes with the determined input parameters of the first phase. In figure 4.1 the methodology, results, and solution design are visualized for the five processes, allowances, and learning curve.

4.1 Available data

As concluded in section 3.6, an analogical method would provide the most accurate production time estimation. However, this method requires reliable production records and data. Within the manufacturing department of Benchmark, various types of data are collected through different processes.

PFS production records data
The application software called PFS stores all production records data and can be easily extracted from the system. These production records are named as PFS data at Benchmark. This data includes start- and ending times of production processes per product and need to be logged by operators. In theory, this data is accurate and well-suited, but there are doubts about the accuracy (see section 2.5). Therefore, a data analysis of the available PFS will be performed and described in section 4.2.

SMT production time data

Production records data of the SMT line are stored in a separate database by the SMT line itself. The line manufacturer designed a dashboard that shows the actual productive, stand-by, scheduled- and unscheduled downtime taken from this database. However, this data can not be exported from this database which is inconvenient.

Fortunately, there is a database that does contain accurate production times. This database was created because process engineers who need to program new products into the SMT line must run a simulation of the SMT process for each new product. The result of those simulations provides an estimated production time with an ensured accuracy of 95% by the SMT line manufacturer. Luckily, the process engineers have documented these times themselves for each product, ensuring reliable data is available.

Component type and manufacturer data

Additional available data that could be used are the component data of the PCBAs. This includes the ODB and BOM data, which are also used in the existing LQT, as described in section 2.3. The ODB data consists of a list of all the components that are placed on the board with their reference (coordinate), description, part number, quantity, number of pins and if it is a THMT (Pre-wave) or SMT component. The BOM is the list with all components and consists of the description, part number, reference (coordinate), and quantity. Additional available data includes the manufacturer name and item group for all components, which can be found in a database.

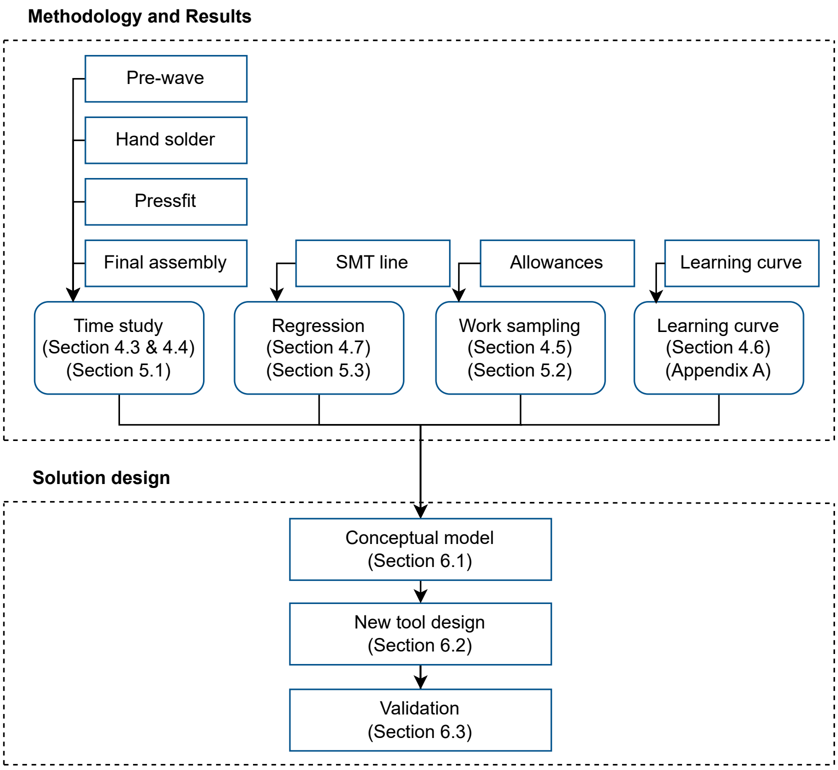


Figure 4.1: Overview of the following chapters methodology, results and solution design visualized using a flowchart.

4.2 Reliability analysis of production records

As the PFS data is suspected to be inaccurate, an analysis is conducted as follows. The accuracy of the PFS data is calculated, using equation 4.1 which calculates the absolute percentage error between the estimation, divided by the actual.

	Overall		Processes							
	Average Accuracy	Average σ	Pre-wave Assembly	σ_{pw}	Hand Solder	σ_{hs}	Assembly	σ_A	Pressfit	σ_{pf}
Median	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Average	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Weighted Median	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Weighted Average	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Number of data points	[illegible]		[illegible]		[illegible]		[illegible]		[illegible]	
Avg. number of PFS data points	[illegible]		[illegible]		[illegible]		[illegible]		[illegible]	

Note: : Median shows superior performance in both the normal and weighted variants.

Figure 4.2: Average accuracy: PFS data - time study data [%]

	Overall		Processes					
	Average Accuracy	Average σ	Pre-wave Assembly	σ_{pw}	Hand Solder	σ_{hs}	Final Assembly	σ_{FA}
Median	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Average	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Weighted Median	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Weighted Average	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Number of data points	[illegible]		[illegible]		[illegible]		[illegible]	
Avg. number of PFS data points	[illegible]		[illegible]		[illegible]		[illegible]	

Figure 4.3: Average accuracy: PFS data - Secondary operator data [%]

$$Accuracy = \left| \frac{Estimation}{Actual} - 100\% \right| \tag{4.1}$$

Here, the actual times for production processes are obtained by time study as described in section 3.2 and by handing out time sheets to be filled in by the operators. The equation takes into account an unbounded accuracy. This problem focuses solely on the deviation, making the distinction between overestimation and underestimation irrelevant in terms of accuracy. Due to the design of the software, the data will naturally contain both overestimations and underestimations, rendering further research on this aspect unnecessary.

Because inherent problems are present in the data, four statistical measures are tested to see which yields the highest accuracy, namely the median, average, weighted median, and weighted average. Besides the average, the median is used because it is less sensitive to extreme values (outliers). The weighted average and median are also used to account for variability between the quantity of produced PCBAs per production record. A higher weight is given when more PCBAs are produced per production record compared to when only one PCBA is produced.

4.2.1 Results

For the comparison with data obtained by time study, the four manual labor processes are analyzed: Pre-wave Assembly, Final Assembly, Pressfit, and Hand Solder. In total, XX data points are included and the results are shown in figure 4.2.

Besides time study, we distributed time sheets to operators that they needed to fill in. This allowed for more data that can be used for analysis and validation and is a precise way of tracking the production times. An example of the time sheet is presented in Appendix D. This approach is seen as additional input since it gathers more data than just a single person can gather with time study. The comparison with the time sheet data included XX data points and is shown in figure 4.3. Again, Pressfit is not verified, because time sheets were not available for this process.

In both analyses, the weighted median achieved the best results, demonstrating the best average accuracy and the lowest variability. Conversely, the normal average showed a very low accuracy of XX%, more than twice that of the weighted median for the comparison of the secondary operator data. When the data is skewed, the median is a more accurate indicator for the center of the distribution, because the average is pulled towards the tails. In this study, the performance of the average is severely inaccurate compared to the median. This supports the hypothesis that the PFS production records are very inaccurate and concludes that they are not suitable for further use.

4.3 Parametric time estimation

Based on the literature review, the ideal solution for Benchmark would be a new LQT developed using an analogical time estimation method. As the inaccuracy of the PFS data is proven, it is not possible to apply the analogical method. As a result, we designed a final solution approach for the production time estimations that integrates both the parametric and analytical time estimation methods. The integration ensures a higher accuracy, where the new parameters are to be determined based on the current production processes.

The production parameters that will be determined, are defined for smaller steps of a production process based on key influencing factors. We identified those key influencing factors, such as the quantity of components, component type, and other component characteristics. The component details need to be extracted from the BOM and ODB data or have to be filled in manually. The smaller steps of a production process will be time studied for the four manual labor processes: Press-fit, Pre-wave, Hand solder, and Final assembly. Regarding the SMT line which contains reliable data, production parameters are defined by a multiple linear regression model. For the other production processes, process engineers are interviewed to define the production parameters. This ensures that necessary details are captured despite not being able to time study these processes due to time constraints.

The existing LQT also uses parameters, but these are less complete, unclear defined, and not time studied. Unlike the existing parameters, the new production parameters account for variability between different production processes that are needed for the production of a PCBA and key influencing factors. The new production parameters will be clearly defined, so they can easily be updated when new PCBAs are produced or when a part of the production process is replaced for example by a faster machine. This new solution approach will be more complete, account for more parameters, and will be determined by rigorous research and extensive analysis. An overview of the solution design is visualized with a flowchart in figure 4.7.

4.4 Method for analyzing time study

The methodology employed for time study is designed to ensure a systematic approach for the data collection and procedures followed to gather and analyze the data and determine production parameters. By following these structured steps, we aim to find accurate production parameters.

Time study is chosen in this research because reliable production data is unavailable. It provides a direct and systematic method to measure the work performance of the operators. By observing and recording the time taken for each task, it helps to establish accurate standards. This approach ensures that decisions are based on actual observations of the reality instead of unreliable or incomplete data.

The first step is to select the processes and products that will be studied. The processes that are time studied are the four manual processes: Pre-wave Assembly, Hand Solder, Pressfit, and the Final Assembly. We picked the products based on their characteristics and whether it contains many interesting features that should be time studied. This is done by having interviews and identifying what the time drivers of a process are, that can eventually be quantified and parameterized.

The data collection will be done with a time-tracking tool to record the time required to complete each task that uses TMUs. Multiple products will be studied to account for variability and ensure data reliability. Some products will be studied twice to check for variability between the operators. The performance of the operators executing the tasks will be evaluated and they will be assigned a performance rating based on observed speed and skill, which will be used to calculate the normal times. To account for factors such as fatigue, delays, and personal needs, allowances will be applied to the normal time. This ensures that the calculated times reflect realistic working conditions. In section 3.3 we will determine this allowance using work sampling and literature. When the allowances are determined the standard times are calculated to reflect a realistic production time for the product. The time measurements in this research are initially recorded using TMUs. However, for this report, all times will be converted into seconds for readability.

The analysis of the time study data involves assigning a parameter name to each element. Ultimately, the values of each parameter will be summed, through which the time required to perform a single instance of each parameter can be calculated. By the end of the analysis, all elements will have an assigned parameter name, allowing for a detailed analysis of the total time needed for this parameter.

As stated in section 3.1.1 the accuracy of the total time estimation of a process can be improved when multiple parameters are considered. This is also applied in the time study of the four manual processes. The mathematical approach to combine the elemental tasks into production parameters for an operation and determine a final time estimate is described below. The mean of the final production time of an operation (μ_T) can be calculated by summing the mean values of each parameter (μ_{p_i}) and multiplying each parameter with the number of units (x_i) included for this product. This relationship is represented in equation 4.2.

$$\mu_T = \sum_{i=1}^{n} \mu_{p_i} x_i = \mu_{p1} x_1 + \mu_{p2} x_2 + \ldots + \mu_{pn} x_n \tag{4.2}$$

The variability or uncertainty in the total production time is given by the standard deviation (σ_T). If the parameters are independent, the standard deviation of the final time can be calculated using equation 4.3.

$$\sigma_T = \sqrt{\sum_{i=1}^{n} (\sigma_{p_i} x_i)^2} = \sqrt{(\sigma_{p1} x_1)^2 + (\sigma_{p2} x_2)^2 + \ldots + (\sigma_{pn} x_n)^2} \tag{4.3}$$

In this research confidence intervals with an ($alpha$) of 0,05 are constructed for each parameter to find the range in which the true mean of the parameter lies. This is done using the t-distribution, because it is suitable for small sample sizes and is better against bias, making it suitable for the time study dataset (“Statistics for Engineers”, 2023). The CI formula is as follows:

$$95\% - CI(\mu) = \bar{x} \pm t_{\alpha/2, df} \frac{\sigma_s}{\sqrt{n}} \tag{4.4}$$

Each sample contains a different number of products in each. Treating these as equal samples would not be fair. to properly account for the number of observations in each sample the number of products is used as a weight.

the standard deviation is determined by taking the square root of the weighted variance calculated in equation 4.5, (*DATAPLOT Reference Manual*, 1996).

$$\sigma_s^2 = \frac{\sum_{i=1}^{N} w_i (x_i - \bar{x})^2}{\sum_{i=1}^{N} w_i - 1} \tag{4.5}$$

4.5 Method work sampling

This section answers a part of the sub-question: ***Which data is required as input for the tool?*** Work-sampling is a proven and effective method for collecting labor utilization data as described in section 3.3. It will be used in this study to determine the productivity levels of the manufacturing department, which is necessary for calculating the final gross hours in the LQT. With work sampling a single observer can study the entire plant operation or focus on specific phases without disrupting the daily routine. Workers pay little attention to the observer, making observations quickly and discreetly, causing minimal interference.

For this study, the tasks that are selected will be explained. Because of the large size of the factory, it is challenging to study the full factory. The scope of this study is the part of the factory with the manual operations with roughly 15 people performing these tasks every day. It consists of the following processes: Touch-up (Manual processes), Hand soldering, Inspection (Final, General, or In-process), Depanelization, Pre-wave Assembly, Sub and Final Assembly, Optical inspection, Gluing, and Other (e.g., assisting with irregular tasks). The processes such as In-process Inspection and Final Inspection, which cannot be distinguished without asking, are grouped into one category, Inspection. The other categories that occur during work sampling and cannot be attributed are idle, walking, talking, and currently working but not around. Instances, where a person is receiving help, are classified under 'Other'.

	Activity type	Activity
Productive	Touch-up / Hand-solder	Touch-up Manual soldering Rework / reprocessing a product
	Optical inspection Outgoing inspection Inprocess inspection Final inspection	Visual inspection Final quality check Inprocess inspection Final assembly inspection
	Depanelization	Depaneling operations
	Pre-wave	Component insertion
	Assembly	Preparing, precutting components Assembling mechanical parts
	Other	Doing unrelated tasks such as helping somewhere Kanban component or tool retrieval Workstation preparation
	Glueing	Applying adhesives
	Walking	walking for tool and material collection Bringing products to next operation
Non-productive	Currently working but not around	Searching for material Searching for tooling Resolving conflicts with engineering
		Personal care Smoking
	Talking	Support Having regular talks with other operators
	Idle	Idleing Being on the phone

Figure 4.4: Structure of the work sampling categories and their related activities, productive is marked in green and non-productive is marked in red.

Each day a randomized schedule for data collection is made with time stamps at which a sample should be taken.

During the observation we will walk past the working stations and observe how many people are performing in each category. The number of observations at that moment is later compared with anonymized employee data indicating how many people are clocked in at that time. This typically takes five minutes and is done by just checking visually as cameras are not allowed due to ITAR. Any discrepancies between these two datasets are categorized as ’currently working but not around’. Operators are observed from a distance to determine their activities, which are categorized to differentiate between tasks.

The data is then analyzed and divided as proportions expressed in percentages. This will determine the percentage of time that operators are performing value-adding activities. The number of required observations is determined with equation 3.6. After all observations are made and filled in the confidence intervals for proportions are calculated using equation 3.5. The data with the worked hours, that is being used is anonymized by human resources so that it is not possible to link the data to any employee.

Limitations in this study are the non-value-adding categories which include idle time and talking, and the most challenging category, ’Currently working but not around,’ which applies when an operator is not in the factory but elsewhere on site for various reasons, such as personal care or smoking breaks. Distinguishing between non-value-adding idle time and value-adding activities within the category is a complex task in this research. For example, the ’Currently working but not around’ category is classified as non-value adding but this category can also include value-adding activities like searching for tools, retrieving materials from the warehouse, or consulting with the engineering department about a product. Furthermore, talking can also be challenging to categorize because experienced individuals might be instructing less experienced colleagues on their work or just having a conversation. Although it is often apparent whether someone is providing assistance or simply engaging in casual conversation, it remains susceptible to error.

4.6 Method learning curve

Determining learning curves enables understanding and improvement of the accuracy for estimating production times because this is a way of incorporating the improvement in performance operators have over time when assembling as they gain experience. However, gathering data to accurately model these curves presents challenges. For this study, we will utilize Wright’s formula as described in section 3.2.3. By utilizing Wright’s formula with the learning curve constant, we aim to model the cumulative average time per unit. Determining the learning curve constant (n) is challenging because of difficulties in data collection and factors that influence learning. These factors include operator proficiency, product and process familiarity, and loss of learning. These factors are described in section 3.2.3 and are hard to quantify for Benchmark.

For this study, we conducted a generalized learning curve describing the learning curve for all manual processes and operators. The learning curve is determined based on empirical data of the time study and is an average of a wide range of products and processes. Since the factory is a high mix, low volume the number of products produced by each operator varies widely and some products will not return for some time, in which they could have forgotten how the product was exactly made. This all adds to the complexity of determining a learning curve.

Unfortunately, the PFS data contains the total time spent on a full order and not on manual processes, which makes the data unusable for determining the learning curve. The data that will be used, are the normal times of the time studies. All these samples will make up the empirical data on which a learning curve will be determined. The cycle time of each product is plotted in Excel with a fitted trendline that is based on Wright’s formula. All the exponents are then analyzed on which an average will be based. Limitations of this study are that the data for the learning curves is limited because the samples and batches that are observed are relatively small. Orders can be in the range of one to sometimes 100 for the smaller PCBAs, which can not be checked because these can take multiple days.

4.7 Method SMT line regression

The SMT line is crucial in the production process, as the electrical components become smaller, manual placement becomes impractical, making the fully automated SMT line essential. Particularly the pick-and-place machines, which are identified as the bottleneck of the SMT line (Vainio et al., 2015). Therefore, the consideration was made that the full production times for the line can be determined by focusing on the bottleneck since the bottleneck determines the maximum throughput of the entire line. This section describes the method for performing a regression analysis on these machines and determine the productive time the line is running for a product. The productive time is the actual time spent on a product and does not include scheduled and unscheduled downtime. A multiple linear regression model is chosen for reasons discussed in section 3.5. Python is used, including the sklearn library (Scikit-learn, 2024), to make the multiple linear regression model with machine learning.

4.7.1 Data preparation

The step-by-step approach for this regression analysis is visualized in a flowchart in figure 4.5. First, we will collect data from two sources. The first source consists of old LQTs of products that contain necessary ODB data:

- Width and length → used to calculate the panel area of the PCBA
- The number of total SMT components
- The number of unique SMT components
- The number of chips
- The number of ICs
- The number of large components

This data from old LQTs are exported and combined into a worksheet that is subsequently loaded into the Python script to perform the regression analysis. The second source is from the SMD dataset, which contains the simulated cycle times and the panel size. The panel size represents the number of PCBs that is fit in a panel. In total, we collected data of 26 PCBAs, resulting in 52 samples as the upper- and downside of the PCBA are used as a single sample.

Further data preparation consist of making a dataset containing all information per PCBA side, which is necessary to be able to train and test the model. This preparation is essential because the cycle time for the SMT line is typically provided for an entire panel, which may include multiple PCBAs. Input values, such as components, must be adjusted to account for a full panel. Similarly, the area measurements must be modified as well.

4.7.2 Data analysis

The dependent variable (marked green in figure 4.5) that is used for the regression are the simulated cycle times of the 52 samples. The final independent variables (marked blue in figure 4.5) are picked based on the found literature for estimating the cycle times of a pick-and-place machine (Vainio et al., 2015). The number of (unique) components are used because each component is stored on a reel. The feeder banks can contain tens of these, from which the pick and place machine picks the component, which means the length of the feeder banks or the number of unique reels can be important. We also selected the length and width of the panel as important since this could relate to how far the spindle has to travel to place a component. The cycle times are calculated for one panel. We also performed the final regression with all available features, but it was found that the variables *Number of chips*, *Number of large components* and *Number of ICs* did not contribute to a good model.

The regression model will be developed in Python with the sklearn library. The ordinary least squares method is used for the linear regression model, because of its simplicity. The assumption is made that the relationship between

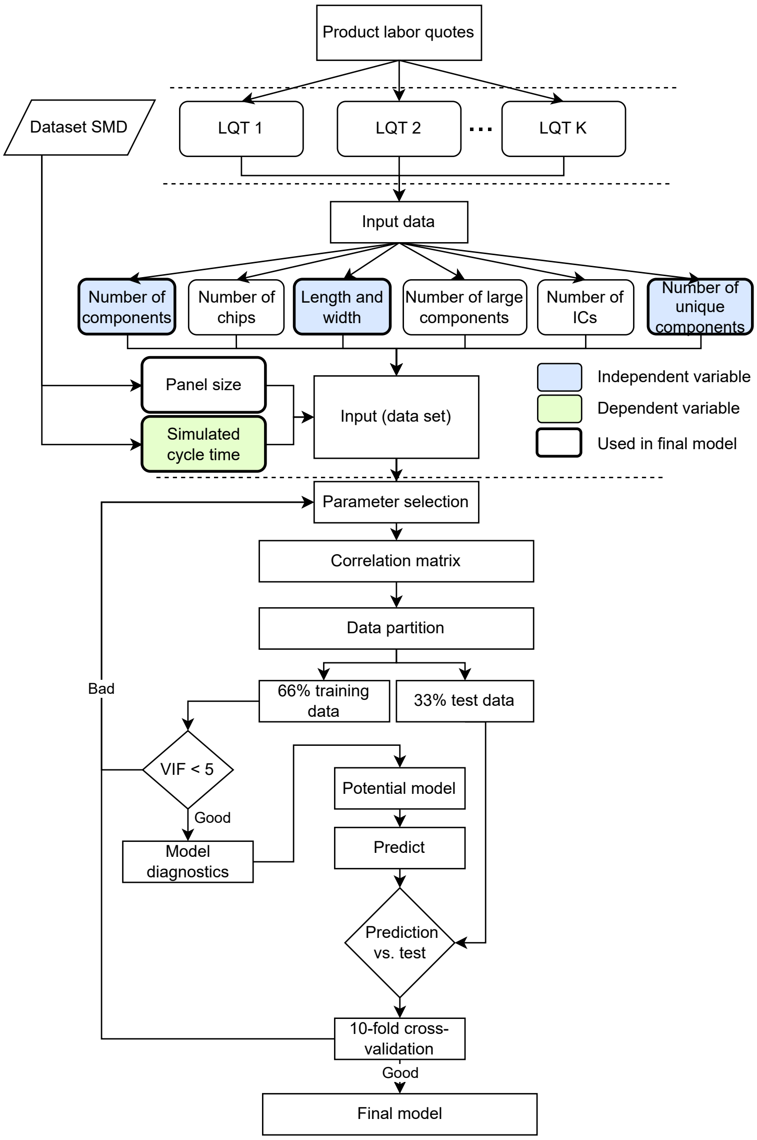


Figure 4.5: Flowchart of the multiple linear regression analysis performed in this study for the pick-and-place machine of the SMT line

the variables is approximately linear. Another assumption made is that the residuals of the model are normally distributed. To ensure robust model evaluation, the dataset is randomly divided with 66% allocated for training and the remaining 33% reserved for testing. To ensure the model is robust a k-fold cross-validation is performed. The dataset is split into k parts, known as folds. The model is trained using $k-1$ of these folds and validated on the remaining fold. To ensure generalization of the model, this procedure is repeated k times, ensuring each fold serves as the validation set once, see figure 4.6. For assessing the accuracy of the model we will look at the metrics MAD and MAPE as explained in section 2.4, and the Mean Squared Error (MSE). This error metric is sensitive to outliers since the error is squared, the formula is given in equation 4.6. For these metrics, the error e will be defined as actual value y_i minus the predicted value $\hat{y}_i$.

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{4.6}$$

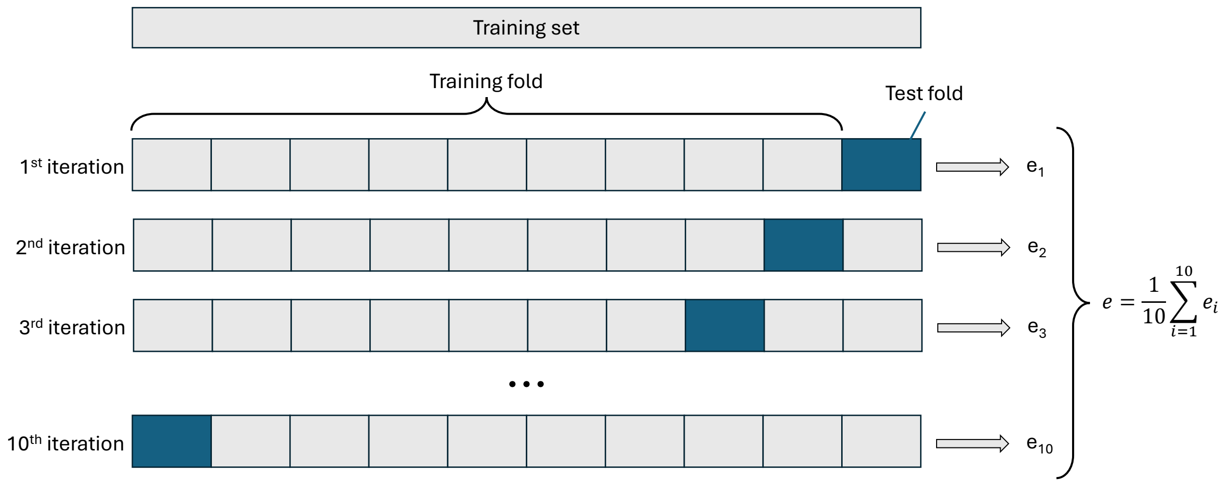


Figure 4.6: 10-fold cross-validation, where the blue testing fold is marked in blue and is different for each model.

For this analysis, the estimation for the pick-and-place of the existing LQT will also be analyzed. In equation 4.7, the formula for the existing LQT is shown to determine the cycle time in seconds for one side of a panel:

$$\text{Cycle time} = \text{Number of SMT Chips} \times 0,2 + \text{Number of SMT ICs} \times 0,4 + \text{Number of SMT Large} \times 1 \tag{4.7}$$

The size of the components was used in this model because larger components require nozzles with a lower capacity, which increases the cycle time.

4.8 Conclusion

In this chapter, four proposed methodologies have been described for determining values for the parameters of 5 production processes, allowances, and learning curve. An overview of each method and type of data that is used is visualized in figure 4.7.

The four time-studied processes will be analyzed by categorizing all time-study elements into parameters. The averages of these parameters will be calculated with confidence intervals to determine the spread in which the true average for each parameter lies. Finding the true average is challenging because it is influenced by variations in the data. To address this a sufficient number of observations is necessary to minimize these effects and reduce the spread of the confidence interval. The confidence intervals will help with quantifying the uncertainty in the estimate and can give guidance in the future if more observations are needed. However, getting a sufficient number within this timeframe is difficult. A balance between the number of observations and the desired confidence level is essential in achieving reliable results in a time study.

The method for a work sampling study is described to empirically determine the productivity level of the manual processes and determine an allowance. With the absence of data in this part it was necessary to collect data and observe the operations to verify the proportion of time each task spent.

Furthermore, a method for applying Wright's learning curve model to analyze the improvement in performance by the operators. The time study data that is gathered will be used to fit a learning curve, that represents the relationship between practicing and gains in efficiency during the assembly.

To determine new parameters for the SMT line a regression analysis will be performed and, the following steps were undertaken. First, data was gathered from existing LQTs and an input sheet of known cycle times. This data was then prepared by cleaning and organizing it for analysis and forming a dataset. Next, the method for the regression model is developed using the prepared data. The reliability of the model will be validated using a k-fold cross-validation. Finally, the accuracy of the model and performance were evaluated by calculating the MSE, MAPE and MAD.

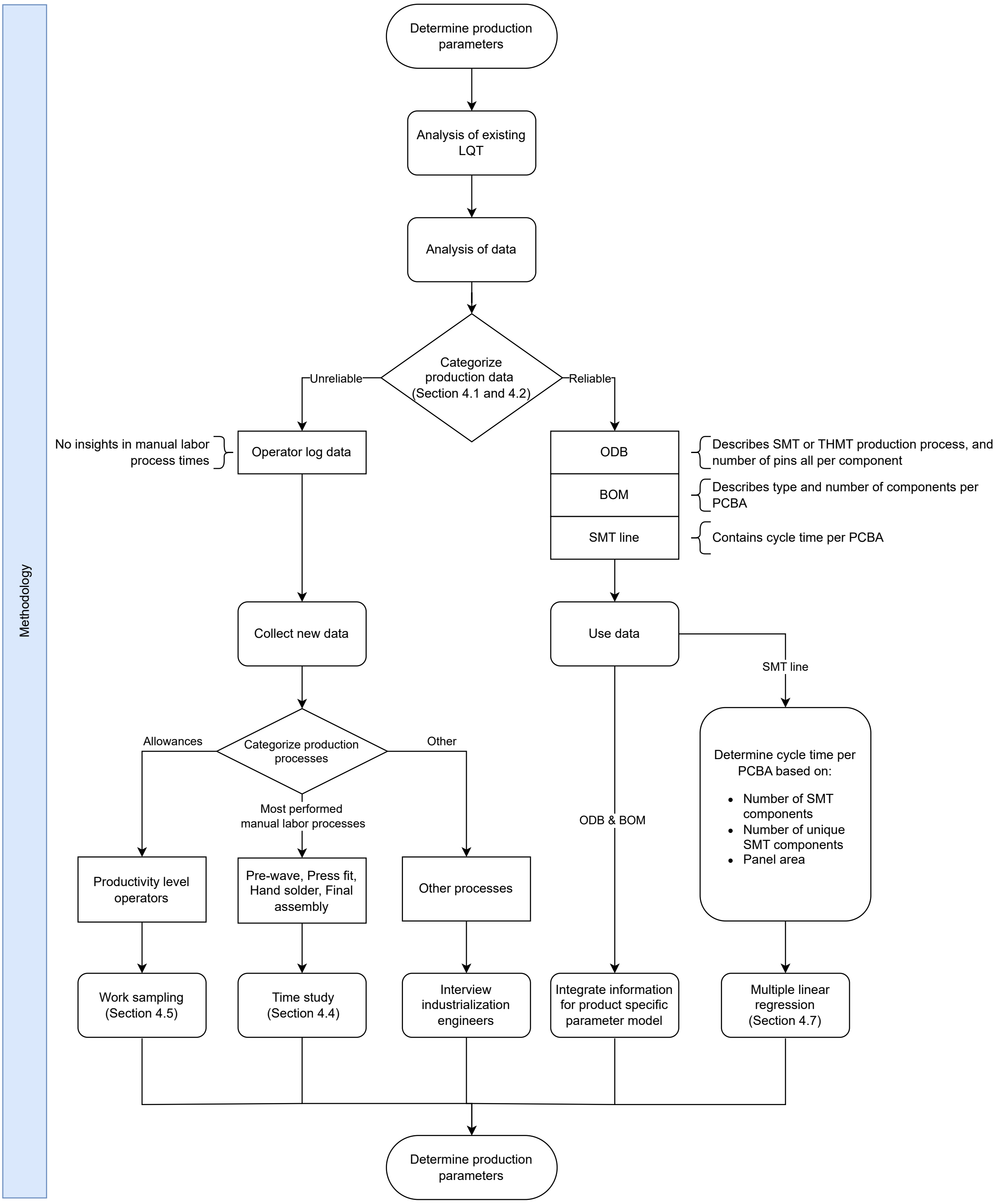


Figure 4.7: Detailed description of the methodology for each of the determined parameters in this research, visualized using a flowchart.

Chapter 5

Results Analysis

This chapter presents the results of the four methods described in Chapter 4. Firstly, the results of the time study show the determined production parameters for each of the four manual processes: Final Assembly, Hand Solder, Pressfit, and Pre-wave Assembly. The production parameters are established with confidence intervals to approach the true average of a parameter.

Secondly, the allowances, which account for fatigue and personal care were determined through a work sampling study. By observing a set of tasks over a set period, we calculated the appropriate allowances to form the standard times. These allowances ensure that the estimated times reflect realistic working conditions, enhancing the accuracy of the estimated final production times.

Thirdly, the results of the regression analysis, used to model and predict the cycle time of the pick-and-place machine for the SMT process, are presented. This approach allowed us to identify the relationship between task duration and influencing factors, providing a reliable basis for time estimation.

Though Wright's learning curve model was applied to assess how the efficiency of the workers improves over time with experience, the findings related to the learning curve have been moved to appendix A. Since the determined learning curve will not be applied in the tool.

5.1 Results time study

We conducted a detailed analysis of time study data by calculating the sample mean ($\bar{x}$) and sample standard deviation(s) for each task observed. These statistics were then used to estimate the overall production times and assess variability, providing insights into the efficiency and consistency of the processes. An analysis is shown in the following sections for each of the four time studied manual processes. The output for each process is a set of production parameters complemented with metrics such as the average, standard deviation, and confidence interval. Confidence intervals are shown to indicate the margin of error of where the true mean for the parameters lies. Explanations of the meaning of each production parameter can be found in Appendix B.

5.1.1 Final Assembly

For Final Assembly information from the BOM is collected, such as screws or mechanical parts. These parts will therefore function as production parameters because they are all quantifiable and depend on the number in the BOM. The assembly process can consist of final and sub, or only final assembly. Sometimes the operation is split, because some components have to be assembled earlier in the production phase. Both operations are executed very similarly, but the difference in the new tool will count the setup times twice if the process is split.

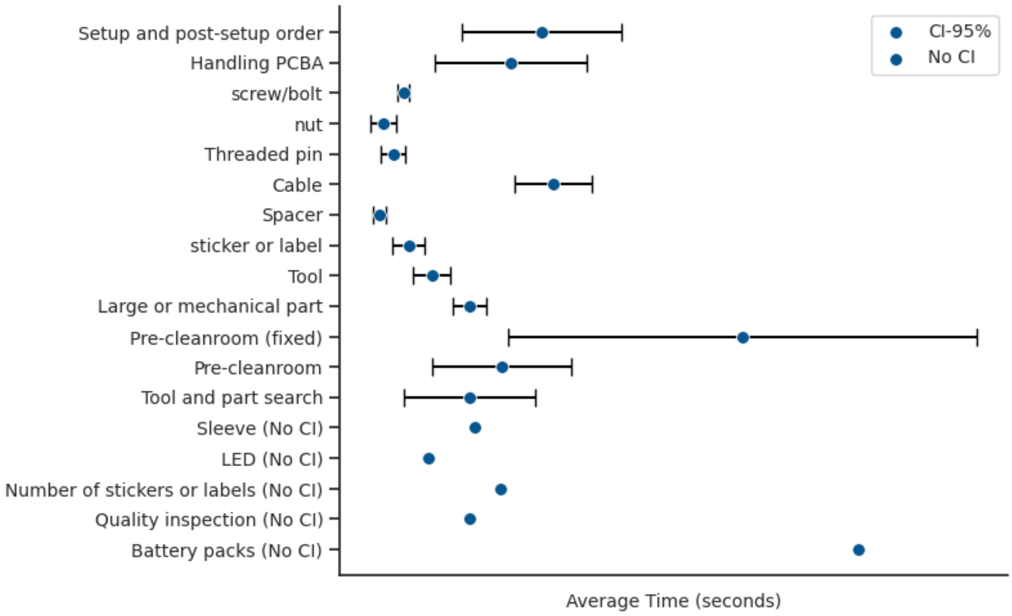


Figure 5.1: Whisker plot showing the assembly parameters with average time and corresponding 95% confidence intervals

Table 5.1: For each parameter, the number of samples and total products within the samples are given. Additionally, the frequency for each parameter is given.

Number	Parameter	Frequency per order	Total quantity	Samples
1	Setup and post-setup order	Once	-	8
2	Handling PCBA	batch size	-	12
3	Screw or bolt	Screws/bolts / PCBA x batch size	108	20
4	Nut	Nuts / PCBA x batch size	16	5
5	Threaded pin	Threaded pins / PCBA x batch size	33	5
6	Cable	Cables / PCBA x batch size	12	7
7	Sleeve	Cable / PCBA x batch size	6	1
8	Spacer	Spacers/ PCBA x batch size	16	3
9	LED	LED / PCBA x Batch size	2	1
10	Sticker or label	Stickers or labels / PCBA x batch size	16	12
11	Tool	Number of unique tools	16	12
12	Large or mechanical part	Large/mechanical parts / PCBA x batch size	32	14
13	Quality inspection	Batchsize	-	1
14	Pre-cleanroom	Variable: PCBA x batch size	-	2
15	Pre-cleanroom	Fixed: Once per order	-	4
16	Tool and part search	Was observed 7 out of 8 time studies	-	7
17	Battery packs	Battery packs / PCBA x batch size	-	1

All of the time studied products are analyzed and each element is categorized into a parameter. The categorization of the elements is shown in the Appendix in figure B.2 and the final values for the parameters are given in figure 5.1 in seconds. Here, the black lines represent the confidence intervals and indicate the margin of error of the true mean. The variability in some of the parameters is high as seen in the standard deviation, due to fewer samples in that parameter. Parameters that have more products in the samples can be seen in table 5.1, where the screw/bolt parameter shows a small spread in the confidence interval and has more than 100 samples. This highlights how more data will improve the accuracy of estimating the true mean for a parameter. The data analysis was conducted by summing the normal times of each element to each parameter and analyzed to determine descriptive statistics for each parameter. The ABC method for the assembly process where the elements are grouped into parameters is shown in figure B.2. Inefficiencies and waste were also observed during the time study, but these are not considered for a quote. Therefore, we did not include these elements as they are out of scope for improving the accuracy of quotes.

5.1.2 Pressfit

Pressfit involves securing through-hole components in the PCB by pressing them into place without using glue or solder. The outcome of this subsection is the analysis of the time study of the pressfit process, conducted to identify the relevant parameters. All elemental operations in the time study were grouped into parameters, shown in figure B.3.

Figure 5.2 presents the pressfit production parameters, determined by breaking the process into elements. In the figure, the mean and confidence intervals are shown. This analysis of the time study data is again shown in Appendix B and derived from five different products. The time drivers were analyzed based on their frequency per order, see figure 5.2, and evaluated to see if they could be combined into a single parameter.

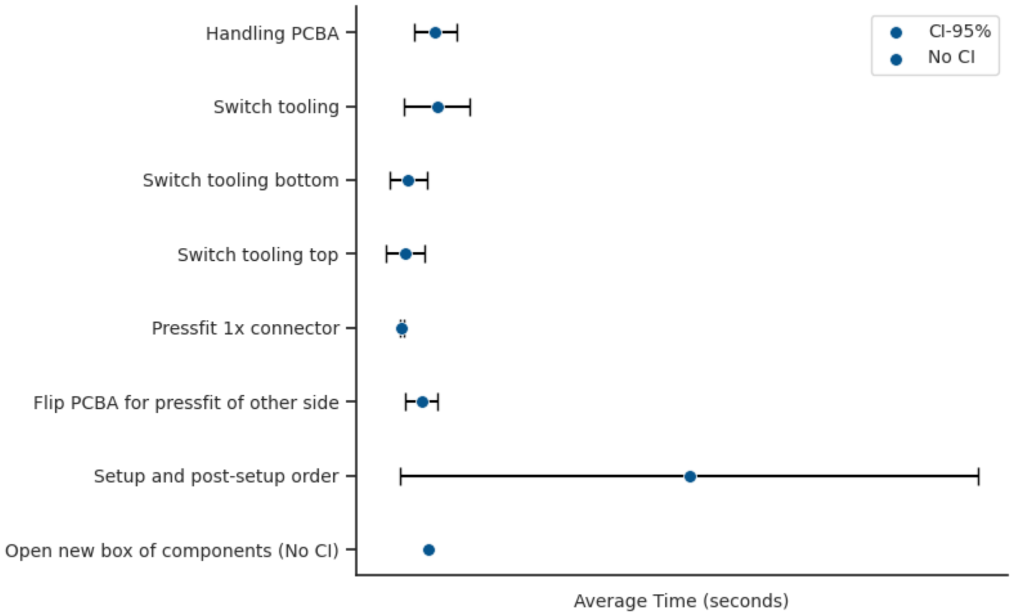


Figure 5.2: Whisker plot showing the pressfit parameters with average time and corresponding 95% confidence intervals

We were allowed to export data from the supplemental pressfit machine. This allowed for a read out of 37.000 samples of passes and fails that happened when a connector is pressed. We sorted the passes and fails and found a failure rate of 4,83%. We also calculated the average time spent on pressing a connector, which is 23,2 seconds. This is only slightly higher than 19,6 seconds that was found with time study. This value is very close to the time study value highlighting the accuracy of time studying a process. The small deviation can be attributed to the fact that the machine completes its cycle before the operator finishes the task. This is primarily due to the additional check an operator performs to ensure the pressfit is successful.

Table 5.2: Parametric values of the pressfit process that will be used in the labor quote tool

Number	pressfit parameter	Frequency per order	Total quantity	Samples
1	Handling PCBA	batch size	-	20
2	Switch tooling both	Tool swaps per product x Batch size	-	12
3	Switch tooling bottom	Tool swaps per product x Batch size	-	7
4	Switch tooling top	Tool swaps per product x Batch size	-	10
5	Pressfit a connector	connectors x Batch size	31	99
6	Number of sides	Batch size	-	6
7	Setup and post-setup	Once	-	5
8	Open new box of components	Connectors in a box x connectors in batch	-	1

5.1.3 Hand Solder

Hand Solder is a labor-intensive operation that should be minimized through effective design for assembly. However, some components will always have to be manually soldered to the PCBA. Sometimes, this operation is also split into two stages, either because certain components need to be soldered later or to reduce the overall operation length. Despite this, the same steps are followed for each hand-soldering process.

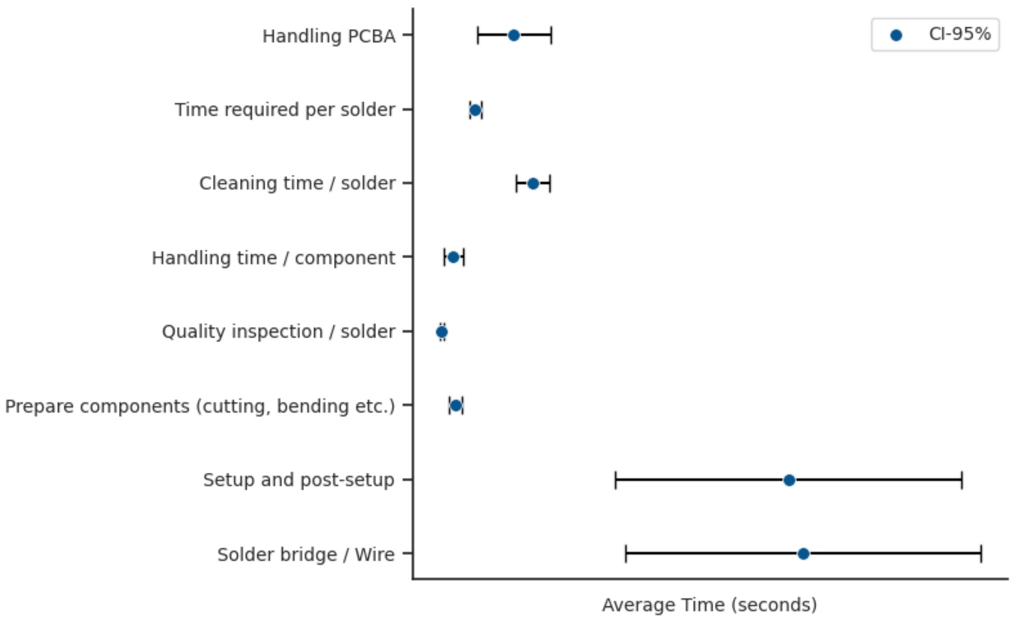


Figure 5.3: Whisker plot showing the hand solder parameters with average time and corresponding 95% confidence intervals

The new production parameters determined with time study are shown in figure 5.3. In this process, the number of leads on the components that have to be hand-soldered and the number of leads that have to be cleaned from flux residue afterward require the most time. During soldering, solder tin contains flux, which could splash and leave a residue. Removing this residue improves the visual appearance of the customer and improves reliability. The elements found with time study are categorized as shown in figure B.4. The number of samples and products that were checked are shown in table 5.3, and a table with all values can be found in Appendix B.

Table 5.3: For the hand solder process each production parameter, the number of samples and total products within the samples are given. Additionally, the frequency for each parameter within an order is given

Number	Parameter	Frequency per order	Total quantity	Samples
1	Handling PCBA	Batchsize	-	10
2	Number of solders	leads / PCBA x batch size	368	17
3	Number of leads to clean	leads / PCBA x batch size	206	9
4	Handling components	components / PCBA x Batchsize	80	10
5	Quality inspection	Batchsize	72	2
6	Prepare components (cutting, bending etc.)	components / PCBA x Batchsize	110	4
7	Setup and post-setup	components / PCBA x batch size	-	2
8	Solder bridge / WIRE	Variable	-	9

5.1.4 Pre-wave Assembly

The new production parameters for the Pre-wave Assembly process are shown in figure 5.4. Pre-wave Assembly steps mainly consist of inserting through-hole components so that the panel of PCBs can go through the selective wave soldering machine. The process can be performed twice if both sides of the PCBA are used, similar to the selective wave operation, which is also done once for each side. Another important type of component that was previously not taken into account for the Pre-wave Assembly is the connectors of LEMO, a connector manufacturer. These components require 4 screws to be tightened and after the selective wave to be loosened, can therefore take up to a minute to assemble. This extends the cycle time drastically because only 10 seconds per component (quoted time for a single pre-wave component) were used for estimation.

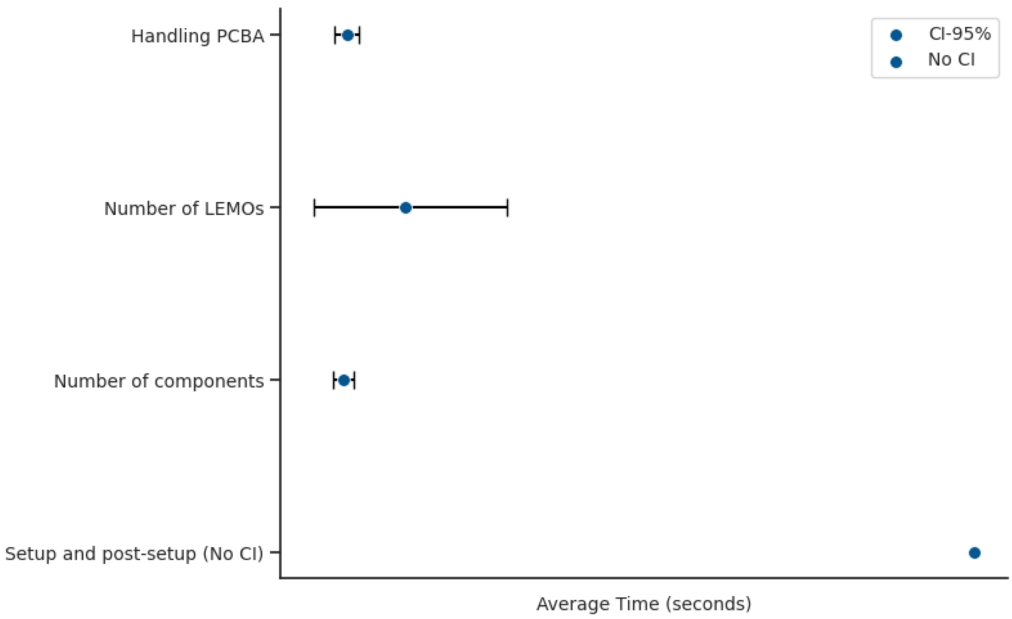


Figure 5.4: Whisker plot showing the pre-wave parameters with average time and corresponding 95% confidence intervals

Table 5.4: For Pre-wave Assembly each of the parameters the number of samples and total products within the samples are given. Additionally, the frequency for each parameter is given

Number	Parameter	Frequency per order	Total quantity	Samples
1	Handling PCBA	Batch size	-	12
2	LEMOs	LEMOs / PCBA x Batch size	40	3
3	Components	Components / PCBA x Batch size	56	22
4	Setup and post-setup	Once	-	1

5.2 Results work sampling

In this work sampling study, we aimed to assess the productivity levels within the manual assembly operations. The results are summarized in table 5.5. The proportions are summarized for each category in figure 5.5.

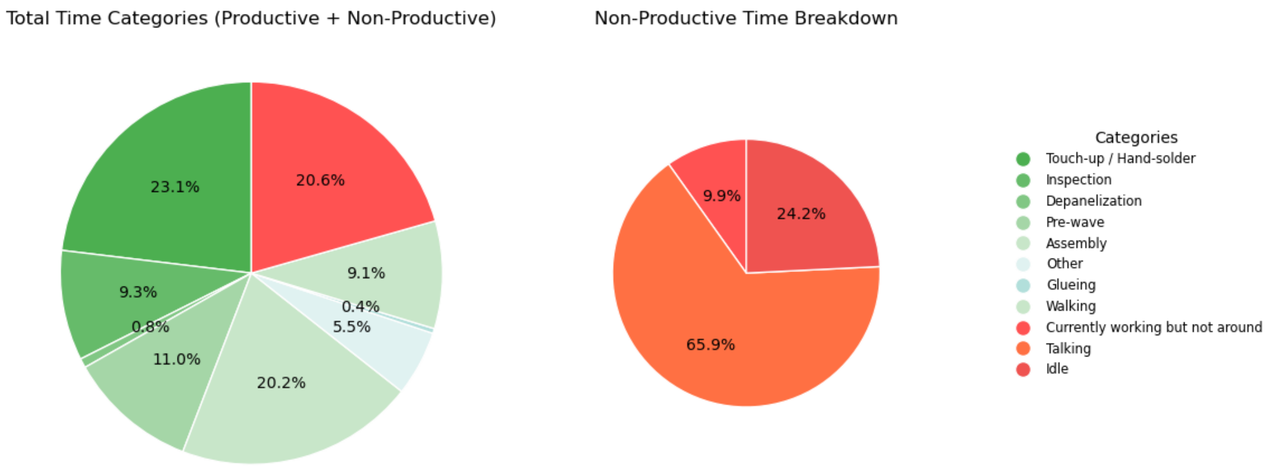


Figure 5.5: Proportion of time spent on Productive vs Non-Productive

Based on the collected data, the findings of the work sampling study show an average productivity level of approximately 0,808, indicating that 80,8% of the time is spent on value-adding activities. The standard deviation σ of the work sampling data is found to be 0,0477, suggesting variability around the mean productivity level. Lower variability implies greater consistency, which is desirable for determining the true productivity level. The confidence intervals for different significance levels α allow us to estimate the range within which the true productivity level lies. The required observations to get a small spread with a confidence interval of $\alpha = 0{,}05$, we needed many more observations, which was not feasible in the limited timeframe of this research. Yet, the determined value still provides valuable insights for decision-making and improving production time estimations.

Allowances

(Maynard & Zandin, 2023) states that an allowance should be based on a work sampling study, given the many factors that influence it. In line with this, the final allowances used in our tool to calculate gross hours from net hours are derived from productivity levels found through the work sampling study. This study revealed that workers spend, on average, 80.8% of their time performing value-adding activities. Therefore, we apply the allowances using Equation 3.3, where normal times are divided by the proportion of productive time, resulting in an approximate allowance of 25%.

Table 5.5: Work sampling confidence intervals

	n=68	
	Coefficient	Estimates (CI)
$\alpha = 0,01$	0,1920	[0,070, 0,314]
$\alpha = 0,05$	0,1920	[0,099, 0,286]
$\alpha = 0,1$	0,1920	[0,113, 0,271]
$\alpha = 0,2$	0,1920	[0,144, 0,240]

We also explored another method from the literature review by (International labour office, 1979). Here we used a questionnaire (see Appendix C), and this results in an average relaxation allowance of 14%. Based on Benchmark's production department, we select the allowance calculated by work sampling for the to-be-developed LQT (Maynard & Zandin, 2023).

Table 5.6: Work sampling productivity levels

	Coefficient
p Productive	0,8080
$\hat{p}$ Non-productive	0,1920
σ Standard deviation	0,0477

5.3 Results regression data analysis

The main objective of this regression analysis is to quantify the factors influencing the cycle time of the pick-and-place machine of the SMT line and determine the final parameters to estimate a cycle time. We hypothesize that the cycle time is significantly affected by several independent variables, including panel area, the number of SMT components on the PCB, and the number of unique components. Table 5.7 shows descriptive statistics of the dataset for the variables used in the multiple linear regression.

Table 5.7: Summary statistics for the dependent variable (Cycle Time) and the three independent variables (Panel area, Number of unique SMT components, and Number of SMT Components).

	Average	**Median**	σ
Cycle Time	51,73	36,00	48,40
Panel area	45885,22	37280,00	28804,77
Number of unique SMT components	37,06	27,50	30,23
Number of SMT components	561,00	393,50	562,45

We conducted a multiple linear regression analysis where we modeled the relationship between the dependent variable and several independent variables. In table 5.8, the output for the ordinary least squares (OLS) method is presented, which estimates the model coefficients by minimizing the sum of the squared residuals between the simulated cycle time and the predicted cycle time. The equation for the pick-and-place machines is as follows:

$$\begin{aligned}\text{Cycle time} = 1,054 + 0,027 \times (\text{Number of SMT components})\\ - 0,002 \times (\text{Number of unique SMT components})\\ + 0,595 \times 10^{-2} \times (\text{Panel area } [\text{mm}^2])\end{aligned} \tag{5.1}$$

Table 5.8: Results of the regression coefficients, standard errors, t-values, p-values, and 95% confidence intervals.

Variable	**Coef**	**Std Err**	**t**	**P>|t|**	**[0,025**	**0,975]**
Intercept	3,2890	3,092	1,064	0,293	-2,927	9,507
Number of SMT components	0,084	0,004	20,740	0,000	0,076	0,092
Number of unique SMT components	-0,006	0,076	-0,077	0,939	-0,158	0,146
Panel area	2,995e-05	5,01e-05	0,598	0,553	-7,07e-05	0,000
Sample Size	52					
R-squared	0,958					
Adj. R-squared	0,955					

The R-squared value for this model is 0,958 indicating that the model fits the data well. The adjusted R-squared is 0,955, which also indicates a good fit, considering the predictors in the model. The variance inflation factors are

Table 5.9: VIF for each variable

Feature	**VIF**
Number of SMT components	2,54
Number of unique SMT components	2,54
Panel area	1,01
Intercept	4,75

calculated and given in table 5.9, where all values are lower than 5. In section 3.5 it is given that values below 5 to 10 indicate that no multicollinearity exists between the variables. The correlation between variables is also checked in table 5.10, where a strong correlation is found between the number of components and the number of unique components as expected.

Table 5.10: Correlation matrix

	Number of SMT Components	**Number of unique SMT**	**Panel area**
Number of SMT Components	1,000	0,778	0,113
Number of unique SMT	0,778	1,000	0,103
Panel area	0,113	0,103	1,000

Performance of the model

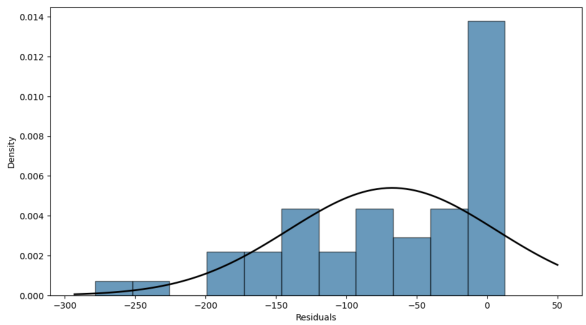
After the models were trained we had to determine the performance of the regression model, which is presented in table 5.11. The MAD for the test set is 7,36 seconds, while the MSE for the test set is 93,93 seconds. A k-fold cross-validation is conducted with 5 and 10 folds to validate the model's performance further. These show a mean MSE close to the test set with only a difference of 12,01 seconds. Furthermore, the MAPE is calculated. This metric can be unsuitable for the values closer to zero in the dataset.

The residuals are plotted in figure 5.7 against the predicted values to see if a random scatter around the horizontal axis is observed. In this case, a small curve or pattern can indicate a possibility of a missing variable or a non-linear relationship being present. In figure 5.6b an error histogram shows the difference between the actual and predicted values for the new tool. In this histogram the normal distribution is plotted and a right skewed distribution is observed, indicating that the actual values are lower than the predicted values. This means the machine is quicker than the regression model expects for some cases.

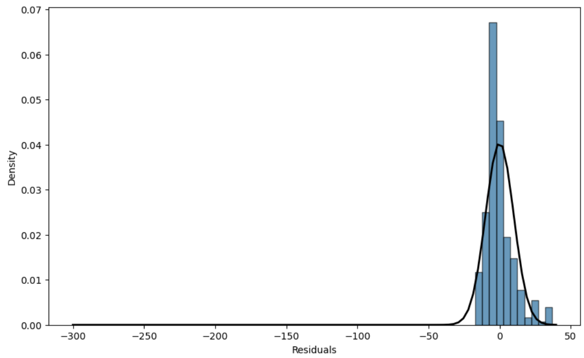
To compare the new regression model, the performance of the existing tool was also analyzed with the same dataset. In figure 5.6a the error histogram for the existing tool is shown, based on the number of chips, integrated circuits

Table 5.11: Performance of the regression model for cycle time prediction of the Pick-and-Place Machine. The same dataset is applied to the formula used in the existing tool to compare the outcomes.

Performance Metric	New tool	Existing tool
MAD (Train)	6,62	-
MAD (Test)	7,36	69,98
MSE (Train)	100,04	-
MSE (Test)	93,93	10014,93
Mean MSE, 5 folds	103,58	-
Mean MSE, 10 folds	105,94	-
Standard Deviation of MSE across 5 folds	58,12	-
MAPE (Train)	16,69%	
MAPE (Test)	23,06%	117,97%



(a) Error histogram of the pick-and-place machines for the existing LQT



(b) Error histogram of the pick-and-place machines for the new LQT

Figure 5.6: Histogram of the error between the actual and predicted cycle time of the Pick-and-Place machine. Error is defined as the actual minus the predicted cycle times, and the horizontal axis is scaled to be equal for both graphs

(ICs), and large components. These variables were selected because these component types can be extracted easily from the ODB data and are distinguished by the number of pins that connect to the PCB.

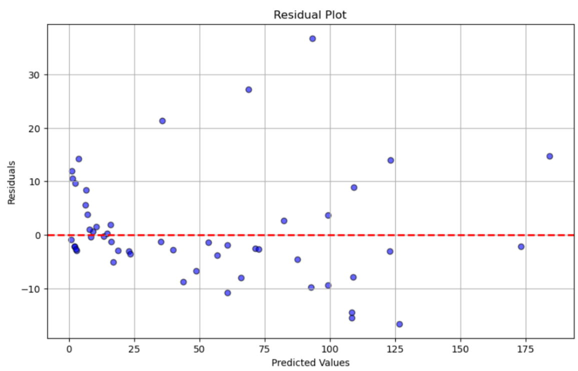


Figure 5.7: Residual analysis for regression model

However, one of the limitations for the regression model is the use of different nozzle heads in the pick-and-place machine, each capable of picking up a varying number of components. Specifically, the machine uses a 12-head nozzle for small components and a 2-head nozzle for larger components. The interplay between these heads can result in inaccurate cycle time estimations. This can also account for some significant overestimations, due to several

PCBAs that can contain many large components. The nozzle heads for placing will have to make more frequent returns and will be slower.

5.4 Other processes

In addition to these processes, for all the remaining processes production parameters are determined to provide a fully functional tool. The parameters for the other processes are defined with the help of other process engineers or other experts such as operators that work with the machine. An overview is shown in table 5.12, where all the bold processes are covered in this thesis.

Table 5.12: Status of the production parameters in the new LQT and how they were determined

Process	Status
SMT line	**Determined and validated with regression in this study**
Vapor phase solder	Determined by interviews with operator
AOI	Determined in accordance with process owner
Touch-up SMT	Determined by interviews with operator
Xray	Determined in accordance with process owner
Kitpull	Determined by logistics
Pre-wave Assembly	**Determined and validated with time study**
Selective wave	Determined in accordance with process owner
Pressfit	**Determined with time study**
Hand soldering	**Determined and validated with time study**
Sub-assembly	**Determined and validated with time study**
Final assembly	**Determined and validated with time study**
Print labels	Determined and validated in this study
Touch-up manual labor	Determined by interviews with operator
Depanel	Determined by time sheets from operator
Coating	Has to be filled in manually in the quote by IE
Wash	Determined by time sheets from operator
Cleanliness testing	Has to be filled in manually in the quote by IE
Visual inspection	Has to be filled in manually in the quote by IE
Final inspection	Has to be filled in manually in the quote by IE
Outgoing inspection	Has to be filled in manually in the quote by IE
Flying probe	Flying probe sheet is implemented in the tool to give an estimate
ICT test	Determined in accordance with process owner
BST, functional, performance test	Determined in accordance with process owner
Burn-in test	Determined in accordance with process owner
Debug	Has to be filled in manually in the quote by IE
Repair	Has to be filled in manually in the quote by IE
Packing	Determined with data from packing personnel
Cleanliness inspection	Has to be filled in manually in the quote by IE

5.5 Summary

In this chapter, the production parameters for four manual processes are determined using time study and analyzed by grouping all tasks into parameters and determining the averages. Appendix B in table B.1 summarizes the new and existing parameters.

Productivity levels are empirically determined using a work sampling study resulting in a value of 80,8%. This means that for the manual assembly operations an allowance of roughly 25% will be added, to account for fatigue and personal care etc, so that the estimated production times will reflect realistic working conditions.

Although learning curves are assessed, the decision is made to use the existing learning curve. The full learning curve analysis determined using Wright's model can be found in Appendix A.

Furthermore, a regression analysis is conducted to determine production parameters for the SMT line. These values are compared with the outcomes of the existing LQT in which a significant difference in accuracy was found.

Finally, the production parameters for the remaining processes were identified through interviews with both operators and process engineers. This ensured that the input for the new tool is complete, allowing for direct implementation.

Chapter 6

Solution Design

In this chapter, the design and development process of the new LQT is shown. We aim to provide a design for the new tool to solve the core problem and address the research question:

How can a tool be developed to integrate and summarize the new production time estimation framework?

In the first part, section 6.1, describes the conceptual model. In Section 6.2.1, we outline the requirements for the model to ensure that the new LQT is both functional and accurate. These requirements form the foundation for the framework of the new model. Section 6.2.2 delves into the design description, offering an overview of the new tool's structure and flow of data. This section explains how the tool integrates with the database for future data analysis on historical data. Finally, Section 6.2.3 focuses on the design of the BOM component categorization algorithm. We describe how the components are categorized into a process type. The categorization process quantifies the production parameters, which together can determine production times. In figure 6.1 a detailed flowchart outlining the second phase of the research is presented, providing a clearer overview.

6.1 Conceptual model Labour Quote Tool

Benchmark's growth has changed the production landscape of Benchmark and challenges have emerged for the increased demand for the manufacturing department. The IEs are tasked with determining accurate production times for a quote for the new product, but the verified inaccuracy in the existing tool are causing significant challenges. The significant challenges stem from the existing tool's lack of a framework for updating the tool and its parameters. Therefore, there is a need for a new tool that can effectively calculate more accurate production times and be easily modified. The new tool will solve these problems by using a new parametric approach similar to the existing parametric tool. However, the new tool is designed based on relevant theories from the literature, so that it aligns with academic and industrial frameworks. As a result, the tool will estimate production times with a higher accuracy, with a better modular framework, give a better overview, and is more user-friendly.

The tool will comprise of multiple modules, as described in 6.2. Three worksheets provide the input data. The first worksheet holds ODB (Cadcam) data, which details the exact locations (coordinates) and information about the components such as the number of pins or the class, which identifies SMT or THMT components, streamlining a process that would otherwise be time-consuming. The second worksheet contains the BOM, including part numbers, part descriptions, and quantities. In the third worksheet, additional information is filled in, which captures details not readily available in the databases. Engineers manually complete this worksheet, providing expert knowledge and information that is otherwise only known to them, to gather all necessary input for creating the quote. The tool can

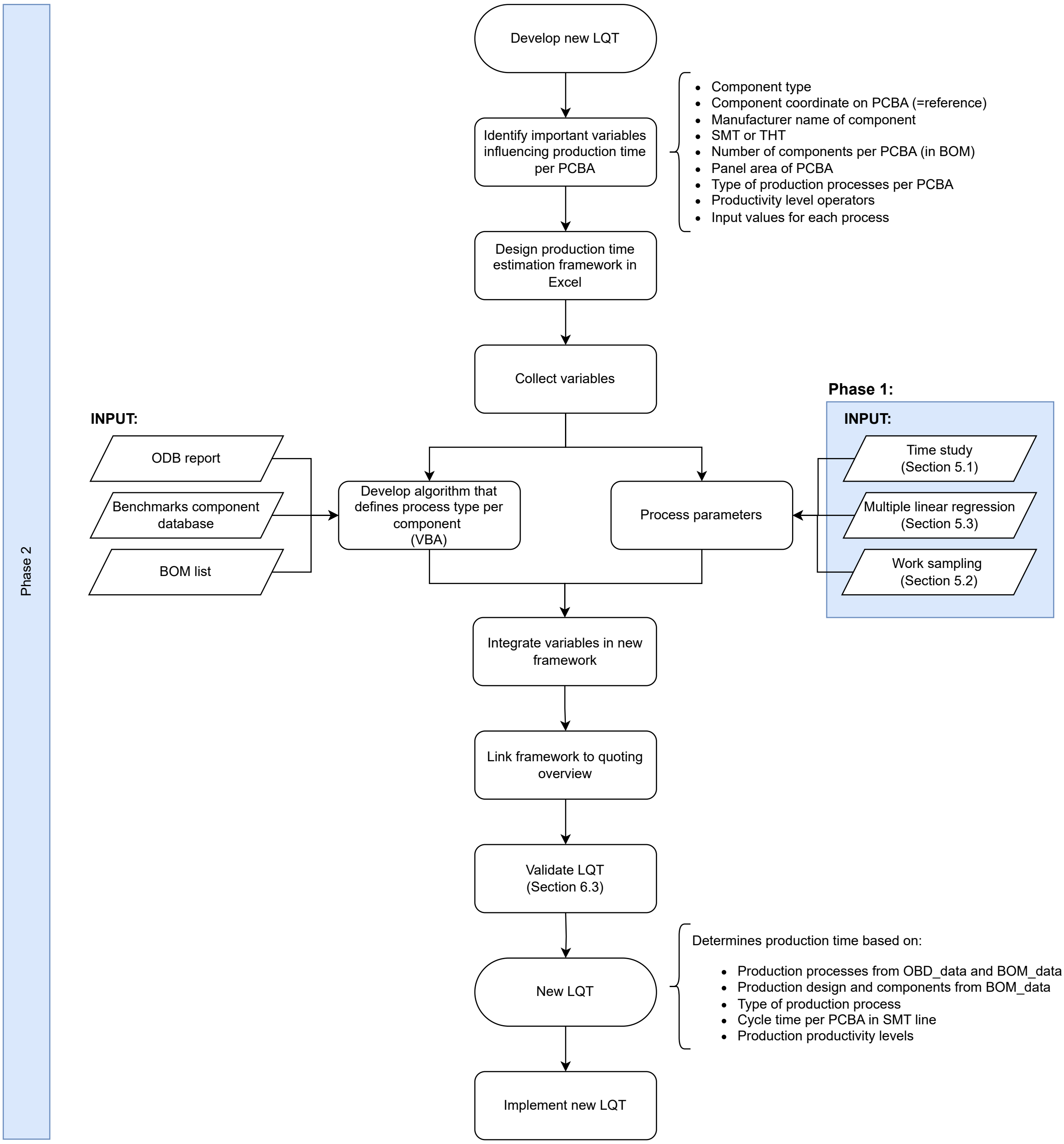


Figure 6.1: Detailed description of the second phase of the research, showing the design of the new LQT, visualized with a flowchart

determine for the majority of the components in which process it has to be assembled using BoM and ODB data to save time for the engineers. All the components that are left and could not be categorized into a process type have to be manually adjusted.

The output of all the information will come together in a different module that contains all the parameter values and their respective quantities, to determine the production times. The quantities of the production parameters are usually based on a one-unit level and are shown next to the value of the parameter, these are multiplied to determine a production time. The quantity is determined with the help of analysis from the BOM and ODB and engineering

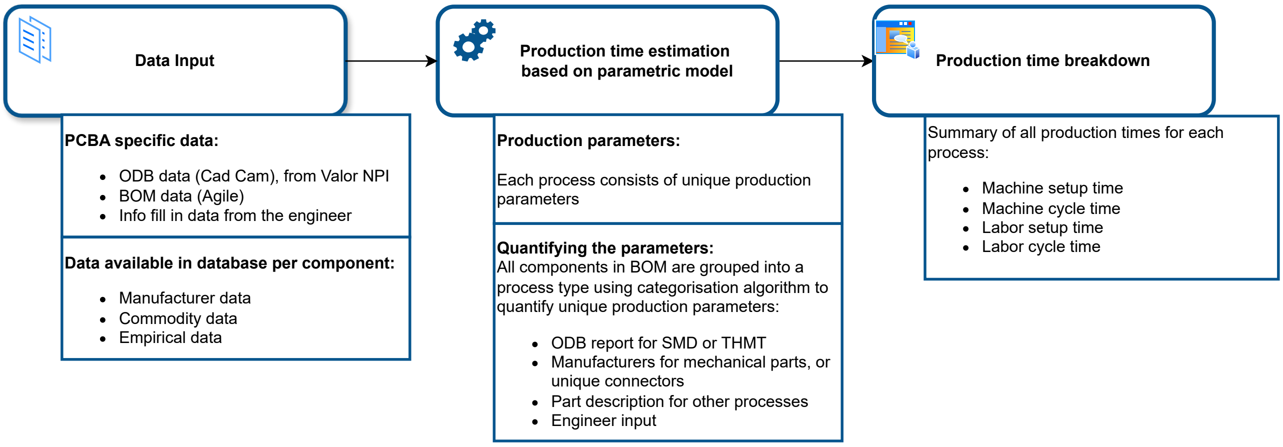


Figure 6.2: Conceptual model of the new tool

knowledge. The production times are separated between setup and cycle times which are all summed in an overview. The final setup and cycle times for the machines and labor are then shown next to each process. The production times will be linked to the final 'Customer X INPUT' and 'QuoteTimes' worksheets of the quoting department. In these worksheets, the batch size will come into play. In the previous worksheet where all the setup and cycle times are summarized, everything is determined for a single PCBA and setup times for a single order without considering the batch size.

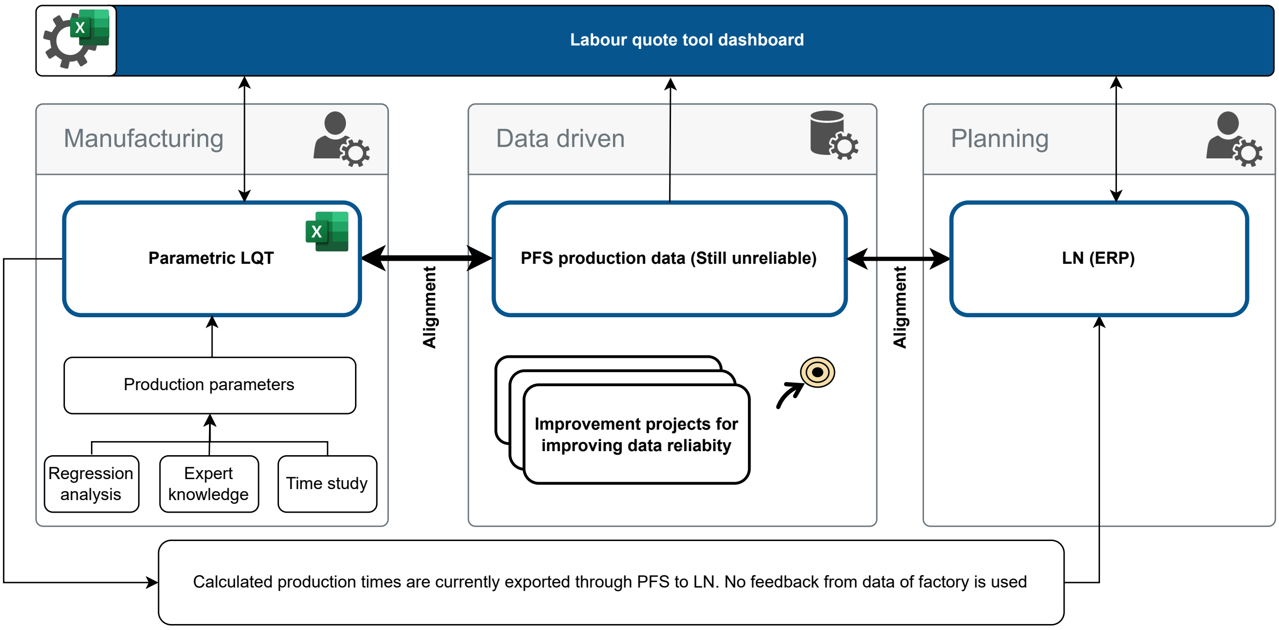


Figure 6.3: Future conceptual LQT that aligns the (still unreliable) production data with the model and ERP system to the departments and improve the accuracy of the production times

To optimize the new tool and also provide a feedback loop from the manufacturing back to the tool. The new tool must be able to gather historical data from the PFS system. Entering a part number and process, after which it will display all previously recorded orders. However, this data is (still) unreliable, as discussed in section 4.2. Ongoing projects aim to enhance the use of production data. Leveraging data-driven methods is essential to achieve more accurate production times, as more data is crucial for improving accuracy and for providing a feedback loop to the LQT. The precision of the tool relies on the accuracy of the input. However, the current logging methods hinder updates, making manual data collection still necessary. Data improvement projects are necessary, and a list of recommendations is provided in the final section 7.2, detailing ways to enhance data accuracy.

Once the data becomes more accurate, it will be possible to align LN, used by planning and other departments for production times, with real-time factory data of PFS, making the tool data-driven. Currently, there is inconsistent feedback on production times, causing the planning department to struggle with inaccurate production times. The parametric tool only uses predefined parameters for production times and can not always account for unforeseen issues from the design and production that could extend production times. The new tool should be able to assist in providing this feedback loop between the departments as seen in figure 6.3.

The future tool can include a dashboard displaying production records from the factory (if the product is already in production), quoted production times, and the production times filled into LN in one overview. This will allow for the alignment of discrepancies in production times between the systems. Consequently, the planning department will receive more reliable data, and the manufacturing department, using the labor quote tool, will gain insights into inaccuracies and can improve the tool accordingly.

Figure 6.4 describes an alternative future data-driven method, based on the literature in section 3.4 for updating the parameters and can be implemented using the future tool once the data becomes more reliable. When all LQTs are collected into a single folder, the parameter values for each product can be extracted with a script. This data can then be used to perform a regression analysis like the SMT line, with the parameters as independent variables and cycle times as the dependent variable. The cycle time can be deducted from the PFS data and is based on the historical records.

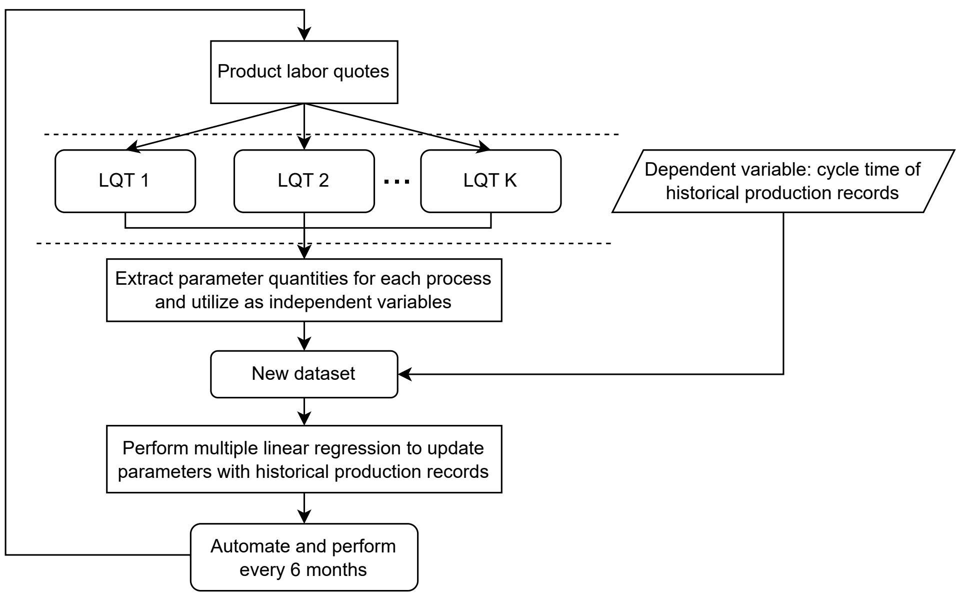


Figure 6.4: Future method for updating the production parameters using the historical production records which are unfortunately still unreliable, visualized in a flowchart.

6.2 Design of the Labor Quote Tool

This section presents the model including the back-end infrastructure of the tool. The solutions to all of the requirements are elaborated here. and will also aim to answer the following sub-question: *How can the new tool be modeled?*

6.2.1 Design requirements

Requirements of the new tool are as follows. The new tool must have the ability to show a clear overview of the production times and how they are derived. The existing tool lacked a proper overview and was referred to as a 'black box' quickly after new features and processes were added, which led to very few people understanding the existing tool. The new tool should have a clear overview of the parameters and should be easily understandable and changeable. A modular approach must be taken so that the production parameters that determine the production times can be easily adjusted and new processes or parameters must be able to be easily added. In design, the concept of 'less is more' is often used, which shows that simplicity can sometimes lead to more effective outcomes.

Secondly, the new tool should calculate the production times for the PFS process steps. The current tool calculates the times in different processes, sometimes grouped versions of these processes, which makes it harder to interpret. This can be challenging for IEs to link a production time to each process step and makes it sensitive to mistakes. The new tool will calculate production times for each PFS step, providing a clearer overview.

Finally, for a successful implementation, the tool must work with the existing quoting worksheets, which is why interviews with the quoting department were conducted to determine their requirements. The worksheets they and program management use will also be implemented again with the new production time estimates of the new tool.

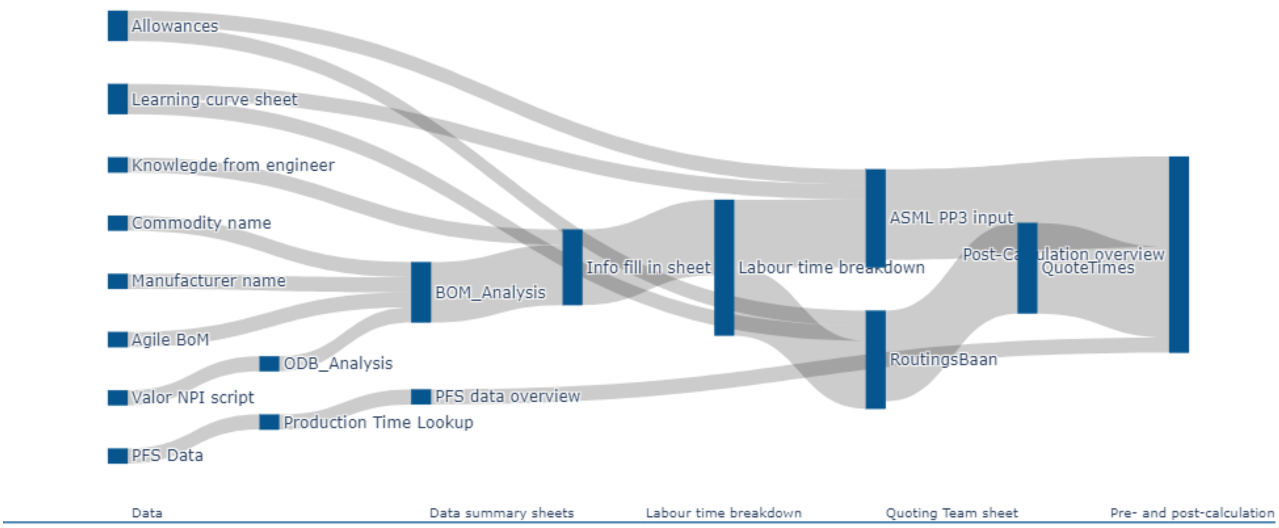


Figure 6.5: Data flow visualized using a Sankey diagram

6.2.2 Design description

The system architecture of the tool is visualized in figure 6.5. It contains 5 types of worksheets. There are the data worksheets that are used for the input data and are generally hidden. The second type of worksheets are the data summary worksheets which are used by the IEs s to input the ODB data in ODB_Analysis, BOM in BOM_Analysis, and their knowledge in the Info Fill In sheet. These worksheets are linked to 'Labor Time Breakdown' which provides the overview of all the production times for each of the processes. Finally, the worksheets for the quoting team are used to summarize the outputs and determine a batch size, which is then used in a different tool to create a quote. The fifth worksheet is still theoretical and has no function since the production records are still unreliable. However, hypothetically this can serve as an important worksheet in a later stage for reasons already explained in figure 6.3.

An overview of the data flows between different worksheets in the tool is illustrated in figure 6.5. An overview of the interface of the tool can be found in Appendix E.

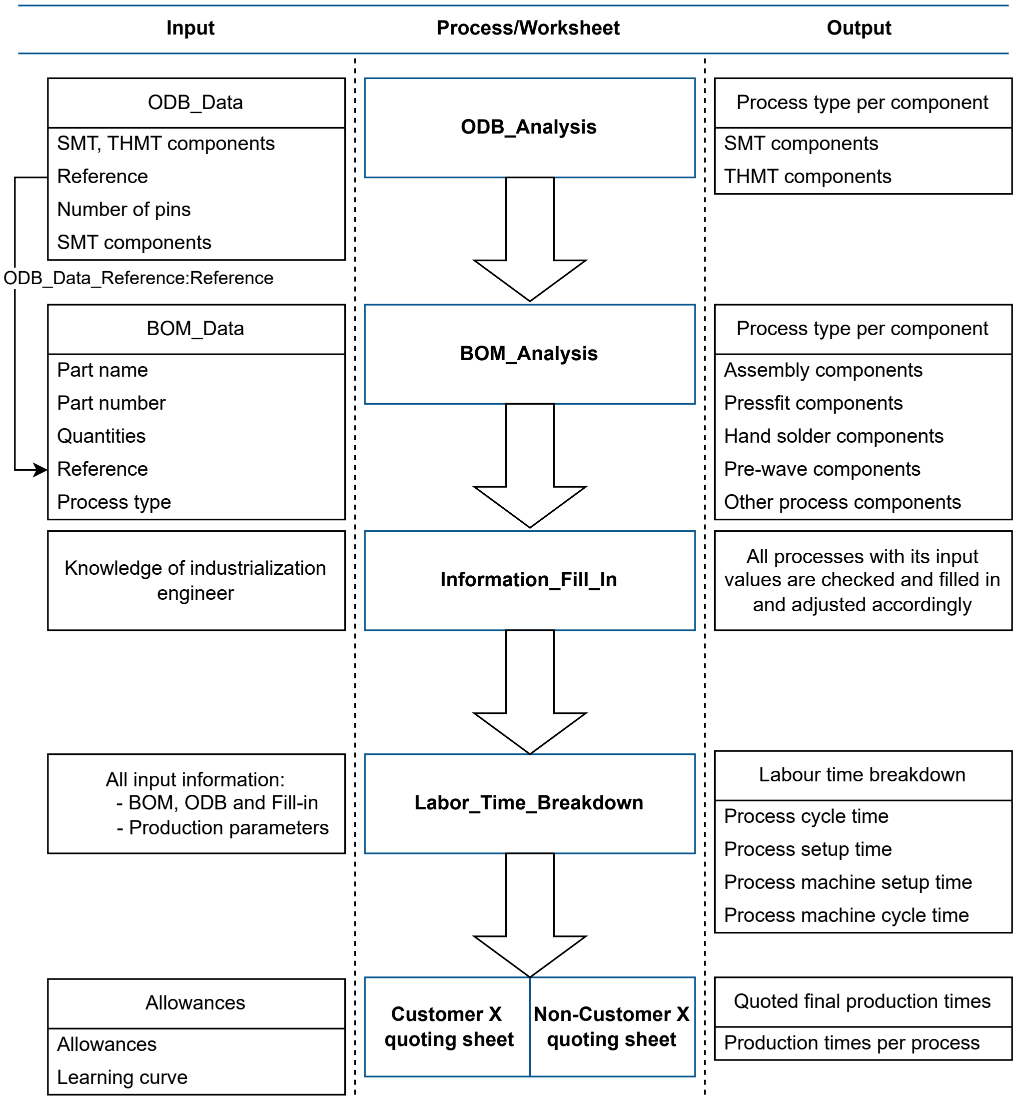


Figure 6.6: Data input variables and output variables visualized for each worksheet

The tool is developed in Excel given the widespread use of Excel programs across most departments at Benchmark. It is developed with the assistance of Visual Basic for Applications (VBA) for better integration and creating the database connection with a library that uses an API for retrieving the historical production records. Excel is currently indispensable for our quoting department, as they rely heavily on the quoting worksheets, due to the specialized tools they have produced that use this worksheet. Another advantage is that all employees have Excel installed on their company devices and know how to work with it, which helps with ease of use.

The manufacturing department at Benchmark encompasses a wide array of processes which are all part of the quote. The time span of this thesis makes it impractical to research all of them thoroughly. So parameters were only determined for several processes through various methods, which are presented in Chapter 4. However, with some guidance from process engineers and operators, estimates for all of the production processes will be implemented in the tool, see section 5.4.

The input and output variables of the tool are visualized in figure 6.6, which shows for each worksheet which input variables it uses and which output variables are determined there. Not all processes are listed in the output of the figure, but all processes can be found in table 6.1.

The tool will incorporate security features by protecting or hiding the worksheets that do not require user input or display calculated values. In the BoM_analysis and ODB_Analysis worksheets, users will only be able to paste the BOM or ODB report, while all other functions are automated through buttons. Additionally, data validation options are included to ensure that only values from a predefined dropdown list can be entered in certain cells.

6.2.3 Design of the BOM component categorization

Unlike the old tool, the new tool determines inputs on a component basis, using the BOM, ODB, and the knowledge of the engineers to determine which process is required for each component. This method makes production times dependent on the number of components being processed, which are connected to specific parameters. Currently, there are eight processes that components can be categorized into, presented in table 6.1. These components are then categorized into these processes using the algorithm in the figure algorithm 1.

Table 6.1: Processes, data sources, and the attributes that determine the process type

Process	Source	Attributes
Assembly	Description	'screw', 'nut', 'front', 'washer', 'metal', 'bolt', 'ring' 'rivet', 'cover', 'Loctite', 'bush', 'thermal pad'
	Manufacturer Name	'Machined', 'Soft tooled', 'Plate'
Prewave Assembly	Description	'str', 'p ' with IsNumeric statement for distinguishing number of pins
	ODB Report	'THMT'
SMT	Description	'SMD'
	ODB Report	'SMT'
Print Labels	Description	'Labels and overlay', 'Special tape', 'Label', 'Sticker'
Pressfit	Description	'pf' not followed by a numeric value
Hand Soldering	Description	'sleeve', 'Raw wire'
Glueing	Description	'Sealing'
Packing	Part Number	Parts used for packaging contain 'ANCI' in part number
Unknown	Description	Default if none of the above conditions are met or if SMT/THMT check column contains an error

Algorithm 1 The algorithm for the process categorization by BOM information

Require: `BOM` is a list of the components
Ensure: Each part's process is assigned based on its name
  for each `part` in `BOM` **do**
    `Compare if part.name is similar to process category 1 to 10`
    if `part.name` equals `process x` **then**
      `part.process` ← `process x`
    end if
  end for

Most components are automatically assembled in the SMT line and categorized by reading the ODB report highlighting the SMT components. The remaining electrical components, typically through-hole components like connectors, require wave soldering or press-fitting. The final category of electrical components consists of components that need to be hand-soldered, usually larger ones too big for automatic assembly, thus requiring manual labor which is minimized as much as possible due to its labor intensity.

After the PCBA is completed with all electrical components, only assembly components remain. These are generally mechanical parts such as metal front plates and fastening materials like screws, nuts, and bolts to mount the PCBA. Other typical assembly components include covers that protect the PCBA and spacers that keep covers and plates at a distance to avoid contact with the components.

Categorizing each component precisely is challenging due to numerous exceptions and variability in product descriptions between the customers. Therefore, the tool includes a feature where components that can not be automatically categorized are flagged as unknown, allowing the industrialization engineers to manually assign them to the appropriate process by filtering the unknowns with a button. This approach significantly reduces the time required for manual categorization, as the program automatically categorizes the majority of components.

6.3 Implementation and tool validation

This section discusses the implementation and validation process, which is crucial for successfully deploying the tool. The implementation covers several aspects including the accuracy and the user experience. The goal of this section is to answer the research question:

How accurate is the improved tool for all products of a key customer of Benchmark?

A thorough validation ensures that the new tool shows improved accuracy, which helps in convincing IEs of its benefits. All the overestimations and underestimations are plotted between 15% margin lines since this range was considered acceptable and functions as an accuracy target by Benchmark. The results of the validation are elaborated on in the following sections. Section 6.3.1 the validation of the time studied processes is presented. In this validation, the second subsection 6.3.2 covers the validation of the work-sampling study. The third subsection 6.3.3 shows the validation of the regression on the SMT line. The last section 6.3.4 presents the results of an user experience questionnaire and a comparison is made between the new and existing LQT in terms of user experience.

6.3.1 Time study validation

The validation was conducted by comparing three operations—Pre-wave Assembly, Hand Solder, and Final Assembly—across the same 16 products that were also used to verify the accuracy in the existing LQT. The validation results of the processes are shown in tables 6.2, 6.3 and 6.4. The production time estimations of the 16 products by the new LQT are tested against two benchmarks: (1) the performance of the existing tool and (2) the actual times estimated by the operators. The overestimations and underestimations are plotted in figure 6.7. Figure 6.8 shows the percentage of products that are within, above, or below the margin lines. In evaluating the performance of estimating the production times, we focus on absolute accuracies rather than averages as described in section 2.4.

The goal of this validation is to evaluate the accuracy of the new LQT in predicting production times. Highlights of the results such as the differences, percentage deviations, and potential areas for improvement are explained below.

Pre-wave Assembly
The Pre-wave Assembly operation demonstrates the smallest improvements in deviations between the new and old LQT's estimates and the estimated times of the operators. The new tool shows a MAPE of 34,3% from actual times recorded by operators. Despite this significant average deviation, the results in table 6.2, still show an improvement over the existing tool, which has a MAPE of 44,8%. Five products displayed significant deviations between the new, existing tool and the average estimated time in the Pre-wave Assembly process:

Table 6.2: Validation of the new tool compared with data from the existing tool for the Pre-wave Assembly process. The values are given in minutes.

	Pre-wave Assembly				
Description	New Tool	Existing Tool	Estimated	New Tool Error	Existing Tool Error
PCBA 1	4,6	8,0	15	-69%	-47%
PCBA 2	2,1	1,6	3	-30%	-47%
PCBA 3	16,2	10,8	14	16%	-23%
PCBA 4	16,9	10,3	13	30%	-21%
PCBA 5	8,5	19,6	15	-43%	31%
PCBA 6	10,1	5,9	15	-33%	-61%
PCBA 7	4,8	2,7	4	20%	-32%
PCBA 8	10,0	7,3	12	-17%	-40%
PCBA 9	3,0	1,5	3	-1%	-49%
PCBA 10	12,6	5,8	10	26%	-42%
PCBA 11	4,3	4,5	10	-57%	-55%
PCBA 12	2,1	4,2	6	-65%	-30%
PCBA 13	4,6	1,9	5	-8%	-62%
PCBA 14	7,0	6,9	15	-53%	-54%
PCBA 15	4,2	1,5	8	-47%	-81%
PCBA 16					
Average				-22,1%	-40,7%
MAPE				**34,3%**	**44,8%**

- PCBA 5: The new tool underestimates the product by -43% and the existing tool overestimates it with 31%.
- PCBA 7 and PCBA 4: These products both show a relatively large overestimation in the new LQT and a large underestimation for the existing tool.
- PCBA 1 and PCBA 11: For these products, a large underestimation of the production time was observed relative to the average estimated time.

Table 6.3: Validation of the new tool compared with data from the existing tool for the hand solder assembly process. The values are given in minutes.

	Hand Solder				
Description	New Tool	Existing Tool	Estimated	New Tool Error	Existing Tool Error
PCBA 1					
PCBA 2					
PCBA 3					
PCBA 4					
PCBA 5	19,75	13,3	19,0	4%	-30%
PCBA 6					
PCBA 7					
PCBA 8					
PCBA 9					
PCBA 10	26,63	39,5	30,0	-11%	32%
PCBA 11	7,06	5,4	10,0	-29%	-46%
PCBA 12	10,63	13,3	15,0	-29%	-12%
PCBA 13	10,48	4,1	10,0	5%	-59%
PCBA 14					
PCBA 15					
PCBA 16	93,72	16,5	88,0	6%	-81%
Average				-9,1%	-32,7%
MAPE				**14,2%**	**43,3%**

Table 6.4: Validation of the new tool compared with data from the existing tool for the final assembly process. The values are given in minutes.

	Final Assembly				
Description	New Tool	Existing Tool	Estimated	New Tool Error	Existing Tool Error
PCBA 1	10,31	9,3	11	-6%	-15%
PCBA 2					
PCBA 3	7,21	8,9	4	80%	122%
PCBA 4					
PCBA 5	10,56	24,4	20	-47%	22%
PCBA 6	5,04	15.2	5	1%	204%
PCBA 7	7,15	14,8	5	43%	196%
PCBA 8	45,71	39,5	35	31%	13%
PCBA 9	18,28	14,6	15	22%	-3%
PCBA 10	11,16	10,6	10	12%	6%
PCBA 11	18,59	20,7	19	-2%	9%
PCBA 12	25,60	16,1	28	-9%	-42%
PCBA 13			9		
PCBA 14	66,04	119,8	75	-12%	60%
PCBA 15	13,89	14,6	15	-7%	-3%
PCBA 16	57,88	90,0	63	-8%	42,9%
Average				8,7%	44,2%
MAPE				**19,7%**	**53,2%**

Hand solder

The Hand Solder operation demonstrates a mixed performance for the new quoting tool in comparison to both the existing tool and the estimated times of the operators. Overall, the new tool shows a MAPE of 14,2% from the estimated times of the operator, indicating a fairly accurate estimate and a large improvement compared to the old tool, with a MAPE of 43,3% for this operation, as shown in table 6.3. However, there are differences in the individual variation, with some products being slightly overestimated and some products being underestimated. Some products displayed significant deviations in the Hand Solder process:

- PCBA 13 and PCBA 16: These products show significant underestimations for the existing tool, while the new tool shows very big improvements. The duration of the hand solder process for the HIPA is one of the longest.
- PCBA 11: This product still shows a big underestimation for both the existing and new LQT.

Final assembly

The validation results for the Final Assembly stage show important insights into the performance of the new LQT when compared to both the existing tool and the estimated average times. The predictions of the new tool show a MAPE of 19,7% when compared to the estimated times by the operator, which shows a significant increase in accuracy compared to the existing tool with a MAPE of 53,2%. The products that displayed significant deviations in the final assembly process are highlighted:

- PCBA 6 and PCBA 7: Both show a very large overestimation for the existing tool.
- PCBA 3: Shows a very large overestimation for both the existing and new LQT.

6.3.2 Work sampling validation

It is difficult to make a validation of the result of the work sampling study, as there is no data available that can be compared to the work sampling result. Due to time constraints, 68 samples were collected, which resulted in a wider spread of the confidence interval. Therefore, more samples could be collected in the future to enhance the accuracy of the allowance determined with the work sampling study. When the new allowance is compared with the existing

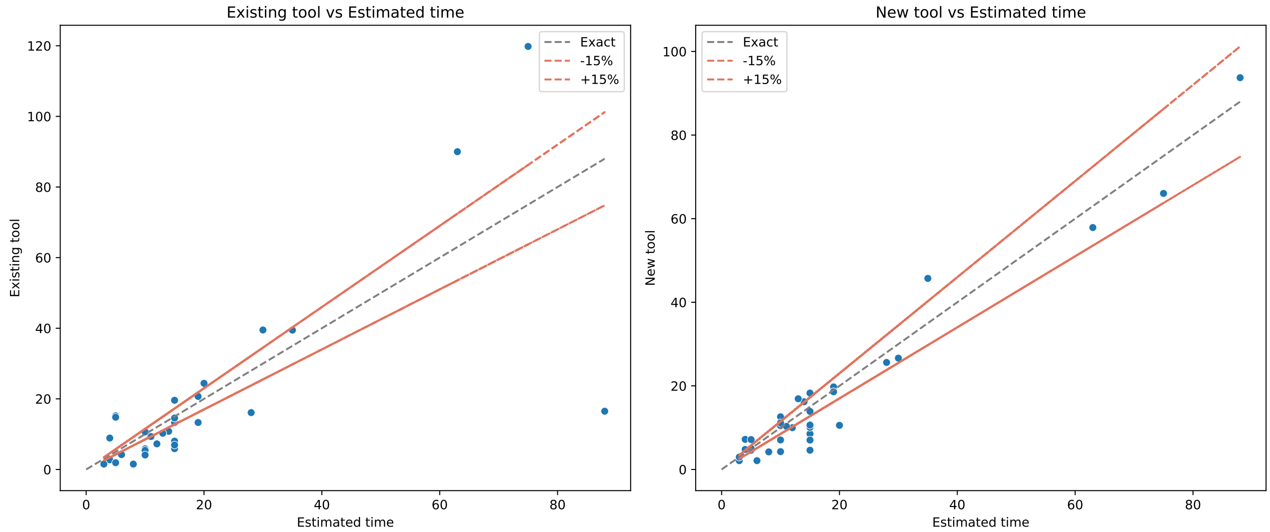


Figure 6.7: Overestimation and underestimation plotted with 15% margin lines for the time studied manual processes

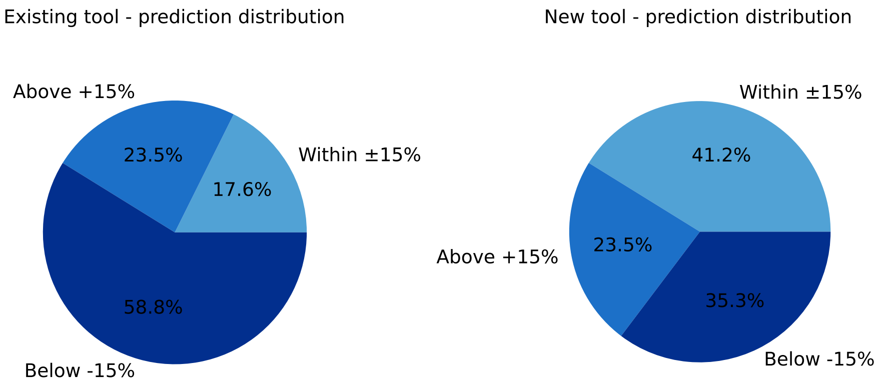


Figure 6.8: Pie chart of the overestimations and underestimations of the new and existing tools showing the percentage of parts that are within the margin, above or below for the time studied manual processes.

LQT (=31%), we observe a difference of 6%. However, this comparison is just informative as no conclusions can be drawn. Literature can also not support the value of 25%, as literature addresses the variability of allowances as it strongly depends on the type of work that is performed. As stated in section 3.3, another method by (International labour office, 1979) for determining the allowance was also performed by filling in a specialized assessment which can be found in Appendix C. This resulted in an allowance of 14%. This is even lower than the value found with work sampling. As (Maynard & Zandin, 2023) addresses that work sampling yields the best result for a manufacturer, we decided to incorporate an allowance of 25% in the new LQT.

6.3.3 SMT line validation

The validation for the SMT line consists of two parts. Firstly, it consists of validating the outcome of the regression of the pick-and-place machine. Here, new products are compared between the result of the regression and the outcome of the simulated times. The second part is focused on the productive time of the SMT line and excludes downtime. This is done by comparing time estimations of the existing LQT with the new LQT for actual production orders. Table 6.5 shows the validation for the pick-and-place machines, where a MAPE of only 11,8% is found for the simulated times highlighting the accuracy of the regression model. This is considered a good accuracy and it fits well within the target of 15%. The overestimations and underestimations are plotted between 15% margin lines in figure 6.9, with the percentages above, within, and below these lines shown in figure 6.10.

Table 6.5: Comparison of simulated cycle time and the cycle time determined by the regression model in the new tool for the Pick-and-Place machine with values provided in seconds.

Product	Side of the PCB	Simulated time	New tool	Percentage
PCBA A	Top	125	124,9	-0,1%
	Bottom	74	85,6	15,7%
PCBA B	Top	32	35,3	10,3%
	Bottom	48	39,3	-18,1%
PCBA C	Top	17	18,6	9,4%
	Bottom	5	5,2	4,0%
PCBA D	Top	70	70,5	0,7%
	Bottom	42	46,4	10,5%
PCBA E	Top	96	82,5	-14,1%
	Bottom	118	123,1	4,3%
PCBA F	Top	4,9	7	42,9%
	Bottom	-	-	-
			MAPE	11,8%

The second comparison is the most important part as it is for the complete SMT line. The tool estimates the total time that the line has to run to finish the order. It was assumed that it would only be necessary to determine the cycle time for the pick-and-place machine, which is the bottleneck, as this process dictates the maximum throughput of the entire SMT line. This validation step compares the actual time spent by the line for a production order of this product with the estimated production time by the new and existing LQT for the SMT line for these products.

Table 6.6: Comparison of the prediction of actual productive time of the SMT line with the new and existing LQT. The time values are given in minutes and the error is expressed in percentages.

Product	Actual time	New LQT	Error in [%]	Existing LQT	Error in [%]
PCBA A	251	199	-20,7%	512,8	104,3%
PCBA B	36	32	-11,1%	68	88,9%
PCBA C	41	36,7	-10,6%	117,7	187,0%
PCBA D	31	29,9	-3,7%	79,7	157,0%
PCBA E	70	82,2	-2,1%	142,5	103,5%
PCBA F	1,1	0,93	-15,2%	8	627,3%
		MAPE	**10,6%**		**211,3%**

In Table 6.6, the regression model shows an accurate estimation for the productive time of the SMT line. The MAPE for the new tool is here 10,6%, which is very good compared to the existing LQT. The existing LQT shows a MAPE of 211,3%, which is poor. Even after excluding an outlier, the MAPE is still 128,1%. Notably, this outlier is not considered an outlier in the new LQT making the results more significant. The results of the multiple linear regression model for the SMT line improve the production time estimations and enhance the performance of the new LQT compared to the old LQT.

However, accounting for periods when the line is on stand-by or experiencing downtime introduces challenges. The multiple linear regression model does not take these times into account. These factors are often unpredictable and can distort the accuracy of the quoted production time for the full line and are present in each production order on the line. In practice, the cycle time for PCB production is often a bit longer than the simulated time because of various uncertainties such as machine failures, human errors, quality reworks, material shortages, or schedule changes. Different combinations of SMT machines and frequent reconfigurations can also increase down or standby time of products and could cause deviations in estimating the full cycle time. Nevertheless, this is not considered as a problem for the new LQT, as downtimes are not supposed to be quoted. However, gaining a deeper understanding of standby times and downtimes could be valuable for a planning department. A potential solution could be handled by introducing a new parameter based on standby and downtime averages. Yet, this has not been implemented in the new LQT because of the irrelevance for quoting.

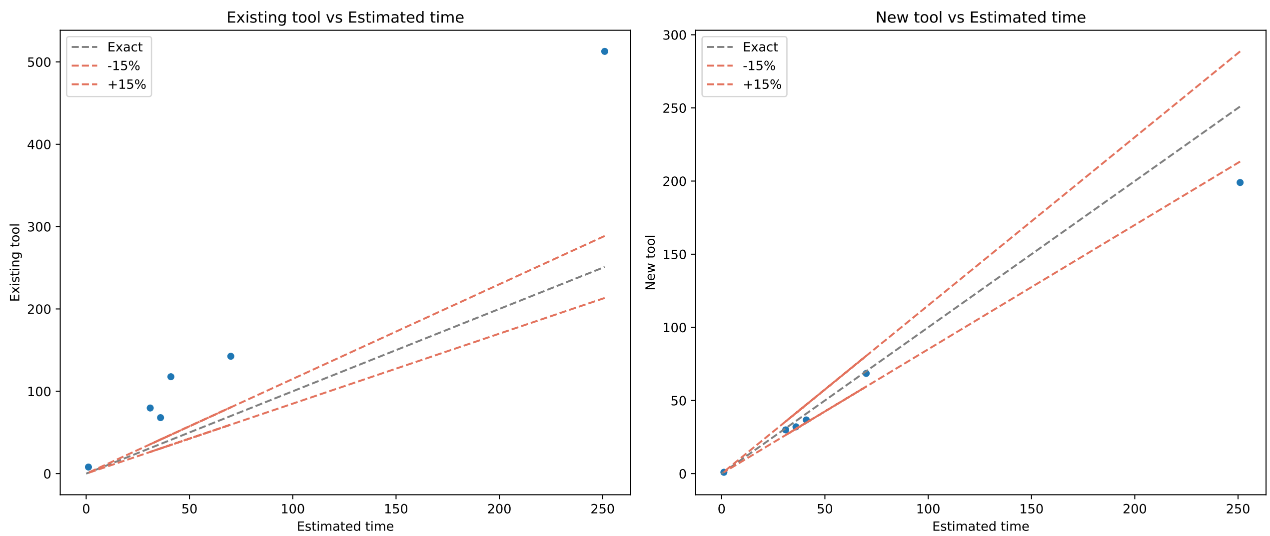


Figure 6.9: Overestimation and underestimation plotted with 15% margin lines of the SMT line

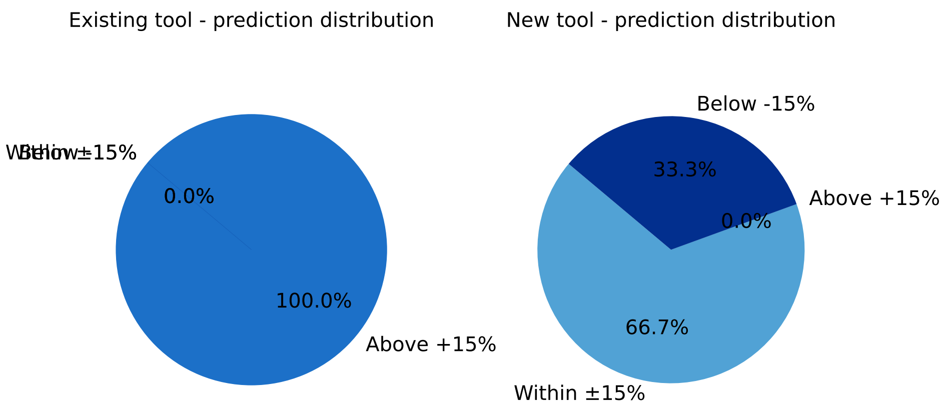


Figure 6.10: Pie chart of the overestimations and underestimations of the new and existing tools showing the percentage of parts that is within the margin, above or below for the SMT line

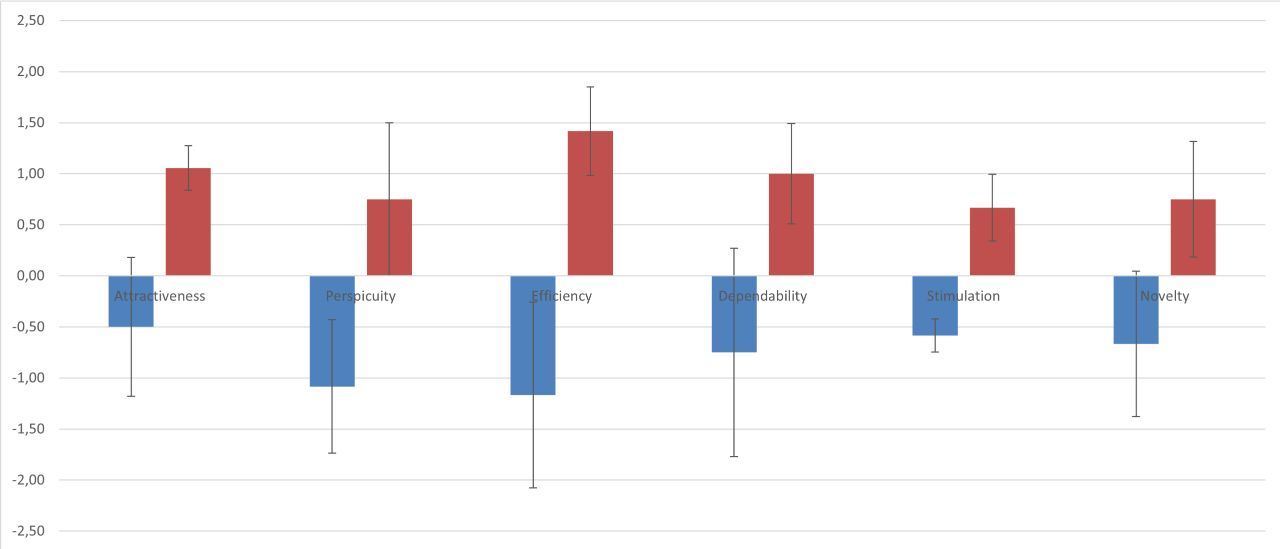


Figure 6.11: The scale means are presented along with their corresponding 95% confidence intervals for the comparison between the existing LQT (represented in blue) and the new LQT (represented in red).

6.3.4 User experience

Next to validating the production time estimation of the new LQT, the effectiveness and usability are also evaluated. We did this by conducting a user experience assessment, where we asked real users to will fill out a standardized User Experience Questionnaire (UEQ). The UEQ measures the means for six user experience aspects: Attractiveness, Perspicuity, Efficiency, Dependability, Stimulation, and Novelty (Hinderks et al., 2018). This approach gives us feedback on the satisfaction of the users and which parts of the tool need adjustment or improvement for further use. Due to the limited number of IEs that have had to use the tool since it was ready and validated. The user testing for the tool was conducted with a small group of only three individuals. Although the sample size is small, their feedback is still valuable and can provide insights into the overall user experience. The results from the user experience questionnaire were analyzed to evaluate user perceptions of the two compared products for six aspects. A two-sample T-test assuming unequal variances was conducted to determine whether the mean values of the existing and new LQT differed significantly for all six aspects. The results are presented in figure 6.11. The analysis was conducted with an alpha level of 0,05. The test revealed statistically significant differences across all measured attributes, except Dependability: Attractiveness ($p = 0{,}0362$), Perspicuity ($p = 0{,}0231$), Efficiency ($p = 0{,}0170$), Dependability ($p = 0{,}0594$), Stimulation ($p = 0{,}0072$), and Novelty ($p = 0{,}0405$). These results indicate that the two products differ significantly across all the dimensions except Dependability.

In summary, the new LQT demonstrated significant improvements in ratings in every measured aspect except for one compared to the existing LQT. These findings were consistent across all user experience categories, with the largest differences observed in Efficiency and Perspicuity.

Chapter 7

Conclusion

This chapter presents the research findings, the developed LQT, discusses the limitations, and explores the theoretical and practical contributions. It also offers recommendations and suggests future research directions. It is organized as follows: section 7.1 covers the answers to the research questions, section 7.2 and 7.3 provide recommendations and address study limitations. Section 7.4 details future research opportunities, and section 7.5 highlights the theoretical and practical contribution.

7.1 Conclusion

The main goal of this research is to minimize the estimation error of the production times of the PCBAs produced at Benchmark Almelo. With the support of the sub-questions and the well-structured phases of this research, we are able to answer the main research question:

> *How can Benchmarks Labor Quote Tool be enhanced to improve the accuracy of the quoted production times?*

Each sub-question will be answered separately. In the first sub-question: *How are the current production times estimated with the existing LQT of Benchmark?* The existing LQT uses production time parameters that are defined a long time ago, are based on an educated guess, and have not been updated after production processes were adapted or automatized. Therefore, the accuracy analysis of the existing LQT performance was found to be low, as shown in 2.4, with a MAPE of 44,8%, 43,3%, and 53,1% for the Pre-wave Assembly, Hand Solder, and Final Assembly, respectively. The Pressfit process could not be included in the validation and verification of the accuracy due to challenges in data collection. Additionally, the existing LQT is sometimes considered a black box due to its unstructured nature and interlinked formulas. Furthermore, the production parameters of the existing LQT lack a framework for regular updates, making it difficult to accurately estimate new products and increases the error for existing products as the parameters become outdated. Finally, interviews with IEs conclude that the existing LQT is user-unfriendly.

Based on the context analysis of the existing tool, the second sub-question can be answered: *Which methods are present in the literature for estimating the production times for the assembly processes?* The literature describes several methods, highlighted in section 3.1, with each method having its advantages in a particular product phase. Applying the analogical method would result in the most precise estimates since it estimates the production times by using production records data to inter/extrapolate between the times of similar products. However, this method requires a lot of reliable and accurate data, which is not available as it has been proven to be unreliable. Therefore, the parametric method is applied because it requires less data and is well-suited for the feasibility phase of a product, as it aligns with the current situation. In addition, the analytical method is applied by breaking down the tasks into smaller elements and is can be suitable for any other phase than the first and second production phases. This integration was valuable due to the added value of breaking down a process into more detailed elements and tasks.

In this section, the third sub-question is addressed: *How can the production times for the processes be determined?* To achieve more accurate production time estimates with the new LQT, this phase involves redefining the production parameters. Firstly, for the pick-and-place machine in the SMT line, these parameters were determined through a multiple linear regression model. The model uses three independent variables (number of components, number of unique components, and panel area) and one dependent variable that will be estimated (cycle time). The validation of the final model resulted in a MAD of 7,4 seconds, on an average cycle time of 51,7 seconds. This represents a significant improvement over the previous tool, which had an MAD of 69,98 seconds with the same average cycle time. A work sampling study is conducted to empirically determine the allowances, which resulted in a productivity level of 80,8%. For the four manual labor processes in the scope of this study, time studies were conducted. Elements were found in the time study and were categorized into production parameters. In this way, it is possible to estimate a production process based on multiple parameters that are quantifiable by the BOM, ODB, and other available input data. The improved parameters showed a great improvement, which is elaborated in the validation section.

With the research for determining new parameters completed, we proposed a solution design for the second phase and answered the fourth sub-question: *How can a tool be developed to integrate and summarize the new production time estimation framework?* Firstly, we designed a framework for redefining the estimation of the manual labor processes. The parameters were redefined using time study, by forming the elemental steps into parameters, these parameters are now based on quantifiable attributes from the input data such as the BOM, ODB, or other component characteristics such as the manufacturer or commodity name. A categorization algorithm has been developed which categorizes components based on extracted manufacturer names, commodity names, BOM and ODB data. The new LQT flags components as unknown if they are difficult to categorize automatically, allowing IEs to manually assign them, but reducing the work of categorizing drastically. For each process in the assembly of a PCBA other input data can be provided by the IEs and in combination with the BOM and ODB data, the input and parameters will be multiplied to calculate the production times.

To answer the following research question: *How accurate is the improved tool for all products of a key customer of Benchmark?* The validity of the new tool was assessed, as detailed in section 6.3.1 for three processes: Pre-wave Assembly, Hand Solder, and Final Assembly. Each process demonstrated a MAPE of 34,3%, 14,2%, and 19,7% respectively. This is an improvement compared to the existing tool, with a MAPE of 44,8%, 43,3%, and 53,2%. For the Hand Solder and Final Assembly process the improvements are significant. The new Pre-wave parameters are similar to the old parameters. The new tool includes a parameter that checks for LEMO connectors that take longer to assemble than a regular component. All three processes have more parameters and are based on time study, and a new framework for determining the parameters, explaining the improvement in accuracy. The user experience questionnaire also indicates that the new tool performed well, showing better results in all but one aspect.

Additionally, the production time of the SMT line was validated and determined with the multiple linear regression model for the pick-and-place machine (bottleneck). The hypothesis was that the full production times for the line can be determined by focusing on the bottleneck since the bottleneck determines the maximum throughput of the entire line. This approach proved to be effective, as it resulted in a MAPE of 10,6% for the productive time of the line. In comparison, the existing LQT gave a MAPE of 211,3%, and even after excluding an outlier, it was still 128,1%. Notably, this outlier is not considered an outlier in the new LQT making the results more significant. This shows that the productive time of the SMT line can be approximated accurately using this approach.

Despite the new methodology based on theories and methods from available literature for improving the accuracy of production time estimations, a zero percent estimation error could not be achieved. There are several reasons listed below:

- In the time study validation, the average production time of products are tested against a value given by an operator. These values are subjective and not the true average per definition. Unfortunately, the exact true average is not available due to the lack of reliable data.
- The model is based on generalized parameters and does not account for complexities that can influence and cause deviations from these parameters.
- Processes vary due to a lack of standardization, the nature of manual work, and variability between operators. These reasons have an impact on the accuracy and can also explain some of the larger deviations that are observed.

The final sub-question is as follows: *Are there ways to improve the new tool's quotation capabilities and make it accurate across all products?* Our approach is visualized in figure 6.3 and is already partially integrated. It involves using feedback loops from the production data of the factory which could help align the estimate of the tool with the actual production times. For this, a worksheet is developed, 'Production time lookup', that connects to the production data database and retrieves all the historical production records. While the data is currently not accurate, once improved, it can be effectively used to improve the accuracy by aligning the data real situation with the parametric model. Another advantage of the new tool is that all the values by which the parameters are quantified for a process can be read out. When multiple LQTs are in a file, all the different parameter quantities parameters can be retrieved. A dataset can be compiled to analyze for several reasons. A new regression analysis can be performed on all these parameters using them as independent variables and all the future reliable data as dependent variables to create a data-driven quotation tool, which will always be up to date. Based on the literature, this could serve as the foundation for a more accurate analogical tool or newly updated parameters.

7.2 Recommendations

In this section, practical recommendations are provided for Benchmark Almelo. The first part of this section provides practical recommendations for improving data reliability through improvements in the software. Proper data logging is a significant issue and these recommendations can change that. The second part of the recommendations is for the new tool.

Data recommendations:
Reviewing the PFS data collection method is important, as it could provide valuable information and could enable smart solutions for accurately estimating production times. It is advisable to redesign the software in a way to prevent inaccuracies by ensuring that errors in data entry are not possible. The system is already present and only has to be updated. In this age, where data becomes increasingly important with Industry 4.0 and Smart Manufacturing, real-time collection, monitoring, and processing of the data from all operations are essential (see section 3.4). Several recommendations for improving the data logging are listed below:

- A PFS software update should change the option the operators have to either record their production times or view the order without logging the production data. This second option often leads to incomplete data collection, as workers may avoid recording to prevent being monitored for speed. Changing the PFS system to remove this choice can ensure the production data is logged reliably. This should be changed in the software and implemented as soon as possible, ensuring more reliable data for future analysis.

- Another important feature for an update should be, that the cycle times for each single product in an order. This way more data on the cycle times can be collected. Currently, the time is logged for a full order with only one starting time and end time for multiple products produced, this reduces the level of detail in the data.

- The PFS software must prevent operators from working on a new order before completing the previous one. Sometimes operators may finish an order but forget to stop recording, continuing with a new order while the system still records the old one. At the end of the day, they might stop recording the old order, completing the new ones in just a few seconds, leading again to inaccurate data.

Tool recommendations:
Besides improving the data reliability we also provided recommendations for the new tool, which are as follows:

- If the data logging can not be improved shortly, then there must be a focus on continuously updating the parameters to estimate the production times. Time study can be applied to other processes.
- Another critical aspect is the IEs should continuously adjust the production times based on feedback from the operators. The new LQT is not yet data-driven and there is no feedback on production times once the products are in production. It is important to adjust the production times when products prove to be more complex than expected. Exceptions occur and the new LQT can not take into account every. The LQT is designed so that IEs can add remarks to their input explaining the discrepancies. These remarks are essential for understanding why certain processes take longer than expected and should later be analyzed to identify potential parameter changes that could improve time estimates.
- Currently the new learning curve is not implemented in the tool, since its analysis is based on limited data. Additionally, the learning curves are applied to batches instead of across the entire product lifecycle as described in the literature. Nevertheless, the existing learning curve that is implemented as discussed, substantially impacts the production time estimates and should therefore be re-evaluated with more data to determine a more accurate result.
- The current batch and proto allowances have to be re-evaluated. A focus should be on a comprehensive analysis of determining accurate values for these allowances and a justification for these values.
- To mitigate the challenge of accounting for standby and downtime periods in the SMT line, it is recommended to implement a better tracking system that can capture these events more accurately. This would allow for more accurate quotations and could also benefit the planning department. A study can be conducted to identify patterns in downtime occurrences, which could help improve the predictability and accuracy of future quotes, enhancing the overall reliability of the productive time estimates.

7.3 Limitations

The conclusions of this study are subjected to several limitations that should be considered. Limitations for the production parameter estimation and time studies are as follows. Given the wide variety of products and their unique exceptions, which cannot all be accounted for or observed, conducting a time study for each one is not feasible. The time study is limited by the trade-off between the number of observations and the accuracy. While more data improves the accuracy, the time available for data collection is limited, and finding a true average for a parameter is difficult and can therefore only be approximated. As a result, deviations can occur for a product. Moreover, because production parameters are averages of multiple time-studied products, it is difficult to obtain precise estimates for each individual product, as an average fails to adjust to the complexity of a certain product. However, when quotes are generated for all products, an average should provide an accurate estimate for all the products together. In this study, several specials and exceptions were also analyzed and combined to calculate an average. This new approach simplifies the data by creating a parameter of the tasks, making it easier to analyze. Nevertheless, this simplification comes with trade-offs such as it will work well for the majority of the products, in some cases, it may struggle with outliers in terms of these parameters. A sufficiently accurate average helps to address this variability among the different products and can be verified by examining the spread of the confidence intervals.

Limitations in the time study validation are that the average production time of products is tested against a value given by an operator. These values are subjective and not the true average per definition. Unfortunately, the exact true average is not available due to the lack of reliable data

During my research, it became evident that the use of Excel VBA is not well-suited for handling certain data processes and is less versatile in terms of available libraries compared to Python. For future data analysis, Python is probably the best option. However, it is worth noting that the Beta version of Excel now includes Python, which could be utilized in the future.

7.4 Future research

Enhancing data reliability remains a critical challenge for Benchmark. Future research should focus on improving the collection of reliable factory data, which helps to provide a feedback loop for determining more accurate production times. By comparing the actual production times of all products, derived from reliable data, with the estimates of the tool, a better evaluation can be made of the product and also the accuracy and effectiveness of the tool. This can be integrated into the tool by developing a dashboard that visualizes the data from all three sources (PFS, LQT, and LN) and highlights the differences between them. This ensures that the production times in PFS and the LQT are aligned, which is crucial for accurate estimates since this data is transferred to LN, which the planning department depends on. This also allows for a data-driven method for updating the parameters in the future, as shown in the flowchart in figure 6.4.

Interesting future research topics can be the current batch and proto allowances. It was observed in some quotes that these allowances were filled in as high as 50%, which leads to a substantial increase in the estimated production times. The research should focus on a comprehensive analysis of determining accurate values for these allowances and justifying the value.

When we developed the regression model for the SMT line, several regression models were explored. We managed to reduce the average error from 70,0 seconds to 7,4 seconds. However, the literature states that the accuracy of existing models can have a margin of around 2 seconds, which is possible by modeling multiple combinations of features and identifying the best-performing model. Despite that, this was not possible in this timeframe and the model found already very promising results. Future research can focus on improving the SMT line regression model. Additionally, the production parameters can be improved for another important machine, the selective wave soldering machine, for which data is available. This machine can have a significant impact on the quote, and the application of a new regression model on this process can improve the total accuracy of the estimates.

7.5 Theoretical and practical contribution

The theoretical contribution of this research lies in the integration of an analytical and parametric estimation approach to determine PCBA production times. The analytical method involves breaking down the work into specific elements identified through time studies. These elements are then converted into parameters that estimate the production times based on quantifiable data from the BOM and ODB reports.

The practical contribution is more significant. The LQT has been implemented, resulting in more accurate production times. The tool is now easier to understand and modify, addressing one of the main criticisms of the existing tool, which was perceived as a "black box". The tool provides a better overview by summarizing everything in a single worksheet as shown in the user experience questionnaire presented in section 6.3.4. This improvement enables the company to produce more accurate quotes and enhances the reliability of production times for the planning department. Additionally, the new tool can also be expanded in the future to retrieve production data from the system and verify the accuracy of the estimated production times.

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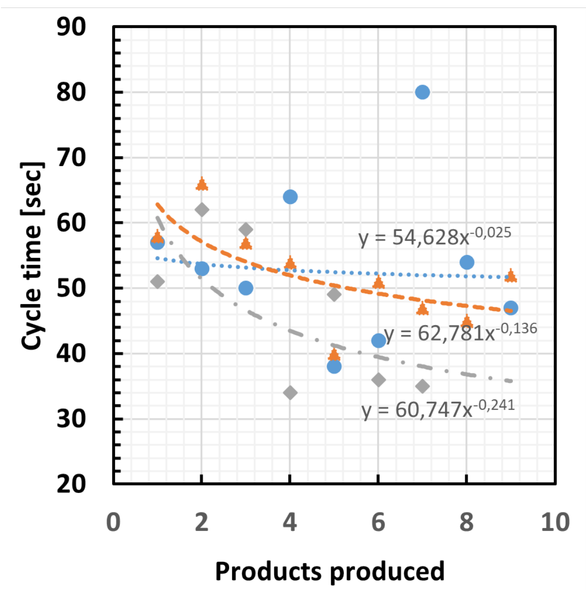
Appendix A

Learning Curve

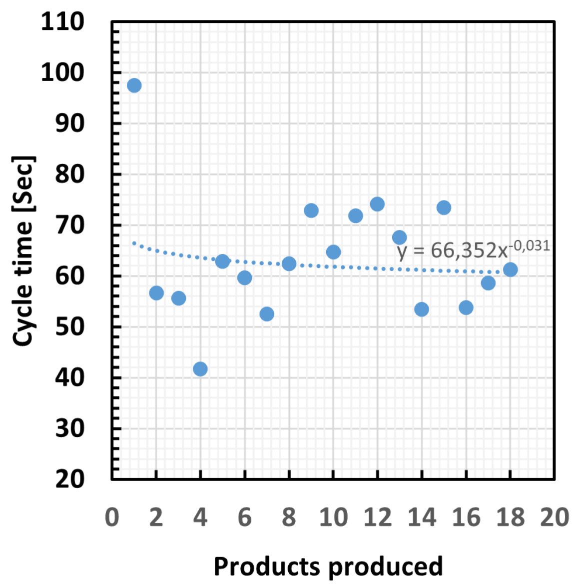
This Appendix shows the results of the analysis to determine a new learning curve for Benchmark. Ultimately, it was chosen to keep using the existing learning curve, which is why the results are moved to the appendix.

A.1 Results learning curves

This section presents the research outcomes that address the challenges associated with learning curves and data logging in a high-mix, low-volume (HMLV) manufacturing environment. This section aims to determine a learning curve constant applicable to Benchmark. Several time-studied orders were selected and analyzed, these orders contain a variety of product and process types.



(a) Same product produced by three different operators



(b) Learning curve for a larger batch of 18 products that was time studied

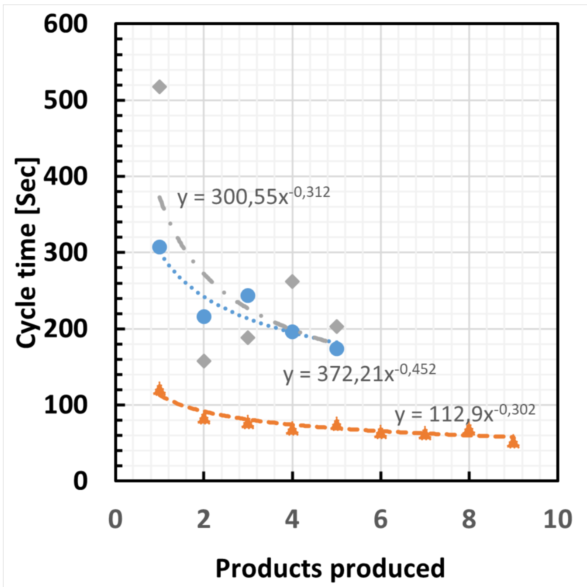
Figure A.1: Learning curve determined for products and processes with a short cycle time of approximately one minute

The first studies show samples of products that have a relatively short cycle time. For the first experiment, the same product is time studied 9, 9, and 7 times by three different operators, the improvements in the cycle time are plotted in figure A.1a. The operators were unaware of when they had last produced this product, and their prior knowledge of it was likely forgotten, though they did have experience with the process step. In figure A.1b, a single product is produced by an operator 18 times. In this sample, there is no clear improvement line in the scatter points but a trendline shows a slight improvement in the cycle time, this is mainly because the first product usually takes the longest and the learning curve is less apparent when the processes are short and contain fewer elements.

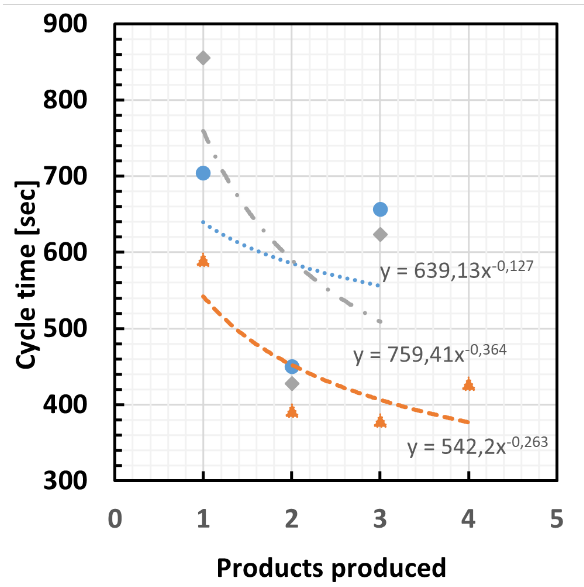
Predicting the learning curve constant for each product and process is challenging, and more data is needed to obtain a more accurate estimate. The previously determined constant was for a product's shorter cycle time of around one minute. In contrast, products with longer cycle times have not been tested.

As depicted in figure A.2a, the learning curves for three products time-studied on the pressfit process reveal improving trends. The curves indicate a reduction in cycle time as the number of products produced increases. The three products all have different initial cycle times and learning curves:

- The first product started with an initial cycle time of approximately 300.55 seconds and shows a steep learning rate, as indicated by the curve equation: $y = 300.55x^{-0.312}$
- The second product began with a higher initial cycle time of around 372.21 seconds but demonstrated an even steeper learning curve, $y = 372.21x^{-0.452}$, indicating a faster reduction in cycle time with each product. This is due to the first product taking much longer than the next products in the order, which can sometimes occur.
- The third product had a relatively slower learning rate with the equation: $y = 112.9x^{-0.302}$, but the values are almost perfectly following the trend line These results suggest that while all products benefit from the learning curve effect, the rate of improvement varies depending on the product and initial complexity.



(a) Learning curve of three products time studied on the pressfit



(b) Learning curves found for two different products in the assembly process

Figure A.2: Learning curve determined for products and processes with a medium-long cycle time of roughly 10 minutes

In figure A.2b, the learning curves for three different products in the assembly process were examined. Similar to the pressfit process, the assembly process also shows a decrease in cycle time as the number of products produced increases. The first product is the the HIPA, indicated with the diamonds, it has an assembly cycle time ranging from 10 to 20 minutes. An operator who assembled three HIPAs consecutively is time studied. After setup, the cycle time recorded for each product is plotted, the learning curve was much steeper than expected in a process with more steps, with a value of $n = -0,364$.

One other product was analyzed time studying two different operators and are indicated with round and triangle points in figure A.2b. The learning curve for the two operators is very different because the first product takes longer. The last product analyzed was a product with a very long cycle time of almost an hour. The cycle times of the three

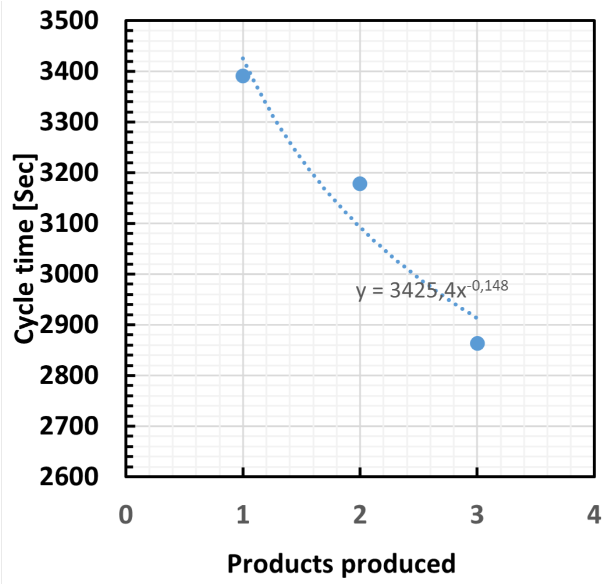


Figure A.3: Learning curve of a time studied product in which the process has a very long cycle time

hand-soldered products are shown in figure A.3. It shows a slightly lower learning rate than in the pressfit and assembly process, but for this process length, there are more elements, which could indicate that the learning effect is lower.

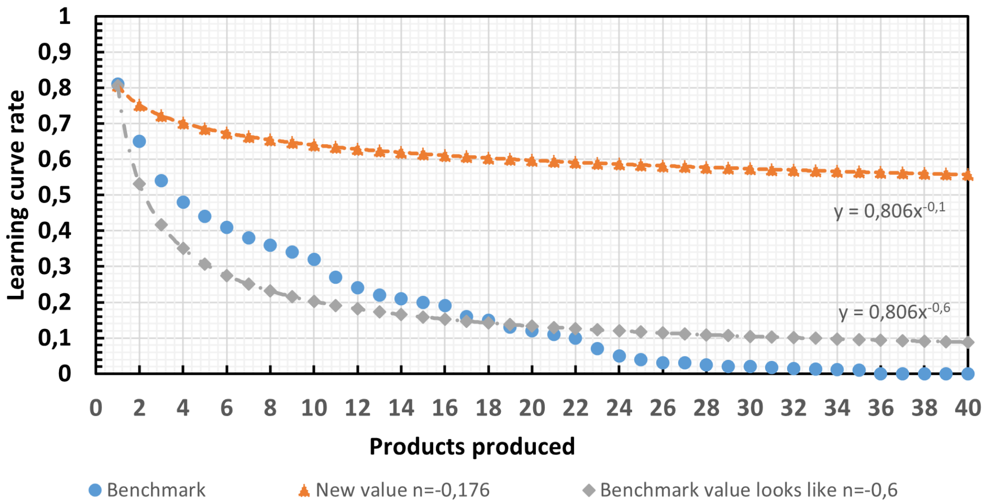


Figure A.4: Learning curve from current tool plotted against new proposed value

The learning curve constant used by Benchmark in the current tool is illustrated in figure A.4. According to Wright's formula, the old learning curve appears to be around n = -0.6. This value is high and has not been observed during my time study. The observed value based on a weighted average is found to be n = -0,176, as depicted in table A.1.

This value is slightly higher than expected.

To ensure the determined value is accurate, I compared it to two values from the literature. The learning curve constants from (Maynard & Zandin, 2023) show learning curve constants ranging from -0.05 to -0.15, almost consistent with the findings. (U. S. National and Space Administration, 2004) suggests that a reasonable approximation for the electronic manufacturing industry is 0,05 to 0,1. The learning curves in the literature are less steep than observed.

Accurately determining the true learning curve for Benchmark's factory is challenging. Collecting more data is difficult because currently only the total time for an entire order is recorded, complicating the analysis of variations in production times for individual products within an order. To determine a more accurate value based on empirical data, more detailed and extensive data collection is required. The lack of detailed data hinders a precise understanding of the learning curve dynamics at Benchmark for various products and processes.

Table A.1: Summary of the learning curve found

Statistic	**Value**
Average	0,218
Weighted average	0,176
Standard deviation	0,137

Given these constraints, a learning curve constant of (n=-0,15) is picked based on the experiments and literature. This constant has been based on the empirical data and also lies in the middle of the values in the literature. we have decided to use the proposed learning curve constant as it provides a reliable approximation based on existing studies.

Appendix B

Time Study Data

In this section, the elemental steps from the time study are categorized into the specific production parameters for each process. The time studies are analyzed, and all the normal times for each element are pasted into each category. Then in the tables below the production parameters with all the normal times found is shown. The resulting metrics are presented below each parameter and consist of the weighted average, weighted standard deviation, minimum, maximum, corresponding t-value, and 95%-CI. In some cases, it was not possible to write all the values down or they were assembled simultaneously. Consequently, these values were split into three columns: total, number, and total divided by number. Therefore, the weighted average and standard deviation consider the number of products produced, ensuring a more balanced consideration for the different sample sizes and production times.

B.1 Parameters assembly

The parameter selection for the assembly process is as follows. each of the 14 parameters will be elaborated upon below.

1. **Setup and post-setup order:** This phase involves retrieving the rack from Work In Progress (WIP) storage and adjusting the suction hood to remove fumes. Post-setup includes transporting products to the next operation, scanning all products, cleaning the workstation, and completing the order in the system.
2. **Handling PCBA:** Each product needs to be taken from the rack, processed, and then returned to storage. Additionally, every product must be recorded as complete in the system.
3. **Screws/bolts:** This parameter accounts for the number of bolts and screws that have to be fastened in the assembly
4. **Nuts:** This parameter indicates the number of nuts that need to be tightened or secured to allow bolts to be fastened properly.
5. **Threaded pins:** Threaded pins, which function similarly to screws and bolts, need to be fastened using specific tools during assembly.
6. **Cables:** When mistakes are made by the designers cables will have to be soldered to connect components on the PCBA.
7. **Spacers:** Spacers are used to prevent mechanical parts from contacting the PCBA.
8. **LEDs:** This parameter measures the time required to mount optopipes or LEDs from the PCBA to the front plate.
9. **Quality inspection:** Sometimes necessary when solderings have been made to see if there is no contamination.
10. **Stickers:** This is divided into fixed and variable components. The fixed component covers the time spent

Description	New LQT	Existing LQT
Pressfit		
Setup time	[illegible]	[illegible]
Pressfit component	[illegible]	[illegible]
Handling PCBA	[illegible]	[illegible]
Switch tooling	[illegible]	[illegible]
Switch tooling bottom	[illegible]	[illegible]
Switch tooling top	[illegible]	[illegible]
Flip PCBA	[illegible]	[illegible]
Open new box of components	[illegible]	[illegible]
Pre-wave Assembly		
Setup and post setup	[illegible]	[illegible]
Inserting a THT component	[illegible]	[illegible]
LEMO connector	[illegible]	[illegible]
Handling PCBA	[illegible]	[illegible]
Hand Soldering		
Setup time	[illegible]	[illegible]
Soldering one component	[illegible]	[illegible]
Handling time one component	[illegible]	[illegible]
Soldering one lead	[illegible]	[illegible]
Cleaning per lead	[illegible]	[illegible]
Handling PCBA	[illegible]	[illegible]
Quality inspection per lead	[illegible]	[illegible]
Preparing component (cutting, bending etc.)	[illegible]	[illegible]
Solder bridge or wire	[illegible]	[illegible]
Assembly		
Setup time	[illegible]	[illegible]
CAD	[illegible]	[illegible]
Electrical component	[illegible]	[illegible]
Glue	[illegible]	[illegible]
Large mechanical part	[illegible]	[illegible]
Small mechanical part	[illegible]	[illegible]
Screw/bolt	[illegible]	[illegible]
Washers	[illegible]	[illegible]
Nut	[illegible]	[illegible]
Other assembly component	[illegible]	[illegible]
Labels (Setup)	[illegible]	[illegible]
Labels (Cycle)	[illegible]	[illegible]
Flowbench (Setup)	[illegible]	[illegible]
Flowbench (Cycle)	[illegible]	[illegible]
LED	[illegible]	[illegible]
Spacer	[illegible]	[illegible]
Sleeve	[illegible]	[illegible]
Bushes	[illegible]	[illegible]
Thermal pads	[illegible]	[illegible]
Handling PCBA	[illegible]	[illegible]
Search time/tool	[illegible]	[illegible]

Note: *: has to be filled in manually

Figure B.1: Production parameters for the existing LQT and new LQT for the manual processes walking to the printer to produce necessary labels or stickers. The variable component reflects the time needed to apply these labels or stickers to the assembly.

11. **Battery packs:** In certain assemblies, battery packs need to be installed. This involves both the time required to assemble the battery pack and the time needed to mount it onto the PCBA.
12. **Flowbench:** This parameter also has fixed and variable components. The fixed part accounts for the time spent walking to the flowbench, a room designed to blow dust away from the table to reduce contamination. The variable part represents the additional time required to assemble mechanical components. In the flowbench, each part is cleaned with pressurized air and alcohol to prevent contamination.
13. **Unique tools:** Each type of fastening component requires specific tooling. This parameter tracks the number of unique tools needed from the inventory for different nuts, bolts, and screws.
14. **Large/mechanical parts:** This parameter reflects the time required to assemble larger mechanical parts, such as a front or cover plate.

B.2 Pressfit

The parameter selection for the presssfit process consists of 5 parameters, each of it is elaborated below:

1. **Setup and post-setup:** This step includes retrieving the rack from the work in progress (WIP) cabinet, setting up the machine by entering the part number, and gathering the necessary tooling from the cabinet to prepare the machine for the first PCB. Post-setup involves transporting the products to the next operation, scanning all products, cleaning the plastic boxes and tooling at the workstation, and finishing the order in the system.
2. **Pressfit connector:** This process involves picking up a component and placing it in the designated holes. Then, the operator presses a button that initiates the machine to perform the pressfit. If no additional tooling is required, the pressfit process does not need any adjustments and can press all connectors on one side of the PCBA without any further setups.
3. **Number of unique connectors:** Each unique connector requires specific tooling, which takes time to set up during the operation. For each product, the tooling must be switched as many times as there are unique pressfit connectors on the PCBA. Both bottom and top tooling may need to be switched simultaneously if certain unique connectors require a bottom bracket for support to prevent the PCBA from bending during pressing.
4. **Handling PCBA:** Each product must be retrieved from the rack and stored again after the operation.
5. **Number of sides:** The number of sides determines if the PCBA has to be flipped and realigned in the machine for a second time.

B.3 Hand solder

The eight parameters for the hand solder process are as follows:

1. **Setup and post-setup:** This parameter involves retrieving the rack from Work In Progress (WIP) storage and adjusting the suction hood to remove fumes. Post-setup includes transporting products to the next operation, scanning all products, cleaning the workstation, and completing the order in the system.
2. **Number of solders:** This parameter accounts for the total number of solders required, based on the number of component leads that must pass through the PCBA.
3. **Number of leads to clean:** After hand soldering, the PCBA surface typically has flux and residue that need manual cleaning. This labor-intensive process involves using a dental hook or brush to scrape off the residue, followed by brushing and blowing off the last particles with pressurized air. The time required depends on the amount of residue, and if covers were applied on other components to reduce the area that can get contaminated with flux.

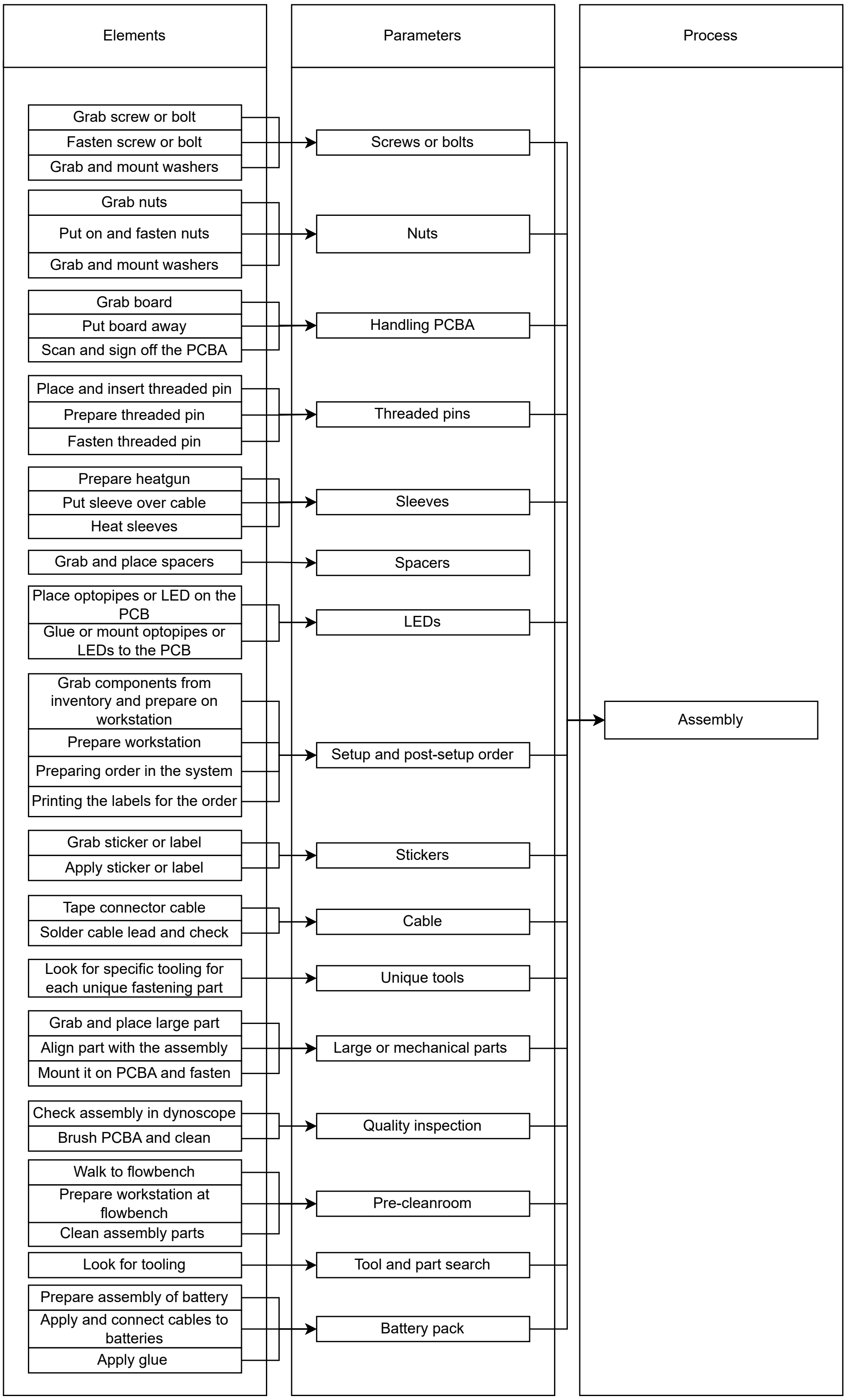


Figure B.2: Analysis of the time study elements and dividing them into parameters

4. **Handling PCBA:** Each product must be retrieved from the rack, processed, and then stored again. Additionally, each product has to be completed in the system.

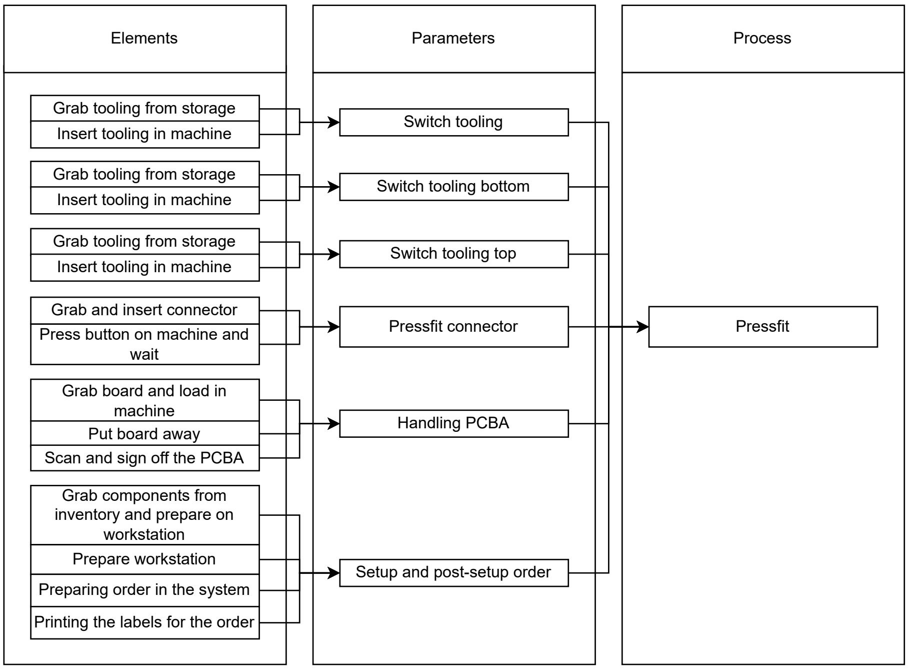


Figure B.3: Analysis of the pressfit time study elements and dividing them into parameters

5. **Quality inspection:** Post-soldering, it is essential to inspect the solder joints to ensure they meet customer specifications and quality standards.
6. **Preparing components:** Components often require preparation before soldering. This includes pre-cutting leads to the appropriate length and bending them to fit the PCBA correctly.
7. **Wires and bridges to solder:** Sometimes, wires or bridges are needed to connect specific PCB contacts, typically due to design errors. Although not common, these tasks add to the production time.
8. **Rework:** Rework may be necessary if a component is damaged during the cleaning process or if a solder joint needs correction. The frequency of rework can depend on the operator's experience and also how careful the operator is while cleaning.

B.4 Pre-wave assembly

The pre-wave assembly contains the fewest parameters, a total of four, each of which is elaborated below:

1. **Handling PCBA:** Each PCBA must be grabbed from the plate and put back the right way so the components can not fall out.
2. **Number of LEMOs:** The LEMO connectors are a special type of connector that require 4 screws to be assembled.
3. **Number of components:** This parameter consists of all the pre-wave components that have to be inserted into the PCB.
4. **Setup and post-setup:** This parameter involves retrieving the rack from Work In Progress (WIP) storage and preparing the workstation. Post-setup includes transporting products to the selective wave, scanning all products, cleaning the workstation, and completing the order in the system.

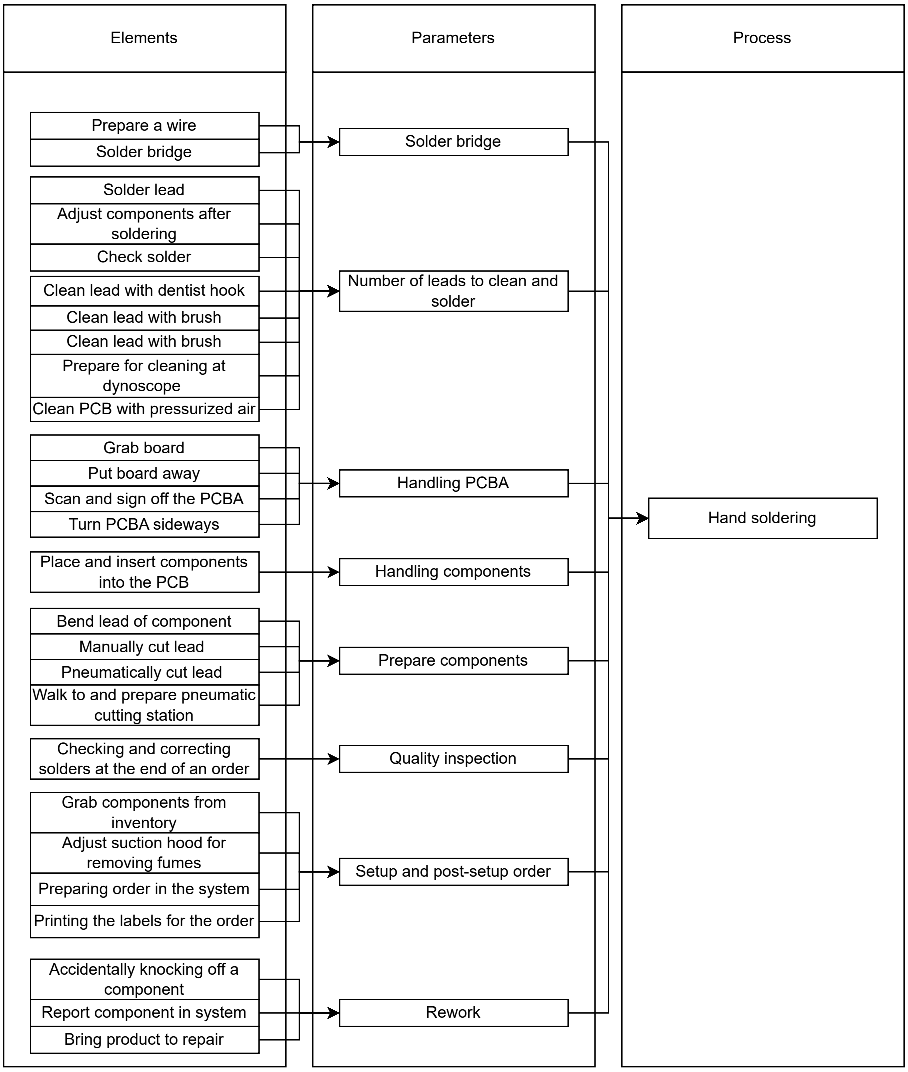


Figure B.4: Analysis of the time study elements and dividing them into parameters

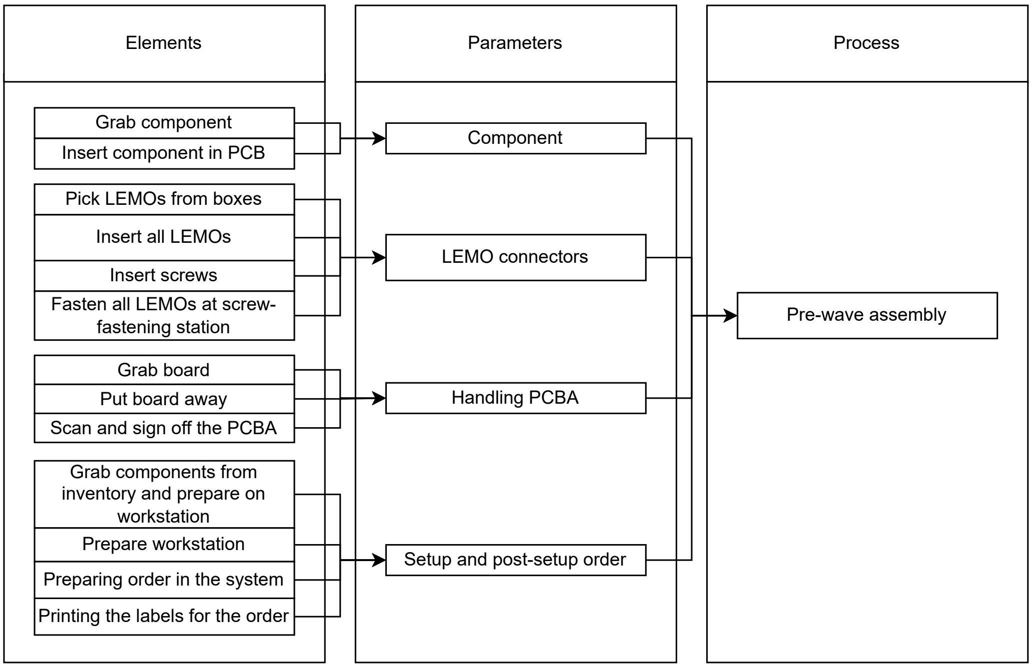


Figure B.5: Analysis of the time study elements in the pre-wave assembly process and dividing them into parameters

Appendix C

Allowances

Besides determining the allowances empirically. For this, we used the relaxation allowance questionnaire from (Maynard & Zandin, 2023), which can serve as another source for determining an allowance. In table C.1, the allowances are determined by allocating points based on a questionnaire for the tasks the operators perform. The final allowance was found to be 14%. The justification for giving the points is given in table C.2.

Table C.1: Points allocated based on the questionnaire for the four manual processes

Allowance	**Pre-wave assembly**	**Pressfit**	**Hand solder**	**Final assembly**
Force exerted	0	0	0	0
Posture	2	2	2	2
Vibration	0	0	0	0
Highly repetitive work	10	10	10	5
Restrictive clothing	1	1	1	1
Concentration/anxiety	4	4	4	4
Monotony	5	5	5	5
Eye strain	0	0	14	4
Noise	0	0	0	0
Temperature and humidity	0	0	0	0
Ventilation	0	0	0	0
Fumes	0	0	0	0
Dust	0	0	0	0
Dirt	0	0	0	0
Wet	0	0	0	0
Total	22	22	36	21
Average	25.25			
Relaxation allowance [%]	14%			

Table C.2: Justifications for the allowances

Allowance	**Descriptions**
Force exerted	The PCB has a maximum weight of 100-500 grams, and are usually unassembled not very heavy
Posture	Sometimes a weird posture is necessary for assembling or getting a better look at the small components
Vibration	No vibrations in any process
Highly repetitive work	Work can be very repetitive for most of the batches
Restrictive clothing	Surgeon gloves are used
Concentration/anxiety	Assembling small and simple batches is 4 points according to table
Monotony	Monotony can be high for larger batch sizes
Eye strain	Cleaning under dynoscopes is tedious after hand soldering. This is roughly 50% of the process depending on the quality of the process.
Noise	Light assembly factory is described as 0 points.
Temperature and humidity	Humidity is close to 0% so no points are allocated
Ventilation	Controlled ventilation system in the factory
Fumes	No fumes are generated during the processes.
Dust	The assembly processes are generally very clean
Dirt	No dirt in partly clean-room
Wet	Environment is very dry

Appendix D

Time sheets

In figure D.1, a timesheet is shown for collecting secondary operator data to use for the verification and validation.

	Orderregistration		Name operator:			
	process step:	**Depanelization**				
Production order	**12NC**	**Setup time [min]**	**Cycle time [min]**	**Number of cuts**	**Machine**	**Number of PCBAS in panel**

Figure D.1: Timesheets used for analysis for determining and validating production parameters

Appendix E

Interfaces of the new tool

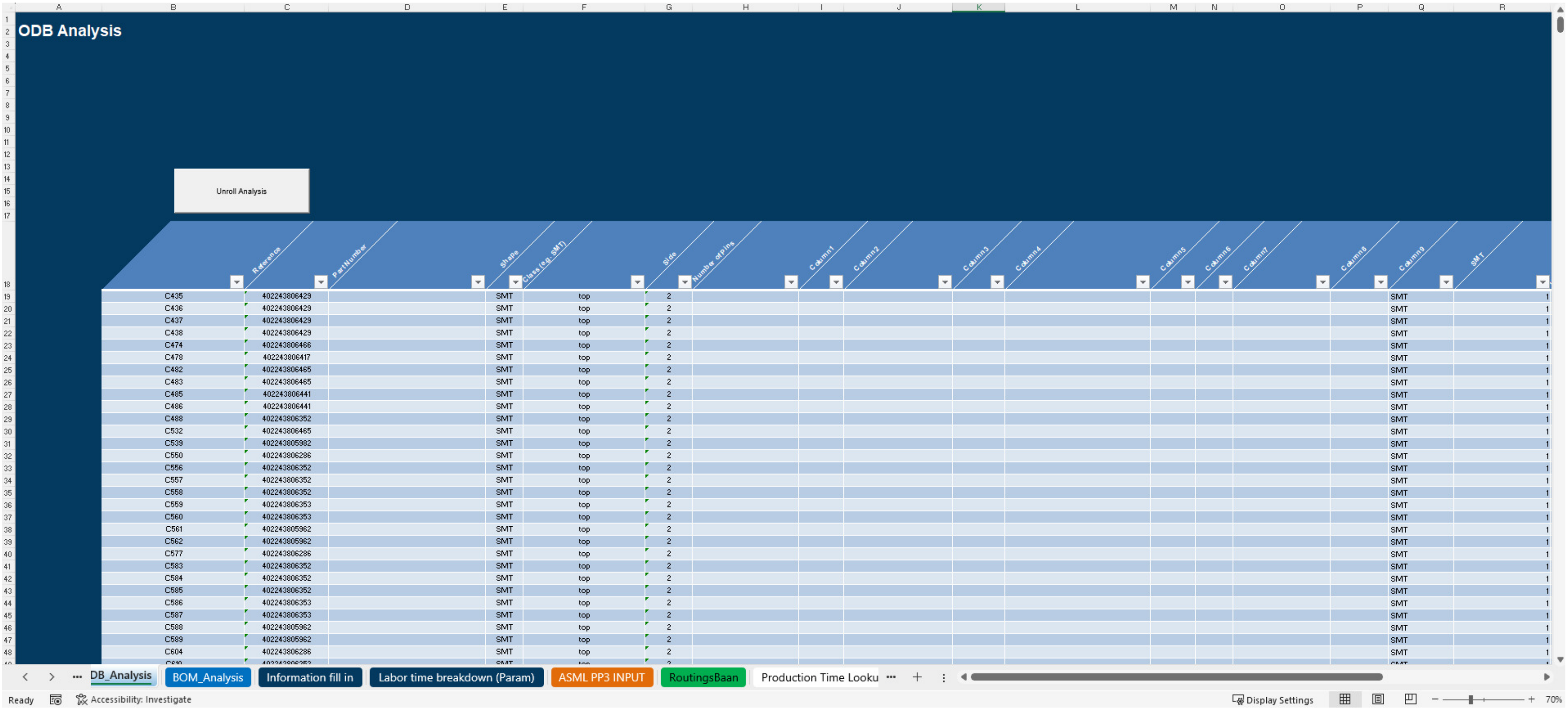


Figure E.1: This is the first input sheet where the ODB (CAD-CAM) report is filled in and analyzed.

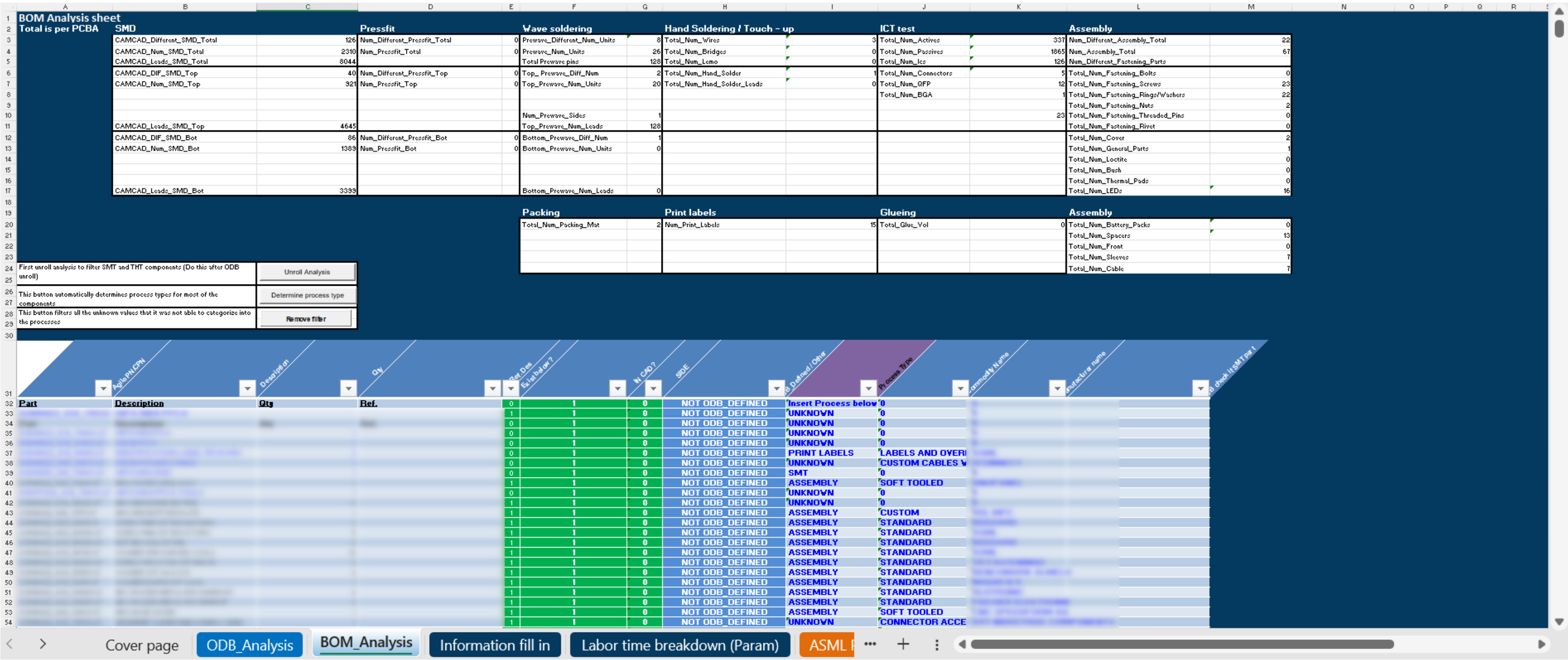
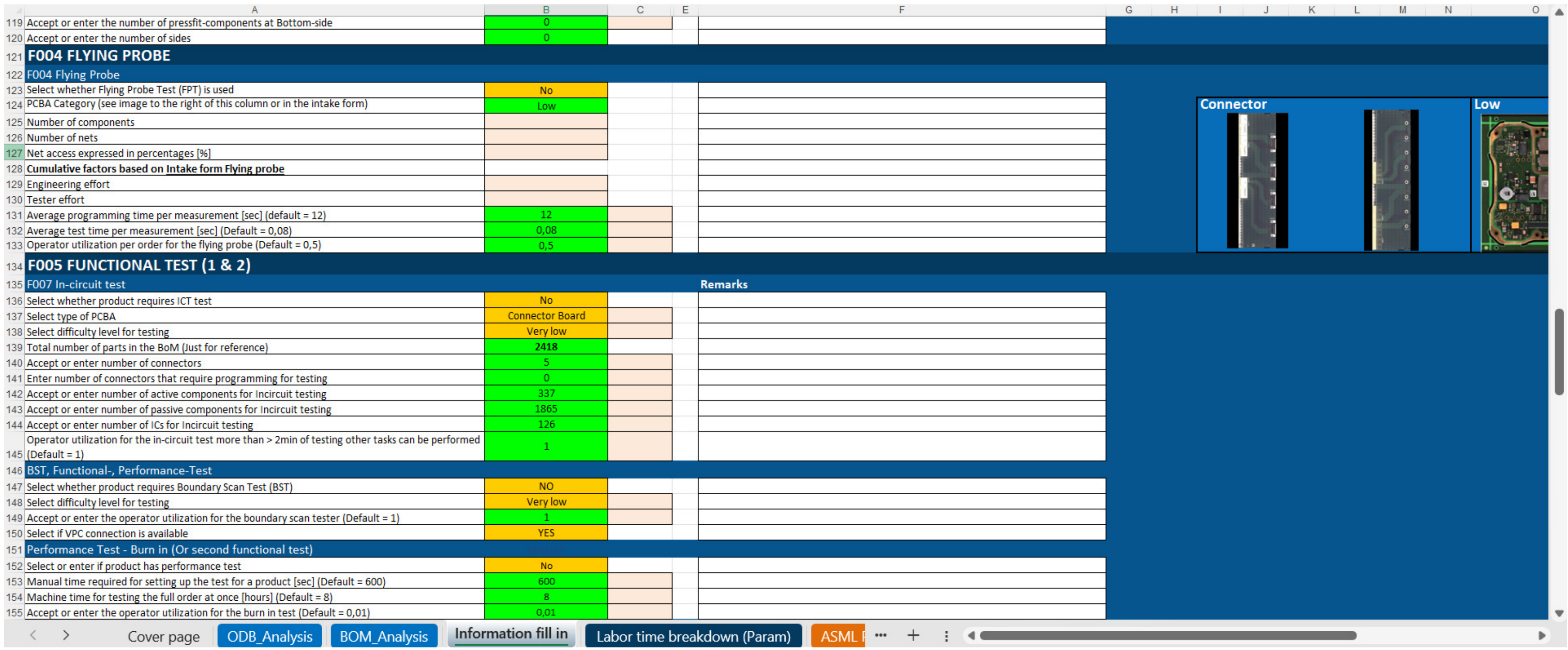


Figure E.2: BOM is loaded into this sheet and analyzed to quantify the parameters for each process.



	A	B	C	E	F
119	Accept or enter the number of pressfit-components at Bottom-side	0			
120	Accept or enter the number of sides	0			
121	**F004 FLYING PROBE**				
122	F004 Flying Probe				
123	Select whether Flying Probe Test (FPT) is used	No			
124	PCBA Category (see image to the right of this column or in the intake form)	Low			
125	Number of components				
126	Number of nets				
127	Net access expressed in percentages [%]				
128	**Cumulative factors based on Intake form Flying probe**				
129	Engineering effort				
130	Tester effort				
131	Average programming time per measurement [sec] (default = 12)	12			
132	Average test time per measurement [sec] (Default = 0,08)	0,08			
133	Operator utilization per order for the flying probe (Default = 0,5)	0,5			
134	**F005 FUNCTIONAL TEST (1 & 2)**				
135	F007 In-circuit test				**Remarks**
136	Select whether product requires ICT test	No			
137	Select type of PCBA	Connector Board			
138	Select difficulty level for testing	Very low			
139	Total number of parts in the BoM (Just for reference)	**2418**			
140	Accept or enter number of connectors	5			
141	Enter number of connectors that require programming for testing	0			
142	Accept or enter number of active components for Incircuit testing	337			
143	Accept or enter number of passive components for Incircuit testing	1865			
144	Accept or enter number of ICs for Incircuit testing	126			
145	Operator utilization for the in-circuit test more than > 2min of testing other tasks can be performed (Default = 1)	1			
146	BST, Functional-, Performance-Test				
147	Select whether product requires Boundary Scan Test (BST)	NO			
148	Select difficulty level for testing	Very low			
149	Accept or enter the operator utilization for the boundary scan tester (Default = 1)	1			
150	Select if VPC connection is available	YES			
151	Performance Test - Burn in (Or second functional test)				
152	Select or enter if product has performance test	No			
153	Manual time required for setting up the test for a product [sec] (Default = 600)	600			
154	Machine time for testing the full order at once [hours] (Default = 8)	8			
155	Accept or enter the operator utilization for the burn in test (Default = 0,01)	0,01			

Figure E.3: The final input interface incorporates the knowledge of the IEs as additional input and allows for the overriding of values if necessary

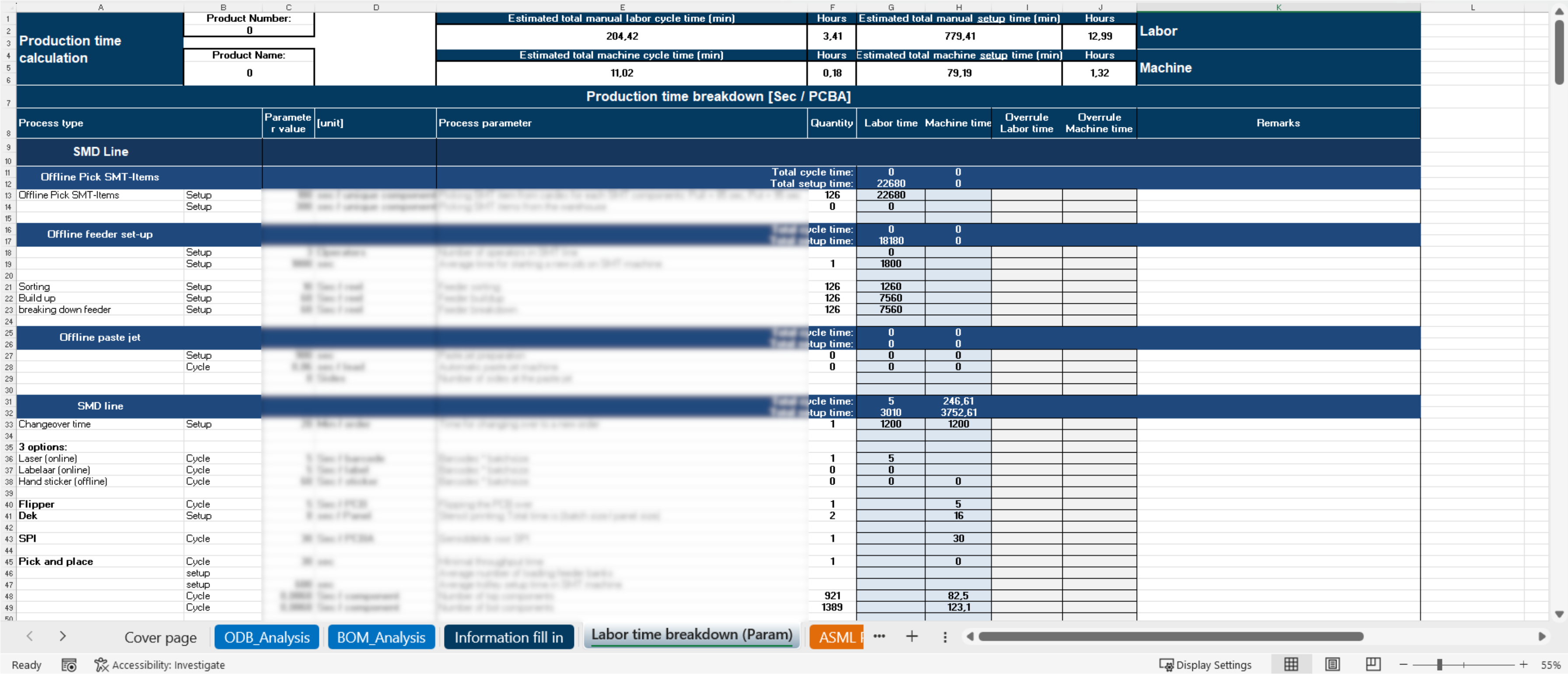


Figure E.4: Interface that displays the production times for all processes, parameters, quantities of the parameters, and differentiating between machine and labor times, as well as cycle and setup times.