

# Simulation and multi-objective optimisation for sustainability of a production flow

A Literature Review and Simulation-Based Case Study of Sustainable Manufacturing

Master's thesis in Production Engineering

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CHALMERS UNIVERSITY OF TECHNOLOGY  
Gothenburg, Sweden 2026  
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## Abstract

Manufacturing companies are increasingly facing growing customer demands to produce more sustainable products across all dimensions of the Triple Bottom Line (TBL), including environmental, economic, and social aspects. To address these challenges, simulation-based optimisation has become a widely used approach in modern manufacturing systems. The aim of this thesis is to investigate how simulation software can support sustainable improvements in an industrial production flow.

The study is based on a systematic literature review and an industrial case study of a robot cell in a heavy equipment manufacturing plant. A Discrete Event Simulation model was developed and analysed using the NSGA-II algorithm to identify improvements in productivity and energy consumption. In addition, an ergonomic assessment was conducted to include the social dimension of sustainability. The systematic literature review together with the case study found the possibilities with using simulation as a tool to sustainably analyse a manufacturing system.

The results from the case study demonstrate that a large share of the energy consumption in the system is non-value-adding and related to idle operation. The optimisation identified multiple Pareto-optimal solutions, showing that energy consumption can be reduced while maintaining or increasing production output. The findings highlight idle power reduction as the most influential improvement.

Overall, the study shows that simulation combined with multi-objective optimisation is a valuable tool for supporting sustainable manufacturing by enabling data-driven evaluation of improvements within the TBL.

Keywords: Simulation, manufacturing, ergonomics, social, improvement, environmental, profit, productivity, multi-objective optimisation, data collection, replications, DES.



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# List of Acronyms

Below is the list of acronyms that have been used throughout this thesis listed in alphabetical order:

DES	Discrete event simulation
NSGA-II	Non-dominated Sorting Genetic Algorithm
PRISMA	Preferred Reporting Items for Systematic reviews and Meta-Analyses
MOO	Multi-objective optimisation
MaxWIP	Maximum Work-in-process
TBL	Is a framework for manufacturing companies where the three dimensions of sustainability are included, environmental, social and financial [1]
Industry 4.0	Is generally about digitalization in industries, manufacturing companies have been using digitalisation as a strategy to improve sustainability [2], [3].



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# 1

## Introduction

### 1.1 Background

With the higher awareness of sustainability in today's society, manufacturing companies have faced a shift in priority towards sustainable manufacturing [4]. Traditionally, improvements have primarily focused on economic efficiency and productivity, however, companies are now experiencing increasing pressure from customers to deliver more sustainable products [5] [6]. As a result, industries are challenged to improve social and environmental sustainability aspects while maintaining high productivity levels. To remain competitive, manufacturing companies must therefore adopt sustainable production strategies that address all dimensions of the TBL [6].

It has come to attention that manufacturing companies have one of the highest energy consumptions [7], [8], [9]. With the developments in the world today, energy use has significantly increased in cost, making a clearer dent financially for the companies. Not only is it costly, but energy use also has a negative effect on the environment [7], [8], [9]. This is why it is important to make an effort to reduce the energy consumption.

With digitalisation as an effect of implementing Industry 4.0 in manufacturing companies, simulation software has become a tool used to work towards sustainable manufacturing. In the case study company, there is a constant ongoing effort to increase the use of simulation software tools, aiming to move towards more sustainable and data-driven decisions. The case study is conducted on a working robot cell within a production flow at a heavy equipment manufacturing company. Using simulation and optimisation to analyse trade-offs between the environmental and financial dimension of the TBL.

### 1.2 Aim

The aim of this project is to analyse a section of an industrial production flow from all dimensions of the TBL using a simulation software. This is achieved through a systematic literature study to identify how previous research has addressed similar challenges, and through an industrial case study of a robot cell in a heavy equipment factory.

## 1.3 Research questions

**RQ1** How can discrete-event simulation combined with NSGA-II be used to identify improvements in energy consumption and productivity of a robot cell?

**RQ2** How can a manufacturing company use simulation to improve the aspects of the TBL?

The research questions will be answered by following the following steps:

1. Conduct a systematic literature review of previous research in the field
2. Analyse the ergonomics of the manual operation for the robot cell
3. Create a simulation with relevant input data
4. Conduct an optimisation of the productivity and energy use of the system

## 1.4 Scope

If the data of the system is not able to be extracted by the end of our data gathering deadline, an assumption will be taken for that data. This will be done by observing the station and discussing with company experts on how the best assumption or combination of data could be made, in each specific case.

The software that is used for this project is currently still in a development phase, meaning that problems can occur and functions might not exist. For this reason, this study will have to work around functions that are non-existent and to try to find the best solution that is possible at the moment. As this is the software that is used by the company, the project will not explore other potential software tools.

An important limitation is to only focus on the production cell level, meaning looking at all equipment and their performance together in a cell. A deep investigation will not be done, such as the individual equipment or the welding process. The data will be extracted as far as possible for the individual equipment to be able to do a production cell simulation and not to optimise the individual equipment's performance or the manufacturing process.

There are many aspects in the social dimension that can be analysed at a production site. To ensure the project remains within scope, the social dimension will focus on physical ergonomics of the manual operations in the system.

## 1.5 Case study company

A heavy equipment manufacturing enterprise, producing wheel loaders of different sizes, want to work more towards using technology for sustainability improvements in production. Currently, many of the productivity improvements are developed

based on engineers' knowledge and input from experienced operators. The manufacturing company wants to make this process more data-driven and sustainable with the use of more simulations.

Today, the few optimisations based on simulation at the company are conducted with productivity as the only factor. As the enterprise is trying to develop the factories with sustainability in mind, with a goal to increase productivity with 6% and reduce energy consumption with 1% every year. This is where factors of the TBL should be taken into consideration when analysing the factory process. An evaluation of how optimising the production flow using multiple objectives could be a decision-making tool. In this project, productivity and energy use will be analysed to determine whether energy consumption can be reduced without negatively impacting productivity, and to focus on both economic and environmental sustainability. The robot cell is highly automated, however there are parts of the operation that are manual. All the dimensions of the TBL affect each other, if the social aspect is not acceptable, then operators might not be motivated to do the assigned work with high quality. This can affect the financial dimension negatively with potential re-manufacturing and unsatisfied customers. Therefore an evaluation of the social dimension is important to get the balance of the three dimensions.



# 2

## Theory

### 2.1 Simulation

Simulation in production is used to try to duplicate real-world manufacturing scenarios in a digital environment [10]. By creating a digital version of the system it is possible to observe and analyse how the system operates without interfering during operation [10]. To be able to produce a simulation that can be validated against the real-world system, the creator needs to make assumptions of the operations and collect data that describes the system's components and their interactions [10].

Discrete event simulation (DES) is a simulation type that has been used since the 1950s [11]. It is one of the most common techniques to analyse and understand manufacturing system's dynamic behaviour. During a cycle anything can happen in the physical model, machines can fail, humans can get sick, and storage space can be empty due to the delay of delivery [12] [13]. What happens during a day during a production run is non-predictable, and that is why DES is a strong and viable tool to mimic this behaviour of dynamic systems [13].

DES can be explained as a modelling of systems in which the state of the variables changes only at discrete points in time [10]. The simulations are analysed by mathematical methods rather than analytical methods. Instead of "solving" the mathematical model, the simulation is "run" to get observations that can be analysed to find different solutions to the real-world system [10]. With DES being dynamic and non-predictable, a simulation cannot only run one time, as it is unknown if that one run was a successfully or failed run [13]. The simulation needs to run several times to get as many different scenarios as possible included in the analysis, to mimic the real-world production as closely as possible.

In every system, there is always one or several bottlenecks or constraints present [14]. A bottleneck or constraint can be identified with the active period of the different operations. The operation with the highest active period is considered to be the bottleneck in the system [14]. An active period in DES is the time that is only reliant on the machine itself, such as the working time, breakdown time, setup time and idle time [14]. In contrary there is time that the machine is affected by other operations such as blocking or waiting [14].

The steady state of a system is something that needs to be analysed carefully, and

first an understanding of if the steady state is needed or not [15][10]. In industries such as heavy equipment and the automotive industry, the production flow does not need a warm-up time unless the system has been emptied. As the system is not emptied, there is no warm-up time needed when starting production. For the simulation to represent real-world production, there is only a need for a warm-up time at the start of the simulation. This is compared to the food industry where the system is emptied at the end of the day and needs a warm-up time every time production is stopped [15] [10].

### 2.1.1 Banks methodology

Banks methodology is a step-by-step flow diagram to help work systematically in simulation studies as seen in Figure 2.1

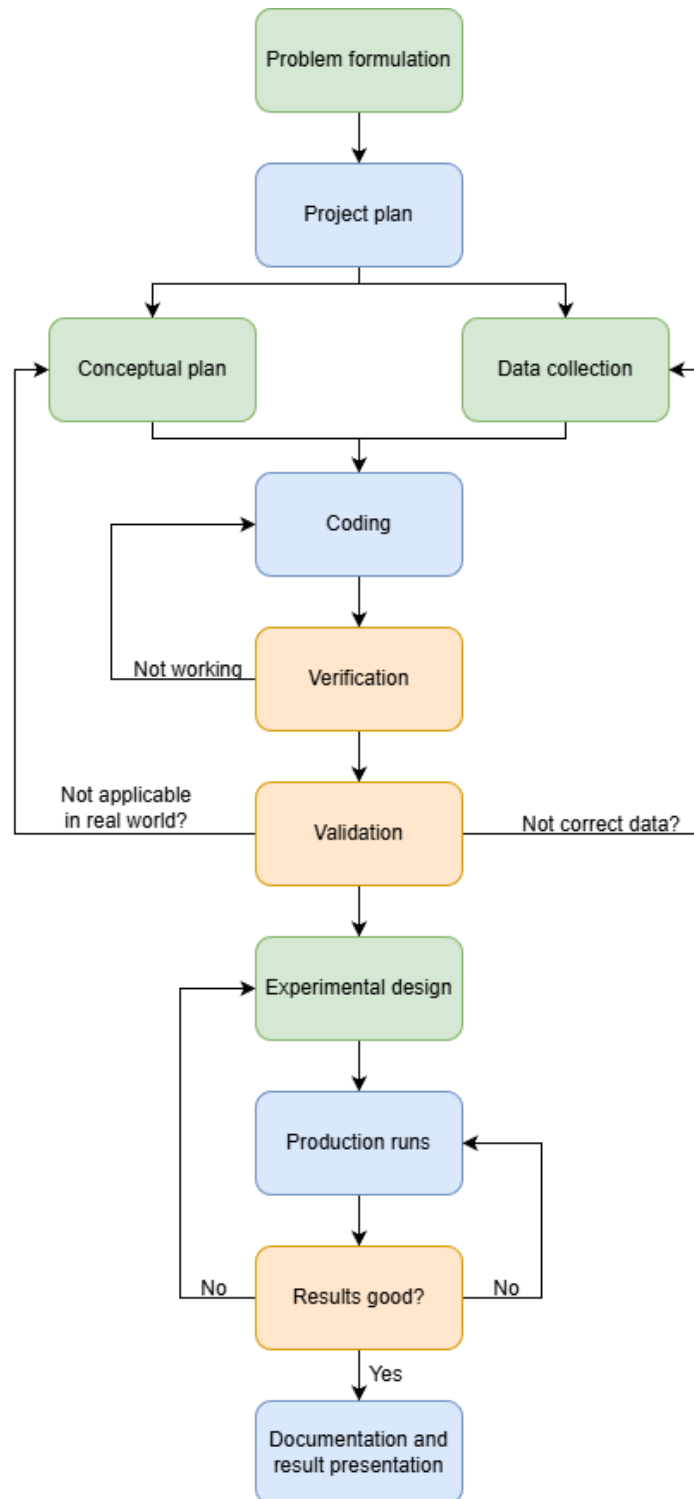


Figure 2.1: Banks methodology, a step by step flow diagram for simulation [10]

- 1. Problem formulation** The problem formulation is the first part of each study where the problem is clearly defined by the policymakers. If the problem is defined by the person doing the study and that person is not the policymaker, it is important that the two parts are in agreement about the problem [10].
- 2. Planning stage** The next step is the planning stage, where the objectives of the study needs to be defined. Here, simulation should also be determined if it is a reasonable solution for the problem. If found appropriate to use simulation, a plan with limitations and defining resources should be made. Lastly the study should have a plan of when the objectives should be met and what the expected type of results of each stage of the process [10].
- 3. Conceptual plan** The conceptual model should be conducted with the problem formulation together with the characterisation of the real-world system in mind. The goal in the conceptual model is to abstract essential features needed to describe the problem and to modify it so that it can be validated to the real-world scenario [10].
- 4. Data collection** There is a continuous interaction between building the model and gathering the necessary input data. As the complexity of a model evolves, the types of data required often change as well [10]. Because data collection typically consumes a large portion of the total simulation effort, it is important to begin this process as early as possible, usually in parallel with the initial stages of model development. The goals of the study largely determine which data must be collected [10].

The data collection method used for this project is following the flow diagram seen in Figure 2.2, suggested by Skoogh as an efficient process that also works with banks methodology [16]. The idea is to follow this method step by step to have the requirements of accuracy clear, to know what input data is needed, and to validate it to avoid as much repeated work as possible [16]. There are three levels of data availability: Category A is available data, Category B is non-available data, but it is collectable, usually manually. Lastly, Category C is non-available data and non-collectable data. It is useful estimations and assumptions with process information from experts, and it can also be based on historical data [16].

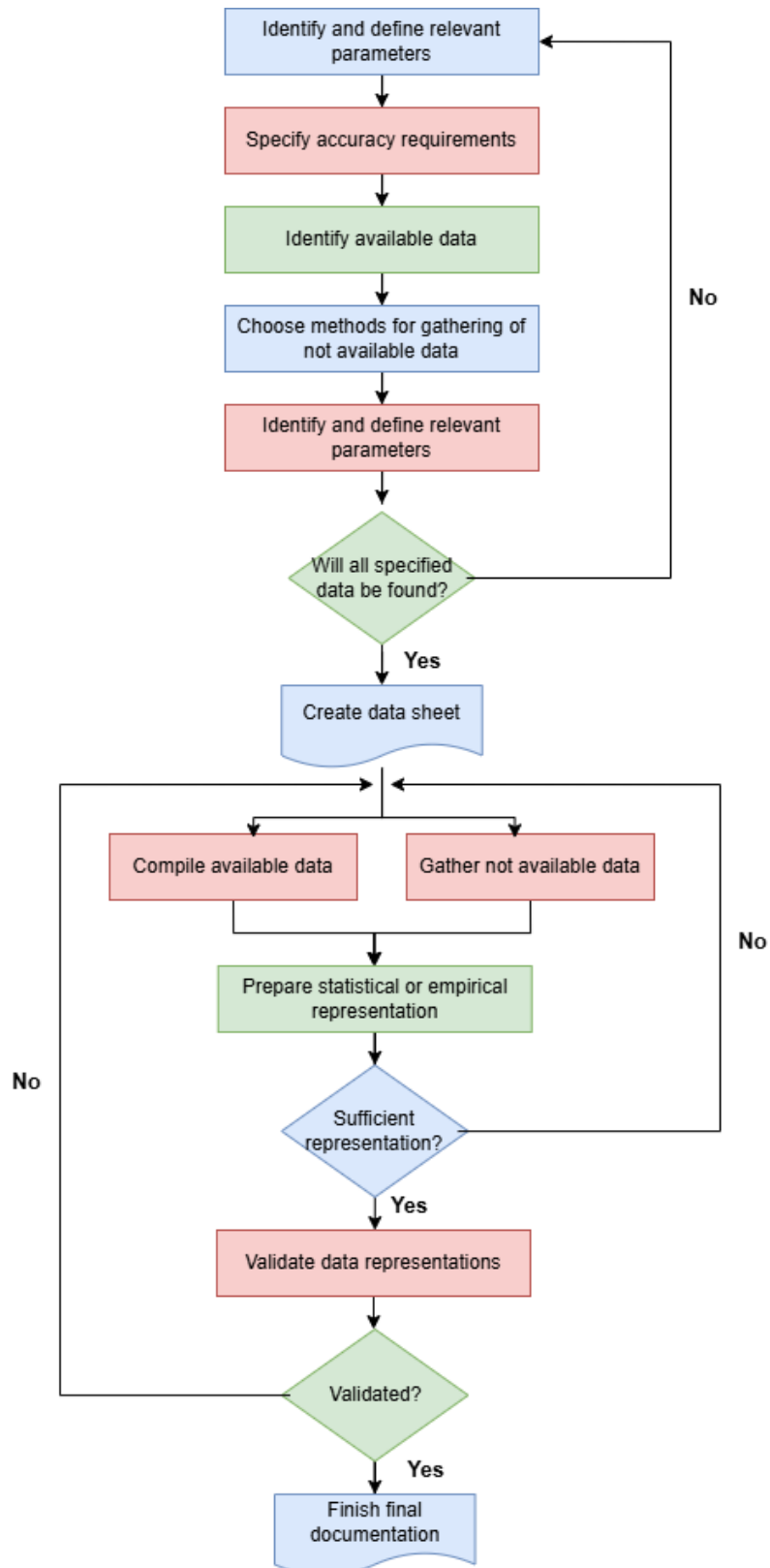


Figure 2.2: Data collection method suggested as efficient and works well with Banks methodology [16]

5. **Creation of simulation model** This is the stage where the model is built, often in a computer simulation software. Most real-world systems produce models that demand substantial information storage and computational effort, which means the model must be expressed in a format a computer can interpret [10]. The use of the term programming is correct, even though, in many cases, the model can be implemented with little or no traditional coding.
6. **Verification** Verification concerns the computer program created to implement the simulation model. The key question is whether the program is functioning correctly. For complex models, it is often impossible to achieve a completely error-free program on the first attempt, and here debugging is usually required. Verification is considered complete once the input parameters and logical structure of the model have been accurately represented in the computer program. In practice, this step relies heavily on careful inspection and common sense [10].
7. **Validation** Validation is typically accomplished through model calibration, an iterative process in which the model's output is compared with the behaviour of the real system. Differences between the two, along with the insights gained from analysing them, are then used to refine and improve the model. This cycle continues until the model's accuracy is deemed acceptable [10].
8. **Experimental design** The alternatives to be simulated must be identified in advance. Often, the choice of which alternatives to evaluate is influenced by the results of earlier simulation runs and their analyses. For each system design under consideration, decisions must be made regarding the appropriate run length and other experimental factors [10].
9. **Simulation runs** Simulation runs, and their subsequent analysis, are used to estimate measures of performance for the system designs that are being simulated [10].
10. **Results and documentation** Program documentation is essential for several reasons. If the modeller or another analyst is going to use the same program and process, the documentations needs to be sufficient enough to recreate something similar to the model and its output. Good documentation builds confidence in the model so that users and decision-makers can rely on its results. It also greatly simplifies future modifications, whether performed by the original modeller or another analyst [10].

## 2.2 Multi-objective optimisation

Multi-objective optimisation is an algorithm used to find one or several solutions that match a maximisation or minimisation of objectives that are usually conflicting in the real world [17]. In practice, to find a single optimal solution in a real-world scenario is impossible, as improving one objective would worsen the other objectives.

The Non-dominated Sorting Genetic Algorithm II (NSGA-II) is a widely used evolutionary algorithm designed for multi-objective optimisation, where problems typically involve different objectives that cannot be optimised simultaneously [18]. Instead of producing a single optimal solution, NSGA-II aims to approximate a Pareto-

optimal set, representing trade-off solutions [8].

Figure 2.3 represents a scatter plot of the conflicting objectives on the x- and y-axis with several the different solutions possible for the objectives. Some of the solutions are more optimal than others, these are the ones on the Pareto front. In Figure 2.3, the solutions on the Pareto front are the green dots, and there are no solutions more optimal than these. This is where the trade-off comes in, to be able to improve one of the objectives, one of them will worsen.

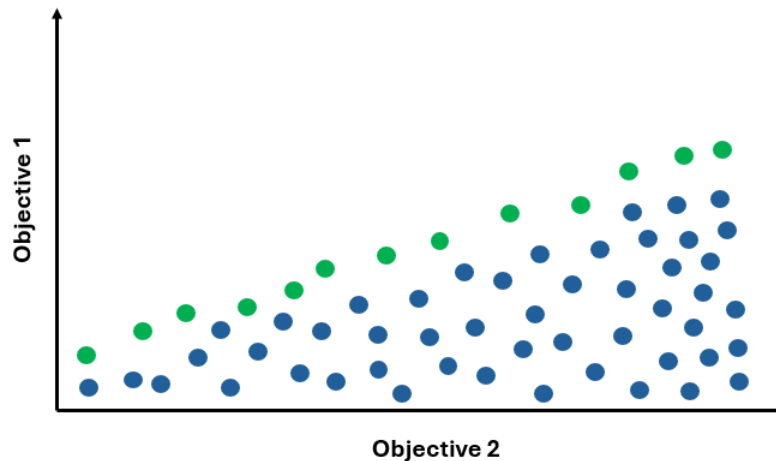


Figure 2.3: Scatter plot to explain NSGA-II, the Pareto front and trade-offs.

Combining simulation with multi-objective optimisation, manufacturing companies will be able to make improvements to the environmental as well as the productivity dimension of the TBL, creating a sustainable method of manufacturing [8].

## 2.3 Ergonomic analysis

Ergonomics in production is important to make sure that the operators do not develop injuries, at least minimise the risk of them [19]. It is the responsibility of the employer to have a good work environment and do risk assessments [20]. Ergonomics can be separated into two larger categories, physical ergonomics and cognitive ergonomics. Physical ergonomics is about the physical load on the human body, the awkward postures and other factors that can increase the risk of injury on the human body [19]. Cognitive ergonomics means the mental part of the human, about understanding the next task, how to interpret tasks, avoiding confusion and making things easy for humans to understand. It should be hard for the operator to complete a task incorrectly, as the tasks should be adapted for the human and not the other way around. All of this is to avoid a mental overload and errors [19].

There are several different methods to use to analyse the physical load of an operation, some analyse one posture, others analyse different issues that can appear at a station. In this study the chosen method is the Manufacturing Ergonomics

0-28	Green
29-66	Dark Green
67-104	Yellow
105-193	Orange
>193	Brown

Figure 2.4: Scale of scores in the MEC Method

Checklist (MEC), which is a method developed by the case study company. It was chosen because of the possibility to do a full analysis of the complete movement of the station. There are 6 topics that are analysed with MEC. Workstation design to understand if the station is designed at an acceptable level with minimal hazardous postures, whether things are accessible, whether work is done on the same level, etc. Upper body, looks at the postures of the neck, back, arm and wrist. Effort, gives an understanding of how much effort/load is needed to perform the different tasks. The logistics are looking at which zones the lifts are carried out in, and if there is any push or pull and the load of them. Work environment analyses the noise, light, temperature and vibrations. Lastly, work organisation is to make sure that standard procedures are used, there is a job rotation, that tools and equipments are used, etc.

The results in the MEC are given as scores, as seen in figure 2.4. From 0 up to 28 is green, and no changes are needed; between 28 and 66, it is okay, and changes are not necessary, but could be positive for the future. Between 66 and 104, it is starting to get problematic, and changes should be considered. Between 104 and 193 it is problematic, and actions need to be taken. Lastly above 193, it is very problematic, and actions need to be taken immediately.

# 3

## Methods

This thesis was conducted using a structured methodological approach that combines a systematic literature review with an industrial case study. The systematic literature review was performed to identify and analyse existing research relevant to one of the study's research questions, providing a theoretical foundation. Building on the literature and answer the second research question, a case study was carried out to investigate a problem in a real-world context. The research design of the project can be seen in Figure 3.1. The DES model was developed following the simulation modelling framework proposed by Banks [10]. Simultaneously with the DES model, an ergonomic analysis was conducted to include all aspects of the TBL in the case study.

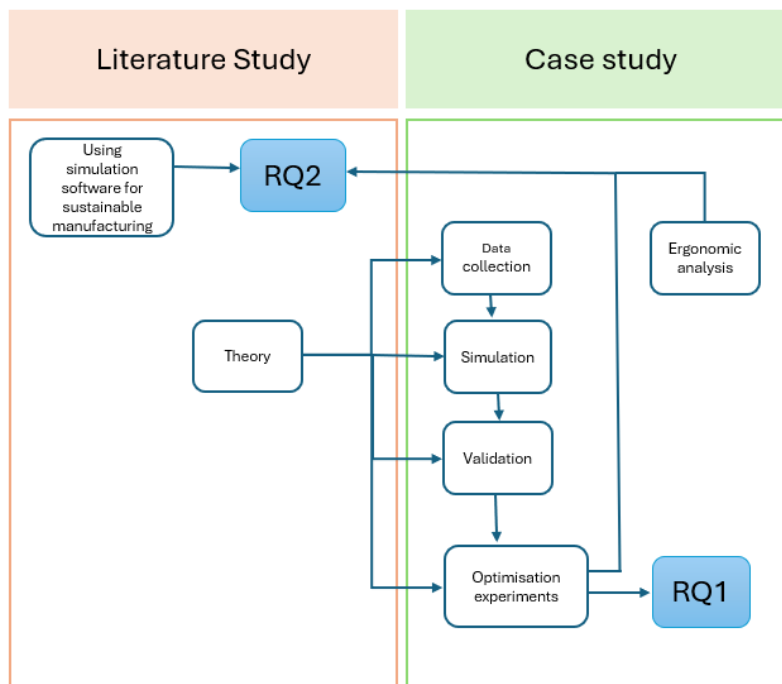


Figure 3.1: Research design of project

### 3.1 Systematic literature review

In this project, a systematic literature review was conducted and the method used for the review was the PRISMA Model, a method used to structurally extract literature for the project research questions. A flow diagram shows the steps used to keep

the study systematic and to show the flow of which articles are excluded from the predetermined criteria.

### 3.1.1 Search terms and inclusion criteria

The search terms were chosen to get results that align with the research question. To get sources that are from a broad spectrum and that included all three of the sustainability aspects, three search terms were produced, as can be seen in Table 3.1.

Table 3.1: Search terms that were used to find sources

Search terms
"simulation*" AND "manufacturing*" AND "improvement*" AND "ergonomics*" OR "social"
"simulation*" AND "manufacturing*" AND "improvement*" AND "environmental"
"simulation*" AND "manufacturing*" AND "improvement*" AND "productivity*" OR "profit"

The inclusion criteria were chosen to limit the search to find relevant articles and to have them available at the current time of research. The articles were sourced from Scopus, which is a database that is accessible through the Chalmers library. This was chosen because it contains a large number of articles, conference papers and case studies which are peer-reviewed and can give relevant information to this study. All the articles chosen in the end had to be accessible in full-text and in English. Finally, the articles had to be published after 2013, as that is when Industry 4.0 was introduced, and this was when the shift to smart manufacturing systems were designed [21]. Finally, the last criterion was that the sources needed to be relevant to the aim and research question of this study.

### 3.1.2 Evaluation of articles

The articles were evaluated against the inclusion criteria to align with the aim and research questions of the project. It was done in different steps to identify relevant articles for this study [22]. Firstly the search terms and the inclusion criteria that were possible to implement into the Scopus search were applied. The articles that were available after this were listed in a document to keep track of which were excluded in the next steps, as in Figure 3.2. As can be seen in the Figure the first step was to review all the titles of the articles and exclude the ones that are not relevant to the study. Next read the remaining abstracts and finally read the main body of the rest of the articles to end up with the final articles. The final number of articles in the study was decided based on the quality and relevance of the articles and are listed in the appendix.

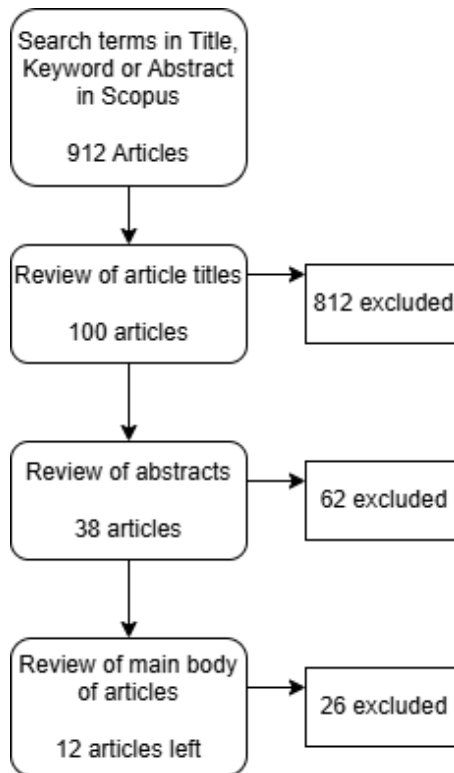


Figure 3.2: The PRISMA flowchart of the exclusion of articles

## 3.2 Ergonomic analysis

To conduct the ergonomics analysis, the operator was filmed with permission. To ensure the input data for the MEC ergonomic analysis was correct reviewed, if uncertain it was possible to go back and check the footage. This way, the ergonomic analysis resulted in an increased reliability. The loading and unloading of the product was filmed. Once it was filmed, the video was observed two times too get a good understanding of the different procedures. The next step was to start with filling out the MEC, which was a sheet in Excel. For all the different issues the video was observed to either count, get a time or to understand if the issue exists in the process. If the issue was not relevant for the station, it was ignored. Once the MEC was complete a general score and a score for each section could be extracted. The overall score served as an indicator of whether the evaluated workstation posed ergonomic concerns.

## 3.3 Banks methodology

To systematically conduct a simulation study the Banks methodology was chosen as it is to be followed step by step according to Figure 2.1.

### 3.3.1 Problem formulation

The problem formulation is described in Chapter 1 of this report together with the research questions. The company had always prioritised optimising only productivity. Now they wanted to be able to optimise two parameters at the same time and find the optimal solution. Together with the company the decision was made to conduct a study to simulate the robot-cell with both productivity and energy data. This would then give a possibility to use MOO that has not been done before at the plant to come up with a process to optimise against both variables.

### 3.3.2 Project plan

A project plan was developed to keep the scope of the project within the defined limits. The project plan accommodated time to learn the software so that the model was built with the best possible knowledge of the software. This was implemented into a Gantt-chart to show where different stages overlap and when deadlines were needed in the study.

### 3.3.3 Conceptual model

When the project plan was decided and the problem formulated to the needed extent, the study went to the next step in Banks methodology, which was the conceptualising of the model. The method to make a conceptual model was mainly to observe the robot cell and discuss sequences with operators and production engineers. Firstly the cell consisted of two welding robots, one handling robot (pick robot), and a fixture for the product that also worked as a flipping table. Observing the operation, the first thing that happened was that a product was lifted from the buffer and loaded into the fixture in the cell, it was then set up and ready to run. The pick robot picked up a part and placed it on the main part, held it in place whilst one or both robots spot-welded the part in place. This operation was repeated until all smaller parts had been spot-welded in place on the main part. The pick robot was in idle whilst the two weld robots welded everything. Then the main part was flipped with the flipping table automatically, and the process was repeated on the other side of the product. Once done, the main part was unloaded and placed in a buffer manually by an operator. The buffer before the operation would be filled with products coming from the storage area. With the observations, the conceptual model could then be brainstormed and discussed.

### 3.3.4 Data collection

The data collection was conducted based on the flow diagram in Figure 2.2 proposed by Skoogh [16].

#### Relevant parameters and the accuracy

The first step in Figure 2.2 was to identify the necessary input data for the base model, followed by the accuracy of them, see Table 3.2.

The number of variants per year was important to have as accurate data, as it would validate the model significantly. This is because different models have different process times and are produced in various amounts. The process time affects the energy consumption, and if the ratio of the different variants were to be incorrect then the base model would not be validated. Shift hours are input data that need to be accurate, but operators don't always follow the shift according to production engineers. What is written on paper is not entirely followed, and therefore the data is not accurate .

Storage capacity was a factor that was assumed to be known, and if not, it would not be hard to get the information by observing. Buffers were also a factor assumed to be able to observe and simple to get information about. The process time for loading and unloading was a factor that was considered to be difficult to extract very accurate data from. It was a manual process, and weekends and longer breaks could affect this time significantly, as well as the different variants potentially needing different times to be handled manually.

There was no clear way of extracting the process time for the different robots for each variant. It was clear early on that calculations and combinations of data was needed, and therefore it was hard to find that the process time would be very accurate. Instead the important part was to get the distribution of different parts, such as welding time, more accurate than the actual process time.

Maximum work-in-process (MaxWIP) is another factor that was assumed to be able to get very accurate as observations is possible and the process of the robot cell is clear. Availability and failures were data that early on was not extracted and something that was being worked on, and it was assumed that as long as the input data exists and can be optimised would be enough for the project. It would still show how the process would be affected with different availability. Lastly, the level of accuracy for the energy data was set to accurate because it was a main factor in the project, and it was known that energy data could be extracted, to what extent was unclear, which is why it is not very accurate, but at least accurate was assumed to be manageable.

Table 3.2: Necessary Input Data and Required Accuracy for the base model

Necessary Input Data	Required Accuracy
Number of produced variant per year	Very accurate
Shift hours	Accurate
Storage capacity	Very accurate
Buffers	Very accurate
Loading and unloading time	Somewhat accurate
Process time for each robot	Somewhat accurate, distribution should be accurate
MaxWIP	Very accurate
Availability	Ok if not very accurate
Working energy for each robot	Accurate
Idle energy for each robot	Accurate

### Availability of data

Next, in Figure 2.2, the available data was identified along with the remaining two levels of data availability, category B and C. Where category A is available data, category B is non-available data but collectable, and category C is non-available data and usually assumed or estimated as mentioned in Section 2.1.1 by Skoogh [16]. Table 3.3 shows the identified data availability.

Table 3.3: Identified availability of data

Data	Availability
Number of produced variant per year	A
Shift hours	A
Storage capacity	A
Weld time data	A
Cycle time log of robot cell	A
Buffers	B
MaxWIP	B
Loading and unloading time	C
Process time for each robot	C
Availability	C
Working energy for each robot	C
Idle energy for each robot	C

### Data gathering for non-available data and define relevant parameter:

The data gathering process according to Figure 2.2 then proceeds to find methods for the data that are not of category A. For the buffer and the MaxWIP, the method for data gathering was decided to be done with observation of robot cell and confirmation from production engineers and operators on site.

**Loading and unloading time:** The loading and unloading process time was estimated and calculated with the category A weld time data. When the program name

in the data is changed, the time between the stop time of the previous program and the start time of the new program is considered to be the loading and unloading time. The stop time is subtracted from the start time, and the mean of that is used as the loading and unloading time. The Outliers, such as weekends are excluded. See Figure 3.3 for an example of stop time and start time.

productionStart	productionStop	programName	IdleTimeSeconds
2026-03-11 07:59	2026-03-11 08:22		259,000000195
2026-03-11 07:43	2026-03-11 07:55		

Figure 3.3: Calculation of idle time between parts, indicating loading and unloading.

**Process time for robots:** The method for gathering the process time of each robot is a calculation and an estimation with the help of the weld time data and the cycle time log. In the weld time data, it was possible to separate the different variants and the different operations during a cycle for the different robots.

The robots working time was divided into four parts. Spot welding before the flip, welding before the flip, spot welding after the flip and welding after the flip. Spot welding is when the pick robot is active, and the process time for the pick robot is extracted from time spent on spot welding. Welding is when the weld robots are active, and the process time for the weld robots are extracted from time spent on welding. See Figure 3.4 data from one product in the cycle has been divided to clarify the division of the different operations.

In the data extracted from the welding time data, the time before and after welding is not included, such as movements and measurements. This time is extracted from the cycle time log data.

### 3. Methods

Date	Time	Duration	Weld nr	Part item number	Machine name
2026-02-06	13:10:28	56,8	12467	410005992261	██████████
2026-02-06	13:09:32	54,2	12466	410005992261	██████████
2026-02-06	13:08:15	72,6	12465	410005992261	██████████
2026-02-06	13:06:58	74,4	12464	410005992261	██████████
2026-02-06	13:04:48	78,6	12463	410005992261	██████████
2026-02-06	13:04:37	4,8	12462	410005992261	██████████
2026-02-06	13:03:59	6,1	12461	410005992261	██████████
2026-02-06	13:02:31	56,9	12460	410005992261	██████████
2026-02-06	13:01:34	54,3	12459	410005992261	██████████
2026-02-06	13:00:19	71,3	12458	410005992261	██████████
2026-02-06	12:59:00	74,2	12457	410005992261	██████████
2026-02-06	12:57:28	78,8	12456	410005992261	██████████
2026-02-06	12:57:17	1,8	12455	410005992261	██████████
2026-02-06	12:56:21	1,8	12454	410005992261	██████████
2026-02-06	12:55:30	7,9	12453	410005992261	██████████
2026-02-06	12:55:21	7,8	12452	410005992261	██████████
2026-02-06	12:55:07	1,7	12451	410005992261	██████████
2026-02-06	12:54:39	1,8	12450	410005992261	██████████
2026-02-06	12:54:20	5,5	12449	410005992261	██████████
2026-02-06	12:53:46	3,6	12448	410005992261	██████████
2026-02-06	12:53:41	3,9	12447	410005992261	██████████
2026-02-06	12:53:28	1,5	12446	410005992261	██████████
2026-02-06	12:53:11	5	12445	410005992261	██████████
2026-02-06	12:52:50	7,4	12444	410005992261	██████████
2026-02-06	12:52:41	7,3	12443	410005992261	██████████
2026-02-06	12:52:29	2	12442	410005992261	██████████
2026-02-06	12:52:08	7	12441	410005992261	██████████

Figure 3.4: Robot 3 data from one cycle on a part 1 and the different operations during the cycle, divided for clear representation of data

**Energy data:** The energy data was collected from the energy meters that were connected to the robot cell. The energy meters made a log of the energy value each time the robot started the program sequence for each variant, and each time it stopped its sequence. The energy values that were used were the `totalEnergyStart`, `totalEnergyStop`, `pickEnergyStart` and `pickEnergyStop`. The calculations of the welding robot active energy was made by taking the total energy use of the robot cell and subtracting the pick robot energy.

$$totalEnergy = totalEnergyStop - totalEnergyStart$$

$$pickEnergy = pickEnergyStop - pickEnergyStart$$

$$weldEnergy = totalEnergy - pickEnergy$$

The idle energy for the robots were calculated by taking the start value of the energy meter and subtracting the previous stop value. The idle energy was then converted to power by dividing the energy by the duration to get a specific idle power for the machine. The different idle powers were then averaged into a mean idle power for the machines.

$$idleEnergy = totalEnergyStart - previous\ totalEnergyStop$$

$$idlePickEnergy = pickEnergyStart - previous\ pickEnergyStop$$

$$weldIdleEnergy = idleEnergy - pickIdleEnergy$$

The energy from the welding robots was calculated depending on the variant of product. This meant that there were 40 energy values that needed to be divided onto the four welding processes. This was done by taking the assumption that the welding power is the same for all of the welders and that the energy is only dependent on the time of the process. The energy is divided by the total process time of all the weld processes and ends in a power that can be used for every process. The same is done for the pick robot power, where each of the 40 variant pick energies is divided by the pick process time to get the pick power for each variant.

**Availability:** The availability was estimated together with production engineers from experience with similar production flows.

**Will available data be found?:** Next, in Figure 2.2, the question of whether specified data would be found, should be asked. The data gathering mentioned above was considered to be able to find and gather. With the answer being yes and proceeding to create a data sheet according to 2.2, the data sheet was created in Excel, where a separate sheet in the Excel file for all different input data was created.

The next step in Figure 2.2 was to simultaneously gather the available data and the non-available data. All the available data was gathered and documented in the data sheet.

**Statistical representation:** Proceeding with Figure 2.2 to prepare statistical representations. Each robot's process time was very consistent, which determined that the process time for the robots was constant. Because the availability was estimated, it was set to a constant. The different energy data were also set as constant, this is because the energy consumption should be the same, and it would be the process time that determines the energy consumption. See Table 3.4 for the overview statistical representation.

Table 3.4: The statistical representation of the input data

Input data	Statistical representation
Process time for each robot	Constant
Availability	Constant
Energy data	Constant

**Representation of data:** Moving on to the next step in Figure 2.2, it was time to understand if the representations of the data was sufficient and accurate enough with the requirement set early in the process, which it was. This lead the process

to the next step in Figure 2.2, validating the data representation.

**Validating data representation:** The data was validated by discussing it with production engineers and maintenance engineers. Once the data was validated, it could be used as input data for the base model.

#### 3.3.5 Base model translation

The software used for this project was inFACTS Studio by EVOMA AB. The software is used as a tool for DES, multi-objective optimisation and advanced data analytics [23]. For this project, inFACTS Studio was used to create a simulation model of the robot cell and to visualise the system digitally. Additionally, the experiment and the multi-variable optimisation functions are included in the software and also used for this project.

From the conceptual model and the data collected, the base model could be created with the use of different operations in the software. Different stations were placed in the simulation model to correlate with the real-world system. These stations are explained in the Appendix in Table B.1 and the outline of the model can be seen in the Appendix in Figure C.1. Firstly, a source for the main part was created, and then an assembly station was created to connect it to the sub-parts of the main part. Next a storage correlating to the real world was placed, followed by a buffer right before the robot cell. This part of the system that is described above was placed in the base model to be able to show the users how the real-world system works and to have the correct data for the input to the robot cell. From this part of the system, however, no process times or energy consumptions were added, as it was one of the limitations of the study not to analyse anything outside the robot cell.

Next in the system, the robot cell was built up with the first process, the loading operation, with a process time and workers connected as seen in the Appendix in Figure C.2. After loading, the automatic process of welding was placed out. As the conceptual model showed, the process was divided into two parts, one before the flip and one after the flip of the variant. Each part has two welding operations for the subparts of the main part. On the side, the pick operation was placed to represent the data for the real-world systems pick robot. An unloading station as an operation was placed at the end of the robot cell, and following that, a sink was placed at the end of the entire system where all the produced parts arrive.

The sub-parts that were connected to the main product had to be created elsewhere in the model and be available when the main product was created in a source. This was done by having a source for each variant with a buffer for each, as there was always variants available if needed. This way, when the main product variant was brought into the system from the main source, the sub-parts of the same variants were brought into the system as well. This can be seen in the lower left in the Appendix in Figure C.1.

The base model was made to accommodate all of the different variants of the products that had available production data. This created a model which had different processing times and energy use on each operation, all depending on which variant was produced. In the operations that had different variant times, tables were used to connect the correct variant to the correct processing time.

In the software, different flows was used to let products flow through machines according to a specified flow. To create flows that simulate the real-world scenario, four different flows were created. In the flow settings the choice to exclude or include variants was possible. In the base model, the Robot1Flow and Robot2Flow were chosen to only include sub-parts 1 and 2, respectively. The flows were then connected to each of the weld robots so that only subpart 1 could go through WeldRobots2\_1 and WeldRobots3\_1, while subpart 2 could go through WeldRobots2\_2 and WeldRobots3\_2. In the flow PartFlow, only the main parts were chosen so that they could go throughout the whole preloading and past loading and to the PickRobot.

In some stages of the model, the parts needed to be processed at the same time and sometimes separated. This was simulated with the use of assembly and disassembly stations as described in the conceptual design, to create a flow where the sub-parts could be processed together. To simulate the Loading and Unloading time, the global variable LoadingUnloadingTime was created to match half of the total time from the data and set to both the operations Loading and Unloading.

The real-world robot cell could only process one variant at a time, and that is where a Max-Wip function was used to limit the process from loading to unloading more than one product.

To simulate the energy use of each of the processes, the variants were connected to a working power which depended on the total energy use that the variant used. This was made in the software's energy profile settings where the power graph was drawn out over time. The idle energy was simulated to not depend on any product and only when the operation was "empty". In the system simulated, only the four weld processes and the pick process have energy simulation connected. The settings of the energy simulations are made in "process resources" where it is possible to connect machines with process profiles for the system to log them together. Process resources were made for both the welding processes as one and the pick process as one, as they had different weld idle energy and needed to be separated.

The workers in the system only work in the process of unloading and loading, and the simulated workers are only connected to the loading and unloading stations. The workers in the simulation are only available at the shift times and have breaks at specific times.

The availability was only added to the first disassembly station before going into the robot cell, this was the closest way to achieve a failure that mimics the real-world

system.

The whole process of creating the base model was iterative, where improvements and changes were made throughout the process. Minor changes were made when more data were accessible, and the parameters of the operations were changed, such as process times.

### 3.3.6 Verification

To move forward in the process of Banks methodology 2.1, the next step was to verify the base model. The verification of the model has been conducted continuously throughout the coding of the base model. Anytime a new operation, table or similar was added to the model, it was tested to understand if it behaved as intended.

The verification test that was conducted continuously was by running the animation to observe the behaviour of the system. If the animation was not behaving as it was intended to, thanks to the continuous testing, the most recent change was most likely to be affecting the anomaly behaviour, and immediate actions could be taken to fix the issue. To verify the model, it was ensured that the simulation behaved in a similar way to the physical robot cell by observation of the real-world system.

### 3.3.7 Validation

Moving down the Banks methodology 2.1, validation is next up. There are many validation methods, the methods that fit this base model were: animation, event validity, extreme condition test, historical data validation and face validity [24].

**Animation validation:** Animation meant to run the animation of the base model and observing it, making sure that the base model was behaving as it was expected to, compare to the real-world system [24]. The animation was run during a 7-day period to observe both weekdays and weekends and make sure that the shifts were correctly executed.

**Event validity:** Conducting event validity meant to compare the events of the model to the data that was gathered from the physical system [24].

**Extreme condition test:** The extreme condition test tests extreme scenarios of the system to make sure that the coding is validated [24]. The tests performed were setting the store to 0, meaning theoretically and as the physical system acts, nothing should be produced. The other test was to set the store of the base model to 10000, which should not change the number of parts produce per year compared to when the source is set to the correct value.

**Historical data validation:** The historical data validation was performed to compare the results from the simulation to the historical data [24]. The number of

produced parts per year and the energy consumption were compared to the historical data for this case.

### 3.3.8 Experimental design

The first step in the experimental design was to do a steady-state analysis. This was done by running the animation for the variant that takes the longest time, and once one product has gone through the entire system, the system is in a steady state, and it gives a warm-up time.

#### Replication analysis

To determine the warm-up time, a start time, horizon time, and the number of replications are needed. The start time was set to 1/1/2026, and the horizon time was determined by getting the number of days the production is up and running during a year, which was 323 days. To determine the number of replications an equation with the use of Students t distribution is used [10]. First a test simulation with 20 replications was conducted to extract the standard deviation and the mean. Additionally, a confidence level of 95% should be achieved [25]. With the desired confidence level the t-distribution could be extracted from the distribution table in the book by Banks [10]. The equation used can be seen in Equation 3.1, which was used to determine the error margin in Equation 3.2 [25].

$$\bar{X}_n \pm t_{n-1, \alpha/2} \frac{S_n}{\sqrt{n}} \quad (3.1)$$

Table 3.5: The variables put in equation 3.1, their definition and value

Variables	Definition	Value
$X_n$	Mean	9030.35
$t_{n-1, \alpha/2}$	t-distribution	2.09
$S_n$	Standard deviation	17.39
n	Sample size	20

$$9030.35 \pm 2.086 \frac{17.39}{\sqrt{20}} = 9030.35 \pm 8.13 \quad (3.2)$$

Once the current state analysis was conducted, the next step was to find optimal scenarios for an improved model. For this study, a systematic method for MOO was followed according to the study by Schmitt [8].

#### Multi-objective optimisation of the model

The first step was to brainstorm hypotheses of future predictions, where four predictions were defined: Reduced Idle power of the robots could mean that the total

energy is reduced; If availability is increased, that would increase the number of produced parts; If loading and unloading time is reduced, there is an increase in the number of produced parts and a reduction in idle power. The three predictions mentioned had the optimisation on the base model. The last hypothesis was a scenario where the optimisation is simulating a model where robots are turned off during the weekends when the production is not active.

With these predictions, the inputs and the outputs could be extracted, see Table B.2. The range of the values in the table was set with input from production engineers and assumptions. A study was done by the production engineers on the cycle time, where all the manual operations were included. This was the value that the optimisation was working to achieve. The idle powers were set to the values in Table B.2. The current idle powers were divided by two, and the availability was estimated by the production engineers to increase by 2%.

Once the optimiser had run for the base model with the settings mentioned above, the scenario with the robots being shut down during weekends was the other experiment to run with MOO. In a discussion with a maintenance engineer, it was mentioned that when the machines have been shut down for a longer period of time, they need more maintenance when they are started again. With this information, an assumption of a potential lower availability was made. The settings for a MOO with the scenario can be seen in Table B.4

Finally the last experiment could be conducted. From the MOO run on the base model, several solutions would be on the Pareto front as optimal solutions. From the Pareto front, one of the solutions was selected. The optimal solution that was chosen was the one that was closest to the average of the actual production output over the last 3 years. The values can be extracted by reading the graph. The base model values were changed to the input values extracted from the one optimal solution on the Pareto front, and the new scenario could be run and analysed.

#### **3.3.9 Analysis of results**

Charts and plots from experiments from simulation runs and optimisation runs were extracted. Using charts and plots, as Schmitt [8] and Roser [14] do, helps visualise and conduct necessary assumptions and analysis to interpret the results. For the base model and its current state analysis, as well as simulation for the one scenario taken from the Pareto front, a utilisation chart and individual energy consumption charts for each of the robots were analysed.

From the utilisation charts, the bottlenecks of the system were identified by identifying the operation with the highest active period, as mentioned in Chapter 2 by Roser [14]. The active time looked at was the working time, the idle time and the breakdown time.

From the MOO experiments, there were two different plots extracted. Scatter plots

and parallel coordinates. The scatter plots were represented with an x-axis and a y-axis, with the two objectives wanted similar to Figure 2.3. It gave all the optimal solutions as well as the solutions on the Pareto front, and this revealed the trade-off between the objectives. The Parallel coordinate plots presented the objectives together with the inputs. With the Parallel coordinates, the changes in the input that would have the most influence on the objectives are data that could be extracted. The Pareto-optimal solutions were evaluated against the current production output, allowing selection of scenarios that have improved energy performance with realistic productivity output. This approach ensures that the selected solution is applicable in an industrial context.

The analysis focused on the changes between the current state and improved scenarios, expressed as percentage differences in energy consumption and productivity. Through this structured analysis approach, combining the objective performance comparison with visual interpretation of system behaviour, the study ensures that the conclusions can be based on systematic and reproducible methods.



# 4

## Systematic Literature Review

Simulation software has been shown to have many benefits for sustainability, and it is possible to do simulations for all dimensions of TBL, environmental, social and financial. There are several different approaches to simulations. There are the more traditional ones where the use of simulation software is conducted to improve one dimension of the TBL, whilst other studies go in with other approaches to try and improve two or all the dimensions of the TBL.

The use of simulation methods all across the industry could reduce energy usage and have a larger impact on a global scale. In the article by Garwood [26], simulation could show a more effective use of energy in both manufacturing and in the building sector. In both residential and commercial buildings, building energy modelling (BEM) simulation could be used to find energy efficiency solutions. In manufacturing, the use of simulation can identify wastes and how utilisation can improve energy use in the manufacturing settings [26].

Multi-objective optimisation (MOO) in [8] was used to optimise the productivity and the energy consumption of the designated production flow at the same time. The concept of MOO is to find trade-off solutions, setting productivity and energy consumption against each other [8]. The simulation was done in a simulation software, and the MOO was done with the mathematical algorithm NSGA-II. The study gave the result of an increase of productivity of 27.9% and a decrease in energy consumption of 23.9% [8].

There are different types of energy simulation that can be conducted according to the article by Shihata [7]. It is stated that energy consumption simulation should firstly be done at a machine level and then work with higher levels over time. It is also important to be aware of the different types of energy consumption when working with machine-level simulation, for instance, there is direct and indirect energy consumption [7]. Direct energy is the energy the machine consumes, and indirect energy is the energy consumed by ventilation, lights, coolers, etc.[7]. Simulation helped to identify where the waste was and where it was the highest. With that information, the enterprise could then analyse that specific part of the process to understand why there was so much waste and what could be done to improve it, which they also successfully managed to do [7].

The use of DES in manufacturing settings as a tool to find more efficient systems in terms of sustainability is something that has been improving over recent years. In

the article by Caggiano [27], the system analysed had energy waste in its de-burring process where DES showed that if the active working time could be reduced, then the per-product energy use could be lowered by 89%. This is also a focus in the article by Singh [28], where DES showed that their machining energy could be reduced by 28% in their machining process with the use of simulation. These articles look mostly at the usage of energy, but it is also possible to look at actual wastes and use DES to reduce the amount of waste, as it is a non-value-adding process. This was studied in the article by Dahan [29] where the use of DES in their process reduced the actual production waste in the system from 2.46% to 2.32%. This shows that the use of eco-process innovations led to fast reductions of the production waste.

Simulation of ergonomics does not only mean that the social dimension of the TBL is improved, but it can also simultaneously increase productivity and decrease environmental emissions [30]. There are software programs where simulation of the ergonomics of workstations can be conducted, as it is studied in the articles by Mares [30] and Olander [31]. Firstly the workstation needs to be built up, and then the manikin can be assigned tasks, with which the simulation tool can perform an ergonomic evaluation. The animation gives a value for the different movements of the body, which shows whether it is a poor work method or not. In the article by Mares [30], there was a clear improvement in the ergonomic issues, no matter which ergonomical evaluation method that was used.

Mares [30] stated that designing the workstation and simulating the ergonomics in the early stages makes a positive impact on the financial dimension as well. Fewer medical bills are needed as less physical strain is experienced by workers, and the quality of the product improves [30]. Even for work stations that exists, simulation can be used to find solutions for ergonomic issues without having to implement physical prototypes [30] [31].

The article by Mishra [32] is a study on a test to integrate a value stream mapping (VSM) into a simulation tool. VSM gives a static view of a production flow, and integrating it with DES, a dynamic understanding of the flow would be given, a more realistic view [32]. In the study the current VSM and a future VSM were simulated, the current VSM was used to evaluate the current state and identify waste areas to be improved. With different methods, improvements were made, and the future VSM was simulated to visualise the improvements and to get statistical values on the improvements. DES simulation in the study was used to identify waste and then show the results of the improvements. The benefits of implementing VSM to simulation are that all the dimension of the TBL are acknowledged [32].

The articles by Onofrejova [33], Abdulatif [34], and Villagomez [35] used DES in the most common way, a base model was built, the theory of constraints was applied to identify the bottlenecks and experiments were done on different scenarios to improve the productivity. All of the articles found that the productivity was improved. The study by Onofrejova [33] found that, other than the productivity being improved, the labour balance showed improvements as well. Even the Abdulatif [34] identified

that there was an imbalance in the flow thanks to simulation. This showed that simulation software is a powerful tool for decision-making, as it can provide a clear and easy visualisation.



# 5

## Results

In this chapter the results of the case study will be presented.

### 5.1 Ergonomic analysis

The results for the ergonomics analysis, according to Table 5.1 shows a score of 21. According to 2.4, it means that the score 21 is the most acceptable score and no actions on improvements need to be taken.

Effort is the factor that weighs the highest on the ergonomic analysis, as seen in Table 5.1. This is a result of the fact that all of the manual handling operations are highlighted under the section effort in the MEC. The operators are handling the product with a crane several times per hour. Placing their arm several times in the red zones during manual handling and picking up a tool to adjust the fixture causing this to have some load. Additionally, using the crane could also be seen as a high risk of jamming, twisting and hurting the human. These added together gave the highest score of the evaluation.

Workstation design was mostly well structured, the factor that caused the higher score was the fact that the operators sometimes needed to walk backwards in the activity. This is a high-risk activity to do in an active factory, and to lower this score, the standard of the operation could be changed.

The work environment section had a very low score of one, which was based on the noise level that the operators are exposed to. The remaining sections of the MEC has scores of zero. For upper body and work organisation the score zero was based on them having a low impact on the operator. The logistics section had a score of zero since it was not relevant for this ergonomic analysis, as in the operation there is no logistics of the kind asked for in the MEC.

Table 5.1: Ergonomic analysis scores

<b>Operation</b>	<b>Score</b>
Workstation design	8
Upper body	0
Effort	12
Logistics	0
Work environment	1
Work organisation	0
<b>Total score</b>	<b>21</b>

## 5.2 Conceptual model

The first model created in this study was the conceptual model, it can be seen in Figure 5.1. As there was a limit in the software, the conceptual model had to be designed with new ways of thinking in mind. It was not possible to have two operations operating on one product simultaneously, and instead the main product, part 1, was split into two parts. This way, two operations can work on two parts at the same time. The concept was to have three parts coming into the cell, the main part, part 1, and its two subparts, parts 2 and 3. This way, the three parts could be separated and moved to three separate operations. A disassembly station would be used to make sure that the parts arrived at the next operations at the same time, and an assembly station would be used to make sure that the parts wouldn't move on to the next operation until all parts had arrived at that assembly station. In Figure B.1 an example has been provided to understand the above description: The three parts are separated, the subparts move to an assembly station to then move on to a disassembly station, first assembly so that all parts can move on to the next operation at the same time, in the disassembly station, the subparts move to separate weld robots whilst part 1 is moved to the pick robot. One after one, the robots will be done with their operation, and each part will arrive at the assembly station at different times. Only once all parts have been "assembled", the next part of the process can proceed. The assembly and disassembly stations is a solution used to manipulate the model when coding is not possible.

As mentioned before, manipulating the base model with code was not possible in the simulation software. For this reason, the material that arrived at the flow, was divided into three parts: part 1 and two sub-parts of that variant, part 2 and part 3, as seen in the Appendix Figure B.1. This was done to be able to operate as the method described above. At the end of the flow, to get the counting correct for the amount of produced parts, the subparts where deleted. Only part 1 moved forward to the sink, which is where the product is taken out of the flow.

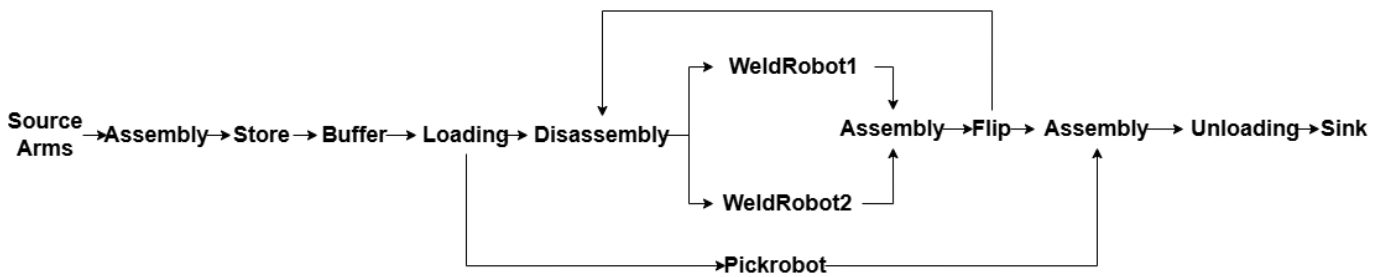


Figure 5.1: Conceptual model of the base model that was built up in the simulation software

### 5.3 Base model

The conceptual model and data collection were translated into a DES model of the robot-cell in the simulation software. The full model can be seen in the Appendix in Figure C.1. Here it can be seen that there are a lot of sources and buffers connected to them. This is to be able to create the sub-parts of part 1, so that the described conceptual model, with assembly and disassembly, can be conducted. Where part 1 and the sub-parts are transported through the system together and separated when needed for processing. A big store was tested with a large amount of sub-parts, this method did not work, as it did not give the product wanted immediately, instead, it was searching for the wanted sub-part.

The loading and unloading were set to a global variant to make sure that if one of them changed, the other did the same. This is because in the real-world system, the time determined for them happen together. In the model, loading and unloading are set as operations even if they can be classified as a setup, this was decided like this to visualise the system. It also helps limit the system to not fit more than one product into the robot cell, as the MaxWIP is set between loading and unloading.

The stations in the robot cell were divided into five processes to represent the real-life process as well as possible. The welding stations in the model are the two weld robots before and after the flip of the product. The picking robot is placed outside of the welding robots as it always finishes before the welding process and has its own energy use and does not need to be in the flow of the welding. The stations have process times that are constant and are dependent on the variant of product that is in the system.

The worker in the base model is programmed to only work during the factory times and has breaks in the workday. The different shifts are added to a shift table where the times are specified.

## 5.4 Validation

**Animation validation:** The animation validation test showed that the shifts were correct, the process time for the different robots was different depending on the variant and during the weekend, the machines were still on but not running. The part of the animation that is not validated but accepted for this project is the failures of the robots. When a robot stops then the robot cell should stop. This is almost happening but not entirely correct.

**Event validity:** The event validity gave the results that the source of the base model was random and produced the correct ratio of variants according to the past few years of data collected on produced parts. A part of the system that is not validated is the production sequence when the parts are produced in pairs. This was not possible to conduct in the simulation software, and the parts are produced in random order.

The store of the base model had the same storage space as the real-world storage space. The buffer had the same amount of space in the base model as reality. Only one product enters the system, and no new product is loaded until the one in the system has been unloaded, behaving as it does in the real world.

**Extreme condition test:** The base model did behave as the real physical system does during the extreme tests. Store set to 0 gave no produced parts, and when the store was set to 10000, there was no change in produced parts per year, as it should have behaved. This validation test was completely validated.

**Historical data validation:** Performing the historical data validation, the results showed that the number of produced parts did correspond well to the real-world data from the company. The energy data was validated very well, where the results from the simulation were very similar when compared with the historical data.

## 5.5 Current state analysis

**Steady state analysis:** The steady state analysis provided a warm-up time of 1.5 h. The number of produced parts for the current state was 9030 per year. The number of replications was based on Equation 3.2, where it showed that 20 was an acceptable number. The calculations gave a marginal error of 8.11 products per year. This is a good error margin as the production output differs by around 275 products from the yearly average.

**Bottleneck analysis:** The bottleneck analysis from the utilisation chart seen in Figure 5.2 shows that the loading and unloading are the biggest bottlenecks. The dark blue unplanned portion of loading and unloading is the time spent waiting for loading and unloading.

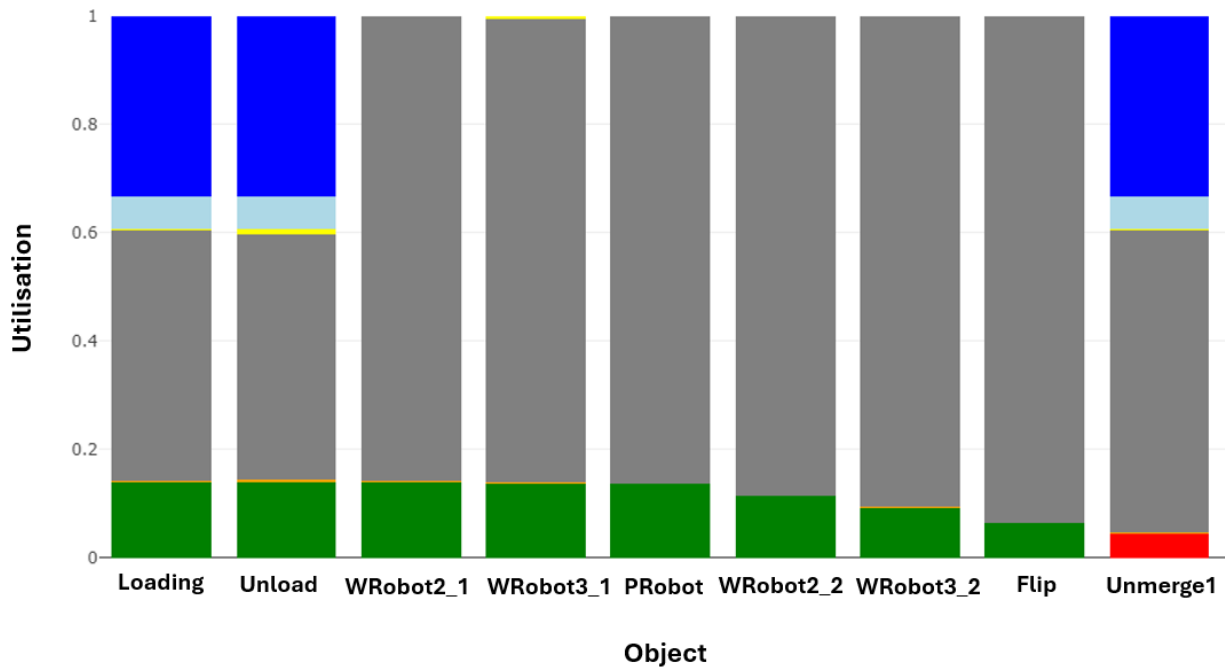


Figure 5.2: Utilisation chart of a simulation of the base model, run for a year

The values from the energy consumption charts in Figures C.3-C.7 in the Appendix are summarised in Table 5.2. The table shows that the pick robot is the bottleneck with the highest idle energy to working energy ratio, with 28.90% idle energy. The welding robots had idle energy ratios of 15.9 to 22.87%, which show that the robots consume a lot of energy in their idle state.

Table 5.2: Energy consumption of current state

Machine	Working energy (kWh)	Idle energy (kWh)	Idle percentage
Pick Robot	1877.84	763.37	28.90%
Robot 2_1	9417.24	1780.19	15.9%
Robot 3_1	9215.13	1772.55	16.13%
Robot 2_2	7687.50	1834.55	19.27%
Robot 3_2	6331.96	1877.04	22.87%
Total	34529.67	8027,70	18,86%

## 5.6 Experiment runs

In Figure 5.3, the Parallel coordinates of the Pareto front for an optimisation on the base model can be seen, with the green lines being on the Pareto front, the most optimal solutions. It is clear that it is possible to produce more products with the same total energy consumption or even lower than that. The plot in Figure 5.3 shows that the optimal improvements to conduct are to reduce the idle power of the

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pick robot and the weld robots, where the majority of the green lines are converged at a single area. The plot in Figure 5.3 shows that improvements on availability is not necessary to achieve a lower total energy consumption and an increased number of produced parts. In the plot, the majority of the green lines converge in an area close to the current state value of 92%. For the loading/unloading, the solutions are spread over half of the range, changes that are done on the loading/unloading only affect the productivity.

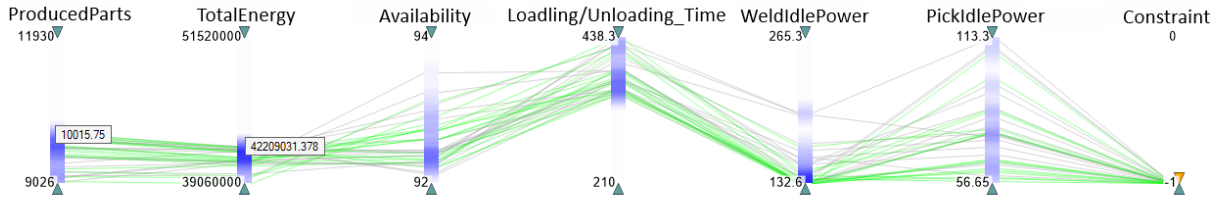


Figure 5.3: Parallel coordinates of the base model with a constraint to not show total energy higher than the current total energy consumption. The green lines are the scenarios on the Pareto front, the most optimal solutions.

Figure 5.4 shows the plot for the parallel coordinates of the scenario when the robots are shut down during the weekends, with the green lines being on the Pareto front, the most optimal solutions. Also, with the constraints for the total energy to not exceed the current state's total energy. The results from the plot are that more products can be produced on the same total energy as the base model scenario. It also shows that the optimal actions to be taken for improvements are to reduce the idle power of the robots, mainly the weld robots. The pick idle power is more spread out compared to the plot in Figure 5.3. Availability and Loading/unloading are more spread out and can affect the system more if improved. It indicates that there is a high non-value-adding energy consumption going on in the system.

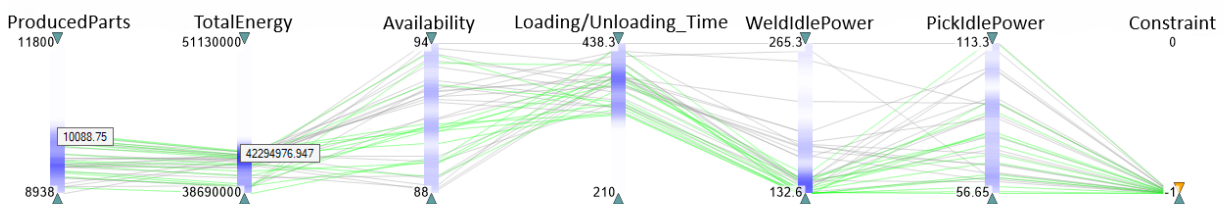


Figure 5.4: Parallel coordinates of the base model with robots shut down during weekends. With a constraint to not show total energy higher than the current total energy consumption. The green lines are the scenarios on the Pareto front, the most optimal solutions.

The collective result from all the plots of the Parallel coordinates of the Pareto front shows that there is a high non-value-adding energy consumption in the system and that reducing the idle power of the robots will help reduce the total energy. It does not matter if the robots are shut down during the weekends or not, the idle power

of the robots is the most important factor that needs improvement.

The scatter plots in Figure 5.5 and 5.6 show the solutions from the optimisation. The green dots in the plots are the solutions on the Pareto front, which shows that the correlation between produced parts and total energy is linear. Comparing the two figures, there are more solutions with lower energy while producing the same amount of parts if looking at the green solutions in Figure 5.5 compared to the one in Figure 5.6. This shows that the shutdown of robots during the weekends could give more energy-efficient solutions from the Pareto front.

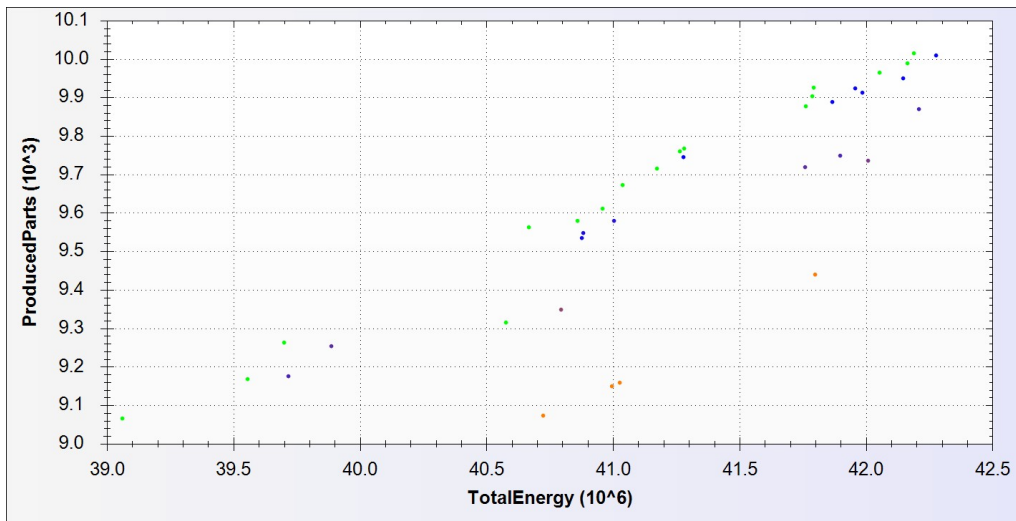


Figure 5.5: The scatter plot of the Pareto front for the base model, with produced parts on the Y-axis and Total energy on the X-axis

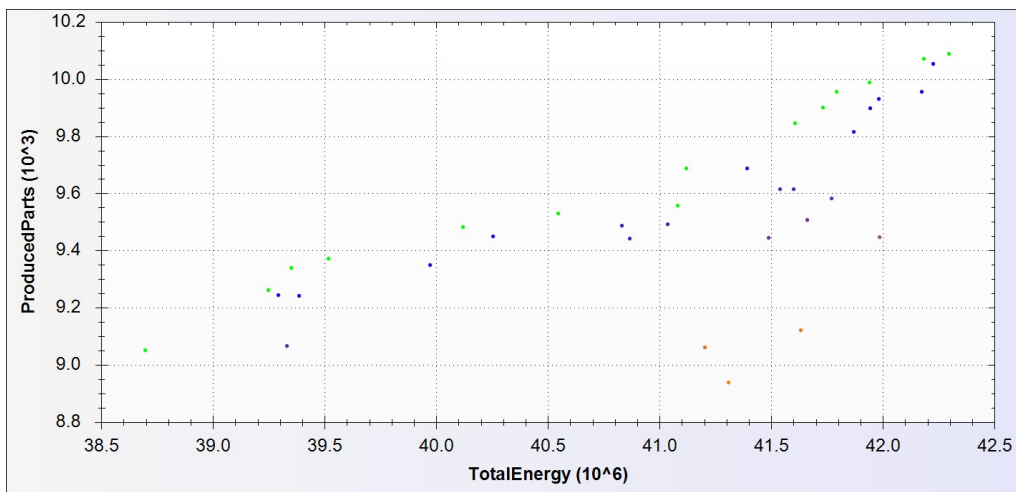


Figure 5.6: Scatter plot of the Pareto front for the scenario with robots shut down during weekends. With produced parts on the Y-axis and Total energy on the X-axis.

**Scenario taken from the Pareto front:** From the Pareto front a solution based on the average production output from earlier years was chosen to understand what

improvements can be made. This is to be able to achieve the production output with lower energy consumption. The chosen solution from the Pareto front can be seen in Figure 5.7. The figure shows that to achieve such a production rate with lowered energy consumption, the idle and working power needs to be reduced. What can also be taken from the figure is that the availability does not need to be reduced, as it works with an availability of around 92%. To be able to produce that amount, the loading/unloading time needs to be reduced to 365 seconds in this case.

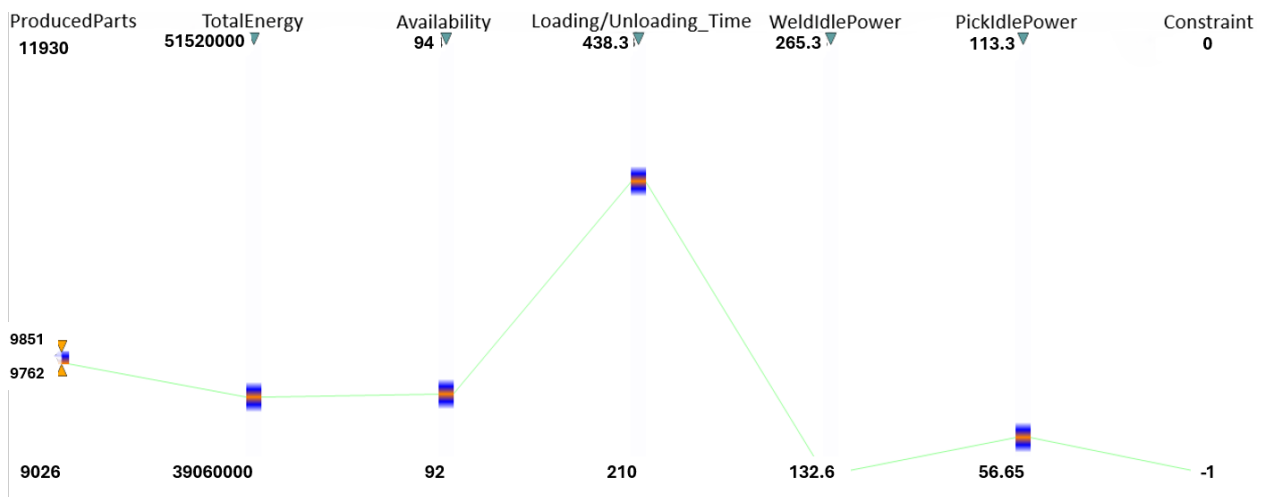


Figure 5.7: One scenario from the Pareto front

Running the model as a simulation with the changes on the inputs from Figure 5.7 gave an output of 9803 produced parts during a year.

The utilisation chart in Figure 5.8 does not differ much from the current state analysis. It still shows that loading and unloading are the primary bottlenecks.

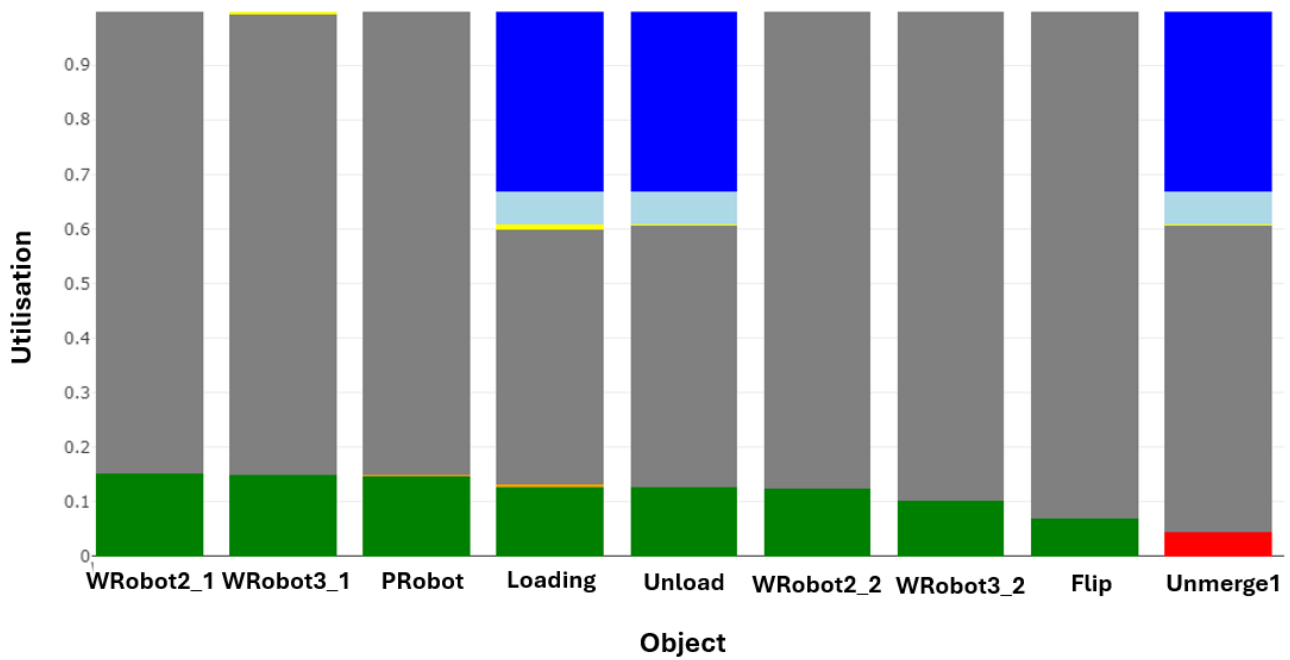


Figure 5.8: Utilisation chart after improvements based on one scenario from the Pareto front

Table 5.3 with the values taken from Figures C.8-C.12 in the Appendix, shows the significant reduction of idle energy for all the robots compared to Table 5.2, where the idle energy is almost double the new scenarios idle energy. In Table 5.4, the amount of improvement between the current state and the scenario from the Pareto front can be seen. The Idle powers have been significantly reduced by almost 50%. The reduction of total energy consumption combined with an increase in the number of produced parts, strengthens the suggestion that more produced parts can be produced if the idle power of the robots is reduced.

Table 5.3: Energy consumption of one solution on the Pareto front from the multi-objective optimisation experiment

Machine	Working energy (kWh)	Idle energy (kWh)	Idle percentage
Pick Robot	2038.08	408.17	16.69%
Robot 2_1	10090.54	879.85	8.06%
Robot 3_1	9991.04	875.65	8.06%
Robot 2_2	8325.52	909.46	9.85%
Robot 3_2	6858.05	932.51	11.97%
Total	37303.23	4005.64	9.70%

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Table 5.4: The percentage of improvement as a result of changing values to one of the solutions on the Pareto front. Comparing the current state and the one solution on the Pareto front.

<b>Machine</b>	<b>Idle current state(kWh)</b>	<b>Idle scenario (kWh)</b>	<b>Percentage reduced</b>
Pick Robot	763.37	408.17	42.26%
Robot 2_1	1780.19	879.85	49.56%
Robot 3_1	1772.55	875.65	50.04%
Robot 2_2	1834.55	909.46	48.59%
Robot 3_2	1877.04	932.51	47.66%

# 6

## Discussion

In this section the results, answers to the research question, the methods of the study and the future work is discussed.

### 6.1 Interpretation of results

The ergonomics analysis had an acceptable score, with no improvements needed or further studies needed. The different sections of the analysis were weighted differently, and they were mostly based on a few problematic issues. If further actions would be conducted, the effort section should be the priority. Due to the fact that it had the highest score of all the sections. However, as the score was non-problematic no further study was conducted.

Loading and unloading were identified as the bottleneck in the utilisation chart, where a lot of the time is spent on waiting for an operator to load and unload the fixture. With this long waiting time, a lot of time that could be spent on having the cell running is instead spent on waiting. This is something that places the robots in more idle power than needed and consumes more non-value-adding energy. Which the results showed that there was a lot of non-value-adding energy consumption. The MOO showed that changing the value of the Loading/Unloading affects the productivity by increasing it.

The results from the current state analysis for the energy consumption showed that the pick robot was the biggest bottleneck, with the highest proportion of idle energy. This is something that matches the observations of the robot cell. Once the pick robot has picked and placed the smaller parts on the main product, the pick robot is then done and in a waiting state until the weld robots are done welding. This is a big waste, especially as the pick robot is not being utilised to do other work but waits for the next operation.

Running the NSGA-II algorithm on the base model, the results showed clearly that reducing the idle power of the robots would still mean that the same number of products or more products could be produced with even less energy. This strengthens the fact that there is a lot of unnecessary non-value-adding energy consumption existing in the system.

Having a lower idle power and yet producing more or the same amount of products

would mean that the share of non-value-adding energy has decreased. This was confirmed by the one solution from the Pareto front that was run as an experiment. The idle power of the robots reduced between 42 and 50% depending on the robot. This is a significant reduction of idle energy. The results also show that the availability does not need to be improved to a greater extent to get significant energy improvements on the system. However, Loading/Unloading is more spread out on the range and affects the productivity. If the value of the Loading/Unloading is lowered slightly, then the productivity increases.

By shutting down the robots on weekends, total energy use decreases, enabling higher production with the same or lower energy as the current state. This means that the energy per produced product must be lower than before. Also, the reason for a higher number of produced parts is the same energy as the current state. However, for even more improvements, the most obvious ones to implement are to reduce the idle power, the same as previous improvements, but with even more focus on the weld robots. With this scenario showing the same improvement solutions, reducing the idle power of robots strengthens the previous results, suggesting a high non-value-adding energy consumption.

### 6.2 Research questions

Research question one aligned the case study together with the literature supporting the study. The case study results showed that the use of DES together with optimisation using multiple objectives gives not just one solution but a set of Pareto-optimal solutions where improvements in energy could be made without reducing productivity. The research question asks if it is possible to use NSGA-II as a tool to find improvements, and as explained, this is possible. The results of the optimisation all depend on the data that is input into the simulation model. It also depends on the simulation software and the possibilities to do the correct simulation inputs and get the outputs that are wanted. To come up with a model that could be used to find solutions to the real-life system also needs the data to be reliable and mirror the system it is simulating. The use of DES is really good if the system needs to be simulated with randomness, such as this system.

The results of the case study correlate to the literature study that was made. The literature study found the usefulness of simulation and specifically DES to find reasonable solutions to sustainability improvements. RQ1 also aligns with the literature study, as the article by Schmitt [8] explains that if a validated DES model is used together with MOO, it is a good tool to find solutions to improve scenarios in the industry.

The second research question of this thesis investigates how a manufacturing company can use simulation to find improvements in the aspects of the TBL. The results from the case study are largely consistent with the sustainability literature found, which highlights simulation as a key enabler for sustainable manufacturing, particularly in the context of Industry 4.0. Prior research consistently shows results that

simulation-based approaches allow companies to analyse complex production systems, which can identify inefficiencies and evaluate improvement scenarios without disrupting operations. The results of this study reinforce this view by demonstrating how DES, combined with optimisation and ergonomic analysis, can support sustainable decision-making at a production cell level.

From an environmental perspective, the literature identifies energy consumption and waste as the most critical environmental challenges in manufacturing systems today [7] [8]. Several of the articles find that simulation is an effective tool to find wastes in energy during non-value-adding periods [7] [29] [28], which also aligns with the case study results. The simulation found that reducing idling energy in the robot cell doesn't affect the production rate, which shows that the idling process is non-value-adding. By using simulation to test scenarios such as reduced idle power and shutdown strategies, the case study confirms that simulation can be used as a tool to support environmental sustainability with reduced energy use and lower emissions.

In terms of economic sustainability, the literature supports that the economic improvements in terms of waste and productivity make the systems more effective. From an economic standpoint, the improvements in ergonomics, which reduce health costs for the business, together with reduced production waste, are aspects that save the manufacturing money. This is supported by the literature, which identifies that simulation can show all of these improvements without interfering with the ongoing operations [30]. The case study shows that a lot of non-value-added energy is consumed during the idle periods of the robot cell. This is a cost for the production that could be looked into to find solutions to save energy. The use of MOO in the case study reflects the literature that it is possible to find trade-off solutions that balance cost, productivity, and sustainability indicators [8]. The Pareto-front analysis provided insights by illustrating several improvements rather than a single optimal solution for reducing the energy use.

Looking from the social sustainability aspect, simulation is not as frequently discussed as economic and environmental is more frequently addressed. However, in the literature review, the articles show increasing interest in integrating ergonomics and other human factors into the analysis of manufacturing. Although the ergonomic analysis in this study was not done digitally, it still supports the literature by focusing on doing a study of all aspects of the TBL. The results showed that the station had acceptable ergonomic conditions in the current state, but it is not possible to simulate how the ergonomic conditions would be after a change to the system.

Overall, the literature aligns with the second research question in each of the three aspects of sustainability in TBL. At the same time, the case study confirms the findings by showing that simulation is a good tool to analyse energy and productivity.

## 6.3 Reflection on the Research Method

During the project, the methods to collect data and the building of the base model have changed over time and were not what was planned from the beginning. Over time insights and discussions revealed that the data was not as apparent as first discussed, and the simulation software was not fully developed. This caused the project to be built on a lot of assumptions and workarounds to get relevant results. For this case study, the assumptions were based on several sources of data, both qualitative and quantitative. To reduce the rate of uncertainty, the study has tried to find as many sources to base the data on as possible. Previous research has shown that such assumptions are common in industrial simulation studies and can lead to problems in data preparation and reduced confidence in results [36]. The uncertainty of the inputs of the model should try to be reduced, but it is very difficult to be fully eliminated [37]. To think that the assumptions have not affected the final results would be unwise. The final results have to be taken into consideration, as they can differ from the real-world system and that they should not be used as a basis for decisions in production. Usually, leadership question the input data in these kinds of simulation studies because of the reliability of the assumptions [36]. That is why the results should be seen as a first stage for further research in the possible optimisation of the system.

### 6.3.1 Data gathering

As the project had a limited time to do data collection, the data availability was very important for the study. As most DES projects spend a third of their project time on data collection [36], this study had to fit in the data collection into a period of just a couple of weeks. This caused this study to not be able to implement new ways to gather the data from the system, as we needed data that was gathered over a longer time.

To get a validated and reliable simulation model, the data that was needed had to be extensive and varied. So when the data collection process started, the discussions together with engineers and maintenance personnel were to find out what kind of data was available. This is when the realisation came that the lack of data from all aspects would cause the model to be based a lot on assumptions, and a combination of different data sources would be needed to be able to build the model. This affects the validity of the simulation model, in ways such as the number of produced parts or the total energy consumption not having the correct value. However, the distribution of the different input data, such as process time and variants produced, did correlate with the real-world system. Therefore, not having the exact correct data, instead having assumptions and estimations, did not affect the results of the research questions. The project did not aim to achieve a specific number of products or a value on the reduced total energy consumption, it was to show what a simulation tool and NSGA-II can help achieve.

In the case that less or no data would have been available, a lot more assumptions

would have had to be made. This could cause the model to not be validated, making it difficult to compare it to the real-world model. As a result, the simulated current state could behave differently compared to the physical system and cause uncertainty in the results from the model. This could then result in the optimal solutions being misleading. This highlights a common challenge in industrial simulation studies, where data availability is often overestimated in the early stages [36]. Even when data exists, it may not be in a format suitable for the specific simulation or may not have the needed specifications.

The energy meters that gave the energy data for the different parts of the robot cell were designed so that one energy meter measured the total energy use of the robot cell, and the other three measured the movements of the robots. So, to get data for the different steps of the welding process an assumption had to be made of how to divide the total energy value into the different steps. The decision was made to divide the energy so that the power is the same for all the welding processes, as that was what other production data showed. This was the best method in the current state to get as reliable data as possible for the simulation model without installing additional energy meters. This could have an impact on the resulting base model, as the welding process is not constant and has differences in the energy use during the process. This also applies to the data of the idle power, which had differences and outliers in the data. In this case, we didn't have time in the study to look that deeply into the data to find out where the higher peaks came from.

The raw time data that came from the different systems were the basis for the simulation model's processing times. The times that were extracted from the weld data logs and the time logs from the robot-cell programs were given as raw data tables to this project. During the data collection, some errors were found when comparing the two data sets, which questioned the validity of the data. This was analysed, and the bugs in the data logs were found and fixed so that the two data sets had the correct time stamps. From the raw data tables, assumptions had to be made as the two sources had to be combined into a specific process time. This caused the data to change from type A data to type C data. This could impact the validity of the time data for a fully validated model. From the combined data, assumptions of how the different processes were divided in time were taken as well. As the process is being optimised at the moment, the processes in the welding process are being changed all the time. So finding a completely validated process is difficult, as the data is changed all the time as well.

Availability and failures are often analysed in a simulation model, as they are something that can be worked on in a process to reduce waste. As the robot cell that was analysed in this case study was quite new in production, the availability was something that had not yet been recorded in the production data. So an assumption of 92% availability was taken together with the production engineer. As availability can affect a process a lot, the decision to have it as an input in the optimisation was made. This is just to see if it can affect the energy use or only productivity.

### 6.3.2 Simulation of base model

During the base model building, many problems occurred with the simulation software that was used. This caused a lot of workarounds and discussions together with the developers of the product to come up with solutions that can work at the moment. In some cases, it was not possible to do what was wanted to do from the conceptual model and had to either just assume a part of the process or skip that moment altogether. This could have negative aspects on the validity of the model and can cause the results to differ from the real-life model. As an example, an error that was found was the conversion of energy in the software. As time is logged in seconds, the conversion from watt-seconds to watt-hours was made, which has a scale of  $1/3600$ , which comes to  $0.0002777$ . The software could only receive five decimals, which made us choose  $0.00028$  as our scaling factor. This gives us an error of  $0.8\%$  in our energy consumption, which was discussed as an acceptable error margin according to the case study company.

As products in the real-world robot cell are produced in pairs after each other, a goal was to get the simulation to be able to produce products in a pair sequence but randomly over the range of products. This was something that was difficult to achieve in the software. The reason that products are produced in pairs after each other is because of the next part of the production flow, where the products are processed together in pairs. However, the scope of the project limited the study to focus solely on this production cell, without analysing the surrounding production processes.

## 6.4 Future work

During the project, many discussions have emerged with potential ideas that could be done for future work under different circumstances. Firstly, the data quality is currently in an initial phase where the production is looking at what data they want. If in the future there were more type A data from PLCs and the robots, simulation on energy and time could be improved by having more accurate data. This is from a validation perspective, as the base model could replicate the real-world system better. A possibility could be to install more energy meters at more specific processes to see what each part of the robot cell is using. This, together with more time data on the robot's active periods, could give a well-validated model.

In future case studies, earlier involvement in the data collection process could significantly improve the efficiency and quality of the simulation. Starting data gathering before the start of the project would allow an understanding of what data is available and whether it meets the requirements of the study. This could reduce the time required for data collection and minimise the need for assumptions during model development. Early findings of a lack of data could change how the company collects relevant data, ensuring that the simulation model correlates with the objective of the study. That kind of approach to data collection could improve both the accuracy and reliability of the results.

The improvement of the software could give a future study a better possibility to replicate the real-world system. The possibility of coding or creating one's own functions in the model could make the simulation of the material flow better and give more specific energy usage results. Having the possibility to divide a process cycle into different energy usage periods could give very accurate energy simulation results. The possibility to implement priorities or to limit the optimisations in the software would also give possibilities to give more relevant results if the study needs to work in a certain range, such as products per year.

If a further study would have been conducted, it would have possibly been needed for the ergonomics analysis to be done with a simulation tool. IPS IMMA has been discussed as the potential tool, it being an ergonomics simulation evaluation tool. Further, if it could have been possible to include the ergonomics analysis in the multi-objective optimisation experiment, that would be a very valuable tool. To be able to find optimal solutions for all the three levels of the TBL. This is something that can be studied further, if it is possible and how to conduct it. One way that has been discussed is to extract the evaluation scores for several different solutions and use the evaluation score as the output for the multi-objective optimisation.



# 7

## Conclusion

The aim of the project was to investigate how simulation software can support sustainable improvements in an industrial production flow. The systematic literature review together with the case study found the possibilities of using simulation as a tool to sustainably analyse a manufacturing system.

From the literature review, the study found that simulation can support manufacturing companies in improving the TBL. This is by allowing data-driven decisions to reduce energy consumption while maintaining productivity and assessing ergonomic conditions.

The results from the case study showed that the production system uses a lot of non-value-adding energy in its welding process. With the use of NSGA-II optimisation, it was possible to identify Pareto-optimal solutions to the system that could decrease the energy consumption without negatively affecting the productivity. The chosen solution from the Pareto front showed that the idle energy was reduced by 42-50% while increasing the number of produced parts. This showed that this type of process has potential to be a tool for finding improvements without compromising the production performance. The ergonomic analysis showed that the workstation currently operates within acceptable limits, indicating that no immediate social sustainability problems were identified at the production cell level.

The study was found to be limited by the availability and accuracy of input data, as well as simplifications required in the simulation model. As a result, the findings should be interpreted as a tool with need of improvement potential rather than exact predictions of system performance. Building on this work, future research could also extend the model by incorporating the social dimension, for example by including physical ergonomics within the MOO framework.

In conclusion, the study shows that simulation together with MOO can be an effective tool for supporting sustainable manufacturing. By identifying and reducing waste such as non-value-adding energy consumption, industries can improve the environmental performance without affecting the productivity, contributing to a more sustainable production.



# Bibliography

- [1] W. S. Yip, H. T. Zhou, and S. To, “A critical analysis on the triple bottom line of sustainable manufacturing: key findings and implications,” *Environmental Science and Pollution Research*, vol. 30, no. 14, pp. 41 388–41 404, Mar. 2023, ISSN: 16147499. DOI: 10 . 1007 / s11356 - 022 - 25122 - x. [Online]. Available: <https://www.scopus.com/pages/publications/85146070340?origin=resultslist>.
- [2] A. Salman, M. R. Khan, M. A. Khan, and M. Moazzam, “Exploring the Adoption of Industry 4.0 in Manufacturing Industry and Its Impact on Sustainable Performance: A Systematic Literature Review,” *Process Integration and Optimization for Sustainability 2025*, pp. 1–23, Oct. 2025, ISSN: 2509-4246. DOI: 10 . 1007 / S41660 - 025 - 00580 - 1. [Online]. Available: <https://link.springer.com/article/10.1007/s41660-025-00580-1>.
- [3] J. Kopeinig, M. Woschank, and N. Olipp, “Industry 4.0 Technologies and their Implications for Environmental Sustainability in the Manufacturing Industry,” *Procedia Computer Science*, vol. 232, pp. 2777–2789, Jan. 2024, ISSN: 1877-0509. DOI: 10 . 1016 / J . PROCS . 2024 . 02 . 095. [Online]. Available: [https://www.sciencedirect.com/science/article/pii/S1877050924002722?ref=pdf\\_download&fr=RR-2&rr=9c4f350bb971f9aa](https://www.sciencedirect.com/science/article/pii/S1877050924002722?ref=pdf_download&fr=RR-2&rr=9c4f350bb971f9aa).
- [4] A. Jamwal, “Two decades of research trends and transformations in manufacturing sustainability: a systematic literature review and future research agenda,” *Production Engineering*, pp. 109–133, 2022. [Online]. Available: [https://www.researchgate.net/profile/Rajeev-Agrawal-5/publication/355181971\\_Two\\_decades\\_of\\_research\\_trends\\_and\\_transformations\\_in\\_manufacturing\\_sustainability\\_a\\_systematic\\_literature\\_review\\_and\\_future\\_research\\_agenda/links/668b8a802aa57f3b8274c4be/Two-decades-of-research-trends-and-transformations-in-manufacturing-sustainability-a-systematic-literature-review-and-future-research-agenda.pdf](https://www.researchgate.net/profile/Rajeev-Agrawal-5/publication/355181971_Two_decades_of_research_trends_and_transformations_in_manufacturing_sustainability_a_systematic_literature_review_and_future_research_agenda/links/668b8a802aa57f3b8274c4be/Two-decades-of-research-trends-and-transformations-in-manufacturing-sustainability-a-systematic-literature-review-and-future-research-agenda.pdf).
- [5] M. Song, M. X. Yang, K. J. Zeng, and W. Feng, “Green Knowledge Sharing, Stakeholder Pressure, Absorptive Capacity, and Green Innovation: Evidence from Chinese Manufacturing Firms,” *Business Strategy and the Environment*, vol. 29, no. 3, pp. 1517–1531, Mar. 2020, ISSN: 10990836. DOI: 10 . 1002 / BSE . 2450 ; REQUESTEDJOURNAL : JOURNAL : 10990836 ; WGROUP : STRING : PUBLICATION. [Online]. Available: [/doi/pdf/10.1002/bse.2450](https://onlinelibrary.wiley.com/doi/abs/10.1002/bse.2450)<https://onlinelibrary.wiley.com/doi/abs/10.1002/bse.2450><https://onlinelibrary.wiley.com/doi/10.1002/bse.2450>.

- [6] A. U. Rahman, F. Wen, and F. Amjad, "Role of sustainable business model, Industry 4.0, crowdfunding, and stakeholders' pressure toward firm's sustainability: A SEM-ANN approach," *Business Strategy and the Environment*, vol. 33, no. 7, pp. 7409–7426, Nov. 2024, ISSN: 10990836. DOI: 10.1002/bse.3869. [Online]. Available: <https://www.scopus.com/pages/publications/85198336957?origin=scopusAI>.
- [7] L. A. Shihata, A. A. Ghaly, and J. Kiefer, "Potentials of Energy Efficiency Improvement in Manufacturing Plants," *55th CIRP Conference on Manufacturing Systems, CIRP CMS 2022*, vol. 107, no. 14, pp. 729–733, Jan. 2022, ISSN: 22128271. DOI: 10.1016/j.procir.2022.05.053. [Online]. Available: <https://doi.org/10.3390/en13143548>.
- [8] T. Schmitt, S. Olives Juan, K. Amouzgar, L. Hanson, and M. Urenda Moris, "Optimizing energy efficiency and productivity in industrial manufacturing: A simulation-based optimization approach with knowledge discovery," *Journal of Manufacturing Systems*, vol. 82, no. 2, pp. 748–765, Oct. 2025, ISSN: 02786125. DOI: 10.1016/j.jmsy.2025.07.008. [Online]. Available: <https://doi.org/10.3390/en12020247>.
- [9] B. S. Linke and J. W. Sutherland, "Introduction to Energy Efficient Manufacturing," in *Energy Efficient Manufacturing: Theory and Applications*, John W. Sutherland, David A. Dornfeld, and Barbara S. Linke, Eds., 1st ed., Wiley, Jan. 2018, ch. 1, pp. 23–30, ISBN: 9781119519904. DOI: 10.1002/9781119519904.ch1. [Online]. Available: <https://www.scopus.com/pages/publications/105008363776?origin=scopusAI>.
- [10] J. Banks, *Discrete-event system simulation*. Pearson Prentice Hall, 2005, p. 608, ISBN: 0131446797.
- [11] M. Abdul Majid, N. Ahmad, A. Abdullah, M. M. Noor, and S. Abdullah Sani, "Simulating Brick Production Through Discrete Event Simulation as a Zero-Waste Initiative for Sustainability," *Lecture Notes in Civil Engineering*, vol. 557 LNCE, pp. 424–431, 2025, ISSN: 23662565. DOI: 10.1007/978-981-97-8348-9\_{\ }52. [Online]. Available: [https://link.springer.com/chapter/10.1007/978-981-97-8348-9\\_52](https://link.springer.com/chapter/10.1007/978-981-97-8348-9_52).
- [12] A. Negahban and J. S. Smith, "Simulation for manufacturing system design and operation: Literature review and analysis," *Journal of Manufacturing Systems*, vol. 33, no. 2, pp. 241–261, 2014, ISSN: 02786125. DOI: 10.1016/j.jmsy.2013.12.007. [Online]. Available: <https://www.scopus.com/pages/publications/84897115618?origin=resultslist>.
- [13] R. G. Ingalls, "Introduction to simulation," *Proceedings - Winter Simulation Conference*, pp. 1374–1388, 2011, ISSN: 08917736. DOI: 10.1109/WSC.2011.6147858. [Online]. Available: <https://ieeexplore.ieee.org/document/6147858>.
- [14] C. Roser, M. Nakano, and M. Tanaka, "Comparison of bottleneck detection methods for AGV systems," *Winter Simulation Conference Proceedings*, vol. 2, pp. 1192–1198, 2003, ISSN: 02750708. DOI: 10.1109/WSC.2003.1261549. [Online]. Available: <https://ieeexplore.ieee.org/document/1261549>.
- [15] A. M. Law, *Simulation modeling and analysis*. McGraw-Hill Education, 2015, p. 776, ISBN: 9780073401324.

- 
- [16] A. Skoogh and B. Johansson, “A methodology for input data management in discrete event simulation projects,” *Proceedings - Winter Simulation Conference*, pp. 1727–1735, 2008, ISSN: 08917736. DOI: 10.1109/WSC.2008.4736259.
- [17] A. H. Ng, C. Dudas, H. Boström, and K. Deb, “Interleaving innovization with evolutionary multi-objective optimization in production system simulation for faster convergence,” *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 7997 LNCS, pp. 1–18, 2013, ISSN: 03029743. DOI: 10.1007/978-3-642-44973-4\_{\}1. [Online]. Available: [https://link.springer.com/chapter/10.1007/978-3-642-44973-4\\_1](https://link.springer.com/chapter/10.1007/978-3-642-44973-4_1).
- [18] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, “A fast and elitist multiobjective genetic algorithm: NSGA-II,” *IEEE Transactions on Evolutionary Computation*, vol. 6, no. 2, pp. 182–197, Apr. 2002, ISSN: 1089778X. DOI: 10.1109/4235.996017. [Online]. Available: <https://www.scopus.com/pages/publications/0036530772?origin=resultslist>.
- [19] C. Berlin and C. Adams, *Production ergonomics : designing work systems to support optimal human performance*. Ubiquity Press, 2017, p. 296, ISBN: 9781911529125.
- [20] Arbetsmiljöverket, *Use of work equipment - Arbetsmiljöverket*, 2025. [Online]. Available: <https://www.av.se/en/production-industry-and-logistics/use-of-work-equipment/>.
- [21] I. Castelo-Branco, M. Amaro-Henriques, F. Cruz-Jesus, and T. Oliveira, “Assessing the Industry 4.0 European divide through the country/industry dichotomy,” *Computers & Industrial Engineering*, vol. 176, p. 108925, Feb. 2023, ISSN: 0360-8352. DOI: 10.1016/J.CIE.2022.108925. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0360835222009135>.
- [22] G. K. Frampton, B. Livoreil, and G. Petrokofsky, “Eligibility screening in evidence synthesis of environmental management topics,” *Environmental Evidence 2017 6:1*, vol. 6, no. 1, pp. 27–, Sep. 2017, ISSN: 2047-2382. DOI: 10.1186/S13750-017-0102-2. [Online]. Available: <https://link.springer.com/article/10.1186/s13750-017-0102-2>.
- [23] *inFACTS Studio - Evoma*. [Online]. Available: <https://evoma.se/infacts-studio/>.
- [24] R. G. Sargent, “Verification and validation of simulation models,” *Journal of Simulation*, vol. 7, no. 1, pp. 12–24, 2013, ISSN: 17477786. DOI: 10.1057/JOS.2012.20. [Online]. Available: <https://www.tandfonline.com/doi/abs/10.1057/jos.2012.20>.
- [25] K. Hoad, S. Robinson, and R. Davies, “Automated selection of the number of replications for a discrete-event simulation,” *Journal of the Operational Research Society*, vol. 61, no. 11, pp. 1632–1644, 2010, ISSN: 14769360. DOI: 10.1057/jors.2009.121. [Online]. Available: <https://www.scopus.com/pages/publications/77957699943?origin=resultslist>.
- [26] T. L. Garwood, B. R. Hughes, M. R. Oates, D. O’Connor, and R. Hughes, “A review of energy simulation tools for the manufacturing sector,” *Renewable and Sustainable Energy Reviews*, vol. 81, pp. 895–911, Jan. 2018, ISSN: 18790690.

- DOI: 10.1016/j.rser.2017.08.063. [Online]. Available: <https://doi.org/10.4271/2006-01-0833>.
- [27] A. Caggiano, A. Marzano, and R. Teti, "Sustainability Enhancement of a Turbine Vane Manufacturing Cell through Digital Simulation-Based Design," *Energies* 2016, Vol. 9,, vol. 9, no. 10, Sep. 2016, ISSN: 19961073. DOI: 10.3390/en9100790. [Online]. Available: <https://www.mdpi.com/1996-1073/9/10/790>.
- [28] A. Singh, D. Philip, J. Ramkumar, and M. Das, "A simulation based approach to realize green factory from unit green manufacturing processes," *Journal of Cleaner Production*, vol. 182, pp. 67–81, May 2018, ISSN: 09596526. DOI: 10.1016/j.jclepro.2018.02.025. [Online]. Available: <https://www.scopus.com/pages/publications/85043605516>.
- [29] S. M. Dahan and S. M. Yusof, "Eco-Process Innovation Performance: Production Waste Investigation through Discrete Event Simulation," *IOP Conference Series: Materials Science and Engineering*, vol. 697, no. 1, p. 012001, Dec. 2019, ISSN: 1757899X. DOI: 10.1088/1757-899X/697/1/012001. [Online]. Available: <https://iopscience.iop.org/article/10.1088/1757-899X/697/1/012001%20https://iopscience.iop.org/article/10.1088/1757-899X/697/1/012001/meta>.
- [30] A. Mares, P. Malega, N. Daneshjo, and O. Yevtushenko, "Sustainable Efficiency Through Ergonomic Design and Optimization of Assembly Workstations," *Sustainability* 2025, Vol. 17,, vol. 17, no. 21, Oct. 2025, ISSN: 20711050. DOI: 10.3390/su17219545. [Online]. Available: <https://www.mdpi.com/2071-1050/17/21/9545>.
- [31] L. Olander et al., "Analysis the Awkward Posture Ergonomic Risk and Workstation Improvement Simulation in Mechanical Assembly Manufacturing Industry using DelmiaV5," *IOP Conference Series: Materials Science and Engineering*, vol. 705, no. 1, p. 012044, Nov. 2019, ISSN: 1757899X. DOI: 10.1088/1757-899X/705/1/012044. [Online]. Available: <https://iopscience.iop.org/article/10.1088/1757-899X/705/1/012044%20https://iopscience.iop.org/article/10.1088/1757-899X/705/1/012044/meta>.
- [32] A. K. Mishra, A. Sharma, and M. Sachdeo, "Development of sustainable value stream mapping (SVSM) for unit part manufacturing," *International Journal of Lean Six Sigma*, vol. 11, no. 3, pp. 493–514, 2020. DOI: 10.1108/IJLSS-04-2018-0036. [Online]. Available: <https://www.emerald.com/insight/2040-4166.htm>.
- [33] D. Onofrejova, ; Janekova, ; Grincova, and Z. Soltysova, "Simulation and evaluation of production factors in manufacturing of fireplaces," *International Journal of Simulation Modelling*, vol. 19, pp. 77–88, 2020, ISSN: 1726-4529. DOI: 10.2507/IJSIMM19-1-504. [Online]. Available: <https://doi.org/10.2507/IJSIMM19-1-504>.
- [34] N. Abdulatif, S. Yasser, I. Fahim, Y. Emad, A. Saleh, and S. Kassem, "Decision Support Using Simulation to Improve Productivity: A Case Study," *2020 International Conference on Decision Aid Sciences and Application, DASA 2020*, pp. 1120–1127, Nov. 2020. DOI: 10.1109/DASA51403.2020.9317043.

- 
- [35] L. E. Villagomez et al., “Discrete Event Simulation as a Support in the Decision Making to Improve Product and Process in the Automotive Industry - A Fuel Pump Component Case Study,” *IFIP Advances in Information and Communication Technology*, vol. 568, pp. 572–581, 2019, ISSN: 1868422X. DOI: 10.1007/978-3-030-28464-0\_{\\_}50. [Online]. Available: [https://link.springer.com/chapter/10.1007/978-3-030-28464-0\\_50](https://link.springer.com/chapter/10.1007/978-3-030-28464-0_50).
- [36] J. Bokrantz, A. Skoogh, D. Lämkkull, A. Hanna, and T. Perera, “Data quality problems in discrete event simulation of manufacturing operations,” *Simulation*, vol. 94, no. 11, pp. 1009–1025, Nov. 2018, ISSN: 17413133. DOI: 10.1177/0037549717742954 ; PAGEGROUP : STRING : PUBLICATION. [Online]. Available: <https://journals.sagepub.com/doi/10.1177/0037549717742954>.
- [37] K. M. Mansour, A. Mohib, M. F. Aly, and A. H. Salem, “An Integrated Framework for Modeling and Simulation Tool Selection and Implementation,” *NILES 2024 - 6th Novel Intelligent and Leading Emerging Sciences Conference, Proceedings*, pp. 76–80, 2024. DOI: 10.1109/NILES63360.2024.10753233. [Online]. Available: <https://www.scopus.com/pages/publications/85212585225?origin=scopusAI>.





# A

## Sources for Systematic Literature Review

Table A.1: Summary of selected manufacturing simulation and sustainability studies

<b>Title</b>	<b>Authors</b>	<b>Year</b>
Sustainable Efficiency Through Ergonomic Design and Optimization of Assembly Workstations	Mares, A.; Malega, P.; Daneshjo, N.; Yevtushenko, O.	2025
Optimizing energy efficiency and productivity in industrial manufacturing: A simulation-based optimization approach with knowledge discovery	Schmitt, T.; Olives Juan, S.; Amouzgar, K.; Hanson, L.	2025
Potentials of Energy Efficiency Improvement in Manufacturing Plants	Thiede, S.; Cerdas, F.; Herrmann, C.	2011
Decision Support Using Simulation to Improve Productivity: A Case Study	Bokhari, Z.; Smith, J.; McGough, E.	2020
Development of sustainable value stream mapping (SVSM) for unit part manufacturing: A simulation approach	Mishra, A. K.; Sharma, A.; Sachdeo, M.; Jayakrishna, K.	2019
Simulation and evaluation of production factors in manufacturing of fireplaces	Onofrejeva, D.; Janekova, J.; Grincova, A.; Soltysova, Z.	2020
Eco-Process Innovation Performance: Production Waste Investigation through Discrete Event Simulation	Dahan, S. M.; Yusof, S. M.	2019
Analysis the Awkward Posture Ergonomic Risk and Workstation Improvement Simulation in Mechanical Assembly Manufacturing Industry using Delmia V5	Hambali, R. H.; Rahim, S. A. A.; Azizan, N.; Zali, Z.; Akmal, S.; Zin, M. H.	2019
Discrete Event Simulation as a Support in the Decision Making to Improve Product and Process in the Automotive Industry – A Fuel Pump Component Case Study	Silva, F.; Pereira, M.; Costa, A.	2018
A simulation based approach to realize green factory from unit green manufacturing processes	Nguyen, T. T.; Dornfeld, D. A.	2014
A review of energy simulation tools for the manufacturing sector	Herrmann, C.; Thiede, S.; Kara, S.; Hesselbach, J.	2011
Sustainability enhancement of a turbine vane manufacturing cell through digital simulation-based design	Ravi, B.; Suri, G.; Kulkarni, S.	2016

# B

## Tables and Figures for Method

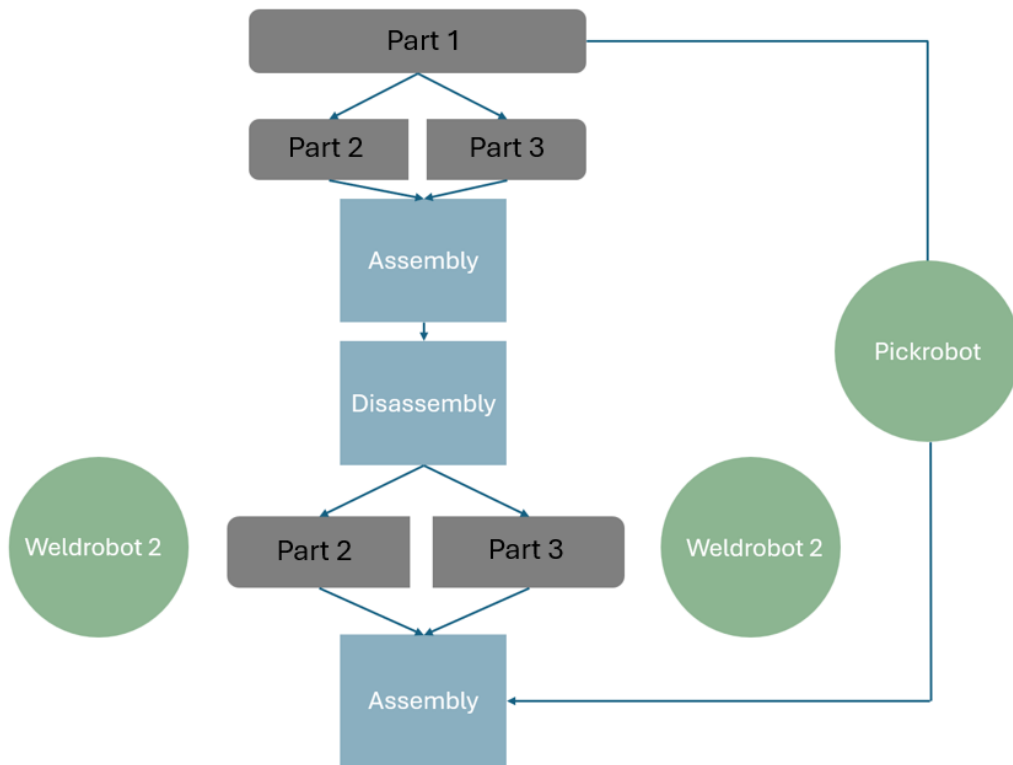


Figure B.1: Conceptual model of the product split into two pieces and showing how assembly and disassembly work

Table B.1: System Elements and their Functions

Element	Description
Sources	Create variants either in sequence or randomly
Store	Stores an amount of products in a storage using first-in-first-out (FIFO) as the exit method
Buffers	Smaller storage units
Assembly	Assembles different parts into a single part
Disassembly	Disassembles parts into their original subparts
Operations	Processes with process times that are either variant-dependent via tables or connected to a variable

Table B.2: Inputs for the multi-objective optimisation on base model

<b>Input</b>	<b>Range</b>
Idle power pick robots	56.65 - 113.3 W
Idle power weld robots	132.68 - 265.36 W
Availability	92 - 94%
Global variable loading and unloading	210 - 438.3 s

Table B.3: Outputs for the multi-objective optimisation on base model

<b>Output</b>	<b>Value</b>
Total energy	Minimise
Produced parts	Maximise

Table B.4: Inputs for the multi-objective optimisation when the robots are shut down

<b>Input</b>	<b>Range</b>
Idle power pick robots	56.65 - 113.3 W
Idle power weld robots	132.68 - 265.36 W
Availability	88 - 94%
Global variable loading and unloading	210 - 438.3 s

# C

## Tables and Figures for Result

Figures and tables from that represents results in Chapter 5

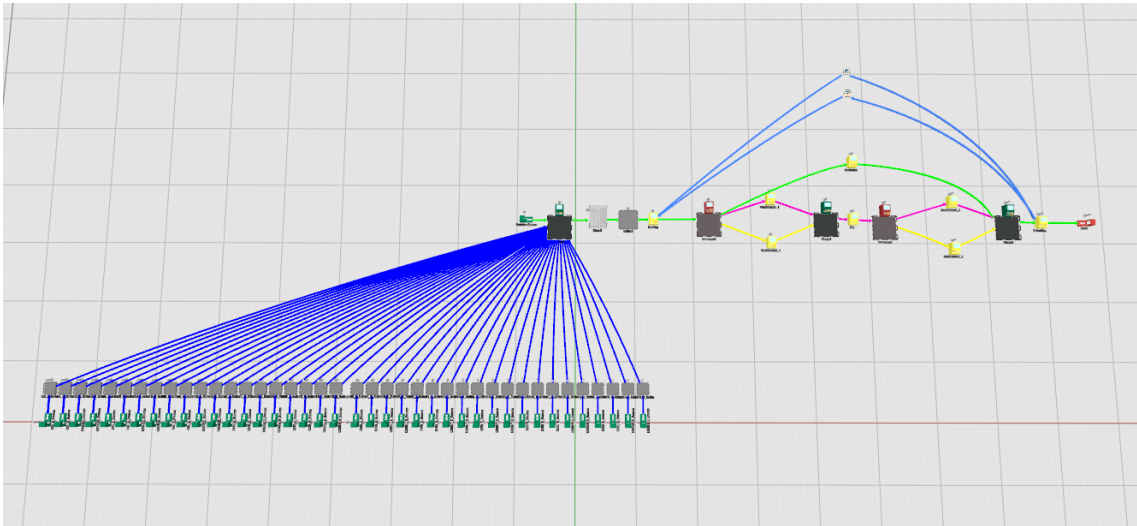


Figure C.1: Full overview of the base model

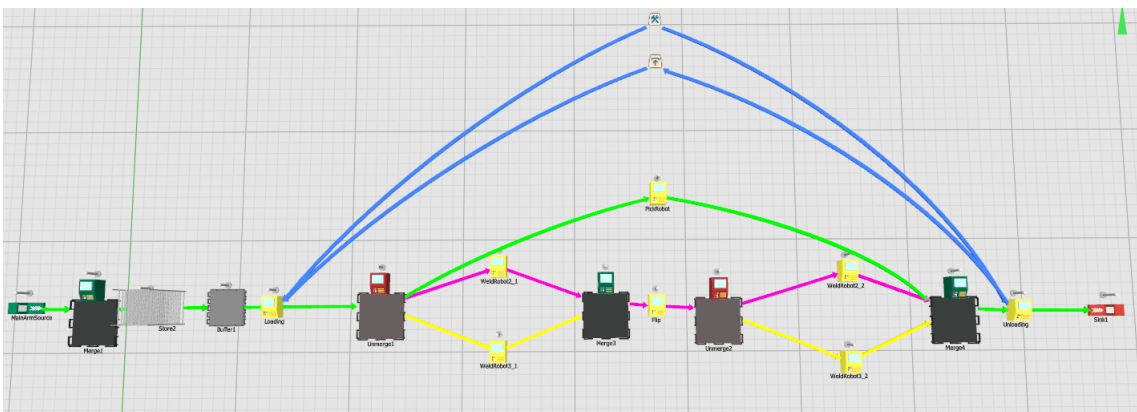


Figure C.2: Overview of the model without sub part creator

### C. Tables and Figures for Result

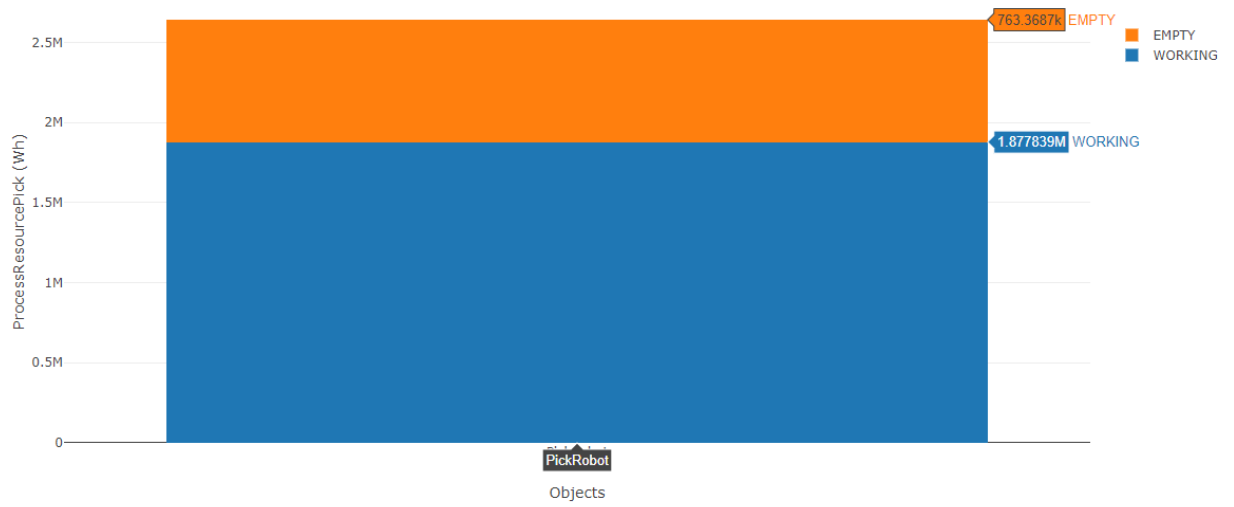


Figure C.3: Energy consumption chart for the pick robot

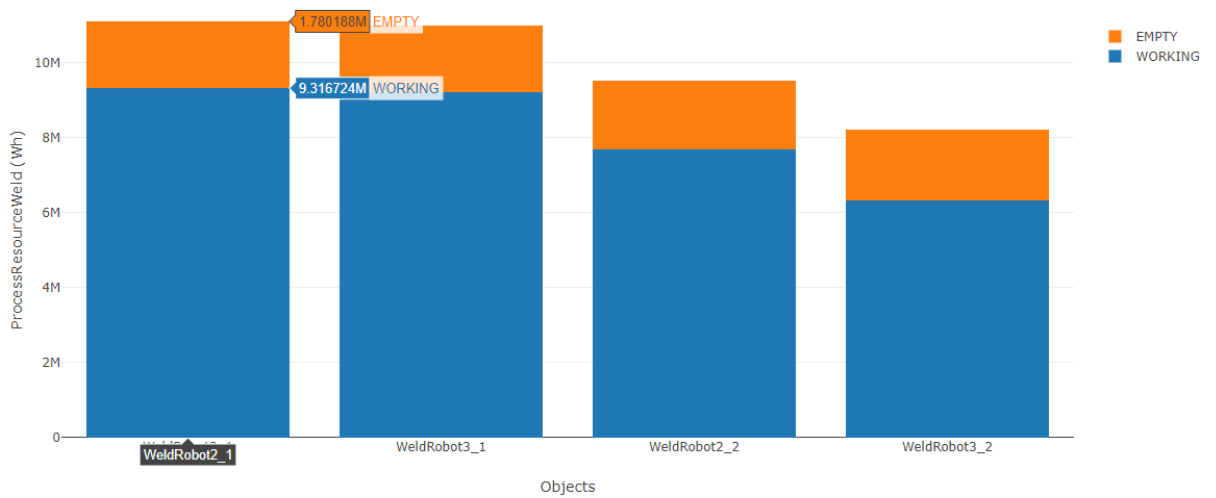


Figure C.4: Energy consumption chart with values of robot 2 before flip

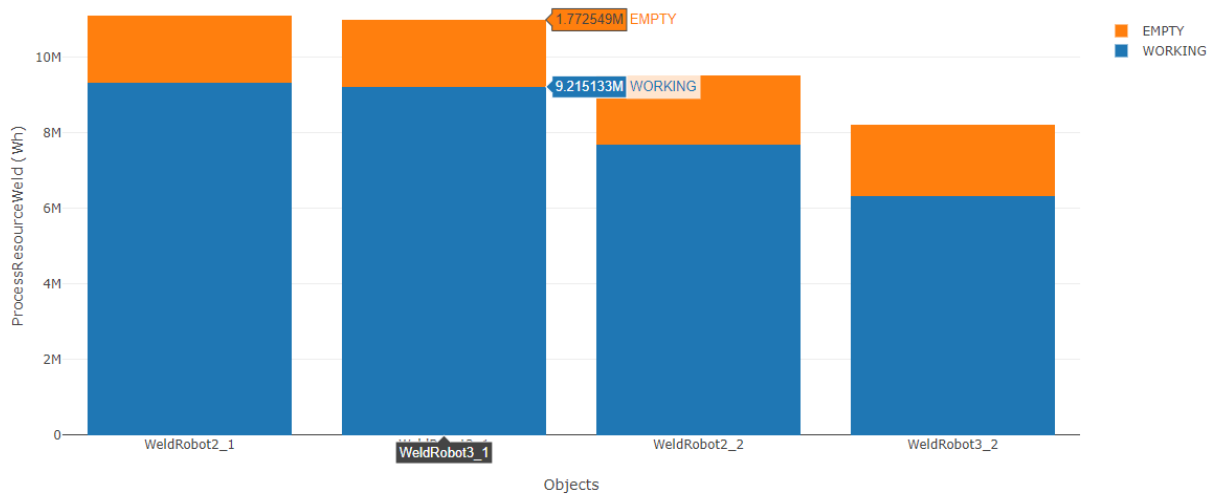


Figure C.5: Energy consumption chart with values of robot 3 before flip

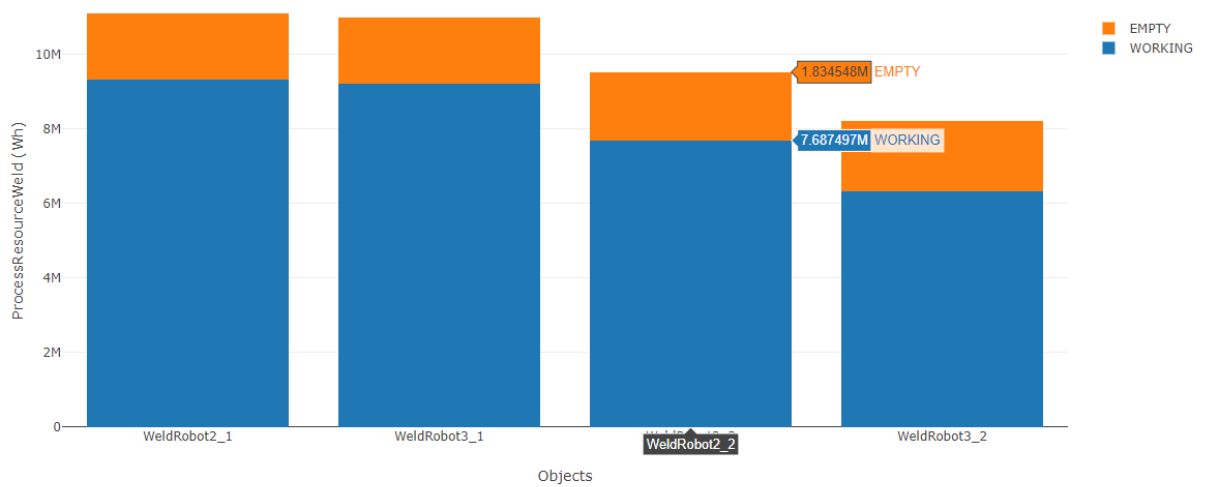


Figure C.6: Energy consumption chart with values of robot 2 after flip

### C. Tables and Figures for Result

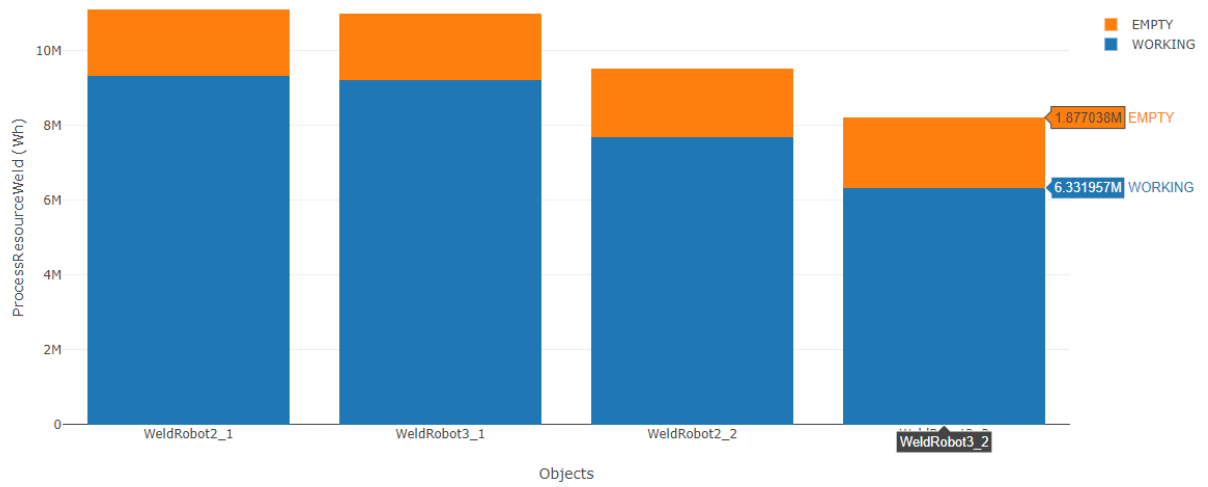


Figure C.7: Energy consumption chart with values of robot 3 after flip



Figure C.8: Energy consumption of pick robot after improvements based on one solution from the Pareto front.

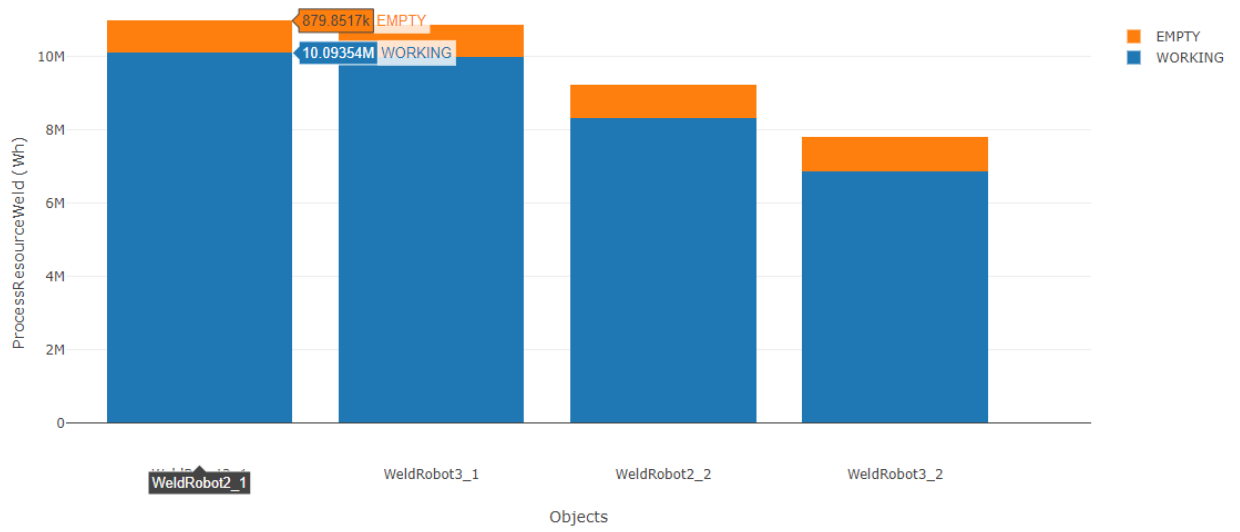


Figure C.9: Energy consumption robot 2\_1 after improvements based on one solution from the Pareto front

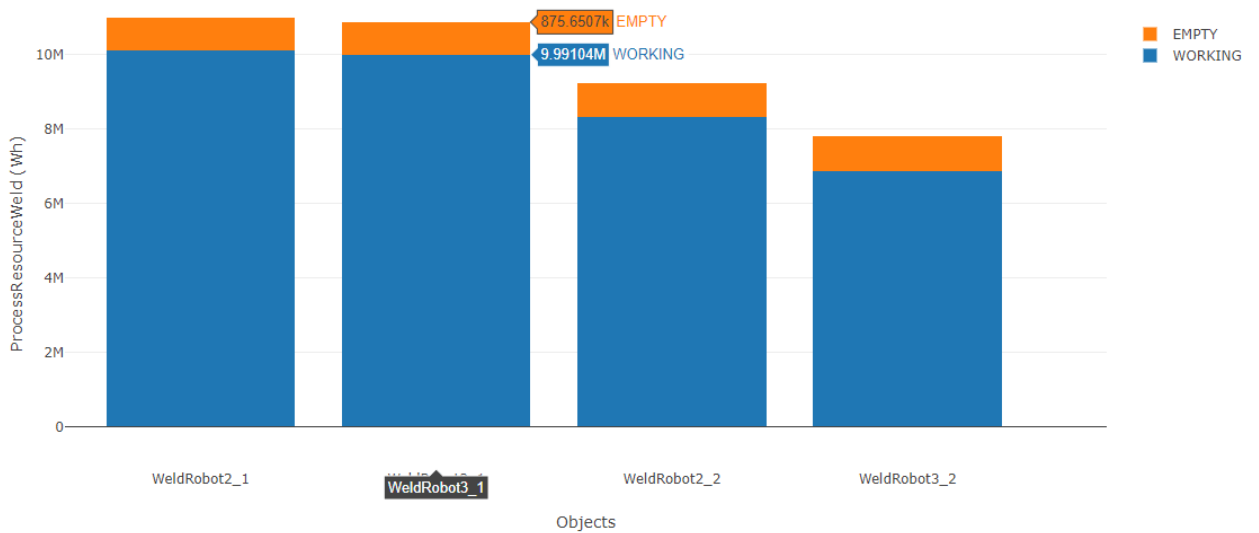


Figure C.10: Energy consumption for robot 3\_1 after improvements based on one solution from the Pareto front

### C. Tables and Figures for Result

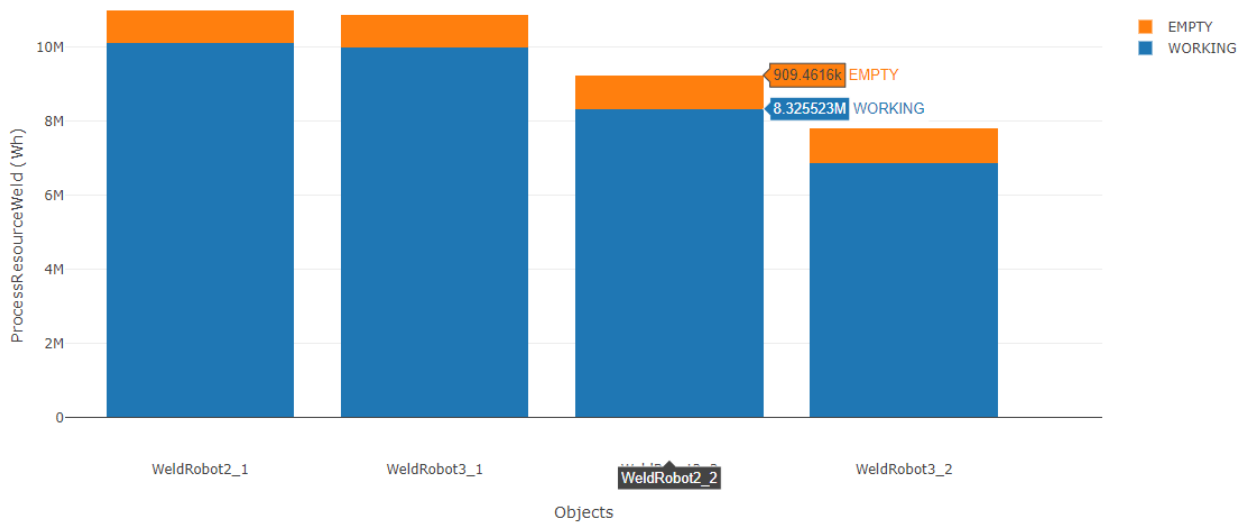


Figure C.11: Energy consumption for robot 2\_2 after improvements based on one solution from the Pareto front

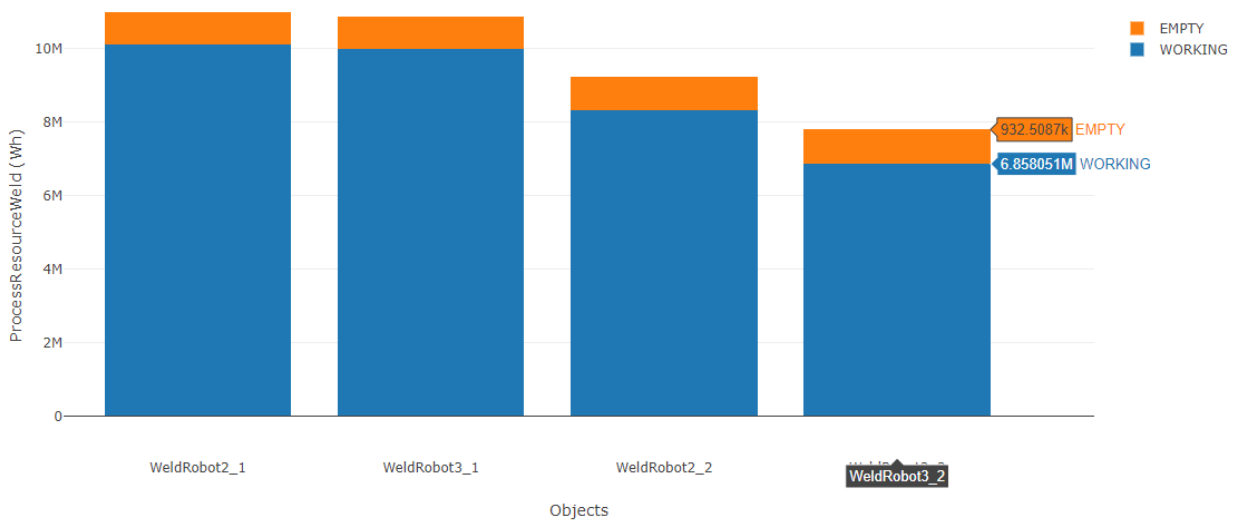


Figure C.12: Energy consumption for robot 3\_2 after improvements based on one solution from the Pareto front

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