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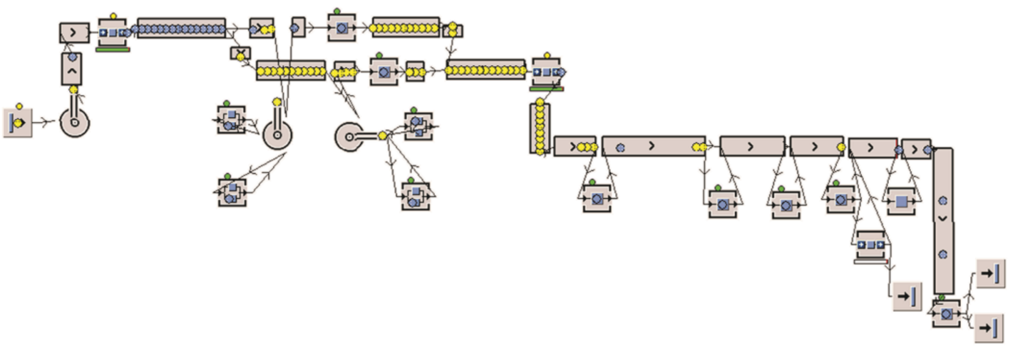

Environmental Footprint and Performance Analysis of a Brake Disc Production Line using Discrete Event Simulation

Master of Science Thesis

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Gothenburg, Sweden, 2013

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Cover:
Simulation model of the analyzed production line

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ABSTRACT

More and more companies become aware of the environmental consequences of their actions and strive to make their production and products more sustainable. Recent studies have developed approaches to combine Discrete Event Simulation (DES) and Life Cycle Assessment for an environmental impact assessment of production systems. This thesis uses experiences from one of these approaches, called EcoProIT, and applies them on a production line in automotive industry to analyze both the environmental impact and the performance of the production system. The purpose is to support the company in their work to improve the production system in terms of both performance and environmental sustainability. A simulation model is built and used to analyze the system. The environmental impact assessment presents the environmental footprint of the studied product, which is 15-20 kg CO_2-equivalents per product, dependent on the variant. Different impact factors are identified and possible improvement areas to decision makers in the company. An important part of the analysis is a mapping of energy consumption of the machines, identifying turning operations as hot spots in the production process. The performance analysis identifies constraints in the production system and reveals more problem areas than already known by the company, in particular insufficient buffer capacities and machine availabilities. Through different experiments in the simulation model, improvement potentials are analyzed and suggestions for changes are developed. An implementation of those suggestions could increase productivity by at least 10-12%. Moreover, this thesis gives further practical experience to the field of using DES for environmental impact assessments and contributes with discussions for a methodology development. Thus the achieved results generate value both for research and for the company.

Keywords: *Discrete Event Simulation, Life Cycle Assessment, EcoProIT.*

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LIST OF ABBREVIATIONS

AP	Acidification potential
CO2-eq	Carbon dioxide-equivalents
CT	Cycle Time
DES	Discrete Event Systems
DoE	Design of Experiments
dTPh	Change in throughput per hour
EP	Eutrophication potential
Eq	Equivalents
FMEA	Failure Mode and Effects Analysis
GWP	Global Warming Potential
IAIA	International Organization for Impact Assessment
LCA	Life Cycle Assessment
LCI	Life Cycle Inventory
LCIA	Life Cycle Impact Assessment
MTTF	Mean Time To Failure
MTTR	Mean Time To Repair
MU	Mobile Unit
n/a	Not applicable
OFAT	One Factor At a Time
OP	Operation
StDev	Standard deviation
TP	Throughput
TPh	Throughput per hour
VCC	Volvo Cars Corporation
VSM	Value Stream Mapping

1 INTRODUCTION

For a company to be competitive it is increasingly important to include sustainability aspects in their strategies (Kiron et. al 2012). Consequently, companies are actively working on analysis and improvement of the environmental footprint of their products (Scania 2012 and Max 2011). A methodology for environmental impact assessment is Life Cycle Assessment (LCA), which assesses the environmental impact of a product through its whole life cycle (Baumann and Tillman 2004).

Another important aspect that affects competitiveness is the performance of companies' production systems. Discrete Event Simulation (DES) is a method commonly used to find problems and investigate improvement potentials in a production environment through the use of computerized models (Banks and Cox 2010).

Chalmers University of Technology and, among others, Volvo Cars Corporation (VCC) are collaborating on a project called EcoProIT. This project aims at facilitating environmental impact analyses, developing a methodology to implement them in DES. Thus, both LCA and DES are united. Previous studies within this project have concluded this to be beneficial in certain applications (Andersson et. al 2012a, Lindskog et. al 2011). This thesis provides the EcoProIT project with additional experience.

Volvo Cars Corporation has a factory in Floby where hubs and brake discs for trucks are produced, as well as connecting rods and brake discs for cars. This study focuses on the production of brake discs for cars. In the brake disc section of the factory, nine highly automated lines produce several brake disc variants. The production line that is the subject for this study produces eight different variants in batches. Cast iron blanks are processed in 6 steps and are automatically transported by robots, elevators and conveyors between the operations. After the production line the pallets are transported by forklifts to a painting process, which is the last step before customer delivery. Figure 1 shows a flowchart overview of the processes necessary to produce one brake disc together with their designation used at the company. Some of the operations are parallel processes with two machines, visualized with branched arrows. For a detailed description of each process step, see Appendix A. Production operations are denoted OP, which is also the term used in this thesis.

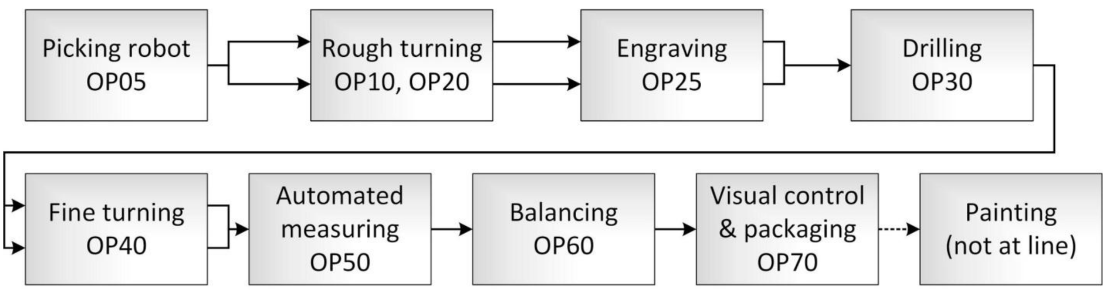


Figure 1 - Production process

1.1 Problem description

Currently there is no information about the environmental footprint of a brake disc at all. Along with VCC's environmental policy (Volvo Cars 2012) there is a requirement to reduce the environmental footprint of the production, leading to environmental sustainability. Moreover, VCC's target for throughput per hour in the brake disc production is not reached, which indicates that there is room for performance improvement.

1.2 Purpose

In order to give VCC the possibility to further improve their production system, a thorough analysis of the current system is needed. To gain a future competitive advantage through a green image, such an analysis should cover environmental aspects to contribute to an environmental sustainable production development. Therefore the purpose of this master thesis is to analyze the environmental footprint of the brake disc production, and support VCC in the investigation and the performance improvement of their production system.

1.3 Goals

- Determine the environmental footprint for a brake disc
- Examine dominant factors influencing the environmental footprint
- Identify productivity constraints in the production system and analyze determining parameters for the system's throughput
- Develop ideas to improve the production system and its environmental footprint.

1.4 Scope

The performance analysis focuses on the production process from raw material input at the picking robot (OP05) to packaging of finished brake discs (OP70). Material supply processes and painting are not included in the analysis.

The environmental impact assessment is done from a cradle-to-gate perspective, including the studied production system and its upstream processes, but excluding downstream processes. (Baumann and Tillman 2004)

The analyses aim at the identification of improvement potentials, not at the development of full solution concepts ready for implementation. The thesis still gives basic improvement ideas and recommendations for further work. Furthermore, only ideas that lie within the scope of action of manufacturing decision makers - i.e. production management and engineering - are considered, as well as supply logistics.

The integration of energy consumption in the simulation model is only done for analysis purposes. No optimization in terms of energy consumption is performed; the experiments and improvements in the simulation model only focus on productivity.

1.5 Outline

In the next chapter, background about DES, its application for performance analyses, and connected methods is given, together with basic knowledge about LCA. Then the methodology of this thesis is described, including information about how a simulation model was built to make two analyses. Chapters 4 and 5 handle the results from the analyses separately, but both use output data from the simulation model. First the results from the environmental impact calculations are shown, and second the performance analyses are presented. In chapter 6, ideas for improvements are elaborated based on the two analyses. Finally, important insights from the used methodology and the results are discussed, and the report ends with a conclusion of the work.

2 FRAME OF REFERENCE

This chapter gives background information necessary to follow the methodology and analysis of this thesis project. Important topics and methods are introduced to give a basic understanding. For deeper insight it is recommended to study the referred literature.

2.1 Discrete Event Simulation

Discrete Event Simulation (DES) is used to simulate events of the real world in a model. In the model the events occur in a sequence. For each event, the state of the system changes, and in between events the model is assumed to be unchanged. Compared to *continuous* simulation, a DES model can skip the sequences where the system is unchanged, allowing it to simulate long periods of time in just a few seconds (Banks et al. 2010).

DES can be applied in many different situations (Banks 1998), but most relevant for this thesis is the analysis of production systems. The events in such a system are e.g. breakdown of a machine or start and end of processing of a product, and examples for the system states are machine states (busy, idle or failed). A production system model is based on parameters, such as cycle time, machine availability and mean time to repair (MTTR), which are represented as stochastic inputs.

Shannon (1998) gives a number of advantages of simulation over mathematical models for analyzing a system. A key advantage is that simulation makes the analysis more credible, since fewer simplifications have to be made. In addition, simulation allows the user to make analyses without interrupting the real production system. What can be analyzed is e.g. the effects of a new organizational structure, reasons for unexpected phenomena, or the limitations and improvement potential of the system. For a comprehensive review of DES, see Banks et al. (2010).

2.2 Theory of Constraints

In a production system, the main constraint – also called *bottleneck* – is the weakest link that limits the performance of the whole system. The bottleneck in a production line can be identified by looking at the behavior of the system, investigating resource utilization, queues between resources or the capacity of resources. The bottleneck is often the resource with the highest utilization where large upstream queues build up and downstream resources starve. A methodology for improving systems based on bottlenecks is the Theory of Constraints (Goldratt and Cox 2012). It focuses on exploiting the constraint since improving any other part of the system would have a very limited effect. It consists of five steps and encourages continuous improvements of a production system. The steps are:

1. Identify the constraint
2. Decide how to exploit the constraint
3. Subordinate all other processes to the above decision
4. Raise the capacity of the constraint
5. If, as a result of these steps, the constraint has moved, return to step 1.

In a production system, one approach to identify the constraint is to look at the parameters of the machines. The machine with the largest cycle time is probably a constraint. However, observations of the system while it is running provide a better picture of the interactions between different resources because effects of buffers and availability become visible. To save time, it is advantageous to observe the system through a DES model where time can be sped up. By using simulation it is easy to study the effects of different alternatives to exploit the constraint through different *what-if* scenarios. DES also provides the possibility to see when and where the constraint moves in the system.

2.3 Design of Experiments

When working with DES to analyze and improve production systems, an important goal is to identify determining parameters affecting the analysis goal (Kleijnen 1998). Simulation software offers the possibility to perform experiments with input and result variables, where different parameter settings can be tested to analyze the influence of the input variable settings on the result variables. A concept for such analyses originating from mathematical statistics is *Design of Experiments (DoE)*. It offers great possibilities in many application areas, such as simulation, product design or quality management, and is described in the following paragraphs based on Bergman and Klefsjö (2010).

The purpose of DoE is to systematically find the determining input parameters – called *factors* – for a designated output variable. To reduce the number of experiments, only two settings for every tested input factor are chosen: low (-1) and high (1). The low setting is the original configuration with unchanged factors, and the high setting is a changed factor configuration. The calculation mechanism of the concept relies on analyzing the change of the output variable when a factor is changed from low to high setting.

Two basic approaches can be distinguished: One-Factor-At-a-Time (OFAT) experiments, and full factorial experiments. OFAT experiments analyze an isolated factor while keeping the other factors unchanged, choose the better option for the factor (low or high), and repeat the procedure for every factor. This approach keeps the number of experiments low (k+1 for k factors) but is avoided in DoE if possible, as it does not cover all possible settings. Furthermore, it looks at all factors separately and cannot analyze if the factors influence each other. If such dependences are suspected and all combinations are to be tested to be sure to find the best solution, a full factorial experiment can be performed. For k factors, the total number of experiments is 2^k. For notation of the experiment, a matrix is made with the factor settings and a result column. A full factorial design with 3 factors is shown in Table 1.

Table 1 - DoE with 3 factors

Experiment	Factor A	Factor B	Factor C	Result y
1	-1	-1	-1	y_1
2	-1	-1	1	y_2
3	-1	1	-1	y_3
4	-1	1	1	y_4
5	1	-1	-1	y_5
6	1	-1	1	y_6
7	1	1	-1	y_7
8	1	1	1	y_8

The effect of a factor is calculated as scalar product of its settings and results, e.g. for the effect of factor C:
$e_C = C \cdot y = -y_1 + y_2 - y_3 + y_4 - y_5 + y_6 - y_7 + y_8$.

As all combinations of factors are included, not only the isolated effects of the input factors, but also interactions between factors become visible. An interaction effect means that the effect of one factor is dependent on the setting of another, e.g. for the factors A and B: $e_{A|(B=low)} \neq e_{A|(B=high)}$. The total number of factors and interactions is 2^k-1 for *k* factors. Interaction effects are calculated similar to the single factors as the scalar product of both factors and the result column, for example the interaction effect AB:
$e_{AB} = A \cdot B \cdot y = y_1 + y_2 - y_3 - y_4 - y_5 - y_6 + y_7 + y_8$.

More insight in DoE and the performed calculations is given by Bergman and Klefsjö (2010) and Kleijnen (1998).

2.4 Life Cycle Assessment

For setting the context of this thesis, an explanation of the concept of Life Cycle Assessment (LCA) is necessary. To start with, the International Organization for Impact Assessment (IAIA) defines impact assessment as "the process of identifying, predicting, evaluating and mitigating the biophysical, social, and other relevant effects of development proposals prior to major decisions being taken and commitments made" (IAIA 2009). A specific methodology – LCA – has been defined by ISO 14040 (1997) as "a technique for assessing the environmental aspects and potential impacts associated with a product." It consists of four phases: Goal and scope definition, life cycle inventory analysis (LCI), life cycle impact assessment (LCIA) and interpretation and communication of the results. The phases are described in the following paragraphs, based on Baumann and Tillman (2004).

2.4.1 Goal and scope definition

At the start, the context of the study is set, as the proceeding and results are dependent on the purpose and goals of the study. Meaningful results require a connection to specific goals, e.g. benchmarking different products or processes. An important step is to define which parts of a product life cycle are to be included. An analysis of the whole product life cycle is called *cradle-to-grave* analysis. Other concepts exist that only include parts of the life cycle; one example is a *cradle-to-gate* analysis that focuses on all activities from raw material extraction to the end of a specific production process (when the product leaves the factory's *gate*.) It is further important to decide what kinds of environmental impact should be analyzed. These are further described in section 2.4.3.

2.4.2 Life Cycle Inventory analysis

A product affects the environment in different ways through materials and energy used in production and transport processes. An inventory analysis maps all material and energy flows that include substances that are harmful to the environment or use scarce resources. The result is a LCI dataset containing all important substances – called *contributors* – and their amount caused by the product during the phases of the life cycle defined in the scope.

2.4.3 Life Cycle Impact Assessment

For the substances included in the LCI, a number of different environmental impacts can be analyzed, such as the depletion of resources, effects on humans and effects on the environment. For more in-depth knowledge about harmful substances and their effect mechanisms on humans and the environments, see Harrison (2001).

During the impact assessment, the inventories are assigned to different impact categories. These impact categories describe potential effects, i.e. effects in a worst-case scenario, not accounting for local differences that could weaken effects. For the classification, a number of methods exists, using either a mid-point or end-point approach. Mid-point methods assess direct (primary) effects, whereas end-point methods also account for secondary or higher-level effects, for example the effect of polluted water on human health and following generations. This thesis uses a mid-point approach.

Some substances are only assigned to one impact category, other affect the environment in several different ways and therefore need to be assigned to multiple categories. Within their impact category, some substances have a stronger effect than others. To lift all substances on a comparable level, characterization is used. This means that one substance per category is chosen as reference, and relative factors are set for the other substances. Those factorized substances are denoted *equivalents* of the reference substance. The next paragraph describes the impact categories relevant for this thesis with their mechanisms.

This thesis uses three impact categories that are rather easy to understand and therefore common in environmental impact assessments: Global Warming Potential (GWP), Acidification Potential (AP) and Eutrophication Potential (EP).

2.4.3.1 *Global Warming Potential*

Some so-called greenhouse gases cause climate change in terms of global warming by absorbing infrared radiation, leading to an increase of temperature in the atmosphere. Examples for greenhouse gases are carbon dioxide (CO_2), methane (CH_4), chlorofluorocarbons (CFC) or nitrous oxides (NO_x). To express the potential contribution to global warming, CO_2 is used as a reference and the other gases are expressed as CO_2-equivalents (CO_2-eq). This means that if the effect of a gas is x times higher than the effect of CO_2, this gas corresponds to x CO_2-equivalents. By summing up the equivalents for all gases, Global Warming Potential is obtained.

2.4.3.2 Acidification

Various substances, such as sulfur dioxide (SO_2), NO_x, hydrogen chloride (HCl) or ammonia (NH_3), release H^+-ions when they are dissolved in water or moist surfaces. This process is called acidification. Acidified water can for example lead to fish mortality or damage forests and buildings. Acidification happens both through direct emissions to water, and through emissions into air that eventually fall down as acid rain or particles that dissolve in water or surfaces on contact. The acidification potential is expressed in SO_2-equivalents.

2.4.3.3 Eutrophication

Eutrophication, sometimes also called *nitrification*, is the environmental impact of "excessively high levels of nutrients that lead to shifts in species composition and increased biological productivity" (Baumann and Tillman 2004). The mechanism is based on nitrogen and phosphorus that lead to the growth of biomass, such as algae. When biomass is decomposed by micro-organisms, oxygen is consumed. The eutrophication process can be described as a cause-and-effect chain: Release of nutrients → biomass formation → biomass decomposition → oxygen depletion. Nitrogen and phosphorus are released into water either directly, e.g. through agricultural fertilizers, or indirectly, e.g. by emission of NO_x to the atmosphere. In the concept of eutrophication potential it is assumed that all those emissions eventually end up in an aquatic ecosystem. The potential is expressed in phosphate (PO_4^{3-}) or NO_x equivalents.

2.4.4 Interpretation and presentation of results

The results can be presented in many different ways and should be adapted to the target group. Several levels of aggregation are available: It is possible to show the detailed contributors from the inventory analysis, to express the result in impact categories, or even to use weighing between these categories to calculate one impact factor. Dependent on the intention, choices can also be made between presenting absolute numbers and comparing different categories to each other with relative numbers.

Baumann and Tillman (2004) present three common methods of result presentation, which are summarized below.

- *Contribution analysis:*
  A contribution analysis gives a detailed overview over all contributing substances and weighs their share in the total impact. Thus, the most harmful contributions can be identified and used as a focus to reduce environmental impact. This method is intended for receivers with advanced chemical knowledge, because its interpretation requires understanding of the contributors and its effects.

- *Dominance analysis:*
  Similar to the contribution analysis, the dominance analysis identifies the most important impacts, but with a focus on phases of the product life cycle. It uses impact categories and compares the contribution of the life cycle phases to these categories. This approach can be used to identify particular harmful processes.

- *Decision maker analysis:*
  The decision maker analysis is a solution-orientated approach and analyzes who has an influence on the different contributions by decisions that can be made. Thus it is possible to assign responsibilities for action. Furthermore it can be narrowed for specific decision makers which areas they should focus on and which areas they cannot change. An example for manufacturing decision makers is given by Löfgren, Tillmann and Rinde (2011).

3 METHODOLOGY

This thesis project was set up as a simulation project to model and analyze the production system. The applied methodology is based on experiences from previous studies in the EcoProIT project gathered by Andersson, Skoogh and Johansson (2012) and Andersson et al. (2012b). It is visualized in Figure 2 and described in this chapter. Further elaboration on the first phases (*set up project* to *data collection*) is given by Dettmann et al. (2013).

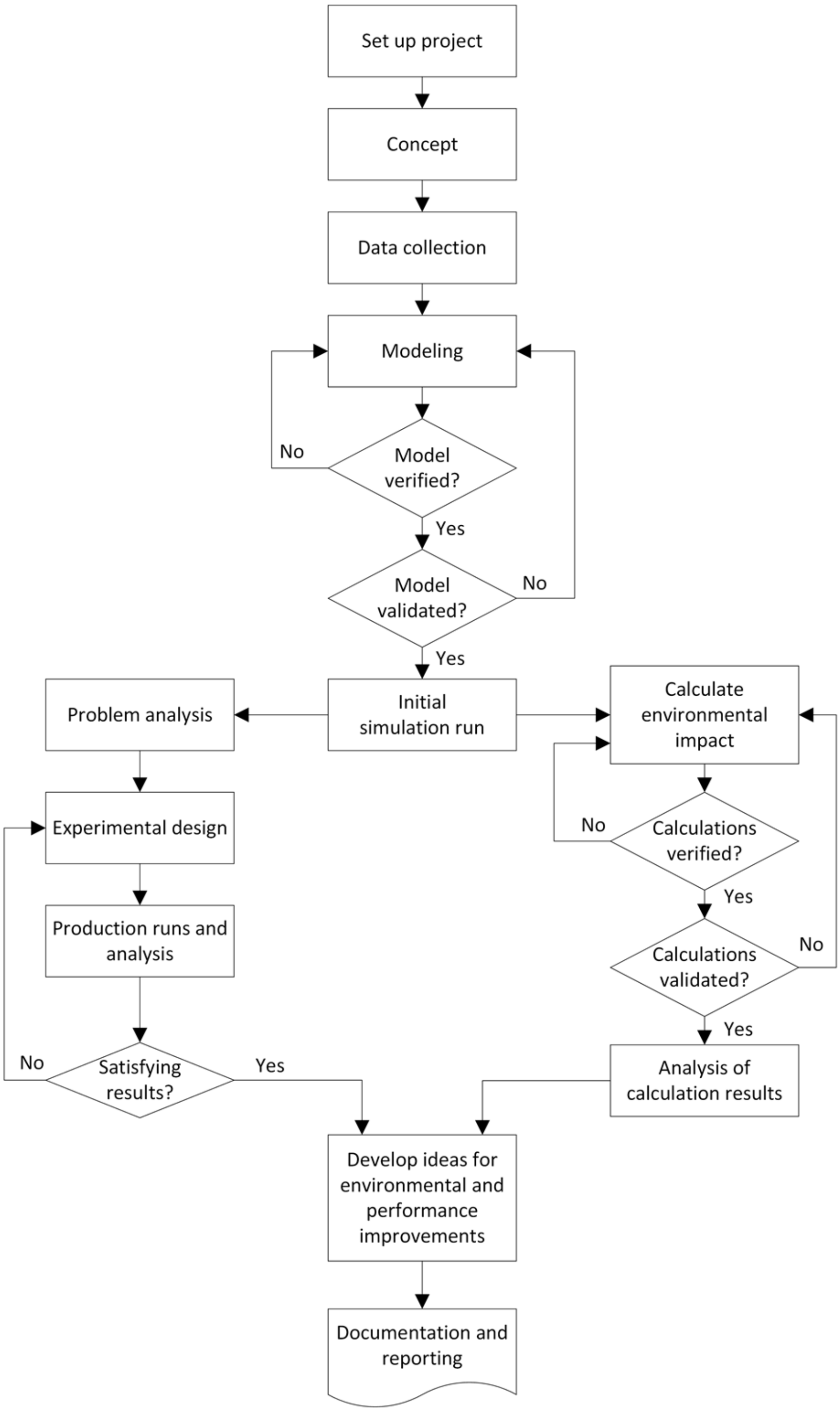


Figure 2 – Used methodology

3.1 Concept

Before collecting data, basic understanding of the process is important in order to decide what data is needed and on what level of detail (Dettmann et al. 2013). To gather this kind of understanding, time was spent at the production line observing the system and interviewing operators and other employees familiar with the production line. This generated qualitative data about process logic, material flow, machine operations and consumables that would be important to account for in the environmental analysis.

Based on experiences from Andersson et al. (2012b) and own observations, it was assumed that electricity would be a main contributor to the environmental impact. It became clear that the machine operations could be divided into several states that would require individual amounts of power. Solding, Thollander and Moore (2009) suggest using the states *working, idling* and *off* but also point out that additional states could be necessary in some cases. In the brake disc line, most machine cycles consisted of one sub-cycle where a part was loaded in the machine and one sub-cycle where the part was processed, presumably resulting in different power levels. Thus, simply using a *working* state would not be detailed enough and it was decided to divide the cycle times into a *loading state* and a *processing state* corresponding to two different levels of power.

All gathered information was compiled into a conceptual model showing the in- and outflow of both material and consumables for each operation. All machine operations are performed without lubricants or coolants. The only outflows from the turning operations – except for the actual product – are metal chips and dust (carbon particles from cast iron). The conceptual model is shown in Figure 3.

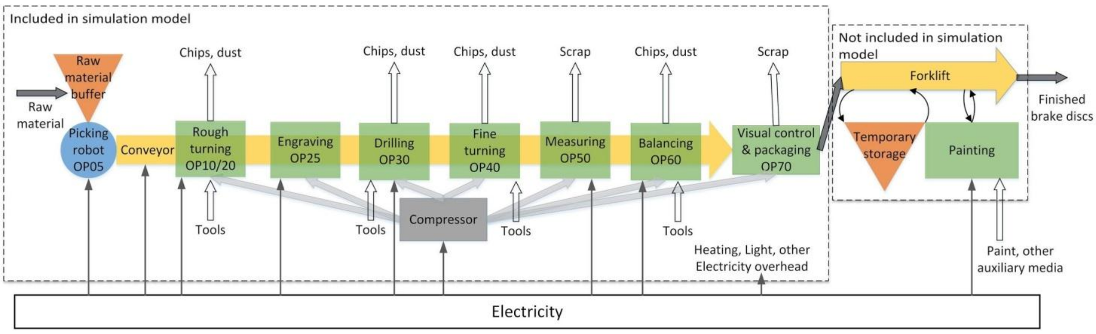


Figure 3 - Conceptual model

Through further observations and comparisons of the real production line the conceptual model was eventually verified after minor corrections. It was validated through *face validation*, i.e. showing the model to people with knowledge about the system and letting them decide whether the information was correct (Sargent 2011). Using this validation technique a production engineer and a process expert gave additional background information about flow logic and consumables in the production system that had not been identified by own observations. This resulted in a list of required data, shown in Table 2.

Table 2 - Needed data for environmental footprint and performance analysis

Category	**Needed data**
Automatic machining processes (OP10 - OP60)	Cycle time per variant Availability MTTR Power level per state (processing, loading, idle) Tool changing frequency and duration of a tool change
Robots	Cycle time per variant Availability MTTR Power level per state (working, idle)
Manual Process	Cycle time Allowances (availability)
Conveyor	Speed Length Availability MTTR Power level while running
Painting	Type and amount of paint per brake disc Energy consumption per brake disc
Whole line	Overhead energy from factory Energy for pressurized air Amount of chips and dust per brake disc Scrap rate
Product	Dimensions Weight
Transports	Distance to supplier Means of transport

A pre-collection of data was made to identify available data and to check if the quality of those data was sufficient. Quality requirements were especially put on cycle times, where information about sub-cycles and variation was needed. The company had measured cycle times for each machine, but only represented as whole cycles, not divided into different machine states. In addition, the times were calculated as average values without information about variation. Therefore it was decided that variation and times for the different states had to be analyzed through own time measurements.

3.2 Data collection

Data were gathered from databases and through own measurements, which were done for cycle times, weight of the product and energy consumption of the machines.

3.2.1 Cycle times

After start and end for each state of the machines and robots had been defined, the state duration was measured with hand-held stopwatches. Initially ten samples per operation and variant were taken to check for variation. Standard deviation and range were calculated from the samples. To assess the real variation of the machine times, reaction time when using stopwatches had to be taken into account. The human reaction time to basic visual impulses is commonly assumed to be around 0.2 seconds (Seow 2008). However, the more information that needs to be processed in the brain, the longer is also the actual reaction time (Hyman 1953). When measuring machine times, it was not always unambiguous when a process started and when it ended. The experience showed that the buttons on the stopwatch were not always pressed precisely, and not only with a time delay, but sometimes also too early. Therefore, a reaction time in both ways could be expected, slightly larger than 0.2 seconds. It was decided to assume a reaction time of ±0.25 seconds, resulting in an uncertainty interval of 0.5 seconds.

This information was used to make assumptions on variation of cycle times: If the measured variation had a range of less than 0.5 seconds, this was attributed only to measurement errors due to reaction time, and the time was assumed to be constant. For operations with a larger range than 0.5 seconds variation was assumed and additional samples were taken, at least 50 samples per operation and variant.

3.2.2 Extraction of distributions

A statistical software was used to extract suitable distributions for representation in the simulation model, sometimes resulting in several possible alternatives. By comparing these results with histograms of the data, distribution models were chosen for each process and verified through own judgment. It could be seen that for each variant there was a different mean value in every operation, but the variation followed the same pattern for all variants. Table 3 shows an overview of the number of samples per operation and if variation was identified or not. The resulting cycle times and distributions for all operations are shown in Appendix B.

Table 3 - Number of samples taken per machine

Operation	Samples per variant	Total number of samples	Variation?
OP05 - Picking robot	70	140*	Yes
OP10 - Rough turning side 1	50	400	Yes
OP20 - Rough turning side 2	20	160	No
OP25 - Engraving	15	20**	No
Robots between OP10 and OP20	10	80	No
OP30 - Drilling	10	80	No
OP40 - Fine turning	10	80	No
OP50 - Measuring	10	80	No
OP60 - Balancing	70	560	Yes

*There are two types of pallets: one where the brake discs are packed following a pattern and the other with a chaotic packing system

**This operation, and its cycle time, is identical for all variants, which was confirmed through 5 additional samples on a second variant.

Cycle times of OP05 - Picking robot

The picking robot needs a separate description, as the mathematical model of its cycle times is substantially different from the other machines. When a pallet of brake disc blanks is placed in the robot cell, the picking robot picks up the blanks with an electro magnet and places them on a conveyor. For each cycle the robot searches the pallet until it finds a brake disc. This search procedure takes a different amount of time for each part, depending on the used packaging type for the pallet. For pallets packed without a pattern, it is also possible that the robot fails to find a part and repeats the search sequence again until it succeeds. While measuring the time for a cycle, it was recorded if the robot had to search once or twice. Consequently, a model of two combined distributions was applied to OP05: on a first level a chance to have one or two attempts, and on the second level a time distribution for the search operation, dependent on the first level result.

3.2.3 Availability and MTTR

In the simulation model information about failures is given as a percentage of uptime (availability) and a mean value for duration of failures per machine (MTTR). Distributions for mean time to failure (MTTF) and MTTR are then automatically calculated for each machine by the software, expressed as exponential distributions for MTTF and Erlang distributions for MTTR.

The factory has a reporting system where operators record breakdowns. By filtering and processing the data from this system, MTTR was calculated through numbers and durations of breakdowns, and availability through total downtime and available time.

3.2.4 Scrap rate

The number of accepted and scrapped parts per variant is recorded in a database. This information could be used to calculate scrap rates as a percentage per variant, which was used in the simulation model.

3.2.5 Energy consumption

To be able to calculate energy consumption, the actual power of the machines was measured with the three-phase power meter *PowerVisa* from manufacturer Dranetz. For every measured machine, the device was connected to the control cabinet, monitoring voltage and current on all three phases. Samples were taken every half second and saved as averages of two values every second, which is the minimal available interval for this device (Dranetz-BMI 2005).

Skoogh, Johansson and Hanson (2011) conclude that the standard deviation of the power levels of machine states is often low enough to be neglected. Thus only as many measurements as needed to calculate a mean value should be taken. In this thesis project the power levels of the machines were monitored during about one hour per machine. As a cycle usually was not longer than 40 seconds, the monitoring time was considered sufficient to get acceptable mean values. To be able to assign the power levels to machine states, the states were recorded in parallel through observations. This was done by synchronizing the observer's clock with the power meter clock and logging state changes with their timestamps. Thus, state changes could be marked in the recorded power data. As the measuring of cycle times had shown that the variation between cycles was very low, it was considered sufficient to record state information for 20 cycles.

For some operations, adaptations to this method were necessary, which are explained below. The power levels for all machines are shown in Appendix C.

3.2.5.1 Rough turning process:

The rough turning process consists of two operations in the same machine (OP10 and OP20), thus making it impossible to measure both operations separately. Whereas the power measurements were an aggregation of both operations, their states still could be recorded separately. The idea was that if the state changes were recorded synchronously, a graphical representation of power data might show those changes by clear shifts in power level. Then it would be possible to calculate average power levels for both operations, based on the number of operations being processing or idle at every point of time.

However, the measured results revealed that both operations could not be represented in the same way. A sample from the measurements is shown in Figure 4. In the same figure the observed states of the two operations are plotted. A high level in the graph means that the corresponding operation was working, and the low level means that the operation was idle. The operations followed a repetitive pattern, causing only certain parts of the cycles to be visible in the data, whereas the remaining parts were overlapping. The separately visible parts were the beginning of OP10 and the ending of OP20. These parts of the cycle had a significant difference in power level due to high energy consumption during startup of the cycle and a low or even negative consumption during the braking phase of the spindle. Consequently, no conclusions for the total average of one cycle could be drawn. Instead both operations were assumed to require the same amount of energy for one cycle.

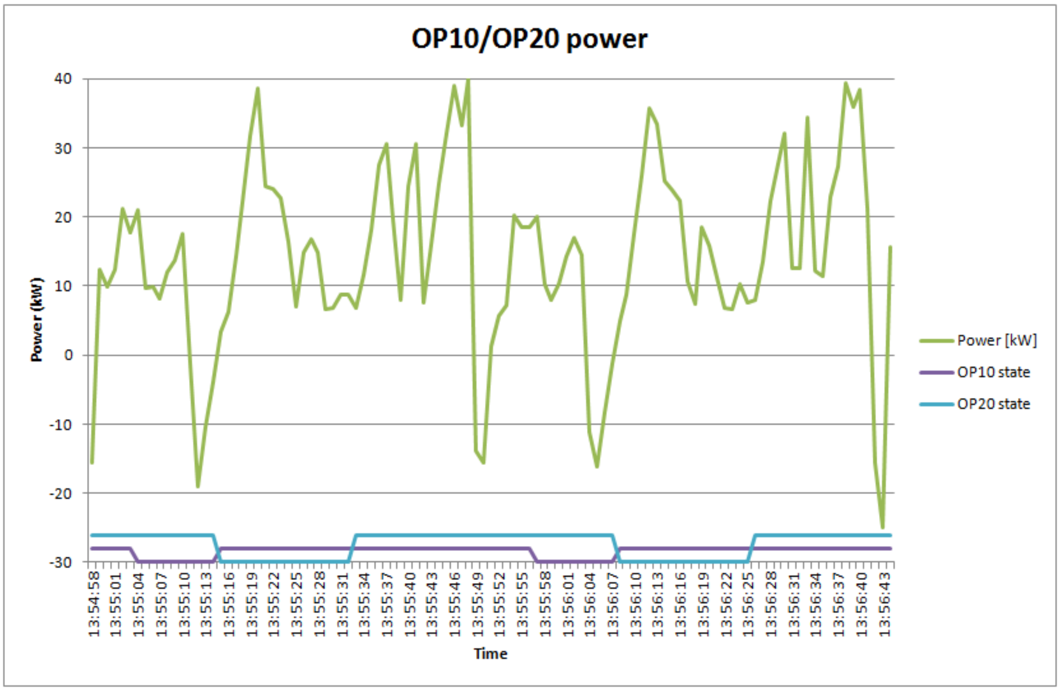


Figure 4 - Power for OP10 and OP20

To calculate average power for a cycle of one operation, all negative power values were replaced with zeros, as the machines were not able to feed energy back into the grid (this also applies to calculations for other operations). After this data processing, the calculations were done using the following formula:

$P_{average} = \frac{\sum_{i=1}^{N} P_i}{n_{10}+n_{20}+2*n_{1020}}$, where:

P_i	Power sample i
N	number of samples
n_x	No. samples for OPx working, with 10 = OP10, 20 = OP20, 1020 = both.

Note that n_{1020} contains a factor 2, as the power in this state includes both operations and therefore needs to be divided by 2 to get the power for one operation.

3.2.5.2 Robots and measuring machine

The control cabinets for the robots and the measuring machine (OP50) were too small to connect the large current probes of the power meter. Hence, the equipment could not be used for those processes. To make an approximation for power level, a current meter could be used for manual current measurement on one phase at a time. Average values for the three phases were then summed up and multiplied with the nominal voltage to calculate power.

3.2.5.3 Conveyor and elevators

Most conveyor segments had no separate power supply, but were connected to the power supply of the closest machine. Therefore a major part of the conveyor consumption is already covered through consumption in the machines. However, one section of the conveyor was connected to a separate control cabinet, including an elevator after OP05, an elevator before OP30 and all segments between them. The measurements here were performed in the same way as for OP50. As the conveyor was continuously running, a constant consumption could be assumed. However, the current varied due to the connected elevators. The measured values showed a minimum power of 2.5 kW and a maximum power of about 3.5 kW. It was assumed that the maximum power was drawn from the grid when both elevators were moving at the same time. Therefore, the minimum power was assigned to the conveyor, and the remaining power was distributed equally to the elevators, resulting in 0.5 kW per elevator.

3.2.5.4 Engraving machine

As the control cabinets for the engraving machines (OP25) were located within a robot cell above the production line, they were not accessible for measurements without disturbing production. The operations in the machine were not visible and could only be analyzed by ear. Consequently, the machine's power level had to be estimated. The following assumptions have been made for the estimation:

- Idle consumption is similar to OP50, as both machines are similar in size and shape. $P_{idle}(OP25) = P_{idle}(OP50)$
- Power needed for processing is similar to OP60 (balancing), as in both cases the brake disc is rotating at low speed and a milling operation with a small tool is performed. $P_{processing}(OP25) = P_{idle}(OP25) + [P_{processing}(OP60) - P_{idle}(OP60)]$

- The power level for loading is in between idle and processing level and is estimated to 50% of processing power (relative to idle).
- $P_{loading}(OP25) = P_{idle}(OP25) + 0.5 * [P_{processing}(OP25) - P_{idle}(OP25)]$

As the assumptions are only rough, it would appear unnecessarily detailed to use all three states. It was therefore decided to aggregate power for processing and loading into a power level for the whole cycle. While measuring times, it was audible that processing accounts for about 40% of the whole cycle, and consequently the cycle power level can be calculated as:

$P_{cycle} = 0.4 * P_{processing} + 0.6 * P_{loading}$

3.2.6 Data for other consumables

Data were also collected for other consumables than energy consumption. These are in particular paint, material, chips, dust, tools and transports.

3.2.6.1 Painting process

The amount of paint used per brake disc had already been calculated at the company to keep track of the consumption and when to order new paint. Detailed information about the painting and the contained chemicals were available in an internal chemicals database. There was also information available about the most energy consuming operation during the painting process, namely two induction heaters using 50 kW each. For each brake disc variant there was information about how many percent of the maximum power was used for each heater and also the duration of the heating.

The datasheet of the paint only accounted for the components it deemed environmentally hazardous, i.e. zinc oxide, ammonia solution and zinc phosphate. Consequently, only those have been used in the analysis. The share of each component was multiplied with the amount of paint used per brake disc to get the mass of each component.

3.2.6.2 Raw material, chips and dust

Information about the type of raw material was taken from drawings of the product. The mass of the finished product was measured by a portable scale. In the same way a brake disc was weighed after each machining operation to calculate the amount of chips per process step. To see how much of the weight reduction was non-recyclable dust, the content of the containers where all dust from the line is gathered was weighed. The containers had been filled during one week of production and the weight was divided by the number of brake discs produced during the same week. The result showed that the amount of dust per brake disc was approximately 5 grams, which is such a small amount that it was seen as negligible.

3.2.6.3 Tools

During production the tools wear differently depending on variant and machine. All machines have a counter for the number of processed brake disc. When reaching a given value, the machine stops and a lamp signals the operator to change the tool. Information about how frequent tool changes occur was gained by asking the operator.

3.2.6.4 Transports

Information about transports – i.e. location of suppliers, type of transport and weight of the goods – was available at the logistics department. The raw material is transported from three suppliers on different locations, two in Germany and one closer to the factory in Sweden. From the supplier in Sweden, the material is always transported by road. For the variants transported from Germany the freight company can choose the most suitable option out of rail or boat. However, when the goods reach Sweden, they are transported by road the last route. For the analysis in this thesis it is assumed that the choice of transport is equally distributed for those variants. An automatic route planning application (Google 2013) was used to estimate the distance covered by truck. Distances covered by train and boat were measured manually using (Geodistance 2013), making rough estimations about the chosen route. Using this information the amount of tonne kilometers per transport was calculated by multiplying distance and weight of the transported goods. Tonne kilometers is the functional unit used for calculation of environmental impact of transports. Appendix D shows the distances traveled per variant from the suppliers. Chips from all variants are sent back to the supplier in Sweden and those transports have also been accounted for in the analysis.

3.2.6.5 Other

Other consumables, such as oils and lubricants for the machine engines were after discussions with process experts considered to be negligible.

3.3 Modeling

A simulation model was built using the DES software *Plant Simulation* from developer Siemens. All aspects regarding performance analysis were included in the simulation model, as well as energy consumption by the machines. All operations, robots and conveyor segments were included as separate objects. Conveyors and brake discs were represented with real dimensions to simulate the capacity on every segment. Parts moving through the production are called *mobile units (MUs)* in the software and will also be referred to under this name in the report. Eight types of MUs, representing the different variants, were defined in the model. Cycle times and availability data were implemented in the machine parameters. Since except for OP60 loading times were constant, it was decided to simulate full cycle times in the model and include loading times only as variables, which were used for calculations after simulation. The main reason for this decision was the lack of an option to divide the working state in the resource statistics into loading and processing.

Furthermore, power states and loading times were included as attributes on the machines to calculate energy consumptions for every passing MU. To be able to simulate the production of a whole year, historical production data of 2012 was used as a production schedule in the model, representing a variant mix. Various data are collected during simulation to be used for calculations and verification, summarized in Table 4.

.

Table 4 - Data collected during simulation

Category	Data
MU statistics	Variant name Aggregated energy consumption for every produced MU
Machine statistics	Throughput per machine Time portion spent in states
Output statistics	Output (no. of MUs) and scrap per variant Total simulated time Aggregated energy consumption for scrapped parts
Productivity	Throughput per hour (hourly record to show the production rate dynamics)

In comparison to the reality, some adaptations and omissions had to be made in the model, mainly due to lack of applicable data or technical deficiencies in the simulation software. Table 5 shows those changes and their motivation.

Table 5 - Changes to reality in the model

Category	Description	Motivation
Operator	In reality, the operator is needed for many different tasks, whereas his only task in the model is to do tool changes.	Many small tasks, e.g. disassembly of empty pallets, cleaning and preventive maintenance are impossible to describe in a quantitative manner, and also irrelevant for the flow.
Part handling in machines	The real machines are always filled with a part, which is not released until a new part arrives. This is not modeled.	This fact only has an impact on the work in progress, which is not considered in the production system analysis of this case. Furthermore, an implementation in program code would be unnecessarily complicated.
Setup	No setups are done in the model, only tool changes.	The whole line is stopped for set-up of the machines, no events are happening. Furthermore, no variation is used in the available data for set-up times. Therefore a simulation of set-up is not needed. Instead only variant changes are logged and exported to be used for external set-up calculation after simulation.
Shifts	In the real environment, operators work in shifts and take breaks. Both are excluded in the model.	As only one task in the model uses an operator and does not require much time, it would not seem reasonable to use a shift calendar for this operator.

3.4 Model verification and validation

Verification of the model was done both continuously during the modeling phase and after modeling. The continuous verification focused on programmed methods and the setting of parameters. Three verification techniques were used: visualization, model instrumentation and debugging (Balci 1994). Verification through visualization was done by observing the flow during simulation and looking for unexpected behavior, especially stops of the flow. If a stop at a certain time was detected, model instrumentation was used to trace the problem by adding code to log information about important parameters and pause simulation before a stop occurs (i.e. setting breakpoints). The behavior was then again observed at low speed. After the identification of problems, debugging was used to revise the model code. The continuous verification process is shown in Figure 5.

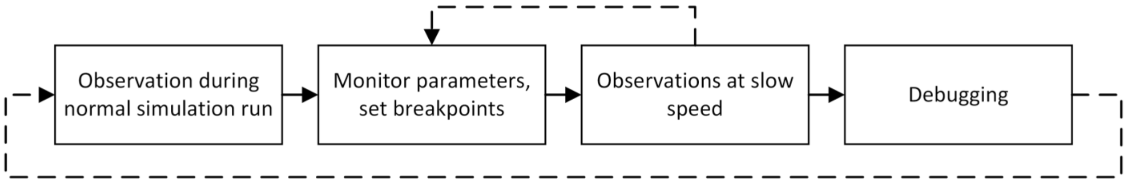


Figure 5 - Verification process

When the model had been built and basically verified by this process, further verification was done by blackbox testing (Balci 1994). The model was run with different variant mixes or single variants as input and the behavior and output were monitored.

After successful model verification, the throughput of the model was validated using an extreme conditions test (Sargent 2011). All breakdowns and tool changes were removed and one variant was simulated at a time. The resulting production rate (i.e. throughput per hour) was then compared to theoretical throughput calculated by the cycle time in the bottleneck.

Further validation was done by comparing the production rate to real values of 2012. As setup is not included in the model, reported setup times of 2012 were added to the simulation time to calculate the actual production rate. The first step was a comparison to the target production rate set by the production planning department. The production of a whole year was simulated with the documented product mix of 2012. Five replications led to a production rate of 108 parts per hour (see Table 6), which corresponds exactly to the company's target of 108 parts per hour. However, the actual production system does not reach the target and had an average production rate of 90 parts per hour in 2012. As the model was based on real reported production data, it should be expected to be close to this value, and not the target value. Consequently, the second validation step was to find the causes for deviation. First indications were gained by conclusions drawn from own observations. These were discussed with production engineers and operators who contributed with their perspectives and experience. During these discussions it became clear that the main reasons were deficiencies in reporting and non-measurable soft factors, which will be elaborated on in chapter 5.1. As no quantitative data was available for those factors, they could not be accounted for in the simulation model. Therefore it was concluded that the model could not get any closer to the reality and a validation via target production rate was considered sufficient.

Table 6 - Simulation output for validation

Run #	Simulation output [parts / h]
1	107.9
2	108.1
3	108.1
4	107.9
5	108.1

3.5 Environmental impact calculations

For all consumables, LCI data were taken from the EcoInvent database (Swiss Center for Life Cycle Inventories 2013) by using the software OpenLCA (Green Delta GmbH 2012). The environmental impact was calculated from LCI data directly in the software. Calculation results are presented in the three categories GWP, AP and EP. Although the consumables – especially paint – are likely to also have toxic impacts in terms of ecotoxicity and human toxicity, these are not accounted for in this report. This decision was made because conceptions of these impact categories are diverse and not transparent and their calculation methods differ substantially (Pizzol et al. 2011). Dreyer, Niemann and Hauschild (2003) concluded that the choice of calculation method is of minor importance and leads to similar results. In this case, the environmental impact is calculated based on the LCI data with the mid-point method CML2001 (CML 2013, Guinee 2004).

3.5.1 LCI data

LCI data was in particular collected for transports, materials and energy consumption. For the short road transports from Skövde, LCI data for a truck carrying at least 32 tonnes have been chosen, and for the longer distances with less goods, data for a truck carrying between 16 and 32 tonnes was chosen. The trucks are assumed to meet the European emission standard EURO5. For the transports by rail, LCI data for rail transport in Germany was chosen, and for the boat transport LCI data for barge transport. Common for all LCIs is that the inventory refers to the entire transport life cycle, including vehicle, road and port maintenance.

For the material, LCI data for cast iron with 35% scrap and 65% pig iron as input material were chosen as this dataset was closest to the actual material. The data includes extraction of material, transportation to the foundry and all processes needed for casting the material blanks.

The chosen LCI data for the environmentally dangerous components of the paint (zinc oxide and ammonia) both include the production of the product and transportations before production. The transport from the supplier has been neglected since the amount of tonne kilometers per brake disc is too small to make a significant difference in the analysis. No LCI data was available for zinc phosphate which is why it has been left out in this analysis. The concentration of the ammonia solution was assumed to be 25%.

The LCI data chosen for energy consumption represents a mixed production of electricity in Sweden and distribution of high voltage electricity. The production mix is based on annual averages from 2004.

Regarding tools, no relevant LCI data could be found for the specific material. It is therefore excluded from the environmental footprint analysis.

3.5.2 Calculation of energy consumption

The recorded data during simulation is exported and processed in Microsoft Excel to perform environmental calculations. The calculation of energy consumption is done both per variant (product) and per operation (machine). Whereas on machine level only time and throughput statistics are exported and the consumptions are calculated afterwards, the consumption per operation on product level – i.e. direct consumption – is already calculated in the simulation software to reduce the amount of exported data and thus also file size. Consumption on machine level and energy allocation are calculated in Excel with the purpose of a better presentation and credibility of the calculations and results. Table 7 shows which data inputs are used for the calculations, divided into data gathered during simulation and static data inputs on the calculation sheet.

Table 7 - Input data for the calculations

	Consumption per variant	**Consumption per operation**
Functional Unit	Product	Machine
Scope	Direct consumption + allocation	Direct consumption only
Simulation Data	Aggregated consumption in the machines (each MU) Variant type for every consumption record Aggregated consumption for scrapped parts (total) Idle time for all machines Total output (no. of parts)	Time in states processing, loading and idle (in %) Total simulation time Throughput per machine
Static Data	Allocation of overhead, painting, compressed air	Power level per state and machine Loading time per machine (calculated via throughput)

3.5.2.1 Calculation per variant

Energy consumption for one product consists of three parts: direct consumption, allocation from process and other allocation. Direct consumption is obtained as an average per variant of all recorded MUs. Allocation from the process is all consumption in the machines that cannot directly be assigned to a finished part, i.e. idle consumption and consumption for processing scrapped parts. This consumption is summed up and equally distributed to all finished parts to calculate an allocation per part. Other allocation covers energy consumption from painting, compressed air and factory overhead and is described separately in the next paragraph. For *VariantX*, the resulting formula is:

$$\mathrm{E(VariantX)} = \mathrm{E_{direct}(VariantX)} + \mathrm{E_{allocation,process}} + \mathrm{E_{allocation,other}}$$

$$= \frac{\sum_{i=1}^{N} \mathrm{E_{direct,i}(VariantX)}}{\mathrm{N(VariantX)}} + \frac{1}{\mathrm{TP}} * \left[\sum \mathrm{E_{idle}} + \sum \mathrm{E_{direct}(scrap)}\right] + \mathrm{E_{allocation,other}}, \text{ with:}$$

$\mathrm{E(VariantX)}$	Average consumption for one part of VariantX
$\mathrm{E_{direct,i}}$	Consumption for part i of VariantX
$\mathrm{N(VariantX)}$	Number of produced parts of Variant X
TP	Throughput of the line, i.e. total number of produced parts
$\sum \mathrm{E_{idle}}$	Summed idle consumption for all machines
$\sum \mathrm{E_{direct}(scrap)}$	Aggregated consumption for all scrapped parts
$\mathrm{E_{allocation,other}}$	Various energy allocation, see next paragraph

3.5.2.2 Allocation

Allocation is needed for energy where information is only available on a factory level, i.e. overhead energy consumption and consumption of the compressed air system. Furthermore, the painting process requires energy which needs to be calculated per product. The results of the allocation are shown in Appendix E and are obtained via the following methods:

- Overhead and compressed air:
  For economic reasons the company has allocated the annual energy consumption to the different functions of the company. Using those numbers, the total consumption for compressed air, lights, ventilation and other overhead consumptions was calculated. By using a plan of the factory layout the relation between all areas used for production and the area used for the studied line was calculated. Through this relation the overhead consumption was allocated to the production line and divided by the number of brake discs produced in the line during one year.
- Painting:
  A major part of energy in the painting process is consumed by the two inductors. Therefore only the energy for this heating is taken into consideration, the painting itself is neglected. For the inductors, maximum power, actual power level and working time is known per variant. Both inductors have a maximum power of 50kW and operate 6 seconds per part. The actual power level (in %) of the inductors varies from variant to variant. Those values are used to calculate the required energy for one brake disc.

3.5.2.3 Calculation per machine / operation

The calculation of energy consumption per machine is mainly based on the time spent in the respective state processing, loading or idle. The exported raw data from the simulation model gives information about the percentage of time spent in the states *Working, Setting-Up, Waiting, Blocked, Failed* and *Paused*. *Working* includes both loading and processing, whereas all other states together represent the state *idle*. The total time in each state is obtained via the percentage (p) and total simulation time. *Loading* is calculated through static loading times and throughputs (TP) of the machine, and then drawn from *Working* to obtain *Processing*. The used formulas for the states are:

$T_{loading}(OPx) = TP(OPx) * t_{loading}(OPx)$

$T_{processing}(OPx) = p_{working}(OPx) * SimTime - T_{loading}(OPx)$

$T_{idle}(OPx) = p_{idle}(OPx) * SimTime = [1 - p_{working}(OPx)] * SimTime$, with:

$T_{state}(OPx)$	Total time spent in s*tate* by machine *OPx*
$TP(OPx)$	Throughput in *OPx*
$t_{loading}(OPx)$	Loading time for one part in *OPx*
$p_{state}(OPx)$	Share of time spent in *State* by *OPx*
SimTime	Total simulation time.

After calculating the times, the total energy consumption (E) per machine can be obtained via the power for each state:

$$E(OPx) = T_{loading}(OPx) * P_{loading}(OPx) + T_{processing}(OPx) * P_{processing}(OPx) + T_{idle}(OPx) * P_{idle}(OPx).$$

Note that the power of a machine state $P_{State}(OPx)$ is not to be confused with the percentage of time $p_{State}(OPx)$ spent in that state.

3.5.3 Verification and validation of calculations

Verification and validation was done for the calculations of energy consumption. As the relation between environmental impact and consumables is linear, it was enough to verify and validate on consumables level (Andersson, Skoogh and Johansson 2012)

The calculations of energy consumptions were verified in two ways. First, a theoretical energy consumption per brake disc was calculated based on static cycle times for the machines, disregarding variation. The result was compared to the calculation per brake disc in the calculation sheet. The second verification step was to compare consumption on machine level with consumption on product level. For this purpose, the aggregated machine energy consumptions in the calculation sheet were summed up, divided by the total throughput and compared with the calculated consumption per product. The result of the verification was a deviation of 0.4% with the first method and 0.5% with the second method (see Appendix F), confirming the integrity of the calculations.

To validate the calculations, the total annual energy consumption of the brake disc line was calculated in two ways. First, the annual consumption of the whole factory was proportionately allocated to the brake disc based on the area use of the brake disc line. Then, the consumption was calculated by multiplying the consumption per product from the calculation sheet with the total production volume. Comparing both values showed a deviation of 2.6% (see Appendix F), which was sufficiently low to validate the calculations, bearing in mind that the allocation via area is only a very rough approximation of the brake disc line's energy consumption.

3.6 Analysis of calculations results

The environmental impact is presented in several ways. First, the total impact per product variant is shown, comparing the different variants. In a next step, several dominance analyses are made where the relative impact of all contributors is presented. The first shows all contributors; the next ones are made based on a decision maker analysis, first from a manufacturing perspective, second a logistics perspective and third from a combined perspective. The dominance analyses based on the decision maker analysis disregard production of raw material remaining in the product, following the example of Löfgren and Tillman (2011). Finally, the contributor *energy* is looked into on a more detailed level and the hot spots in energy consumption are revealed.

3.7 Performance analysis

The performance analysis of the production system is mainly done through simulation, but also by interviews with production engineers and operators to cover labor factors, which can have a significant impact on the production system's productivity and efficiency (Zandin 2001).

The first part of the analysis looks at the results gained from interviews and observations in the real system. Then the Theory of Constraints is applied, starting with a cycle time focus to identify the main constraint for throughput. Third, simulation runs are performed and observations and gathered statistics in utilization charts are analyzed to reveal productivity losses.

These three perspectives are combined to predict determining factors for productivity and formulate questions for experiments. Finally, Designs of Experiments are done with the factors and tested in the model to analyze the improvement potential of the system.

4 ENVIRONMENTAL IMPACT ASSESSMENT

The production system is analyzed in terms of environmental impact and performance. This chapter presents the environmental impact assessment, whereas performance is analyzed in the next chapter.

4.1 Impact assessment

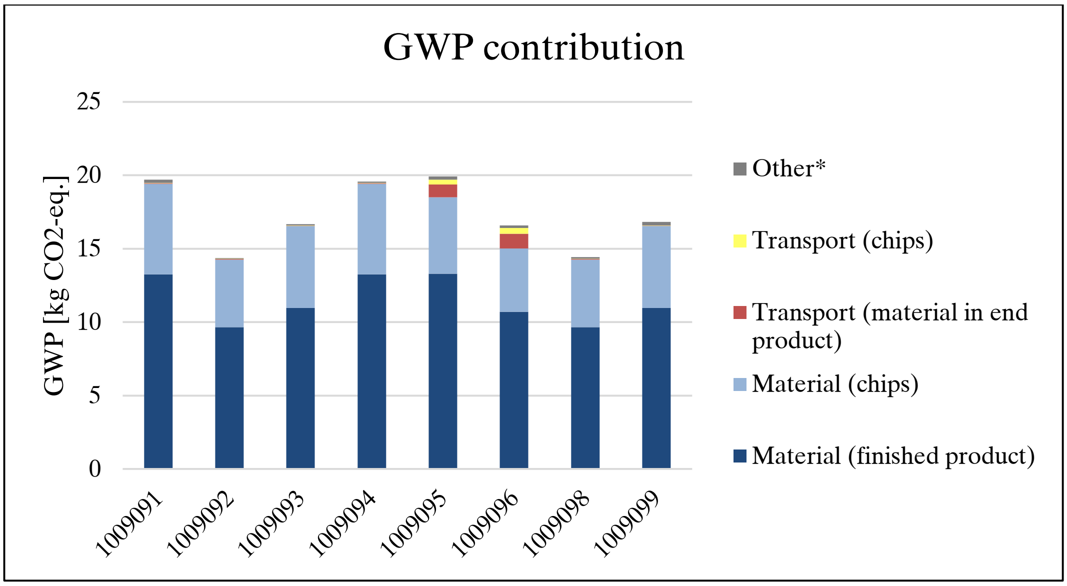
This section presents the results from the environmental impact assessment in terms of GWP, AP and EP of the brake disc variants produced in the line. Table 8 shows each characterization value for each variant (using internal variant numbers) with the variant contributing the most to the environmental impact highlighted. All impacts are expressed in kg of equivalents (Eq) per brake disc.

Table 8 - GWP, AP and EP per brake disc

Variant	GWP [kg CO_2-Eq]	AP [kg SO_2-Eq]	EP [kg NO_x-Eq]
1009091	19.7	0.0749	0.0563
1009092	14.4	0.0546	0.0411
1009093	16.7	0.0634	0.0477
1009094	19.6	0.0744	0.0559
1009095	19.9	0.0754	0.0597
1009096	16.6	0.0616	0.0501
1009098	14.4	0.0549	0.0413
1009099	16.8	0.0639	0.0481

The characterization values differ between the variants. To compare: the emission goal of the European Union for passenger cars in 2015 is an average of 130 grams of CO_2 per kilometer (European Commission 2012). The environmental impact of the production of one brake disc of variant 1009095 would in that case be comparable to the use of an average car on a distance of about 150 kilometers.

To analyze the origin of the impact, a dominance analysis is shown in Figure 6. The contributors are *material, transport, electricity* and *paint*. Material and transport contributions are divided into the subcategories *finished product*, *chips* and *scrap*, dependent on where the material ends up. *Electricity* consists of electricity from the process – for finished products, including the painting process, and for scrap – and overhead energy from the factory. *Paint* means the chemicals used in the painting process. Since the dominance analysis looks approximately the same for GWP, AP and EP, the following analyses are limited to GWP to make the analysis simpler to follow.



*Other: Material (scrap), transports (scrap), electricity (finished product, scrap, factory), paint

Figure 6 – GWP dominance analysis

It can be observed that production of raw material (including both material for finished products and for removed material, i.e. chips) accounts for the major share of environmental impact. The product weight of the variants (raw) varies from 9.5 kg to 12.6 kg (see Appendix G for weight of each variant), which is the main reason for the differences in impact shown in Figure 6.

Furthermore, a special role for 1009095 and 1009096 can be identified. Whereas the other variants are similar in the distribution of contributors, these two variants show a clearly visible impact of transports. This can be related to significantly different transport distances: Variants 1009095 and 1009096 are delivered from suppliers located in Germany, whereas the others are supplied from the Swedish supplier close to the factory.

However, before making any further analysis of the contributing factors, the decision makers that can affect them need to be considered in order to make the analysis relevant for the target users. A matrix of contributors, their type of connection to the product and the related decision makers is shown in Table 9. Further explanation of how these contributors are effectible by decisions are presented in Appendix H.

Table 9 - Contributors and their decision makers

	Finished product	**Chips**	**Scrap**	**Factory**
Material	Product design	Product design, supplier (casting)	Manufacturing, product design	n/a
Transport	Product design, logistics & purchasing	Product design, logistics & purchasing	Manufacturing, logistics & purchasing, product design	n/a
Electricity	Manufacturing	n/a	Manufacturing	Manufacturing
Paint	Product design	n/a	n/a	n/a

In this thesis, the target users of the analysis are the decision makers present at the production site, i.e. *manufacturing* and *logistics*. Categories that are not related to these decision makers are excluded from further analyses. This applies to material for the finished product and chips, and paint. This further enables a more detailed analysis of the other factors that otherwise are difficult to distinguish due to the dominance of material, following the example of Löfgren, Tillmann and Rinde (2011). Figure 7 and Figure 8 visualize the GWP from all contributors relevant for manufacturing and logistics decision makers, related to their importance within the specific decision makers' scope of action.

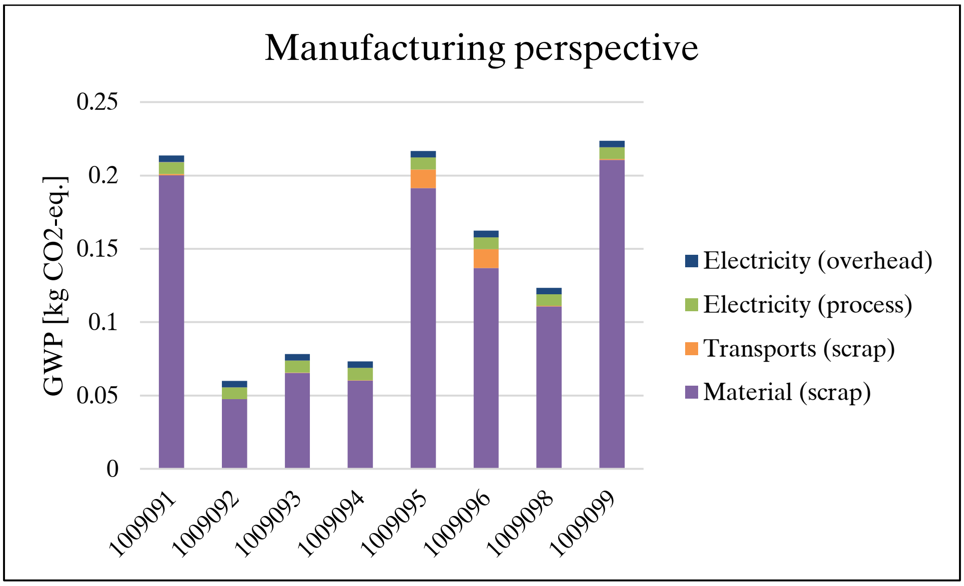


Figure 7 – Dominance analysis for manufacturing decision makers

From a manufacturing actor's perspective, scrapped material is the dominant contributor for all variants. A slight difference between the variants is again the transport for material supply due to the different locations of the suppliers. However, even the transport of material for scrapped products can be seen as caused by the occurrence of scrap in the process. With this root cause thinking, all contributors – except process electricity – can be related to the parameter *scrap rate*. This parameter accounts for about 95% of the contribution within manufacturing' scope of action. Comparing the variants, it can be seen that the impact for variants 1009091, 1009095 and 1009099 is highest, whereas variants 1009092-1009094 have a rather low impact. These differences can mainly be traced back to different scrap rates of the variants, combined with different product weights.

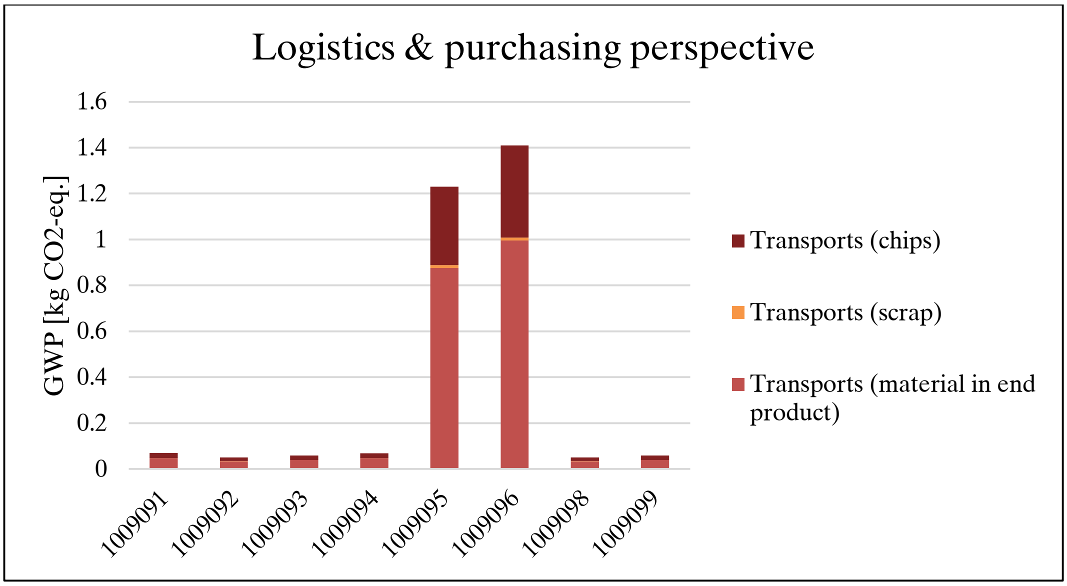


Figure 8 - Dominance analysis for logistics decision makers

Decisions made with relation to logistics obviously affect transports, especially through the choice of supplier. When only looking on transports, the different supplier locations heavily affect the environmental impact, with variants 1009095 and 1009096 from Germany having a more than 10 times higher impact than the others. A clear improvement potential can be identified for those two variants.

Both perspectives can be combined into an analysis from a factory's point of view. This perspective includes all decision makers present at the factory in Floby and expresses the common improvement potential. The dominance analysis is shown in Figure 9.

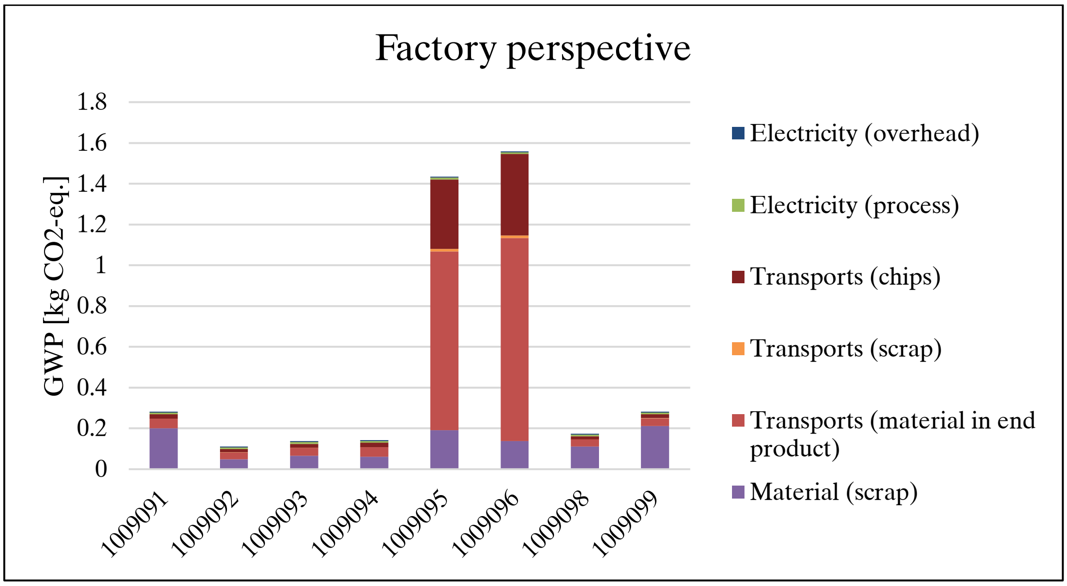


Figure 9 – Dominance analysis from a factory perspective

This perspective confirms transports from variants 1009095 and 1009096 as dominant. Apart from those, the second largest factor is scrap, especially contributions by scrap material. Electricity is only a rather small contributor. However, electricity is a very relevant contributor for decision makers in manufacturing. This is due to the fact that many actions that would lead to reduced environmental impact, e.g. reduced cycle and idle times or reduced scrap rate, would at the same time lead to increased performance of the production line. Therefore, a more detailed analysis of the energy consumption is made in the next section to see the hot spots that should be the focus of improvement.

4.2 Energy consumption

With energy consumption two dominance analyses are made. The first has a product focus and compares the different variants, showing both the differences between the variants and the variation from part to part of the same variant. The second analysis has a process focus and compares the different operations to identify hot spots in the process.

4.2.1 Variants

Using results from a simulation run of one year's production, statistics for the energy consumption are calculated including mean value and standard deviation (StDev) for each variant, shown in Table 10. Total consumption includes both direct consumption, i.e. the energy that can be directly attributed to processing of a part in a machine, and allocated consumption consisting of idle and breakdown consumption, accumulated energy for scrapped parts, overhead, compressed air and painting.

Table 10 - Energy consumption per brake disc

Variant	Total consumption (mean kWh / part)	StDev / Variant
1009091	1.125	0.009
1009092	1.100	0.008
1009093	1.128	0.010
1009094	1.134	0.013
1009095	1.128	0.009
1009096	1.112	0.012
1009098	1.079	0.008
1009099	1.103	0.006
StDev	*0.019*	

It becomes clear that the variation per variant is very small, which can be related to the fact that most cycle times are constant. Moreover, also the difference in consumption between the variants is small. Therefore it can be approximated that every brake disc has a similar energy consumption.

4.2.2 Process

Figure 10 shows an analysis of the energy consumption in the process. Idle and setup consumption, and consumption from conveyors have been aggregated, as both designate allocated energy calculated from the simulation model. The energy consumption of most conveyor segments is also included in the machines' idle consumption. Idle consumption accounts for the major part of this category.

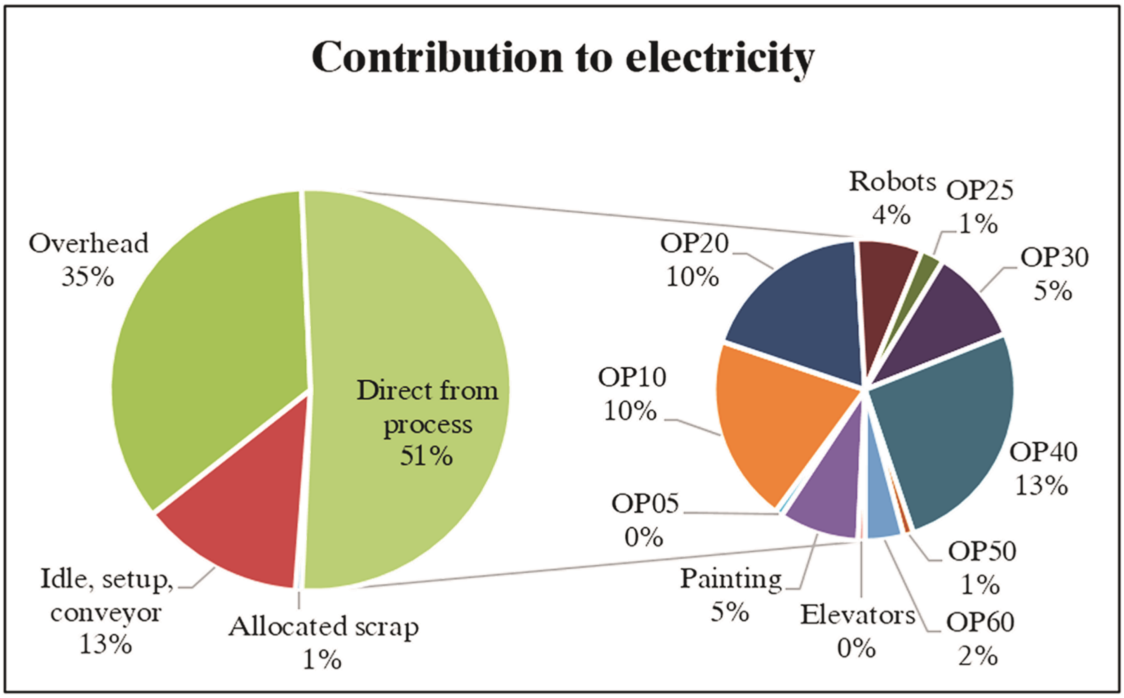


Figure 10 - Dominance analysis of electricity in the process

The largest contributor is the direct energy consumption from the process, i.e. from the machines. The rough turning machine performing OP10 and OP20 stands for 20% of the consumption and is identified as the hotspot (aggregating both operations). The secondary hotspot is OP40. The reason for this is a combination of long cycle times and high power levels during processing (11 and 14 kW respectively, see Appendix C).

4.3 Result summary

To summarize the environmental impact assessment, the most important results are:

- The most important contributor is material
- Disregarding material, the most important contributor within manufacturing decision maker's scope of action is scrap rate
- The most important contributor from a factory perspective is transports
- The impact of transports is clearly higher for variants 1009095 and 1009096 supplied from Germany
- Energy consumption has a minor role on impact from a factory perspective, but a more important role from manufacturing perspective
- Rough and fine turning are the hot spots in the process
- The main difference in impact between the variants is related to weight
- Energy consumption is nearly the same for all variants, variation is low due to mostly constant cycle times

5 PERFORMANCE ANALYSIS

This chapter presents the outcome from the performance analysis, starting with the results from observations and discussions with production engineers and operators.

5.1 Results from discussions and observations

A main outcome of the discussions and observations is a lack of quality in data reporting. During the time studies in the line, the authors had observed a lot of short machine breakdowns and other disturbances of the flow. However, the reported breakdown statistics did not show a corresponding high number of stops. Consequently, a hypothesis was formulated that the reported statistics do not cover all real breakdown times. A manufacturing engineer independently assumed that breakdown times are longer in reality than the reported times, and that very short machine stoppages may not be reported at all.

The hypothesis could be confirmed by interviewing the operators. It became clear that breakdown times are not reported directly. Instead, they are reported at the end of the shift. Thus the reporting is only a rough estimation of the times; especially short stoppages are aggregated. The operator estimated from his own experience that the amount of breakdown time is higher in reality. The manufacturing engineer further revealed that also setup times are longer than reported, as the reported setup times often only include direct work on the machines and no waiting, movements or time for run-up after setup. These deficiencies in time reporting lead to high uncertainties on the quality of historical data. As these data are used both for production planning and the simulation model, those findings are believed to contribute significantly to the deviations between planned and real productivity.

Other factors can be related to the availability of the operators. Whereas during long breaks the line is stopped with purpose, it continues to run during shorter allowances. However, if a machine fails in such a time window, the line stops as there is no operator available to fix the problem. This was suspected as another reason for productivity losses and could also be observed several times. Moreover, both the operator and the manufacturing engineer stated that the packing station at the end of the line would not always be manned, leading to blocking of the line. According to instructions, the line at this station should be emptied before taking a break to serve as a buffer for the break. Consequently, improvement potentials can be seen concerning operator availability. Furthermore, the buffer capacity before this packing station may not be sufficient to cover operator absence.

5.2 Cycle time analysis

To find cycle time constraints, the cycle times for all operations have to be compared per variant. As a preparatory step, the data are brought to a comparable level, i.e. parallel machines are aggregated and mean values are taken for distributed times. Table 11 shows all these cycle times. For every variant the longest (bold, red) and the second longest (italic, blue) cycle time have been marked.

Table 11 - Cycle times (s)

	OP05	OP10/ OP20*	OP25	OP30	OP40	OP50	OP60	OP70
1009091	18.4	20.5	15.1	**25.0**	*22.9*	21.6	22.1	16.6
1009092	18.4	19.9	15.1	**28.0**	22.0	21.6	*24.7*	15.4
1009093	18.4	19.8	15.1	**28.2**	22.6	21.6	*23.6*	16.6
1009094	18.4	20.5	15.1	**28.1**	22.9	21.6	*24.1*	16.6
1009095	17.8	20.0	15.1	**26.1**	*23.6*	21.6	22.4	16.6
1009096	17.8	20.8	15.1	**29.8**	21.3	21.6	*25.2*	15.4
1009098	18.4	19.9	15.1	**23.1**	22.0	21.6	*22.6*	16.6
1009099	18.4	19.8	15.1	**23.5**	*22.6*	21.6	22.2	16.6

*Cycle time from rough turning cell consisting of two operations and a robot. Calculated from time for the whole cell, divided through its total capacity of 3 products (1 per operation and 1 on robot head).

It is clearly visible that the drilling machine OP30 has the longest cycle time in the process, independent from the variant. It is followed by OP40 for some and OP60 for other variants. By just looking at cycle times and ignoring other factors like variation or breakdowns, OP30 can be expected to be the main constraint in the process. Variation particularly affects the cycle time of OP60. As this time already has a mean value that is second highest in the process for many variants, OP60 can also be assumed to become a constraint in some cases.

5.3 Results from simulation

A simulation is done with the real product mix of 2012 and as much simulation time as needed to produce this mix. The first step of the analysis in the model is a live observation of the flow. Figure 11 shows the typical appearance of the production system during simulation. It is visible that OP30 divides the behavior of the system - in the upstream part of the line, buffers are filled up and machines are blocked, whereas in the downstream part the buffers are empty and machines sometimes starve (although they are currently working in the screenshot).

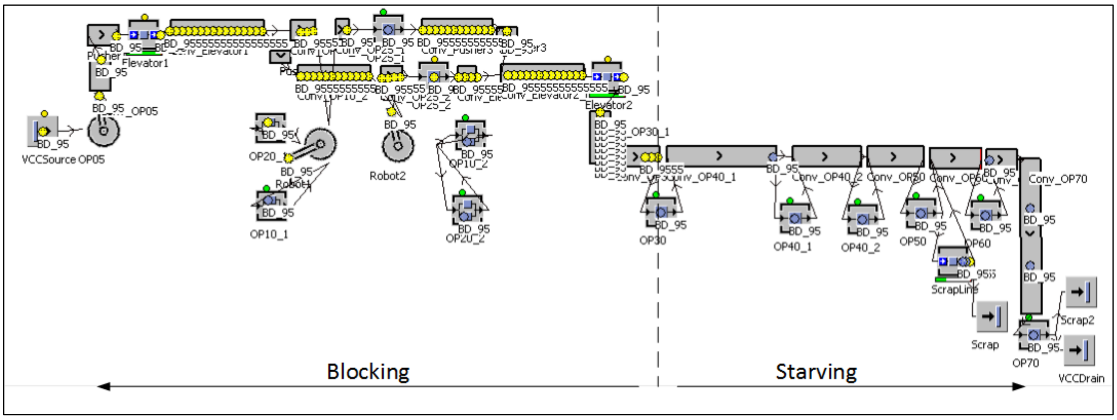


Figure 11 - Behavior of the simulation model

This observation mirrors the expected behavior of OP30 being a constraint. A further indicator is the utilization of OP30, which is highest in the system (see Figure 12).

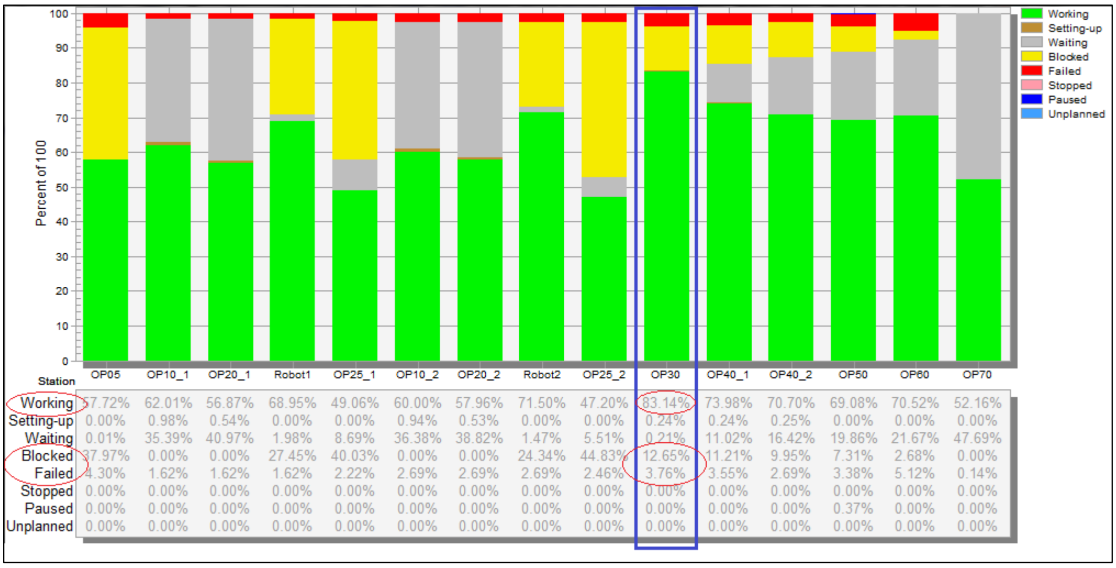


Figure 12 - Resource statistics

Combining both indicators – starving/blocking behavior and utilization – OP30 can be identified as bottleneck (Goldratt and Cox 2004). However, since the utilization at the bottleneck should be maximized, 83% utilization of OP30 can be regarded as rather low. Figure 12 shows that the operation is blocked 12.65% of simulation time. This fact leads to the expectation that there must be another constraint, placed in the downstream flow of OP30. As the cycle times are shorter than OP30 for all operations, it can be assumed that the second constraint is not cycle time-related. As OP30 is part of a serial line and all operations can fail, a hypothesis can be formulated that the blockage of the operation can be caused by breakdowns on downstream machines. Based on the failure statistics, availabilities can be calculated, as shown in Table 12. All base values are taken from Figure 12 except the conveyor availability, which is taken directly from the simulation model. OP70 is not considered, as its availability is almost 100%.

Table 12 - Availabilities of OP30 and downstream operations

OP30	**OP40:1**	**OP40:2**	**OP50**	**OP60**	**Conveyor**
96.24%	96.45%	97.31%	96.62%	94.88%	96.37%

Breakdowns on the downstream machines have different effects on OP30. OP50 and OP60 are single serial machines that directly stop the flow on a breakdown. A breakdown on a conveyor element has the same effect, as the whole conveyor line stops in this case. OP40 on the other hand is a parallel process with two machines, which means that production can continue when one of the machine fails, but with only half capacity.

When a downstream machine fails, this affects OP30 with a time delay, i.e. OP30 is not blocked before the buffers in between are filled up. The conveyors between the machines work as buffers, their capacity is shown in Table 13.

Table 13 - Downstream buffer capacity for OP30

OP30→OP40:1	OP40:1→OP40:2	OP40:2→OP50	OP50→OP60
3	1	3	1

It becomes clear that the buffer capacities are low and cannot keep up the flow for a long time when a machine fails. OP50 and OP60 will stop almost simultaneously when one of them fails, as only one part can be buffered between them. From an availability perspective, they can thus be regarded as one machine by multiplying their availabilities (Li and Meerkov 2009). Taking into consideration that also the conveyor leads to an immediate stop, its availability can also be aggregated with OP50 and OP60. This results in the following aggregated availability:

$$\text{Availability}_{\text{agg(OP50,OP60,Conv)}} = \text{Availability}_{\text{OP50}} * \text{Availability}_{\text{OP60}} * \text{Availability}_{\text{conv}}$$

$$= 0.9662 * 0.9488 * 0.9637 = 0.8835$$

This means that the downstream flow after OP30 is stopped 11.6% of the time due to breakdowns in OP50, OP60 or the conveyor. This number is close to the blocking percentage of OP30, which was 12.6%. However, the numbers can as said not be related directly without considering all buffer capacities. The accumulated buffer capacity between OP30 and OP50 is 7 parts, see Table 13. Taking the cycle time on OP30 into account it is possible to calculate the time until the buffers are filled and OP30 is blocked, given that one of the described machines fails:

$$T_{\text{breakdown to blockage}} = CT_{\text{OP30}} * \sum \text{buffer capacity}_{\{\text{OP30...OP50}\}}$$

Dependent on the variant, a worst case with the fastest cycle time (23 s) and a best case with the slowest cycle time (29.8 s) can be analyzed, resulting in a time span between 2:41 and 3:29 minutes. Calculating with a buffer capacity of 7 parts implies the assumption that the buffers are empty at the time the breakdown occurs.

To evaluate the dependence of OP30 on downstream breakdowns, the Mean Time To Repair needs to be taken into consideration. The thought behind this is: If the MTTR is low, the repair might be finished before the buffers are filled and OP30 would not be affected, whereas for large MTTR the time until the buffers are filled could become insignificant. Table 14 shows relevant MTTR values.

Table 14 - MTTR [min]

OP40:1	OP40:2	OP50	OP60	Conveyor
41:30	27:26	11:31	13:27	35:42

The values show that MTTR is significantly longer than the time it takes to fill the buffers. Furthermore, another aspect needs to be considered: After repair, OP30 cannot start producing again immediately, as it is still blocked. First, the downstream machines start producing and emptying the buffers; OP30 does not produce before the direct downstream buffer is freed. In an approximation, it can be assumed that both effects - i.e. time until buffers are filled after breakdown and time until production restart after repair

- cancel out each other. Then as a consequence, the downtime of OP50, OP60, or the conveyor can be directly approximated to blocking time in OP30.

Until now, the analysis of breakdowns only focused on the serial elements OP50, OP60 and the conveyor. However, also breakdowns of OP40 will lead to a blocking effect on OP30. Even though OP40 is a parallel process and one machine continues processing when the other fails, the cycle time of this process is much higher than OP30 and will become an immediate constraint when one of the machines fails. As production goes on, it just takes more time until OP30 is affected, compared to a direct stop of the flow. If the MTTR was low, OP30 might not be affected at all, as the failure could be fixed before the buffer is filled. As Table 14 shows, this is however not the case - especially OP40:1 has a long MTTR. Therefore it is natural that OP30 will be constrained by a failure in OP40. This will nevertheless presumably have a weaker effect than failure on the other machines, as OP30 will only be blocked a part of the time, not totally. It is imaginable that this time stands for the remaining blocking percentage on OP30 not accounted for by OP50, OP60 or the conveyor.

Other possible reasons for blocking of OP30 are not seen as applicable, as the downstream cycle times are lower than for OP30 and - except for OP60 - stable with no variation. Even for OP60, the variation boundaries are not high enough to cause a queuing effect, especially because there are buffers available. Therefore it can be concluded that the blocking of OP30 is solely caused by downstream breakdowns. The strongest impact can probably be attributed to OP60, which has the lowest availability of all operations. The specific impacts per operation need to be tested and proven with experiments.

Besides blocking, there are also performance losses due to breakdowns on OP30 itself. The operation is failed 3.78% of the total time, which is the third largest failure rate. Another operation with a similar downtime is OP05, having the second largest rate of all machines with 4.30%. However, all processes between OP05 and OP30 are parallel, and there are large buffer capacities. Therefore, breakdowns on OP05 are not regarded critical, at least as long as OP30 is the main constraint of the process.

5.4 Experiments

In the previous analysis, two main problems have been identified: OP30 acting as a bottleneck due to its cycle time, and further losses through blocking of this bottleneck. Blocking is caused by failures of the downstream machines in combination with buffer capacities that are too low to cushion the effects of the failures. Taking also failures on OP30 into account, the utilization of this bottleneck operation is only 83%.

Consequently, this utilization is in need for improvement. As different causes impact this utilization, improvements for all causes need to be tested. Running simulation experiments changing the different impact factors, the causality between the factors and the utilization of OP30 (with throughput per hour as response variable) can be statistically analyzed. The result will be an identification of improvement potential that is the basis to develop improvement suggestions. Table 15 summarizes the findings, the possible influencing factors and formulates questions for experiments.

Table 15 - Analysis findings and analysis questions

Findings	• OP30 is the cycle time constraint • 12.6% blocking of OP30, supposedly due to downstream failures • Low downstream buffers of OP30, creating dependence on downstream machines • 3.8% failure of OP30

Analysis questions	• Increasing availability on one machine - which one leads to the strongest increase in output, i.e. how strong is the correlation between blocking in OP30 and downstream failures?
	• Where should an extra buffer be placed?
	• What gives most increase in Output:
	  o Reducing CT in OP30
	  o Increasing availability on OP50/OP60/conveyor
	  o Or increasing buffer between OP30 and OP50?
	• How much total % increase in throughput is achievable through all those measures?

5.4.1 Experiment description

The questions in Table 15 are used to create an experimental plan. The experiments are mostly based on the concept Design of Experiments (see chapter 2.3 and Bergman and Klefsjö 2010). Experimental factors are chosen as input parameters and set to the levels high and low. The high level is a hypothetical setting to test the maximum positive effect (improvement potential) of the factor, not necessarily achievable at full extent in practical implementation. Whereas availability experiments are planned as full factorial design, the buffer experiments are made one-factor-at-a-time (OFAT) because these experiments aim at finding the optimal place for a buffer – implying that only one buffer is to be changed. The cycle time experiment only has one factor that is tested for several different levels. The experimental plan is summarized in Table 16.

Table 16 - Performed experiments

Availability	a) Set availability to 100% (remove failures) for the conveyor, OP40, OP50 and OP60 (full factorial design). b) Remove failures on OP30. Then combine with previous experiment.
Buffers	Set buffers after OP30, OP40 and OP50 to 20 parts (OFAT).
Cycle time	Reduce the cycle time at OP30 for all variants simultaneously. Six levels: 0 seconds reduction to 5 seconds reduction.

As main output values, throughput per hour (TPh) and the blocking portion of OP30 are used. This blocking portion is important to be able to confirm a direct correlation between blocking of OP30 and total system throughput, proving OP30 as a bottleneck.

Furthermore, the failure portion of OP30 is included as output value to assure results are comparable, i.e. ensuring that a change in blocking portion is not influenced by a change in failure portion caused by the random nature of failures. This information can be used to normalize the blocking portion for different experiments.

All experiments are performed with a simulated period of 100 days, using 10 replications per experiment and a warm-up time of 100 hours.

5.4.2 Experiment results

The results of the experiments are presented in the following tables and paragraphs. As the standard deviation in the experiments was not more than 0.6%, only mean values are presented without information about variation.

5.4.2.1 Availability

Table 17 shows the availability experiments. The absolute throughput per hour (TPh) and the relative change in throughput (dTPh) are shown. From dTPh, factor effects are calculated by multiplying the factor column with the result column, as explained in chapter 2.3. For analysis of the correlation between downstream failures after OP30 and the throughput, the factor effects are compared to the change in failure portion per factor (dFail), which is obtained via machine availability:

$$dFail = 1 - Availability.$$

The correlation indicator is defined as efficiency η of the change:

$$\eta = \frac{-\mathrm{dFail}}{Effect}.$$

Table 17 - Availability experiments

A OP40	B OP50	C OP60	D Conv	TPh	dTPh
-1	-1	-1	-1	107.1	-
-1	-1	-1	1	110.8	3.4%
-1	-1	1	-1	112.0	4.6%
-1	-1	1	1	116.2	8.5%
-1	1	-1	-1	110.2	2.9%
-1	1	-1	1	114.0	6.4%
-1	1	1	-1	115.3	7.7%
-1	1	1	1	119.4	11.5%
1	-1	-1	-1	110.0	2.7%
1	-1	-1	1	114.0	6.5%
1	-1	1	-1	115.0	7.4%
1	-1	1	1	119.0	11.1%
1	1	-1	-1	113.4	5.9%
1	1	-1	1	117.3	9.5%
1	1	1	-1	118.2	10.4%
1	1	1	1	122.3	14.2%
2.8%	**3.0%**	**4.8%**	**3.7%**	**Effect**	
-3.1%	-3.4%	-5.2%	-3.6%	dFail	
91.6%	***88.7%***	***91.1%***	***101.6%***	η	

From the results it is visible that the failures in the analyzed operations have a clear impact on throughput. Together, the failures imply a theoretical increase of 14.2% in output when removed completely. However, the table also shows different effects for the factors, i.e. the chosen operations for failure removal. When comparing the factors, it is important to not only look at the effect on dTPh, since this hides the fact that the factors account for different amounts of failure portions. It appears natural that the operation with the highest amount of failures also leads to the highest improvement when *all* failures are removed. Therefore, the efficiency η includes this aspect and expresses the improvement potential relatively to the reductions of failures.

Before the factors are further analyzed, interaction effects have to be checked, as Table 17 only shows the main effects. Interaction effects (in dTPh) are shown in Table 18.

Table 18 - Interaction effects of failures

AB	AC	AD	BC	BD	CD	ABC	ABD	ACD	BCD	ABCD
0.0%	-0.1%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	-0.1%	0.0%	0.0%

These calculations reveal that interaction effects are negligible and it is enough to focus on the four main effects. Figure 13 visualizes the efficiency of the changes on these four factors.

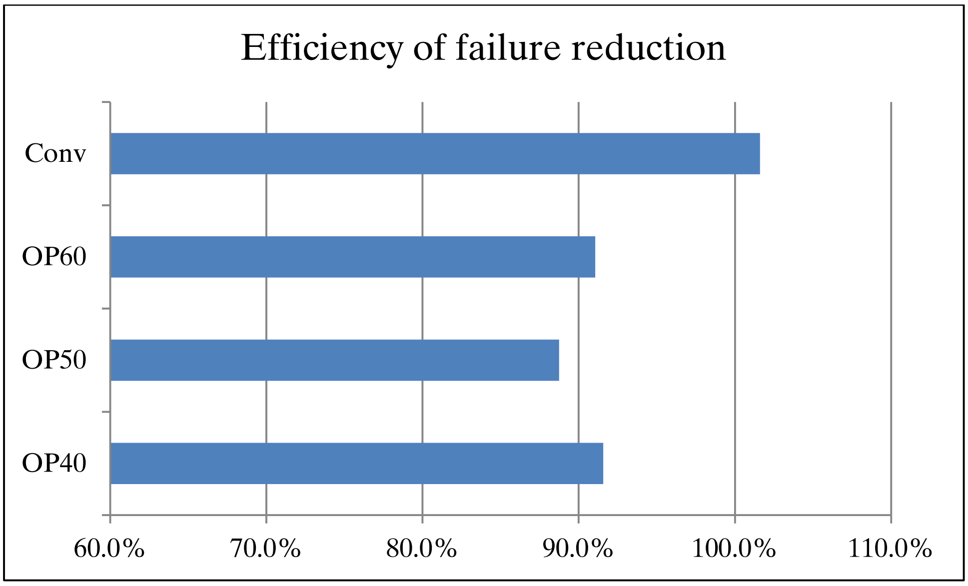


Figure 13 - Influence of OP30 downstream failures on throughput

What can be seen is that for the operations OP40, OP50 and OP60, reductions of cycle times can be transformed to productivity gains with an efficiency of 90%. This confirms the close relation between these failures and the throughput that was predicted after the first analysis of the simulation model. Interestingly, changes at OP40 show the highest efficiency of the three operations, even though the opposite was assumed earlier due to the use of two parallel machines. This leads to the conclusion that OP40 is not at all less important than the other machines. However, OP60 has the lowest availability of all three operations and can therefore be assumed to have the greatest room for improvements.

Even more efficient than reduction of failures on one of the three operations are improvements on the conveyor. There is a positive correlation of slightly more than 100% between failures of the conveyor and the system's throughput. This can probably be traced back to the fact that the conveyor is connected to all machines that will be blocked at the same time when the conveyor fail, leading to a stoppage of the whole line. Consequently, improvements of conveyor availability can be assigned priority.

As OP30 has been identified as a bottleneck, it can be assumed that failures on this operation are direct performance losses. This is first tested isolated for OP30, then in interaction with the downstream machines. Table 19 shows the experiment results.

Table 19 - Availability experiments with OP30

OP30	OP40	OP50	OP60	Conv.	TPh	dTPh	dFail	η
1	-1	-1	-1	-1	111.52	4.22%	-3.77%	111.9%
1	1	1	1	1	126.95	18.65%	-19.15%	97.4%

These numbers prove that breakdowns at OP30 are direct performance losses, the performance gains by removing failures is even higher than the removed failure percentage. Combining this experiment with the previous results, the efficiency of the combination of all actions becomes 97.4%

However, the experiments were made removing all failures of a machine, making it 100% available. This is not a realistic scenario. Instead it is likely that only a part of the breakdowns can be removed by improvements. It is in this case not certain that the efficiency of the measures is the same, i.e. there is a linear correlation between throughput and failures. This can be analyzed through further experiments testing different availability levels. The availability is increased in steps of 0.5% and again the efficiency in terms of throughput increase is calculated. Figure 14 visualizes the development of productivity improvements dependent on availability gains, calculated as linear regression of the samples obtained through the new experiments.

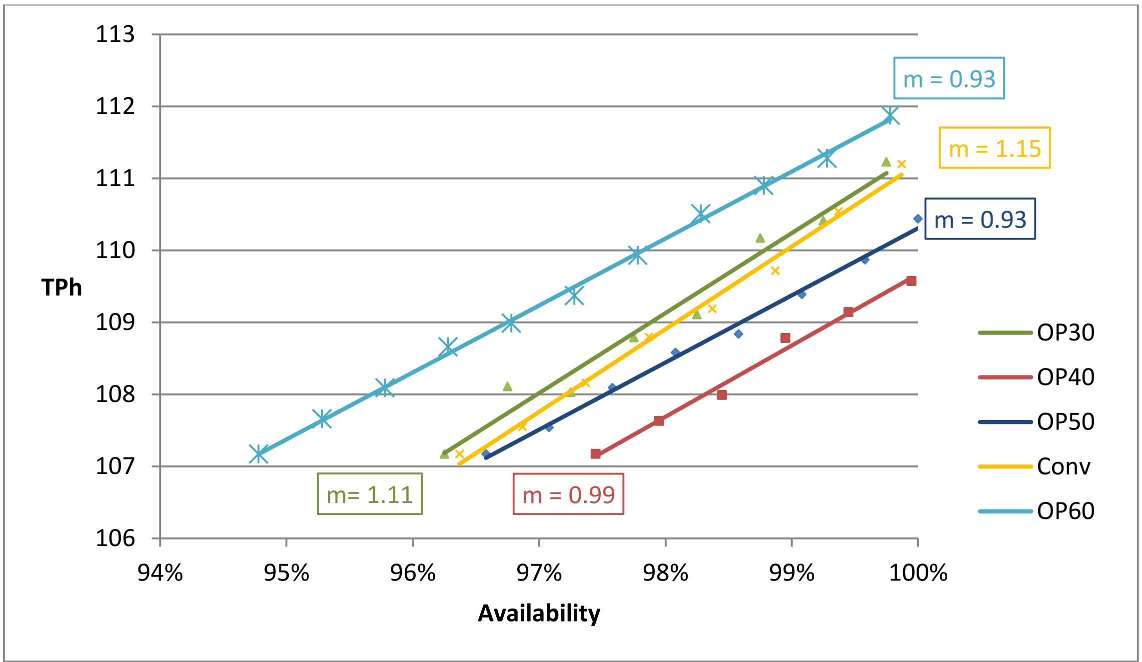


Figure 14 - Correlation of availability and TPh

The results show that the correlation of availability improvements and throughput is linear anyway. The calculated efficiency corresponds approximately to the slope *m* of the regression lines. It is clearly visualized that TPh rises at different rates for availability improvements on the machines, with the conveyor and OP30 being steepest.

5.4.2.2 Buffers

The main goal of the buffer experiments is to identify the optimal location for an additional buffer. Table 20 shows the results for the different locations, expressed as absolute throughput values and relative changes.

Table 20 - Buffer experiment

Buffer OP30	Buffer OP40	Buffer OP50	TPh	dTPh
3	3	1	107.11	
20	3	1	112.29	4.84%
3	20	1	111.05	3.68%
3	3	20	109.73	2.44%

The experiments show that the effect of an increase in buffer size depends on the location of the buffer. Best results were obtained for an additional buffer between OP30 and OP40, with an increase in throughput per hour of 4.8%. Consequently this can be seen as the optimal location for an extra buffer. The logical next step is to also analyze buffer size. Therefore, more experiments are done using the buffer between OP30 and OP40. Several additional sizes are tested and their results presented in Figure 15. Especially to be named is the capacity of 7 parts. This value is chosen because the conveyor in the real system would have space for approximately 7 parts, but is currently limited to 3 parts. As stated, these buffers are at this point assumed independent from technical feasibility, which is why buffer sizes up to 100 parts are shown.

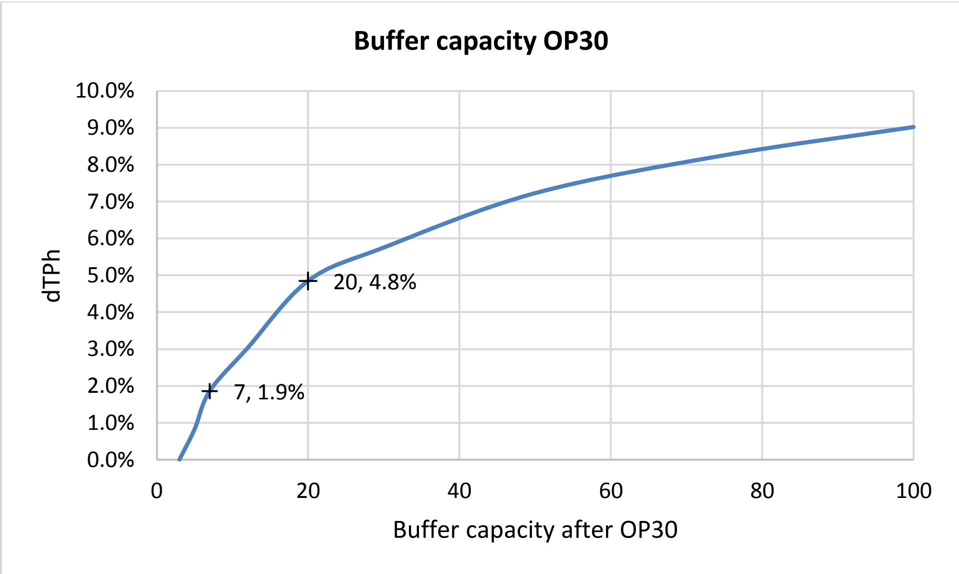


Figure 15 - Additional buffer experiments

As it can be seen, the throughput rises continuously along with the buffer size. However, the steepness of throughput increase is changing and two special points can be identified: The largest step is taken for buffer size of 7 parts, and the curve gets much flatter for buffer sizes higher than 20 parts. This interval of buffer capacity can be seen optimal from a combined performance and economic perspective. It depends on technical feasibility and economic limits which actual setting would be favorable. This will be discussed in section 6.2.2.

5.4.2.3 Cycle time

To present the results of the cycle time (CT) experiments, not only throughput is shown, but in this case also blocking portion of OP30 (see Table 21). The results are visualized in Figure 16.

Table 21 - Cycle time experiments

OP30 CT	OP30 blocking	TPh	dTPh
-	12.97%	107.25	
-1s	13.25%	111.05	3.55%
-2s	14.96%	112.86	5.23%
-3s	17.60%	113.85	6.15%
-4s	20.39%	114.58	6.84%
-5s	23.17%	115.38	7.58%

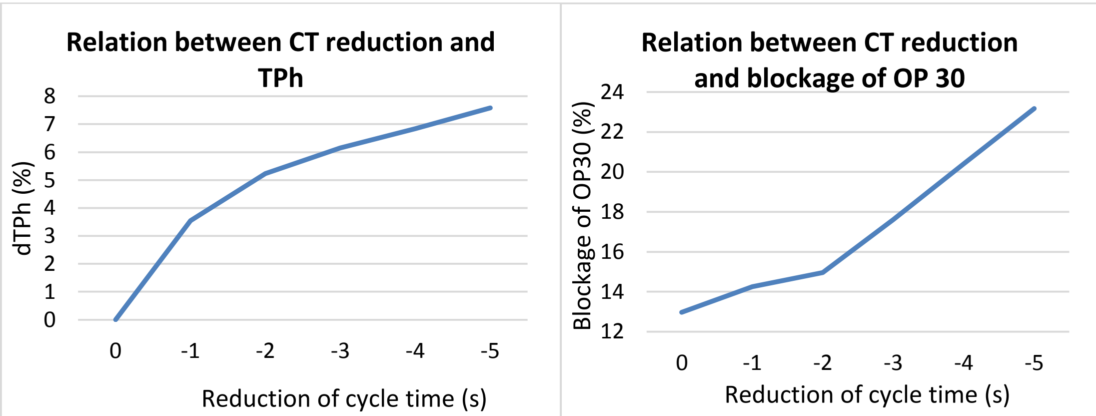


Figure 16 – Results from cycle time reduction of OP30

It becomes clear that the throughput increases continuously, but at a slowing rate. At the same time, the blocking portion increases slightly for a cycle time reduction of 1 and 2 seconds, and much more for the higher reductions. The increase in output is obviously weakened by a blocking effect for a cycle time reduction of more than 2 seconds. A reason for the increase in blocking could be that the bottleneck shifts from OP30 to other operations when the cycle time of OP30 is reduced. Table 22 shows the cycle times for OP30 and the downstream machines after a reduction of 2 seconds in OP30. The longest cycle time per variant is marked orange and bold, the second longest time blue and italic.

Table 22 - Cycle time constraints after cycle time reduction

	OP30	OP40	OP50	OP60
1009091	**23.0**	*22.9*	21.6	22.1
1009092	**26.0**	22.0	21.6	*24.7*
1009093	**26.2**	22.6	21.6	*23.6*
1009094	**26.1**	22.9	21.6	*24.1*
1009095	**24.1**	*23.6*	21.6	22.4
1009096	**27.8**	21.3	21.6	*25.2*
1009098	21.1	*22.0*	21.6	**22.6**
1009099	21.5	**22.6**	21.6	*22.2*

This shows that the cycle time constraint has shifted to downstream machines for two variants.

5.4.2.4 Combined experiments

To determine which of all analyzed factors are most determining for the production system and thus most important to focus on in an improvement process, the experiments need to be combined, compared, and tested for interactions. For this purpose, the strongest factors that have been identified are used, and a full factorial DoE is performed. Table 23 shows the factor settings used, Table 24 presents the results of the experiment including the calculated effects of the main factors, and Table 25 shows the interaction effects. For the availability factors, an improvement of 2% has been used, as this is more realistic than removing all failures completely.

Table 23 - Factor settings for DoE

	OP30 CT reduction	OP30 Buffer capacity	OP60 Availability	OP30 Availability	Conveyor Availability
Low (-1)	-	3	94.88%	96.24%	96.37%
High (1)	-1s	20	96.88%	98.24%	98.37%

Table 24 – Combined experiment DoE

	CT reduction of OP30	Extra capacity OP30	Availability of OP60	Availability of OP30	Availability of Conveyor		
	A	B	C	D	E	TPh	dTPh
	-1	-1	-1	-1	-1	106.9	
	-1	-1	-1	-1	1	109.2	2.1%
	-1	-1	-1	1	-1	109.0	2.0%
	-1	-1	-1	1	1	111.5	4.3%
	-1	-1	1	-1	-1	108.8	1.8%
	-1	-1	1	-1	1	111.3	4.1%
	-1	-1	1	1	-1	111.0	3.8%
	-1	-1	1	1	1	113.3	6.0%
	-1	1	-1	-1	-1	111.1	3.9%
	-1	1	-1	-1	1	113.7	6.3%
	-1	1	-1	1	-1	113.4	6.0%
	-1	1	-1	1	1	115.9	8.4%
	-1	1	1	-1	-1	113.2	5.9%
	-1	1	1	-1	1	115.4	7.9%
	-1	1	1	1	-1	115.2	7.7%
	-1	1	1	1	1	117.5	9.9%
	1	-1	-1	-1	-1	110.8	3.6%
	1	-1	-1	-1	1	112.9	5.6%
	1	-1	-1	1	-1	113.0	5.6%
	1	-1	-1	1	1	114.9	7.5%
	1	-1	1	-1	-1	112.5	5.2%
	1	-1	1	-1	1	115.1	7.6%
	1	-1	1	1	-1	114.9	7.4%
	1	-1	1	1	1	117.1	9.5%
	1	1	-1	-1	-1	114.2	6.8%
	1	1	-1	-1	1	116.2	8.7%
	1	1	-1	1	-1	116.0	8.4%
	1	1	-1	1	1	118.4	10.7%
	1	1	1	-1	-1	115.8	8.3%
	1	1	1	-1	1	118.2	10.5%
	1	1	1	1	-1	117.9	10.2%
	1	1	1	1	1	120.4	12.6%
Effect (TPh)	**3.2**	**3.8**	**1.9**	**2.1**	**2.3**		
Effect (dTPh)	**3.0%**	**3.5%**	**1.8%**	**2.0%**	**2.2%**		

Table 25 - Combined experiment interaction effects

AB	**-0.5%**	**ABC**	**0.0%**	**ABCD**	**0.0%**
AC	0.0%	ABD	0.0%	ABCE	0.0%
AD	0.0%	ABE	0.0%	ABDE	0.1%
AE	-0.1%	ACD	0.1%	ACDE	0.0%
BC	-0.1%	ACE	0.1%	BCDE	0.0%
BD	0.0%	ADE	0.0%	ABCDE	0.0%
BE	0.0%	BCD	0.0%		
CD	0.0%	BCE	-0.1%		
CE	0.0%	BDE	0.1%		
DE	0.0%	CDE	0.0%		

The results in Table 24 show that buffer capacity after OP30 is a determining factor for the production system's throughput, having the strongest effect of all factors, followed by a cycle time reduction. However, this needs to be related to the actual buffer size. The results are only valid for a capacity of 20 parts, and the effect of buffer capacity would be lower for smaller sizes. The previous buffer experiment (compare Figure 15 on page 43) can be used as a basis for decisions about desired buffer capacity. At the same time, the effect of cycle time is only valid in the given height if a reduction of a whole second on all variants can be achieved. Nevertheless, both effects – buffer capacity and cycle time – are strong and show a clear improvement potential on these areas.

Improvements of availability show roughly the same efficiencies as obtained in the previous experiment (see Figure 14 on page 42), at least for OP60 and the conveyor. The effect of OP30 is slightly lower than expected before, but still achieves an efficiency of about 100%. The conveyor is confirmed to have the greatest improvement potential relatively to its availability. Availability improvements would turn out particularly strong if they are combined: Whereas improvements on only one machine have a weaker effect than buffer or cycle time improvements, a combined availability approach could become more dominant than the other factors.

The interactions between any of the factors are low, which means that gains on those factors almost come to full effect, independent from each other (Bergman and Klefsjö 2010). Only cycle time and buffer capacity have a light interaction with each other.

5.4.3 Summary of experiment results

The experiments have shown that all three approaches – reducing cycle time on OP30, increasing downstream buffer capacity and reducing failures – are beneficial parameters for the production system's throughput. The greatest improvement potential can be identified in the cycle time of OP30 and an additional buffer located between OP30 and OP40. A cycle time reduction of more than two seconds has limited potential as it causes the bottleneck to shift downstream for some variants. Reduction of failures should focus on the conveyor, followed by OP30 and OP60. The theoretical improvement potentials of the factors are summarized in Table 26.

Table 26 - Summary of improvement potential

Parameter / Changes to the system	Improvement potential (dTPh)
Availability Conveyor OP30 OP40, OP50, OP60 All combined	per % increase in availability: 1.09 % 1.00 % ~ 0.90 % 0.97 %
Buffer capacity after OP30	1.86 % for capacity = 7 4.84 % for capacity = 20
OP30 cycle time reduction 1s OP30 cycle time reduction 2s	3.55 % 5.23 %

6 IMPROVEMENT AREAS

This chapter presents improvement ideas for both environmental impact and production system performance. As defined in the scope of this thesis, the intended use of the suggestions is rather a basis for discussion and further analysis than an implementation concept.

6.1 Environmental impact

In this section, different ideas for reducing the environmental impact are presented. They focus on the intended receiver's scope of action, i.e. manufacturing and logistics decision makers at the factory in Floby,

6.1.1 Transport

For two variants (1009095 and 1009096) transports stand for a significantly large part of the total environmental impact. Actions should be taken to reduce that impact in order to even out the environmental impact between the variants. The impact from transport is linearly connected to the amount of tonne kilometers which is calculated through the multiplication of transported weight and traveled distance. Decisions regarding transport distance are related to logistics. Deciding to choose a supplier closer to the manufacturing site would reduce the environmental impact.

The transport of chips and scrap is also affected by decisions regarding logistics. Nevertheless, all removed material and scrap is returned to the closest supplier already today, and it is therefore more relevant to look at the amount of transported material, i.e. chips and scrap. The amount of chips is affected by decisions about the design of product blanks and the casting process of the blanks. Reducing the amount of material that needs to be removed in the machining operations would reduce the amount of chips, which would lead to fewer transports. The quality of the casting process should be discussed together with suppliers and is important to take into consideration for the choice of suppliers.

The parameter left to influence by decision makers in production is scrap rate. From a manufacturing decision maker's point of view, the scrap rate accounted for a significantly high amount of the environmental impact. Higher scrap rate both increases unnecessary energy consumption and the weight of the returning transports. Therefore, measures should be taken to reduce the scrap rate, which is desirable from an economical perspective as well.

6.1.2 Energy consumption

Both identified hotspots are operations of the same nature, namely turning operations. Therefore it is needed to investigate how parameters of such an operation affect energy consumption in order to know how to set those parameters. Taha et al. (2010) and Campatelli (2009) conclude that increased feed and cutting depth both decrease the energy consumption. In terms of those parameters, OP10 and 20 are optimized since the desired depth of cut is reached by one cut only. OP40, on the other hand, is a fine turning operation giving the brake disc a higher surface quality. In such operations it is desirable to decrease the feed and cutting depth, which increases energy consumption. Guo et al.

(2012) present an approach to optimize the cutting parameters for minimal energy consumption and a given surface quality. It is a two-step approach where in the first step cutting speed, feed and cutting depth are set in such a way that the minimum requirement on surface roughness is reached. In the next step the optimal values from an energy consumption point of view are calculated, which might lead to a better surface quality than the minimum requirements. This approach is suggested to determine optimal parameters for OP40.

Taha et al. (2010) point out that changes in products are linked to changes in energy consumption in a turning process. For example, smaller product diameters lead to a higher spindle speed that increases energy consumption. However, it is concluded that changing parameters that increase the power level often shorten the cycle time significantly, resulting in a lower energy consumption in total. This leads to the recommendation that actions should be taken to reduce cycle time. Nevertheless, new power measurements have to be made if the process is changed to see if the time reduction is large enough to compensate for the increased power level.

6.2 Performance

Three approaches to improve performance have been identified in the analysis: cycle time, buffer capacity and availability. The following sections give ideas on these areas.

6.2.1 Cycle time

The company is aware of the improvement potential for cycle time and constantly working on cycle time reductions for OP30. The analysis proved an improvement potential for this approach, which is why continued work on cycle time reductions is advisable.

At the same time, the analysis showed limits of cycle time improvements. Cycle time in OP30 is not the only constraint of the system, and the bottleneck shifts downstream for improvements of more than 2 seconds on the variants 1009098 and 1009099. It is therefore recommended to work on cycle time reductions only up to a limit of 2 seconds and then focus on the other two factors *downstream buffer* and *availability*.

Still, it has to be pointed out that the conducted experiments reduced cycle time simultaneously on all variants. Looking closer at the cycle times, it can be seen that they differ a lot for different variants: from about 23 seconds for 1009098 to almost 30 seconds for 1009096 (see Table 11 on page 33). It would seem logical that it is technically more challenging to reduce the cycle time on a variant that already has a short time, than to work with the variants that need the longest cycle times for processing. The authors suggest making decisions based on technical feasibility and starting with the variants where the best possibilities to reduce cycle times are seen.

6.2.2 Additional buffer

The analysis revealed a high improvement potential for adding buffer capacity between OP30 and OP40. Two solutions are imaginable: allowing a higher capacity on the existing conveyor segment, or adding an additional conveyor. The first alternative is related to the current limit of three parts set by process logic. Physically, more parts could fit onto the conveyor segment. The full conveyor space cannot be used anyway, as there is a device in the middle of the conveyor flipping parts upside-down. This is necessary as OP30 and OP40 need to receive the part in opposite orientation. Consequently, the improvement potential of this solution is limited (1.9% for 7 parts), but at the same time inexpensive.

Adding a new conveyor could increase the buffer size significantly and would enable a capacity of 20 parts as tested in the experiments. In the current production layout, there is unused space between OP30 and OP40 at the backside of the machines (see Figure 17). This could be used as a location for a new conveyor that would replace the old flow between the machines. The flipping device could be placed in the middle section, respective to the current situation.

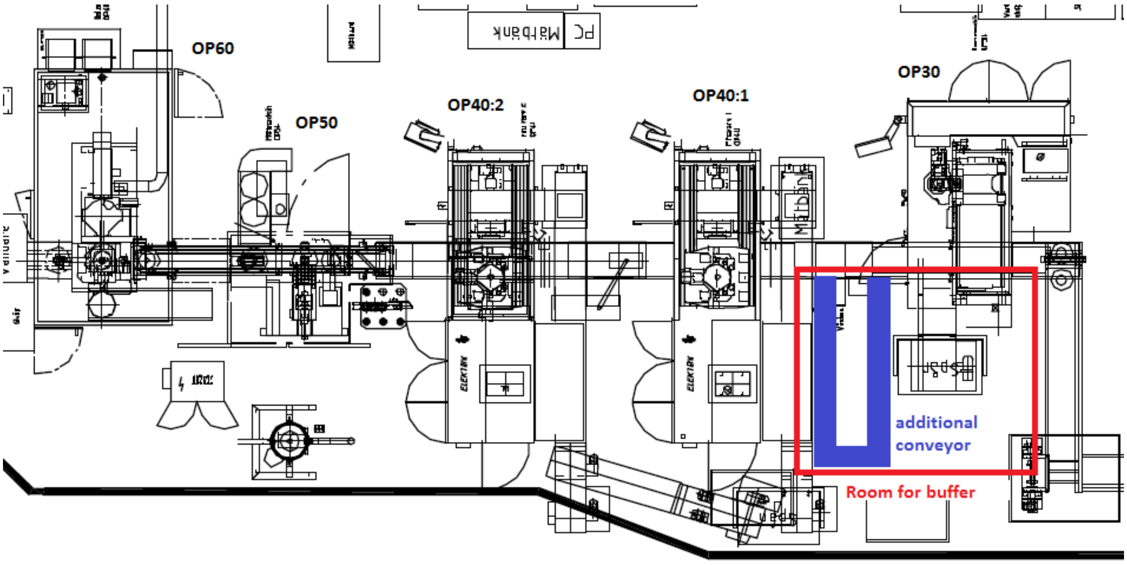


Figure 17 - New conveyor as additional buffer after OP30

Even though this solution offers great improvement potential (4.8% increase in productivity for a capacity of 20 parts), it requires at the same time investments in a new conveyor. It is therefore suggested to make an economic evaluation of the idea to decide if the solution is worth considering.

6.2.3 Availability

The greatest improvement potentials related to availability were identified for the conveyor and OP30. If the downtime of these operation can be reduced, this will result in direct productivity gains with a correlation of at least 100%. The conveyor is connected to all machines and will strongly impact the process if improved. Concerning OP30, it is alarming that this operation has the second lowest availability in the production system with 96.25%. It is clearly recommended to work on the reliability of this machine.

The authors suggest doing further investigations on the conveyor and OP30 to identify the causes for breakdowns, e.g. using a root cause analysis or Failure Mode and Effects Analysis (FMEA, see Bergman and Klefsjö 2010). As breakdowns are logged in a central company databases, these entries should be systematically analyzed.

If the required human resources are available, it is further advisable to look at the operations OP40, OP50 and OP60. The approach to find improvements would be the same.

The analysis had revealed that the real availabilities are lower than reported, leading to the target throughput not being reached. However, this does not mean that the planned values should be adapted. Machine breakdowns are seen as a current problem of the production system that lead to productivity losses. Therefore those should be fixed instead, and the target values should be kept as goals for improvements.

7 DISCUSSION

Several aspects of this thesis, including collected data, modeling of the production system, analysis results and improvement ideas, have room for discussion. This chapter broadens the perspective for these aspects and gives further information and reflections.

7.1 Simulation model

When building availability models for the machines based on collected breakdown statistics, different kinds of breakdowns have been aggregated to one value per machine. However, looking closer at the collected data shows that short and long breakdowns can be distinguished: There are a lot of short breakdowns (3-5 minutes) and a few very long breakdowns (one or several hours). The calculated MTTR is only a virtual value that lies in between long and short stops, whereas in reality the machine actually never has a stop that has about the length of MTTR. Anyway, this makes no difference in the simulation, both types of representation would give exactly the same results, as the mean value covers and levels out different losses on breakdown. Nevertheless, a separate analysis of short and long breakdowns may be of interest for the development of improvements to decide which type of breakdowns should be focused on.

The validation of the simulation model only relies on qualitative data based on observations and interviews. For a more reliable validation, it would have been good to support the information with quantitative data. Still, the analyses done with the model can be seen as reliable because they use relative values, showing relative increase in output instead of absolute throughput per hour. The actual improvement potential could be seen as even higher, since in reality the availably is lower than in the model.

To assess the extent of deviation in breakdown reporting, different scenarios can be tested in the simulation model. Assuming that the deviation of productivity mainly is caused by reporting deficiencies, the question is: In which configuration of machine breakdowns does the simulation model reach exactly the throughput of the real system? To clarify this matter, experiments have been set up reducing the availability of OP30 and all downstream machines. They are simultaneously reduced by the same amount, step by step until the throughput reaches 90 parts per hour, which was the real average system throughput per hour in 2012. The result of this simulation is an availability reduction of about 4.0% per machine. This means that the real availabilities of the machines can be assumed to be about 4% lower than reported. Then the availabilities of the machines would be between 90% and 95%. This is an indicator of the real improvement potential regarding machine availability.

Analyzing the real improvement potential with a completely validated model would require new input data for breakdowns. As the recorded data are not reliable, breakdown data would have to be collected over an extended period of time. The used data are collected over a period of a whole year. Collecting new data would not assess real mean values and variations if they only were collected during a shorter time period, such as the execution time of the thesis project. Even if new data were collected, they would only be applicable if their credibility could be assured. With the current recording methods this can be doubted. One way to assure credibility would be to introduce an automatic logging system where machines would record directly when they fail, avoiding the need to record data manually.

As however such a system was not available, the uncertainty of collected data was large, doing own measurements would have taken a tremendous amount of time and the statistical relevance would have been limited, the experiments that were executed can be seen as sufficient to generate satisfying results. It can be assumed that the conclusions would have been the same even if other breakdown data had been used. The analysis of breakdowns showed a linear relation between machine availability and throughput (see Figure 14 on page 39). This indicates that the results would have been similar even for lower availabilities. Factors as buffer sizes or cycle times have been analyzed separately and had low interactions with availabilities. Therefore all conclusions can be seen as valid, independent from the actual availabilities.

7.2 Environmental impact assessment

For the environmental impact of machine tools – i.e. silicon nitride ceramics for cast iron applications – no LCI data could be identified. Anyway, as the consumption of tools is low and the parts very small, it can be assumed that their impact is negligible compared with other factors. The same reasoning is valid for the third component of the paint, zinc phosphate, as it is only a fraction of the 7 grams of paint used per brake disc.

When looking at the results of the environmental impact assessment, the values in the three categories GWP, AP and EP appear very different. It has to be pointed out that these categories have to be interpreted separately and have to be seen as complementary. No aggregation into one category can be done without weighing the factors. For weighing there are very different methods available and their results are always subjective (Baumann and Tillman 2004). Therefore, this thesis does not aggregate the factors.

7.3 Improving environmental impact

The analysis shows that most of the improvement potential is related to extraction and production of raw material, accounting for approximately 90% of the environmental impact. This improvement potential is not within the manufacturing actor's perspective. Instead, this factor is rather affected by product design and choice of material.

As a great improvement potential can be identified, some thoughts on this are presented even though they are out of the defined scope of the thesis. Ways to reduce impact from material are either redesigning the product blanks to contain less material, changing the material, or both. Smaller blanks would lead to less material losses and reduce the amount of material in the casting process, leading to lower impact from raw material production and transports. Changing the material needs to be looked into very carefully before making a decision to avoid sub-optimization. If a lighter material, such as aluminum, was chosen, the brake discs would have a lower weight which might lead to a lower impact. However, the impact from extraction and production of aluminum has a much higher environmental impact per kilogram than cast iron (which was tested replacing cast iron LCI data with aluminum LCI data in the environmental impact calculations). This would cancel out the effect from the lighter material. In addition, changing the material would impose changes on the production process and product properties, and needs to comply with customer requirements. These aspects would have to be investigated. To make use of the improvement potentials, a cooperation with product development and customer relationship management is recommended.

It may seem natural that another effect from reducing product weight would be a reduced impact from transports since that impact is calculated from both distance and transported weight. Looking at the calculations, a reduced weight also leads to lower impact results. In reality however, it is likely that the transports will still contain the same number of brake discs, even though the weight of the blanks is reduced. Thus, the actual impact per brake disc from transports would remain unchanged.

From the logistics perspective, the most relevant factor to consider is transports, which is obviously affected by the location of suppliers. However, location is not the only criterion to consider when selecting suppliers. In a comprehensive literature review on multi-criteria decision making approaches for such selections, Ho, Xu and Dey (2009) list the most popular decision criteria. From 78 journal articles, hundreds of criteria were grouped into categories, whereof *Safety and environment* was the least popular, only featured in 3 articles. The ambition of this thesis is to emphasize the possibilities and importance of being environmentally sustainable, i.e. the importance to consider the environment in many aspects, including supply chain. Therefore it is recommended to take that aspect into account when selecting suppliers.

7.4 Measuring and calculating energy consumption

The energy consumption for different variants has been calculated using individual cycle times per variant, but a common average power level measured for only one variant. This calculation is an approximation relying on the assumption that energy consumption is proportional to cycle times. However, this may not be the case in reality. The differences in cycle time may be related to activities on a low power level, having a limited effect on the consumption of the cycle. To obtain totally reliable results, power measurements would have to be made for every variant, which would be very time consuming. Nevertheless, the applied approach did not use whole cycle times, but divided the process into loading and processing. Whereas the variation in power is high during processing and may differ between the variants, power for loading is on a comparably stable level (see the example of one cycle in OP40 shown in Figure 18). The energy consumption during loading can therefore be assumed to be only time-dependent, not variant-dependent. Moreover, the machining operations for the different variants performed during processing are very similar. Their time difference is only a few seconds, which is low compared to the total processing time. Consequently, the approach of calculating energy consumption for all variants based on only one measured variant is seen as a sufficiently good approximation of the real consumption.

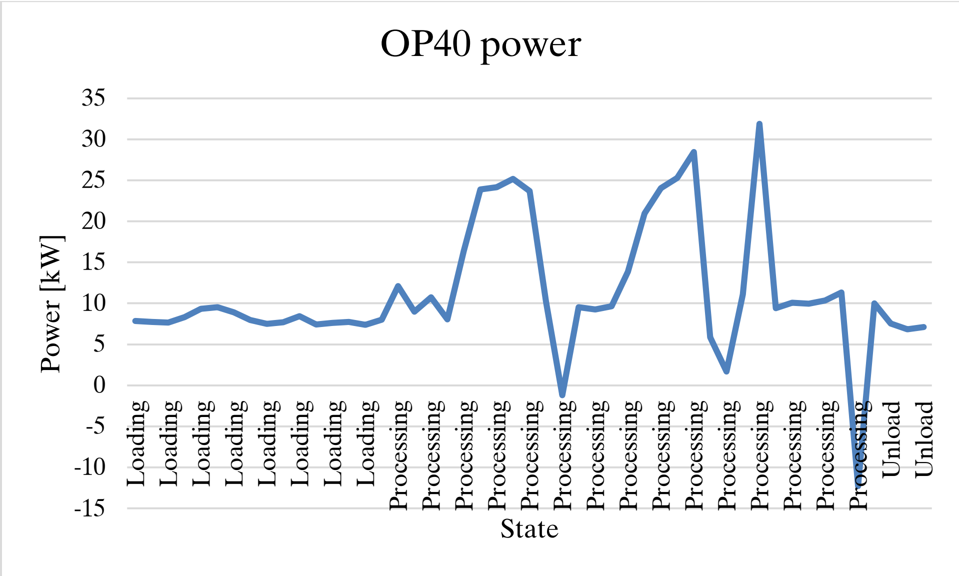


Figure 18 - Power in OP40

In the process shown in Figure 18 – as well as in most other operations of the line – loading time accounts for a significant part of the process. Improvements of such a process can either work with reducing loading or processing time. The approach presented in section 6.1.2 suggested working with activities during processing, reducing both cycle time and energy consumption.

Another approach could be to apply lean thinking on a machining operation like this. Lean thinking focuses on identifying and removing waste in a process, and offers tools like value stream mapping (VSM) to focus on non-value-adding activities (Liker and Meier 2006). Transferring a VSM approach to the energy consumption in a manufacturing process could be beneficial. Similarities in thinking can be seen; especially in the example shown in Figure 18, loading activities can be regarded as non-value-adding, i.e. waste of energy. Reducing these non-value-adding portions would reduce both cycle time and energy consumption. The authors see a need for research on this area and suggest further studies on a methodology to apply VSM on machining operations and their energy consumption.

The division of a machine cycle into loading and processing was specific for the studied processes. It was suitable in this case since small activities that were aggregated to loading accounted for up to 40% of a machine cycle. However, this cannot be generalized for all kinds of processes. In other cases, it may be sufficient to use whole machine cycles and calculate an average power level for the cycle. The machine cycle can then be regarded as a black box and simulation studies can focus on non-value-adding times on a line level, i.e. idle and breakdown times. A disadvantage of this approach would be the requirement to make power measurements for every product variant and operation, as the energy information would not be detailed enough to draw conclusions from one variant to another. Nevertheless, there are two advantages with this approach: First, time in data collection can be saved, as no further division of cycle times is necessary and earlier cycle time records may be available and ready to use. Second, model building can be simplified, as only one type of times needs to be used, and energy consumption can be calculated as a simple multiplication. The choice of approach should be made dependent on the process and the intended use of the study.

7.5 Combining DES and LCA

In the scope of this thesis an optimization of energy consumption through simulation was excluded. The environmental impact assessment revealed that energy consumption only accounts for a minor part of the environmental impact, limiting the efficiency of energy improvements. This indicates that it was an adequate decision to only focus on performance improvements in the simulation model. Moreover, the analyses showed that also the variation of impact between products is very low in the studied production system. Many cycle times are static and have no variation at all, and energy consumption was almost the same for single products of one variant. This leads to the question if it was necessary to even simulate energy consumption, or if it would have been enough to make totally static calculations without using DES.

It needs however to be discussed how a full combination of DES and LCA could be beneficial. Widok, Wohlgemuth and Page (2011) and Andersson, Skoogh and Johansson (2012) concluded that DES offers great potential for quantifying sustainability aspects, benchmarking products and processes from an environmental perspective and developing production in a sustainable way. In the example of this thesis, the developed DES model can help VCC in adapting their production planning and development to include energy consumption. Using static methods would shift the focus to only the processing activities, missing the non-value-adding parts of energy consumption, i.e. idle, blocked and breakdown state. DES gives the possibility to take those into account and develop improvements to reduce energy consumption. At the same time, it reveals environmental consequences of changes to the production system, as pointed out by Löfgren and Tillman (2011). Even though the energy consumption only accounts for a very small part of the total impact, it can still be beneficial to take it into account for improvements of the system. Especially from a sustainability perspective, environmental aspects should not be left out when making decisions on production systems. Even small improvements contribute to a sustainable development and can increase environmental awareness. Furthermore, energy optimizations can be advantageous for marketing purposes, striving for a green image and following the company's environmental strategy.

Moreover, it can be seen as an advantage to gather all data centrally in one model instead of using two different datasets (i.e. performance data in DES and environmental data, such as energy consumption, in separate calculations). Uniting these data can reduce the risk of calculation errors and makes the model and calculations more suitable to adaption after changes in the production system. Consequently, the authors regard the combination of DES and LCA as a beneficial approach for similar future studies.

8 CONCLUSION

This thesis analyzed a brake disc production line at Volvo Cars Corporation in terms of environmental impact and performance. The environmental footprint of a brake disc has been determined and a detailed dominance analysis of the contributing factors has been made. Furthermore, productivity losses have been identified and their improvement potentials have been assessed. Based on the findings, ideas for improvement both of environmental impact and performance have been presented. Finally, ideas for reducing energy consumption have been given.

The environmental impact calculations resulted in an impact of about 15-20 kg CO_2-equivalents per brake disc, dependent on the variant. The analysis showed that raw material accounts for the major part of the impact. At the same time, decision makers in manufacturing rather have an influence on scrap rate, supply transports and energy consumption. This thesis recommends an interdisciplinary cooperation between manufacturing, logistics and product development to make use of improvement potentials for environmental impact.

A dominance analysis for different product variants revealed that energy consumption has a very low variance and is almost the same for all variants. The main difference in impact can be attributed to different weights of the variants. Furthermore, different location of suppliers leads to deviating impacts of transport.

The performance analysis identified OP30 as a bottleneck, alongside with other constraints and revealed three areas of productivity losses: cycle time of OP30, buffer capacity after OP30 and machine availability for OP30, its downstream machines and the conveyor. These areas offer great possibilities for improvements. The thesis recommends to not only work on cycle times, but also on the other areas, especially buffer capacity between OP30 and OP40. An introduction of an extra buffer would increase productivity by 5%. Also improving availability of the bottleneck operation OP30 and the conveyor is particularly beneficial, generating 1% higher output per increased availability percentage per machine. When working on all three areas, Volvo could increase their productivity by at least 10-12%, dependent on which changes are made.

Besides the parameters quantitatively analyzed through simulation experiments, also other qualitative factors influencing productivity have been identified. Particularly the reporting of machine breakdowns is in need for improvement, affecting planning through not reliable statistics. Furthermore it is recommended to further investigate machine stoppages.

The performed analyses provide Volvo Cars Corporation with deeper insight in their brake disc production by revealing problems, quantifying improvement potentials and assessing the environmental impact of a product. The presented ideas for improvement offer a basis for discussion that can eventually lead to a further development of the production and the environmental impact. Thus, this thesis contributes to a path towards environmental and economic sustainability.

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APPENDIX

A Process description

OP05 - Picking Robot

The cast iron blanks are stored in pallets, either packed randomly ("chaos-packed") or packed following a pattern ("non-chaos-packed"), depending on which provider they are shipped from. When a pallet is placed in the right position, a picking robot equipped with an electro magnet takes the components out of the loaded pallet (unit by unit) and places them on a conveyor. For each cycle the robot searches the pallet until it finds a brake disc to lift which might take a different amount of time depending on if the pallet is chaos-packed or not. In addition, the components may have different orientations (up or down) when placed on the conveyor, and therefore a flipping device on the conveyor flips the part after placement if necessary.

OP10/OP20 - Rough turning

In this phase, the product is shaped by cutting away parts of the geometry on both sides of the disc. The machine is a two-chamber automated turning station, operating on one product in each chamber simultaneously. Loading and unloading is done by a picking robot with a tool that can handle two products at the same time. On top of the machine there is also a flipping device.

This is a parallel process with two identical machines and robots. If one of the machines is down, the other machine can still work. The conveyor splits into two lanes before the first machine and is united again after the engraving operation (OP25).

OP25 - engraving

Information about the part is engraved on the surface. The conveyor runs through the machine, and there is one machine on each of the two tracks.

OP30 - drilling

Several holes are drilled into the disc. The machine has a multi-tool head, so that all holes can be drilled at the same time. The tool configuration is specific for the different variants. All variants have 5 holes, some of the variants have one additional countersink hole which is drilled in sequence after the first five holes.

OP40 - fine turning

The geometry is shaped in detail to meet the dimension and surface quality requirements. This is a parallel process with two machines, placed in a serial layout. The logic deciding which machine is entered by the part is as follows:

- If machine 1 is empty, the part enters it.
- If machine 1 is full and machine 2 empty, the part enters machine 2.
- If both machines are full, the part waits on the conveyor before machine 1.

The conveyor in the machines has a bypass function, which means that it can pass the machine without being picked up for processing. Parts always enter one machine for processing and bypass the other. As in OP10/OP20 the line can still run if one of the machines is down.

OP50 - measuring

Several measurements of the part are taken and logged automatically. If tolerance limits are exceeded, the part is scrap and taken out of the flow. The space for scrapped parts is limited and has to be emptied by the operator from time to time.

OP60 - balancing

The part is turned at a high rate and the part is tested for rotation imbalance. Small corrections to balance are made by milling a slot on the outer surface in the unbalanced region. This may be repeated until the wanted balance is reached. The pick and place device in the machine has a capacity of two parts, so that parts can be swapped directly (one processed part and one waiting part on the head).

OP70 - Visual control and packaging

This is the only manual workstation in the process. The part is lifted on an automated lifting tool and visually inspected for material defects. Acknowledged parts are put into a finished products pallet, and failed parts into a scrap pallet.

Conveyor system

The conveyor system consists of several straight lanes, pushers, elevators and splitters. Most of it is accumulating, only the section from OP60 to OP70 is non-accumulating.

After the process - painting

An anti-corrosive painting is applied to several areas of the surface. The parts flow through the painting system on a conveyor. The path is cyclic; entrance and exit are in the same area. Parts are transported from the production line to the painting area via a forklift.

B Cycle times and distributions

Variants	OP05	OP10:1	OP20:1	OP10:2	OP20:2	OP25	OP30	OP40:1	OP40:2	OP50	OP60
1009091	lognorm(15.8,1.42)	Uniform (36.02,42.5)	37.5	Uniform (38.98, 41.84)	39.2	30.1	25.0	28.2	30.3	17.2	lognorm(17.28,1.12)
1009094							28.1				lognorm(19.34,0.99)
1009092		Uniform (31.92, 38.5)	34.0	Uniform (33.54, 36.28)	35.7		28.0	26.6	28.4		lognorm(19.93,1)
1009098							23.1				lognorm(17.8,1.07)
1009093		Uniform (35.65,41.6)	35.3	Uniform (38.26, 40.85)	33.4		28.2	29.5	28.1		lognorm(18.81,1.21)
1009099							23.5				lognorm(17.44,1.3)
1009095	lognorm(17.9,1.074)	Uniform (36.94, 43.94)	34.5	Uniform (39.32, 41.7)	37.0		26.1	30.5	30.9		lognorm(17.56,1.28)
1009096		Uniform (30.21, 36.0)	37.8	Uniform (32.87, 34.93)	42.6		29.8	25.3	27.1		lognorm(20.43,1.72)

	OP05	OP10:1	OP20:1	OP10:2	OP20:2	OP25	OP30	OP40:1	OP40:2	OP50	OP60
Loading (added)								18.2	14.7	4.4	4.8
Loading (included)						18.3	9.2				

	OP05	OP10:1 / OP20:1	OP10:2 / OP20:2	OP25	OP30	OP40:1	OP40:2	OP50	OP60
MDT [h]	0.12	0.33	0.29	0.32	0.17	0.69	0.46	0.19	0.22
MTBF [h]	2.94	21.50	10.79	12.84	4.42	18.83	17.92	5.60	4.30
Availability	0.96	0.98	0.97	0.97	0.96	0.96	0.97	0.97	0.95

	OP70	Conveyor
MDT [h]	0.23	0.60
MTBF [h]	191.10	16.38
Availability	1.00	0.96

C Power levels

All values are given in kW.

	Idle	Loading	Processing
OP10	2.35	10.89	
OP20	2.35	10.89	
OP30	4.64	4.69	10.07
OP40	7.56	8.26	13.84
OP60	2.80	3.79	3.88

Constant:

OP05	0.90	
conv. OP05-OP30	2.55	
Elevators (each)	0.48	
Robot OP1020	1.04	3.11
OP25	1.70	

D Transportation distances

From	To	Type of transport	Distance (km)
Fritz Winter, Stadtallendorf	Gothenburg	Train	1100
	Travemünde	Trailer 25 tonnes	460
Schwäbische Hüttenwerke, Tuttlingen-Ludwigstal	Gothenburg	Train	1400
	Travemünde	Trailer 25 tonnes	850
Travemünde	Gothenburg	Boat	500
Volvo Powertrain, Skövde	Floby	Truck + trailer, 37 tonnes	50
Gothenburg	Floby	Trailer 25 tonnes	110

E Allocated energy consumption and from painting process

All consumptions expressed in kWh per brake disc.

<table>
<tr><th></th><th colspan="4">From simulation</th><th colspan="3">Static, pre-allocated</th><th></th></tr>
<tr><th></th><th>Idle</th><th>Scrap</th><th>Setup</th><th>Subtotal</th><th>Overhead + compressed air</th><th>Painting</th><th>Subtotal</th><th>Total</th></tr>
<tr><td>1009091</td><td rowspan="8">0.128</td><td rowspan="8">0.006</td><td rowspan="8">0.019</td><td rowspan="8">0.153</td><td rowspan="8">0.38958</td><td>0.04917</td><td>0.43875</td><td>0.59157</td></tr>
<tr><td>1009092</td><td>0.04583</td><td>0.43541</td><td>0.58824</td></tr>
<tr><td>1009093</td><td>0.05833</td><td>0.44791</td><td>0.60074</td></tr>
<tr><td>1009094</td><td>0.04917</td><td>0.43875</td><td>0.59157</td></tr>
<tr><td>1009095</td><td>0.05000</td><td>0.43958</td><td>0.59241</td></tr>
<tr><td>1009096</td><td>0.04583</td><td>0.43541</td><td>0.58824</td></tr>
<tr><td>1009098</td><td>0.04583</td><td>0.43541</td><td>0.58824</td></tr>
<tr><td>1009099</td><td>0.05833</td><td>0.44791</td><td>0.60074</td></tr>
</table>

Allocations from simulation are calculated from total consumptions via the number of produced brake discs per variant. Overhead and compressed air have been allocated from the factory level using the share of area of the brake disc production (3.5%). Painting energy is based on two inductors with a power of 50kW that are heated 6 seconds each. The inductors are only driven at a part of their maximum power. The calculations are shown below.

Variant	**Inductor 1**	**Inductor 2**	**Energy**
92/98	0.3	0.25	0.0458 kWh
93/99	0.4	0.3	0.0583 kWh
94/91	0.22	0.37	0.0492 kWh
95	0.25	0.35	0.0500 kWh
96	0.3	0.25	0.0458 kWh

F Verification and validation of energy consumption calculation

VERIFICATION

RESULT	kWh/MU	Total kWh calculated
theoretical	0.52673	303,813
via MU stats	0.52469	302,639
via OP stats	0.52193	301,049

	Delta / MU	Total Delta	%
MU stats - theory	-0.00204	-1,174	**-0.39%**
OP stats - MU stats	-0.00276	-1,590	**-0.53%**

VALIDATION

factory consumption	25,983,174 kWh
proportion brake discs	3.51%
Consumption via area	912,009 kWh
Calculated consumption	739,396 kWh
TPh ratio model/real world	1.20
Adapted consumption	887,275 kWh
Deviation	**-2.71%**

For validation, the total consumption is calculated first via area and factory consumption from the real world, then from simulation. As the simulation model produces at a higher rate than the real system, the production time needs to be factorized to the real production time; thus also the energy consumption is adapted to make the values comparable for validation.

G Weight of each variant

All weights are shown in kilograms.

Variant	Raw material	Finished product	Chips
1009091	12.60	8.54	4.06
1009092	9.50	6.46	3.04
1009093	11.08	7.4	3.68
1009094	12.60	8.54	4.06
1009095	12.19	8.77	3.42
1009096	9.90	7.06	2.84
1009098	9.5	6.46	3.04
1009099	11.08	7.4	3.68

H Decision makers' influence on contributors

Contributor		**Parameter**	**Decision**	**Decision maker**
Material	finished product	type of material	choice of material	product design
Material	scrap	amount	scrap rate	manufacturing
Material	chips	amount	removed material	product design
Transports	finished product	weight	choice of material	product design
Transports	finished product	distance	choice of supplier	logistics & purchasing
Transports	scrap	density	choice of material	product design
Transports	scrap	amount	scrap rate	manufacturing
Transports	scrap	distance	choice of supplier	logistics & purchasing
Transports	chips	density	choice of material, removed material	product design
Transports	chips	distance	choice of supplier	logistics & purchasing
Electricity	finished product	process	process optimization	manufacturing
Electricity	scrap	amount	scrap rate	manufacturing
Electricity	factory	other processes	other	other
Paint	finished product	type and amount	design of paint	product design