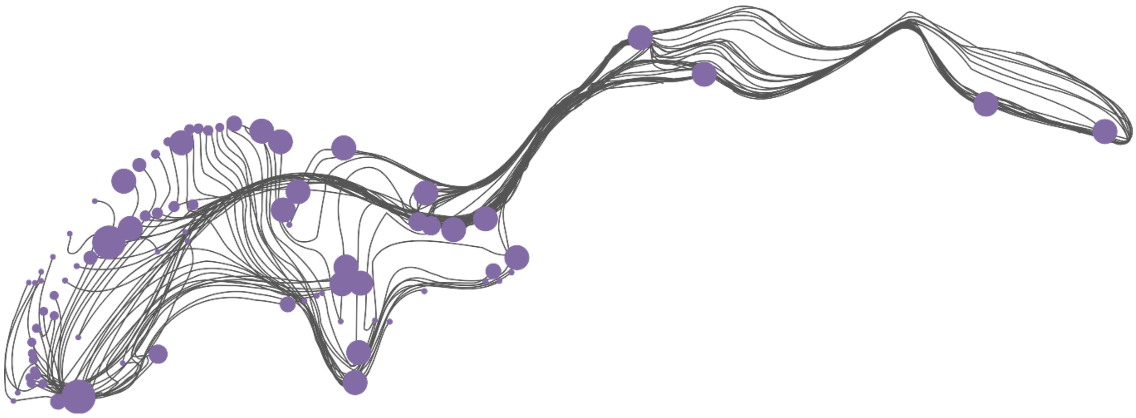

UNIVERSITY OF TWENTE

MASTER THESIS

Improving the supply chain at Twence Hengelo

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Management Summary

Twence is a company that produces raw materials and energy from waste and biomass. The costs of not providing energy is significantly high, so it is important that Twence always produces at 100% of their capacity. Since the economic crisis, the waste market became more unpredictable. This made Twence decide that a big bulk storage called TOP should be constructed to ensure producing at maximum capacity. Now, a couple of years later, the supply of waste is stable and Twence still has a lot of stock in TOP.

The objective of this research is to give Twence more insight into their supply chain. Twence suspects that the amount of stock in TOP is too high and since the waste in stock needs to be produced within three years, TOP also leads to a lot of costs. The objective of the research is translated to the following main research question:

How can Twence improve their internal supply chain in order to optimize the performances of their processes, while minimizing the costs of idle time of the machines and of internal transport?

Current situation and research approach
This research starts with an analysis of the current situation at Twence. We find that, over an entire year, the TOP inventory stays almost constant and the total supply of waste fits with the requirements. However, the daily pattern shows that the daily supply of waste is unpredictable and thus, the risk arises that there is not enough supply of waste to the buffers of the incineration lines. Deciding to use TOP for diverting or retrieving waste is based on human estimation, whether the buffer for the incinerator contains too much or too little waste. On a daily basis, the requirements for Twence to continue processing the entire day, consist of the amount of waste that can be incinerated in a day. We find that this amount correlates with the calorific value of the waste. We suggest that the supply of waste, as well as decisions about diverting or retrieving waste can be made based on calorific value of waste. We find an equation that determines the processing time for a given amount of mass of waste with a given calorific value. A literature study is performed in which we find the model of Obroučka et al. (2015), which is suitable for composing batches of waste to retrieve based on the calorific value.

We set up different decision structures about diverting and retrieving waste, which we then implement in our simulation model. Experimental factors we vary are:

- Amount of TOP capacity. When selecting a TOP capacity, we make the assumption that the initial TOP inventory is 80% of the capacity.
- Contract restrictions. Clients are restricted to supply within a specified margin, based on either the mass, calorific value or processing time of waste.
- Decision conditions. The decisions conditions currently only include mass, so the level of waste in the buffer is expressed in mass. We examine the effect when calorific value is also included, such that the level of waste in the buffer can be expressed in processing time.

- The buffer levels on which diverting or retrieving needs to be done. We vary with low and high thresholds to determine when to retrieve or divert.

Results
When keeping contract restrictions and decision conditions similar to the current situation, we find that increasing the buffer levels, at which retrieving should be done, from 15% for both buffer 1+2 and buffer 3 to 45% for buffer 1+2 and 20-25% for buffer 3, and decreasing the TOP inventory from 80 Kton to 32 Kton, leads to an average costs per week of €3.283,27, where in the current situation these costs are €10.414,81 (savings of 67%). Even lower costs can be attained when Twence restricts the clients not only on the mass, but also on the calorific value, by means of restricting to a margin on the supplied processing time. The TOP inventory could then be even lower (5 Kton capacity, 4 Kton average inventory), which would lead to costs per week of €2.440,17 (savings of 75%).

We perform a sensitivity analysis to examine the impact of several assumptions we made. From our results we find that 40 Kton is the optimal TOP capacity when given the choice between 5, 40 or 80 Kton. We find that the costs per week could be lower when choosing a TOP capacity that was not within the experimental factors: a 25 Kton TOP capacity yields the lowest costs per week.

Twence has another incinerator just for biomass, which consists mainly of wood already on specification and unbroken wood that needs to be made to specifications first at extra costs. The current costs per week of the biomass incinerator are €28.095,14 (validated in the model as €27.775,19). We find that with the changes of: (i) increasing the buffer level from 15% to 25%, (ii) including calorific value in the decision conditions, (iii) lowering the woodbank capacity (TOP for biomass) to 15 Kton, and (iv) increasing the ratio of wood on specifications versus unbroken wood to 3:1, costs per week of €21.566,84 can be attained. This would be a reduction of almost 23%.

Conclusions and recommendations
We conclude that Twence could save up to 67% and 23% on the costs per week for respectively the waste and wood incinerator. These cost reductions seem large, but this is mainly caused by the fact that with a lower TOP inventory and a higher minimum buffer level, there is less need for retrieving and less risk on idle time. In our model we assume that the clients of Twence respect the allowed margin of ±10% for the weekly supplies. Currently, this is not the case, so already a large part of the cost savings can be achieved by making the clients respect the allowed margins.

The current TOP inventory of 90 Kton should be reduced to about 20 Kton, when Twence keeps the contract restrictions purely on the mass of the waste. Twence should perform more research on how the calorific value of waste can be more easily determined. Currently this is only done after incineration, but when it is possible to determine this clearly before incineration, Twence should put restrictions in the contracts on the calorific value as well, such that the processing time can be better controlled and cost savings can be increased for the waste incinerator up to 75%. The TOP inventory can then be reduced even further to about 16 Kton.

List of Abbreviations

AEC	Waste Energy Plant
BEC	Biomass Energy Plant
Calo	Calorific value of waste/biomass (in KJ/h)
Kton	Kilo ton (1000 tons)
M&S	Marketing and Sales department
Mass	Mass of waste/biomass (in tons)
TOP	Temporary Storage
TAS	Twence Waste Sorting

Preface

About 7 years ago I set foot in Enschede to start my study. Although it took me a while to figure out what I really wanted, I enjoyed every moment of it. I started out with a bachelor Applied Mathematics, but soon I switched to the bachelor Industrial Engineering and Management, which was more up my alley. After completing the bachelor within three years, the next step was to gain a master's degree. For my master I decided to do the Industrial Engineering and Management master as well, following the Production and Logistics Management track. This journey took me to the place where I am now, behind my desk finishing my master thesis.

When searching for a graduation assignment, I came across some interesting projects guided by Martijn Mes. Surprisingly none of these projects made the cut, since Martijn introduced me to a company called Twence. A meeting was set up with me and the project leader at Twence who's name was, funny enough, also Albert. Together with a small project group at Twence, Albert Vos introduced me to this project and now 7 months later, the project no longer has any secrets for me.

At Twence, I started working in the project group together with Raymond ter Haar, Robert Reinders, Frank de Nobel and Albert Vos. They gave me a welcoming feeling and were open to any suggestions or questions that I had. Actually this applied to the entire company, since all new people I met, gave me the same feeling.

Throughout the entire project, a lot of support was provided by Martijn Mes and Matthieu van der Heijden from the University, but also from Twence I never felt left alone. Especially in the beginning of the project, it was hard to focus on specific goals, but thanks to all the support, I eventually succeeded in doing so.

Lastly, I want to thank my friends and family for all their support and encouragement. Not only for the time during this project but throughout all the years of studying here in Twente. Marlies in particular, you probably will not believe me, but without you, I do not think I would have made it this far.

A lot of effort and hours are put into this report, so I hope you enjoy reading it.

September 2016, Hengelo
Albert Leijenhorst

Contents

1 | Introduction

In this chapter, we introduce the main problems that are treated in this thesis. First the motivation for this research is discussed in Section 1.1, followed by the problem statement in Section 1.2. After that, we state our project goal (Section 1.3) and research questions (Section 1.4). At the end of this chapter, we discuss the scope of the project in Section 1.5 and our approach in Section 1.6.

1.1 Motivation

Twence is a company that produces raw materials and energy from waste and biomass. They contribute to reducing CO2 emissions, reintroducing raw materials, and reducing the use of fossil fuels. They extract raw materials from waste supplied by customers in the Netherlands, Germany and the United Kingdom. There are therefore customers that sign a contract with Twence to get rid of their waste and biomass but also customers that sign a contract for buying energy.

In 2011, Twence made the decision to start a project called "Waste Mining". Due to the economic crisis, the expectation was that the supply of waste could be in danger, which would lead to stagnant machinery. It would be beneficial for Twence to ensure supply by digging up waste from landfills. Twence has a lot of space available for storage, so a plan was made to dig up waste in order to gain inventory. This provided Twence with security about the supply of raw materials for their processes.

Twence now has about 100 kilo tons (Kton) of waste in their bulk storage, enough for almost 60 days of processing without supply. Because of rules and regulations, all waste that is in storage can only be kept there for at most 3 years. This roughly means that in a year on average 33 Kton waste needs to be retrieved from storage. This causes a lot of costs and Twence does not know if these costs outweigh the benefits of having this amount of inventory. They wonder whether they could work with, for example, half of their current amount of bulk storage or even without it. In this study, we therefore explore the effects of these different scenarios.

1.2 Problem Statement

First of all it is important to understand the current way of working at Twence. In Section 1.2.1 we describe the waste flows and give more insight in the physical movements of the waste. After that we explain more about the quality of waste in Section 1.2.2. In Section 1.2.3 we conclude the problem statement in which we state the main topic of this research.

1.2.1 Waste flows

There are several types of waste arriving at Twence. In this research we focus on the largest stream, the combustible waste.

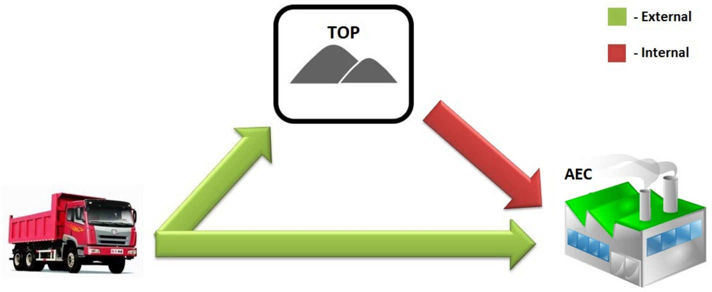


Figure 1.1: Flow from waste to AEC

In Figure 1.1 we see the path that combustible waste follows when arriving at Twence. A truck arrives at Twence where it is weighed in. Next the truck gets directions towards either the Waste Energy Plant (AEC) or the Temporary Storage (TOP). When the buffer of the AEC has room, the truck is sent to the AEC to drop the waste in the buffer. If the buffer is full, the truck needs to be diverted and delivers its waste at the TOP, which serves as bulk storage.

The most cost effective route for Twence is when the client is sent directly towards the AEC. This is because the client then pays for the transportation to the machines. When clients are diverted to TOP, Twence eventually has to transport the waste from TOP to the AEC themselves, which leads to internal transport (red arrow in Figure 1.1) with associated costs. The probability of the occurrence of these costs need to be taken into consideration when making decisions about contracting supply. When the supply is more than the requirements it could be the case that the waste of many clients end up in the bulk storage, which leads to additional costs.

1.2.2 Quality

The waste that Twence processes is used for generating energy. This process works best when the incineration is done as constant as possible. This can be achieved by having a constant homogeneous mix of waste. The characteristics of the waste that influence the incineration process can be seen as the quality of the waste.

To give an example, waste with high moisture content is more difficult to incinerate. This is because of the fact that it takes a lot of energy to evaporate the water from the waste. This means that when trying to incinerate wet waste, the fire is not as powerful as with incinerating dry waste. Therefore, more waste is needed to maintain the same level of fire power as when having waste with low moisture content. These characteristics of waste need to be taken into consideration when making a decision about which waste to incinerate. Seasonal effects could be that waste, that is stored at the bulk-storage, gets wet from rain. The waste still needs to be incinerated, so Twence needs to make decisions about what mixture of high and low quality raw material is needed in order to achieve a constant performance level. It is not only the opinion of Twence, but also our opinion that a lot can be gained from making decisions based on the calorific value of the waste.

1.2.3 Problem

The way in which decisions are made, on what ground they are made, and when they are made are key factors in this research. Twence diverts almost 12% of their supplies to the bulk storage, and is currently making decisions only based on quantities. Together with the amount of supplies that already lies in bulk storage, this results in an average storage costs of €600.000 per year including the costs for the storage location, diverting, and retrieving. In order to reduce the amount of supplies that need to be diverted to the bulk storage, Twence could stop accepting new contracts. However, a trade off needs to be made between having costs for diverting supplies, or having the risk of costs for stagnant machines. When decisions are also based on the quality of the supplies, the percentage of diverted supplies could be even higher, because a perfect mix of different qualities of waste could be more important than the costs for diverting. These trade-offs are examined in this research in order to give Twence more insight in their supply chain and current way of working.

1.3 Project Goal

In the section about the motivation for this research we reflected upon the amount of inventory that Twence holds. This leads to additional costs from transporting the waste to the machines. The question is whether it is worth to have assurance of supply if this leads to high costs.

Apart from retrieval of waste due to rules and regulations, also a mismatch between supply and requirements is a cause of costs for transporting supplies to the machines. The amount of supply that is contracted should closely follow from the given requirements, otherwise the AEC can not process the amount of incoming waste and Twence is forced to redirect the arriving supplies.

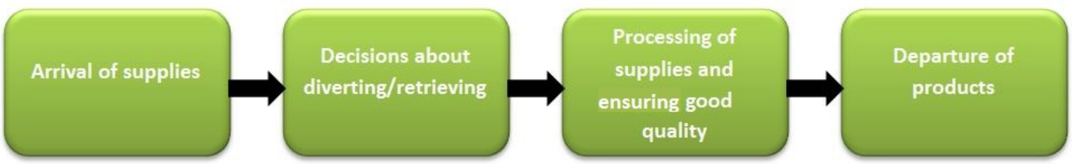


Figure 1.2: Twence Supply Chain

Twence wants to gain more insight in the supply chain, which is defined in Figure 1.2. To achieve this, Twence has set up the following project goal:

"Analyse the current supply chain elements and design interventions to achieve an efficient and cost effective supply chain, which is characterized by clear decision making, effective planning, optimal inventory control, and good quality performances."

To determine what kind of interventions need to be made, we need to analyze all decisions that are made in this supply chain. When all these decisions are clear, a model can be designed to give insight into the effects that these decisions have.

By cost effective we mean that we want to minimize the costs, given the choices Twence makes. This involves the costs that are made as a consequence of the decisions made. So when Twence decides that it wants to operate without bulk storage, the costs that occur due to stagnant machines should be minimized. When they do make use of bulk storage for combustible waste, they want to minimize the costs regarding the replenishment from bulk storage.

For this research we derive a more tangible project goal based on the goal set by Twence, which is the following:

Analyze the decisions that are involved with diverting and retrieving waste and provide insight about how Twence can improve their internal supply chain while minimizing costs.

From the project goal, we derive a couple of performance indicators. These are summarized in our research goal by stating that costs need to be minimized. All performance indicators in the goal of Twence can be reduced to minimizing costs. An effective planning ensures that there is always enough supply as is required. When this does not match, costs arise. The same holds for the term optimal inventory control. Goal of this research is therefor to provide insight into the trade-offs that need to be made while taking into account the costs that arise with each decision made.

1.4 Research Questions

To keep focus on the project goal, we formulate research questions. First we state our main research question:

How can Twence improve their internal supply chain in order to optimize the performances of their processes, while minimizing the costs of idle time of the machines and of internal transport?

We formulate the following subquestions in order to provide a good answer to the main research question. All these subquestions are answered in a separate chapter.

1. What is the current situation of the internal supply chain at Twence?
   In the Chapter 2, we discuss the current situation. We describe the different

processes at Twence. We state which decisions are made and who are responsible for these decisions. The performance of different processes is shown as well as the effects of having a large inventory.

2. What can be found in academic literature to support this research?
   In the academic literature a lot can be found about supply chain performances. We perform a search regarding the available academic literature about optimal inventory control in combination with waste processing in Chapter 3.

3. What models can we construct that support optimal decision making?
   With a well-structured model, we provide insight in the logical steps that need to be made while taking decisions. In Chapter 4, we design a conceptual model of which the results are evaluated later on.

4. What are possible interventions to improve the internal supply chain?
   In Chapter 5, we design different scenarios that involve changes in the way of planning and variation in the size of the bulk storage. Possible interventions are that the quality of the waste should be included in the planning or that the bulk storage is not used, such that deliveries should be just-in-time.

5. What performance can be expected when using the designed model and proposed interventions versus the current performance?
   We evaluate different scenarios by means of programmed version of our model in Chapter 6. We make conclusions about the proposed interventions and perform a sensitivity analysis.

6. How can we use these findings in order to improve similar entities at Twence, such as the Biomass Energy Plant?
   For clarity of our research, the Waste Energy Plant is the main point of attention. We adapt our model to fit with this other entity . We evaluate this in a separate case study about the Biomass Energy Plant in Chapter 7.

7. How can Twence implement these interventions in their current supply chain?
   To make sure the proposed interventions are correctly implemented, we provide suggestions about how Twence can adopt these interventions and fit them into their current supply chain in Chapter 8.

1.5 Scope

To clarify the scope of this research, we first give a simplified illustration of the internal waste flows in Figure 1.3.

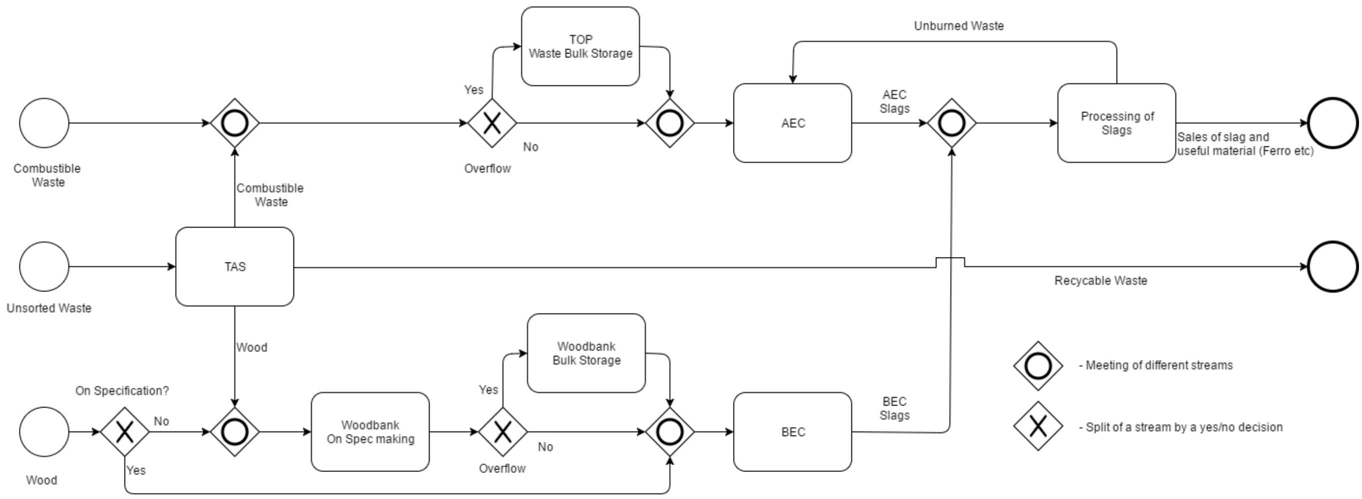


Figure 1.3: Internal waste flows of Twence simplified, based on (Nijkamp, 2016)

In Figure 1.3 we see 3 incoming waste flows from the left, namely:

- Waste supply for the Waste Energy Plant (AEC)
- Unsorted waste for Twence Waste Sorting (TAS)
- Wood supply for the Biomass Energy Plant (BEC)

These are the largest incoming supply flows. The waste supply for the AEC is the included in our scope and is the main subject of this research. The wood supply for the BEC is discussed in a separate case study conducted after the main research. The unsorted waste flow is not included in our scope. As output from the TAS there are the sorted recyclable materials, of which some is also wood and combustible waste as output. The TAS therefore functions as an internal supplier for the AEC and BEC. For this research we focus on all incoming waste flows towards the AEC, which means that the output of the TAS is taken as given and will be added to the total supplied amount of waste for the AEC.

The processes in the main entity, the AEC, will mostly be seen as a black box operation. As discussed earlier in Section 1.2.2, the quality of the waste and influences the process. The quality influences the throughput that can be achieved in the AEC. This corresponds with the third block of the supply chain seen in Figure 1.2. We do not take into account all the supplementary products that need to be added to execute the process, but we treat the entity such that we have supply going in, and products coming out, not caring about what the precise operation in the entity itself is. The only thing we focus on, is the effect that the quality of the raw materials has on the process time. When it would be the case that some outcomes will have a positive effect on the lifetime of the incinerator or on the efficiency of the process in terms of supplementary products, this will only influence the results in a case of almost equal costs.

For the arrival of supplies, the original intention is to not take into account the time of arrival. Twence does not want to work with time-slots, therefore, we only look at the arrivals on a daily basis. The amount per day can be regulated in some cases by the Marketing and Sales department (M&S) and it is interesting to see what effects this could have.

The last part of our scope is about the planning process, which refers to the second block in Figure 1.2. Here decisions are made about the supply for that day or week and we focus on optimizing this process. These decisions are defined as short-term decisions. We might also need to look at the long-term decisions, since these provide the room that clients have to deviate from their agreed deliveries. We explain this extensively in Section 2.3.

The degradation of the machinery, due to the consistency of the raw materials, is something that is out of the scope of this research. Also the transportation of the outgoing products, for example energy or heat is out of the scope of this research. This is because it is not possible to make changes in the way of transporting these without making costly changes. We do look at the quality of the raw material which should be at a certain level such that good quality outgoing products are ensured.

Summarizing, the following subjects are included in the scope of this research:

- Incoming supply of combustible waste.
- Decisions regarding:
    - Choice of incineration line.
    - Retrieving/Diverting supply.
    - Deviation agreements in contracts.
    - Capacity of bulk storage.
    - Taking quality into account.

The following subjects are out of the scope of this research:

- Specific arrival times of incoming supply during a day.
- Incoming supply of unsorted waste.
- Incoming supply of biomass. (Separate Case study)
- Degradation of machinery.
- Outgoing products.
- Financial rates in contracts.
- Exact working of the incinerators (incl: Supplementary materials).

1.6 Research Approach

The main goal of this research is to provide insight about how Twence can optimize their supply chain. In order to achieve an optimal solution, a lot of possibilities should be taken under consideration. A lot of factors are taken into account in the current decisions-making process, but for example quality is a factor that is not one of them. In this research, we aim to give an overview of all major factors that can play a role in the decision-making at Twence and how they influence their supply chain in order to find an optimal situation.

Our research starts with the gathering of data about the current performance and which decisions play a key role in the decision making, which is presented in Chapter 2. After that we perform a literature study in Chapter 3 about how typical characteristics in the waste energy management influence the process, which inventory control models are available, and what types of models are suitable for this type of research. We present a conceptual model in Chapter 4, which is followed by Chapter 5, in which we program our conceptual model and design our experiments. In Chapter 6 we present our numerical results and analyze our findings. In Chapter 7, we follow up with a case study about the other main entity of Twence, the BEC.

In our case, we are dealing with a lot of information and a lot of relations, which makes it difficult to use a mathematical model without becoming too complex. Simulation models have the advantage that input can be easily generated and different experiments can be modeled with few alterations. Because we want to find what the influence is of the different factors that play a role in the decision-making, we need to analyze a lot of different possibilities whereby we constantly make the decisions depend on different combinations of factors. To achieve a clear overview of the effects of all major factors that play a role in the decision-making, we use discrete-event simulation. Law and Kelton (2000) state that discrete-event simulation concerns the modeling of a system as it evolves over time by a representation in which the state variables change instantaneously at separate points in time, which is a suitable choice for modeling our situation.

2 | Current Situation

To get more acquainted with the different operations that take place at Twence, we start the chapter with a brief process description in Section 2.1, where we discuss what happens when supplies arrive at Twence. A more detailed explanation about the different facilities can be found in Appendix A. After the process description we discuss the current performance on different areas in Section 2.2. We end this chapter with Section 2.3, where we discuss different decisions that are made regarding the supply chain at Twence.

2.1 Process description

Before analyzing the current situation we first describe the processes that occur at Twence regarding the supply chain. We pretend we are tagging along with a delivery which will go through all the steps, starting from the point where it leaves the client.

When a delivery arives at Twence it must first be weighed and some information must be given at the entrance checkpoint. At that point, Twence just knows three things, namely: the amount, the type of supply (combustible waste, unsorted waste, etc.), and the client who supplies. In this case, we assume that we are following a delivery of combustible waste. In a pre-assignment plan is written on which incineration line the deliveries of a certain client need to be incinerated. So regardless of the amount and quality of the current delivery, we are send to a certain incineration line. The delivery arrives at the incinerator, and is dumped in a buffer. A crane mixes all the waste that is currently in the buffer. The crane drops the waste into a funnel where it is incinerated. A schematic view of this is given in Figure 2.1.

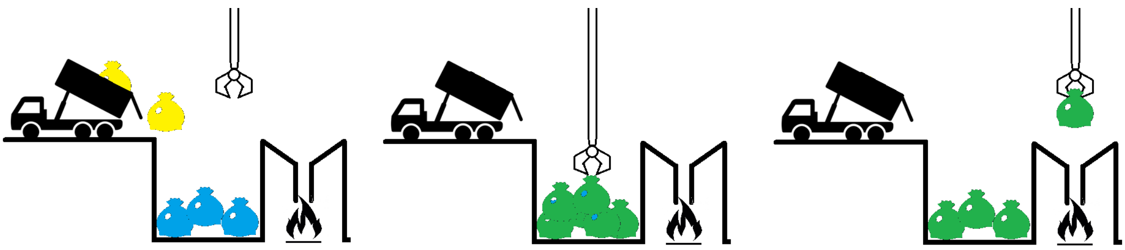


Figure 2.1: A schematic view of the journey to incineration

As said, in the plan it is stated which client is assigned to which incineration line. Sometimes on-line interventions need to be done in order prevent problems. If the amount of waste in the buffer of the incinerator (Figure 2.1) is above a certain level, things like mixing the waste and accepting all deliveries become impossible. In that case, the planner makes a modification in the plan and informs the checkpoint about this new plan. This could mean that only deliveries of a certain client need to be sent to another incineration line, or even to the bulk-storage. But this could also mean that deliveries of all clients need to be sent to bulk-storage.

When the buffer of an incinerator begins to run low, extra supply needs to be scheduled. The first option is, that clients from the other incineration line are scheduled on the low running line, in which case the checkpoint needs to be informed. The other option is that supply is retrieved from bulk storage, in which case the internal transport department needs to be informed. In the current situation it does not matter which option is chosen, and decisions are based on amounts and the limits of what is possible.

2.2 Supply chain performance

In the current situation, a number of things have influence on the performance. We discuss these in the same order as how the waste arrives at Twence. We start with client statistics in Section 2.2.1 followed by Section 2.2.2 about how good the supplies are matching with the requirements. After that, we discuss the inventory development of the last years at Twence (Section 2.2.3). Subsequently we review the related costs in Section 2.2.4.

In the current situation, decisions are not based on the quality of waste. Nevertheless, we finish the performance section by analyzing some quality factors of the current situation in Section 2.2.5.

2.2.1 Client Statistics

The supply chain of Twence starts with the clients that provide the supplies. Twence has a lot of different clients varying from small clients that deliver waste only once a month to large clients that deliver multiple batches of waste per day. We illustrate the distribution of these types of clients in Figure 2.2.

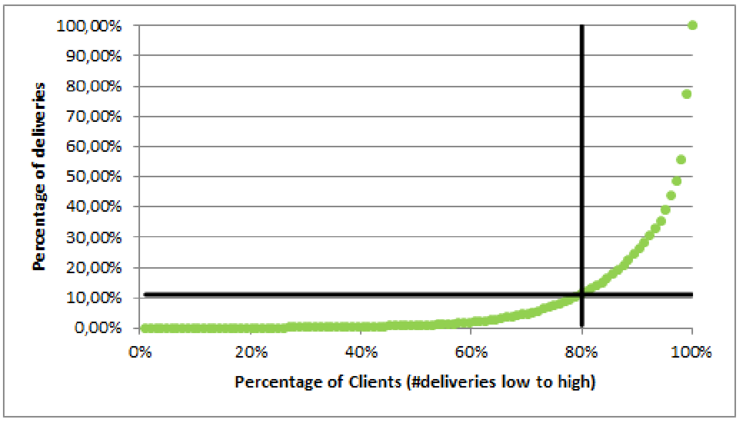
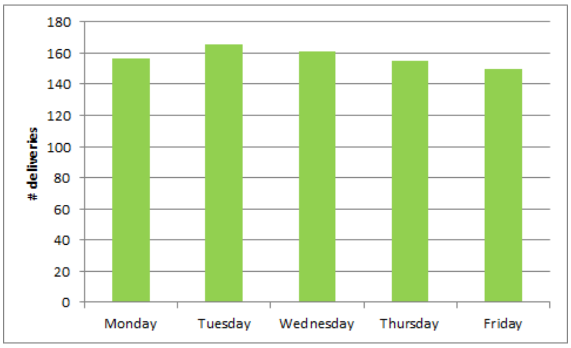
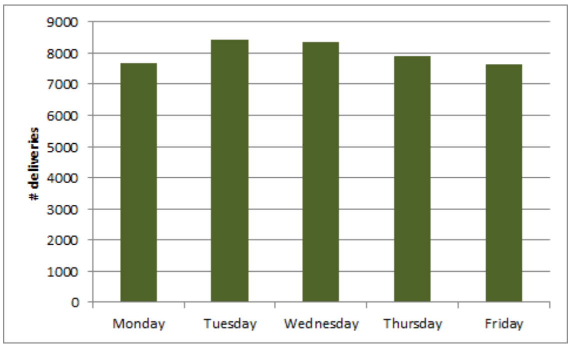


Figure 2.2: Distribution of small clients and large clients

We recognize the Pareto principle in this chart, because we can see that 20% of the clients provide 88,88% of the deliveries (35541 of 39982 deliveries) and even 92% of the volume. We are interested in which day of the week most of the deliveries take place. Because deliveries almost never take place in the weekend, we suspect that more deliveries take place at the beginning of each week. We show the results in Figure 2.3.



(a) Average number of deliveries



(b) Total number of deliveries

Figure 2.3: Amount of deliveries per day of the week

We see that, opposed to what we suspected, Monday is not the most popular day for the deliveries. Most deliveries are done on Tuesday and Wednesday. If we look at the five clients with the most deliveries in Table 2.1, these patterns also occur.

	Monday	Tuesday	Wednesday	Thursday	Friday
Twente Milieu N.V. HHA	18,5%	21,4%	20,6%	20,3%	19,2%
Avalex B.V.	19,1%	21,4%	22,0%	19,5%	17,9%
Seneca Environmental	20,7%	23,0%	20,1%	17,6%	18,6%
ATTERO B.V.	19,2%	19,4%	20,3%	21,4%	19,7%
Van Gansewinkel Nederland B.V.	18,9%	21,2%	19,1%	18,5%	22,3%
Average	19,31%	21,27%	20,41%	19,47%	19,54%

Table 2.1: Distribution of deliveries op the top 5 clients

We see that the differences are very small and the deliveries are almost equally divided over the weekdays.

2.2.2 Contracts versus Requirements

Matching the supplies of the clients with demand is important for Twence. In the first place, Twence does not want to have under-supply because this causes idle time in the incinerators. On the other hand, when Twence has structural over-supply, the holding costs of all those supplies increase rapidly. The effect that idle time in the incinerators and the amount of inventory has on the costs is discussed in Section 2.2.4. In this section we give an indication about how Twence has performed on matching the acquiring of contracts and thus supplies, with the requirements of the processing facilities in order to achieve maximum production.

In Figure 2.4 we see the combined chart of realized supplies and requirements.

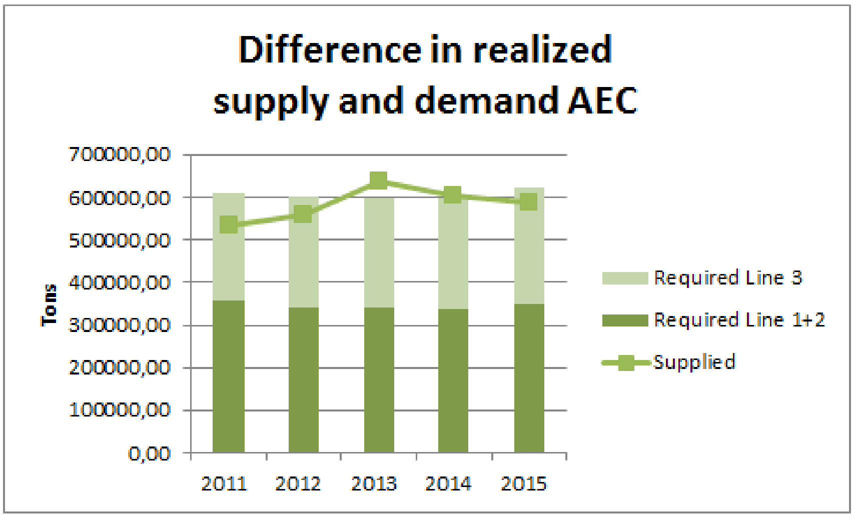
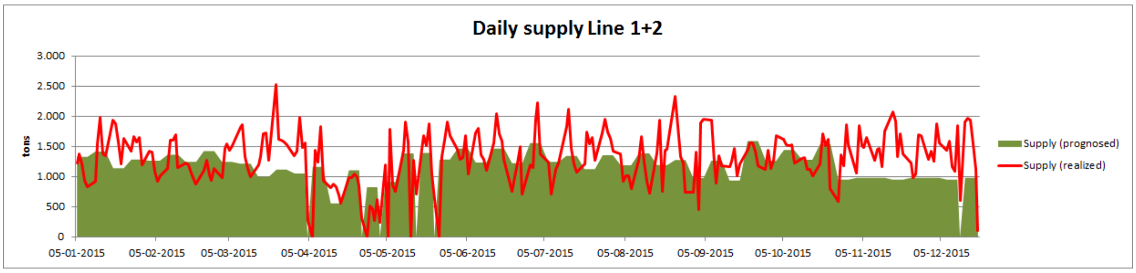


Figure 2.4: Realized differences at AEC

We see that over an entire year, the supplies and the requirements do not differ much from each other. However, this is after an entire year, so we can not see any fluctuations that happen during the year. In Figure 2.5 we show the daily supplies and how much the forecast was. These results are from the year 2015.



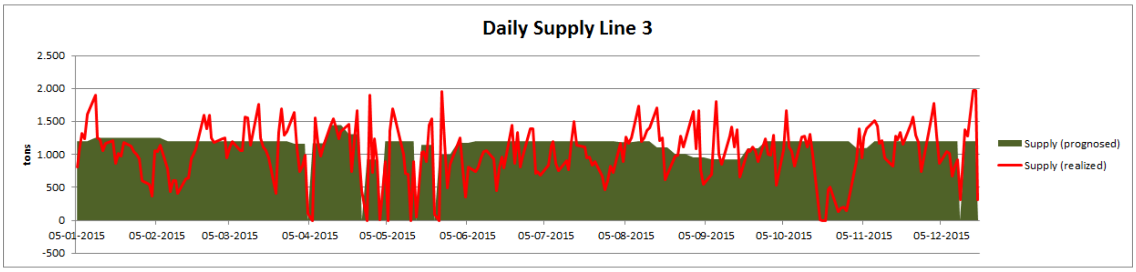
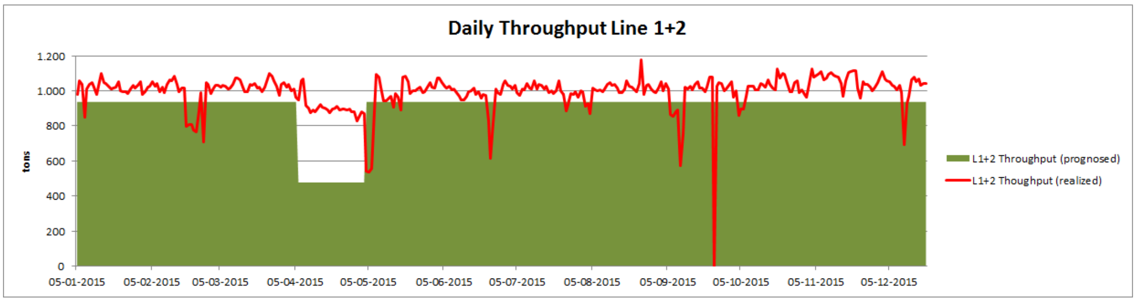


Figure 2.5: Daily Supplies (Twence BV, 2015)

If we zoom in on an entire year and look at the supply on a daily basis, we see a lot of deviation from the forecast. In Figure 2.5 we see the prognosed (based on contract agreements) and realized daily supply and we see that there is a reasonable amount of deviation. The big drops in supply can be explained by unscheduled stops that required the supply to stop. But apart from that, the amount of deviation in the regular periods results in a lot of work for the planner group that monitors the requirements and the supplies on a daily basis. The short term planning must be executed very precisely because of the fluctuation in supply. When the planner group does not take into account any form of safety margins, it could happen that the buffer of the AEC becomes empty and the incinerators stop working. Therefore, this research focuses on the improvement of the decisions that are made on the short term.

When we look at the requirements (i.e., throughput) shown in Figure 2.6, we notice that these are relatively stable. Again, the few interruptions that causes the throughput to drop to zero are due to short unscheduled stops.



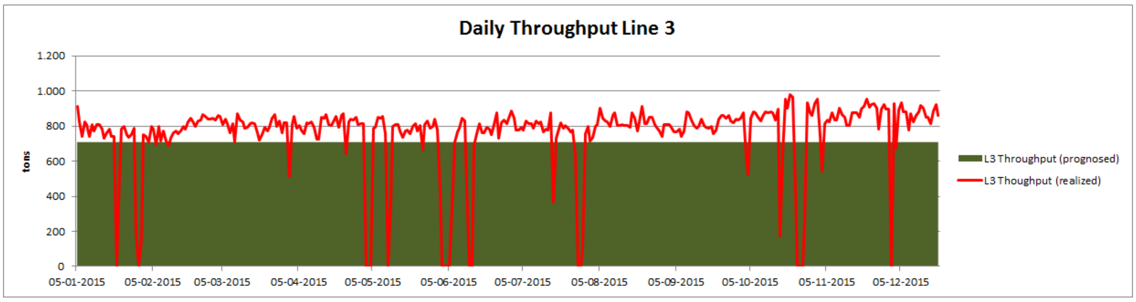


Figure 2.6: Daily Throughput of Line 1+2, and 3 (Twence BV, 2015)

The forecast for Lines 1+2 and 3 are straight lines and with the only exception that Line 1+2 is interrupted once due to a scheduled stop. Straight line forecasts have a big influence on the daily planning. If the forecast for the throughput indicates that on a daily basis 900 tons of waste is processed, but in reality line 1+2 processes 1000 tons per week, there is a shortage of 100 tons per day. This would lead to retrieval of waste from TOP, that could have been prevented by having a safety margin of waste in the buffer to cover the time it takes to adjust the amount of waste supplied by the clients.

2.2.3 Inventory development

One of the triggers for this research is the amount of inventory at Twence. In Table 2.2 information about the buffers and TOP is shown.

In Table 2.2, we see some figures about the possible levels of waste in the buffers. In the weekends, there will not be any external suppliers, so on Fridays at the end of the day, according to Numan (2013) the desired level in the buffers should be at

	Minimum	Maximum	Fridays
Buffer Line 1&2	1.500	5.500	4.500
Buffer Line 3	2.000	10.000	3.000
TOP	0	200.000	n.a.

Table 2.2: Capacities of TOP and buffers (Numan, 2013)

a minimum of respectively 4500, and 6000 tons for Line 1&2, and Line 3. The minimum of the buffers in the table is based on the daily throughput plus an additional 1000 tons. This is because the bottom layer in the buffer is of very bad quality and causes trouble when being incinerated, so it should be mixed with new waste. The maximum is based on the available space.

In the current situation, the minimum of the buffer is just for the daily throughput. This could also be used for the fluctuations in supply, but this is accommodated by the bulk-storage (TOP). To ensure a stable incineration process, the waste in the buffers needs to be mixed such that a homogeneous mass is formed. This mixing is done best, when the buffers are not filled up to their maximum. The ideal buffer levels are therefore when the buffer is filled to a maximum of about 85%.

In the desired situation, Twence would know by looking at the amount of waste in the buffers whether diverting or retrieving is necessary. These lower and upper levels are therefore very important because those should prevent idle time or mandatory diverting. This research will therefore also provide insight on what the optimal levels are at which reaction of Twence is required.

TOP development over the years

In 2011, Twence made the decision to start a project called "Waste Mining". Due to the economic crisis, the expectation was that the supply of waste could be in danger, which would lead to stagnant machinery. As can be seen in Figure 2.7 this led to a big increase of the inventory of waste.

When only looking at the inventory development over an entire year, we can not conclude that Twence also can manage their process with less inventory. One must keep in mind that this inventory is only needed when the buffers of the incineration lines are beneath a certain threshold, which indicates that the risks of not having enough waste to incinerate is too high. Therefore, we should also look at the inventory development of the buffers of the AEC on a daily basis. Unfortunately, data on the weekly or daily amount of inventory in the buffers of earlier years is poorly registered. Therefore we use another method to find out the fluctuations in the bulk storage, TOP.

To find out if the risks of not having enough waste or wood to incinerate is too high, we look at the number of times that waste was retrieved from TOP. In the current

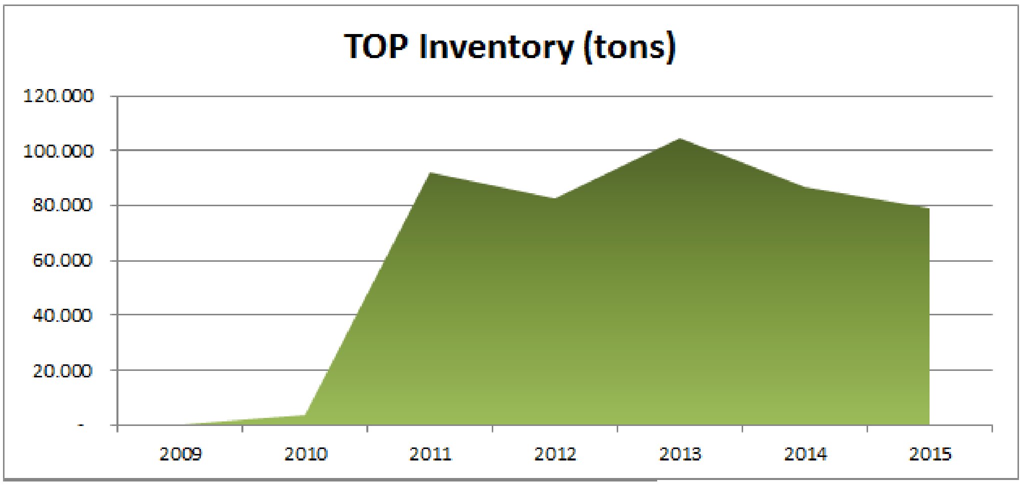


Figure 2.7: Inventory development

situation, when there is a shortage in the buffer and risk of downtime occurs, waste needs to be retrieved. So retrieval is an indication of risk of downtime, and we can use this to find out whether there was a lot of risk of downtime in 2015 and a big bulk storage, TOP, was necessary. In Figure 2.8, we see the amount of waste that is retrieved from TOP and see the total inventory per day expressed in the number of days that is needed to process the entire inventory.

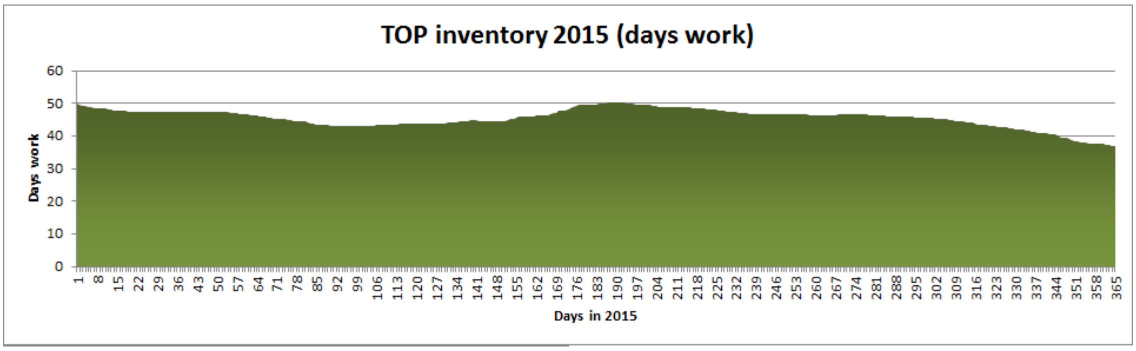


Figure 2.8: Top inventory in days work per day in 2015

When looking at the mutation of TOP inventory over the entire year, we can conclude that given the average amount of retrieval per day, the amount of bulk inventory is rather high.

2.2.4 Costs

In this subsection we discuss the most important costs that are affected by the decision making process. First, the costs for diverting and retrieving waste are discussed, followed by the costs for stagnant incinerators.

Costs for Bulk-storage

We want to know what the costs are for having waste in bulk storage. The site of

Twence is large enough and Twence has a permit to store supplies until a maximum of 200.000 tons of waste. Only when that maximum is exceeded extra costs are made, because of a new rampart that needs to be build.

A recent calculation has been made about the costs of transporting 1 ton of waste to and from there respective bulk storages (Nijkamp, 2016). In Table 2.3 we see the total amount of retrieved and diverted waste per year. The total costs for diverting a ton of waste and then retrieving that same ton of waste are also given. This leads to a average costs per week for diverting and retrieving of €10.414,81 for the last 4 years, and even €11.447,69 for the last year. Refreshed waste is the amount of waste that is replaced in TOP with new waste. So it is equal to the minimum of the diverted and retrieved waste in a year, divided by the TOP inventory. We see that the percentage of refreshed waste is more than the on average required 33% per year. It is not bad to refresh more waste in a year, however, we see that this is a trend over the last years.

	2012	2013	2014	2015	Average
Retrieved Waste (tons)	51.139	50.764	60.512	37.729	50.036
Diverted Waste (tons)	51.140	70.233	45.765	51.202	54.585
Total Costs (€/ton)	10,69	7,02	12,99	14,19	11,22
Percentage refreshed	52,97%	65,52%	56,47%	53,73%	57,17%

Table 2.3: Total transport to/from bulk storage and associated costs

Costs for Idle time

Apart from the planned maintenance stops, Twence always have to run at full capacity, so with the incinerators burning at all time. This ensures the maximum of electricity and heat that can be produced and gives a constant supply of energy. Therefore, there always needs to be enough fuel in the form of combustible waste for the AEC, to keep the incinerators running on full capacity. Because they run on full capacity, any unplanned stop or drop in throughput can not be recovered. Lower throughput or downtime are both included in the availability, which then drops. The costs for every hour of downtime are summarized in Table 2.4.

	Summer	Winter	Average
Incineration Line 1&2	2.380	2.620	2.500
Incineration Line 3	2.420	2.780	2.600

Table 2.4: Downtime costs per hour (€)(Bloemhof, 2015)

The difference between summer and winter is because the energy consumption is higher in winter. We see that the costs can increase rapidly when the incinerators are out of waste to incinerate. Therefore, it is of the utmost importance to make sure that always enough waste is available to incinerate.

2.2.5 Quality control

In the current situation, Twence does not take into account the quality of the waste as much as they would want to do it. One of the reasons for this is that it is hard to determine the quality of a certain batch of waste. Twence now has a couple of quality inspectors. Their job is to approve the waste based on visual inspection. For example, mattresses are not preferred within batches of waste with destination TAS or AEC.

Apart from the visual aspects, waste also has some non-visual characteristics. A very important one is the calorific value. Calorific value is expressed in MegaJoule per Kilogram, which means that the higher the calorific value, the more energy can be won. As said, Twence has two incineration lines which have as difference that line 1+2 is more suitable for waste with low calorific value (around 9MJ/Kg), and line 3 for high calorific waste (around 11MJ/Kg). Incinerating a stream of waste with constant calorific value reduces costs through the more efficient use of adjuvants. Currently, a start is made on analyzing the effect of the calorific value on the throughput. Twence is working on a contribution margin model, which indicates the effects on the costs of incinerating waste of a certain customer on a certain incineration line.

It is not only the opinion of Twence, but also our opinion that a lot can be gained from making decisions based on the calorific value of the waste. Twence already monitors the calorific value after the incineration, but does not base any decisions on it. From the data on calorific value, we analyzed the effect of the calorific value of waste on the throughput of the incineration lines. The results are shown in Figure 2.9

The throughput that is used in this graph is based on the amount of waste that is processed on a given day. The operator of the incineration line has the job to always make sure that a constant amount of steam is produced in order to ensure the best quality output of electricity and heat. The higher the throughput, the higher the amount of waste was, that was needed to ensure this constant production of steam.

It can be seen in Figure 2.9 that, apart from some outliers, a linear relation occurs between the calorific value and the throughput of a certain incineration line. From Figure 2.9, we can conclude that per incineration line, the calorific value is negatively correlated with the throughput, a low calorific value results in a high throughput, i.e., more waste is needed to achieve the same level of output. It could be that a given calorific value leads to a level of throughput when multiplied by a factor (due to the possible linear relation). When we divide the throughput by the calorific values, the factors for incineration lines 1+2 and 3 seem to be around about 19 for line 1+2 and 10 for line 3. We fit a normal distribution for the factor that, when multiplied with the calorific value, gives us the expected throughput. The results are shown in Table 2.5.

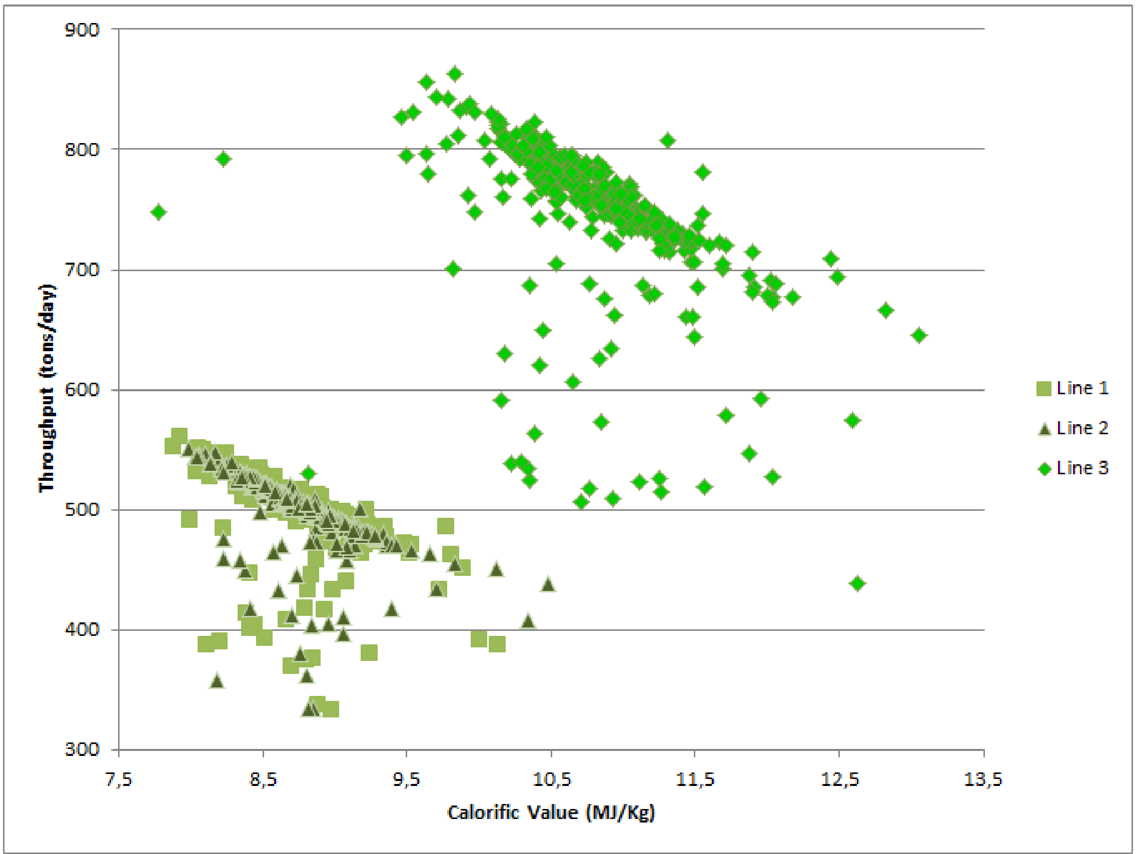


Figure 2.9: Correlation between Calorific value and Throughput

Factor	Distribution
$Factor_{Line1}$	Multimodal with p(x) = 0,533·Normal[x; 19,0950 ; 0,0399] + 0,467·Normal[x; 19,5774 ; 0,0565]
$Factor_{Line2}$	Normal[19,5890 ; 0,0778]
$Factor_{Line3}$	Normal[10,3462 ; 0,0747]

Table 2.5: Fitted distributions for the factor (Throughput/Calorific value)
Explanation on the fitting of distributions can be found in Appendix B

The waste is used as fuel for the incinerators. Twence gets paid to incinerate waste, therefore it is logical that Twence wants to incinerate as much waste as possible whilst keeping the AEC processing. This means that Twence would want to incinerate mainly waste with low calorific value, because this leads to high throughput and the need for a lot of fuel.

For example, waste with a high moisture content has a low calorific value, so one would think that Twence could simply wet the waste. But a high moisture content also leads to faster corrosion and unburned residu, which leads to additional maintenance costs and even unplanned downtime, so this is not profitable at all.

When the calorific value of a ton of waste is known, the factor from Table 2.5 can be used to determine the total time needed to process this ton of waste by using Equation 2.1.

$$Factor \cdot Calorificvalue \cdot Mass = Processingtime; \qquad (2.1)$$

Knowing the calorific value of arriving waste leads to two advantages. The first is that Twence could pay attention to making sure the incinerator lines have a constant calorific value as input. As stated before, a constant calorific value reduces the costs for incineration because of less need for adjuvants. This does not mean that the calorific value should be at a certain level. The second is that with the combination of calorific value, mass and our calculated factor, Twence knows how much process time is needed and how long it will take before the incinerator line becomes idle.

Now Twence only knows the amount of mass that is currently in the buffers of the incineration lines. Ideally, Twence also knows the calorific value of the content in the buffer. Then Twence can decide per arriving client, which incineration line is more suitable to go to, based on the match between the calorific value of the content currently in the buffer and the batch of waste with a certain calorific value, to which incineration line this client should be send.

Therefore, it would be convenient for Twence to know the calorific value of waste per client. Unfortunately, there is currently not enough data available to determine this seperately for each client. We only have data on the calorific value of the seperate incineration lines and therefore, we analyze whether the calorific value of the supplies of all clients combined on a specific incineration line follows a certain distribution. We analyze the results obtained from the measurements and calculations that are done after waste is burned. This is the same data on which we based Figure 2.9. A summary of the analysis is given in Table 2.6.

Line	**Distribution**
$Calorificvalue_{Line1}$	Normal[8,705 ; 0,460]
$Calorificvalue_{Line2}$	Normal[8,736 ; 0,528]
$Calorificvalue_{Line3}$	Normal[10,229 ; 0,810]

Table 2.6: Fitted distributions for the calorific value

First we tried to fit a distribution for line 1 and 2 together, because the waste is also scheduled for these lines together and the lines share a buffer so no distinction on forehand can be made. With the combined data, a normal distribution did not give a proper fit although the data did have signs of being normally distributed. We also tried to fit the normal distribution for the lines apart from each other. This gave a good enough value to conclude that we are dealing with a normal distribution for the three separate lines with the parameters as shown in Table 2.6.

2.3 Decision making

In order to provide a clear overview of all the decisions that need to be made in the internal supply chain of Twence, we distinguish between long-term and short-term decisions. As stated in Section 1.6, we want to design different scenarios and every scenario includes different decisions. Therefore, we first discuss all the long- (Section 2.3.1) and short-term decisions (Section 2.3.2) that are key to the current situation. After that, we take summarize these decisions in Section 2.3.3 and point out which decisions could also be taken into consideration.

2.3.1 Long-term decision making

To make sure that machines are always running, Twence has to ensure supply. In the current situation, M&S is responsible for ensuring the external supply. This means that they have to contract enough supply of waste and wood in order to utilize the full capacity of the machines. For the long-term decisions, we look at a period of one to five years ahead.

In Figure 2.10 we see the relations between the supply planning and the supply requirements and who is responsible for it. The Operations department (Operations) is responsible for making a requirements planning. This planning is given to M&S from which they can conclude how many supply they should contract for the upcoming period. The requirements planning is based on the capacity of the machines, however, in a year Twence has to cope with planned stops for maintenance. Bases on this information the requirements for a certain year are determined which is communicated to M&S. They provide a year plan for the supply in the extent to which this is possible. This leads to a forecast at the start of a year for the supply and the requirements on a weekly basis.

We state the long term decisions in the current situation as being:

- How much ton waste is needed to keep the incinerators running at full capacity?
- How much ton waste is supplied based on the acquired contracts?
- How much bulk storage capacity should be available for this year?
- How much deviation in agreed quantities should be allowed per week?

For the current situation, the decisions are taken as presented in Table 2.7. For all these decisions, the timespan is the upcoming year.

In Table 2.7, by a possible deviation of $\pm 10\%$ is meant that a client can deviate from their weekly agreed amount with at most 10%. A client agrees on supplying 1.0 Kton per week, this means that he could supply an amount of 1.1 Kton one week and 0.9 Kton the next week. Whenever a client exceeds these boundaries, Twence calls the client and discusses a new amount to be supplied in the upcoming weeks in order to get the average back within the $\pm 10\%$.

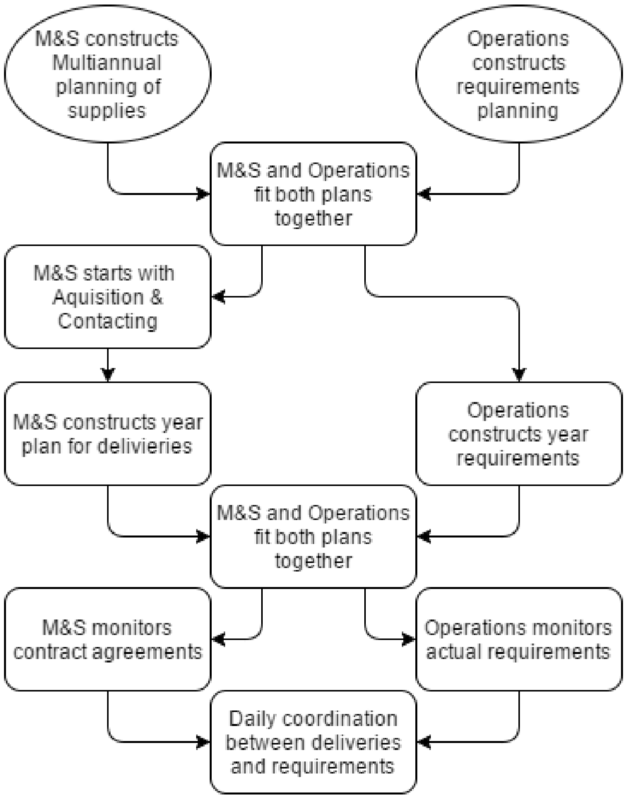


Figure 2.10: Relations between Supply and Requirements

Decision	AEC
Required Waste for full capacity	600 Kton
Acquired contracts	610 Kton
Capacity of Bulk-storage	100 Kton
Possible deviation	±10% per week

Table 2.7: Taken decisions in current situation

2.3.2 Short-term decision making

With short-term decisions we mean decisions that need to be made for the upcoming days, weeks or months to at most a year ahead. During the year, it happens that the requirements change due to for example the quality of the waste. This change should be compensated by decreasing or increasing the supply. However, sometimes M&S can not change the pace of the supply due to the contracts with the clients. When this is the case, there are three possible situations:

- Unable to **decrease** supply
  Overflow: The supply is higher than the requirements which leads to an increase in the utilization of the buffer. If the buffer is full, the waste needs to be diverted to TOP or send to an alternative location (competitors).
- Unable to **increase** supply (Current Situation)
  Underflow: The supply is lower than the requirements which leads to an

decrease in the utilization of the buffer. If the buffer is empty, the waste needs to be retrieved from TOP, which in the current situation is possible.

- Unable to **increase** supply (Situation without TOP)
  Underflow: The supply is lower than the requirements which leads to an decrease in the utilization of the buffer. If the buffer is empty, the incinerator will stop, which leads to costs as shown in Table 2.4. Supplies should be increased as soon as possible.

As said, Twence has contracts with its clients that provide them with a margin of 10% by which they can over- or under supply the agreed amount over the entire year. The decisions about whether to divert or retrieve the incoming waste and wood is made in a consultation with all involved employees. This consultation takes place two times per week and consists of a delegation from M&S and a delegation from Operations. Together they take care of the planning of the internal logistics. In the current situation these planners have the responsibility to ensure an efficient flow of waste or wood towards the desired destination, while making sure that the entities are neither over supplied as under supplied.

In Figure 2.11 we see the decisions that need to be made regarding orders that are planned in. The figure gives an overview of the situation in which Twence has to deal with a possible overflow.

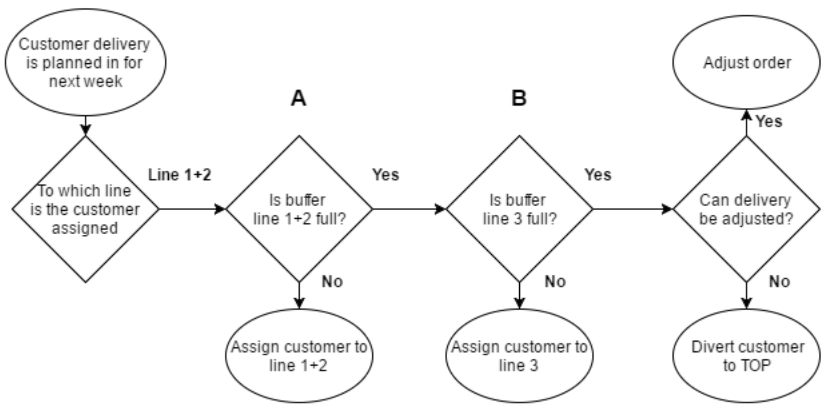


Figure 2.11: Decisions when waste arrives at Twence
Same structure holds for line 3 (interchange A and B)

From Figure 2.11 we can conclude that in the situation of overflow, we have three options. We state the decisions for deliveries planned on line 3. The decisions are the same with planned deliveries on line 1+2, only the lines need to be interchanged in the following statements.

- Delivery is planned on incineration line 3, but risk of overflow arises:
  1. Reschedule delivery to line 1+2
  2. Adjust delivery amount in consultation with client
  3. Divert delivery to TOP

With little modifications we can immediately list the decisions in a situation of underflow:

- Delivery is planned on incineration line 3, but risk of underflow on incineration line 1+2 arises:
    1. Reschedule delivery to line 1+2
    2. Adjust delivery amount of line 1+2 planned deliveries in consultation with client
    3. Retrieve waste from TOP

In the current situation, these are the decisions that are made and they are based on mass. Just as with the long term decisions, we will point-wise state these decisions:

- On which line should the waste be scheduled?
- When is diverting necessary based on the level of waste in the buffer?
- When is retrieving necessary based on the level of waste in the buffer?
- When is retrieving necessary based on the age of the waste in TOP?
- When should waste be rescheduled to the other line?
- When should waste be send to an alternative location?

Also the short term decisions can be summarized for the current situation. The results are shown in Table 2.8.

Decision	**AEC**
Schedule waste on which line	Line 1+2 or Line 3
Diverting	If the level of tons of waste in the buffers is above 85% of the total capacity
Retrieving	If the level of tons of waste in the buffers is below 15% of the total capacity or if TOP Waste is about to become older than 3 years
Rescheduling	If the level of tons of waste in one of the buffers is above 85% or below 15% of the total capacity
Alternative location	If buffers and TOP are full or if diverting capacity is reached

Table 2.8: Taken decisions in current situation

As discussed in Section 2.2.3 about the inventory development, the thresholds, represented by 85% and 15% in Table 2.8, are very important. In the current situation, there is no clear view on what these optimal thresholds are. We discussed some of the findings from a report by Numan, but these findings also do not provide clear guidelines. From personal observations we concluded that the thresholds are now mainly based on human estimates. When the buffer is almost full (85%) we divert, and when it looks almost empty (15%), we retrieve. In our opinion, with a clear research about what the optimal thresholds are, Twence could save a lot of costs from unnecessary diverting or retrieving.

2.3.3 Optional decisions

In the previous sections we discussed decisions that are applicable to the current situation at Twence. These decisions already give room to experiment with, but there are some optional decisions, which could be inplemented in the planning process or even replace some of the current decisions. We list a number of optional decisions:

- Should calorific value be restricted in the contract?
- How much deviation in agreed calorific value should be allowed?
- When is retrieving necessary based on the amount of processing time in the buffer?
- Should retrieved waste be selected by calorific value?
- Should waste be rescheduled to the other line, due to the average calorific value of the waste in the buffer?

As mentioned in Section 2.2.5, the calorific value has effect on the process effiency by means of the amount of adjuvants needed for incineration. With the calorific value it is also possible to determine the processing time of a ton of waste. The additional decisions we listed all include the calorific value in the decision making and have influence on the costs and efficiency of the supply chain at Twence.

2.3.4 Recap on current situation

Throughout Chapter 2, we highlighted a number of remarkable things, indicating that there are some things that could be improved regarding the decision making.

First of all in Section 2.2.2, we noticed that the supplies and requirements matched over an entire year. However, during the year, a lot of fluctuation was found in the weekly supplies. Therefore it is important to determine proper thresholds in the buffers to cope with the fluctuation in the weekly supplies. Currently the thresholds are around 15% and 85% and based on the mass of the waste. The forecasts for the throughput of the different incineration lines were straight lines, whereas the real throughputs had more fluctuation. The calorific value is something that could be taken into consideration in order to achieve a proper forecast for the throughput.

In Section 2.2.3, we presented the inventory development of the bulk storages. Those were constant, indicating that during a year there is not much fluctuation in the bulk storages. So in order to save costs, the maximum capacity of the bulk storages could be lowered.

In Section 2.2.4, the costs associated with having too much or too less supplies were presented. The costs for downtime, shown in Table 2.4, are so high, that the most important goal of Twence is to never have unscheduled downtime. The storage costs do not outweigh the cost of downtime, but are still a reasonable amount of the entire rate that Twence receives for combustible waste. Currently a lot more waste is diverted and retrieved than is required based on the expiration date. This leads to a average costs per week for diverting and retrieving of €10.414,81 for the last 4 years, and even €11.447,69 for the last year. We use the costs per week as our first performance indicator.

We have shown in Section 2.2.5, that there is a correlation between the calorific value of waste and the throughput. Calorific value effects the throughput, so Twence could also consider to determine the requirements based on the calorific value. With that Twence can make better forecasts about the throughput, because when only looking at the mass of the waste, equal portions of waste with different calorific values will give different throughputs. We stated that having a constant calorific value as input increases the process efficiency. Currently, the standard deviation of the calorific value is 0,491 and 0,810 for resp. incinerator lines 1+2 and 3. Efficient processing is something that Twence desires and although we do not have insight in the costs of variations in calorific value, we still use the standard deviation of the calorific value in the buffer as our second (but less important) performance indicator.

To get a clear idea about the next steps in this research and find out how decisions on these subject are commonly approached, we perform a literature study in Chapter 3.

3 | Literature study

In this research it is important to know what the conditions are under which Twence should decide to divert to or retrieve from bulk-storage, which can be seen as a kind of safety storage. We therefore, look at different inventory models to see how this is handled in general (Section 3.1). Another issue we addressed, was the quality of the waste. We want to know if the effect of the quality is really that important or that Twence does not need to take the quality into account while making decisions (Section 3.2). The last part of our literature study is about ways in which we can analyze and model all these different variables in the most efficient way (Section 3.3).

3.1 Inventory policies safety stocks

There exists lots of academic literature about inventory policies working with safety stocks. Natarajan and Goyal (1994) point out that there are two kinds of uncertainty to deal with, namely, demand-side and supply-side uncertainty. Inventory models deal with these uncertainties by introducing a distribution for lead time and for the demand as is done in Van der Heijden and De Kok (1992). In their research a (R, S) inventory system is used where the lead time of an order has a probability distribution function as well as the demand per customer. (R, S) inventory systems are widely used and discussed in for example Hadley and Whitin (1963) and Peterson and Silver (1979).

Rawata and Altiokb (2008) introduce three policies for inventory control. All work with the same review period, but differ on other parameters. One has a safety stock level equal to the order up to level. So whenever the inventory level drops blow the safety stock, it is replenished back to the safety stock level. The second policy works with a dynamic safety stock based on the intensity of demand. The last policy has an order up to level higher than safety stock, which is calculated every S periods.

When working with different product types or varying product qualities the heuristics of Zhou et al. (2011) can be studied. They introduce a pull policy with and without sorting of the different types of products that are used for remanufacturing. In the policy without sorting, if the inventory level is below the safety stock, the inventory is supplemented with returned products, ignoring their quality. In the policy with sorting, first the returned products with the lowest remanufacturing costs are used. This means when looking at the way in which the safety stock is maintained, it does not matter how many products of each quality are available. In the case described in Zhou et al. (2011) it would be best to have as much returned products with a quality that results in low remanufacturing costs.

In our research, we are dealing with a client that needs to be served all the time (i.e., Service level 100%). Also the demand is known, when the calorific value is known. The most important thing is to prevent stockout. In all previously mentioned literature, and especially in Graves (1996) and Moinzadeh and Aggarwal (1997), it is stated that the amount of safety stock should be enough to reduce the probability of stockout to the desired level. We can not use policies directly found from these articles. However, the general idea we found about that more safety stock is needed for less probability of stockout, is useful for our research and we determine the situations in which stockout could occur in order to determine the safety stock.

3.2 The effect of calorific value

Calorific value is the value that indicates how much energy can be gained from a certain object. For Waste-to-Energy plants this is of importance because most of the time they have a target energy level they need to achieve. We first discuss the effect of variation in the input of calorific value after which we discuss some possibilities to counteract on this variation.

Several articles discuss the need of knowing the calorific value of waste to ensure a stable combustion process. Touš et al. (2014) and Fordham et al. (2003) state that a variation in the input of calorific value causes variation in the steam parameters and results in an irregular production of energy.

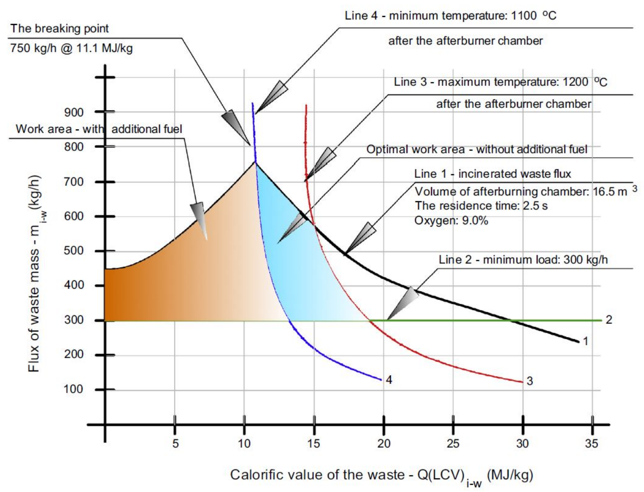


Figure 3.1: Optimal range of calorific value for incineration(Bujak, 2015)

In the article of Bujak (2015) different types of waste, partially based on their calorific value, are examined to investigate how much additional fuel is needed to incinerate these different types. With conditions set to specific points, they show what the effect of calorific value is on the waste flux in Figure 3.1. Based on calorific value, an optimal area can be determined where no additional fuel needs to be added in order to attain a proper combustion process. Therefore it would be convenient to reduce the variation or increase the predictability of the calorific value of the input.

To counteract upon the variation in calorific value, different solutions have been proposed. Van Kessel et al. (2002) suggests the use of an on-line control system, that determines the calorific value of the waste that is put into the incinerator. This system could be used to alter other input parameters to obtain optimal combustion conditions with the given calorific value. Calabrò (2010) examines the effect of waste separation on the calorific value. He concludes that the reduction in energy available in the residual waste is linked to mass reduction of the residual waste due to separate collection. Obroučka et al. (2015) conduct research about batch formation of the waste for incineration plants. They state that the best way to have a constant steam output is to make sure that all input characteristics are stable and therefore, when these characteristics are known, different batches should be made separating different groups of input characteristics.

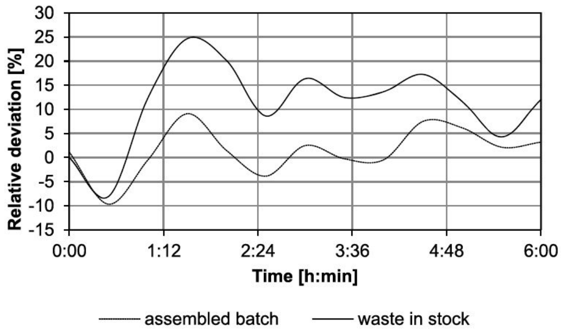


Figure 3.2: Deviation of calorific value relative to its desired value when using selected batches (Obroučka et al., 2015)

All suggested counteracts are agreeing about one main feature. The calorific value needs to be known on forehand to ensure the most efficient combustion process. However the problem is that in general the calorific value is calculated during (Van Kessel et al., 2002) or after the incineration. Obroučka et al. (2015) use numerical simulation to recreate the separate batches with different calorific values they use, but suggest that long-term surveys of municipal waste composition could give an indication about the characteristics of different loads of waste. This is mainly useful within our research, since we are dealing with different clients from which mean characteristics could be determined.

3.3 Decision support models

To optimize the decision making, the direct consequences of decisions need to be known and therefor also the effect of the input characteristics on these outcomes needs to be known. We discuss two options where a model is suggested to control these input characteristics of the waste. First we discuss two options that concern the collaboration between the treatment facility and the supplier. After that we address three works that consider the supply as a given, and suggest solutions to work with this in an efficient way.

3.3.1 Models concerning collaboration

Zhang et al. (2014) and Šomplák et al. (2014) focus on the companies or municipalities that bring their waste to Waste-to-Energy plants.

Zhang et al. (2014) develop a multi-echelon supply chain model which includes not only the waste incinerator, but also the waste collectors and the distribution centers as shown in Figure 3.3. Šomplák et al. (2014) develop a model that considers multiple incineration facilities. When a client wants to deliver waste to an incinerator, a gate fee needs to be paid. In the model of Šomplák et al. (2014), the gate fee depends on several things including the capacity of the facility. In this way, waste is distributed evenly over the different facilities.

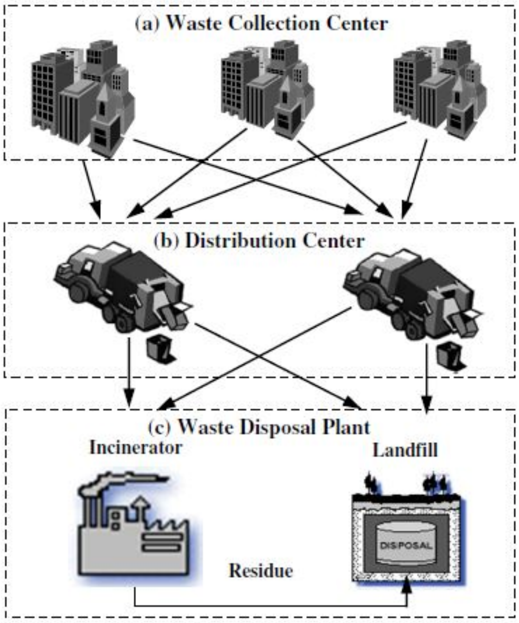


Figure 3.3: Multi-echelon network of solid waste management (Zhang et al., 2014)

Both models are however not applicable to our research. The model of Zhang et al. (2014) has just a few amount of suppliers whereas in our situation we have 104 different clients who most of the time also have different suppliers. This would be too large and complex to implement in the model. Also the model of Šomplák et al. (2014) is not applicable because in our research there is only one waste incinerator.

3.3.2 Models with given supply

In Leskens et al. (2005), Asthana et al. (2010), and Obroučka et al. (2015) we find three models that provide solutions for dealing with a given supply in the most efficient way.

Leskens et al. (2005) and Asthana et al. (2010) both provide mathematical models that simulate the waste incineration process and its input settings. The aim in Leskens et al. (2005) is to use the model for predictive control of the process. They endorse the fact that a stable process is the most profitable, but point out that the economic, i.e., maximization of waste throughput, and environmental objectives, i.e., the confinement of some flue gas components, are sometimes conflicting with each other. Leskens et al. (2005) use a predictive control model that is implement in the incineration system. The model calculates the deviation of the current trajectory and the desired trajectory and provides the system with the input parameters to minimize this deviation. The same can be said about Asthana et al. (2010), who also provide a mathematical model that provides insight into the effects of several operation parameters. Their model could serve as a basis for additional research about the influence of operating parameters.

Obroučka et al. (2015) provide two mathematical models for batch production of incinerated waste. They distinguish two different options. The first is where the waste is supplied in containers. The containers are gathered and contain a certain amount of waste and need to be included in their entirety when chosen to be part of a batch. With a mathematical model, a score is determined for each combination of containers based on the weighted priority and urgency of the containers. The priority is determined by giving weights to the different variables that they monitor (calorific value, sulfur and chlorine content). The urgency is determined by an equation that takes into account the age of the waste.

The second option is where the waste supplied and then is sorted and stored in boxes. These boxes have their own characteristics, coherent with the monitored variables. These boxes are at certain moments in time replenished and a combination needs to be made from the boxes, to get a batch of waste for incineration. In their mathematical model, Obroučka et al. set a maximum of 800Kg per batch which should consist of partials of 100Kg, selected from the various boxes (For example 400 from A, 300 from B, 100 from C). In this option, the mathematical model does not work with an equation for the urgency. This is due to the limited number of boxes, and the batch size the model uses is too small such that not all the required waste can be used in a single batch. As a solution for this, Obroučka et al. state two conditions that need to be fulfilled. These are that when a box is filled to 85% of its capacity or the box was not part of the batch for 5 times.

Both mathematical models are used to evaluate all possible combinations of containers or parts from different batches in order to find the optimal combination. The score of a batch is determined by the priority of the monintored variables which should match the desired value. Further away from the desired score, means a higher score, where the batch with the lowest score is the optimal batch to pick.

When looking at the models that take the supply as a given, which is also the case in our situation, we conclude that only the model introduced by Obroučka et al. (2015) is applicable for our situation. Especialy the first option Obroučka et al. discuss, could be altered to match our situation. Leskens et al. (2005) and Asthana et al. (2010) both focus too much on the input parameters of the entire combustion process, which is out of the scope of our research. Just as with the model of Obroučka et al. (2015), we could separate the supplies into different groups based on their calorific value. With their model we could provide a predictable calorific value input which would lead to a predictable output. In the next subsection we extensively discuss the first mathematical model introduced by Obroučka et al. (2015).

3.3.3 Mathematical model by Obroučka et al.

When we discuss the model by Obroučka et al., we come across a couple of indices and variables. We describe these indices and variables in Table 3.1.

Input	
N	Number of containers
Pv	Number of monitored thermo-chemical quantities
$Limit$	The time limit after which a container is considered to be over-aged
$Step$	The number of times that the period after which a container becomes at an appreciably age fits within $Limit$
Indices	
j	Container (1,...,N)
i	Monitored variable (1,...,Pv)
Input parameters	
q_{od}	Lower limit of batch weight of waste (Kg)
q_{do}	Upper limit of batch weight of waste (Kg)
m_j	Weight of container j content (Kg)
an_j	1 when container j content is part of the batch, 0 otherwise
w^i	Weight of variable i
h^i	Weighted average of monitored variable in the previous batches
κ_j^i	Value of variable i in container j
$priority^i$	Importance of monitored variable i (0,...,100)
max^i	Maximum value of output variable i
$urgent_j$	Variable characterizing the age of container j
u_j	The age of container j

Table 3.1: Variables from the model by Obroučka et al.

The mathematical model of Obroučka et al. has the goal to find the optimal composition of the next batch of waste to incinerate, for every time period by selecting different storage containers with waste. This is done by the goal function shown in Equation 3.1.

$$\min Kr = \left\{ \sum_{i=1}^{Pv} w^j \cdot \left[h^i - \frac{\sum_{j=1}^{N} \kappa_j^i \cdot m_j \cdot an_j}{\sum_{j=1}^{N} m_j \cdot an_j} \right]^2 \right\} \cdot \frac{\sum_{j=1}^{N} (1-an_j)\cdot(1+urgent_j)}{\sum_{j=1}^{N}(1-an_j)} \tag{3.1}$$

Equation 3.1 gives the value for Kr by which the optimal batch can be determined. *"The criterion Kr is a dimensionless expression of conformance of the batch parameters currently compiled from the previous batch. The combination of batch that has the lowest value of Kr is considered to be optimal."* (Obroučka et al., 2015) We discuss Equation 3.1 step by step in order to clarify the workings of the model.

All the total weight of a composed batch is bounded by a lower weight limit q_{od} and upper weight limit q_{do}, shown in Equation 3.2.

$$q_{od} \leq \sum_{j=1}^{N} m_j \cdot an_j \leq q_{do} \tag{3.2}$$

Equation 3.2 ensures that the sum of the weight of all containers that are included in the batch perfectly matches the capacity of the incinerator.

Equation 3.1 starts with the sum over all w^j. This stands for the importance of different monitored variables i. In the case of Obroučka et al. these monitored variables are:

1. Calorific value, $priority^1 = 80\%$
2. Sulfur content, $priority^2 = 10\%$
3. Chlorine content, $priority^3 = 10\%$

The sum of the priorities of all i should be equal to 100%, as is also the case with Obroučka et al.. The importance is then calculated by Equation 3.3.

$$w^i = \frac{priority^i}{100} \cdot \left(\frac{1000}{max^i} \right)^2 \tag{3.3}$$

The part in the square brackets in Equation 3.1 determines how much the value of the composed batch deviates from the desired value. For all containers, κ_j^i is multiplied with the weight (m_j) of its container and is only taken into account when the container is part of the composed batch (an_j). This is then divided by the sum of the weights of all containers present in the composed batch, in order to find the weighted average of variable i in the composed batch. h^i is the weighted average value of all previous batches, and the goal is to maintain an as constant as possible waste inflow based on several variables. The weighted average of variable i in the composed batch is subtracted from h^i to determine the deviation. The deviation is then multiplied by its importance, which concludes the first part of Equation 3.1.

The last part of Equation 3.1 addresses the urgency of a container. As is also the case in our research, over-aging of the waste should be prevented. The model determines the urgency of a container by Equation 3.4.

$$urgent_j = \left[max \left\{ u_j - \frac{limit}{step}; 0 \right\} \right]^2 \tag{3.4}$$

The number of periods that a container is waiting is given by u_j. *Step* is the number of periods until container j becomes at an appreciably age and *Limit* is the maximum age of a container. To give a small example about the workings of this equation we assume the following values:

- $u_1 = 17$ months old, $u_2 = 24$ months old
- $Step = 3$ (So from $\frac{36}{3}$ months the age becomes appreciably evident)
- $Limit = 36$ months

From Equation 3.4 follows the urgency of both containers:

- $urgent_1 = (max\{17-\frac{36}{3}; 0\})^2 = 25$
- $urgent_2 = (max\{24-\frac{36}{3}; 0\})^2 = 144$

We see that container 2 gets the highest urgency which is also the correct outcome because container 2 is older than container 1.

The urgency is used in the goal function, which brings us to the last part of Equation 3.1. We separate the last part of the goal function in Equation 3.5, to provide some clarity about this part.

$$\frac{\sum_{j=1}^{N}(1 - an_j) \cdot (1 + urgent_j)}{\sum_{j=1}^{N}(1 - an_j)} \tag{3.5}$$

The composition of containers with the lowest value from the goal function is the composition that is optimal to add as the next batch. In Equation 3.5 we will see that leaving out the box with a high urgency, results in a high value for Kr. We continue with the example given before, and use this as input for Equation 3.5.

In our example, we still have the previously mentioned containers 1 and 2, and we want to find out what a better composition is: a batch consisting only of container 1, or a batch consisting only of container 2. Looking at Equation 3.5, we see that in the denominator we need to take the sum of the urgencies of all containers that are **not** part of the composition. By dividing this by the total amount of containers that are not part of the composed batch, we get the average urgency of the containers left out of the composition.

- **Composition 1:** Only container 1
  This means that for Equation 3.5 we get a value of $\frac{144+1}{1}$
- **Composition 2:** Only container 2
  This means that for Equation 3.5 we get a value of $\frac{25+1}{1}$

Again the equation provides the correct output. The value of the urgency in the goal function when excluding an older batch from the composition becomes higher than when the oldest container is included in the batch. A higher value, will lead to a higher value for Kr and is thus a sign that this composition is not optimal.

We can perform a simulation that includes the model by Obroučka et al., in order to find out what the effects could be of keeping a close watch on the average calorific value in the buffers of the incinerators of Twence.

3.4 Conclusions from the literature study

In the literature about inventory policies we discovered that with most of the available inventory policies, the safety stock increases when the target service level increases. Because no literature is available that describes our situation, where we can make a homogeneous mix of our stock which heavily affects the demand, we are limited to the general knowledge found about the relation between safety stock and service level. This leads to the main finding that the safety stock depends on the target probability of stockout, which is in our case very close to zero.

In the second part of our literature study we examined the effect of calorific value. All literature found on this subject supports the idea that the calorific value of the waste used in incinerators should be as constant as possible to obtain the best performance. This adds another positive effect to our idea that with a constant calorific value, the demand of the incinerator can be much better predicted.

From the part about the decision support models, we found a relevant study by Obroučka et al. They perform a small simulation study, but our aim is to incorporate their model in our bigger simulation model combined with the guidelines from Law and Kelton (2000) in order to test different scenarios. Their idea of taking calorific value into account when composing a batch of waste to incinerate is directly applicable to the situation at Twence. We only need to alter the model in such way that the containers or boxes used in their models represent the situation with TOP.

In the next Chapters we first design a conceptual model, mainly based on the model by Obroučka et al.. After that we program this model, turning it in a simulation model in order to test different scenarios.

4 | Conceptual Model

Based on the current situation and insights we found from our literature study, we design our conceptual model. To examine different scenarios we develop a simulation model for which we introduce our approach in Section 4.1. After that we discuss in Section 4.2 the concept of restricting clients to a range of supplied mass per week, or otherwise to a range of supplied calorific value or processing time per week. After the concepts for the supply are determined, we need to make decisions about how to handle these supplies. A decision model is set up for the two main decisions that need to be taken when looking at the incoming supplies, the first being when to divert waste, the second when to retrieve waste. Both will be discussed in a separate Section (4.3 and 4.4).

4.1 Approach

In this research we develop a simulation model. From our literature study we found that Law and Kelton provide a series of steps for a sound simulation study. The steps are shown in Figure 4.1.

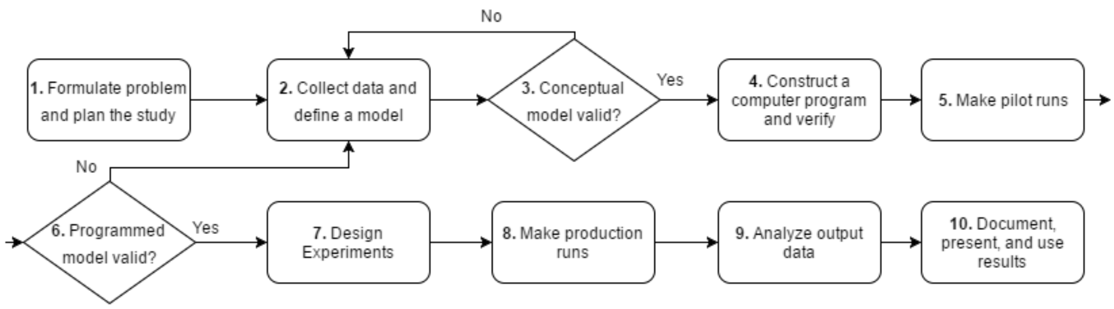


Figure 4.1: Steps in a simulation study (Law and Kelton, 2000)

Step 1 was done in Chapter 1 and in this chapter we discuss the steps 2 and 3, although a part of step 2 (Collect data) was done in Chapter 2. We design conceptual decision models suitable for the situation at Twence. The main focus for the decisions that need to be made are about the restrictions on the arriving supplies, the diverting of waste, and the retrieving of waste. After we designed our conceptual models, we translate these models into a programmed simulation model in Chapter 5.

4.2 Restrictions on supplies

In Chapter 2 we concluded that Twence only makes decisions based on the mass of the waste. At the end of Chapter 2 we made a first suggestion towards making decisions based on calorific value of the waste in order to improve the predictability about how much waste is needed to keep both incinerators running at full capacity. In Chapter 3 we found that a constant calorific value inflow leads to a more efficient incineration process. In our conceptual model we make use of the fact that when working with a more constant inflow of calorific value is desired, it could be more convenient to restrict clients to deliver supplies within a margin for the calorific value in stead of the mass. Currently, this is only done to a small extent because it is not yet possible to accurately determine the calorific value of waste before incineration. Therefore, we make an assumption about the knowledge of the calorific value.

Assumption 4.1: Calorific value of incoming waste is known upon arrival.

Restricting the clients on a certain range of calorific value will be implemented in the same way as the current restriction on the mass of waste, so on a weekly basis.

The effects of restricting the clients to a certain calorific value and not to an amount of mass results in a less predictable mass of waste that is supplied, but for the mass that is supplied, the prediction about the processing time is more reliable. We choose a margin of ±5% and not 10%, because the current deviation in calorific value is already most of the time within 10%. We expect that with a better prediction of the calorific value, better predictions can be made about the processing time and therefore, better decisions can be made about what to do with the current incoming delivery.

Apart from limiting clients to either the mass of the calorific value, one would suspect it would be even better to limit clients on both. Therefore, we design a third option, where we restrict the client to a range of expected processing time as calculated from Equation 2.1, i.e. more mass in case of low calorific value and vice versa.

In Chapter 5 we explain more about the workings of these restrictions. To test the results of these contract restrictions on the supplies, we design scenarios in which we implement these restrictions. After evaluating the results of simulating these scenarios, we are able to answer the questions that arised at the end of Chapter 2 about the optional decisions of restricting the clients on the calorific value or even processing time in the contracts.

In Figure 4.2 we show the current situation and our proposed new situations.

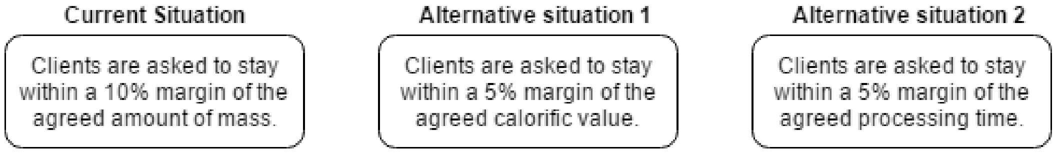


Figure 4.2: Three possibilities for restricting supplies

4.3 Diverting

When supplied waste can not be brought to the buffer of the incinerator, it needs to be diverted to the bulk-storage (TOP) or the delivery needs to be adjusted, which we already discussed in Section 2.3.2. For our decision model we assume that whenever supplies arrive at Twence, nothing can be adjusted anymore and Twence accepts the delivery.

Assumption 4.2: Twence cannot adjust deliveries and has to accept all supplies arriving at Twence.

Assumption 4.3: A maximum of 1500 tons can be diverted per week due to truck capacity.

To design a decision model for diverting waste, we need to take a closer look at part A and B in Figure 2.11. In order to prevent unnecessary diverting, a couple of things need to be specified:

- On which line should the waste be scheduled?
- When is diverting necessary based on the level of waste in the buffer?
- Should waste be rescheduled to the other line?
- Should waste be send to an alternative location?

The first question is one that is already determined on forehand by making two more assumptions about the arriving supplies.

Assumption 4.4: All supplies arrive at the start of the day and no distinction is made between the clients.

Assumption 4.5: All the waste that is supplied has already been pre-assigned to incinerating line 1+2 or incinerating line 3.

The pre-assignment of an incineration line is needed for the regular flow of waste. When buffer levels increase or decrease too much, it is an option to switch waste to another incineration line. The other three questions need to be answered for all the arriving supplies.

Preferably, the buffer of the incinerator is not filled to its maximum capacity, which is due to the need of spare capacity in case of retrieving and the room needed for mixing the waste in the buffer. When the waste is properly mixed, the incinerator receives a constant calorific value, which leads to a more efficient incineration. Therefore, we can not just use the capacity limit as a threshold for when waste needs to be diverted, but we need to create some spare capacity.

We design a decision model in order to determine a threshold, that stands for the buffer level at which actions need to be taken. We first make an assumption about the amount of waste that is examined at once.

Assumption 4.6: 10 ton of waste is examined at once, due to crane capacity.

Chunks of 10 ton can be easily taken from trucks and thus we can make decisions for these amounts of waste. Now we can set up the decision model for diverting waste, shown in Figure 4.3. We examine the situation in which all supply has arrived at Twence and then by chunks of 10 ton a decision is made about whether to send the waste to its scheduled incinerator line or perform another option. The level of waste in the buffer is determined before adding the new 10 ton.

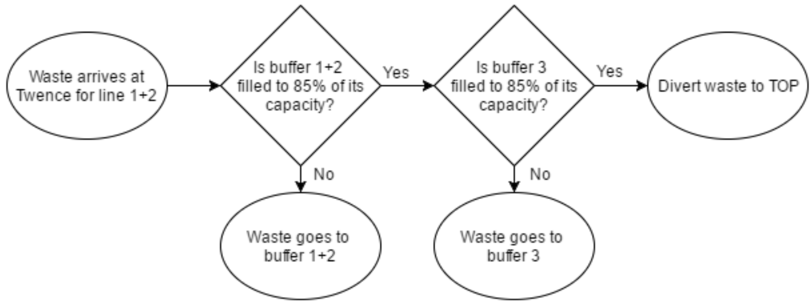


Figure 4.3: Decisions model for diverting waste

For this example, we set the threshold to 85% of the buffer. Experiments should indicate what the optimal threshold is. In our experiments we base the potential values of the threshold on the probability of the buffer becoming full. A more extensive explanation about the choice for potential thresholds follows in Chapter 5 where we design a programmed version of our model and design our experiments. We base the potential values for the desired total amount of processing time on an upper bound for the supplies, which we determine also in Chapter 5.

When diverting is not possible

It could be the case that the outcome of our decision models results in the decision to start diverting. However, it could be the case that diverting is not possible. This happens when the capacity of TOP is reached, or the maximum amount of diverted waste for that week is reached due to truck capacity. The solution for this is that, when diverting is not possible, we check whether one of the buffers still has room for the waste (i.e., is not full). When buffers are completely full mixing waste in the buffer and retrieving waste is not possible, which is not desirable. When the buffers are full and diverting is also not possible, the waste needs to be sent to an alternative location (competitors) which leads to extra costs. The situation when diverting is not possible is shown in Figure 4.4.

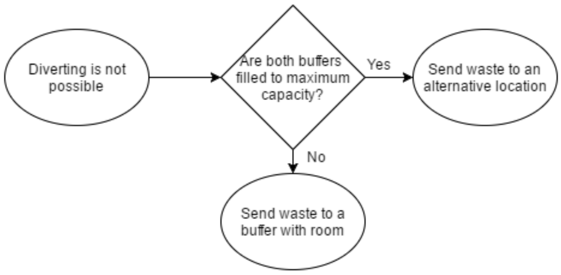


Figure 4.4: When diverting is not possible

4.4 Retrieving

Retrieving waste is done to prevent waste in bulk-storage from over-aging, and to prevent the incinerators from becoming stagnant. In the model we check every day whether waste is over-aging within one month which is long enough due to the following assumption.

Assumption 4.7: Due to truck capacity, 2400 tons of over-aging waste can be retrieved per week, which is done in batches of 600 tons.

This assumption justifies the idea that with one month ahead we are always on time to retrieve over-aging waste. Following from Assumption 4.3 and 4.7, the total combined truck capacity for diverting is lower than the total combined truck capacity for retrieving according to Twence. Therefore, there could never be more waste diverted to TOP than there could be retrieved and thus it is always possible to retrieve fast enough to prevent over-aging. At the start of a weekday, TOP is checked for over-aging waste. If there is waste in TOP that expires within a month, retrieving is initiated according to Figure 4.5. If retrieving is not possible due to full buffers, a competitor needs to be contacted to incinerate the waste for Twence.

In the current situation, Twence uses human estimation about whether the buffer level is too low when making the decision to retrieve or not. The current decision model used at Twence is shown in Figure 4.5.

In Figure 4.5, the human estimation about the low buffer level is shown in the figure as 15% of the storage capacity and as with diverting, an optimal level should be determined by means of our programmed model. When the result of the decision model is to start retrieving, the retrieval process is initiated.

Include calorific value into decisions
In the current situation, only the mass of the waste is taken into account and so, retrieving currently works with the following agreements:

- The selection of the waste that needs to be retrieved is by means of FIFO (First In First Out). So the oldest waste is retrieved first.

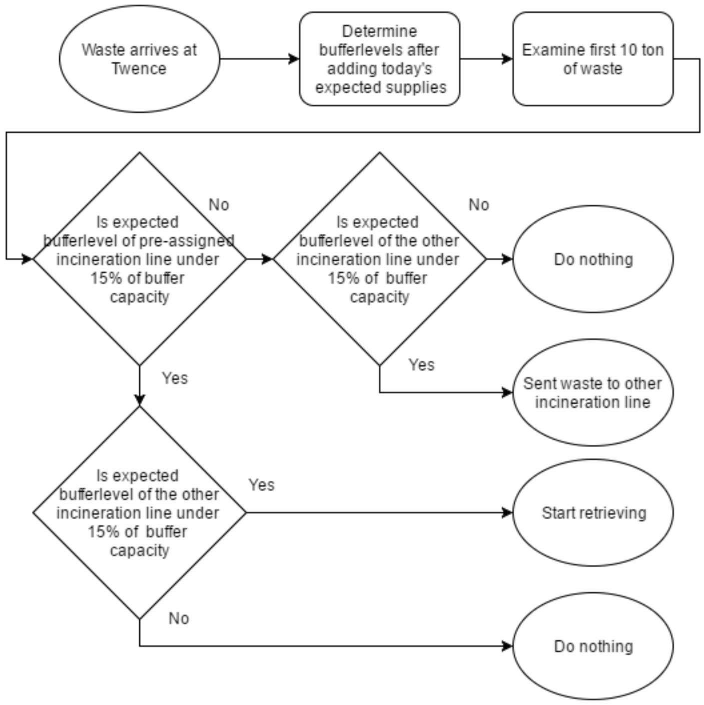


Figure 4.5: Decision model of retrieving in current situation

- The waste is separated in different heaps to distinguish the age.
- It is preferred to retrieve as much waste as possible in a single drive, such that transport utilization is maximized.
- When waste is over-aged and retrieving is not possible due to full buffers, the waste is send to competitors.

In our research we examine the possibilities of taking the calorific value into account in two ways. The first is to take the calorific value into account when waste is already in the buffer of an incinerator. The second is to select the waste that needs to be retrieved not solely on the age, but also on the calorific value.

We already discussed in Section 2.2.5 that with the calorific value, the processing time of waste can be determined. When Twence knows the average calorific value and the mass that is currently in the buffer, the total processing time can be determined. We design an alternative decision model for retrieving waste regarding the level in the buffer by taking calorific value into account. The only alteration that needs to be made to Figure 4.5, is that the 15% of the buffer capacity should be replaced with: *a desired amount of processing time which is chosen such that the probability of idle time is small enough.*

We also want to examine the possibility of selecting waste for retrieving not solely based on age, but also on calorific value. An additional advantage of this, is that the efficiency of the incineration process could be increased. From our literature study we found an interesting model that we apply to the situation of Twence. The model of Obroučka et al. could be a good alternative way to determine what waste to retrieve at Twence. In the literature study we discussed their mathematical model, and now we convert this to the situation of Twence.

Application of the model to our situation
For the model of Obroučka et al. to be applicable to the situation at Twence, we need to convert the model to our situation. To do this, we adapt all equations necessary in order to get a model suitable for our situation.

To adapt the goal function in Equation 3.1 in a proper way, we follow the same order as used with describing the model of Obroučka et al.. Thus, we start with Equation 3.2 where Obroučka et al. determines the total weight of the batch to be used. We set up the following rules for determining the total weight of a batch for our situation:

- The maximum mass in a batch waste that can be retrieved is 600 tons.
The total retrieving capacity is 2400 tons, which is done in batches of 600 tons just as in the current situation. This corresponds with full truck load amounts.

- Waste is stored in 5 different locations in TOP, based on the calorific value.
So on every location waste of the same calorific value is stored, also separated into different heaps according to age.

- The maximum mass from a single location is bounded by 600 tons divided by the number of locations used in the batch. So in a batch composed from 4 locations, the mass from each location is bounded by $\frac{600}{4} = 150$ tons.
This limits the number of possibilities that need to be examined, which otherwise would be 600^5

- Spare room in a batch that occurs when a location has not enough waste to reach the upper bound, can be used by other locations.
First it is checked whether more waste is needed to be retrieved. If so, the remaining capacity is filled with waste from the other locations

With these rules we rewrite Equation 3.2, to Equation 4.1.

$$an_j \leq m_j \cdot an_j \leq \frac{600}{\sum_{j=1}^{N} an_j} \quad \forall j, \quad an_j \in 0 or 1 \tag{4.1}$$

So when an_j is 0, the total retrieved mass from that location is 0. When an_j is 1, at least 1 ton of waste is used in the batch.

Next we take a look at Equation 3.3. Because in our situation, we have only one monitored variable, namely the calorific value, we skip Equation 3.3 in our model.

The Equation 3.4 about the urgency of the waste in a specific container, or in our case location, is used directly in our model. *Limit* is in our case 3 years, and for

Step we take a value of 6 months. Also Equation 3.5 can be implemented directly, which leads to the following goal function for our situation, shown in Equation 4.2.

$$\min Kr = \left[h^i - \frac{\sum_{j=1}^{N} \kappa_j^i \cdot m_j \cdot an_j}{\sum_{j=1}^{N} m_j \cdot an_j} \right]^2 \cdot \frac{\sum_{j=1}^{N} (1-an_j) \cdot (1+urgent_j)}{\sum_{j=1}^{N} (1-an_j)} \tag{4.2}$$

So Equation 4.2 examines, how much the weighted average monitored variable (calorific value) deviates from the desired value h^i, in our situation the average calorific value of the current buffer content. This deviation is squared and multiplied with the average urgency of the left out locations. The urgency gets higher when waste of a location is becomes older. When evaluating the values for Kr, explained by Obroučka et al. as a dimensionless expression of conformance of the batch parameters currently compiled, we are looking for the lowest value and thus a combination of locations such that the weighted calorific value is closely to the desired calorific value and the urgency of the left out locations is not that high.

Model example

Situation 1: *The bufferlevel of buffer 1+2 is determined to be lower than 15% of its capacity after adding the expected supplies of today, and there is also not enough waste expected to be supplied to reschedule from the other incineration line. This means retrieving is necessary.*

- Low thres. buf. 1+2 = 825 tons
- Low thres. buf. 3 = 1.500 tons
- Calorific value of buf. 1+2 content = 9,25
- Exp. lvl of buf. 1+2 = 600 tons
- Exp. lvl of buf. 3 = 1.500 tons
- Calorific value of buf. 3 content = 10,86

We only need to retrieve waste for buffer 1+2 and we see that one batch is enough. Now we need to find out which composition of TOP waste we want to retrieve. First we state some example characteristics of TOP.

- Loc. 1 calorific value = 8,11
- Loc. 2 calorific value = 9,31
- Loc. 3 calorific value = 10,77
- All loc. contain 600 ton waste.
- Loc. 1 oldest waste = 14 months
- Loc. 2 oldest waste = 7 months
- Loc. 3 oldest waste = 3 months

Next we examine all possible compositions in Table 4.1. We defined an_j as a variable that determines whether a location is used in the composition (1) or not (0). m_j is the mass of the waste used from that location, calculated with Equation 4.1. The compositions using none or all of the locations are left out because this would give a guaranteed 0 from Equation 4.2.

Now we want to calculate the score of each composition using Equation 4.2. The first part of the equation contains h^i and κ_j, which are in this example defined as:

- h^{Buf1+2} = Calorific value of buf. 1+2 content = 9,25
- κ_1 = Loc. 1 calorific value = 8,11

Comp	an_j			m_j		
Nr.	an_1	an_2	an_3	m_1	m_2	m_3
1	1	0	0	600	0	0
2	0	1	0	0	600	0
3	0	0	1	0	0	600
4	1	1	0	300	300	0
5	0	1	1	0	300	300
6	1	0	1	300	0	300

Table 4.1: All possible combinations

- κ_2 = Loc. 2 calorific value = 9,31
- κ_3 = Loc. 3 calorific value = 10,77

The second part of Equation 4.2 takes the urgency $urgent_j$ into account. $urgent_j$ is calculated from Equation 3.4, where we take *step* 6 months and *limit* 34 months. The values for $urgent_j$ for every location becomes:

- $urgent_1 = 69{,}44$
- $urgent_2 = 1{,}78$
- $urgent_3 = 0$ (since waste in location 3 is not older than the *step* value)

In Table 4.2 we show the outcome of Equation 4.2 for every composition (the bold values are best). We first define two other situations to show the difference in results.

Situation 2: *Waste in the locations is resp. 5, 30 and 30 months old*
Situation 3: *Calorific value of waste in location 1 is 4,00*

Comp	Kr		
Nr.	Sit. 1	Sit. 2	Sit. 3
1	2,45	770,81	52,06
2	0,13	1,07	**0,13**
3	84,59	686,32	84,59
4	0,29	172,95	6,73
5	43,96	**0,62**	43,96
6	**0,10**	21,41	9,66

Table 4.2: Results from Equation 4.2

We see that in situation 1, it is important to choose location 1, because it is the oldest. To compensate for the calorific value, the model selects the composition that also includes location 3, such that the average calorific value approaches the target of 9.25. In situation 2, the age of the waste in location 2 and 3 almost reaches the maximum, therefore the model selects composition 5, that consists of location 2 and 3, although the average calorific value is 10.04 (»9.25). In situation 3, the model does not want to select location 1 due to the low calorific value. Since it now has nothing to compensate for the high calorific value of location 3, it selects the composition only consisting of location 2.

4.5 Recapitulate on the conceptual model

In this chapter we presented our conceptual model. In Section 4.2 we stated our ideas about the possibilities to restrict clients on their supplies. We found three options, which are:

- Restrict clients on the supplied mass of the waste.
  This means that the clients need to keep the mass of the waste in a delivery within a specified margin.
- Restrict clients on the supplied calorific value of the waste.
  This means that the clients need to keep the calorific value of the waste in a delivery within a specified margin.
- Restrict clients on the supplied processing time
  This means that the clients need to keep the calorific value of the waste and the mass of the waste in balance such that the processing time is with a specified margin.

In Section 4.3 and 4.4 we discussed the decision models for diverting and retrieving. For both actions, certain thresholds need to be determined. These thresholds indicate the moment from when one of both decisions needs to be taken.

In the current situation, the decision models for diverting and retrieving both only work with the mass of waste. Our decision model uses the total processing time, that can be calculated with the calorific value, to determine whether retrieving is necessary. To determine which waste needs to be retrieved, we adapted the model from Obroučka et al. that determines which composition of different locations with waste having different calorific values is needed to get the optimal batch of waste to retrieve.

Just as with the models in the current situation, our decision models work with thresholds that indicate from when actions need to be made. In Chapter 5 we program our conceptual model. This leads to a simulation model and with that model we perform a variety of experiments to test different scenarios and to answer the following questions:

- Should clients be restricted on mass, calorific value, or processing time?
- At what threshold should waste be diverted?
- At what threshold should waste be retrieved?
- Should decisions about when to retrieve and what to retrieve include calorific value?

The results of these experiments will be evaluated by means of the performance indicators we found in Chapter 2, which are:

- Costs per week. (€10.414,81)
- Standard deviation of calorific value in both buffers. (0,491 and 0,810)

5 | Simulation Model

In this chapter we present our simulation model. We perform steps 4 to 7 from Figure 4.1 in this chapter. We start with a model description in Section 5.1. After describing the working of the model we present the model input in Section 5.2. In Section 5.3 we validate the model and we end this chapter in Section 5.4 with our experimental design.

5.1 Model description

In this section we present our simulation model by providing a short model description and an overview of the modeling assumptions. The technical description of the model can be found in Appendix C.

5.1.1 Process description

In Figure 5.1 we show a simplified representation of the process we are modeling.

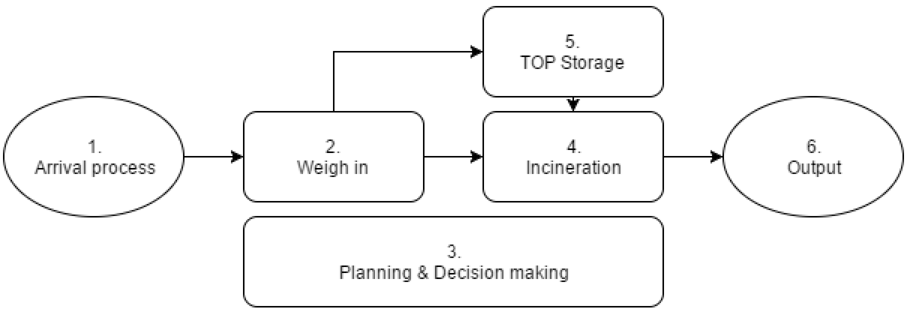


Figure 5.1: Simplified representation of modeled process

We discuss all parts of the process and, where possible, show how we implement our conceptual model in our simulation model.

1. Arrival Process
The simulation starts at the beginning of each week with determining the supplies of that week. After that, the supplies are divided over the weekdays according to an empirical distribution explained later on. The incoming supply is already pre-assigned to an incineration line and has a calorific value. In our conceptual model we discussed the possible restrictions for clients for their supplies (Section 4.2) and concluded that for the arrival process we have three possibilities, namely:

- Restrict the clients on the amount of mass of the waste (current situation)
- Restrict the clients on the calorific value of the waste (alternative 1)
- Restrict the clients on the supplied processing time (alternative 2)

We implement these possibilities in the model as shown in Table 5.1.

	Designed from historical data	
	Mass of supplies per week	Calorific value of supply per week
Contract restrictions on Mass	Uniformly distributed with mean amount ± 10%	Normally distributed (Table 2.6)

	Designed for experiments	
	Mass of supplies per week	Calorific value of supply per week
Contract restrictions on Calorific Value	Normally distributed by $\mathrm{N}(\mu; 0, 1\mu)$	Uniformly distributed with mean value ± 5%
Contract restrictions on Processing Time	Follows from Equation 2.1	Uniformly distributed with mean value ± 5%

Table 5.1: Supply set-ups

The goal of these 3 possible contract restrictions is as follows. The first, contract restrictions on Mass, is a resemblance of the current situation. These settings are based on historical data. The second, contract restrictions on Calorific value, is our first alternative for the current situation. In this situation, we assume that restricting the clients on calorific value and not on mass of waste, leads to less fluctuation in the calorific value of waste that is supplied, but more fluctuation in the mass of waste that is supplied. Therefore, we use distributions that have a bigger standard deviation than in the current situation for the mass, and a smaller standard deviation for the calorific value. In the second alternative to the current situation, contract restrictions on both the mass and the calorific value, the aim is to control the supplied processing time. In Section 2.2.5 we found that the processing time can be determined when the mass and the calorific value is known. So when we make contract restrictions on both the mass and the calorific value of the waste, we indirectly restrict clients on the processing time they supply.

To make contract restrictions on the processing time, we use Equation 2.1. This equation calculates the processing time by multiplying the mass with the calorific value with a factor depending on the incineration line. Given that we pre-assign waste to an incineration line, we use the average of the corresponding factor. In our situation, this will be as follows:

- 604800 seconds of processing time needed per week for lines 1, 2 and 3
- Processing time waste for line 1 = 19,32 * Calorific value * Mass
- Processing time waste for line 2 = 19,59 * Calorific value * Mass

- Processing time waste for line 3 = 10,35 * Calorific value * Mass

Because waste for incineration lines 1 and 2 come together as being for incineration line 1+2, we add the processing time for a week, and take the average of the factor. This leads to the following equations:

- Proc. time waste for line 1+2 = 1.209.600 = 19,455 * Calorific value * Mass
- Proc. time waste for line 3 = 604.800 = 10,35 * Calorific value * Mass

So when we say we restrict the client in their contract on the processing time, we actually restrict them on the mass as well as the calorific value. We restrict clients to a range of ± 5% on the processing time, and we model this such that a processing time and calorific value are drawn from the uniform distribution and both lead to a specific amount of mass. The mean calorific value that we use for the uniform distribution, is the historical mean.

At the beginning of each week in the simulation model, depending on the restrictions of the contracts, an amount of supplies for that week is determined using the distribution of Table 5.1. This is done for incineration line 1+2 and incineration line 3 because of the earlier mentioned pre-assigned incinerators that clients have. This week amount is divided over the week by using an empirical distribution. From historic data we select all weeks without holidays in order to get a selection with week distributions. This selection counts as a representative sample of all weeks. From this sample we randomly select a week distribution and use that for the current week. The week distributions can be found in Appendix D. The motivation for this distribution is the fact that when we use a separate distribution per weekday for the percentage of supplies that arrives, the last day becomes dependent of the other days.

On each day the waste scheduled for that day is created, where every 10 tons of waste has a pre-assigned calorific value according to the contract restrictions and the incineration line that is pre-assigned.

2. Weigh In
The weigh in is the place where the supplies arrive at Twence. Waste arriving at the weigh office initiates the planning and decision making about what the next destination should be of the waste. At the weigh in itself nothing special is happening.

3. Panning & Decision making
In the planning department decisions are made about the next destination of the arriving waste, but the department also controls the buffer levels. The planning department is triggered by every 10 ton of waste that arrives at the weigh in. First we describe the implementation of the model for the diverting, and then we do the same for the retrieving.

3a. Panning & Decision making: Diverting

For the decision model, the planning department checks for every 10 ton of waste whether it fits in the buffer of its scheduled incinerator. So when the waste is pre-assigned to go to incinerator line 1+2, the planning department checks the level of waste in the buffer only taking the mass of that waste into account. When the level of waste in the buffer is above a chosen threshold, the planning department checks whether the level of waste in the buffer of the other incineration line is also above its threshold. If so, the waste needs to be diverted if possible, and otherwise the waste is send to the other incineration line. If diverting is not possible, the planning department checks whether the buffers have any room and if not, the waste is sent to an alternative incineration company. We display the course of the decisions in Algorithm 1. The buffers of the incineration lines we discuss in the algorithms are a shared buffer for incineration line 1+2, and a buffer for incineration line 3.

```
When a batch of waste arrives at Twence.
if Level of mass in buffer of pre-assigned incineration line > High Threshold then
    if Level of mass in buffer of other incineration line > High Threshold then
        if TOP Capacity reached OR Diverting limit reached then
            if Both buffers are full then
                Sent waste to an alternative incinerator.
            else
                Sent waste to a buffer that is not full. (preferably buffer of
                  pre-assigned incineration line
            end
        else
            Divert waste to TOP.
        end
    else
        Sent waste to buffer of other incineration line.
    end
else
    Sent waste to buffer of pre-assigned incineration line
end
```

Algorithm 1: Course of decisions for diverting; Based on Figure 4.3

3b. Panning & Decision making: Retrieving

The planners also need to decide when waste needs to be retrieved. As said, every time that waste arrives at the weigh office, the planning department is informed. When the levels in the buffer do not exceed the threshold for diverting, it could be the case that retrieving is necessary. Then, again a similar course of decisions is initiated in our simulation model. In Algorithm 2 we show the decisions for retrieving for the current situation, so the situation in which the decisions are purely based on the mass.

In our conceptual model for retrieving, we include the calorific value in the decision making. As said, with the calorific value we can determine the processing time and

```
When a batch of waste arrives at Twence.
if Level of mass in buffer of pre-assigned incineration line < Low Threshold then
    if Level of mass in buffer of other incineration line < Low Threshold then
        if TOP is empty OR Retrieving limit reached then
            Sent waste to buffer of pre-assigned incineration line.
        else
            Sent waste to buffer of pre-assigned incineration line.
            Initiate Retrieving
        end
    else
        Sent waste to buffer of pre-assigned incineration line
    end
else
    if Level of mass in buffer of other incineration line < Low Threshold then
        Sent waste to buffer of other incineration line.
    else
        Sent waste to buffer of pre-assigned incineration line.
    end
end
```

Algorithm 2: Course of decisions for retrieving. Based on Figure 4.5

thus, we can calculate the total processing time present in the buffer and base the decision to retrieve or not on that. This is because of the simple fact that it does not matter how much waste is in the buffer, as long as the processing time of that waste is long enough to keep the incinerator burning until the next delivery. Because in the model we have a delivery every day of the week, the maximum days without a delivery that needs to be bridged is two days. Thus for our conceptual model, Algorithm 2 is only altered in the first two if statements, and we state the changes shortly in Algorithm 3.

```
if Level of Total Processing Time in buffer of scheduled incinerator < Low
  Threshold then
    if Level Total Processing Time in buffer of other incinerator < Low Threshold
      then
        ...
    end
    ...
end
```

Algorithm 3: Changes relative to Algorithm 2

Apart from checking for the need of retrieving at every arrival of waste, the planning department can also be triggered due to the over-aging of waste already stored in TOP. At the start of each day we check the age of the waste in TOP, and when it is near the 3 year mark, retrieving is initiated. The implementation of the retrieving process is more extensively discussed at the description of the TOP Storage.

4. Incinerator lines

In the simulation model, the part of the incinerators includes 3 incinerator lines of which the first two share their buffer (line 1+2). When waste arrives at the incinerator, it is stored in a buffer after which it is processed by the incinerator. Since the new waste is mixed with the waste currently in the buffer, the calorific value of the waste in the buffer is redetermined. The processing time of the waste is determined as soon as it leaves the buffer. To determine the processing time, we take the calorific value of the waste and multiply this with a factor (Equation 2.1). This process is visualized in Figure 5.2.

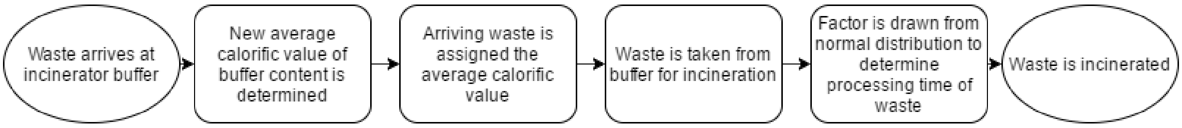


Figure 5.2: Process from buffer to incineration

5. TOP Storage

In TOP Storage we distinguish two situations, namely, incoming waste and outgoing waste. We discuss both situations, starting with the ingoing waste.

5a. TOP Storage: Ingoing waste.

TOP receives incoming waste whenever the planning department decides that diverting is needed. The way in which waste is stored depends on the way in which the planning department makes their decisions. There are two options:

- **Making decisions, not taking the calorific value into account**
  (Current situation) Waste is stored on a large location in heaps separated by age (week of arrival).
- **Making decisions, taking calorific value into account**
  (Alternative situation) Waste is stored on five different locations in heaps separated by age (week of arrival), being arranged for waste with:

  1. Calorific value ≤ 8
  2. Calorific value ≤ 9
  3. Calorific value ≤ 10
  4. Calorific value ≤ 11
  5. Calorific value > 11

When waste arrives at its arranged location, the time of arrival is registered in order to determine the duration of being in TOP Storage.

5b. TOP Storage: Outgoing waste.

Whenever waste needs to be retrieved, the same two situations as with the ingoing waste are distinguished. When the planning department makes decisions based on purely the mass of waste (Figure 4.5), the waste is stored in one big location and then retrieving just is done by selecting waste to a maximum of 600 tons per batch, from oldest to newest.

When the planning department does take the calorific value into account, the waste is stored in the five arranged locations. Retrieving is then done, following our adapted model based on Obroučka et al. (2015) as discussed in Section 3.3.3 and 4.4. So a batch of waste is composed by combining waste from the different locations, according to the optimal composition found by the adapted model of Obroučka et al..

At the beginning of each weekday, the age of the waste in TOP is checked. The register that is used is arranged with the oldest ton of waste in the top line, so only that line needs to be checked. Obviously, for the situation in which the waste in stored at 5 locations, the age of the oldest waste at each location needs to be checked. Whenever the age of the waste reaches the over-aging limit, retrieving is initiated according to the situations discussed before.

When waste leaves TOP, the calorific value of the waste could be lower due to the weather conditions and the length of stay in TOP. The amount of decrease is based on a deterministic process whereas a certain age of the waste that leaves TOP, results in a certain amount of decrease in calorific value. Equation 5.1 is used in the model to determine the decrease. A more detailed explanation of the equation is shown in Appendix E.

$$Decrease = 0,00001 \cdot (12 \cdot Ageinyears)^2 + 0,0014 \cdot (12 \cdot Ageinyears) - 0,0936; \quad (5.1)$$

6. Output
In the output of the process itself, nothing special happens. The waste is incinerated and is drained from the model. In Section 2.3.4, we listed our performance indicators, the costs per week and the standard deviation of the calorific value in the buffers. We discuss how these are gathered.

- Average costs per week
  At the end of every week, the amount of diverted and retrieved waste, the amount of waste sent to an alternative incinerator, and the amount of idle time of the incinerators are multiplied by their respective costs. At the end of a run, the average over all weeks is taken.
- Both standard deviations in caloric value of contents of buffers. This provides us with an average of the weekly made costs and by comparing this with the current average costs per week, we determine which settings are optimal for Twence.
  At the end of the week, the average calorific value in a buffer is saved and at the end of a run the standard deviation is calculated. This gives us an indication about the fluctuation in calorific value that is incinerated. Because we know that the input of constant calorific value is positive for the efficiency of the incineration, we would like to know which experiments provide the optimal settings in order to achieve the lowest standard deviation of calorific value that is incinerated.

5.1.2 Assumptions

In Chapter 4 we already came across some assumptions. These assumptions were mostly used for the conceptual models we designed. Here we list all assumptions we make to have a clear overview. The assumptions include the already stated assumptions from Chapter 4 and are supplemented with some assumptions for our simulation model. We state the assumptions, separated by categorizing themes.

Client arrival assumptions

- Calorific value of all incoming waste becomes known upon arrival.
- Holidays are not taken into account.
- Processing continues 7 days a week, but arrivals are only on weekdays.
- Opening hours of Twence are not taken into consideration, all supply arrives at the start of a day.
- No distinction is made between clients. All scheduled arrivals for an incineration line are combined.
- Based on the results found in Figure 2.9 and Table 2.6, when contracts are restricted on mass, the calorific values of waste are drawn from a normal distribution shown in the model input discussed in Section 5.2.

Planning assumptions

- The buffer levels can be checked every day in real time.
- Decisions made by the planning department are executed immediately.
- In the model for the current situation, all supply is accepted by Twence.
- All the waste that is supplied has already been pre-assigned to incinerating line 1+2 or incinerating line 3.
- 10 ton of waste is examined at once, due to crane capacity.

Storage assumptions

- When decision conditions include calorific value, the waste is separated in storage in 5 classes.
- When working with a certain TOP Capacity, the initial average inventory is set to 80% of the capacity.
- Calorific value decreases because of rainfall according to a deterministic process as shown in Equation 5.1.
- Transportation time between TOP and the incinerators is negligible.
- A maximum of 1500 tons of waste can be diverted to TOP per week.
- A maximum of 2400 tons of waste can be retrieved from TOP per week.

Process assumptions

- There are no failures or maintenance shutdowns scheduled in our experiments.
- Processing times are based on calorific value, mass and factor (Equation 2.1).

- Although it is preferred that waste is incinerated on its scheduled line, no other effects or costs occur when incinerating waste on an incinerator other than the scheduled one.

5.2 Model input

In this section, we state all data that is used as input for our simulation model. All parts of the process (Figure 5.1), are addressed separately. We start with defining the variables in Table 5.2.

Input parameters: Contract restrictions: Mass	
$Mass_{Line1+2}$	Uniform[6.435 ; 7.865]
$Mass_{Line3}$	Uniform[5.175 ; 6.325]
$Calorificvalue_{Line1}$	Normal[8,705 ; 0,460] *
$Calorificvalue_{Line2}$	Normal[8,736 ; 0,528] *
$Calorificvalue_{Line3}$	Normal[10,229 ; 0,810]
Input parameters: Contract restrictions: Calorific value	
$Mass_{Line1+2}$	Normal[7.150 ; 715]
$Mass_{Line3}$	Normal[5.750 ; 575]
$Calorificvalue_{Line1}$	Uniform[8,2698 ; 9,1403]*
$Calorificvalue_{Line2}$	Uniform[8,992 ; 9,1728]*
$Calorificvalue_{Line3}$	Uniform[9,7176 ; 10,7405]
Input parameters: Contract restrictions: Processing time	
$Mass_{Line1+2}$	(Uniform[29.548 ; 32.637] / $Calorificvalue_{Line1}$) + (Uniform[29.530 ; 32.618] / $Calorificvalue_{Line2}$)
$Mass_{Line3}$	Uniform[55.933 ; 61.779] / $Calorificvalue_{Line3}$
$Calorificvalue_{Line1}$	Uniform[8,2698 ; 9,1403]*
$Calorificvalue_{Line2}$	Uniform[8,992 ; 9,1728]*
$Calorificvalue_{Line3}$	Uniform[9,7176 ; 10,7405]
Input parameters: Costs	
$C_{Diverting}$	€7,29 per ton**
$C_{Retrieving}$	€6,31 per ton**
$C_{Alternative}$	€25,00 per ton**
$C_{IdleTimeLine1}$	€0,69 per second (Table 2.4)
$C_{IdleTimeLine2}$	€0,69 per second (Table 2.4)
$C_{IdleTimeLine3}$	€0,72 per second (Table 2.4)
Input parameters: Processing time	
$Factor_{Line1}$	Multimodal with p(x) = 0,533·Normal[x; 19,0950 ; 0,0399] + 0,467·Normal[x; 19,5774 ; 0,0565]
$Factor_{Line2}$	Normal[19,5890 ; 0,0778]
$Factor_{Line3}$	Normal[10,3462 ; 0,0747]

Input parameters: Other	
Legally determined max. age	3 years
80K TOP, age of each ton	Uniform[0 days ; 1.054,00 days]
40K TOP, age of each ton	Uniform[0 days ; 925,93 days]
5K TOP, age of each ton	Uniform[0 days ; 181,40 days]

Table 5.2: Model input for the simulation model
*Since waste arrives for incineration line 1+2, and both lines have the same processing capacity, the calorific value is assigned by taking the distribution chosen for line 1 or 2 with a probability of 50% for each.
** Calculated from data found in Nijkamp (2016)

Motivation for the choice for the distributions can be found in Appendix B.

5.3 Verification and validation

Before we start with designing experiments, we need to verify and validate the model. Verification is to check whether the model is correctly implemented and the input is done right. Validation is to make sure that the outcome of the model does not strike with reality and that the model transforms the input to output in a correct way. To make sure we make a good verification and validation, we need to compare our model with historical data. For this, we use the model input with contracts based on mass as seen in Table 5.2, but we change the mass that arrives such that it matches the historical data exactly. That way, we can determine whether the model reacts in the same way as in reality.

5.3.1 Verification

To check the correctness of the model, we first made sure that the model was working properly. We examined the animation of the model and debugged it while programming it. By making several pilot runs we checked the correctness of the model by looking at several factors, such as the throughput and calorific value. We summarize this in Table 5.3.

	Historical		**Model**	
	Mean	stDev	Mean	stDev
Supply per week Line 1+2	6.788	897	6.788	897
Supply per week Line 3	5.776	1.432	5.776	1.432
Calorific value (1+2)	8,75	0,56	8,72	0,50
Calorific value (3)	10,23	0,81	10,24	0,83

Table 5.3: Verfication of historical data and model data

The results in Table 5.3 approach the historical values closely. Because the distributions are based on the historical data, the calorific values would exactly match eventually when we would take a infinite run length. The values for the supply match perfectly as they were directly implemented as input.

5.3.2 Validation

To validate the model with reality, we use data from 2015, provided by the Planning department of Twence. From these data we know the arrivals and the amount of diverted and retrieved waste for every week and we edit the model to follow these amounts. If we keep the arrivals and the amount of diverted and retrieved waste per week the same, we can validate the way in which we define our processing time (Equation 2.1). For the second part of our validation, we no longer use the historical data on the amount of waste diverted and retrieved, and let the model decide when to do this.

The planning department made a forecast about the amount of mass in the buffers for all incinerators combined for 2015. We validate the model by comparing the amount of mass in the buffers combined following from the model with the forecast. The results are shown in Figure 5.3.

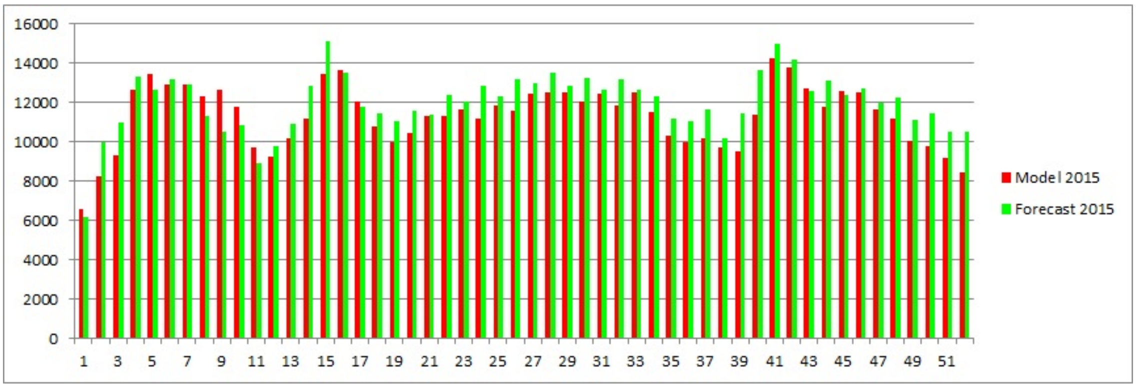


Figure 5.3: Combined bufferlevels (1+2 & 3), Forecast versus Model

In Figure 5.3 we see that the model follows the forecast very well. From Table 5.2 and Equation 2.1, we know that the determination of the calorific value and therefore also the processing time is based on a stochastic process. Therefore, the processing time of the waste will never be a 100% fit with the historical data and that explains the small differences in Figure 5.3.

In Figure 5.3 we only validated the processing of the waste, this because we used the same amounts for diverting and retrieving as in the data from 2015. If we want to validate whether our model also reacts on similar moments in time about diverting or retrieving, we need to let the model make these decisions. So instead of copying the data from 2015 about diverting and retrieving, we now let the model decide when to divert or retrieve waste based on the conceptual models from Figure 4.3 and 4.5. In Table 5.4 we show the thresholds used in the decision models, set to a level that corresponds with the current situation.

	Utilization		Utilization
$HighThreshold_{Line1+2}$	85%	$HighThreshold_{Line3}$	85%
$LowThreshold_{Line1+2}$	15%	$LowThreshold_{Line3}$	15%

Table 5.4: Thresholds used for validation

Apart from the amount of mass in the buffer, retrieving could also be initiated when waste in TOP is almost over-aging. Because we do not know exactly what the age of every individual ton of waste in TOP was at the start of 2015, we do not take the over-aging of waste into account. Therefore, we expect that the model has a lower average amount of waste in the buffers, due to the absence of the mandatory retrievals. The results are shown in Figure 5.4.

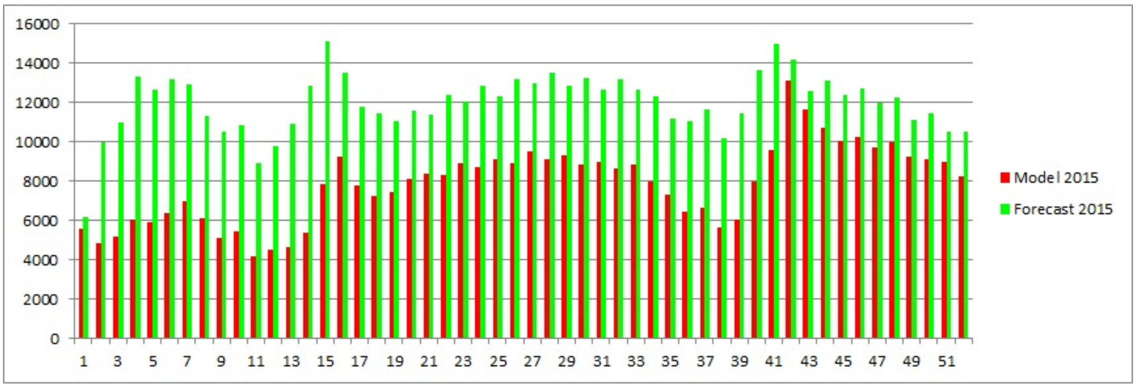


Figure 5.4: Combined bufferlevels (1+2 & 3), Forecast versus Model (Model decides when to divert or retrieve

We see in Figure 5.4 that, just as we suspected, the average amount of waste in the buffers is lower than in the forecast. However, the model follows the same flow as the forecast, indicating that the model reacts in the right way.

In the end we see that the model approaches the forecast. Reason for this is the diverting and retrieving to prevent over-aging. In the forecast, almost every week, an amount of 1400 tons is retrieved. From week 5 onwards, 1500 tons are also diverted in the forecast. This means that in the beginning the historical buffer levels are supplemented with 4 times 1400 tons of waste, which leads to a difference of 5600. After this, every week a difference of 100 tons is recovered (1500 diverting minus 1400 retrieving). Therefore, in the beginning, the difference is about 5600 tons and in the end around 900 tons which originates from the 47 weeks times 100 tons.

At this point, we validated the model in two ways, the first with diverting and retrieving amounts based on historical data and the second where the model decided the amounts for diverting and retrieving. Both times, the model performed the way we expected it to do, and it corresponded with reality.

Lastly, we need to validate the arrival process and costs in order to make sure we make a good comparison. To do this, we run the model, that makes the decisions itself, 20 times and for a period of 30 years to ensure reliability. We then take the average over the results to compare these with the costs we found for the current situation. We first show the comparison between the realized arrivals and the arrivals from our model in Figure 5.5.

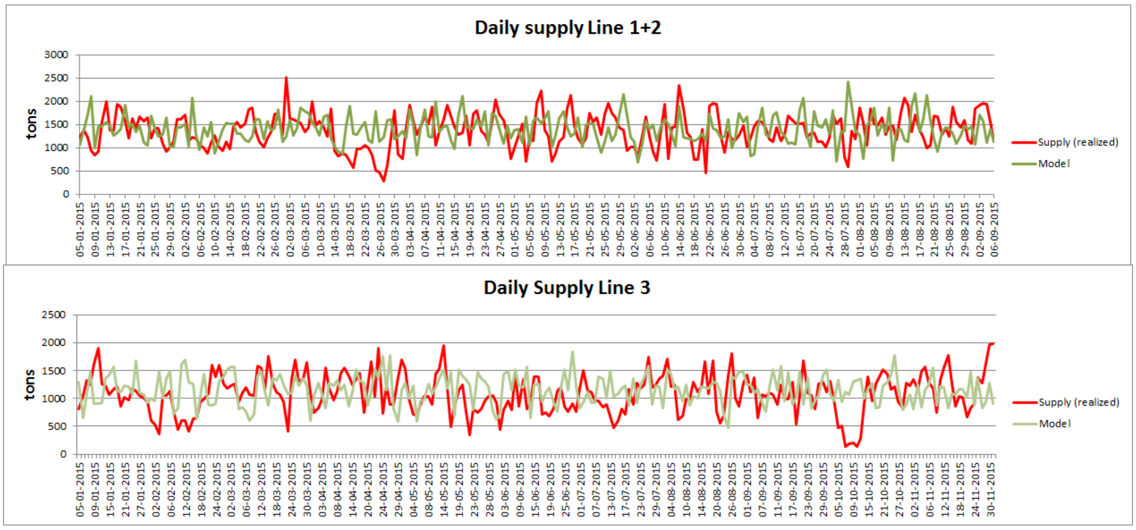


Figure 5.5: Comparison between model arrivals and real arrivals

We see that the arrivals look similar to the real arrivals. In Table 5.5 we show the characteristics of the model run versus the realization.

	Settings						**Output**				
	Contract restrictions	Decision conditions	Mean arrivals* Line 1+2	Mean arrivals* Line 3	St dev arrivals* Line 1+2	St dev arrivals* Line 3	Divert Costs/Week	Retrieve Costs/Week	Alternative Costs/Week	Idle time Costs/Week	Average Costs/Week
Real	Mass	Mass	1.359,15	1.084,30	372,87	355,75	5.016,27	4.933,42	465,12	0	10.414,81
Model	Mass	Mass	1.421,90	1.150,01	301,01	273,47	4.874,01	4.573,52	425,64	70,84	9.944,01

Table 5.5: Performance indicator validation. *All arrivals are per day

We see that the costs per week are a bit lower, which can be explained by the fact that the model has a lower standard deviation than the real arrivals. Twence aims to have the clients supply their waste within a 10% margin of a specified mass. Currently this is not executed perfectly by the clients. We decide to keep the arrival process the same for now, since we then can examine the situation Twence has when clients stick to the contracted agreements. We later on perform a sensitivity analysis on the deviation from these margins to see what the effect is on the best found solution.

5.4 Design of experiments

In this section we introduce our experiments. We show the experimental factors in Figure 5.6.

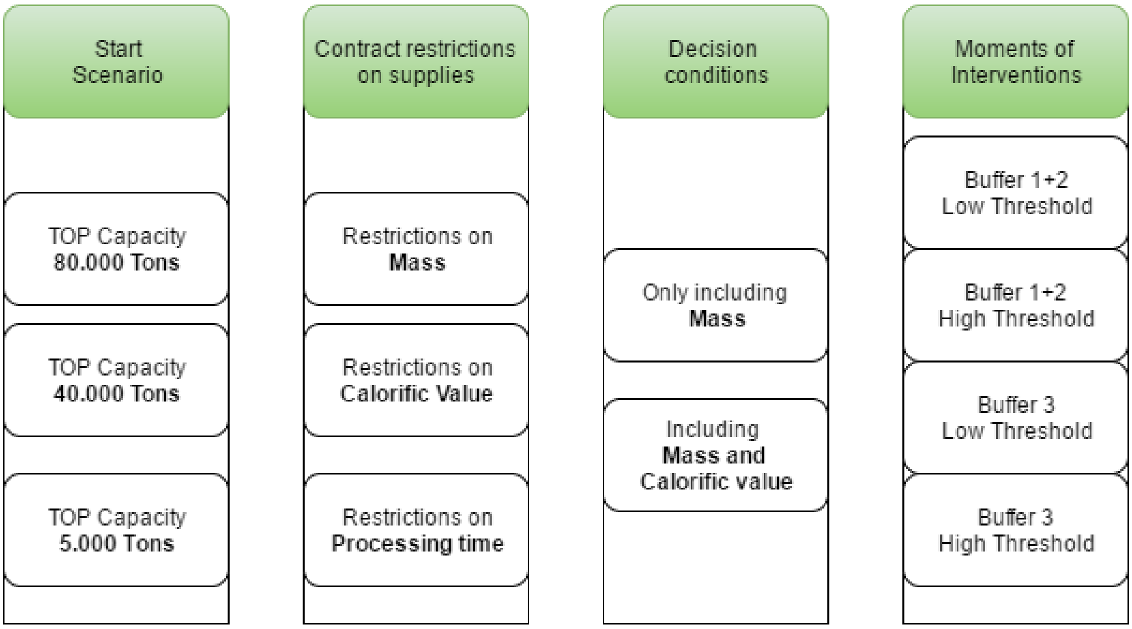


Figure 5.6: All different groups in which experimental factors arise

Start Scenario
First we design three scenarios, which are based on the level of bulk-storage. In the current situation, Twence has 80.000 tons of waste in bulk-storage, they expect that the overall costs arising in the supply chain is much lower when the amount of waste in bulk-storage is much lower and suggested that it should be around 5 Kton. A bulk-storage of 5 Kton results in an almost just-in-time situation where the coordination between Twence and its suppliers must be perfect. Another option could be that the optimal amount of bulk-storage lies between these extremes, which is why we designed these three scenarios, being a capacity of 80 Kton, 40 Kton and 5 Kton.

As mentioned in the assumptions in Section 5.1.2, when we choose for a TOP capacity, we examine the effect of having always around the 80% of the capacity as averagel inventory. This leads to starting inventories of respectively 64 Kton, 32 Kton and 4 Kton. We limit the TOP to a specific capacity because we want to be clear about the required space and capacity needed for the different scenarios. Because it is not logical to start with a TOP filled to its capacity, we made the assumption of starting at a level of 80%.

- **Start scenario: TOP Capacity 80 Kton**
  The TOP is limited to 80 Kton. The initial inventory will be 64 Kton.
- **Start scenario: TOP Capacity 40 Kton**
  The TOP is limited to 40 Kton. The initial inventory will be 32 Kton.

- **Start scenario: TOP Capacity 5 Kton**
  The TOP is limited to 5 Kton. The initial inventory will be 4 Kton.

Contract restrictions
The second part is about the restrictions stated in the contracts about the supplies, that can follow the current situation or our designed options. The contracts of the clients are currently based on an amount of mass of waste. Over an entire year, a client needs to supply this amount of mass evenly over the year and in total they may deviate 10%. Because the processing time of the waste is determined by the calorific value of the waste it might be logical to base a contract on a specific calorific value or even a specific processing time, such that less unnecessary diverting or retrieving occurs. In Table 5.2 we displayed the input for this experimental factor.

Decision conditions
The third experimental factor is about the decision conditions. In Chapter 4 we designed our conceptual model, which included decisions models about diverting and retrieving. This experimental factor can be set to make decisions based on mass, whereas the simulation model uses the models from Figure 4.3 for diverting and Figure 4.5 for retrieving. The other setting is that the decision conditions also include the calorific value. The simulation model will then use the proposed decisions models for retrieving. In short we state the differences:

- **Decision conditions: Mass**
  Diverting decision: based on level of mass of the waste being above a certain percentage of the capacity (high threshold).
  Retrieving decision: based on level of mass of the waste being below a certain percentage of the capacity (low threshold).
  Retrieve from TOP: based purely on age, a batch is taken from TOP.
- **Decision conditions: Mass, Calorific value**
  Diverting decision: based on level of mass of the waste being above a certain percentage of the capacity (high threshold).
  Retrieving decision: based on level of mass of the waste being below a certain amount of processing time (low threshold).
  Retrieve from TOP: based on the Obroucka model, a composed batch is taken from TOP.

Moments of intervention
We want the supply chain to be cost effective, so the causes of costs need to be minimized. The moments of actions are defined as thresholds that represent a percentage of the buffer level expressed in mass or in total processing time. The goal is to find the optimal thresholds at which actions take place. So at the optimal minimal buffer level of buffer 1+2, actions need to be done in order to make sure that the incinerator does not end up without waste. At the same time, there needs to be a maximum level such that enough space is reserved for mixing waste or for mandatory retrieving. This group will have a lot of effect on the amount of experiments that we are going to do, because we could examine all combinations from 0

to 100%. To keep the number of experiments to a reasonable amount, we calculate what logical thresholds would be. The results are shown in Table 5.6 and the calculations can be found in Appendix G.

Low $Threshold_{Line1+2}$	High $Threshold_{Line1+2}$*	Low $Threshold_{Line3}$	High $Threshold_{Line3}$*
35%	60%	15%	60%
40%	65%	20%	65%
45%	70%	25%	70%
	75%		75%
	80%		80%

Table 5.6: Thresholds used during experiments
*High Thresholds are always the same for both buffers, motivation in Appendix G

Our experimental design consists out of four phases:

- **Phase 1:** Examine which effects supplies and starting inventory have on the development of TOP.
- **Phase 2:** Examine the results when we vary all experimental factors.
- **Phase 3:** Examine the most promising results for a longer period of time.
- **Phase 4:** Examine the effects of assumptions and model input by means of a sensitivity analysis.

These phases are explained in the next subsections.

5.4.1 Experimental design phase 1: Supplies and inventory conditions

If we want the results of our experiments to depend solely on the experimental factors we choose, we need to make sure that the starting conditions no longer have influence on the results. There two things that could impede this process, namely:

- Amount of supplies.
- Initial conditions of the TOP waste.

We want to examine what the costs are of having different amounts of initial TOP inventory. However, to yield stable results, i.e., performance not heavily depending on a run length, the TOP inventory should be at an almost constant level throughout the entire experiment. If we examine a TOP inventory of 40.000 tons, which after five years is just 5.000 tons, we cannot make a proper comparison. Also, the initial conditions of the starting TOP waste can influence the costs. If we set the initial conditions such that all the starting TOP waste is almost over-aging, a lot of retrieving needs to be done directly from the start, and we can not make a fair evaluation of the strategy chosen for an experiment.

In phase 1 we examine, for all combinations of contract restrictions and decision conditions, what the amount of supplies should be, for which the TOP approaches steady state. The running time of the simulation model is very long, therefore, in phase 1, we just want to examine when the TOP inventories reach steady state. When this happens, we look at the conditions of the waste in TOP so we know what conditions lead to steady state behavior. For phase 2, we set the initial conditions of the starting TOP inventory to the values we found in phase 1 that led to steady state. In Table 5.7 we see the experimental settings for phase 1. The low thresholds for buffer 1+2 and buffer 3 are respectively 35% and 15%, the high threshold is 80% for both. We make 30 runs with a length of 15 years.

TOP Capacity	Contract restrictions	Decision conditions	Amounts of supply (tons/week)
80K, 40K, 5K	Mass	Mass	12850, 12900, 12950
80K, 40K, 5K	Mass	Calo. Value	12850, 12900, 12950
80K, 40K, 5K	Calo. Value	Mass	12850, 12900, 12950
80K, 40K, 5K	Calo. Value	Calo. Value	12850, 12900, 12950
80K, 40K, 5K	Both	Mass	12850, 12900, 12950
80K, 40K, 5K	Both	Calo. Value	12850, 12900, 12950

Table 5.7: Experimental settings for phase 1

The extensive results from these experiments can be found in Appendix F. A summary of these results is shown in Table 6.1.

5.4.2 Experimental design phase 2: All experiments

In phase 2, we take the results from phase 1 about the supplies and use these for the experiments used in phase 2. We combine all experimental factors that we earlier explained into experiments. We run these experiments for a shorter period than desired since it takes a lot of computational time to reach steady state. Since from phase 1 we will find the conditions of the TOP inventory and the amount of supplies needed for steady state, we use these conditions and supplies in phase 2 without warm up. After we examined the results from phase 2, we take the most promising experiments, which we then run for a longer period of time excluding a certain warm-up period (phase 3).

Number of experiments

From the experimental factors, we can derive the total amount of experiments that we need to do:

- Group 1: TOP Capacity (**3 Options**)
- Group 2: Contract restrictions (**3 Options**)
- Group 3: Decision conditions (**2 Options**)

- Group 4: Moments of interventions (**45 Options**)

We keep the high thresholds for both buffers the same, because incoming waste will mainly be distributed first over the two buffers before being send to TOP (motivation in Appendix G). This leaves us with $3 \cdot 3 \cdot 5 = 45$ combinations for the thresholds. This leads to a total of $3 \cdot 3 \cdot 2 \cdot 45 = 810$ experiments. A summary of the amount of experiments is shown in Figure 5.7.

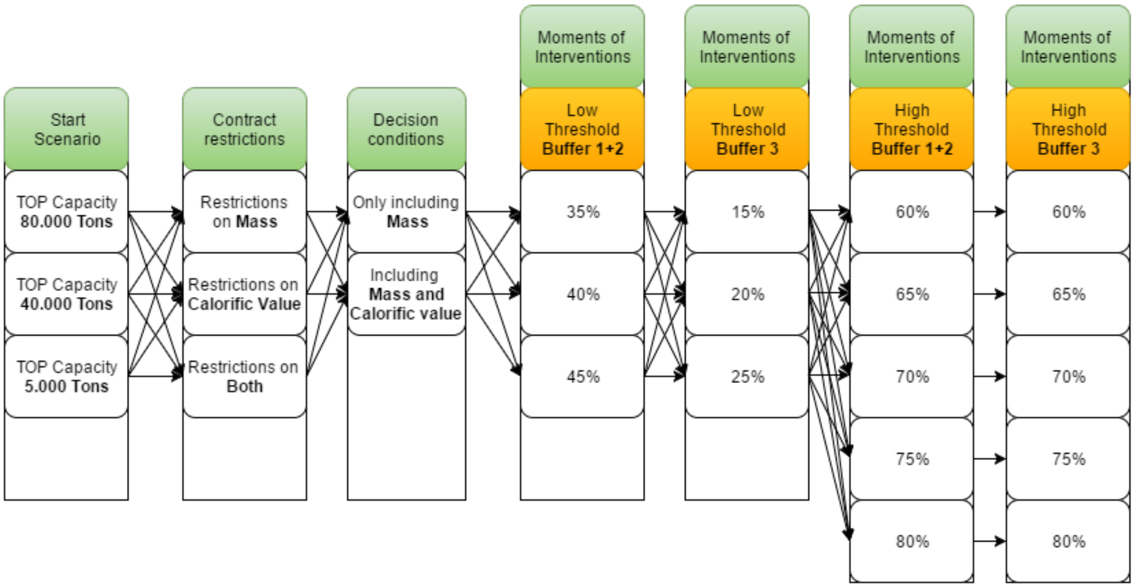


Figure 5.7: All combinations of different experimental factors for phase 2

Number of replications and run length

We need to define the number of replications and the run length of the simulation experiments. First we discuss the type of simulation which is then followed by the number of replications and run length.

In this simulation study we are dealing with a plant that is (preferably) running 24 hours a day. Therefore we do not have a natural event that ends the simulation and we are dealing with a non-terminating simulation. In a non-terminating simulation it is preferred to find a steady state from which we can read the performance. In the first two phases, we do not work with a warmp up period because we first determine the conditions under which steady state arises in phase 1, and find promising results in phase 2. In phase 3, we do work with a warm up period.

We want reliable values for our performance measurement, therefore we need to make sure that the confidence intervals for these measures do not get too wide. From Law and Kelton (2000) we found two strategies for constructing point estimates and confidence intervals. The first is the fixed-sample-size procedure, where a single simulation run of an arbitrary fixed length is made, and then one of a number of available procedures is used to construct a confidence interval from the available data. The second is the sequential procedure, where the length of a simulation run is sequentially increased until an acceptable confidence interval can be constructed.

We choose to use the fixed-sample-size procedure, in combination with the replication/deletion approach as proposed by Law and Kelton, but without the warm up period for our first two experimental phases. We have to make n independent replications of length m observations (weeks). We chose a run length of 780 weeks (15 years) and determine the smallest number of replications n such that:

$$\frac{t_{n-1,1-\alpha/2}\sqrt{S_n^2/n}}{\bar{X}_n} \leq \gamma'.$$

We compute $\bar{X}_n$, the average of the n replications, and S_n^2, the variance in the n replications. $t_{n-1,1-\alpha/2}$ is the student t-value for $(n-1)$ degrees of freedom and a confidence interval of $(1-\alpha)$ and γ' is the corrected relative error.

The required number of replications is determined for the performance measure costs per week, and for every initial TOP inventory the number of replications is determined separately. In Appendix H a more detailed explanation is given about what the required number of replications are when using a confidence interval of 90% and a relative error of 10%. In Table 5.8 this information is summarized.

Start Scenario	Minimum number of replications needed	Number of replications used
80.000 Tons	12	20
40.000 Tons	23	25
5.000 Tons	>30	100

Table 5.8: Required number of replications

The number of replications increases a lot when we start with a TOP capacity of 5 Kton (inventory of 4 Kton). This is due to the big effect that the costs for idle time have. With a 5 Kton TOP capacity, the probability of having idle time becomes larger, and thus more often costs for idle time will occur. Because these costs are substantially higher than other costs, the costs per week are unstable and more replications are needed to gain confidence.

5.4.3 Experimental design phase 3: Most promising results

In phase 3 we take the most promising results from phase 2 and perform longer simulation runs for these experiments. We determine a warm-up by using the Welch method and take this into account whilst extracting the results from these longer experiments. We define "most promising" by looking at two criteria for the results within the categories defined in Table 5.9.

TOP Capacity	Contract restrictions	Decision conditions
80K, 40K, 5K	Mass	Mass
80K, 40K, 5K	Mass	Calo. Value
80K, 40K, 5K	Calo. Value	Mass
80K, 40K, 5K	Calo. Value	Calo. Value
80K, 40K, 5K	Both	Mass
80K, 40K, 5K	Both	Calo. Value

Table 5.9: Categories for phase 3

- **Best within own category**
  It is not unexpected that the results will heavily depend on the chosen contract restrictions. We do not want to restrict ourselves to just looking at a single type of contract restriction and therefore, we divided our experiments in different categories, as shown in Table 5.9. In Phase 3, we examine the best results within each category.
- **Better than current situation**
  Because we want to gain insight on how to improve the supply chain of Twence, we conclude that it is not necessary to examine experiments that are already best in their category but still have higher costs per week than in the current situation.

5.4.4 Experimental design phase 4: Sensitivity analysis.

After examining the results from phase 3, we select the experiments with the best results and perform a sensitivity analysis. We made assumptions in this research that might effect the results or assume situations that are not realistic.

The following assumptions shall be subjected to our sensitivity analysis:

- Section 6.4.1: The choice for a TOP capacity of 5, 40 and 80 Kton.
- Section 6.4.2: The deviation for the uniform distribution in contracts.
- Section 6.4.3: All supply arrives at the start of a day.
- Section 6.4.4: Calorific value decreases because of rainfall.
- Section 6.4.5: No costs or other effects occur when not incinerating waste on its scheduled incinerator.

With our sensitivity analysis, we hope to provide more insight on the effect of certain assumptions made on the results we found from phases 1-3.

5.5 Conclusions

In this chapter we presented our simulation model. We gave a model description and explained the model input. After that, we verified and validated the model and concluded that the results of the different interventions from the model, represent reality sufficiently accurate.

We presented our experimental design, which consists out of four phases. In phase 1 the goal is to find with which amount of weekly supplies leads to a steady TOP inventory. When a steady state is reached, we determine the age distribution of all waste in TOP. We take the found weekly supplies amount and age of waste in TOP as initial conditions for phase 2. After analyzing these results, we examine the most promising results for a longer period of time in phase 3 and perform a sensitivity analysis in phase 4. The results of the four phases are shown in Chapter 6.

6 | Numerical Results

In this chapter we present the results of our simulation experiments. We first discuss the results for phase 1 in Section 6.1. In Section 6.2 we single out the top three results based on the costs per week per TOP capacity, contract restrictions and decision conditions (phase 2). The results for phase 3 are discussed in Section 6.3. For phase 4, we perform a small sensitivity analysis on our results in Section 6.4 after which we make our final conclusions about the results in Section 6.5.

6.1 Experimental results phase 1: Supplies and inventory conditions

In phase 1 we want to find the amount of supplies that would lead to an almost constant level of TOP inventory throughout an entire experiment. This is to yield stable results, i.e., performance not heavily depending on the run length. We want to find an average weekly amount of supplies that leads to a stable TOP inventory whether we start with an initial inventory of 64 Kton, 32 Kton, or 4 Kton. This is because the experiments can no longer be compared when some experiments need to process more waste than others, since then there is a higher probability of making costs. Therefore, we use the same amount of weekly supplies for every experiment.

In Table 6.1 we present the results for the amount of supplies needed to keep a relatively constant level of TOP inventory. In Table 6.1 we also state the conditions of the waste in TOP whenever TOP reaches steady state. A more detailed explanation of these results can be find in Appendix F.

Supplies for Line 1+2	7.150 tons/week	
Supplies for Line 3	5.750 tons/week	
Intial conditions 80K TOP: age of the waste	Uniform[0 days	; 1.054,00 days]
Intial conditions 40K TOP: age of the waste	Uniform[115,74 days	; 1.041,67 days]
Intial conditions 5K TOP: age of the waste	Uniform[640,60 days	; 822,00 days]

Table 6.1: Results from phase 1

The results from phase 1 will be used as input for the next phases.

6.2 Experimental results phase 2: All experiments

We present our results in three tables, one for each TOP capacity. Each table shows the top three results for the different combinations of contract restrictions and decision conditions.

- Table 6.2: Results for experiments with TOP capacity of 5 Kton.
- Table 6.3: Results for experiments with TOP capacity of 40 Kton.
- Table 6.4: Results for experiments with TOP capacity of 80 Kton.

Results for TOP capacity of 5 Kton (init. & avg. inventory 4 Kton)
First we show the results of the different configurations used with a TOP capacity of 5 Kton.

Settings						**Output**							
Contract restrictions	Decision conditions	Low Thres. 1+2	Low Thres. 3	High Thres.	TOP Capacity	St.dev Cal.val 1+2	St.dev Cal.val 3	Divert Costs/Week	Retrieve Costs/Week	Alternative Costs/Week	Idle time Costs/Week	Average Costs/Week
Mass	Mass	0,45	0,25	0,80	5000	0,99	0,24	186,54	166,86	404,63	3.908,74	4.666,76
Mass	Mass	0,45	0,25	0,75	5000	0,98	0,24	204,49	181,21	405,09	3.893,69	4.684,48
Mass	Mass	0,45	0,20	0,80	5000	0,76	0,85	182,98	163,57	403,14	3.939,39	4.689,06
Mass	Calo	0,45	0,25	0,80	5000	0,93	0,71	234,58	208,95	415,82	4.073,54	4.932,89
Mass	Calo	0,50	0,25	0,80	5000	0,80	0,90	238,65	212,29	418,45	4.077,49	4.946,88
Mass	Calo	0,45	0,25	0,75	5000	0,98	0,69	258,10	228,14	418,64	4.050,45	4.955,33
Calo	Mass	0,55	0,25	0,80	5000	1,51	1,48	253,64	228,44	731,28	14.332,88	15.546,24
Calo	Mass	0,55	0,25	0,75	5000	1,51	1,46	294,86	263,02	732,49	14.330,93	15.621,30
Calo	Mass	0,55	0,25	0,70	5000	1,50	1,44	350,86	310,38	733,30	14.282,68	15.677,22
Calo	Calo	0,45	0,25	0,80	5000	2,02	1,32	270,62	240,55	808,57	16.483,05	17.802,79
Calo	Calo	0,45	0,20	0,80	5000	1,84	1,58	263,78	234,32	811,06	16.833,70	18.142,85
Calo	Calo	0,45	0,15	0,80	5000	1,68	1,76	264,28	234,15	823,99	17.463,25	18.785,67
Both	Mass	0,40	0,15	0,75	5000	0,14	0,34	195,39	175,85	94,18	550,03	1.015,45
Both	Mass	0,50	0,20	0,70	5000	0,14	0,35	217,23	192,19	113,23	614,71	1.137,37
Both	Mass	0,45	0,20	0,70	5000	0,26	0,35	207,61	190,33	80,36	688,50	1.166,80
Both	Calo	0,45	0,15	0,75	5000	0,07	0,32	284,64	251,01	119,27	446,07	1.100,98
Both	Calo	0,40	0,25	0,75	5000	0,25	0,14	271,17	242,01	118,15	594,68	1.226,01
Both	Calo	0,45	0,15	0,70	5000	0,10	0,41	266,27	238,96	90,12	644,49	1.239,85

Table 6.2: Top 3 results per category for experiments with TOP capacity of 5 Kton

In Table 6.2 we see that when have a TOP capacity of 5 Kton (and thus an average inventory of 4 Kton), the costs per week are lowest with contracts restricted on both the mass and the calorific value (processing time). To attain the lowest costs per week with these restrictions, Twence should not take the calorific value into account when making decisions. The total costs per week consist of the costs for diverting, retrieving, sending waste to an alternative location, and the costs for idle time. The big differences in costs are mainly caused by the way in which the contracts are restricted. When only restricted on the calorific value, the amount of waste that is supplied per week is the most uncertain. When having just 4Kton on average in the inventory (less than 2 days of processing), we see that this leads to a lot of costs for idle time. At the same time, with just a maximum of 5Kton for storage, the capacity for processing over-supply is small. This is shown in the costs for sending waste to an alternative location (competitors), which is also higher when the supplies are more uncertain.

Results for TOP capacity of 40 Kton (init. & avg. inventory 32 Kton)
Secondly, we show results for experiments with a TOP capacity of 40 Kton.

Settings						**Output**						
Contract restrictions	Decision conditions	Low Thres. 1+2	Low Thres. 3	High Thres.	TOP Capacity	St.dev Cal.val 1+2	St.dev Cal.val 3	Divert Costs/Week	Retrieve Costs/Week	Alternative Costs/Week	Idle time Costs/Week	Average Costs/Week
Mass	Mass	0,45	0,20	0,80	40000	0,12	0,06	1.582,34	1.379,70	207,25	3,20	3.172,48
Mass	Mass	0,45	0,25	0,80	40000	0,12	0,06	1.582,33	1.379,66	207,61	3,24	3.172,84
Mass	Mass	0,45	0,15	0,80	40000	0,12	0,08	1.582,15	1.379,70	207,43	11,40	3.180,68
Mass	Calo	0,45	0,25	0,80	40000	0,18	0,07	3.091,15	2.695,11	373,59	18,20	6.178,05
Mass	Calo	0,45	0,20	0,80	40000	0,18	0,07	3.091,54	2.695,05	373,37	18,58	6.178,54
Mass	Calo	0,45	0,15	0,80	40000	0,18	0,08	3.090,71	2.694,14	373,19	25,44	6.183,48
Calo	Mass	0,45	0,25	0,80	40000	1,27	0,13	1.439,19	1.305,68	419,68	3.092,16	6.256,71
Calo	Mass	0,45	0,20	0,80	40000	1,22	0,38	1.438,97	1.305,62	420,08	3.164,65	6.329,33
Calo	Mass	0,45	0,25	0,75	40000	1,37	0,12	1.493,61	1.346,47	422,80	3.467,56	6.730,43
Calo	Calo	0,45	0,25	0,80	40000	1,39	0,33	2.409,56	2.150,36	584,93	4.704,22	9.849,06
Calo	Calo	0,45	0,20	0,80	40000	1,36	0,48	2.409,02	2.150,23	588,20	4.949,58	10.097,03
Calo	Calo	0,45	0,25	0,75	40000	1,54	0,30	2.533,35	2.246,70	574,83	5.209,81	10.564,70
Both	Mass	0,45	0,20	0,80	40000	0,06	0,05	1.558,28	1.352,77	50,64	0,00	2.961,68
Both	Mass	0,45	0,25	0,80	40000	0,06	0,05	1.561,41	1.355,32	50,64	0,00	2.967,37
Both	Mass	0,45	0,15	0,80	40000	0,06	0,05	1.565,28	1.357,86	50,64	0,00	2.973,78
Both	Calo	0,40	0,25	0,80	40000	0,09	0,06	2.853,39	2.468,89	72,61	8,31	5.403,20*
Both	Calo	0,40	0,20	0,80	40000	0,09	0,06	2.853,39	2.468,89	72,61	8,31	5.403,20*
Both	Calo	0,40	0,15	0,80	40000	0,09	0,06	2.853,39	2.468,89	72,61	8,31	5.403,20*

Table 6.3: Top 3 results per category for experiments with TOP capacity of 40 Kton
*Exactly same costs occur since buffer contents are always between low and high thresholds.

In Table 6.3 we can clearly see the effect of the adapted Obroucka model in the results. The model is used in the experiments where the decision conditions include the calorific value. This means for the retrieving that not always the oldest waste is selected first. Since on average every year about 10 Kton waste needs to be retrieved from TOP due to over-aging, there is not much room for not taking the oldest waste first. Although the adapted Obrouka model takes the over-aging into account, we still see in the results that the costs for retrieving but also diverting (TOP is still constant on average) are in some cases almost 2 times higher when the decision conditions include the calorific value. The best results are again found from the experiments with restrictions on both the mass and calorific value. As already explained, because of the higher costs for retrieving and diverting, the lowest costs per week can be attained by not including the calorific value into the decision conditions.

Results for TOP capacity of 80 Kton (init. & avg. inventory 64 Kton)
Lastly we present the results for experiments with a TOP capacity of 80 Kton.

Settings						Output						
Contract restrictions	Decision conditions	Low Thres. 1+2	Low Thres. 3	High Thres.	TOP Capacity	St.dev Cal.val 1+2	St.dev Cal.val 3	Divert Costs/Week	Retrieve Costs/Week	Alternative Costs/Week	Idle time Costs/Week	Average Costs/Week
Mass	Mass	0,45	0,25	0,80	80000	0,10	0,06	3.198,28	2.750,67	51,15	0,50	6.000,61
Mass	Mass	0,45	0,15	0,80	80000	0,10	0,06	3.198,63	2.751,16	51,15	0,50	6.001,45
Mass	Mass	0,45	0,20	0,80	80000	0,10	0,06	3.198,68	2.751,16	51,15	0,50	6.001,50
Mass	Calo	0,40	0,25	0,80	80000	0,15	0,07	6.263,33	5.444,87	476,06	34,52	12.218,78
Mass	Calo	0,40	0,15	0,80	80000	0,15	0,07	6.263,33	5.444,87	476,06	34,52	12.218,78
Mass	Calo	0,40	0,20	0,80	80000	0,15	0,07	6.263,33	5.444,87	476,06	34,52	12.218,78
Calo	Mass	0,45	0,25	0,80	80000	0,87	0,08	3.167,44	2.778,34	358,13	1.175,46	7.479,37
Calo	Mass	0,45	0,20	0,80	80000	0,86	0,16	3.169,10	2.778,34	365,54	1.256,70	7.569,69
Calo	Mass	0,45	0,15	0,80	80000	0,89	0,29	3.173,15	2.781,25	369,28	1.485,70	7.809,38
Calo	Calo	0,45	0,25	0,80	80000	0,95	0,10	5.047,38	4.479,86	817,95	1.857,34	12.202,52
Calo	Calo	0,45	0,20	0,80	80000	0,97	0,17	5.036,02	4.470,44	825,74	1.901,08	12.233,27
Calo	Calo	0,45	0,15	0,80	80000	0,98	0,23	5.039,11	4.470,36	826,38	2.191,80	12.527,65
Both	Mass	0,45	0,20	0,80	80000	0,07	0,05	3.155,02	2.725,56	0,00	0,00	5.880,58*
Both	Mass	0,45	0,15	0,80	80000	0,07	0,05	3.155,02	2.725,56	0,00	0,00	5.880,58*
Both	Mass	0,45	0,25	0,80	80000	0,07	0,05	3.155,02	2.725,56	0,00	0,00	5.880,58*
Both	Calo	0,45	0,20	0,80	80000	0,08	0,07	6.173,24	5.295,83	72,27	0,00	11.541,34*
Both	Calo	0,45	0,15	0,80	80000	0,08	0,07	6.173,24	5.295,83	72,27	0,00	11.541,34*
Both	Calo	0,45	0,25	0,80	80000	0,08	0,07	6.173,24	5.295,83	72,27	0,00	11.541,34*

Table 6.4: Top 3 results per category for experiments with TOP capacity of 80 Kton
*Exactly same costs occur since buffer contents are always between low and high thresholds.

The results of the experiments with the largest TOP configuration again show the difference in costs affected by the adapted Obroucka model for retrieving waste. Again we see, that when the decisions conditions include the calorific value, the costs for retrieving (and thus diverting) increase. The costs for idle time are in almost all cases lower than with the other TOP configurations, which is logical since with more TOP inventory, there is more obligatory retrieving and thus there is less chance of the buffers getting empty. With the 80Kton TOP capacity and thus the average TOP inventory of 64Kton, the lowest costs per week can be attained again by means of restricting the clients on both the mass and the calorific value (so on processing time).

Effect of including calorific value into decision conditions.
As explained before, we noticed that the results for the experiments where the calorific value was included in the decision conditions were always worse than the experiments where the calorific value was not included. We explained that this was probably because the adapted model of Obroucka does not always take the oldest waste from TOP. We mean by this that for example, if waste is retrieved in week 7, and it is not the oldest waste, it could be the case that in week 8, overaged waste needs to be retrieved and so twice as much retrieving is done. This is an extreme example since the model of Obroucka does take the over-aging into account, but it is still the case that more waste needs to be retrieved due to over-aging.

In Figure 6.1 we show the amount of times that the model has requested retrieving due to over-aging of waste during 20 simulation run replications. The red line represents the experiment where only the mass is included in the decision conditions, the blue line represents the experiment where also the calorific value is included. The first graph is for a TOP capacity of 5 Kton, the second for 40 Kton and the bottom is for 80 Kton TOP capacity. The horizontal axis shows the different weeks and the vertical axis shows the number of times retrieving is requested due to over-aging. We see that the graphs show that for the 40 Kton and 80 Kton TOP capacity, the blue line is almost always above the red line. This indicates that with these settings the “Calo” variant, in which decision conditions include calorific value and the adapted Obroucka model for retrieving is used, has more obligatory retrieving.

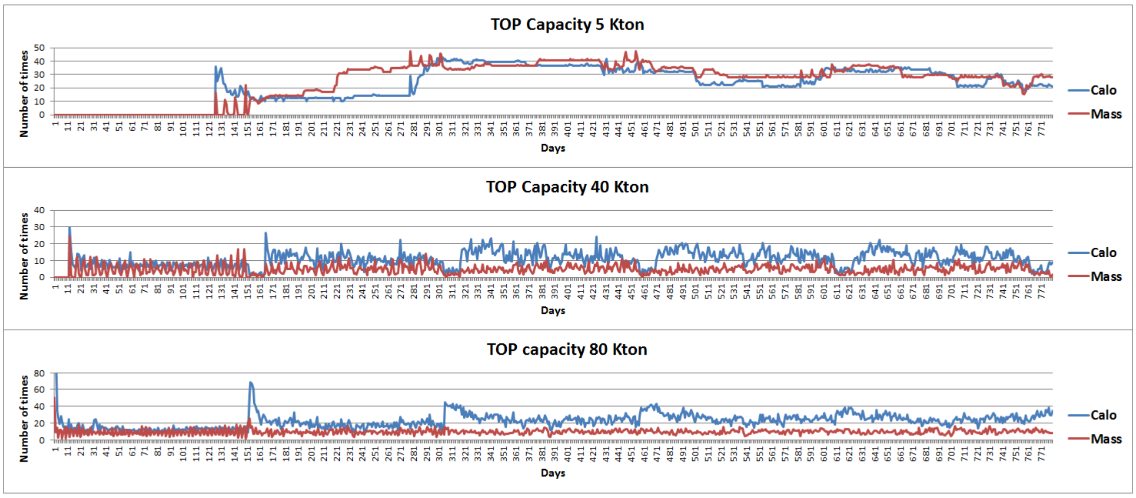


Figure 6.1: Amount of times retrieving is requested due to over-aging

Effect of the different thresholds.
In Appendix G we explain more about the choice for the different thresholds we use in our experiments. When looking at the low thresholds for buffer 1+2 that mostly occur between the best results, we see that for all TOP capacities this is 0,45. When decision conditions do not include the calorific value, this number stand for the percentage of capacity that should be filled in the buffer and otherwise retrieving is initiated. When decision conditions include calorific value, this number stands

for the percentage of 10 days of processing time that should be in the buffer, and otherwise retrieving is initiated. So in most cases, for buffer 1+2 there should be at least 2475 tons of waste or in the other case 4.5 days of processing time available.

Figure 6.2 shows the effect of the different thresholds we used. For every TOP capacity, contract restrictions and decision conditions combination we had 27 combinations of thresholds. In Figure 6.2 we show the results for 80 Kton TOP capacity, with contract restrictions and decision conditions set to “Mass”. In Figure 6.2 we see all 27 combinations of thresholds with their associated costs per week. For example, a certain experiment results in a costs per week of €7020,91 (not shown in Table 6.4) and has the following thresholds: Buffer 1+2 low 35%, Buffer 3 low 20%, and the high threshold is 70%. All these thresholds are shown in Figure 6.2 with the green dots. This is done for all 27 combinations of thresholds. For every combination of TOP capacity, contract restrictions and decision conditions, we created similar figures but we only show one here.

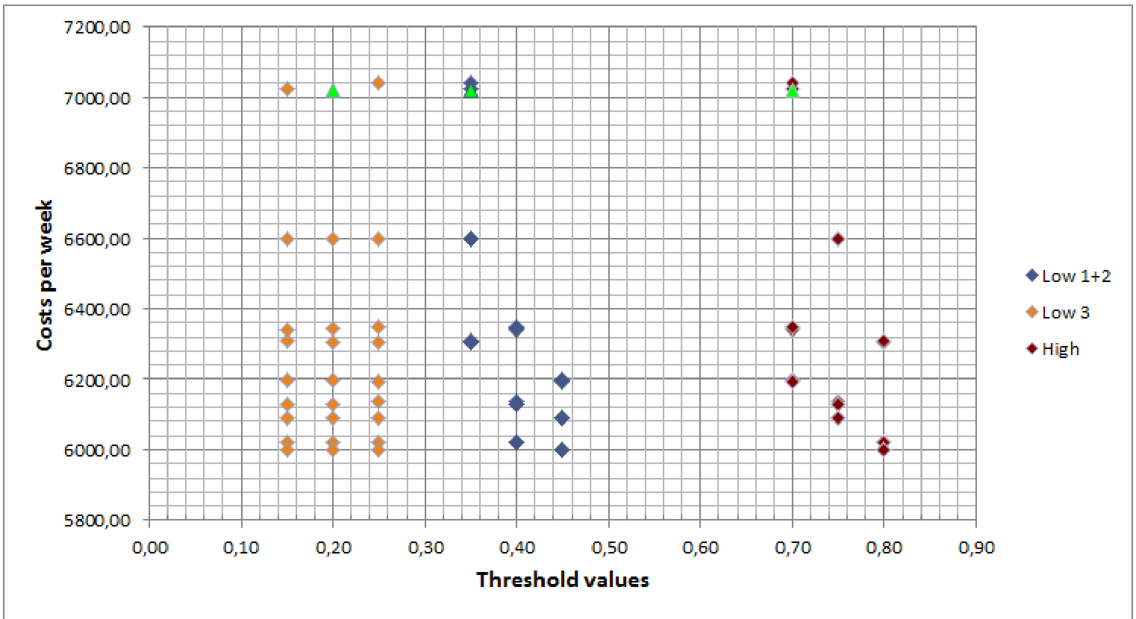


Figure 6.2: Effect of different thresholds for 80 Kton TOP capacity, contract restrictions and decision conditions set to “Mass”

From Figure 6.2 we conclude that the low threshold for buffer 1+2 is important, as well as the high threshold. Both show that a higher value for the threshold shows a lower costs per week. The low threshold of buffer 3 does not show a clear preference for a certain threshold. The other results are shortly summarized without showing the similar figures.

For the 5 Kton TOP capacity experiments, we notice that no big differences occur in the costs when only the thresholds change slightly. From all results we concluded that the low threshold of buffer 1+2 for the 5 Kton TOP capacity experiments was sometimes even too low. We therefore also performed another set of experiments where the low threshold could increase to 0,50 or even 0,55. This is why these thresholds sometimes show up as being the best, although they originally were not within the range of that experimental factor (Table 5.6).

For the experiments with 40 Kton and 80 Kton TOP capacity we also examined whether we needed to increase the range of the experimental factors but overall results showed that this was not necessary. Within the best results of the 40 Kton and 80 Kton TOP capacity experiments we mainly see that only the low threshold of buffer 1+2 is of importance. Within configurations, this is the threshold that is always the same for the top three results, whereas the low threshold of buffer 3 takes all values possible within the given range but has almost no influence on the costs per week.

The high threshold is 0,80 with most of the best experiments but we chose not to increase this threshold because this would interfere with the wishes of Twence to save room for mixing the waste in the buffers.

Comparing with the current situation.
In the current situation, Twence works with contract restrictions on mass, and decision conditions exist solely of mass. If we compare all the experiments where we have the same combination, we get the results as shown in Table 6.5.

Settings						Output						
Contract restrictions	Decision conditions	Low Thres. 1+2	Low Thres. 3	High Thres.	TOP Capacity	St.dev Cal.val 1+2	St.dev Cal.val 3	Divert Costs/Week	Retrieve Costs/Week	Alternative Costs/Week	Idle time Costs/Week	Average Costs/Week
Mass	Mass	0,45	0,20	0,80	40000	0,12	0,06	1.582,34	1.379,70	207,25	3,20	3.172,48
Mass	Mass	0,45	0,25	0,80	40000	0,12	0,06	1.582,33	1.379,66	207,61	3,24	3.172,84
Mass	Mass	0,45	0,15	0,80	40000	0,12	0,08	1.582,15	1.379,70	207,43	11,40	3.180,68
Mass	Mass	0,45	0,25	0,80	5000	0,99	0,24	186,54	166,86	404,63	3.908,74	4.666,76
Mass	Mass	0,45	0,25	0,75	5000	0,98	0,24	204,49	181,21	405,09	3.893,69	4.684,48
Mass	Mass	0,45	0,20	0,80	5000	0,76	0,85	182,98	163,57	403,14	3.939,39	4.689,06
Mass	Mass	0,45	0,25	0,80	80000	0,10	0,06	3.198,28	2.750,67	51,15	0,50	6.000,61
Mass	Mass	0,45	0,15	0,80	80000	0,10	0,06	3.198,63	2.751,16	51,15	0,50	6.001,45
Mass	Mass	0,45	0,20	0,80	80000	0,10	0,06	3.198,68	2.751,16	51,15	0,50	6.001,50

Table 6.5: Results for experiments similar to the current situation

We see that the lowest costs per week are attained when lowering the TOP capacity (and thus the average inventory) to 40 Kton (32 Kton). This is because with too much TOP inventory, the costs for diverting and retrieving become larger, and with too less TOP inventory, the costs for idle time become larger. It is interesting to find out whether there is an even better inventory level possible. We examine this in Section 6.4, where we perform a sensitivity analysis on this subject.

We also see that compared to costs per week in the current situation(€10.414,81), the costs per week in our experiments are already much better. There are two reasons for this. The first reason is that the TOP inventory that we examine in our experiments is lower than the TOP inventory in the current situation. For the past two years the average TOP inventory of Twence was around 90 Kton (Figure 2.7). When we assume that 1/3rd of this inventory needs to be refreshed in a year, at the costs of €7,29 per ton (diverting) and €6,31 per ton (retrieving), the minimum costs, when no idle time occurs and no waste is sent to competitors, is already €7.846 per week.

The second reason is that currently, more waste is diverted and retrieved than necessary. Looking at the calculation we just made, it shows that the minimal costs per week for diverting and retrieving are respectively €4.205,77 and €3.640,38. Looking at the figures we showed in Table 5.5 in Section 5.3 about the validation, we see that currently the costs per week for diverting and retrieving are together around €2.100 more. Our model does not have incentive to divert or retrieve more waste than necessary. This is why the results will most of the time approach the minimal costs for diverting and retrieving for a given amount of TOP inventory.

6.3 Experimental results phase 3: Most promising results

In this section, we provide the results of phase 3 of our experiments. In Table 5.9 we defined in which categories we search for the most promising results. Since we already made this selection when showing the results in the previous selection, we now only need to determine which of these experiments have lower costs than the current situation (€10.414,81). For these experiments we determined a warm up period for which an extensive explanation is shown in Appendix I. In Table 6.6 we show the results of phase 3.

In Table 6.6 we separated the experiments by their TOP capacity and their combination of contract restrictions and decision conditions. For Twence it could be the case that the choice for a certain scenario is not only based on its costs per week. In our experiments we charge no costs for the TOP capacity since the space is already available. But it could also be the case that unused capacity leads to gains by starting other projects. Therefore, Twence should make a trade-off between the amount of TOP capacity they want to use and possible other uses of the TOP capacity.

Within every category of TOP capacities, we see that the experiments yield the lowest costs per week when the contract restrictions are set on both the mass and the calorific value, to try and control the supplied processing time. Only with a TOP capacity of 5 Kton, and thus an average inventory in TOP of 4 Kton, the experiments where decision conditions include the calorific value come close to the

Settings						**Output**						
Contract restrictions	Decision conditions	Low Thres. 1+2	Low Thres. 3	High Thres.	TOP Capacity	St.dev Cal.val 1+2	St.dev Cal.val 3	Divert Costs/Week	Retrieve Costs/Week	Alternative Costs/Week	Idle time Costs/Week	Average Costs/Week
Mass	Mass	0,45	0,25	0,80	5000	1,18	0,36	198,52	173,92	409,59	3.672,65	4.454,68
Mass	Mass	0,45	0,20	0,80	5000	0,92	1,05	196,32	172,19	409,29	3.721,47	4.499,27
Mass	Mass	0,45	0,25	0,75	5000	1,18	0,37	216,73	189,74	407,61	3.693,38	4.507,46
Mass	Calo	0,50	0,25	0,80	5000	0,95	1,06	271,06	236,81	412,77	3.781,76	4.702,40
Mass	Calo	0,45	0,25	0,80	5000	1,10	0,84	272,78	238,19	414,45	3.795,56	4.720,98
Mass	Calo	0,45	0,25	0,75	5000	1,13	0,85	295,54	258,01	411,85	3.825,11	4.790,51
Both	Mass	0,50	0,20	0,70	5000	0,48	0,89	181,74	158,86	124,86	1.974,71	2.440,17
Both	Mass	0,40	0,15	0,75	5000	0,42	0,95	171,09	149,94	123,77	2.156,43	2.601,23
Both	Mass	0,45	0,20	0,70	5000	0,78	0,86	176,80	152,89	109,55	2.322,62	2.761,87
Both	Calo	0,45	0,15	0,75	5000	0,13	0,86	250,78	218,57	124,56	1.617,30	2.211,20
Both	Calo	0,45	0,15	0,70	5000	0,16	0,88	274,64	238,04	137,08	1.778,55	2.428,31
Both	Calo	0,40	0,25	0,75	5000	0,95	0,37	237,58	205,96	132,14	2.138,55	2.714,23
Mass	Mass	0,45	0,20	0,80	40000	0,16	0,12	1.547,43	1.345,52	301,75	88,57	3.283,27
Mass	Mass	0,45	0,25	0,80	40000	0,17	0,08	1.553,79	1.351,83	306,42	71,35	3.283,40
Mass	Mass	0,45	0,15	0,80	40000	0,15	0,19	1.552,07	1.349,54	303,00	131,25	3.335,86
Mass	Calo	0,45	0,20	0,80	40000	0,28	0,19	3.149,49	2.733,78	368,59	225,95	6.477,80
Mass	Calo	0,45	0,25	0,80	40000	0,29	0,13	3.194,79	2.773,14	368,84	215,33	6.552,10
Mass	Calo	0,45	0,15	0,80	40000	0,24	0,25	3.182,48	2.762,08	369,65	248,76	6.562,97
Calo	Mass	0,45	0,25	0,80	40000	1,64	0,61	1.038,24	903,92	244,26	8.212,32	10.398,74
Calo	Mass	0,45	0,20	0,80	40000	1,53	1,04	1.032,63	899,13	247,26	8.389,86	10.568,87
Calo	Mass	0,45	0,25	0,75	40000	1,70	0,57	1.113,79	969,31	250,06	8.301,25	10.634,41
Calo	Calo	0,45	0,25	0,80	40000	1,79	0,85	1.651,15	1.436,07	330,51	9.815,55	13.233,28
Calo	Calo	0,45	0,20	0,80	40000	1,70	1,06	1.692,11	1.470,34	331,51	10.070,36	13.564,32
Both	Mass	0,45	0,25	0,80	40000	0,10	0,06	1.470,22	1.281,86	84,97	42,64	2.879,68
Both	Mass	0,45	0,15	0,80	40000	0,06	0,15	1.434,36	1.251,25	84,86	148,06	2.918,52
Both	Mass	0,45	0,20	0,80	40000	0,16	0,17	1.534,79	1.332,23	95,23	483,05	3.445,28
Both	Calo	0,40	0,20	0,80	40000	0,09	0,08	2.858,17	2.482,46	149,08	0,63	5.490,33
Both	Calo	0,40	0,25	0,80	40000	0,13	0,08	2.836,34	2.464,30	149,08	66,28	5.515,99
Both	Calo	0,40	0,15	0,80	40000	0,11	0,17	2.866,49	2.488,83	149,64	147,48	5.652,44
Mass	Mass	0,45	0,20	0,80	80000	0,12	0,08	3.417,57	2.961,47	309,87	4,31	6.693,22
Mass	Mass	0,45	0,25	0,80	80000	0,12	0,08	3.416,41	2.961,11	310,97	5,68	6.694,17
Mass	Mass	0,45	0,15	0,80	80000	0,11	0,11	3.419,57	2.963,90	310,60	17,15	6.711,22
Calo	Mass	0,45	0,25	0,80	80000	1,32	0,31	2.089,11	1.840,42	219,21	4.416,02	8.564,75
Calo	Mass	0,45	0,20	0,80	80000	1,27	0,61	2.078,66	1.832,05	219,85	4.455,88	8.586,43
Calo	Mass	0,45	0,15	0,80	80000	1,17	0,91	2.146,92	1.887,94	223,92	4.925,43	9.184,22
Both	Mass	0,45	0,20	0,80	80000	0,07	0,07	3.316,04	2.866,60	73,12	0,00	6.255,76
Both	Mass	0,45	0,15	0,80	80000	0,07	0,07	3.337,86	2.883,46	74,70	0,00	6.296,02
Both	Mass	0,45	0,25	0,80	80000	0,07	0,07	3.359,97	2.903,36	73,22	0,00	6.336,54

Table 6.6: Results for all experiments from phase 3

costs per week attained when not including the calorific value in the decisions conditions. In two occasions the costs per week are even lower. The costs per week for the experiments with a 5Kton capacity consist mainly of the costs for idle time.

Looking at the experiments with a TOP capacity of 40 Kton, and thus an average inventory of 32 Kton, we can conclude that including the calorific value in the decision conditions always lead to higher costs per week. Surprisingly, the costs per week rise above the costs per week in the current situation in four occasions. These are all four when the contract only has restrictions on the calorific value. These costs per week are again mainly caused by the costs for idle time.

The experiments with a 80 Kton TOP capacity (64 Kton average TOP inventory) also show that the best configuration for the contract restrictions is where the restrictions are set on both the mass and the calorific value. Again, when the restrictions are solely set to the calorific value, the supplies are more uncertain, which shows in the costs for idle time. Even with a TOP inventory of 64 Kton it can be the case that the buffers become empty, since the retrieving capacity in a week could be reached.

Reaching steady state.
As we can see in Appendix I, even after a warm up period of 20 years, some experiments did not reach steady state regarding the costs per week. These experiments tend to need even more than 100 years for a warm up period to reach steady state, which would take too much running time. This causes the experiments to be dependent on the run length. Unfortunately, since the running time is too long take make even longer runs, we need to be careful in making conclusions about some of the results we found. To show the extent to which some of the results are adversely affected by the failure to achieve steady state, we provide a confidence interval (α=0,1) for the costs per week found for each experiment. An experiment with a wider confidence interval indicates that the costs per week achieved a less steady state than experiments with a narrow confidence interval.

In Table 6.7 we quickly see which experiments did not reach steady state. These experiments most of the time have a broad confidence interval. This is caused by the irregular costs occurring for idle time. These costs are too large in comparison with the costs for diverting, retrieving or sending waste to an alternative location. So whenever idle time occurs, the average costs per week are heavily affected. Typical experiments with a high probability of having high costs for idle time are the experiments with a TOP capacity of 5 Kton and the experiments with contract restrictions only on calorific value. Due to the low costs per week, the experiments with contract restrictions on both the mass and the calorific value also have a broad confidence interval relative to their average costs per week. However, with these experiments we mostly see that even the high end of the 90%-confidence interval is smaller than the costs per week of experiments with the same TOP capacity and inventory.

Settings						Output		
Contract restrictions	Decision conditions	Low Thres. 1+2	Low Thres. 3	High Thres.	TOP Capacity	Average Costs/Week	90%-C.I Low	90%-C.I High
Mass	Mass	0,45	0,25	0,80	5000	4.454,68	3.612,26	5.298,17
Mass	Mass	0,45	0,20	0,80	5000	4.499,27	3.636,32	5.355,92
Mass	Mass	0,45	0,25	0,75	5000	4.507,46	3.646,48	5.369,49
Mass	Calo	0,50	0,25	0,80	5000	4.702,40	3.845,12	5.554,14
Mass	Calo	0,45	0,25	0,80	5000	4.720,98	3.883,67	5.554,33
Mass	Calo	0,45	0,25	0,75	5000	4.790,51	3.946,82	5.630,20
Both	Mass	0,50	0,20	0,70	5000	2.440,17	1.633,18	3.247,49
Both	Mass	0,40	0,15	0,75	5000	2.601,23	1.708,45	3.494,52
Both	Mass	0,45	0,20	0,70	5000	2.761,87	1.862,22	3.661,64
Both	Calo	0,45	0,15	0,75	5000	2.211,20	1.703,82	2.718,72
Both	Calo	0,45	0,15	0,70	5000	2.428,31	1.506,38	3.350,49
Both	Calo	0,40	0,25	0,75	5000	2.714,23	2.086,05	3.342,78
Mass	Mass	0,45	0,20	0,80	40000	3.283,27	3.116,04	3.447,62
Mass	Mass	0,45	0,25	0,80	40000	3.283,40	3.108,01	3.456,39
Mass	Mass	0,45	0,15	0,80	40000	3.335,86	3.173,91	3.495,31
Mass	Calo	0,45	0,20	0,80	40000	6.477,80	6.120,67	6.830,82
Mass	Calo	0,45	0,25	0,80	40000	6.552,10	6.200,50	6.899,51
Mass	Calo	0,45	0,15	0,80	40000	6.562,97	6.214,96	6.906,72
Calo	Mass	0,45	0,25	0,80	40000	10.398,74	8.345,93	12.449,81
Calo	Mass	0,45	0,20	0,80	40000	10.568,87	8.443,25	12.684,42
Calo	Mass	0,45	0,25	0,75	40000	10.634,41	8.606,28	12.661,97
Calo	Calo	0,45	0,25	0,80	40000	13.233,28	11.433,02	15.028,00
Calo	Calo	0,45	0,20	0,80	40000	13.564,32	11.793,10	15.330,05
Both	Mass	0,45	0,25	0,80	40000	2.879,68	2.588,08	3.166,03
Both	Mass	0,45	0,15	0,80	40000	2.918,52	2.636,30	3.195,59
Both	Mass	0,45	0,20	0,80	40000	3.445,28	2.946,39	3.939,11
Both	Calo	0,40	0,20	0,80	40000	5.490,33	4.938,73	6.037,70
Both	Calo	0,40	0,25	0,80	40000	5.515,99	4.993,25	6.034,56
Both	Calo	0,40	0,15	0,80	40000	5.652,44	5.241,06	6.059,66
Mass	Mass	0,45	0,20	0,80	80000	6.693,22	6.446,63	6.935,64
Mass	Mass	0,45	0,25	0,80	80000	6.694,17	6.456,31	6.927,79
Mass	Mass	0,45	0,15	0,80	80000	6.711,22	6.480,01	6.938,40
Calo	Mass	0,45	0,25	0,80	80000	8.564,75	7.298,54	9.827,33
Calo	Mass	0,45	0,20	0,80	80000	8.586,43	7.322,57	9.847,24
Calo	Mass	0,45	0,15	0,80	80000	9.184,22	7.989,48	10.375,60
Both	Mass	0,45	0,20	0,80	80000	6.255,76	5.847,90	6.658,72
Both	Mass	0,45	0,15	0,80	80000	6.296,02	5.897,54	6.689,59
Both	Mass	0,45	0,25	0,80	80000	6.336,54	5.982,24	6.685,89

Table 6.7: Confidence intervals for all experiments from phase 3

Best experiments
From phase 2 to phase 3, only the top three results are examined for every category (defined in Table 5.9) and only if they have lower costs per week than the costs per week in the current situation. For our sensitivity analysis we again make a selection of the remaining results. First we point-wise state some short statements about phase 3:

- In almost every experiment, the variant where calorific value is included in the decision conditions, results in higher costs per week.
- Within every TOP capacity category, the experiments with the contract restrictions on both mass and calorific value have the lowest costs per week.
- Restricting contracts only on calorific value always yield the highest costs per week.

Based on these statements we make a selection of experiments. These experiments can be seen as the best results following from the first three phases and are stated in Table 6.8.

Settings						**Output**						
Contract restrictions	Decision conditions	Low Thres. 1+2	Low Thres. 3	High Thres.	TOP Capacity	St.dev Cal.val 1+2	St.dev Cal.val 3	Divert Costs/Week	Retrieve Costs/Week	Alternative Costs/Week	Idle time Costs/Week	Average Costs/Week
Mass	Mass	0,45	0,25	0,80	5000	1,18	0,36	198,52	173,92	409,59	3.672,65	4.454,68
Both	Mass	0,50	0,20	0,70	5000	0,48	0,89	181,74	158,86	124,86	1.974,71	2.440,17
Mass	Mass	0,45	0,20	0,80	40000	0,16	0,12	1.547,43	1.345,52	301,75	88,57	3.283,27
Both	Mass	0,45	0,25	0,80	40000	0,10	0,06	1.470,22	1.281,86	84,97	42,64	2.879,68
Mass	Mass	0,45	0,20	0,80	80000	0,12	0,08	3.417,57	2.961,47	309,87	4,31	6.693,22
Both	Mass	0,45	0,20	0,80	80000	0,07	0,07	3.316,04	2.866,60	73,12	0,00	6.255,76

Table 6.8: Selection of the best experiments following from the first three phases

6.4 Experimental results phase 4: Sensitivity analysis

In this research we made a number of assumptions for the input of the simulation model. We want to examine the impact of these assumptions by means of a sensitivity analysis. First we made an analysis on the choices we made when designing our experiments. These feature the following topics:

- Section 6.4.1: The choice for other TOP capacities.
- Section 6.4.2: The deviation for the uniform distribution in contracts.

After this, we continue with performing sensitivity analysis on some modeling assumptions, for which we use the best experimental settings, as shown in Table 6.8. These include the following topics:

- Section 6.4.3: All supply arrives at the start of a day or not.
- Section 6.4.4: Calorific value decrease because of rainfall.
- Section 6.4.5: No costs or other effects occur when not incinerating waste on its scheduled incinerator.

In figures we present in Sections 6.4.3- 6.4.5, we make use of the abbreviation "MM" and "BM", which stand for the combination of contract restrictions and decision conditions (so Mass, Mass, and Both, Mass).

6.4.1 Examining different TOP sizes

To differentiate between different amounts of TOP capacity without examining too many options, we chose to work with 80 Kton (current), 5 Kton (expected best by board) and 40 Kton (in between) for the capacity of TOP. We found that the lowest costs per week are achieved with a TOP capacity of 5 Kton (and thus an average inventory of 4 Kton) when restricting clients on both the mass and calorific value. When only restricting the clients on the supplied mass, the lowest costs per week are attained with a TOP capacity of 40 Kton (Table 6.8). We are interested in the development of the costs per week when varying only the chosen TOP capacity. Therefore, we plot three lines, all based on a different contract restriction. The result is a graph that shows the optimal TOP capacity for the fixed settings. The result is shown in Figure 6.3 for the experiments with restrictions on mass and on both mass and calorific value, and in Figure 6.4 for the experiments with contract restrictions only on the calorific value. We use two separate figures to emphasize the differences. The mark on the lines in the graphs shows at what level of TOP the minimum costs per week occur.

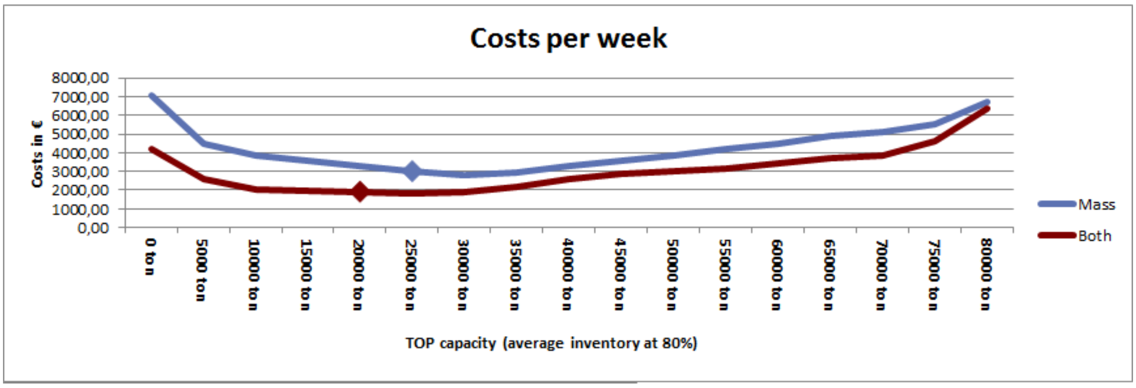


Figure 6.3: The costs per week for different TOP capacities with fixed settings

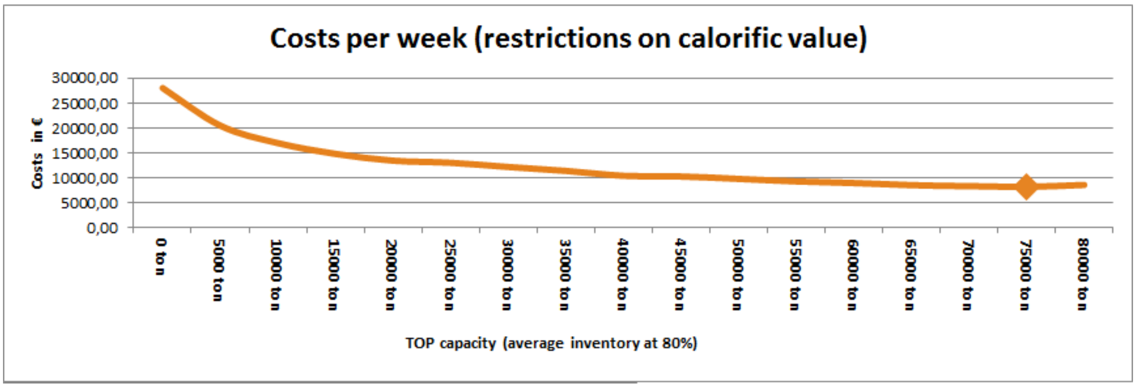


Figure 6.4: The costs per week for different TOP capacities with fixed settings (only calorific value restrictions)

We know that the amount of work that is supplied in a week is the most uncertain when the contract restrictions are just on the calorific value. Figure 6.3 shows that the more certain the amount of work that is supplied is, the lower the costs and the TOP inventory can be.

6.4.2 Examining different margins for the contract restrictions

In Table 5.1 we stated the set-ups for the modeling of our contract restrictions. The situation where the contracts are restricted on mass is based on the current situation at Twence. In the validation we did, we concluded that although Twence wants to keep the clients within the ±10% margin, this does not always happen and the variability in the supplies is actually a bit larger.

In Figure 6.5 we show the effect of the margin we set for the uniform distribution of the weekly supplies. As explained earlier, when contract restrictions are solely on mass, the clients are provided with a margin in which their weekly supplies should be. The weekly supplies are in the model distributed over the days according to an empirical distribution. In Figure 6.5 we have the horizontal orange and gray lines, that respectively stand for the standard deviation in the daily supplies for incineration line 1+2 and incineration line 3. The bars in Figure 6.5 show the resulting daily standard deviation, for the possible margins used for the weekly supplies on the x-axis.

Figure 6.5 shows that although Twence would like to restrict the clients to a 10% margin on a weekly basis, the current situation indicates that the margin is rather around 17,5%. Now we need to find out what the effect of this is on the desired amount of TOP inventory.

We already concluded in Section 6.4.1 that when there is more uncertainty about the supplies, the costs per week become larger. We now want to find out what the effect is of the margin that Twence sets for its clients. So in Figure 6.6 we show,

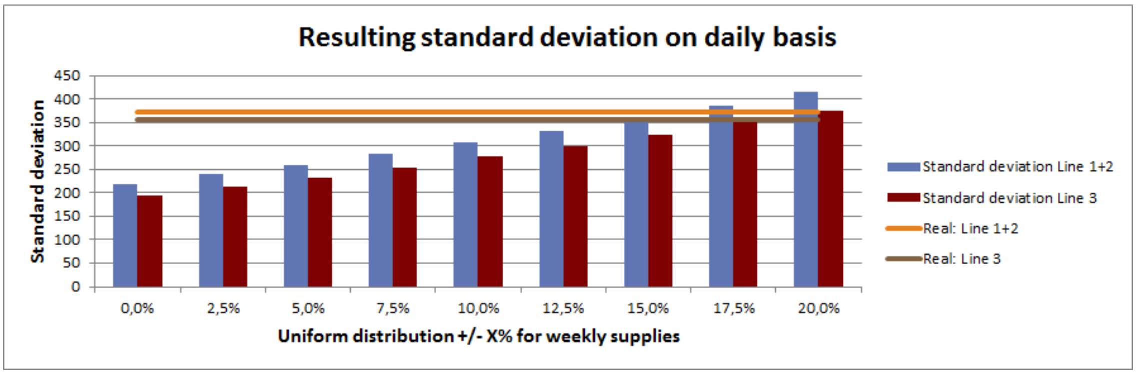


Figure 6.5: The resulting standard deviation on a daily basis, when having an X% range in the uniform distribution for the weekly supplies

how the costs per week per different TOP size develop when the margin increases from ±0% to ±20%.

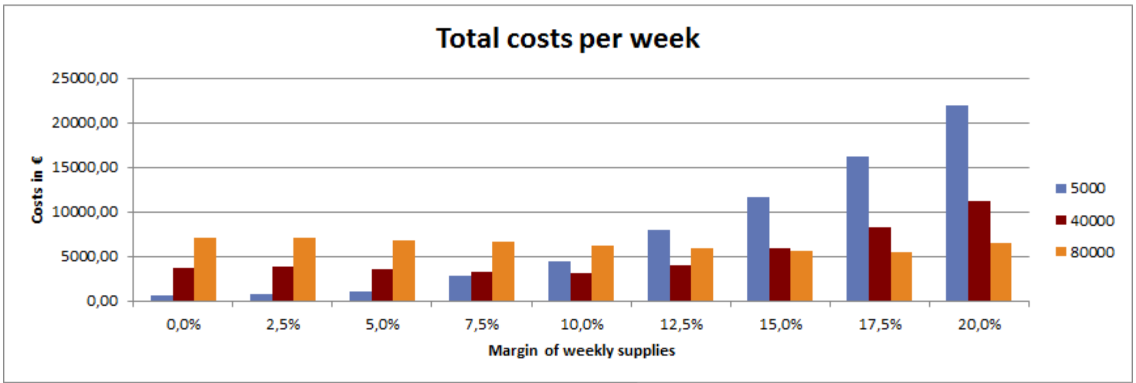


Figure 6.6: The costs per week for different TOP capacities and different margins

We see that with a margin on the allowed weekly supplied of 0-7,5% a TOP capacity of 5 Kton is best, with a margin of 10-12,5% the 40 Kton TOP capacity is best, and with a 15% or higher margin the experiments with a TOP capacity of 80 Kton were best.

For a small TOP inventory, the conclusion can be made that with more certainty about the supplies, the costs per week can be lower. In the situation where Twence has just a small TOP inventory, which is the case when the TOP capacity is 5 Kton and the average inventory is 4 Kton, the costs increase very rapidly when the uncertainty increases. All these costs occur mainly due to idle time in the incinerator lines. With the 40 Kton and 80 Kton variant, we first notice a small decrease before we see an increase. In Appendix J we depicted the costs specifications to explain the development of the cost per week when increasing the margin on the restrictions on mass. In Figure J.1a and J.1c we see that when the margin on the allowed weekly supplies is increased, the costs for diverting and retrieving decreases and the costs for sending waste to an alternative location (competitors) increases. We designed the average supplied waste such that it would lead to an almost constant level of TOP inventory throughout an entire experiment. Since every ton of waste that is sent to an alternative location is not coming back, on average, the TOP inventory will decrease when more waste is sent away. With a TOP capacity of 5 Kton (less than three days of supplies) this does not show in the costs, because in this situation the TOP inventory is already more sensitive to the deviation in the supplies. With a larger TOP inventory, over time this will show, since, as said, the waste that is sent away does not come back. The costs for diverting and retrieving therefore decrease due to less TOP inventory, and in the beginning this decrease in costs outweighs the costs for idle time as shown in Figure J.1b.

The overall conclusion for increasing the margin on the allowed weekly supplies, is that the effect is heavily depending on the costs for idle time. The probability of idle time is the largest when having a small TOP inventory and thus the negative effect of a bigger margin in the contract restrictions, is also bigger.

6.4.3 Arrivals spread over the entire day

In the current situation, Twence gives the clients no restrictions on the time of arrival other than their opening hours. Currently most clients are at the gate of Twence at the start of Twence its opening hours, causing a lot of supplies to come in at the same time.

Our current setting makes no distinction between clients and lets all supplies arrive at the start of the day. Although Twence does not prefer working with time slots, we want to examine the effect of spreading the arrivals over the entire day.

To spread the arrivals over the entire day, after determining the amount of supplies that arrive on a day, we divide the total amount of seconds in a day by the amount of arriving mass in tons. We multiply this interarrival time by 10 because we made the assumption that we look at chunks of 10 tons. We show an example in Table 6.9 and the results are shown in Figure 6.7.

Day	$Mass_{Line1+2}$	$Mass_{Line3}$	Inter-Arrival time in seconds (1+2 ; 3)
Monday	2.100	1.770	411,4 ; 488,1
Tuesday	1.420	1.190	608,5 ; 726,1
Wednesday	1.550	800	557,4 ; 1.080,0
Thursday	1.540	880	561,0 ; 981,8
Friday	1.230	1.070	702,4 ; 807,5

Table 6.9: Example of the inter arrival times

When the arrivals are spread over the day, the level of waste in the buffers is also at a more constant level. This means that the necessity of retrieving and diverting waste decreases, since the buffer levels are less likely to reach the thresholds. A negative effect of this can be seen in Appendix J, where we have made a specifi-

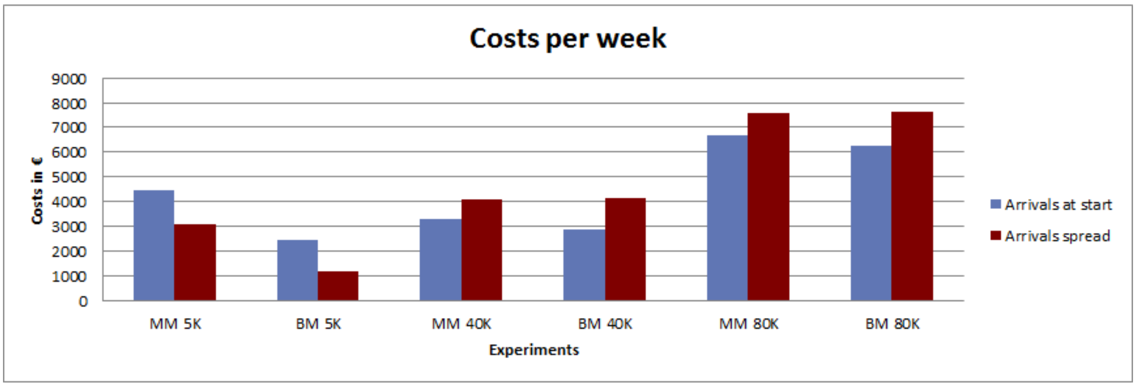


Figure 6.7: Comparison of costs per week for spread arrivals

cation of the costs in Figure J.2. We see in Figure J.2a a slight increase in the costs for diverting and retrieving, and in Figure J.2b we see a large decrease in the costs for idle time. The costs for sending waste to competitors in Figure J.2c show a large increase. The reason for these increases and decrease in the costs, can be explained by the earlier mentioned necessity of retrieving and diverting. The lack of this necessity is shown in the costs for idle time, which for the first experiment are cut in half and for the other experiments are even 0. This does mean that the main reason for retrieving waste from TOP comes from the over-aging. This is the reason that the costs for sending waste to an alternative location increase so much, since the level of waste in the buffers is now on a more constant and higher level so it is not always possible to fit the retrieved waste into the buffers.

From the comparison of spreading the arrivals versus having all arrivals at the start of the day, we can conclude that whenever the TOP inventory is at a low level, the costs are reduced. Whenever the TOP inventory is at a higher level, such as 32 Kton or 64 Kton, it is important to keep refreshing the waste in TOP on a regular basis. Waiting for the waste to over-age leads to obligatory retrieving, which is not always convenient. So spreading the arrivals only leads to lower costs per week when having a low TOP inventory or when refreshing the waste in TOP is done on a regular basis.

6.4.4 Decrease of calorific value by rainfall

When calculating the amount rainfall in a year, we make use of yearly averages whereas it is logical that during the summer it rains less than during the fall. So when we use a formula for the decrease of calorific value due to rainfall, where only the time of being in storage, apart from the time of year, is important, the results may differ from reality. We therefore examine two other situations, namely:

- **No rain:** In this situation we examine the effect of not taking into account the rain at all. We discard the equation that decreases the calorific value after the waste leaves TOP.

- **Winter rain:** In this situation we assume that during the summer period (week 13 to 39), there is no rain and thus no effect on the calorific value. However, in the other weeks, it rains twice as much. Therefore the effect on the calorific value is in these weeks twice as high.

The results are shown in Figure 6.8.

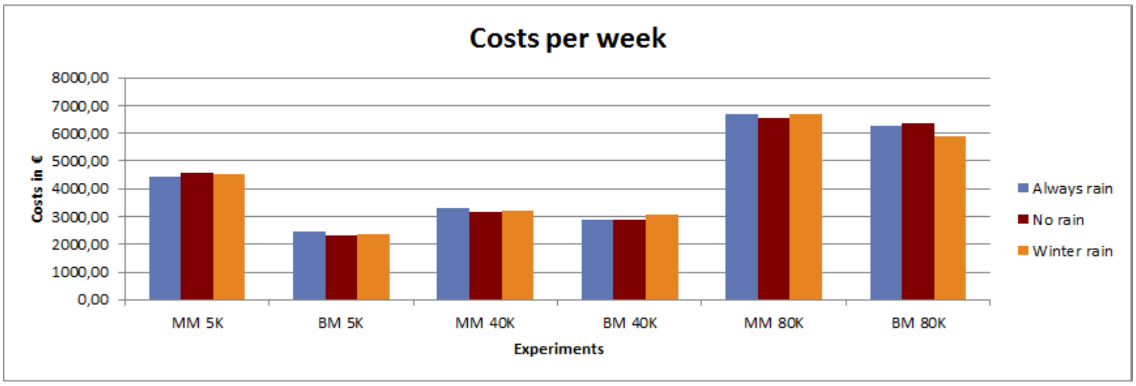


Figure 6.8: Comparison of costs per week for different weather behaviour

We see in Figure 6.8 that the decrease in calorific value caused by the rain, does not have a big impact on the results. We see for all situations, that the values are closely together and that there is no clear pattern. This makes us believe that the differences shown in Figure 6.8 are because of stochastic fluctuation.

6.4.5 Process efficiency

We assumed that no extra costs or effects occur when waste, scheduled for incineration line 1+2 (usually low calorific value), is incinerated on incineration line 3 (usually for high calorific value). However, in Chapter 3 we found that having a constant input causes a more efficient incineration process. We want to examine the impact of allowing waste to be incinerated on an other incinerator instead of its scheduled one. In Figure 6.9 we see the impact of only incinerating waste on its scheduled line.

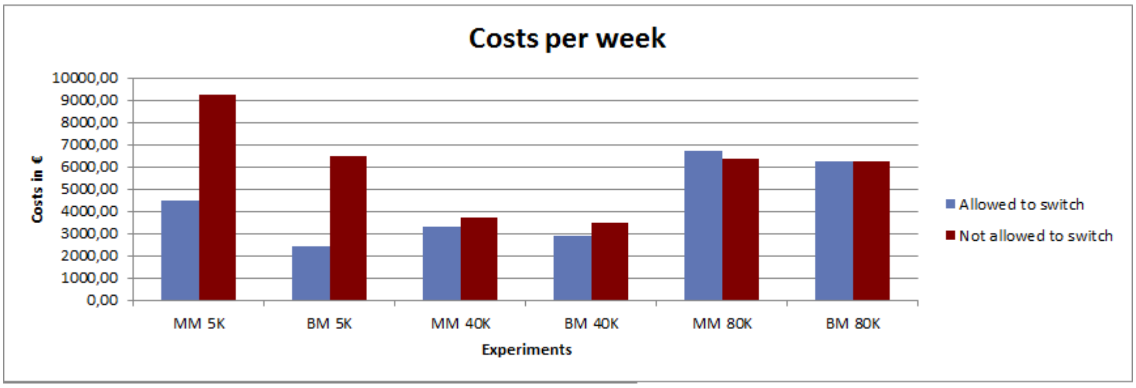


Figure 6.9: Comparison of costs per week when not allowing to switch between lines

Only for the MM 80 Kton TOP capacity experiment, we see a decrease in the costs per week. Since with a low TOP capacity and inventory, the incineration lines mostly depend on the supplies from clients, the costs per week increase when switching between lines is not allowed. When the possibility to compensate for less supplies on one of the incineration lines is prohibited, we see the costs per week increase. Looking at the cost specification, we see that the costs for idle time are the main cause of this increase, which are shown in Figure 6.10.

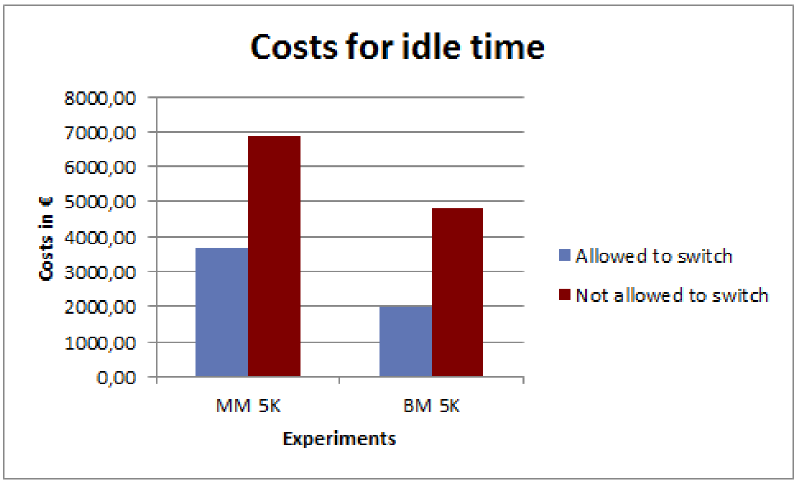
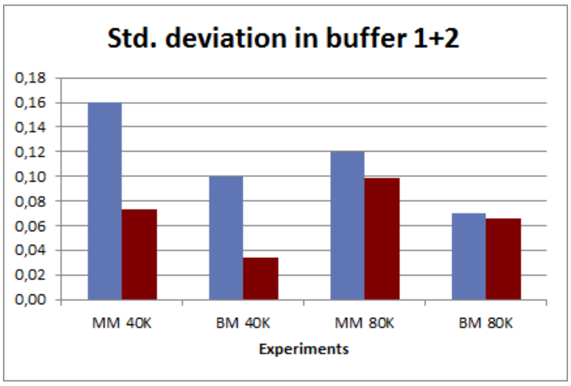
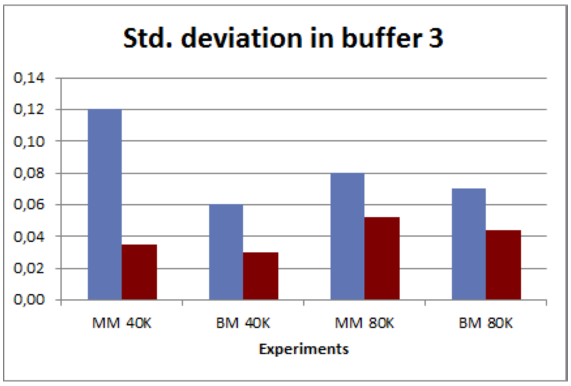


Figure 6.10: Comparison of costs for idle time when not allowing to switch between lines

The extra costs that could occur by not incinerating waste on its scheduled incineration line mainly comes from the fact that the standard deviation of the characteristics of the waste becomes too large. In that case, a lot of monitoring needs to be done and adjuvants need to be added in order to keep the incineration as efficient as possible. To see whether prohibiting switching between incineration lines actually helps on that, we compare the standard deviation of the calorific value in both buffers in Figure 6.11. We exclude the results from the 5 Kton TOP capacity experiments, since the standard deviation is not very representative due to the amount of idle time.



(a)



(b)

Figure 6.11: Comparison of standard deviation in both buffers

As expected, the standard deviation of the calorific value in both buffers decreases, when the incineration lines only accept their own waste. It is up to Twence to decide whether having higher standard deviation at lower costs per week is better than reducing the standard deviation at a higher costs per week.

6.5 Conclusions

In this chapter we presented the numerical results of our experiments. Our experimental design consisted of four phases.

Experimental results phase 1
In phase 1, we found that the TOP inventories are stable when the supplies are on average 12900 tons per week.

Experimental results phase 2
In phase 2, we used the results from phase 1 as input, such that we started all experiments we defined in Figure 5.7 with the conditions that lead to steady state behaviour.

Phase 2 showed that a 40 Kton TOP capacity (32 Kton avg inventory) yielded the most promising results when adopting the currently used contract restrictions. When changing the contract restrictions to both mass and calorific value (processing time), a 5 Kton TOP capacity yielded the best results. When the adapted model of Obroucka is used, often an increase in the costs for diverting and retrieving occurs, due to the over-aging of the waste from large TOP inventories. The thresholds only have a moderate effect on the costs per week relative to the contract restrictions, decision conditions, and the TOP inventory.

Experimental results phase 3
In phase 3 we concluded that the best experiments were the experiments with contract restrictions on both the mass and the calorific value. Because for some of our experiments, the average costs per week did not reach steady state, we provided a 90%-confidence interval for all experiments to show to which extend the results were affected. From the three TOP options we examined, we saw that for that configuration, a TOP capacity of 5 Kton and average TOP inventory of 4 Kton yielded the lowest costs per week.

Experimental results phase 4
In phase 4 we performed a sensitivity analysis. We first examined some of our more general chosen inputs. These showed that the amount of TOP capacity and inventory that leads to the lowest costs is lower, when the predictability of the supplies increases. After that we performed a sensitivity analysis on a selection of the best results from phase 3 as shown in Table 6.8.

From the sensitivity analysis on the selection of experiments we concluded the following:

- When the margin on the allowed weekly supplies is increased, the need for more TOP inventory increases.
- Spreading the arrivals over the entire day leads to lower costs per week when working with a low TOP inventory. For a high TOP inventory, spreading the arrivals over the entire day only leads to lower or equal costs per week when the TOP inventory is refreshed on a regular basis.
- The decrease in calorific value due to the rainfall during the year has no effect on the costs per week.
- If switching between incineration lines is not allowed, the costs per week increase when working with a low TOP inventory, but the standard deviation of the calorific value in the buffers decreases. When working with a high TOP inventory the effect of allowing switching between incineration lines is moderately visible, but would not lead to a big decrease in the costs per week.

In Chapter 7 we take our designed model and simulation model from Chapter 4 and 5 and apply these to a similar situation; namely, the other incinerator at Twence, the Biomass Energy Plant.

7 | Case Study: Biomass Energy Plant

Apart from processing waste, Twence also processes biomass. The goal of this case study is to adapt the current model to make it suitable for the biomass incinerator. There is also a bulk-storage for the biomass, so we could use the model again to find the optimal way of working for the Biomass incinerator.

Main information
Biomass consists mainly out of wooden parts. There are certain specifications regarding the wooden parts. The parts should be within a given size to be labeled as "on specification" (on spec). Otherwise it must be shreddered into smaller pieces first. The wooden parts that are already on spec are brought directly to the Biomass Energy Plant (BEC). Only in extreme cases, wood on spec is brought to the bulk-storage, because due to the weather the wood could get outside of specifications. The wood that is not on spec is called unbroken wood. Unbroken wood is brought to the woodbank, which also serves as a bulk storage. In the woodbank, unbroken wood is shreddered after which it is stored until it is transferred to the BEC. In Figure 7.1 we see the flow for the wooden parts. In the rest of this case study, we refer to biomass as wood.

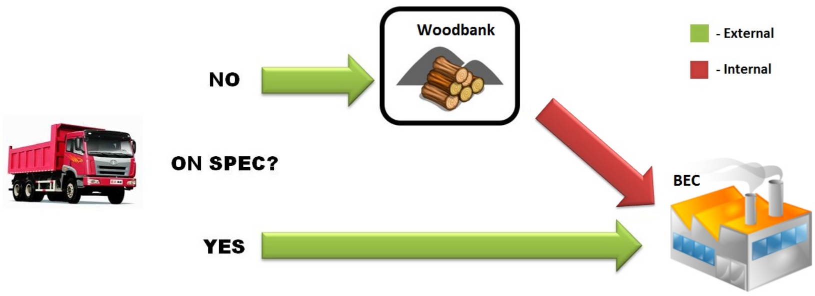


Figure 7.1: Flow from wood to BEC

Just as for the AEC, we summarize the performance indicators from the current situation for comparison. This is done in Table 7.1.

Performance Indicators	Value
Average costs per week for diverting/retreiving	€28.095,14
Ratio wood on specification versus unbroken wood	2,05 : 1

Table 7.1: Performance indicators

Input changes
To adapt the model to the situation of the wood incinerator, we first need to gather

some key information needed as input for the model. This information is summarized in Table 7.2.

Input parameters: Contracts based on Mass	
$Mass_{OnSpec}$	$Ratio$ · Uniform[3.020 ; 3.691]*
$Mass_{Unbroken}$	(1-$Ratio$) · Uniform[3.020 ; 3.691]*
$Calorificvalue_{BEC}$	Normal[11,7994 ; 0,63864]
Input parameters: Costs & Revenues	
$C_{DivertingOnSpec}$	€2,29 per ton
$C_{DivertingUnbroken}$	€10,91 per ton
$C_{Retrieving}$	€6,11 per ton
$C_{Alternative}$	€25,00 per ton
$C_{IdleTimeBEC}$	€0,53 per second
$Revenues_{OnSpec}$	€-21,81 per ton
$Revenues_{Unbroken}$	€-5,44 per ton
Input parameters: Processing time	
$Factor_{BEC}$	Multimodal with p(x) = 0.5·Normal[x; 14,5225 ; 0,7323] + 0.5·Normal[x; 16,6867 ; 0,5965]*
Input parameters: Other	
Legally determined max. age	3 years
BEC Buffer Capacity	3.500 tons

Table 7.2: Input for the adapted model
*This is determined similar as for the AEC

Since for the AEC we only have one type of arrivals, only the costs are of influence. For the BEC we have the distinction between unbroken wood and wood on spec. Both have different costs and revenues. The balance between acquiring unbroken wood or wood on spec is something we include in our experimental factors. We validated the model in the same way as the model for the AEC. This results in costs per week of €27.775,19.

Model and experiment changes

Contrary to the AEC, the BEC consists of a single incinerator and therefore also a single buffer. Thus in the model we also implement only one buffer and we delete the control rules about shifting deliveries from one buffer to another.

The experimental factors change in such a way that we only have one buffer to be concerned about. Recalling the groups of experimental factors from the regular model (Figure 5.6), we adapt these as shown in Figure 7.2. To keep the number of experiments limited, we do not vary the contract restrictions and only use a restriction on the mass just as in the current situation. We have shown in the results for the AEC, that contract restrictions only on calorific values always give higher costs per week, and contract restrictions on both the mass and the calorific value always gives lower costs per week.

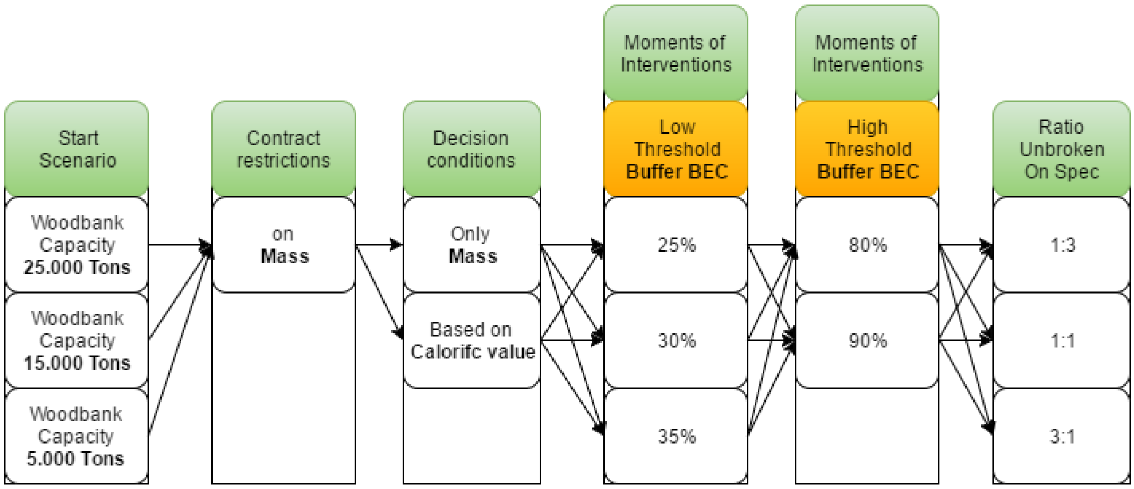


Figure 7.2: All combinations of different experimental factors for the BEC

We check three low thresholds and two high thresholds and we experiment with three different ratios between the arrivals of unbroken wood relative to wood on spec. This results in a total of (3*3*2*3=) 54 experiments for this case study.

Results and conclusions

After performing all experiments, we show for each Woodbank capacity what the best performing experiments are, based on costs per week or process efficiency. The best performing experiments are shown in Table 7.3.

Woodbank Capacity	Contract Restrictions	Decision Conditions	Low Thres. BEC	High Thres. BEC	Ratio	Average Throughput /Week	St.dev Calorifc Value Buffer BEC	Average Costs/Week
5000	Mass	Calo	0,25	0,90	0,75	3.277,21	1,184	22.204,75
15000	Mass	Calo	0,25	0,90	0,75	3.307,24	1,207	21.566,84
25000	Mass	Calo	0,25	0,90	0,75	3.318,11	1,222	21.943,33

Table 7.3: Best results for the BEC

The costs per week in the current situation were €28.095,14 with a Woodbank capacity of 30 Kton (inventory at 24 Kton). We see that all experiments have lower costs per week than in the current situation. The experiment with a Woodbank capacity of 15 Kton and thus an average inventory of 12 Kton, has the lowest costs per week of all experiments.

Looking at all results at once, we notice that the ratio is always set to 0.75. This means that 75% of the supplies consists of wood on specifications. This is also the main reason for the decrease in the costs per week. We see that since 25% of the supplies automatically go to the Woodbank, the effect of having more or less inventory is moderate. Having a higher percentage of wood going to the Woodbank, leads to more costs per week.

For the thresholds, we conclude that the high threshold should be 90% and the low threshold 25%. Because of all experiments the decision conditions include the calorific value, this means that the low threshold should be set to 2.5 days of processing time.

The ratio that Twence currently uses is almost 2:1 (0.67), but from the experiments we can conclude that increasing this ratio to 3:1 (0.75) already leads to a decrease in the costs. Because all experiments show the highest ratio as the best, it would make sense to perform more research on different ratios and test whether this is the best ratio or Twence should increase the ratio even more.

8 | Conclusions and recommendations

In this Chapter we present the conclusions of our research (Section 8.1), followed by recommendations for Twence (Section 8.2). We also make some suggestions for further research.

8.1 Conclusions

The goal of this research was to give Twence more insight in their supply chain. In Chapter 1 we translated the goal into a main research question namely:

How can Twence improve their internal supply chain in order to optimize the performances of their processes, while minimizing the costs of idle time of the machines and of internal transport?

We designed subquestions to help us answer the main research question. Chapter 2 gave us the answer to the subquestion *What is the current situation of the internal supply chain at Twence?* A lot of fluctuation in the supplies occurs on a daily basis. The inventory of the bulk-storage, called TOP, increased a lot in 2011 and since then, the TOP inventory stays rather constant. Because of the over-aging of waste, TOP inventory needs to be processed within three years, which causes mandatory retrieving. We conclude that Twence could do with less TOP inventory. We found that the calorific value of waste has a direct link with the throughput and thus the requirements of Twence. To cope with the fluctuation in the supplies and the risk of not having enough waste to incinerate, the calorific value of waste could be used to make better forecasts. The costs per week in the current situation are €10.414,81.

In Chapter 3 we performed a literature study about safety stocks, waste incineration efficiency and decision support models for waste incinerators. This answers our second subquestion *What can be found in academic literature to support this research?* The amount of safety stock should be such that the probability of stockout is at the desired level. We found that the process of waste incineration is most efficient when the input parameters are as constant as possible. The model described by Obroučka et al. (2015) can be applied to the situation of Twence, since it not only looks at the amount of waste that is selected for incineration, but also takes characteristics like calorific value into account.

What models can we construct that support optimal decision making? was the third subquestion, which we answered in Chapter 4. We set up models for diverting and retrieving for two situations. The first being the same as the current situation, where decision conditions only include mass, the second where they also include calorific value. For the latter model, we adapted the model of Obroučka et al. for the retrieving part. We suggested three types of contract restrictions, namely on mass, calorific value or processing time. The models we set up described what to do in certain situations, but not when to do it. Therefore we needed to perform a simulation study in which we tested what the level of waste in the buffer of the incinerator should be before Twence should start diverting or retrieving.

In Chapter 5 we designed our simulation model. We set up our experimental design, that answers the subquestion: *What are possible interventions to improve the internal supply chain?* Our experimental design consists of four phases. In the first phase we determine the level of supplies needed to have a constant TOP inventory. In the second phase we perform experiments according to Figure 5.7. We select the most promising results for the third phase of our experimental design, which we ran for a longer period of time in order to get more reliable results. In the fourth phase we perform a sensitivity analysis.

The results of our experiments were presented in Chapter 6, answering the subquestion: *What performance can be expected when using the designed model and proposed interventions versus the current performance?* In Table 8.1 we show for three TOP capacities the best results, when having contract restrictions only on mass, and contract restrictions on both the mass and the calorific value.

Settings						**Output**						
Contract restrictions	Decision conditions	Low Thres. 1+2	Low Thres. 3	High Thres.	TOP Capacity	St.dev Cal.val 1+2	St.dev Cal.val 3	Divert Costs/Week	Retrieve Costs/Week	Alternative Costs/Week	Idle time Costs/Week	Average Costs/Week
Mass	Mass	0,45	0,25	0,80	5000	1,18	0,36	198,52	173,92	409,59	3.672,65	4.454,68
Both	Mass	0,50	0,20	0,70	5000	0,48	0,89	181,74	158,86	124,86	1.974,71	2.440,17
Mass	Mass	0,45	0,20	0,80	40000	0,16	0,12	1.547,43	1.345,52	301,75	88,57	3.283,27
Both	Mass	0,45	0,25	0,80	40000	0,10	0,06	1.470,22	1.281,86	84,97	42,64	2.879,68
Mass	Mass	0,45	0,20	0,80	80000	0,12	0,08	3.417,57	2.961,47	309,87	4,31	6.693,22
Both	Mass	0,45	0,20	0,80	80000	0,07	0,07	3.316,04	2.866,60	73,12	0,00	6.255,76

Table 8.1: Selection of the best experiments following from the first three phases

Since currently the possibilities of evaluating the calorific value of a large batch of waste before incineration are limited, we also presented the results in which the contract restrictions do not change relative to the current situation. We concluded that a cost savings of 67% per week can be realized, when the TOP inventory is reduced to about 32 Kton and the margin of ±10% in the contract restrictions is respected. When evaluating calorific value becomes easier, the contract restrictions should be altered to restricting clients on both the mass and the calorific value. The cost savings could increase to about 75% when TOP inventory is reduced to about 4 Kton, when contract restrictions are respected.

In phase four, we examined the impact of our assumptions. Spreading the arrivals over the entire day leads to lower costs per week when working with a low TOP inventory. The decrease in calorific value due to the rainfall during the year has no significant effect on the costs per week. If switching between incineration lines is not allowed, the costs per week increases when working with a low TOP inventory, and the standard deviation of the calorific value in the buffers decreases.

We looked at the influence of the margin within which the clients can vary their supplies and looked at TOP capacities and inventories in steps of 5000 ton. We conclude that Twence can reduce their costs per week the most when the TOP capacity is 25 Kton (inventory 20 Kton), when restricting clients on both mass and calorific value.

In Chapter 7 we considered a case study: *How can we use these findings in order to improve similar entities at Twence, such as the Biomass Energy Plant?* We adapted our model to fit the characteristics of the BEC and varied the same experimental factors with the addition of the ratio between unbroken wood and wood on specification. We conclude that it is most profitable for Twence if they contract more wood on specification than unbroken wood. We suggest keeping the woodbank capacity around 15 Kton.

8.2 Recommendations on implementations and further research

The only subquestion we did not answer yet is *How can Twence implement these interventions in the current supply chain?* We provide some recommendations regarding all experimental factors on how to use these results.

TOP and Woodbank capacity

For the AEC, we saw in the results that the lowest costs per week can be achieved by reducing the TOP inventory to a level of 20 Kton. For the woodbank inventory, we recommend reducing this to about 12 Kton. This is more convenient regarding the available space but it also brings down the costs per week. For the AEC as well as the BEC holds that this should be achieved by temporarily reducing the amount of supplies, since the incinerators are running on full capacity as much as possible. The only problem is that the contracts with clients are usually set for a period of more than 5 years. This means that these implementations may take a while before they can take place.

The further research regarding the bulk-storages should focus on reducing the costs for diverting and retrieving.

Contract restrictions

When the possibilities of evaluating calorific value are improved, the contract restrictions for clients for the AEC should be on both the mass and the calorific value. Currently Twence states that they use a ±10% margin in their contracts but they need to focus on keeping clients to that restriction, because this margin currently is higher. When the current contract restrictions are better respected and clients stay within the margin of ±10%, cost savings of 67% per week could also be achieved with the current contract restrictions. For the BEC, more wood on specification should be contracted.

Twence must perform further research on how to evaluate the calorific value of waste before incinerating it. When the calorific value of a batch of waste can be evaluated beforehand, restrictions could be set on the allowed calorific value that should be supplied. This provides more insight in the supplied processing time and allows Twence to reduce their TOP inventory.

Decision conditions

We recommend to include only the mass in the decision conditions for the AEC. For the BEC the results showed that the decisions conditions should also include the calorific value. Basing the decisions on calorific value would mean that the layout of the woodbank needs to be altered such that a distinction can be made between the different qualities of stored wood.

We recommend to perform more research on the benefits of optimizing the process efficiency, since the addition of adjuvants could possibly be reduced and in our research we did not take any costs for this into account.

Thresholds

The thresholds we found from our best experiments can guide as an indication. We do recommend to make use of a lower threshold of 40% and 20% for respectively the buffer 1+2 and buffer 3 for the incineration lines of the AEC. The upper thresholds always came out to be 80%, which was the highest option we examined. This could indicate that the optimal thresholds are even higher. We recommend keeping the upper thresholds at the level of 80%, since this does not interfere with the mixing of the waste.

For the BEC, there is no clear indication on how much capacity is available in the buffer. This buffer is a big hall, with the incinerator in the middle. We recommend to clarify how much of the capacity is used and how much is available in the buffer of the BEC. When this is known, the thresholds we found could be applied, which would be about 30% for the lower, and 90% for the upper threshold.

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A | Facilities at Twence

Twence is a company that specializes in processing waste flows and biomass. They process these materials into raw materials and energy. Twence brings these products back in circulation and provides sustainable energy. By doing this, Twence contributes to reducing the use of fossil fuels and a reduction of CO2 emissions.

Twence is located in Hengelo and is an important economic powerhouse in the region. They are the biggest producer of sustainable energy in the provence of Overijssel and belong to the top of the sustainable energy producers of the Netherlands. The waste flows that Twence processes are not only from the Netherlands, but also from Germany and the United Kingdom. At Twence, sustainability has a high priority and they also want to contribute to projects that involve nature conservation, environmental education and culture. The ultimate goal of Twence is to have a waste-free society with optimal reuse of goods and recovery of raw materials. Eventually all energy should be produced from renewable sources, but until this has been realized Twence will commit to using non-reusable waste for the production of energy.

A.1 Twence Waste Sorting

Twence Waste Sorting (TAS) is the department where mixed waste streams are divided in re-usable sub-streams. A lot of waste that comes in contains materials that are recyclable. The mixed waste streams that are processed by TAS consists of large domestic waste, dry industrial waste and construction and demolition waste. The TAS has a processing capacity of about 120.000 tons of waste a year. Even before the real processing starts, the waste is separated into three streams, namely, waste that is too big to process, waste which is already suitable for reuse, and the waste that needs processing. Waste from the latter category is dropped on a conveyor belt and is passed through a sieve, which prevents parts that are too big and could get stuck in the installation. The remaining parts move on to an automated sorting line that consists of magnets and blowers that separate different types of waste.

After passing the automated sorting line, the remainder is passed through the sorting cabine. Here a manual separation takes place, where remaining waste like wood, paper, metals and foils are sorted.

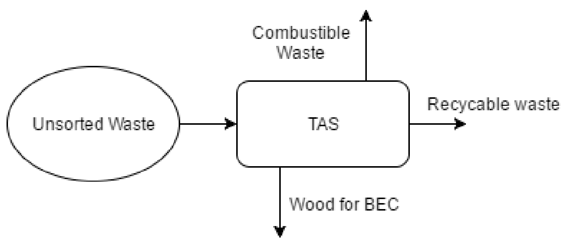


Figure A.1: Streams in/out TAS

In Fig A.1 we see a schematic view of

the streams which TAS has influence on. As said, different types of waste enter the sorting department, where they are sorted out and split up into different streams. The following substreams are being sorted in TAS:

- Paper
- Wood
- Debris
- Metals
- Carpet
- Drywall
- Plastics
- Cardboard

All of the combustible waste and wood that is output from TAS is processed by Twence, the other materials are made suitable for reuse by external parties.

A.2 Waste Energy Plant

Waste that is not suitable for reuse, but that is flammable, is processed by Twence in the Waste Energy Plant (AEC). By burning this waste, Twence generates energy. The AEC processes more than 600.000 tons of waste per year.

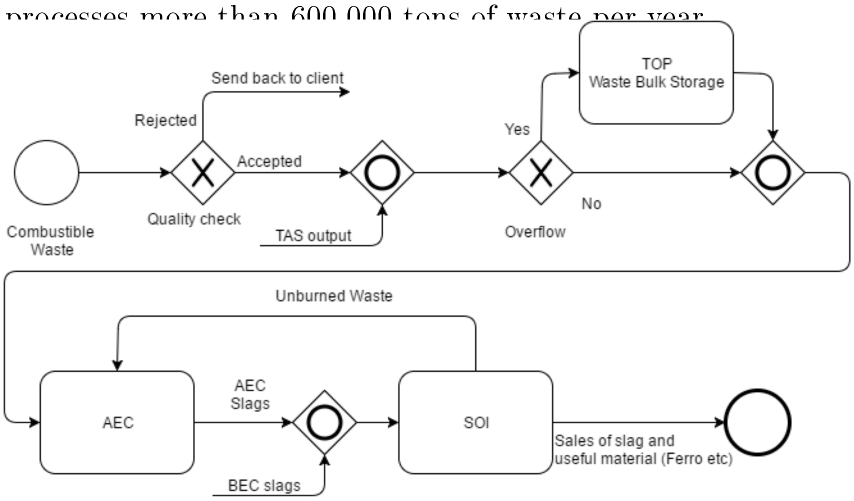


Figure A.2: Waste streams to AEC

In Fig A.2 we see a schematic view of the stream towards the AEC. Incoming waste is first checked on whether it meets the agreed arrangements and is then rejected or send onwards. We notice a couple of streams from other entities that are also directed towards the AEC and see where in the flowchart the temporary storage is located. After that we have the AEC and the SOI, which stands for 'slag work-up installation'. In the SOI, the residues of the incineration, better known as slag, are processed. In the rest of this section, the working of the AEC is explained further.

The waste stream that enters the AEC is checked by sampling on a conveyor belt. It is checked whether the waste complies with a strict set of criteria and is suitable for the combustion process. After the check, the waste is transported into a bunker in which it is mixed. The reason that all the waste in the bunker is mixed together is because of the fact that it serves as fuel for the AEC. By mixing it, the fuel will be of the same composition and is of equal calorific value. This is important because when waste has a low calorific value, it is harder to burn properly and it takes the AEC more time to process it, with as a result that the processing capacity drops. Also fluctuations in the calorific value of the waste in the AEC leads to undesirable peaks and lows in the energy production.

Twence has three incineration lines that each consist of the following parts:

- Kettle
- Turbine
- Exhaust gas cleaning

The waste is going through a funnel after which it arrives in the kettle where the incineration takes place. This takes about 45 minutes and is done with a temperature of between 850 and 1.100 degrees Celsius.

The kettle has hollow walls that contain water. The heat of the incineration process makes the water evaporate causing steam. This steam is guided through hollow pipes that lead to a turbine that powers a generator, which produces electricity. Twence supplies this electricity to the municipalities in Twente and the public power grid. Also some low pressure steam is used by a neighbour of Twence, AkzoNobel, and the residual heat is used for a part of the heat network of Enschede.

The exhaust gas cleaning is the biggest and most important part of the AEC. Here the exhaust gases are cleaned by a series of filters. This ensures a minimal emission of harmful substances and is well within the stringent standards that apply. When looking at the facility of Twence, a big chimney is visible. The plume of gas that arises from it, consists mainly of water vapour.

The lines are tradionally split up in two groups namely, Line 1+2 and Line 3. This is because of two main differences between these groups. The first difference is about the age of the technology that is used. When Twence was founded, only line 1 and 2 were built. With the technology that was known at that time, purifying the exhaust gasses was difficult to do. Lots of processes were needed to comply with regulations . Later, when line 3 was built, technology had improved and easier methods for cleaning exhausts gasses were discovered and used in this line.

The second difference is about the calorific value of the waste. Line 1+2 works best with waste that has a low calorific value. This has to do with the effect that low calorific waste has on the machine but also the type of exhaust gasses and residues that low calorific waste usually gives. Forecasts about the rise in calorific value of waste, due to for example waste separation, was one of the reasons for the construction of an installation that could handle this better, which eventually became line 3.

A.3 Biomass Energy Plant

In the Biomass Energy Plant (BEC), different kinds of wood are processed. Twence uses scrap wood, mainly so called B-wood (which is wood that has been painted or treated), woody parts that are non-compostable and the coarse parts from the green waste. The electricity that the BEC produces is 100% green and provides enough electricity for 44.000 households, which is equivalent to a city of 85.000 people.

In Fig A.3 we see a flowchart of the waste streams that are directed towards the BEC. The wood that is not on specification is called unbroken wood. In the flowchart we see that unbroken wood is directed towards the woodbank where it is made to specification. Here we also have the temporary storage location for unbroken wood. In the bioconversion, the big parts are sieved, which is called sieve overflow and this is transported to the BEC. Because sieve overflow is usually wet material, it is not so good for the machinery in the BEC. therefore, the guideline is that a mix of raw materials for the BEC is made, which consists up to 15% of sieve overflow.

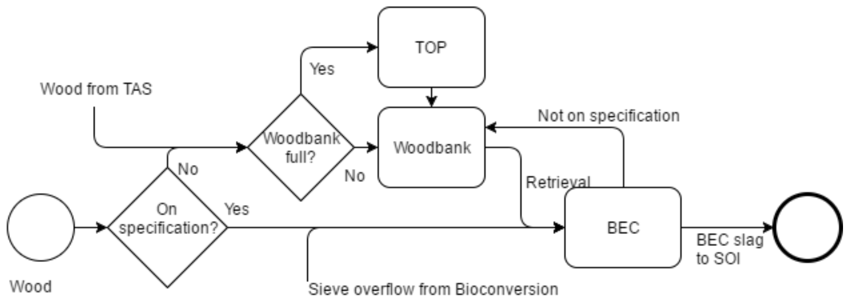


Figure A.3: Flow regarding BEC

If the wooden parts are too big for the BEC, they are shreddered first. After this, the wooden parts are between 10 and 50 centimeters in size. In the bunker of the BEC all the shreddered wood is mixed with the non-compostable and green waste parts. This homogeneous mass, biomass, is placed on a shifting floor where the mass is transferred onto a conveyor belt that brings it to a filter. In this filter, magnets remove all the metal parts from the biomass. After passing the filter the mass is transported up to about 25 meters where it is placed in a buffer from which the mass is dosed on the grid of the incinerator.

In the oven, the biomass is incinerated at a temperature of about 1.000 degrees Celsius, which takes about 45 minutes. The fire heats a big kettle and a system of water-filled pipes that creates steam. Just like with the AEC, the steam drives a turbine that produces power.

Also the BEC has an exhaust gas cleaning section that filters all harmful substances from the emission. The exhaust gases pass a couple of components where different kinds of operations take place. The fly ashes are separated, and after that excipients are blown into the flue gas stream. The gas passes a cloth filter that filters out all kinds of fine particles. The last step is the passing of the DeNOx installation and after this the gases leave through the chimney which at the end has all different types of measuring equipment. Emissions from the BEC remain well within the limits of the strict laws and regulations.

Isolation is done by having a impermeable layer on the bottom. This consists of a layer of sand-bentonite, a material that when it comes into contact with moisture expands and becomes impenetrable. In addition, a layer of foil is placed on top of that. When the maximal height is reached, the same layer covers the top in reversed order, followed by a layer of cover ground.

Gases and fluids that escape from the big pile of waste are collected by drainage and gas pipes. The fluids are purified and used for the different processes that happen within Twence. The gases are transformed into electricity and heat.

Beneath the protective layer, also a system of drainage pipes is placed. These pipes are just for control and can be used to check whether leakage has occurred in the protective layer.

Twence has the responsibility for the eternal aftercare of the dump sites. This means that also in the far future, Twence must ensure that the sites are compliant with the IBC-criteria.

B | Determining Distributions

Throughout the entire report, a lot of distributions have been used. We provide an overview in Table B.1, in which we show the fitted distribution and the figure in which we show the fit.

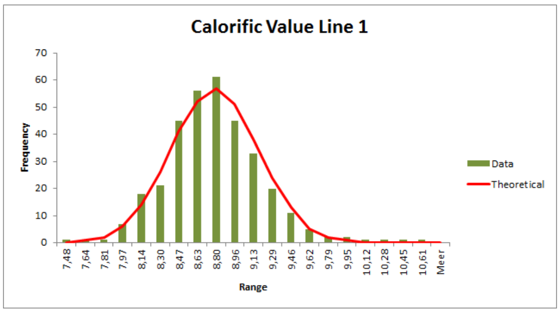
Distributions		
$Calorificvalue_{Line1}$	Normal[8,705 ; 0,460]	B.1a
$Calorificvalue_{Line2}$	Normal[8,736 ; 0,528]	B.1b
$Calorificvalue_{Line3}$	Normal[10,229 ; 0,810]	B.1c
$Calorificvalue_{BEC}$	Normal[11,7994 ; 0,63864]	B.1d
$Factor_{Line1}$	Multimodal with p(x) = 0,533·Normal[x; 19,0950 ; 0,0399] + 0,467·Normal[x; 19,5774 ; 0,0565]	B.2a
$Factor_{Line2}$	Normal[19,5890 ; 0,0778]	B.2b
$Factor_{Line3}$	Normal[10,3462 ; 0,0747]	B.2c
$Factor_{BEC}$	Multimodal with p(x) = 0,5·Normal[x; 14,5225 ; 0,7323] + 0,5·Normal[x; 16,6867 ; 0,5965]*	B.2d

Table B.1: All fitted distributions

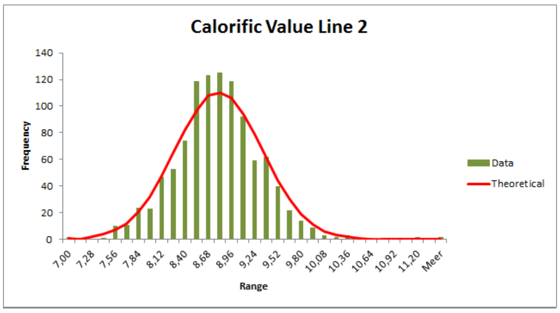
For all distributions of the calorific values, we performed a Chi-Square test. The values all pass the test, as their test value is lower than the Chi-Square value as can be seen in Table B.2. For the factor distribution, we did not find a theoretical distribution that would fit with the data. The distributions we used, were the closest match and we validated them by using them as input for Section 5.3. In that Section, we verificate and validate our model, in which first, the only differences with the reality were these distributions. The results closely matched the reality so we can assume that the distributions we chose, are a close enough fit.

Fit for data from	Distributions	Test value	Chi-Square
$Calorificvalue_{Line1}$	Normal[8,705 ; 0,460]	28,568	28,869
$Calorificvalue_{Line2}$	Normal[8,736 ; 0,528]	39,785	44,985
$Calorificvalue_{Line3}$	Normal[10,229 ; 0,810]	28,706	28,869
$Calorificvalue_{BEC}$	Normal[11,7994 ; 0,63864]	38,075	38,885

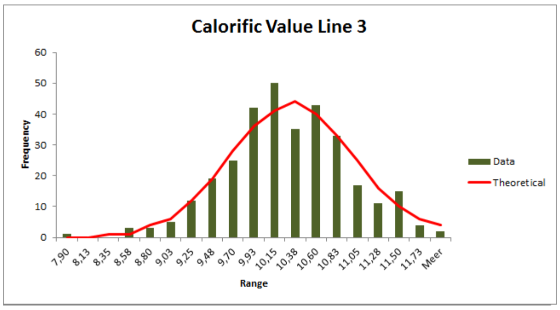
Table B.2: Chi-Square test for calorific value distributions



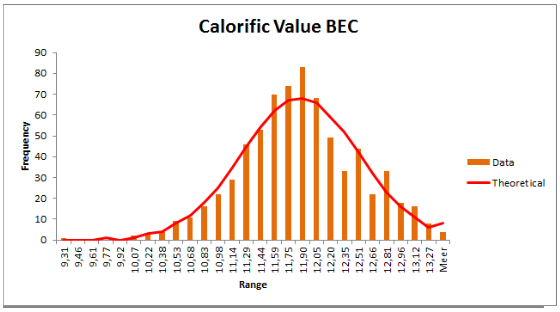
(a) Calorific value for waste on line 1



(b) Calorific value for waste on line 2

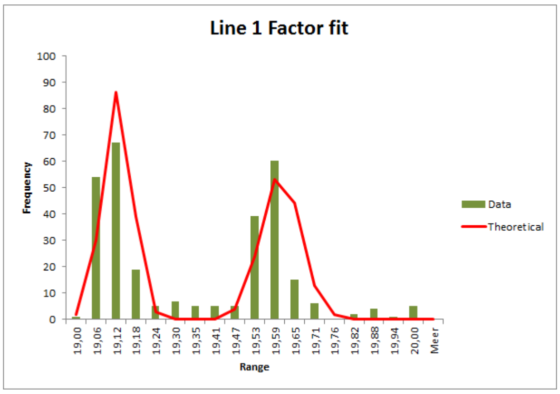


(c) Calorific value for waste on line 3

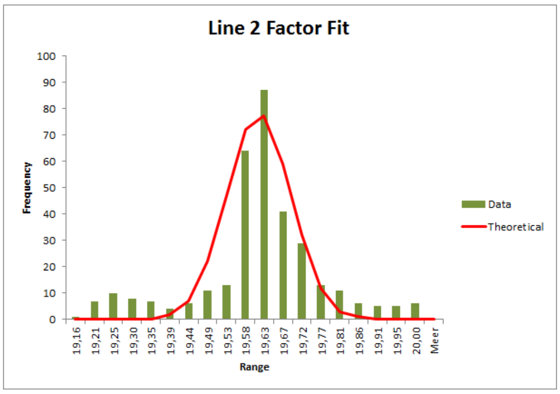


(d) Calorific value for wood

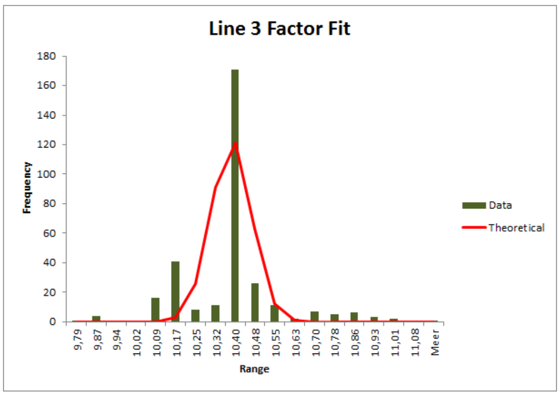
Figure B.1: All fitted distributions for the calorific value



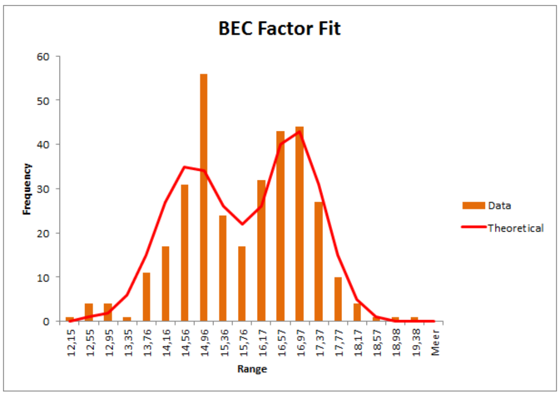
(a) Calorific value for waste on line 1



(b) Calorific value for waste on line 2



(c) Calorific value for waste on line 3



(d) Calorific value for wood

Figure B.2: All fitted distributions for the factor

C | Simulation Model

In Chapter 5 we already discussed the pocesses of the model. In this Appendix we discuss the methods and tables. First we show an overview of the simulation model in Figure C.1 and the technical underlay in Figure C.2.

Figure C.1: Overview of the model.

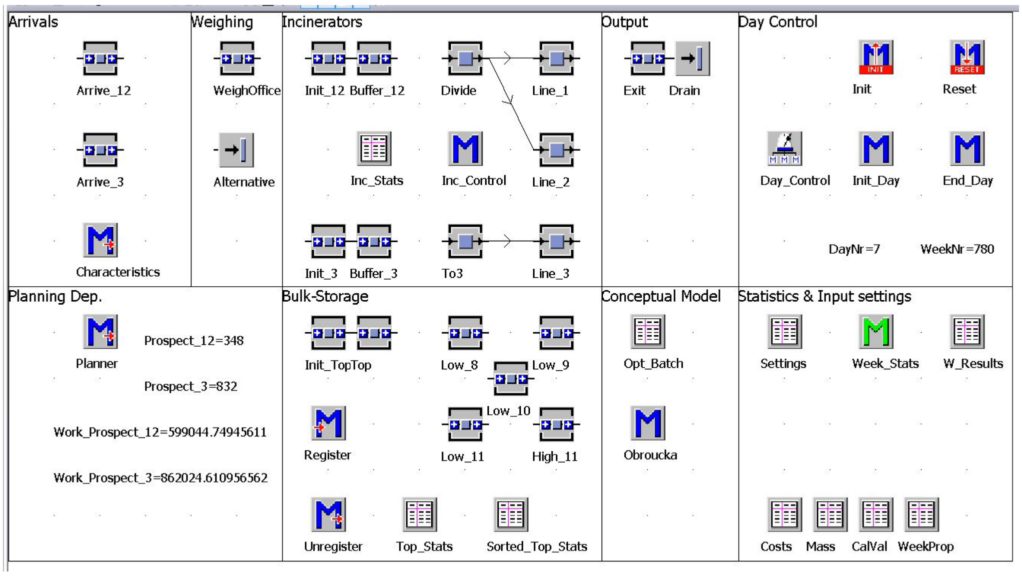


Figure C.2: Technical view of the model

Here we provide a list of all methods that are used, and we discuss them directly.

- Day Control: Init, Init_Day, End_Day
  In *Init* we clear all variables, delete all moveables, and set up the upcoming run with the settings determined by the *ExperimentManager*. The *Init_day* method is activated at the start of each day. It creates the amounts of waste scheduled for each line as stated in table *WeekProp*. Also in *Init_day*, the

age of the waste in TOP is checked by looking at the tables TOP_Stats and $Sorted\_TOP\_Stats$.
End_Day is triggered at the end of each day and triggers $Init\_Day$ to start the new day. It also checks whether a week is past and if so $WeekStats$ is triggered as well.

- Arrivals: Characteristics
The Characteristics method is triggered by arriving waste in $Arrive\_12$ and $Arrive\_3$ makes sure that every waste part gets a calorific value assigned. Depending on the basis for the supplies, the calorific value is determined by a uniform distribution or by a normal distribution as discussed in Chapter 4 and 5.

- Planning Dep.: Planner
In the planner method our conceptual models about diverting and retrieving are implemented (Algorithm 1 and 2). The planner method is triggered either by waste passing through the $WeighOffice$ or by $Init\_Day$ due to over-aging inventory. When retrieving is needed and the decisions are based also on calorific value, the method Obroucka is triggered.

- Conceptual Model: Obroucka
In the *Obroucka* method, we state all equations regarding the Obroucka model adapted to our situation. The score for all batches is put in the table *Opt_Batch* which can then be consulted by the *planner* method to pick the right batch.

- Incinerators: Inc_Control
$Inc\_Control$ draws the factor from the distribution as determined in Appendix B. With that factor, the processing time of the waste is determined. $Inc\_Control$ controls all movements in the incinerator. It moves the waste from the buffer to the incinerators but also from the incinerators to the exit. The statistics of the buffers are also monitored by $Inc\_Control$ and saved in table Inc_Stats.

- Bulk-Storage: Register, Unregister
When waste is diverted it arrives at TOP. There it triggers the method *Register*, which is used to keep track of the amount of waste in TOP but also the date of arrival. When decisions are based on mass only, the table TOP_Stats is used. When decisions are also based on calorific value, the diverted waste is sorted into seperate locations, which is registered in the table $Sorted\_TOP\_Stats$.

- Statistics: Weekstats
In $WeekStats$ the statistics of that week are logged. These are saved in the table $W\_Results$.

D | Week distributions

0.218844333	0.246258888	0.217195525	0.167913704	0.149787551
0.128631445	0.215671908	0.276627812	0.191058315	0.18801052
0.235463871	0.228847913	0.190972222	0.146371078	0.198344916
0.189105883	0.221906724	0.209622754	0.219603646	0.159760992
0.242524576	0.241942498	0.185956851	0.15713371	0.172442366
0.157784715	0.22364672	0.2230574	0.235855639	0.159655526
0.228845001	0.223935692	0.199183031	0.184687453	0.163348823
0.202390056	0.231193674	0.189009107	0.17069949	0.206707672
0.141560971	0.210816271	0.222645484	0.206787585	0.218189689
0.254622201	0.260062058	0.18641713	0.158751013	0.140147597
0.165763793	0.183251229	0.236405863	0.238651095	0.17592802
0.28468455	0.182873133	0.182000651	0.177821327	0.172620339
0.173134677	0.183748291	0.252978736	0.189944736	0.200193561
0.213923469	0.232657671	0.219116273	0.185136126	0.14916646
0.202053393	0.202405425	0.213852278	0.205465398	0.176223506
0.192875099	0.219570268	0.199493312	0.245280889	0.142780431
0.215125629	0.18891397	0.193735523	0.248407324	0.153817554
0.236826842	0.248253795	0.18661092	0.176995456	0.151312986
0.190734285	0.248754871	0.209289153	0.19449897	0.156722722
0.144931337	0.192083576	0.235969442	0.290163473	0.136852173
0.151610594	0.146125999	0.246677747	0.281343523	0.174242137
0.239259588	0.137014804	0.169897122	0.216711382	0.237117103
0.237778412	0.275689217	0.190945434	0.156975235	0.138611702
0.163200815	0.234627269	0.207881075	0.22247995	0.171810891
0.203191467	0.230486969	0.205109835	0.193043441	0.168168288
0.267783079	0.180691267	0.197343978	0.196903904	0.157277772
0.217301542	0.286451374	0.21388012	0.158477811	0.123889154
0.198587676	0.277288223	0.109041167	0.206282408	0.208800527
0.312863929	0.245555103	0.177811974	0.164855286	0.098913708
0.114786354	0.21804628	0.070747573	0.293151178	0.303268615
0.29420722	0.186336822	0.136564776	0.203915251	0.178975932
0.190738948	0.205909097	0.240465506	0.165085761	0.197800688
0.202852195	0.218091974	0.216251488	0.197506421	0.165297922
0.16899069	0.215153193	0.171199364	0.192100528	0.252556225
0.217967989	0.207027761	0.203190315	0.205824174	0.165989761
0.221602193	0.223377268	0.191252482	0.191483718	0.172284339
0.175567598	0.249060808	0.220543798	0.237067155	0.11776064
0.09038579	0.208466936	0.180240746	0.286109671	0.234796857
0.139574064	0.244153129	0.200670715	0.196043628	0.219558463
0.178904018	0.203580047	0.206262835	0.164638891	0.24661421
0.246244375	0.227799237	0.15906107	0.202634884	0.164260434
0.185343995	0.149111629	0.15805271	0.255030679	0.252460987
0.174303941	0.192117641	0.168921987	0.254279072	0.210377358
0.201482501	0.221285403	0.16651307	0.156420161	0.254298865
0.224844915	0.23083136	0.228181086	0.182690168	0.133452471

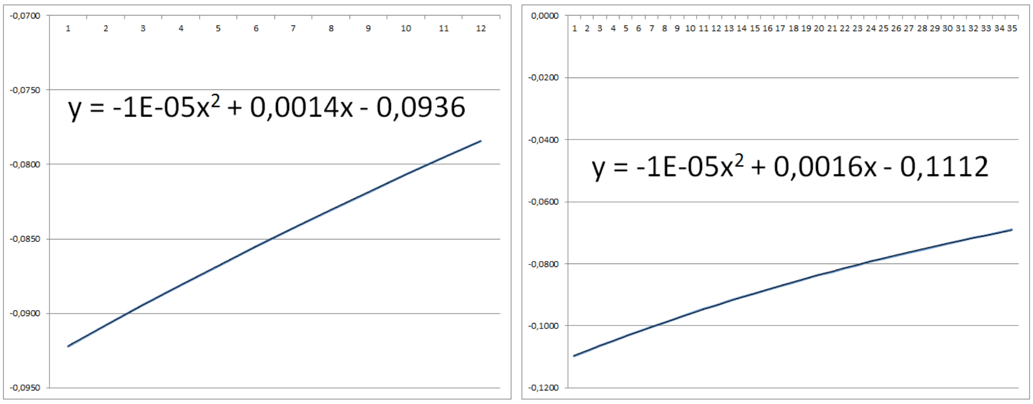
Table D.1: Week distributions for line 1+2

0.134817219	0.173085665	0.219609717	0.205441134	0.267046265
0.288148168	0.189864908	0.185192251	0.160978018	0.175816655
0.231628636	0.163991133	0.193521385	0.185941979	0.224916867
0.239786048	0.222077188	0.213590541	0.198079875	0.126466349
0.130790652	0.087274345	0.255509036	0.252226337	0.274199631
0.274770983	0.154776642	0.214494394	0.211014042	0.144943939
0.146714025	0.150489668	0.218688966	0.230668475	0.253438865
0.227680784	0.19870411	0.227210846	0.178758794	0.167645467
0.21535498	0.219630546	0.164656486	0.191148914	0.209209073
0.166193013	0.165714143	0.246208161	0.243250433	0.17863425
0.287009891	0.204284489	0.182483751	0.172739458	0.153482411
0.067194286	0.21926107	0.27839651	0.213242396	0.221905738
0.309219344	0.208606584	0.13995326	0.154968343	0.18725247
0.207536077	0.221462248	0.200963016	0.177515658	0.192523
0.238409446	0.121362134	0.199635026	0.272312082	0.168281312
0.173913774	0.174949476	0.150328028	0.242048133	0.258760588
0.264874937	0.289604156	0.177198192	0.080655729	0.187666987
0.161593066	0.176746491	0.206405648	0.226597174	0.228657622
0.236237819	0.114651273	0.20105151	0.244442858	0.203616541
0.267178382	0.160744155	0.248574508	0.150819611	0.172683344
0.282404697	0.28246975	0.145959374	0.151220563	0.137945615
0.17429109	0.235615244	0.251171276	0.180292312	0.158630078
0.165486848	0.138942756	0.216300449	0.272399539	0.206870407
0.234107259	0.200004195	0.200994148	0.176522159	0.188372239
0.206518226	0.142086101	0.182934787	0.248818389	0.219642498
0.203497085	0.155074041	0.220714785	0.204105545	0.216608544
0.249786918	0.172285507	0.179325854	0.196228447	0.202373274
0.312222669	0.221769802	0.228381885	0.111780401	0.125845243
0.175441552	0.178036385	0.230072827	0.198493993	0.217955243
0.289645941	0.189177288	0.292050367	0.132949371	0.096177033
0.121582309	0.243674929	0.313236826	0.17373811	0.147767826
0.219054402	0.243442474	0.190581678	0.235509417	0.111412029
0.205846411	0.201089773	0.213870821	0.205711059	0.173481936
0.245010248	0.198186978	0.19568816	0.254875453	0.106239161
0.18697263	0.292832932	0.193856799	0.183031312	0.143306328
0.211726915	0.215792577	0.186377008	0.219928801	0.166174699
0.140998468	0.202673494	0.210375003	0.146223742	0.299729293
0.152639441	0.234840615	0.160939675	0.214838578	0.236741691
0.240891166	0.228729039	0.186534878	0.192966896	0.150878021
0.141442036	0.21923859	0.21120133	0.229116863	0.199001182
0.236045861	0.249938436	0.205657451	0.18920639	0.119151862
0.115448064	0.134527984	0.263589631	0.275616269	0.210818052
0.213027873	0.22337566	0.16046341	0.166865745	0.236267313
0.196541261	0.193816666	0.213223071	0.210528862	0.18589014

Table D.2: Week distributions for line 1+2

E | Storage

Twence did calculations to find out the effect of moisture on the calorific value. The results were that the water itself has a calorific value of -2,7 MJ/Kg. With that, a calculation can be made about the average decrease in calorific value if water is added to 1 Kg of waste. The results are shown in Figure E.1. Where on the X-axis we have the number of periods that it takes for the proportion of water to reach the % found in Table E.1.



(a) Decrease function fit for waste **(b)** Decrease function fit for wood

Figure E.1: Decrease function fits

From information about the average amount of rainfall and evaporation of the rain (KNMI, 2010), we found that on average in a year there is a rain surplus of 240 liters of water per m^2.

	Max. Tons	Max. Area	Surplus rainwater
TOP	200.000	77.500	9,3%
Woodbank	60.000	70.600	28,24%

Table E.1: Tons of waste/wood per m^2

Table E.1 shows how much waste or wood is stored in the bulk storage per m^2. In a year, 0,240 tons rainwater per m^2 is added on top of 2,58 tons of waste and 0,850 tons of wood. This means that in a year the percentage of water that is added is 9,3% for waste and 28,24% for wood, which result in the following equations for the drop in the calorific value when adding the time proportion in years.

$$Decrease_{Waste} = 0,00001 \cdot (12 \cdot Ageinyears)^2 + 0,0014 \cdot (12 \cdot Ageinyears) - 0,0936;$$

$$Decrease_{Wood} = 0,00001 \cdot (35 \cdot Ageinyears)^2 + 0,0016 \cdot (35 \cdot Ageinyears) - 0,095;$$

Therefore, when supplies are retrieved from TOP, the time spent on TOP is calculated and the effect on the calorific value is determined and adjusted.

F | Experimental phase 1

In phase 1 we examine, for all combinations of Supplies and Decisions bases, what the amount of supplies is, for which the TOP approaches steady state. We perform these experiments with the broad thresholds such that the development of TOP mainly depends on the supplies. In Table 5.7 the model input for phase 1 can be found. For this phase we vary the amount of supplies as shown in Table F.1

Lines	**Range**	**Steps**
$Supplies_{Line1+2}$	7.000 - 7.300 per week	25
$Supplies_{Line3}$	5.600 - 5.900 per week	25

Table F.1: Range of supplies

The results are shown in graphs, from which we want to determine what the right amount of supplies is, to reach a steady state for the TOP inventory. Preferably, we find one value for each combination of model input shown in Table 5.7, this to ensure that we can make a fair comparison between the experiments.

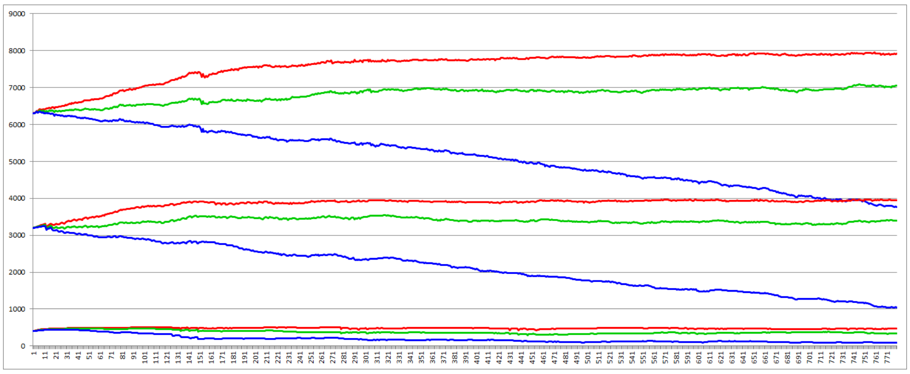
In Figure F.1 we see the resuts for all configurations with three amounts of supplies that we have selected. All the TOP Capacity options are combined per [Mass,Mass], [Mass,Calo], [Calo,Mass], [Calo,Calo] ([Basis for Supplies, Basis for Decisions]). In Table F.2 we what the lines in the graphs represent.

Red line	Supply of 7.175 and 5.775
Green line	Supply of 7.150 and 5.750
Blue line	Supply of 7.125 and 5.725
Y-axis	Amount of TOP inventory
X-axis	Weeks

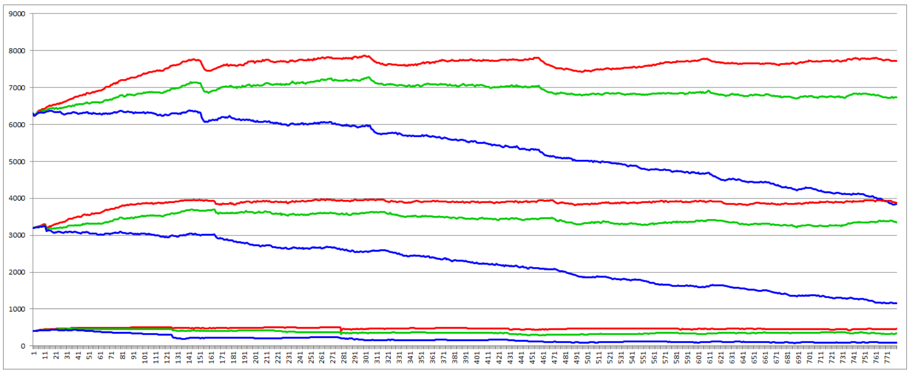
Table F.2: Explanation of Graphs in Figure F.1

In Figure F.1 we show for each configuration and each initial TOP Capacity three lines that correspond with three amounts of supplies that give a clear image of the effects.

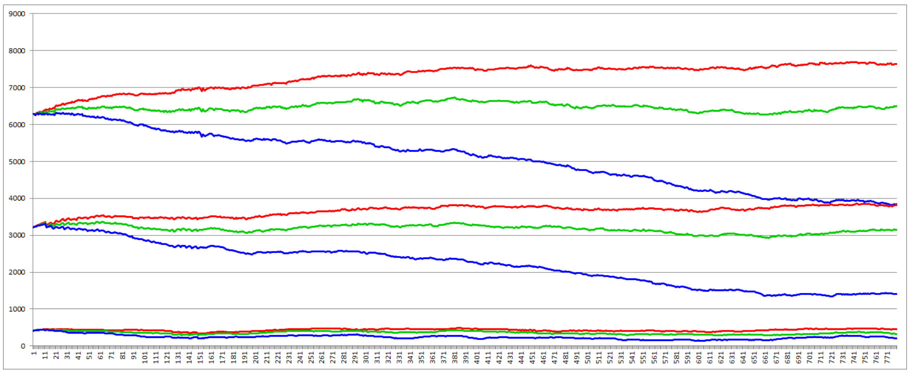
- Red line: Usually approached the TOP capacity. Only with the [Calo,Calo] configuration, the line seems stable.
- Green line: In all situations this line stays stable. Again only with the [Calo,Calo] configuration as exception, where the green line has a descending trend.
- Blue line: This line is in every situation descending.



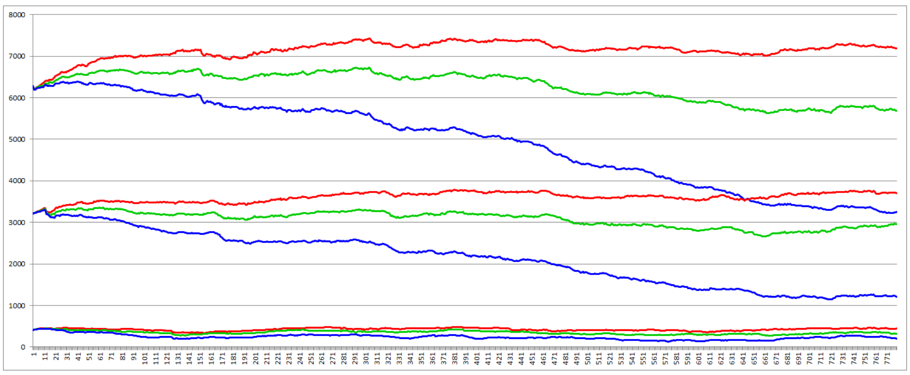
(a) TOP Development 5K, 40K, 80K, Mass-Mass



(b) TOP Development 5K, 40K, 80K, Mass-Calo



(c) TOP Development 5K, 40K, 80K, Calo-Mass

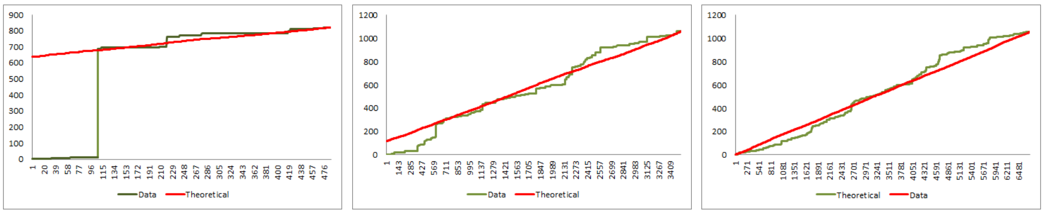


(d) TOP Development 5K, 40K, 80K, Calo-Calo

Figure F.1: TOP Development 5K, 40K, 80K

Since we want to make a fair comparison, we choose as input for our model the supply amounts used for the green line. Although the line does not result in the steady state we would like for the [Calo,Calo] configuration, the TOP still is above the 40K so we should be able to still make a constructive conclusion about the amount of TOP inventory.

From Figure F.1a, F.1b it is clear, but also in Figure F.1c and F.1d we see that the initial conditions of the TOP inventory has a big influence. In week 156, the lines have a small hick-up, which is not surprisingly right after the first 3 years. For every initial TOP amount we looked at the distribution of the age of the waste. In Figure F.2 we show the sorted ages (y-axis) of the TOP waste (x-axis).



(a) TOP Ages (5K) **(b)** TOP Ages (40K) **(c)** TOP Ages (80K)

Figure F.2: TOP Age 5K, 40K, 80K

In Figure F.2 we see a different spread for the different ages among the TOP inventory. We notice a jump in the ages in Figure F.2a (large jump) and F.2b (small jump), from which we can conclude that it the amount of time that it costs to refresh all waste in TOP is shorter then three years. Especially with the 5K TOP, where we see a jump in age of more than 600 days. Since we need to get into steady state first, we can not exactly determine at which moment in time this jump starts. We fit a uniform distribution in which we take into account the spread of the age of the waste after the jump. We use this distribution in our experiments so that the waste in TOP starts as young as possible given the amount of time it takes to refresh within three years. The results are shown in Table F.3.

Intial conditions 80K TOP	Uniform[0 days ; 1.054,00 days]
Intial conditions 40K TOP	Uniform[0 days ; 925,93 days]
Intial conditions 5K TOP	Uniform[0 days ; 181,40 days]

Table F.3: Range of Ages

G | Experimental factors: Thresholds

Because we can not test for all possible thresholds, we need to make a good estimation about what should be the optimal thresholds. From Section 3.1 we know that safety stock is used to prevent stockouts, and thus that the safety stock should at a level such that the probability of a stockout is beneath the desired level.

We want to prevent stockout, so we need to bridge two days without supplies. Buffer 1+2 therefore needs to bridge four days, and buffer 3 just the two days. We need to set the threshold such that at any time, the amount of waste in the buffer is higher than respectively four and two days of incinerating.

When we calculate the maximum amount of work present in a buffer, we use the mean for the calorific value and the factor. This because the capacity is respectively 5500 and 10000, which is enough to assume the mean is a correct estimation. The maximum amount of work present in a buffer is calculated by Equations G.1 and G.2.

$$AmountofWork_{Buffer1+2} = 19,45456 \cdot 8,7205 \cdot 5.500 = 10days20hours; \tag{G.1}$$

$$AmountofWork_{Buffer3} = 10,3462 \cdot 10,2290 \cdot 10.000 = 12days6hours; \tag{G.2}$$

For the low bounds of the thresholds we need to use the distributions we found for the factors and the calorific value. We want to choose the value such that 95% of the distribution is higher than our value.

In Table G.1 we show the distributions for both the configuration in which supplies are based on mass, and in which supplies are based on calorific value.

With the 0.05 percentile values for the calorific values and the factors, we can determine a kind of low bound for the amount of work present in the buffer by using these values in Equations G.1 and G.2. To determine what the threshold needs to be, we divide the amount of days that the buffer needs to bridge by the total amount of work in the buffer. We summarize the results in Table G.2.

For the low thresholds we thus experiment with [35%, 40%, 45%] and [15%, 20%, 25%] for respectively buffer 1+2 and buffer 3.

In our experiments, we assume that the TOP inventory is in a steady state so we can assume that the amount of waste supplied in a week is on average equal to

Which line	Distribution	0,05 percentile
$Calorificvalue_{Line1}$	Normal[8,705 ; 0,460]	7,9457
$Calorificvalue_{Line2}$	Normal[8,736 ; 0,528]	7,8642*
$Calorificvalue_{Line3}$	Normal[10,229 ; 0,810]	8,8773
$Calorificvalue_{Line1}$	Uniform[7,8345 ; 9,5755]	7,9216*
$Calorificvalue_{Line2}$	Uniform[7,8624 ; 9,6096]	7,9498
$Calorificvalue_{Line3}$	Uniform[9,2061 ; 11,2519]	9,3084
$Factor_{Line1}$	Multimodal with p(x) = 0,533·Normal[x; 19,0950 ; 0,0399] + 0,467·Normal[x; 19,5774 ; 0,0565]	19,028*
$Factor_{Line2}$	Normal[19,5890 ; 0,0778]	19,461
$Factor_{Line3}$	Normal[10,3462 ; 0,0747]	10,223

Table G.1: 0.05 percentile values for calorific values and factors
*We take the lowest of the two values for Line 1 and Line 2

Buffer	**Average**		**LB Mass**		**LB Calo**	
1+2	260 hours	(36,92%)	228 hours	(42,11%)	230 hours	(41,74%)
3	294 hours	(16,33%)	252 hours	(19,05%)	264 hours	(18,18%)

Table G.2: Maximum amount of work in the buffer (percentage for 4 or 2 days)

the amount of waste to be processed in a week. Because on only five of the seven weekdays waste is supplied, roughly every day (7/5) of the daily needs are supplied. Because of the range for our supplies we could have more supplies than needed in a week. We therefore look at the 0.95 percentile to determine the high threshold, as shown in Table G.3.

Supplies based on		Monday	Tuesday	Wednesday	Thursday	Friday
Mass	Supplied	1,526	1,526	1,526	1,526	1,526
	Processed	1	1	1	1	1
Calo	Supplied	1,6303	1,6303	1,6303	1,6303	1,6303
	Processed	1	1	1	1	1

Table G.3: 0.95 percentile for the supplies

So the first four days a surplus of 2,104 and 2,5212 arises. Thus at the start of Friday there should be room in the buffer for that surplus and the waste supplied on friday. This means for the different supply bases, that there should be room for $\frac{2{,}104+1{,}526}{7}$ [Mass] and $\frac{2{,}5212+1{,}6303}{7}$ [Calo] percent of the arrivals.

The average supplied amount per week is set to 12.900. The surplus for which space should be reserverd than would be respectively 6.690 and 7.651. Because we want to prevent sending waste to an alternative incinerator, we can subtract the amount of waste that can be diverted in a week which is 1.500 at maximum. In Table G.4 we summarize this information.

Supplies based on	Surplus	Maximum diverting	Total buffer capacity	$\frac{Surplus-Diverting}{Totalcapacity}$
Mass	6.690	1.500	15.500	33,48%
Calo	7.651	1.500	15.500	39,68%

Table G.4: Determing % to reserve

Because in our conceptual model, if one buffer is above its threshold we send the waste to the other buffer, in percentage terms it does not matter whether we take different high thresholds for both buffers. When both buffers are filled to their high threshold, the total buffer capacity is used for the average of the two high thresholds. Therefore for convenience we say that we choose one threshold for both buffers. The high thresholds we thus experiment with are [60%, 65%, 70%, 75%, 80%].

H | Determine number of replications

As discussed in Section 5.4.2, we give some more explanation about the determination of the number of replications. We explained why we do not exclude our warm up for our first phase. In Figure H.1 we see the test in which we determine the number of replications needed. Unfortunately, 30 replications were not enough for the experiments with a TOP Capacity of 5K. Therefore we chose to do 100 replications. Because of the running time of the model, this is the maximum number of replications we can perform in order to keep the running time acceptable. The advantage of performing our experiments in multiple phases, is that we perform longer runs for the most promising experiments, so when the experiments with a TOP Capacity of 5K are within this group, we test again for the number of replications.

0,1000	Mean of costs per week	Mean of costs per week	Mean of costs per week	Mean of costs per week	Mean of costs per week	Mean of costs per week	Mean of costs per week	Mean of costs per week	Mean of costs per week	Mean of costs per week	Mean of costs per week	Mean of costs per week	
0,0909	MM5000	MM40000	MM80000	CM5000	CM40000	CM80000	MC5000	MC40000	MC80000	CC5000	CC40000	CC80000	
2	5,261	0,593	0,265	0,335	0,595	0,655	5,086	0,934	0,347	0,477	0,274	0,287	
3	2,291	0,193	0,123	0,310	0,306	0,218	2,212	0,268	0,140	0,410	0,206	0,173	
4	1,709	0,128	0,077	0,180	0,200	0,124	1,636	0,155	0,088	0,232	0,130	0,099	
5	1,419	0,103	0,059	0,221	0,158	0,091	1,350	0,125	0,086	0,230	0,091	0,073	
6	1,285	0,080	0,045	0,177	0,123	0,071	1,226	0,097	0,068	0,181	0,071	0,056	
7	1,148	0,065	0,037	0,155	0,105	0,059	1,063	0,080	0,055	0,178	0,071	0,047	
8	0,960	0,118	0,064	0,243	0,142	0,069	0,901	0,128	0,088	0,245	0,100	0,057	
9	0,919	0,106	0,059	0,309	0,180	0,107	0,858	0,115	0,078	0,303	0,131	0,062	
10	0,756	0,121	0,069	0,296	0,169	0,105	0,713	0,127	0,079	0,299	0,130	0,059	
11	0,634	0,124	0,070	0,269	0,151	0,094	0,602	0,128	0,073	0,271	0,117	0,061	
12	0,608	0,116	0,065	0,262	0,145	0,090	0,576	0,117	0,067	0,262	0,111	0,056	80000
13	0,602	0,107	0,060	0,245	0,136	0,082	0,570	0,108	0,063	0,246	0,108	0,052	
14	0,529	0,099	0,056	0,229	0,125	0,078	0,503	0,104	0,058	0,229	0,101	0,048	
15	0,477	0,108	0,059	0,210	0,116	0,072	0,456	0,115	0,059	0,211	0,094	0,046	
16	0,473	0,104	0,058	0,251	0,134	0,068	0,452	0,112	0,057	0,254	0,118	0,047	
17	0,455	0,103	0,058	0,234	0,125	0,064	0,433	0,107	0,053	0,237	0,110	0,045	
18	0,459	0,097	0,055	0,229	0,119	0,061	0,436	0,101	0,051	0,231	0,103	0,043	
19	0,458	0,092	0,052	0,217	0,112	0,059	0,433	0,096	0,048	0,218	0,098	0,043	
20	0,459	0,087	0,049	0,210	0,106	0,056	0,435	0,090	0,046	0,212	0,093	0,040	
21	0,450	0,088	0,051	0,200	0,101	0,054	0,425	0,090	0,047	0,201	0,088	0,039	
22	0,449	0,083	0,049	0,192	0,096	0,054	0,424	0,085	0,045	0,191	0,084	0,037	
23	0,450	0,080	0,047	0,182	0,092	0,052	0,423	0,082	0,043	0,182	0,080	0,036	
24	0,450	0,076	0,045	0,173	0,090	0,051	0,421	0,078	0,041	0,173	0,079	0,036	40000
25	0,443	0,075	0,044	0,174	0,089	0,051	0,414	0,076	0,041	0,175	0,080	0,035	
26	0,415	0,072	0,042	0,166	0,088	0,051	0,389	0,074	0,040	0,167	0,078	0,034	
27	0,394	0,076	0,044	0,160	0,084	0,050	0,371	0,078	0,041	0,161	0,075	0,035	
28	0,392	0,073	0,043	0,154	0,081	0,048	0,369	0,075	0,040	0,154	0,072	0,034	
29	0,388	0,072	0,042	0,148	0,078	0,047	0,365	0,074	0,040	0,148	0,070	0,034	
30	0,381	0,073	0,043	0,144	0,075	0,045	0,359	0,072	0,039	0,145	0,068	0,033	
More													5000

Figure H.1: Test for number of replications

I | Experimental phase 3

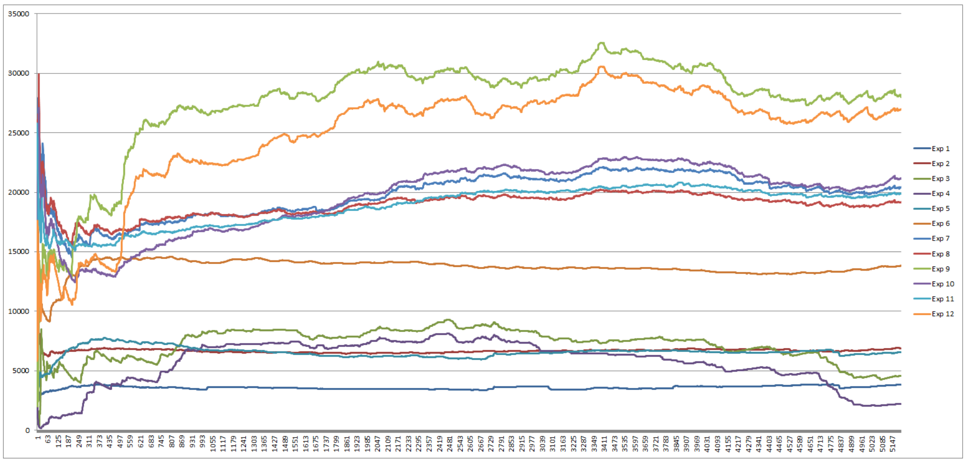
For phase 3 we want to perform much longer runs with excluding the warm up period in order to get very reliable results. We check with the welch method what the appropriate warm up period should be. We test this with the 12 worst performing experiments by looking at the TOP inventory and the costs per week. First we show the settings of the experiments with which we tested for the warm up period, and after that, the welch graphs are shown.

Settings							
Exp Number	Supply Basis	Decision Basis	Low Thres. 1+2	High Thres. 1+2	Low Thres. 3	High Thres. 3	TOP Capacity
1	Mass	Mass	0,40	0,60	0,25	0,60	40000
2	Mass	Mass	0,45	0,60	0,20	0,60	80000
3	Mass	Mass	0,35	0,60	0,25	0,60	5000
4	Mass	Calo	0,35	0,60	0,25	0,60	5000
5	Mass	Calo	0,45	0,60	0,25	0,60	40000
6	Mass	Calo	0,45	0,60	0,25	0,60	80000
7	Calo	Mass	0,35	0,65	0,15	0,65	40000
8	Calo	Mass	0,35	0,60	0,20	0,60	80000
9	Calo	Mass	0,35	0,60	0,25	0,60	5000
10	Calo	Calo	0,35	0,60	0,25	0,60	40000
11	Calo	Calo	0,35	0,60	0,25	0,60	80000
12	Calo	Calo	0,35	0,70	0,15	0,70	5000

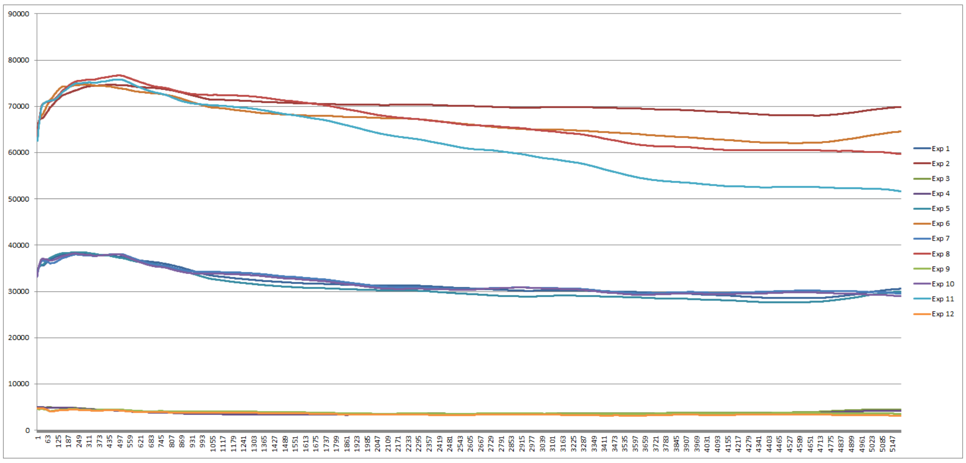
Table I.1: Experiments for the Welch method

Unfortunately, even with a run length of 100 years, we still have a few experiments that do not provide a steady state when we look at the costs per week in Figure I.1a. In Figure I.1b we notice just a single experiment in which the TOP inventory seems to not be in a steady state. From the lines that do achieve steady state we can determine that the warm-up period lasts for almost 1040 weeks (20 years). So for our extra long runs we decide to take 20 years for the warm-up period, and a total run length of 120 years.

From Figure I.1a we can easily see that 6 of these 12 experiments have much higher costs per week than the other experiments. These are all experiments with calorific value as the basis for the supplies. Therefore we can almost already conclude that these experiments will not come out on top, even if the other settings are optimal. Since we now took the 12 worst experiments of the 36 best experiments, the differences will be small and therefore, no big movements are expected. We also



(a) Welch Method for the costs per week



(b) Welch Method for the amount of TOP inventory

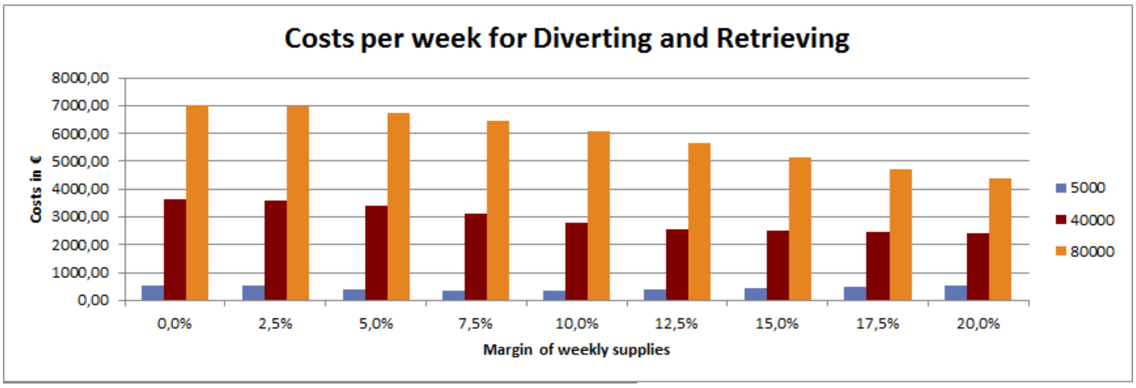
Figure I.1: Welch Method

determine the number of replications again, of which the results are in Table I.2.

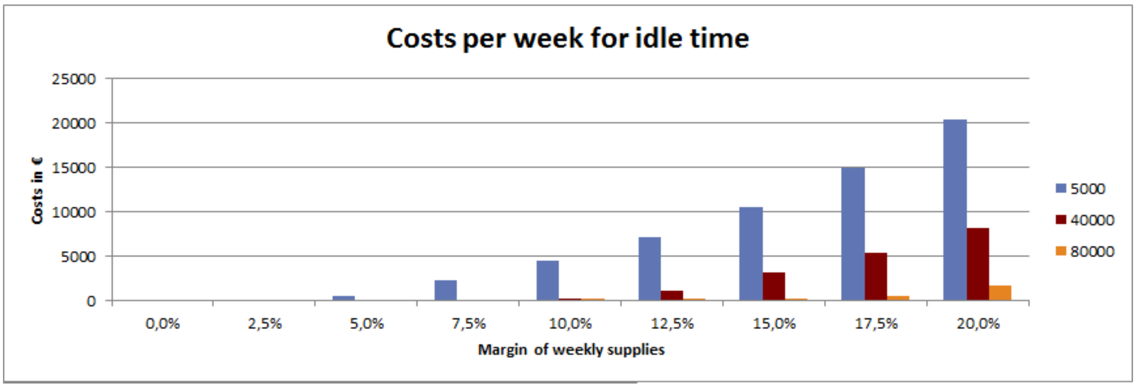
Start Scenario	Minimum number of replications needed	Number of replications done
80.000 Tons	6	15
40.000 Tons	11	15
5.000 Tons	>25	70

Table I.2: Required number of replications for phase 3

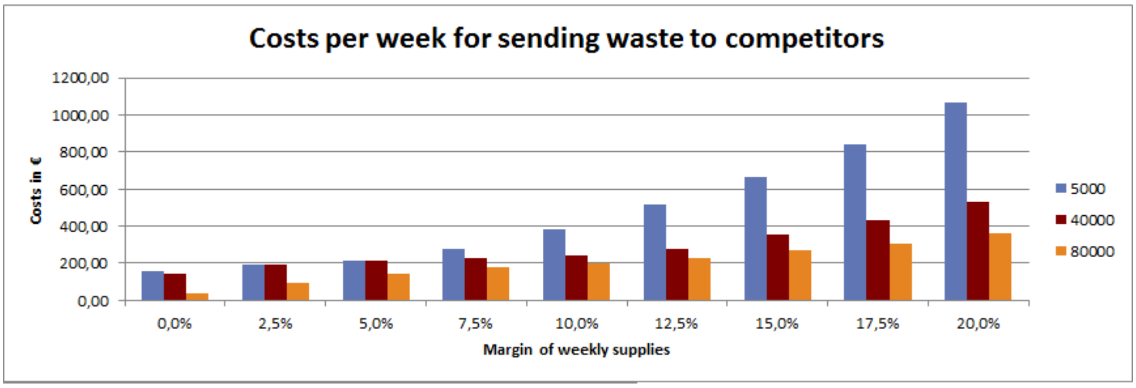
J | Sensativity analysis



(a) Costs per week for diverting and retrieving

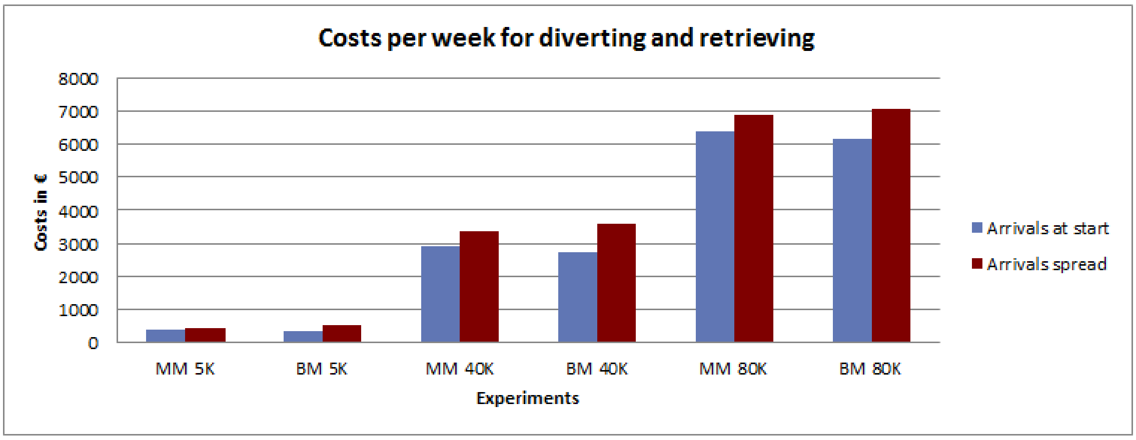


(b) Costs per week for idle time

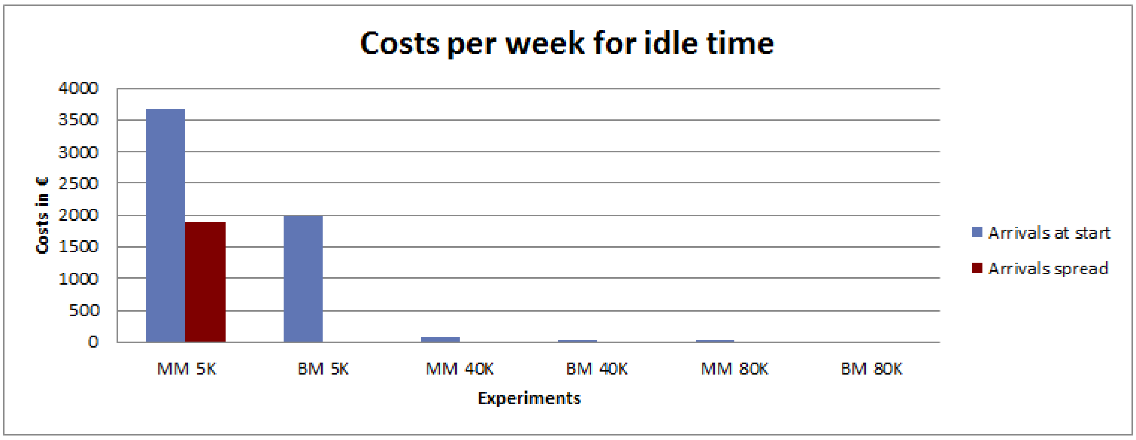


(c) Costs per week for sending to competitors

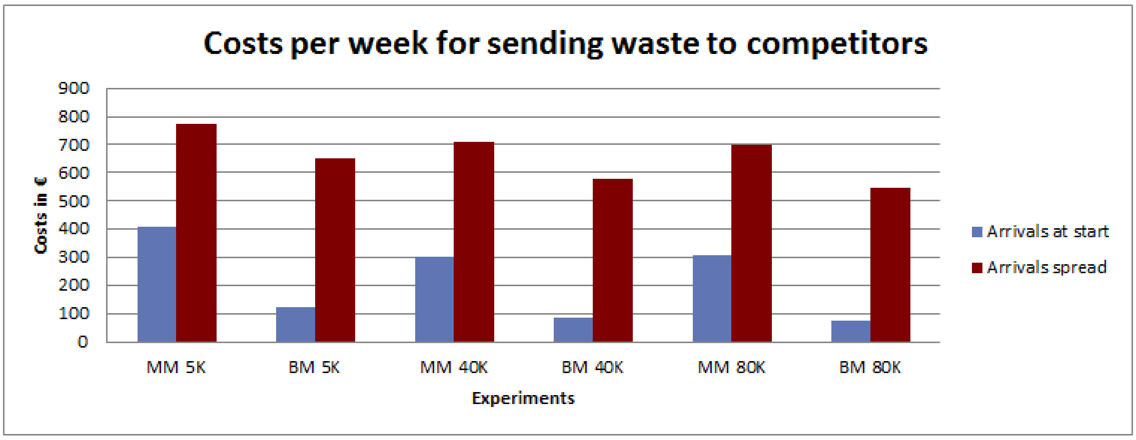
Figure J.1: Costs specification for varying the margin



(a) Costs per week for diverting and retrieving



(b) Costs per week for idle time



(c) Costs per week for sending to competitors

Figure J.2: Costs specification for spread arrivals