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Thinking out of the hot box

A simulation study aimed at the increase of hot charging and average charging temperature at the hot strip mill of Tata Steel IJmuiden by using hot boxes

Master Assignment

Industrial Engineering & Management

TATA

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Management Summary

Tata Steel IJmuiden produces steel strip products for application in construction works, automobile industry and as packaging material. Steel is produced from iron ore. First, the iron is melted from the ore in a blast furnace and casted into ladles. After several ladle treatments, the pig iron becomes liquid steel. The liquid steel is then casted into the continuous casting machines, which create a solidified string of steel. At a temperature of around 900°C, slabs are cut from the string and brought to the slab yard. Here, slabs are stored and cool down until they are demanded at the hot strip mill. The hot strip mill reheats the slabs to approximately 1,200°C and rolls them into thin, coiled sheets.

As part of cost reduction, sustainability, and increasing sales volume, Tata Steel IJmuiden is striving for decreasing throughput times, stocks, and energy consumption. An important initiative contributing to these goals is the so-called 'hot charging', in which the temperature of the slabs charged at the furnaces of the hot strip mill is above a certain minimum.

In this research we have investigated the contribution of heat preservation boxes (i.e. hot boxes) to the hot charging initiative. We performed a simulation study using historical data of two quarters. The research objective was:

> *"Develop an operational concept for Tata's future hot boxes in order to increase the percentage of hot charging and average overall charging temperature"*

We first made an extensive analysis of the current situation, which we thereupon translated into a simulation model. We used the simulation model to (1) imitate a quarter of a year of production and (2) to investigate an ideal situation with hot boxes. The first answers the question what could have been the benefit of hot boxes if they were already in use during the simulated quarter. The latter shows how the performance can be optimized based on different scenarios. To test the logistical performance in the current situation, we also carried out a pilot.

Results from the first simulation showed that an increase of $XXX\%$ in hot charging and an increase of XXX°C in average charging temperature can be obtained by designating a fixed number of slab types and without changing production planning. The effect is an expected annual energy saving of € XXX and an increase in annual furnace capacity of approximately XXX kTon.

Results from the second simulation showed that an increase of $XXX\%$ in hot charging and an increase of XXX°C in average charging temperature can be obtained by dynamically designating slabs to the hot box, in a more stable planning environment. The effect is an expected annual energy saving of € XXX and an increase in annual furnace capacity of approximately XXX kTon.

In the pilot, by using different destination labels, we designated a fixed number of slab types to a predetermined area at the slab yard. This was our 'virtual hot box'. The goal of the pilot was to test logistical performance on slab allocation and slab movements at the slab yard. We examined whether the expected hot box slabs received the correct destination label and if they were correctly transported to the virtual hot box. Based on the results, we concluded that under the current way of working abovementioned benefits cannot be gained entirely yet.

Our general conclusion is that hot boxes will definitely have a positive effect on increasing hot charging at Tata Steel IJmuiden. The financial benefits are evident, but before they can be realized, a set of operational improvements has to be implemented:

- No longer coupling of customer orders to physical stock
- Introduction of new slab destination labels to distinguish between hot box- and non-hot box destined slabs
- Computerize a prioritization rule in the BètaPlanner (i.e. an IT-system), such that first hot slabs outside the hot box are scheduled, then hot slabs in the hot box, and, finally, cold slabs outside the hot box
- Investigate the possibilities to align operational planning of oxygen steel plant and hot strip mill

Hence, our recommendation is to implement these improvements prior to start building the hot boxes.

Preface

This report is the result of the graduation project to finish my master program Industrial Engineering and Management at the University of Twente. Seven months, I joined the project group 'hot charging' at Tata Steel IJmuiden, which aims at reducing energy usage, lead times, and stock levels.

During my time at Tata Steel, I learned a lot. Not only in the world of steel making, but also by being part of a project group and getting things done in a highly hierarchical company. The people I met as well as the heavy processes in the steel making industry made an overwhelming impression on me and finally made me decide to jump on a job offer at the Supply Chain department.

The realisation of my project would, however, not have been possible without the help of a select company. First of all, I thank all Tata Steel stakeholders in the hot charging project for their cooperation. Special thanks go to Emiel Bosma, Govert Kockelkoren, Adriaan Gaasbeek, Frans Pesschier, and Anne Jan de Vries for guiding me through the organisation and providing me with the necessary data, information, and feedback.

Second, I thank Adriaan Gaasbeek, Jan Sieraad, and Adrie Verhagen for giving me a place to work and a great time at the AOV department. Their doors were always open and the breaks and lunches were a pleasant distraction from my work.

Furthermore, I thank Martijn Mes and Marco Schutten, supervisors of the University of Twente, for their support and feedback. Our meetings and discussion were very useful and pointed me to the right direction.

Last but not least, I thank my family and friends for their support, their sociability, and their implicit faith in a good end, not only for this project, but for my entire student life.

Amsterdam, September 2011

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1 Introduction

Tata Steel is a worldwide operating company with steel factories all over the world. At the production site in IJmuiden, in 2010, 6.6 million metric tonnes of high-quality and sheet steel was produced. Most products are delivered as coils and some as slabs. Mainly they are applied in construction works, in the automobile industry, and as packaging material.

The process starts with iron ore. In a so called blast-furnace, the iron is extracted from the ore. It is then called 'pig iron'. Next, the liquid pig iron is transported to the oxygen steel plant (OSF2) at a temperature of around 1,500˚C. In the OSF2, the pig iron has several treatments until liquid steel is formed. Then, the liquid steel is casted in a funnel-shaped bin. At the bottom of the bin a string of solid steel is formed. From this string, slabs are cut in different lengths, with a standard thickness of 225mm and variable width. After this, the slabs are transported by train to the slab yard (AOV). Here, huge cranes pick the slabs from the trains and store them until they are requested by the hot strip mill (WB2). Once requested, the crane picks the requested slab from its storage and takes it to the WB2 area, which is connected to the AOV.

Picture 1.1 - The slab yard (AOV) at Tata Steel IJmuiden

The AOV is an important stock point, because the Customer Order Decoupling Point (CODP) lies at this point. Upstream from this point, the OSF2 is producing according to a make-to-stock (MTS) principle; this process is not directly influenced by customer orders. Moreover, the production in large batches has some important economies of scale for the OSF2. Downstream from the CODP, the WB2 is mainly manufacturing to order (MTO). This means the WB2 can pick a slab from the AOV and roll it to dimensions the customer wishes. Before rolling, the slabs are reheated in one of the four furnaces to a temperature of 1,250˚C and then rolled into a long sheet, varying in thickness between 1.5 and 25mm. This sheet is then coiled and ready for transport to one of Tata's cold rolling mills or directly to the customer

This research aims at the interaction of the OSF2 and the WB2, which is physically taking place at the AOV, where slabs are stored for a period varying from one day to several months, before they are requested by the WB2 or sold to a third party. We first explain the motive for this research in Section

1.1. Then, we introduce the research objective and main research question (Section 1.2), followed by the supporting research questions (Section 1.3). We end up with the research scope in Section 1.4.

1.1 Research Motive

As part of cost reduction, sustainability, and increasing sales volume, Tata Steel IJmuiden is striving for decreasing throughput times, stocks, and energy consumption. An important initiative contributing to these goals is the so called 'hot charging', in which the temperature of the slabs charged at the furnaces of the WB2 is above a certain minimum.

Currently, most slabs are stored at the AOV, which causes them to cool down to the temperature of the ambient environment. Hence, the total stock level varies between XXX and XXX kTon and only XXX% of all slabs is charged within 24 hours. The steering committee 'hot charging' is responsible for the project 'hot charging' and set up a program to reach a higher average slab temperature when charging at the WB2. The foundation for this project is fourfold:

- Hot charging leads to energy savings at the furnaces of the WB2
- Hot charging leads to CO_2-reduction and hence a reduction of required CO_2-allowance certificates
- With a higher start temperature, the throughput time of the furnaces will decrease and hence lead to an increase in furnace capacity
- There is an increasing demand for high strength steels, which are, due to quality reasons, not allowed to cool down quickly. The current situation does not allow for an increase in production of these high strength steels

Several options have been investigated by the steering committee and it was decided to cope with the 'hot charging' problem by the use of hot boxes. These are isolated storage boxes and can keep slabs warm up to five days and hence contribute to a higher average slab temperature at insertion in the furnaces. In the steel industry this is a well-known concept and amongst others applied at Voest (Austria) and Port Talbot (UK, Former Corus). Currently, the investment proposal for the first three hot boxes is waiting for approval from the management. The goal is to eventually build 12 hot boxes.

1.2 Research Problem and Objective

Although the use of hot boxes is a proven concept and described in the literature as highly contributing to hot charging, the operational details of using hot boxes differ from plant to plant and are not explained in the literature. Therefore, Tata's most important question is how to use the hot storage boxes in daily operations. A logistical controlling concept must be developed. Hence the objective of this research is:

> *"Develop an operational concept for Tata's future hot boxes in order to increase the percentage of hot charging and average overall charging temperature"*

The research objective leads to the following main research question:

"What factors are influencing hot charging through hot boxes and how to deal with these factors to maximize the overall average slab temperature using hot boxes?"

The goal is to gain insight in the parameters influencing hot charging. First, the current production and logistical parameters must be analyzed for their relevance and to check the validity for the chosen solution direction. Subsequently, an operational concept must be developed for the use of the hot storage boxes in daily operations. For this purpose the management asked to come up with a simulation model. Eventually, the operational concept must be tested in reality.

1.3 Research Questions

The research questions below support the main research question and research objective. The goal is to acquire information from both practical situations and scientific literature and give structure to the report. Scientific literature might lead to new or different views on the production environment and can hence be set alongside the current production performance. The research questions guide the research.

First, we want to know which aspects of the research are already explained in the scientific literature, so we can place the research in a scientific framework. We also want to know what logistical models exist and if they are applicable to our research. Chapter 2 gives more insight in both issues and answers research question 1:

1. *How can we position the research problem in the literature?*

Second, we analyze the current situation to understand the production processes. We use detailed production data of half a year. This analysis is included in chapter 3 and gives answer to research question 2 and its sub-questions:

2. *What is the current situation?*
   a) *Why are stock levels at the AOV varying between XXX and XXX kTon*
   b) *Why are some slabs charged within 24 hours and others after a much longer period?*
   c) *What are selection criteria for a slab to be candidate for the hot storage boxes?*
   d) *Which procedures or routines can be obstructive for the hot boxes?*

Based on our knowledge of the current situation, we create a model, which represents the processes involved in this research. In Chapter 4 we elaborate on the various factors we include in, or exclude from the model. Hence, this chapter gives an answer to research question 3 and its sub-questions:

3. *How do we model the production processes?*
   a) *Which factors are important for the simulation model and which can be omitted?*
   b) *Which factors do we vary in the simulation model to test operational performance?*

In Chapter 5 we describe how we transform our paper model into a simulation model. Chapter 6 shows what performance can be reached using this simulation model. With the results we are able to answer research question 4:

4. *What hot charging performance can be reached by the use of hot storage boxes?*

Finally, we test our findings from the simulation study in a pilot. Chapter 7 expounds on this pilot, the necessary steps to implement the findings from Chapter 2 to 6, and answers research question 5:

5. *How can the findings from this research study be translated into an operational concept?*

The research ends with a set of conclusions and recommendations in Chapter 8. In this chapter, we also answer the main research question from Section 1.2.

1.4 Research Scope

To keep the research conveniently arranged and achievable within six months, it is important to give some boundaries to the research. As mentioned in the introduction part, this research aims at the interaction between OSF2 and WB2 (see also Figure 1.1). Hence, the input of OSF2 is not taken into account and considered to be sufficient to reach slab demand. Also the output of WB2 is considered to be fixed, namely the combined demand of Tata's downstream production processes and direct customer sales. Finally, direct sales of slabs to customers are not taken into account, since these slabs do not contribute to hot charging. Appendix 1 also shows which product flows are important for this research.

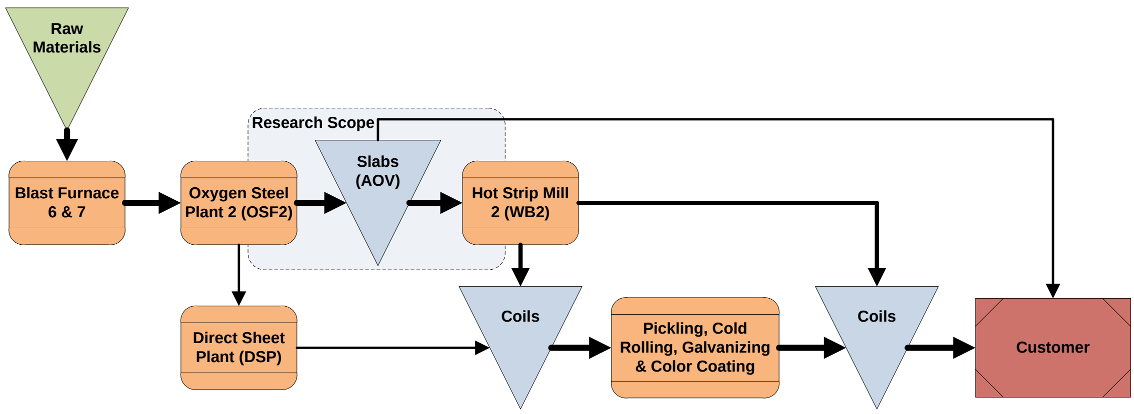


Figure 1.1 - Research scope

2 Scientific Background

This chapter describes the most important scientific literature concerning this research. We will elaborate on several fields in supply chain management (Section 2.1), give a short introduction in the world of steel making in Section 2.2, and end up with a description of a how a simulation study is built up in Section 2.3.

2.1 General Supply Chain Concepts

As explained in Chapter 1, this research is aimed at the interaction of two processes. Since these processes have such different logistical constraints, creation of stock in between is unavoidable. This section expounds on the various supply chain aspects that come with stock creation. First, we describe the extent of influence of the customer in the supply chain (i.e. the CODP), followed by the characteristics of stock keeping.

2.1.1 Customer Order Decoupling Point

The customer order decoupling point, or CODP, is the point in the value chain where the product is tied to a customer order. Upstream of this point, production is mainly forecast driven and make-to-stock (MTS). Downstream of this point, production is customer order driven and according to assemble-to-order (ATO) or make-to-order (MTO) principle (Olhager, 2010; Christou & Ponis, 2009). The CODP is sometimes also referred to as the order penetration point, or OPP (Olhager, 2003). In this research we will use the term CODP. Olhager (1990) also elaborates on the distinction in push- and pull manufacturing strategies. In the traditional push strategy, orders are released at the start of the production chain and then pushed through the production processes, whereas the pull strategy is a more serial ordering system in which buffer stocks at several stages can be found in order to maintain short delivery lead times (see Figure 2.1). Furthermore Christou and Ponis (2009) argue that *“a competitive and proactive organisation should make every possible effort to combine the advantages of both pull and push-based controls into an optimal interplay on the verges of both sides of the CODP”* (p.3064).

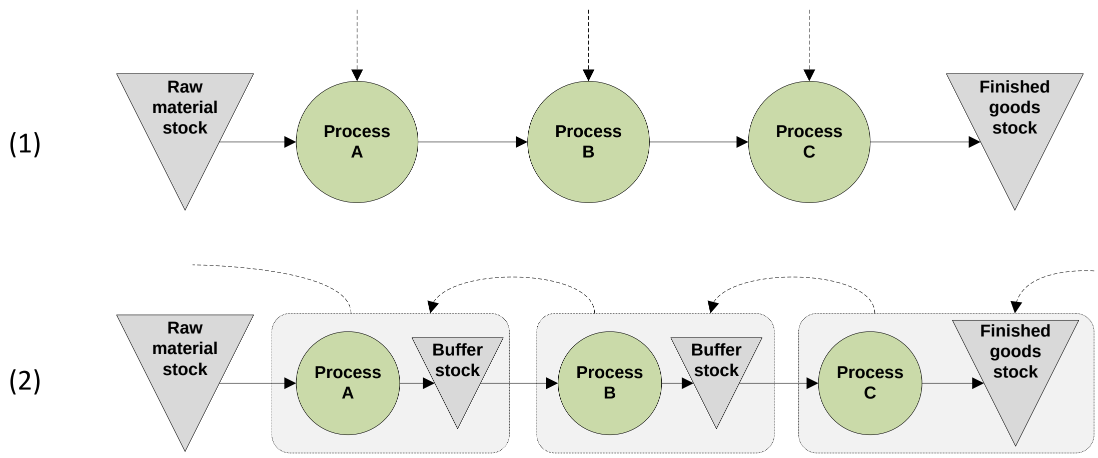


Figure 2.1 - Push (1) vs. Pull (2) strategy

2.1.2 Stock Keeping Unit

For managing stocks, as depicted in Figure 2.1, we cannot consider every product to be equal. Hence, often the term stock keeping unit (SKU) is used. Silver et al. (1998) define an SKU as *"an item of stock that is completely specified as to function, style, size, colour, and usually location"*. With location, the author means holding products at two different geographical locations (i.e. two equal products, that are held in two different warehouses are generally considered as two different SKUs).

Silver et al. (1998) further explain that in a multi-SKU inventory generally the term SKU-usage, expressed in terms of money, is rather used than SKU-demand. They show that typically around 20 percent of all SKUs account for 80 percent of annual dollar usage, which argues that not every SKU should be handled or controlled at the same way. Hence, they come up with ABC classification for SKUs. Figure 2.2 depicts such a classification in a Distribution by Value analysis (for calculation see Section 3.2 or Silver et al., 1998, p. 34). If all SKUs have more or less the same value, we can say that A-items are highly frequent. C-items, on the other hand, are low-frequent. Section 3.2 includes an ABC-analysis of the slabs at Tata Steels' slab yard.

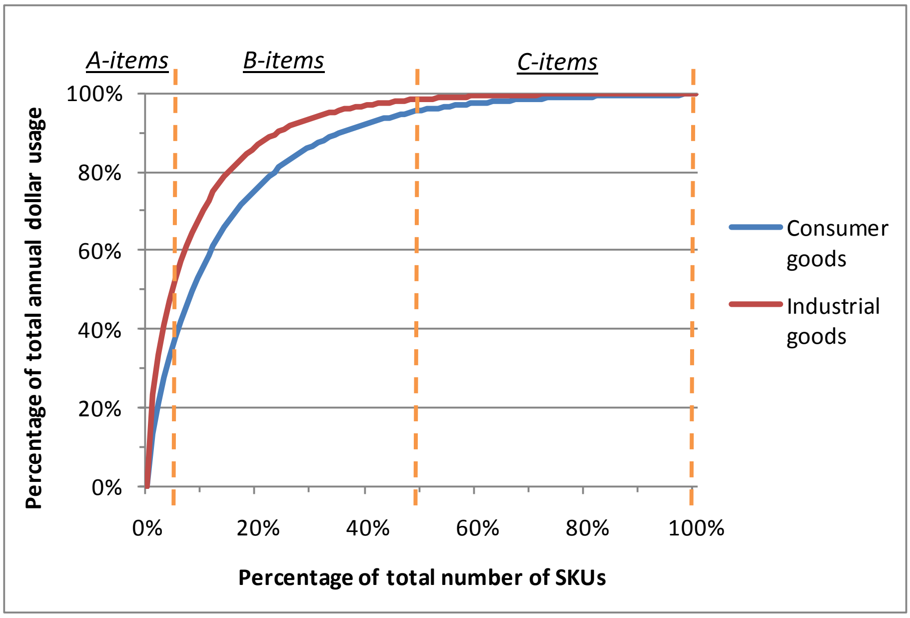


Figure 2.2 - DBV-graph: annual dollar usage of SKUs (adapted from Silver et al., 1998)

2.1.3 Stock Composition and Layout

Now we have explained the CODP and the various types of products, the question rises how the number of SKUs should be managed with respect to the CODP? Olhager (2010) explains this as follows: upstream the CODP we mostly see standard components (i.e. generic stock) in high volumes, whereas downstream the CODP products are customized (i.e. specific stock), in much lower volume and with unpredictable demand.

Furthermore, Silver et al. (1998) describe several sorts of stock. We describe the five most relevant for Tata's slab stock and compare them with reality in Section 3.3.

- **Cycle stock:** stock as result of producing in batches. These batches are, amongst others, the result of economies of scale or technological (volume related) restrictions on machinery
- **Safety stock:** stock kept on hand to allow for uncertainties in demand or supply in the near future
- **Pipeline stock:** also referred to as work-in-progress (WIP). It contains products on transport between two adjacent processes in a multi-echelon distribution or production system. WIP can be calculated by Little's Formula (1961): $WIP = Demand\ rate\ \times Throughput\ time$
- **Anticipation stock:** stock for known periods of increased demand or decreased supply
- **Obsolete or dead stock:** products for which no buyer can be found, or which have become outdated (e.g. fashion wear)

Gu et al. (2010) examined ways to deal with different SKUs, SKU classes and types of stock in a warehouse. They explain that warehouse optimization is getting a more important issue and rapid development of computer hardware and software gives more opportunities to realize this.

To control inventory, it is necessary to distinguish between several sorts of stock (Silver et al., 1998). Using terminology properly is important to overcome vagueness in decision making. From Silver et al. (1998) the following equation can be adapted (N.B. since the term 'backorders' is mainly used in spare part management, we rather use the term 'reserved stock'):

$$Inventory\ Position = (On\ hand) + (Pipeline) - (Reserved)$$

On hand stock is stock that is physically available in the warehouse. Hence, this can never be negative. The same holds for pipeline stock, but this stock is not physically available in the warehouse yet. Reserved stock consists of the products you 'promised' to buyers; it is still available in the warehouse, but you cannot use it for other customer orders. If the number of promised products exceeds the number of products available in the warehouse and the pipeline, the inventory position can become negative.

2.1.4 Capacity Utilization

In queueing theory (Little, 1961), the utilization u of a resource depends on the arrival rate λ and the average service rate μ of the resource; $u = \lambda/\mu$. Since storage capacity cannot really be seen as a resource (i.e. it has no service rate μ), in our research we rather use the term 'fill rate' as performance indicator for the fraction of a certain storage capacity that is occupied. In a lot of supply chain management literature fill rate is rather a service rate than a fill rate (e.g. Silver et al., 1998); it indicates the fraction of demand which can be delivered directly from the shelf.

2.2 Basics of Integrated Steel Manufacturing

This section describes the working of an integrated steel plant. First, we explain how liquid steel is transformed into slabs and then into sheets. Then, we expound on the extent the processes of casting and rolling can be coupled, resulting in the so-called 'hot charging'.

2.2.1 Integrated Steel Plant

Cowling and Rezig (2000) briefly describe how a typical integrated steel plant works: first liquid steel is created by melting together pig iron, scrap, and alloying materials. Then, the liquid steel is casted into a steel string with a so-called continuous slab caster. After casting, slabs are rolled into thin sheets at the hot strip mill. In most cases a slab yard is situated between the steel plant and the hot strip mill. This has two main reasons:

- The two processes have rather different scheduling characteristics and batch sizes
- At the hot strip mill coils are 'pulled' by the customer, whereas the constant supply of pig iron demands a push-type process at the steel plant

So, as explained by Olhager (2010) in Section 2.1, the CODP lies at the slab yard.

2.2.2 Hot Strip Mill

The hot strip mill produces steel coils by rolling the steel slabs to thin sheets. For this purpose, first the slabs are subjected to a high temperature (i.e. around 1,200°C) in a furnace. Then the slabs are subjected to high pressure, by pushing them through a series of rolls. Because of the contact with the slabs, the rolls wear out quickly and have to be changed regularly. Hence, production planning occurs in short shifts of a few hours. Such a shift is called a rolling schedule. In between two adjacent rolling schedules, several or all rolls have to be replaced. Because of the wear out of the rolls, a rolling schedule has a typical shape: first the rolls must me warmed up with easy material (soft and narrow slabs). Then difficult material (wide, hard slabs) can be rolled, gradually decreasing slab width, because of the marking on the rolls where the edges of the slab meets the roll. The result is what in the steel industry is referred to as the 'coffin shape' (see Figure 2.3). The content is subject to special rules regarding quality, width jumps between two slabs, end thickness, length of rolled sheets (i.e. 'wear kilometres') and customer order size (Cowling, 2003).

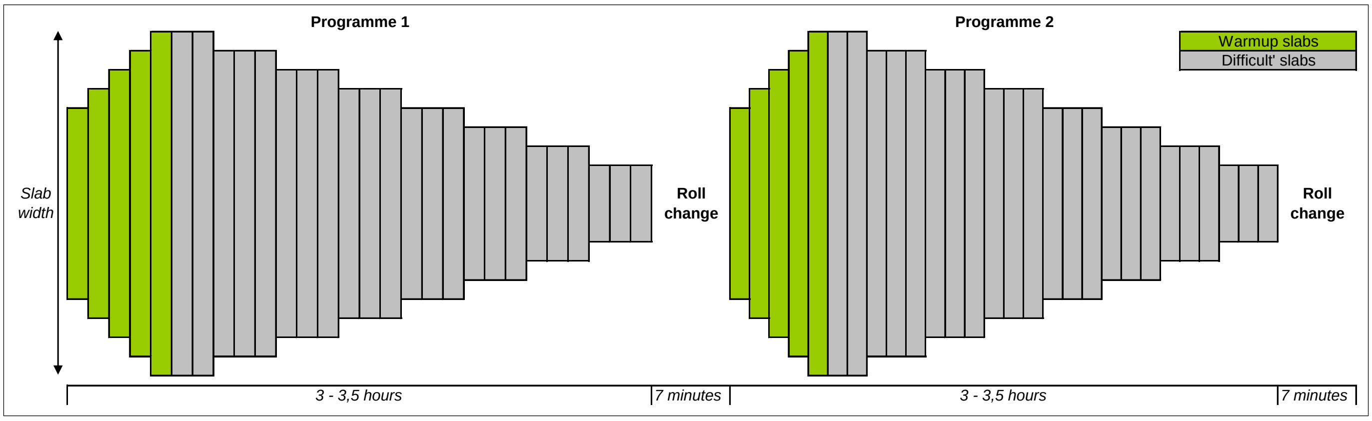


Figure 2.3 - Example of two adjacent rolling schedules (N.B. times are averages for Tata Steel IJmuiden)

2.2.3 Hot Charging

Driven by cost reduction, environmental issues and quality improvement, most steel plants are striving for so-called 'hot charging'. Hot charging means: charging a slab within a limited time period after casting. Since slabs cool down rapidly at the slab yard, charging a slab quickly after casting means energy preservation in the slabs (Cowling & Rezig, 2000). The most important benefits of hot charging are (Knoop & Van Nerom, 2003):

- Reduction of energy costs
- Reduction of greenhouse gas emission
- Reduction of stock (both stock levels and handling)
- Decrease of delivery time
- Decrease of furnace throughput time and, hence, increase in furnace throughput and minimization of furnace as bottleneck station

Knoop and Van Nerom (2003) say that a slab is charged hot, if it is charged within 12 hours after casting. Since the hot strip mill and the steel plant have such different process constraints, 100% hot charging can never be reached. The limited time period between casting and charging can, however, be extended by the use of heat preservation boxes (i.e. hot boxes). This is also known as 'indirect hot charging'. By adding this isolated storage capacity, the limited time period of 12 hours can be extended to 48 hours (Knoop & Van Nerom, 2003). Although the concept of hot boxes is described in the literature, there is no model or best practice of how to use them in daily operations.

2.3 Characteristics of a Simulation Study

This section describes the general principles of a simulation study according to Law (2006). In our research, we use discrete event simulation to model the use of hot boxes at Tata Steel IJmuiden. We first explain what discrete event simulation is. Then, we expound on the design of a simulation study in terms of number of runs, run length and warm-up period.

2.3.1 Discrete Event Simulation

Simulation is one of the most powerful analysis tools available for the design and operation of complex processes or systems. Shannon (1975) defines 'simulation' as follows: *"Simulation is the process of designing a model of a real system and conducting experiments with this model for the purpose either of understanding the behavior of the system or of evaluating various strategies for the operation of the system".* In a simulation study a 'system' is the collective of entities, which act and interact to reach a certain desired output. The 'state' of a system can be defined as a set of variables describing a system at a certain moment in time. For example, a post office with three counter clerks and x customers in queue can be seen as a system. Since the state of this system only changes when the number of customers or the number of counter clerks changes, this system is called 'discrete'. We speak of a continuous system if (some) variables change constantly (e.g. velocity of a vehicle). Simulation of a discrete system (i.e. discrete event simulation) allows us to step from event to event.

There are two types of variables in a simulation model. In the first place, variables that you want to change, to test the systems' performance. These variables are the so-called experimental factors. In the second place, there are variables that do change, but always within a certain range, disregarding the value of the experimental factors. For example, in a painting shop we want to determine the optimal number of painting machines to reach a 95% on-time-delivery, then our experimental factor is to change the number of painting machines, but the processing time on each machine can still vary between, say, 4 and 6 minutes.

Since generation of values for variables is a stochastic process (i.e. they are determined by a certain probability distribution), the output of two simulation runs with the same configuration may vary. Hence, to smoothen out deviations, it is necessary that runs have a certain length and we perform multiple runs of each experiment.

2.3.2 Number of Replications, Run Length and Warm-up Period

As explained, to smoothen out deviation, we have to perform multiple runs (i.e., replications) in order to end up with reliable measurements. This means that we keep all variables the same, but draw different numbers with the same probability distribution. Furthermore, it is important to determine when the system reaches a steady state. This means this system is not dependent on initial conditions anymore. The state before the steady state is called the transient state or warm-up period. Rule of thumb is that the run length is at least five times the warm-up period, but the longer the run length, the better. Figure 2.4 depicts an example of a post office with 15 service desks. When the post office opens, the first customers will not experience any waiting time, since none of the service desks is occupied. After a while this system will reach a steady state, because there is a balance between incoming customers and served customers. For each run of each experiment we have to delete the transient state data, since we are not interested in this data (i.e., this data does not give a good representation of reality).

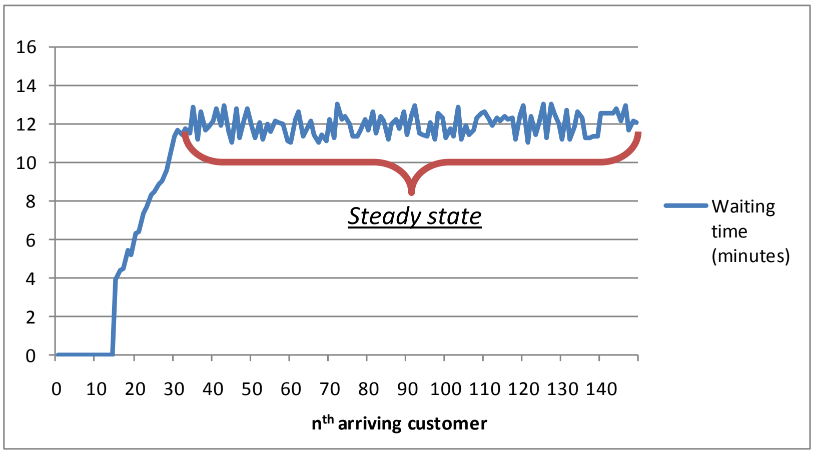


Figure 2.4 - Steady state of waiting time in a post office system

Now suppose we have a simulation model with:

- Two experimental variables: $x = 2$
- Three levels per variable: $y = 3$
- Run length: $m = 10$ weeks
- Warm-up period: $h = 1$ week, and
- Number of replications: $n = 5$

Since we have $x \times y$ different setups, we have $2 \times 3 = 6$ experiments. Running each experiment five times ($n = 5$) means we make $6 \times 5 = 30$ simulation runs. For each simulation run we remove data from the warm-up period (see Figure 2.5).

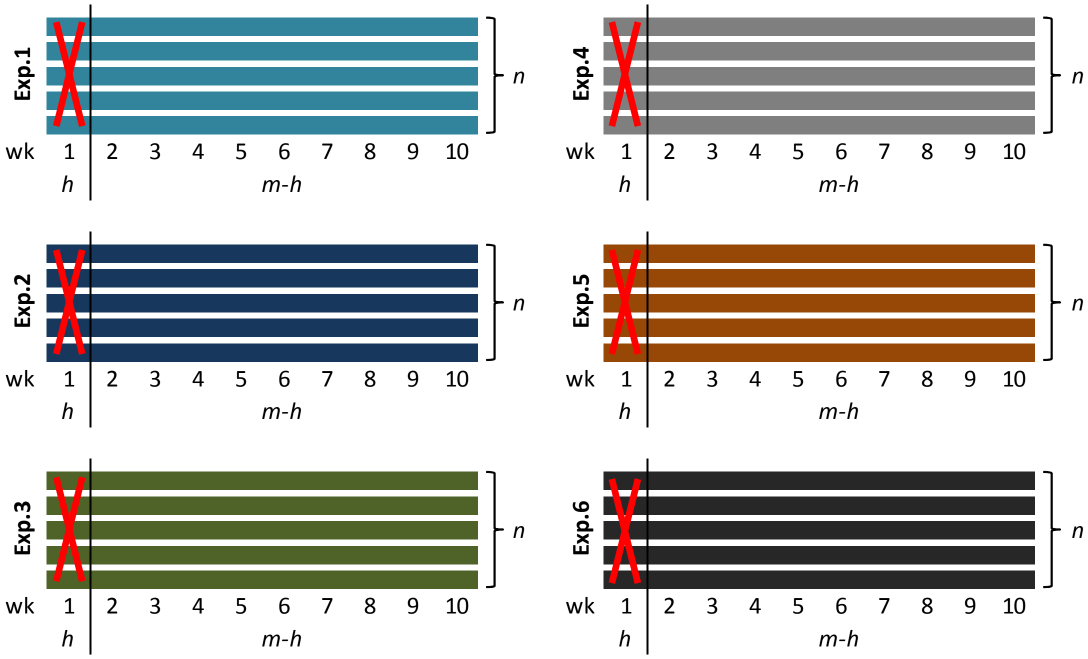


Figure 2.5 - Example of an experimental design

After finishing all simulation runs, the data is analyzed to see which experiments performs best at the predetermined key performance indicators. The optimal solution can thereupon be tested on its robustness by performing a sensitivity analysis.

2.4 Conclusions

In the previous sections, we have explained the most relevant topics regarding the research. With this information, we can answer the first research question:

How can we position the research problem in the literature?

The integrated steel plant principle, as explained in Section 2.2, applies to Tata Steel IJmuiden. Furthermore, from the fact that the CODP lies at the slab yard and the process at the integrated steel plant have such different restrictions, we can conclude that stock creation (i.e. having a slab yard) is unavoidable. Tata Steel wants to improve the hot charging percentage at the hot strip mill by using hot boxes, as described by Knoop and Van Nerom (2003). However, detailed implementation and operational concepts are not described in the literature, so we have to develop a concept ourselves. For this, we make use of discrete event simulation, as described in Section 2.3.

3 Analysis of Current Situation

This chapter describes the current way of working of casting slabs and rolling them to coiled sheets. We start with explaining the production processes in chronological order. So, in Section 3.1 we explain how slabs are produced out of iron ore. Section 3.2 elaborates on the different kind of slabs that are created, followed by the way they are stored (Section 3.3). The next step in the process is rolling the slabs in the hot strip mill. This is explained in Section 3.4. In Section 3.5 we explain how both processes are planned and scheduled. Finally, the throughput time between casting and rolling is important in this research, since it determines the volume that is charged hot. Hence, this is treated separately in Section 3.6. The chapter closes with a set of conclusions in Section 3.7.

3.1 From Iron Ore to Slab

This section describes the first production step in an integrated steel plant: the casting of steel slabs. We first discuss the process in general. Then, we deepen the analysis on batch size and the different qualities that are casted at Tata Steel IJmuiden.

3.1.1 Process Description

The production site in IJmuiden is set up as an integrated steel plant (Section 2.2): from the iron ore fields at the south of the production site, iron ore is transported to the blast furnaces (HO6 and HO7). Here, the iron is extracted from the ore and at a temperature of around 1,500˚C poured into so called torpedo wagons. These wagons transport the pig iron to the oxygen steel plant (OSF2). At OSF2, the pig iron is first desulphurized, then it is poured in a converter, where oxygen is blown into the steel to remove carbon. Due to this process, temperature rises. To control the temperature, scrap is added.

Figure 3.1 - Pig iron is poured into a converter

Figure 3.2 depicts the steel making process at OSF2. In the converter, this mix is heated with pure oxygen to remove carbon. The result of this process is what we know as liquid steel. Then, this liquid steel is poured into a ladle of around 350 ton. Each ladle gets a secondary ladle treatment at one of the finishing stations (stirring station, vacuum degasser, or the ladle furnace) to create different qualities of steel. When the treatment is finished, the ladles are transported to either the Direct Sheet Plant (DSP) or the Continuous Slab Casters (CGMs). Tata Steel has two slab casters: CGM21 and CGM22. Annually, around 20% of the volume is sent to the DSP and 80% to the CGMs. At the DSP, liquid steel is casted and rolled immediately. Since this process is not in the scope of this research, we do not describe the details of this process here.

When a ladle arrives at one of the CGMs, it is poured into a tundish. Underneath the tundish, two strings of solid steel are formed. The strings have a standard thickness of 225mm and can vary in width between 800 and 2,120mm. From the strings, slabs are cut with a length between 5,500 and 12,000mm. In this way slabs with varying qualities and dimensions can be created.

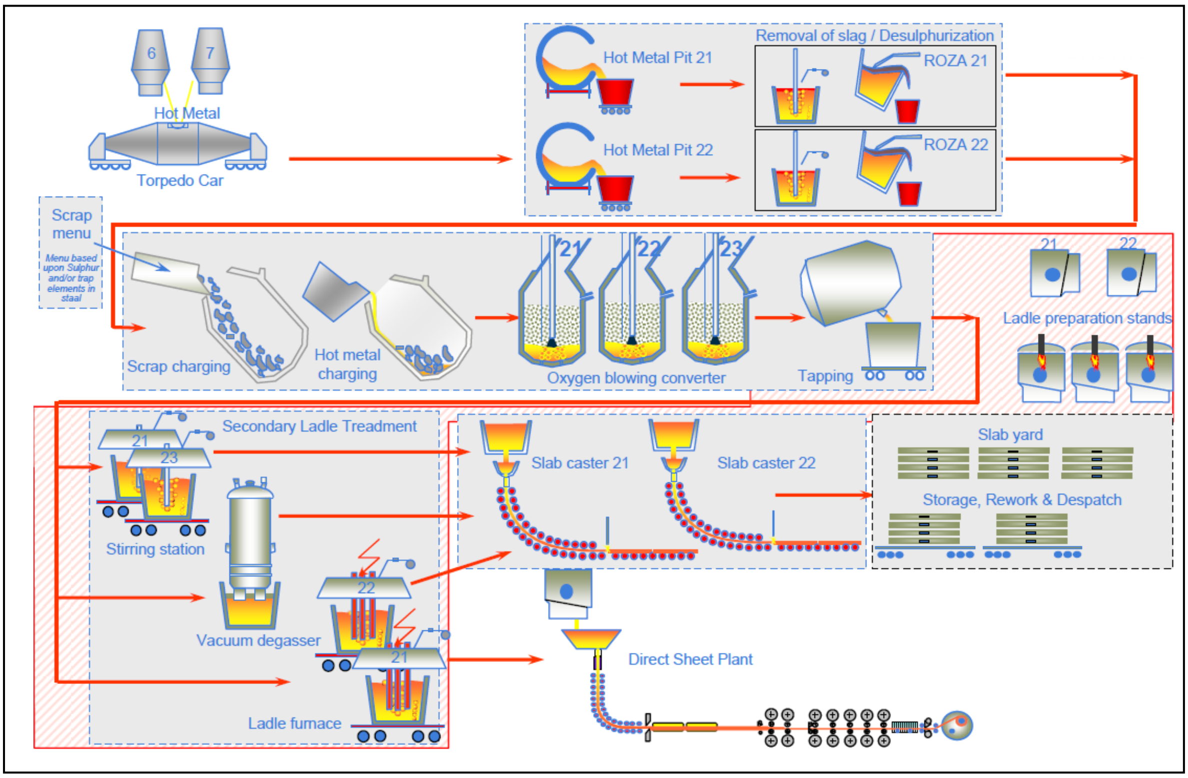


Figure 3.2 - Steel making process at OSF2

Ladles with the same quality can be poured immediately after each other. A batch is formed by sequencing a certain number of ladles and is called a 'series'. Depending on quality, different series can be sequenced, without changing the tundish. Although this results in a transitional area in the string, and hence an undesired quality of a few slabs, this is much cheaper than changing the tundish. If two series cannot be sequenced, because of quality reasons or tundish wear out, a new series has to be started. This causes a head- and tail slab on the string. Furthermore, such a casting-stop, either planned or unplanned, leads to a production loss of one hour.

After the slab is cut from the string, it is deburred and then stored at the SKV for a short period. The SKV is a small buffer point, which is used to form batches. This is necessary to load the trains with enough slabs, before transporting it to the AOV.

3.1.2 Batch Size and Volume

As said, a ladle contains around 350 ton of liquid steel. This is, hence, the minimal amount of one quality to be casted in the CGMs. In practice, however, a series consists of much more ladles, because of economies of scale and a higher failure risk when starting a new string. Depending on quality and order size, most series have a length of 10 to 20 ladles. Given the fact that a slab is on average 23 ton, this means a short series of 10 ladles consists on average of $(10 * 350)/23 \approx 150$ slabs of the same quality, but with varying width and length. Hence, a long series of 20 ladles consists of around 300 slabs with the same quality, but with varying width and length. Since slab weight varies between 10 and 32 ton, depending on its dimensions, the number of slabs per series can vary.

On average, 136 kTon is produced at OSF2 per week. From this volume, around 26 kTon is sent to the DSP and around 110 kTon is casted into slabs. With an average slab weight of 23 ton, this means on average 4,780 slabs per week.

3.1.3 Order Qualities, Drop Qualities, and B-Qualities

Steel-making is a complex and stochastic process. This means that not always the desired quality is reached. If this is the case, one speaks of Drop- or B-qualities. A drop-quality has still good mechanical properties. B-qualities, on the other hand, have significantly lower mechanical properties. Though a drop-quality is not desired, it is a known phenomenon and therefore these qualities can still be used for certain customer orders. A B-quality on the other hand is an inconvenient drop-quality that cannot be used for customer orders (immediately). In the steelmaking process on average 90% is of ordered quality, 8.5% is drop-quality and 1.5% is B-quality (see Figure 3.3).

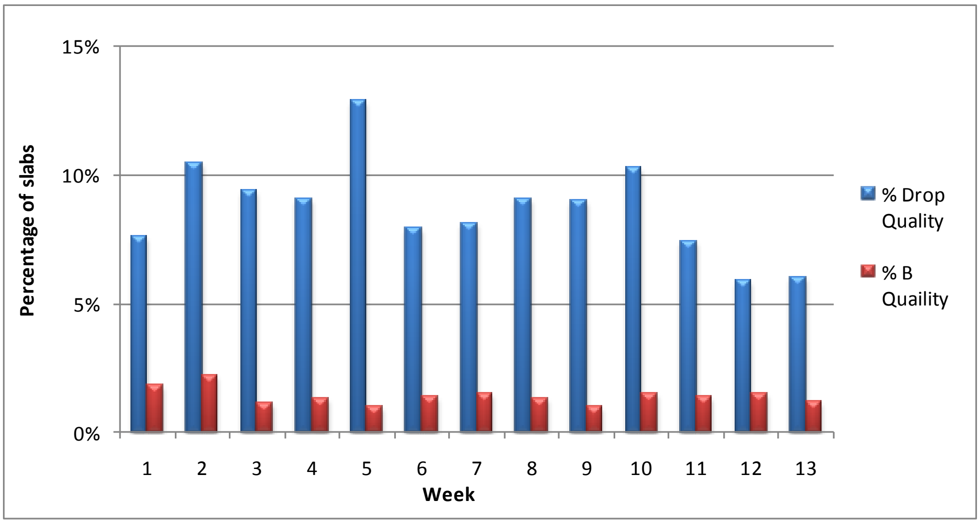


Figure 3.3 - Percentage Drop- and B- qualities and percentage A-slabs

3.2 Slab Specifications

The result of the casting process is a large variety of slabs. This section expounds on the different types of slabs. First, we discuss whether a slab is fit for purpose or needs rework (Section 3.2.1). Then, we explain how a large variety of qualities and dimensions leads to an enormous amount of SKUs (i.e. unique slab specifications, Section 3.2.2). Section 3.2.3 explains how destinations labels are used to deal with the various types of stock. Finally, Section 3.2.4 ends up with the temperature behavior of a slab.

3.2.1 A-slabs and O-slabs

During casting, CGM21 and CGM22 are constantly switching qualities and widths. As explained in Section 3.1, some qualities can be sequenced in casting, others require the start of a new string. Because of these changes, slabs of transitional quality, head- and tail slabs are created. Furthermore, due to width adjustments during casting, tapered slabs are created. These deviant slabs cannot be used immediately and need rework. They are called 'A-slabs', whereas good slabs are labeled 'O-slabs' and are fit for purpose. Once the adjustments or inspection have been done, the A-slab has become O-slab. The ratio in slabs is around 85% O-slabs and 15% A-slabs (see Figure 3.3). The throughput time of A-slabs is somewhere between 3 and 14 days. Since slabs have cooled down after 24 hours – this is explained in Section 3.2.4 – A-slabs are currently of insignificant matter for hot charging.

3.2.2 Qualities and Dimensions

Because of the large amount of different qualities and wide range of different dimensions, a lot of different stock keeping units (SKUs) can be found. However, some of them are quite standard and fast-moving; others have an unusual dimension or quality, causing them to be stored for a long period. Figure 3.4 shows the 27 most frequent qualities, covering 75% of total volume. The other 25% is covered by the remaining 123 qualities.

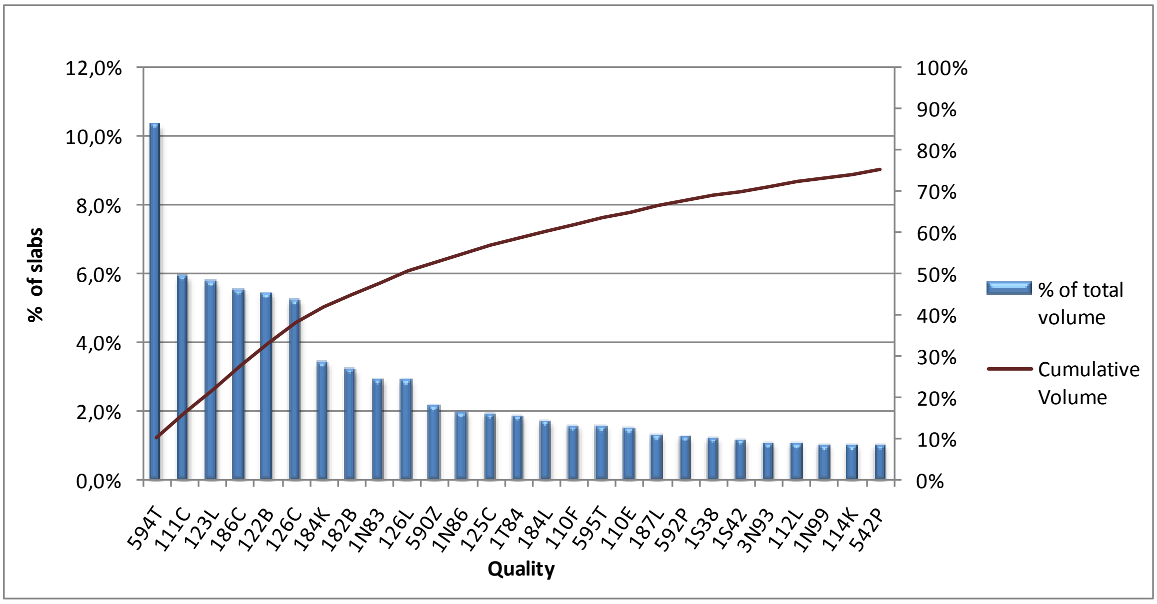


Figure 3.4 - 75% of volume was covered by 27 qualities (period: 19/12/2010 - 19/06/2011)

We see that the first 6 qualities cover almost 40% of total volume. This does, however, not mean that these qualities will be the most frequent for the next period: discussions with the planning Supply Chain department revealed that some qualities are only used for a short period. Some other qualities will be replaced by new qualities, with better mechanical properties, to supply niche markets.

A similar frequency analysis can be made up for the width/length combinations of the slabs (see Figure 3.5). The larger the circles in the figure, the more frequent the width/length combination. We see that a length of 8,000mm is the most frequently used slab length. The same holds for a width of 1,300mm. However, the most frequent combination (width * length) is 1,300*10,800mm. The large dots indicate the degree of standardization of slab dimensions. Table 3.1 shows the approximately 50 standard width/length combinations Tata Steel is striving for. However, due to width adjustments during casting and other irregularities in the process, around 10% of the slabs does not meet these standard dimensions (e.g. during casting the width of the string was decreased, resulting in a tapered slab. To make the slab useful again, a piece had to be cut of).

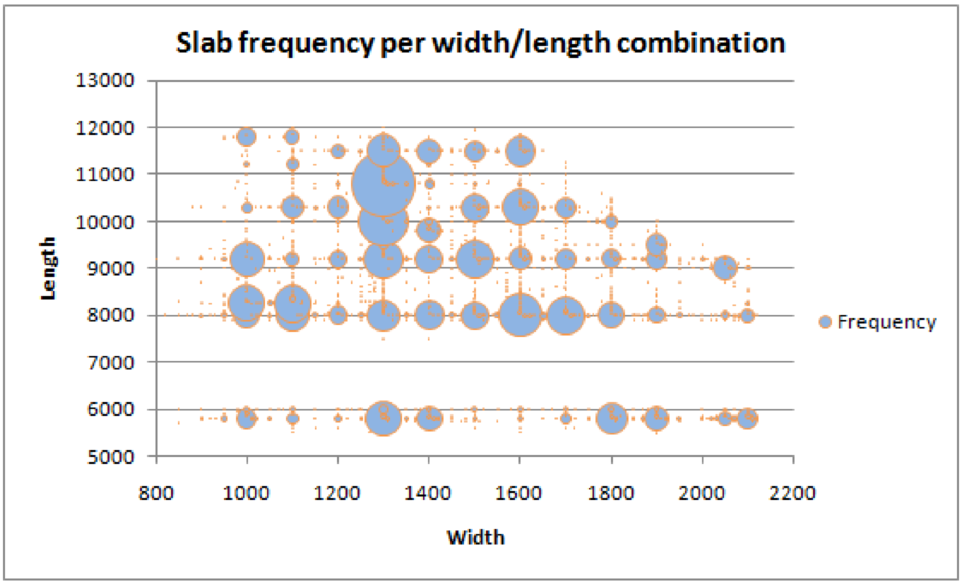


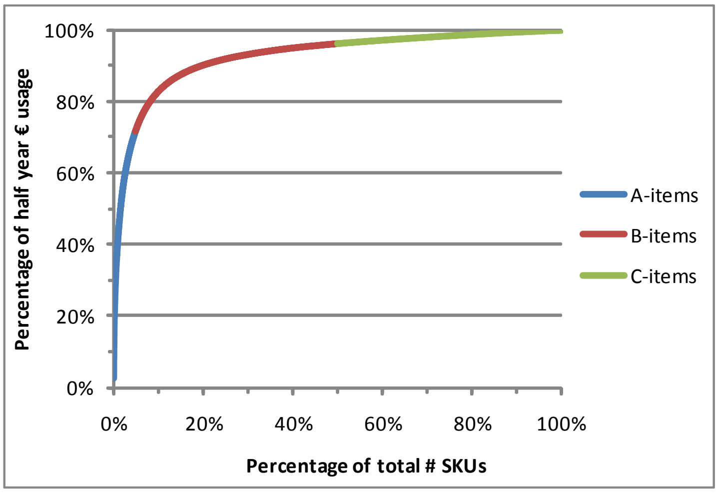
Figure 3.5 - Occurrence of all width/length combinations (period: 19/12/2010 - 19/06/2011)

width\length	5.800	8.000	9.000	9.200	9.500	9.800	10.000	10.300	10.800	11.200	11.500	11.800
1.000	10,0	13,8		15,9				17,8		19,4		20,4
1.100	11,0	15,2		17,5				19,6		21,3		22,5
1.200	12,0	16,6		19,1				21,4			23,9	
1.300	13,1	18,0		20,7			22,5		24,3		25,9	
1.400	14,1	19,4		22,3		23,7					27,9	
1.500	15,1	20,8		23,9				26,7			29,9	
1.600	16,1	22,2		25,5				28,5			31,9	
1.700	17,1	23,5		27,1				30,3				
1.800	18,1	24,9		28,7			31,2					
1.900	19,1	26,3		30,3	31,2							
2.000	20,1	27,7		31,8								
2.050	20,6	28,4	31,9									
2.100	21,1	29,1										

Slabs resulting in too heavy coil weight

Table 3.1 - Width/length combinations of 90% of the slabs (period: 19/12/2010 - 19/06/2011)
N.B.1: green fields indicate if a combination is standard. The number resembles the weight of the combination
N.B.2: slabs heavier than 32 tons result in too heavy coils and cannot be handled downstream the supply chain

Combining slab quality and dimension leads to a unique slab specification (i.e. an SKU, see Section 2.1). So, each SKU has a unique combination of quality, width and length. Figure 3.6 depicts an ABC-analysis (see Section 2.1) made for all slabs of half a year. For this analysis, we multiplied the number of slabs per SKU with its weight and the value per ton, for which we took €500 for this instance. What strikes the most, is that 66.3% of gross earnings of this quarter comes out of 307 different SKUs (i.e. only 5% of total number of SKUs)



Item type	Number (
	%
A-items	5,0%
B-items	45,0%
C-items	50,0%
TOTAL	100,0%

Figure 3.6 - ABC-analysis of slabs (half year)

Some special attention has to be paid to certain qualities that are not allowed to cool down entirely. These high alloyed slabs have a special chemical structure, which causes internal strain when cooling down. To reduce the risk of breaking, these special qualities receive a maximum allowed throughput time between casting and charging at WB2. Therefore, they are called 'obliged hot charging' slabs. Examples of obliged hot charging qualities and their maximum allowed throughput times are included in Table 3.2.

Qualities
3CAK, 3NAS, 3Q91,3QAL, 3QAR
1FAU, 1FAW, 2F62, 2FAA, 2FAB, 3F65, 3FAY, 3N94
2NAT, 3N93
3F62

Table 3.2 - Special qualities (break-slabs) with time bounds (4th quarter, 2010)

3.2.3 Slab Destination Labels

If a slab is an O-slab, it is of good quality and of allowed dimensions and can hence be coupled to a WB2-order. However, in reality not all O-slabs are assigned to an order immediately (e.g. there was a demand for 4,000 ton of a certain quality. Due to the ladle size of 350 ton, a series of five ladles ($12 \times 350 = 4{,}200\,ton$) had to be casted. This means 200 ton is not order-coupled at that moment). To deal with the various types of stock, Tata Steel uses destination labels to indicate the type of stock and allocate the slabs:

- **WB2**: Order coupled (80% delivery within a week; 20% delivery after more than a week)
- **WB2-A**: Slab with nonstandard dimension, but could be coupled to an order
- **WBW**: Order coupled and obliged hot charging slabs, due to quality reasons (quick charging at furnaces, see Table 3.2)
- **VRD-IC**: Obsolete stock until customer is found (often B qualities or unusual dimensions)
- **VRD-G:** Tactical stock (buffer stock: in case of unplanned interruption of slab supply, the WB2 can stay operational)
- **VRD-S**: Strategic stock (in times of long planned maintenance upstream in the supply chain)
- **THIRD**: Third party stock

WB2, WB2-A, WBW, and THIRD can be seen as cycle stock. VRD-IC is Tata's obsolete or dead stock. VRD-G is Tata's safety stock and VRD-S is meant as anticipation stock (see Section 2.1).

3.2.4 Temperature of a Slab

The temperature development after casting is important for this research. There for used the research made by Burghardt and Hoogland (2011) to describe the cooling down phenomenon. When a slab is cut of the CGM string, it has a temperature of around 900˚C. Depending on throughput time between SKV and AOV, the slab arrives with a temperature of between 500˚C and 600˚C at the AOV. During storage in the AOV, the slab will cool down further. Depending on slab width and height of the stack it is stored in, the cooling down period varies significantly. The formula in (1) calculates the theoretical slab temperature T_t after t hours.

(1) $$T_t =$$

Where:

T_t = Slab temperature at time t

T_0 = Start temperature of a slab

T_{Amb} = Ambient temperature

W = Width of a slab in meters

n = number of slabs in a stack

Th = Thickness of a slab in meters (standard 0,225m)

t = number of hours after slab birth

α = constant = -0.053

β = constant = 0.848

For a slab with a width of 1300mm (most occurring), this results in the temperature fall displayed in Figure 3.7. One can see the enormous difference of cooling down in a stack of eight slabs and as a single slab. The temperature in a stack is the temperature in the middle of a stack. This means the upper slab will most likely be colder than the centre of the stack. Figure 3.7 also depicts the average charging temperature after t hours, as measured in reality (half year of data). However, deviation from this average is very high, and sometimes even exceeds the theoretical graphs as displayed in the figure. Appendix 2 shows some more detailed information on the process of slabs cooling down.

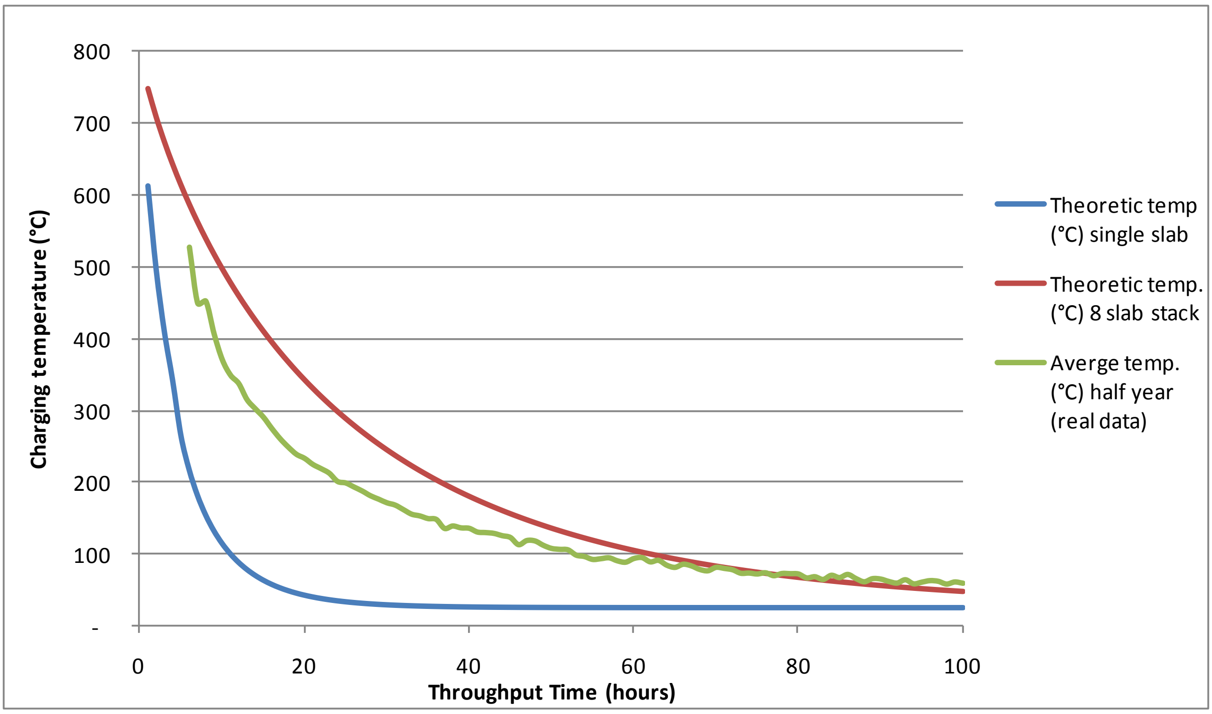


Figure 3.7 - Cooling down of slabs (source: Burghardt & Hoogland, 2011)

Burghardt and Hoogland (2011) also modeled the expected temperature distribution. They use the same formula as in (1), but with $\alpha = XXX$ or periods when the hot box is open and $\alpha = XXX$ for periods when the hot box is closed. Figure 3.8 depicts this expected temperature distribution for the hot boxes. We see that slabs are expected to cool down very slowly; approximately 15°C decrease per 24 hours. Unfortunately, Burghardt and Hoogland were not able to benchmark this with other steel producers.

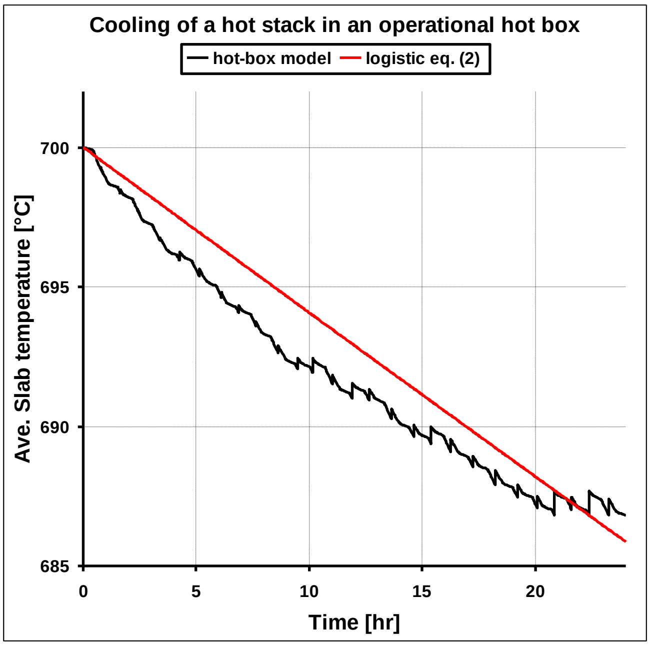


Figure 3.8 - Expected temperature distribution in hot box (source: Burghardt and Hoogland, 2011)

Since it is not clear whether a slab is stored singly or in a small or large stack during a period [0…T], it is for a random number t in period [0…T] hard to say what the slab temperature is at that time. On the other hand, the higher the slab temperature, when charging at the furnaces of the WB2, the less gas is needed in the furnaces to reheat the slab to 1,200˚C. To measure the performance on charging hot slabs (i.e. hot charging) Tata Steel uses as a KPI that every slab charged within 24 hours after casting is considered as 'hot charging'. This means that the KPI for hot charging is based on throughput time instead of slab temperature as one might expect.

The temperature distribution over the supply chain is displayed in Table 3.3. The large range of temperature for the AOV and the Ready Section (this will be explained in Section 3.3) is the result of high throughput time variation and the way a slab was stored.

	Slab casters	SKV	AOV	RS	End Furnace
Average temperature (˚C)	**1200**	**900**	**20 - 800**	**20 - 400**	**1250**

Table 3.3 - Temperature distribution over the supply chain (OSF2 to WB2)

3.3 Storage of a Slab

From the SKV, the slabs are transported to the AOV by train. Depending on destination, slab type and type of stock, the operator at the AOV decides in which area of the AOV the slab will be stored. This section explains where (Section 3.3.1) and how much (Section 3.3.2) slabs can be stored. In Section 3.3.3, we analyze how stock is composed and allocated within the storage areas.

3.3.1 Storage Areas

The AOV has two different types of storage; halls and outer storage fields. Both are divided into sections and in each section a number of stacks can be stored. The stacks have a maximum height of 16 slabs, due to equipment limits. Slabs are transported by train to the storage areas. For slab transportation within the halls cranes are used; each hall has one or two overhead gantry cranes. Exception is the PG hall, where slabs are transported by shovels. The PE and PH hall also have a half gantry crane. For transport from one hall to another two crosswise cranes are used. Contrary to the gantry cranes, which move over overhead transport rails, the crosswise crane is moving over solid ground. The outer storage fields are also divided into sections, where a number of stacks can be stored. Here, shovels are deployed to move slabs.

3.3.2 Storage Capacity

Although the outer storage areas have a much higher capacity, most stock can be found in the halls, since the majority of the slabs have WB2 as destination. For this research we will only consider the O-slabs in the PE and PF hall. Reason is that the slabs at the outer storage areas and PH and PG hall are cold and hence not interesting for direct or indirect hot charging.

Figure 3.9 gives a detailed overview of the PE and PF hall. The slabs arrive at one of the rail tracks, whereupon the overhead gantry cranes will pick the slabs and store them in an available section. The different sections are indicated by numbers. These numbers indicate the distance in meters from the

Western (left in the figure) part of the hall. One can also see the amount of stacks per section. For example, in section 198 in the PE hall 12 stacks can be stored. The maximum number of slabs per stack is 16. Figure 3.11 shows how two slabs are picked from a stack and brought to the ready section.

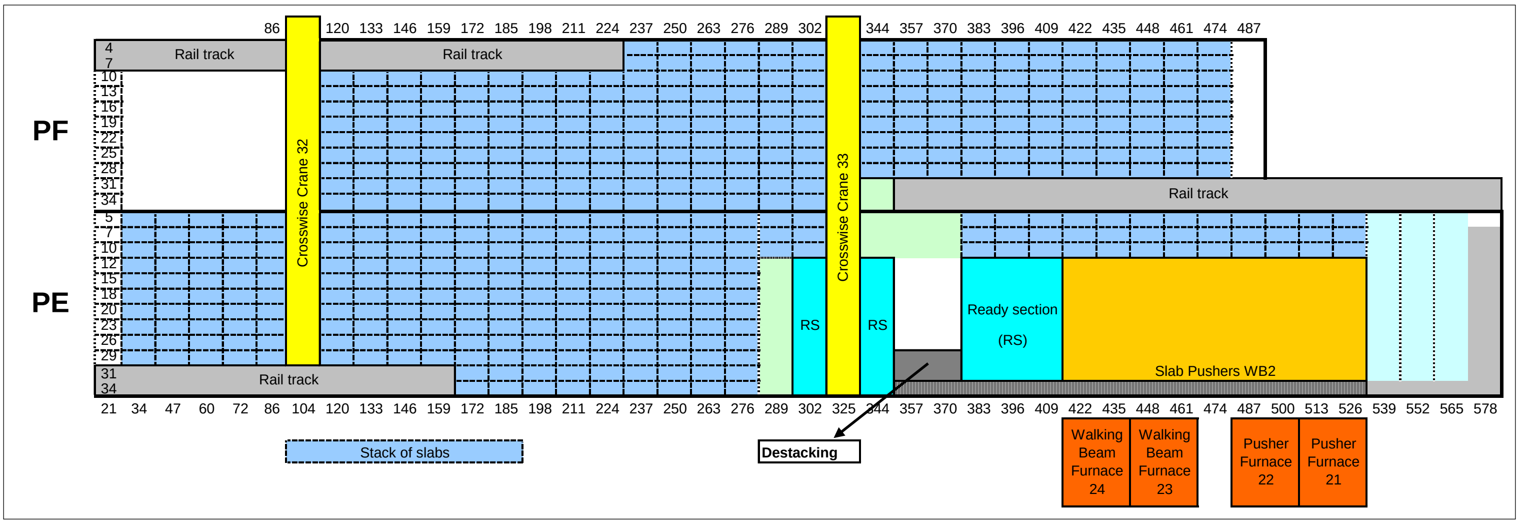


Figure 3.9 - Detailed overview of PE and PF hall

Furthermore one can see the Ready Section (RS) and the rest of the WB2-section in Figure 3.9. These areas will be explained further in Section 3.4. The workable capacity of the PE and PF hall together is 90 kTon (i.e. a guideline for maximum stock), but the theoretical capacity is much higher.

Figure 3.10 - Overview of PF hall

Figure 3.11 - Overhead gantry crane picks 2 slabs from a stack and brings them to the RS

3.3.3 Stock Composition

As explained in Section 3.2, we are dealing with a large number of SKUs. Some SKUs are casted in large quantities of slabs, others have a rather small volume: near, or equal to one slab. Storing this wide range of SKUs can be seen as a sort of paradox: from a heat-preservation point of view, slabs must be stored in as large as possible stacks. In this way slabs will cool down slowly. From a logistical point of view, on the other hand, slabs must be stored in uniform stacks of one type of SKU to increase slab availability and decrease the number of handlings (e.g. there are a lot of handlings if a

slab must be dug out of a 16 slab-high stack). Since the first would only lead to a workable situation with a low number of SKUs and for the latter there is not enough hall capacity, the real situation is somewhere in the middle; high-volume SKUs are placed in uniform stacks of 16 slabs high (if possible), low-volume SKUs are allowed to be mixed in a stack.
To keep the stock clean, the AOV's operating system (POSS) uses several rules. The most important rules for stock keeping are:

- **Low frequency:** if the number of slabs of one SKU in one hall is at most five, it is considered as low frequent
- **High frequency:** if the number of slabs of one SKU in one hall is larger than five, it is considered as high frequent
- **Minimal travelling distance:** if a slab must be delved out, POSS will only look in the closest 25% of the hall to replace slabs. This is because delving is often the result of delivering slabs to the WB2, which has high priority, since an empty ready section means unnecessary downtime for the WB2.

Actions of POSS are static. For example, delivery of slabs to the ready section always has the highest priority. If the stock level in the ready section reaches a certain level, then the unloading of trains has the highest priority and so on. Within this prioritizing, the POSS system deals with different prioritizing concerning slab frequency. For example, if a train with high frequent slabs is unloaded, POSS will start a new stack much earlier, than if the train was loaded with low frequent slabs. The same rules apply for delving or replacing slabs.

After analysis of the stock composition, it turned out that these rules and way of prioritizing not always lead to a good stock composition. Table 3.4 depicts six randomly chosen, high frequent SKUs that were present in stock in the PE and PF hall at a certain moment in time. We can see that, for example, SKU '594T 1700 8000' has 70 slabs on stock. Rounding this up to a number of stacks, we expect $\left\lceil \frac{70}{16} \right\rceil = 5$ stacks. However, in reality, these 70 slabs were spread over eight different stacks. This means that either these slabs are mixed with other SKUs or the maximum stack height is not entirely used.

SKU	# slabs in PE/PF hall	Exp # stacks	True # stacks
122B 1300 10800	147	10	13
594T 1700 8000	70	5	8
122B 1300 9200	56	4	7
184K 1300 10000	46	3	6
182B 1300 10000	18	2	9
187L 1300 10800	15	1	5

Table 3.4 - Example of stock composition of 6 SKUs

Discussion with the programmers of POSS revealed that there are several causes for this problem:

- When a slab is selected for a rolling schedule (see Section 3.4), the stack where it is stored, is blocked for placing other slabs

- If a slab is coupled to a customer order, it receives another order number than non-coupled slabs that have a stock order number, hence it is recognized as a different SKU by POSS
- If two slabs of the same SKU have a different destination code, POSS recognizes them as two different SKUs
- When delving in a stack, POSS only looks for an optimal stack position in the closest 25% of the hall, even if the ready section is full (i.e. there is enough supply for the WB2), whereas a much better stack position might be available in the rest of the hall.
- There is no optimization between the PE and PF hall

For this reasons it can occur that a certain slab type, that we expect to be one SKU, is seen as different SKUs by POSS. Hence, it can occur that a high number of slabs with the same quality and dimensions is still low frequent in the system. This results in an inefficient use of storage capacity and a delving factor (see Section 3.4), that is higher than necessary.

Lokatie	Plakident	Lengte	Breedt	Dikte	Gew.	Ref	Instruct	Bestem	Kwal	Ordernr	Blk	WW	F	B
PF -172- 11-M-13	S7660 107	8006	1300	225	18311	(4282-3)	GEEN	WB2	186C	43695A 0200	N	1131	7	Wl
PF -172- 11-M-12	S7717 402	10799	1300	225	24621		GEEN	WB2	110F	22635CC0100	N	1134	7	Wh
PF -172- 11-M-11	S7655 206	7988	1300	225	18389		GEEN	WB2	110E	22635CC0100	N	1134	7	Wh
PF -172- 11-M-10	S7638 203	10897	1310	225	25058		GEEN	WB2-A	122B	69947BL0100	N	1133	7	Wl
PF -172- 11-M- 9	S7669 105	9997	1300	225	22934	(4282-111)	GEEN	WB2	186C	45115A 0100	N	1131	7	Wl
PF -172- 11-M- 8	S7668 104	10004	1300	225	22974	(4282-112)	GEEN	WB2	186C	45115A 0100	N	1131	7	Wl
PF -172- 11-M- 7	S7668 103	10000	1300	225	22934		GEEN	WB2	186C	53284A 0100	N	1131	7	Wl
PF -172- 11-M- 6	S7668 101	9988	1300	225	22914		GEEN	WB2	186C	53284A 0100	N	1131	7	Wl
PF -172- 11-M- 5	S7668 102	10003	1300	225	22954		GEEN	WB2	186C	53284A 0100	N	1131	7	Wl
PF -172- 11-M- 4	S7669 101	9993	1300	225	22934	(4282-66)	GEEN	WB2	186C	45107A 0100	N	1131	7	Wl
PF -172- 11-M- 3	S7668 107	9995	1300	225	22914	(4282-75)	GEEN	WB2	186C	45146B 0100	N	1131	7	Wl
PF -172- 11-M- 2	S7668 106	10004	1300	225	22954	(4282-76)	GEEN	WB2	186C	45146B 0100	N	1131	7	Wl
PF -172- 11-M- 1	S7668 105	9986	1300	225	22954	(4282-68)	GEEN	WB2	186C	45104A 0100	N	1131	7	Wl

Figure 3.12 - Example of a wrongly composed stack

Figure 3.12 shows an example of the problems in POSS. We see a print screen of POSS showing a 13 slab high stack. The lowest nine slabs are of the same quality (186C) and dimension ($1{,}300 \times 10{,}000$mm; variance in length is within allowable range), and hence of one SKU. When those slabs arrived at the AOV, they all had the same stock order number consisting of its quality and dimension; 186C1001301 (186C for quality, 100 for length and 13 for width). At some moment in time, the slabs are coupled to an order. For example, for the lowest slab, the stock order number is replaced by a customer order number (45104A 0100). Since the nine slabs with initial stock order number 186C1001301 are divided over five different customer orders, POSS now recognizes them as low frequent (i.e. 'Wl'). Because the entire stack of nine slabs had become low frequent, the POSS prioritizing rules allowed to store other SKUs on top of the nine slabs.

Furthermore, under 'Ref' we see in which rolling schedule the slab is programmed (e.g. 4282-68 means rolling schedule 4282, slab sequence 68). Since the tail of the rolling schedule (4282-111 and 4282-112) is programmed higher in the stack than the middle of the rolling schedule (e.g. 4282-75), which is charged earlier, this will definitely lead to unnecessary delving in this stack, since slabs are of the same SKU and thus interchangeable.

3.4 From Slab to Coil

In this section we explain the next step from the integrated steel plant: rolling slabs to (thin) coiled sheets. First, we describe the process in general (Section 3.4.1). Then, in Section 3.4.2, we go deeper into the heating process of the furnaces. We end up with explaining the delving phenomenon (Section 3.4.3), which occurs when picking slabs.

3.4.1 Process Description

The next step in the process is the hot rolling of slabs at the WB2, where slabs are rolled to thin, coiled sheets (see Figure 3.13).

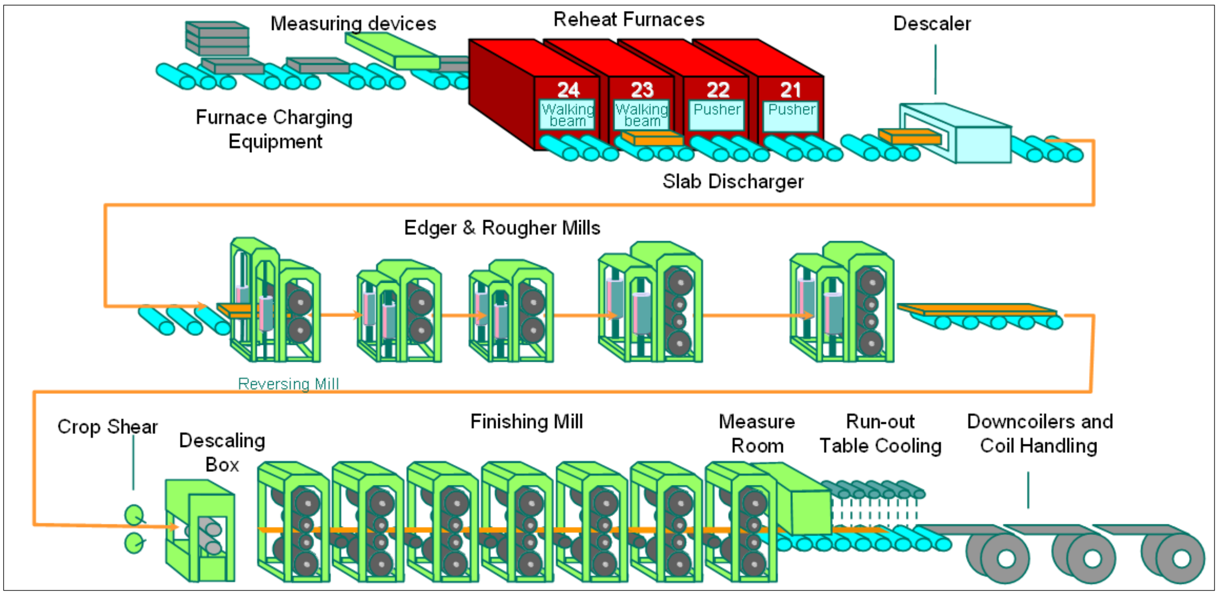


Figure 3.13 - Hot rolling process at WB2

Once slabs are selected (in a rolling schedule, see Section 2.2), they have to be transported to the WB2 area; the cranes in PE/PF hall pick up the slabs and bring them to the Ready Section (RS, see Figure 3.9). In the RS, small stacks of slabs are created. These stacks are then destacked to the furnace charging equipment (sort of conveyor). The slab is then officially handed over to the WB2.

Before the slabs can be rolled, they first must be reheated to a temperature of around 1250˚C. This so-called end-furnace temperature depends on the final thickness of the coil: a slab for a coil with thickness 1.5mm requires a higher end-furnace temperature than a slab for a thicker coil. The WB2 has four continuous reheating furnaces to reheat the slabs.

The slabs have to be charged in the furnaces in the right sequence because of:

- The coffin shape determines the sequence of the slabs (see Section 2.2)
- The four furnaces have the same throughput time per slab
- The slabs can only be conveyed from one direction

For an arbitrary rolling programme the charging of the furnaces can therefore be found in Figure 3.14. (N.B. a real programme consists of around 130 slabs and in each furnace fit around 20 slabs.)

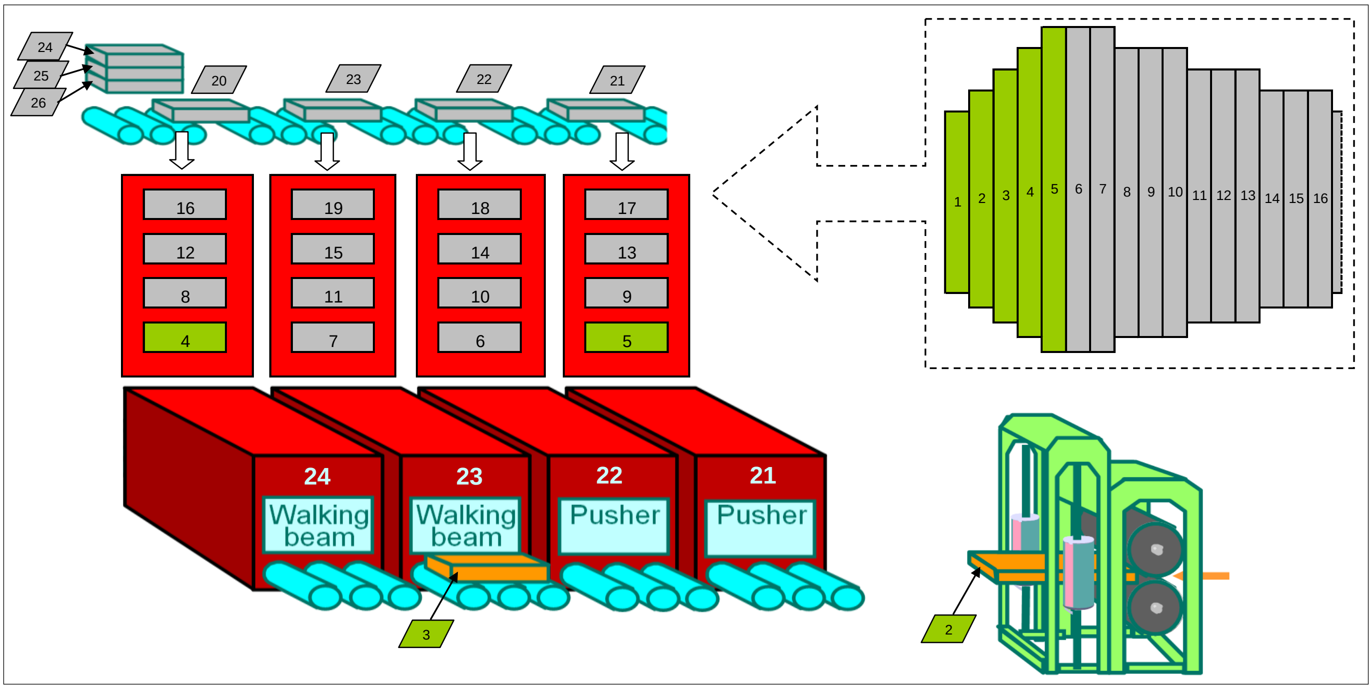


Figure 3.14 – Loading of the furnaces for an arbitrary rolling schedule

In Figure 3.14, slab #3 just came out of furnace 23 and will be conveyed to the edger and roughing mills. Next slab in process is slab #4, which will be discharged from furnace 24. By discharging slab #4, slab #8, #12 and #16 are moved forward, which creates space for charging slab #20. If slab #4 is conveyed to the edger and roughing mills, slab #5 will be discharged from furnace 21, creating space for charging slab #21, etc. This sequencing process is continuous and will only be interrupted if a furnace is turned off (e.g. for maintenance). In that case one speaks of a two- or three-furnace operation. It is plain that, if the slabs are not delivered conform the order as displayed in Figure 3.14, this has a major impact on the succeeding rolling process.

3.4.2 Furnaces

The WB2 has two types of furnaces (see Figure 3.14). Two out of four furnaces are pusher furnaces; the other two are walking beam furnaces. In the pusher furnace, a slab inserted at the back end pushes out a hot slab at the front end (i.e. the slabs are sliding over rails until they reach the front end). In the walking beam furnaces, the slabs or moving by the use of walking beams and can hence be taken out without inserting a new slab. This is however not desired, since the furnaces must, from an energy point of view, always be loaded maximally. Each furnace is divided into three zones; the load zone (13m), the mid zone (9m), and the end zone (8m). Each zone can be heated separately. After the load zone the slab temperature has reached around 900˚C. After the mid zone a surface temperature of around 1,200˚C is reached yet, but it takes to the end of the end zone until the slab core has reached the same temperature. The end-furnace temperature depends on the final thickness of the coil. If the final thickness is approaching the minimum of 1.5mm, the slab gets a high index number (i.e. a number that indicates the slab needs to be longer in the furnaces to reach the desired higher end-furnace temperature). So, if a slab with a high index number is enclosed by two slabs with a low index number, this means these two slabs need to stay longer in the furnace, even though their end-furnace temperature might be sufficient yet.

The higher the charging temperature of the slabs, the less time and gas is needed to reheat them. If the volatility in temperature of the entire charged volume becomes lower, the energy effect and, especially the increasing capacity effect, becomes stronger (i.e. it is better to charge 10 slabs at 250˚C, than three at 600˚C and seven at 100˚C, even though this yields the same average temperature).

The current gas consumption of the furnaces is split up per furnace type, because their thermal efficiency differs:

- Walking beam furnace: XXX GJ/ton
- Pusher furnace: XXX GJ/ton

Furthermore, historical data on average charging temperature shows that each 100˚C increase in average charging temperature, yields XXX GJ/ton (walking beam furnace) to XXX GJ/ton (pusher furnace) savings on gas consumption (Van der Meulen, 2009). Although this relation is presumably not linear, it will satisfy for the marginal improvements made in this stage of the project. So, given the fact that a gigajoule of gas costs around €XXX, WB2 produces around 110,000 ton per week, and assuming that this volume is divided equally over the four furnaces, a temperature increase of 100˚C would yield XXX euro savings per week. (N.B. savings due to capacity increase of the furnaces are not taken into account in this calculation.)

3.4.3 Delving Factor

When slabs are programmed in a rolling schedule, the cranes in the PE and PF hall gather all slabs and place them in the right sequence in the RS. Most of the time slabs can be picked from the top of a stack, but sometimes the requested slab is in the middle of a stack (as in Figure 3.12) and has to be dug out. This is called 'delving'. The delving factor is an indicator for the efficiency of the AOV. It is calculated as follows (and can, hence, be larger than 1):

$$Delving\ Factor = \frac{\#\ non\text{–}requested\ slabs}{\#\ requested\ slabs}$$

In Figure 3.15 one can see an example of a delving factor calculation. In this case, two slabs in a nine slab-high stack are requested by the WB2. However, three slabs have to be removed to another stack to reach the two requested slabs and bring them to the ready section. The AOV currently works with an average delving factor between 0.7 and 1.0.

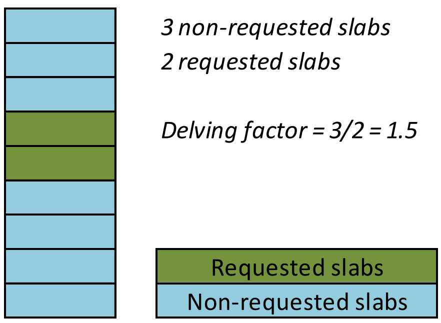


Figure 3.15 - Example of a delving factor calculation

3.5 Planning and Scheduling the Process of Casting and Rolling

Now we know the most important details of casting and rolling, we want to analyze how these processes are planned and scheduled in the production chain. In this section we expound on the general planning process (Section 3.5.1), followed by the detailed scheduling procedures of the OSF2 and WB2 in Sections 0 and 3.5.3 respectively.

3.5.1 Planning and Ordering

The order book is kept up to date by the Sales department. Every Wednesday, a set of coil orders for the new week is launched by the Supply Chain Planning department. The new week is a period from Saturday to Saturday, so at maximum there are orders for 10 to 11 days ahead. This ‘week schedule’ of the WB2 leads to a demand for a certain set of slabs (slabs of different quality, dimensions and their quantity). Based on this set of demanded slabs and the available slab stock, a week schedule for the Oxygen Steel Plant (OSF2) is made.

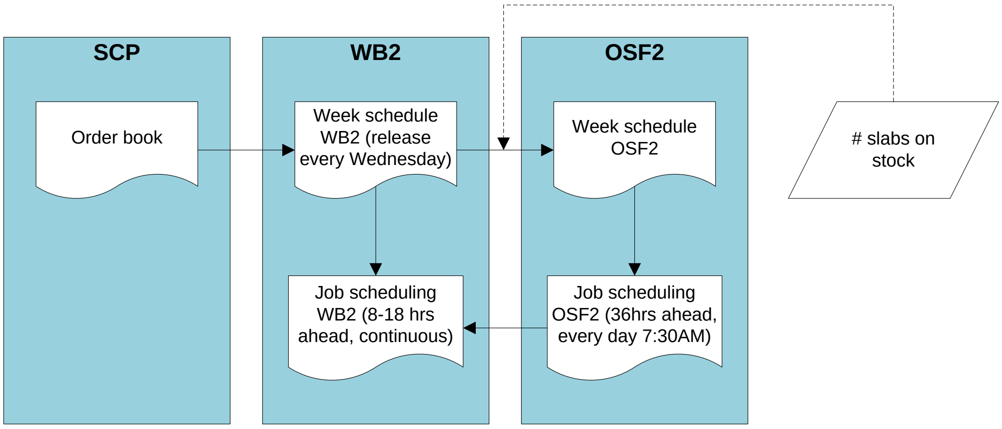


Figure 3.16 - Tactical and operational planning framework

3.5.2 Job Scheduling of OSF2

The OSF2 week schedule combined with the available resources form the basis for the daily casting plan. The casting plan can be seen as the job scheduling for OSF2, in which the sequence of slabs (quality, dimension and amount) in the string is set. The casting plan is made every day at 7:30 AM, for around 36 hours ahead. The entire process of planning and scheduling is displayed in Figure 3.16. After observing the OSF2 planning a couple of things can be noticed. Within the job schedule of 36 hours:

- Series are broken down before the end of the series
- Series are shifted to other machines
- Series are added
- Short test series for new, special qualities, are suddenly added

Discussion with the planning department revealed that these changes are caused by several problems:

- In case of irregularities in the OSF2 processes or declining pig iron buffer, some series must be shifted, since a machine is not available

- Too many people can influence or adapt the schedule, without really knowing what the consequences of their changes are
- For years, the OSF2 workers have learned to maximally use all available capacity, so they adapt the schedule to achieve this, without knowing what the downstream effect is on stock levels, increasing delivery times and changes in planning and scheduling
- In favour of customer orders, the steel ordering department adds, changes or removes series in the daily scheduling

These problems lead to variation in series length, varying time between supply of certain qualities and unexpected increase of decrease of stock levels at the AOV. This makes it for the AOV very difficult to anticipate and allocate slabs to an optimal storage position. Figure 3.17 shows half a year production for the four most frequent qualities (i.e. casting volume of the four most frequent qualities, this consist of multiple SKUs). As can be seen, not one week is similar to another in terms of portfolio and volume.

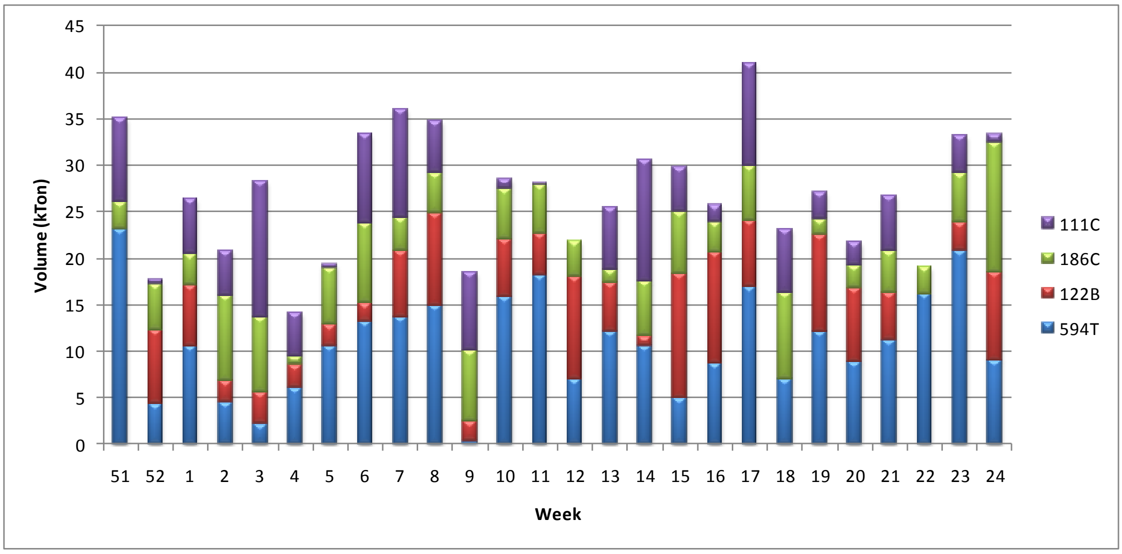


Figure 3.17 - kTon per week of 4 most frequent qualities (N.B. average volume/week is 110 kTon)

3.5.3 Job Scheduling of WB2

For the scheduling of the WB2, an iterative software tool, called ‘BètaPlanner’, is constantly trying to create a feasible rolling schedule regarding availability, slab demand, and rolling restrictions (width jumps, quality changes, wear kilometres, etc.). Once a rolling schedule is composed, it is sent to the AOV’s operating system (POSS). Normally there are two to four rolling schedules planned ahead. This has two main reasons:

1. The AOV needs time to delve out the correct slabs and bring them to the ready sections
2. Creation of a rolling schedule itself takes time and can hence not be started too late

The different scheduling processes as well as the different process constraints, lead to a large variety in throughput times of slabs between casting and rolling. This will be further explained in Section 3.6.

3.6 Throughput Times between Casting and Charging at the WB2 Furnaces

In this research, the throughput time is defined as the time between casting (slab birth) and charging at the furnaces of the WB2. Since process parameters of OSF2 and WB2 differ a lot, it normally occurs that a casted volume of one quality is charged gradually over time at the furnaces of the WB2.

Figure 3.18 shows the average throughput of a certain daily volume. This means that after casting a certain volume, 32% of this volume was charged within 24 hours, 60% within 48 hours, etc. Since it takes sometimes more than 100 days before the entire daily volume is charged, the tail of this graph is not displayed here. The dotted lines represent the same volume, but then split up to A-, B-, and C-items. We see that a certain volume of A-items is charged much quicker than B- and C-items. This is generally, because this volume consists of slabs of the ordered quality and dimension. We also see that the over 90% of the A-item volume is charged within a week. If we compare this to the

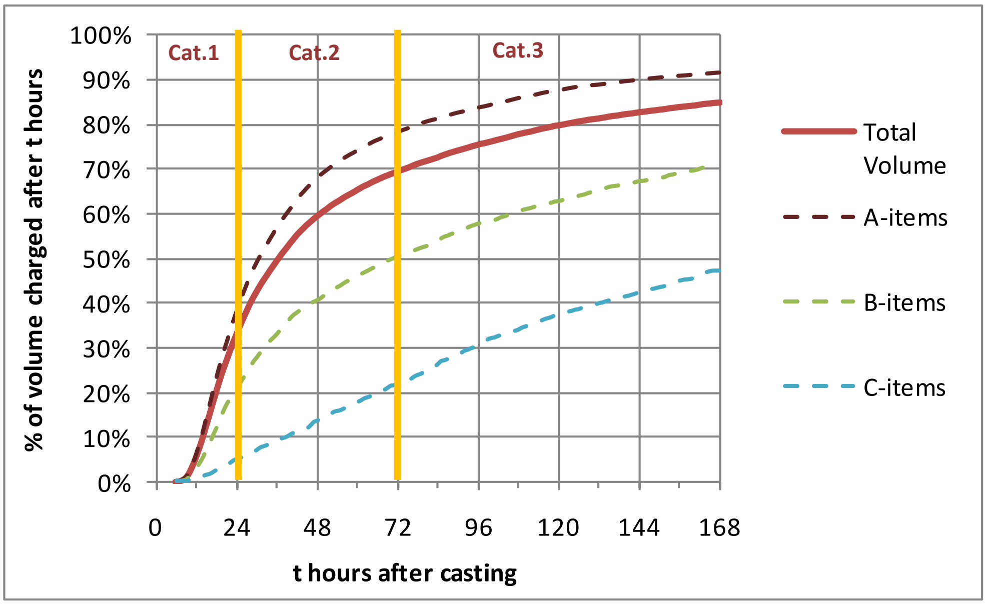


Figure 3.18 - Average charging period of daily volume (2nd quarter 2011)

Since the throughput pattern from Figure 3.18 has such a long tail, three categories are used to indicate the throughput times:

- **Category 1:** Slabs charged at WB2 within 24 hours after casting: *"≤24 hours"* (i.e. the actual 'hot charging')
- **Category 2:** Slabs with throughput time between 24 and 72 hours: *"≤72 hours"*
- **Category 3:** Slabs with throughput time longer than 72 hours: *">72 hours"*

In Category 1 and 2 we will mostly see fast-moving SKUs. These are most likely A-items, but can also be B- or C-items (e.g. a small volume of obliged hot charging slabs, see Section 3.2.2). Category 3 slabs are mostly B-quality slabs, for which it takes time to find a customer on the market. Excess slabs, which were necessary to complete a series, are often category 3 as well, because they do not have a customer order yet (N.B. these slabs can be A- or B-items). So, we want to clarify that these three categories must not be confused with A-, B-, and C-items.

The steering committee 'hot charging' has set two goals to improve throughput times at the start of 2011. First, at the WB2, the percentage charged within 24 hours must be at least 35%. Second, the percentage of slabs charged within three days must be at least 75%. The remaining 25% consist of slabs with a long expected throughput time, such as A-slabs or slabs without order. After six months the targets are almost reached. Reason for this throughput time improvement is a better cooperation between the supply chain department and the job scheduling departments of both OSF2 and WB2, i.e. they are striving for a more coherent planning over the supply chain based on daily demand.

3.7 Conclusions

Now we have analyzed the current situation we can answer research questions 2.a. to 2.d.

2.a. Why are stock levels at the AOV varying between 60 and 100 kTon?

Several reasons can be found for high stock levels:

- Because of economies of scale, often a multiple of 350 tonnes (i.e. one ladle) of one quality is casted at once (i.e. the series length is between 10 and 20 ladles), whereas the WB2 handles a small quantity per SKU per rolling programme. Hence, cycle stock is created.
- Steel making is a stochastic process, so sometimes an undesired quality is reached. For these slabs (i.e. obsolete stock), a new customer has to be found. During this time, the slabs are stored.
- Too many changes in daily planning disturb the flow of products and make it very difficult to couple operational planning of OSF2 and WB2. Hence, safety stock is needed to buffer operations.
- In case of planned maintenance upstream the supply chain (either blast furnace or oxygen steel plant), the hot strip mill must be kept running. For that, anticipation stock is needed.

2.b. Why are some slabs charged within 24 hours and others after a much longer period?

The reasons for high stock levels (see question 2.a.) are also causing long throughput times. Furthermore, throughput times are longer because:

- A-slabs require inspection or dimensional adjustments. This is an extra operation between casting and charging and costs extra time.
- Excess slabs are ordered to complete a series, but are not (directly) order-coupled
- To complete a series, sometimes it is necessary to cast slabs that have a due date up to 5 weeks ahead or cast them as excess slabs
- For B-quality slabs a customer has to be found on the market. This can take weeks and during this time the slabs remain at the AOV.

2.c. What are selection criteria for a slab to be candidate for the hot storage boxes?

Based on their throughput time and frequency we decided to choose A-items to be good candidates for the hot boxes. Generally, this means a slab must meet the following criteria:

- Common order qualities
- Standard dimension
- Cycle stock, so no dead-, safety-, or anticipation stock

- Expected throughput time of more than 24 hours ($E[TPT] > 24$ hours)

The last criterion is to prevent storing slabs, for which the planning department expects to charge them within 24 hours ($E[TPT] \leq 24$ hours), in the hot boxes. We do not add a criterion for maximum expected throughput time, since on average over 90% of the A-item volume is charged within a week. At that moment the expected temperature of a hot box slab is still around 600°C (based on Figure 3.8).

2.d. Which procedures or routines can be obstructive for the hot boxes?

The first problem is that the OSF2 production planning is changing constantly. This can lead to an unexpected emptiness or overload of the hot boxes. Whereas an overload of the hot box is not a big problem, an empty hot box means missed hot charging opportunities. This can be solved by allocating a sufficient number of candidate slabs to the hot box. The second problem evolves from the coupling of customer orders to slabs (as explained in Section 3.3.3). In the hot box, this would mean unnecessary delving and, hence, a too long period in which the hot box is opened (i.e. the hot box is cooling down).

We use the selection criteria of research question 2.3 in our simulation models. This will be explained in Chapter 4 and 5. Chapter 7 describes how the problems from research question 2.4 return in the pilot and implementation.

4 Modeling of the System

Before we can set up a simulation model of production chain OSF2 → AOV → WB2, we first model this process on paper. Some factors are of less importance for the research, so we decide to omit them from the simulation model. This chapter explains why we take these decisions. Furthermore, we set up two different simulation models. We start with a model based on historical data. Then, we extend the results by setting up a model based on stochastic data. Section 4.1 explains why we choose to use two different models. It also expounds on the pros and cons of both models. In Sections 4.2 and 4.3, we explain respectively how the historical- and stochastic models are set up. In Section 4.4, we elaborate on the performance measurement of both models. We close this chapter with answering research question 3 in Section 4.5.

4.1 Historical Versus Stochastic Simulation

It proved difficult to fit appropriate probability distributions on important factors such as SKU arrival rate, SKU volume, and rolling schedule creation. Hence, we decided to start with a simulation based on historical data of one quarter. We obtained detailed data on slab birth, creation of rolling schedules, and charging of slabs and put this in the simulation model. This means, we cast and charge around 62,000 slabs (in 13 weeks), divided over 135 different qualities and 6,100 SKUs. Per experiment, we then vary both the number of SKUs and its volume that is sent to the hot boxes. This is explained in more detail in Section 5.2.1. The result of this model represents the benefits that could have been reached if the hot boxes were already in use during the simulated quarter.

Since we are more interested in what performance can be reached in the future, we also set up a stochastic model, using several probability distributions. Even though a normal distribution did not fit the historical demand data, we still use the normal distribution to generate demand for 5 different qualities. The result is, that slab demand for these qualities is more frequent and in a smaller quantity range. In general, this means we cast and charge around 2,000 slabs per week and can run this for a long period. Depending on the experiment, the volume is divided over a certain number of SKUs. Section 5.2.1 explains this in more detail. Because this model allows us to act in a more dynamic way, we are also able to test three different slab allocation rules for the hot boxes (see Section 4.3.2). Both models have some pros and cons. These are depicted in Table 4.1.

	Pros	Cons
Historic Simulation	- Exact reproduction of reality: ▪ Include downtime ▪ Include entire portfolio	- Unable to 'predict' the future - Statically assign SKUs to hot box - Can only run for a limited period - Data tables slow down model
Stochastic Simulation	- Higher predictive value - Dynamically assign slabs to hot box - Can run for a long period - Fast running model	- Hard to simulate exceptions: ▪ No downtime included ▪ Only a few SKUs compared to reality

Table 4.1 - Pros and cons of using a historic data and stochastic data model

4.2 Model Based on Historical Data

In this model we use historical production data as input for the simulation model. This section describes how we model the production flow and can be split up in three parts: first, we explain how slabs are created and transported to the AOV (Section 4.2.1). Then, we amplify on the way slabs are stored (Section 4.2.2). Section 4.2.3 describes the last step; the selection of slabs for a rolling schedule. Finally, Section 4.2.4 depicts the factors we do not take into account for this research.

4.2.1 Slab birth and transportation to AOV

Once a slab is cut from the string, it receives its specifications and is then stored in the SKV. From there, it is transported to the AOV section. The time of storage and transport is on average 2.5 hours and can be estimated with a Gamma distribution (α = 5.45 and β = 0.59, see Appendix 3). We modelled this as if the slab is in the SKV this entire time.

After storage in the SKV, the slabs are transported to the AOV. This takes no time. At the AOV is decided where a slab must be stored. If we are dealing with an A-slab, the slab is sent to the PH hall. If we are dealing with an O-slab, then the model checks whether we are dealing with an obliged or chosen hot charging SKU. If this is the case, then, depending on the experiment, the slab receives a special label. If this is not the case, the slab is sent to the PE/PF hall, where it is stored until it is requested by the WB2. The entire process from casting to storage in AOV is displayed in Figure 4.1.

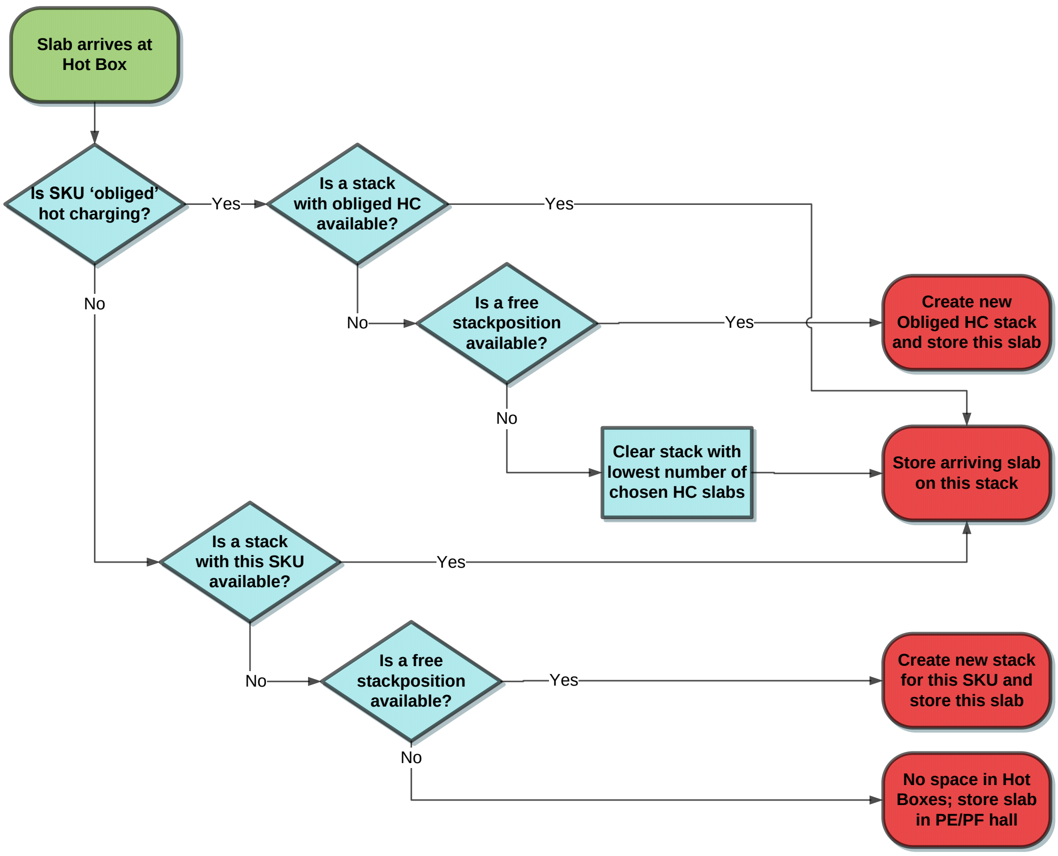


Figure 4.1 - Flowchart for storage at SKV and transportation to AOV

A-slabs stay for a period of 12 hours to 7 days in the PH hall. After that, they are brought to the PE/PF hall and considered as O-slab. In reality, inspection of a slab takes much less time than dimensional adjustment of a slab. Also the time of dimensional adjustment can vary a lot, depending on the type of process. Since we do not know which operation is needed to recover the A-slab, we draw a uniformly distributed number between 12 and 168 hours to determine the slabs' processing time in the PH hall.

4.2.2 Storage of a slab in the hot boxes

Since the hot boxes are new, we compare the situation of the hot boxes to the current situation and current allocation rules in the PE/PF hall.

The hot boxes will be built in sections 357, 370, and 383 in the PF hall. This means we have three sections with each nine stacks (see Figure 3.9). Each stack has a maximum height of 16 slabs. So, in total, we have a theoretical capacity of $3 \times 9 \times 16 = 432$ slabs or, with an average slab weight of 23 tons, around $432 \times 23 \div 1{,}000 \approx 9.9$ kTon.

As explained in Section 3.3, the AOV aims to create uniform stacks of one SKU. In the model, we will use the uniform stack principle for the chosen hot charging (chosen HC) slabs, because these SKUs arrive in large quantities. Obliged hot charging (obliged HC) slabs, on the other hand, often arrive in small quantities and in a large variety of dimensions (i.e. many SKUs), so if the uniform stack principle is applied for these SKUs, only small stacks can be created, occupying a large area in the hot box. This would mean an inefficient use of the hot box capacity. Hence we allow the model to store the obliged HC slabs in mixed stacks.

Since we do not reserve space for obliged HC slabs, it can occur that there is no stack position available for arriving obliged HC slabs. In this case, it is necessary to clear one or more stacks with chosen HC slabs, because the obliged HC slabs must be stored in a hot box at any time. For this instance we choose the stacks with the lowest number of stored slabs. This decision does not apply for chosen HC slabs: if these slabs arrive and there is no space available, they are placed outside the hot box. Figure 4.2 depicts the entire process of allocating and storing a slab.

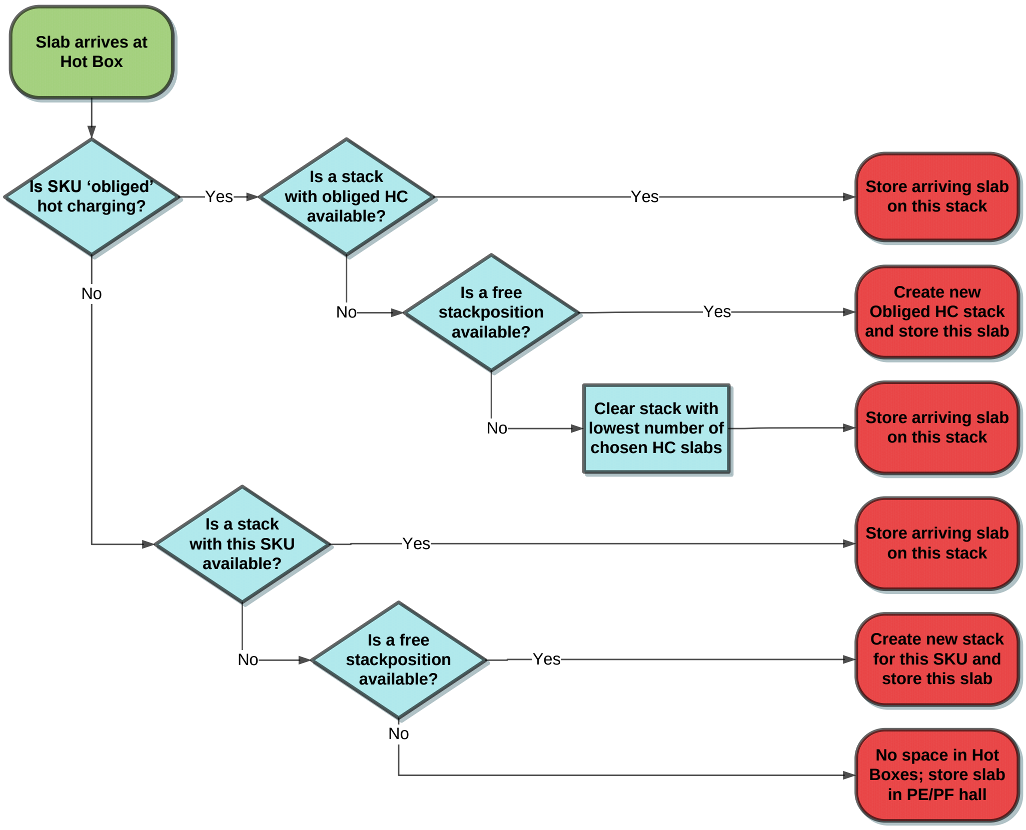


Figure 4.2 - Storage of a slab in a hot box

4.2.3 Slab is requested by the WB2 and brought to the Ready Section

With the future hot boxes it is really important to distinguish between hot and cold slabs when picking slabs for a rolling schedule. Since there can be hot slabs in the hall as well is in the hot boxes, for each SKU, three phases can be distinguished:

1. Slab in PE/PF hall and slab age is less than 24 hours (hot slab)
2. Slab in hot box (hot slab)
3. Slab in PE/PF hall and slab age is over 24 hours (cold slab)

So, for each slab in a rolling schedule, we first look if a slab with slab age less than 24 hours is available in the PE/PF hall. If this is not the case, we look in the hot boxes. If both are not available, we are forced to pick a cold slab from the PE/PF hall. We call this the prioritization rule. With this prioritizing rule, we ensure that first all hot slabs from the PE/PF hall are programmed, then the hot slabs in the hot box and finally, the cold slabs from the PE/PF hall.

Once a slab is programmed, it is brought to the ready section. From here, slabs are charged into the furnaces. However, depending on number of production hours planned ahead, slabs spend between 2 and 5 hours in the ready section, before charging at the furnaces. This time is important, because during this time hot box slabs cool down much faster than inside the hot boxes. The entire process of picking slabs in the sequence of a rolling schedule is depicted in Figure 4.3.

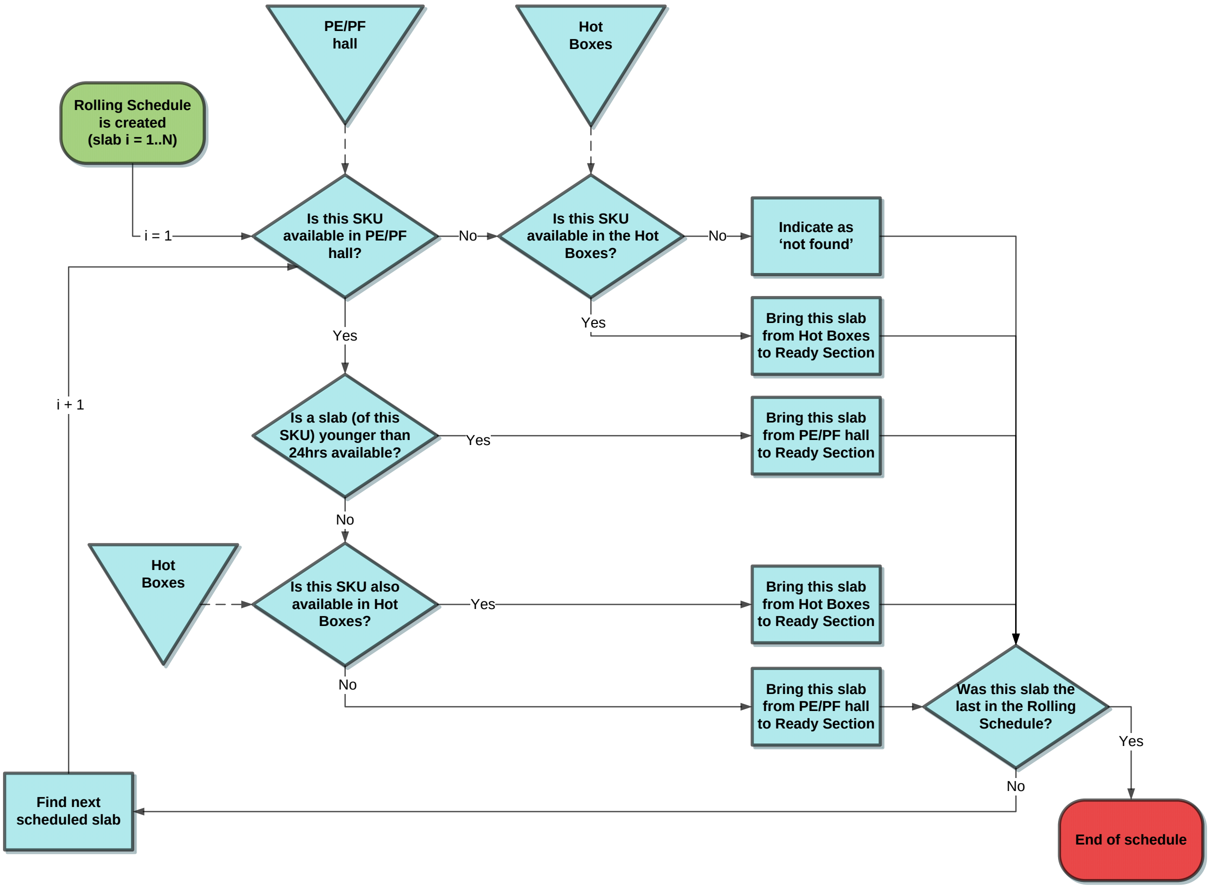


Figure 4.3 - Pick slabs from PE/PF hall and hot box in sequence of rolling schedule

4.2.4 Omitted Factors

In the model, no distinction is made between the PE and PF hall, whereas in reality, these are separate halls with separate entrances for the train. Also, the crane operations in PE/PF hall and SKV are not taken into account. This has two reasons:

1. Crane capacity is assumed to be sufficient, since there is no significant volume increase
2. In reality, depending on slab type and situation, the cranes pick up to 4 slabs in one grasp. This phenomenon is hard to simulate, while it has an enormous impact on crane usage. On the other hand, this phenomenon does not affect hot charging of slabs, so it is not really necessary to include this in the simulation model

We do not include downtime in an entire hall: in reality, a couple of times a year, both cranes in one hall are in maintenance. If this is the case, then the hall is 'blocked' and it is not possible to store or request slabs for a short period. We restrict ourselves to the situation, where there is at least one crane per hall in operation, so no 'blocking' can occur.

In the model, we only use physical stack composition for the hot boxes, because setting up modeling rules for the entire PE/PF hall needs a lot of extra time and research. In practice, it often occurs that two or more SKUs are stored at one stack. Although this results in a higher delving factor, it might have a positive effect on the fill rate of the hot boxes, since stacks are 'blocked' less often. Furthermore the model works with a fixed number of chosen hot charging SKUs, that where the most frequent SKUs over a period of 13 weeks. In reality, selection of SKUs can be dynamic: if a low frequent SKU is casted, but in a high volume, the supply chain department can decide to send (a part of) the volume to the hot boxes. This more dynamic situation is approximated with the model based on stochastic data.

Cooling down in a hot box is expected to be slower if the hot boxes are closed (Section 3.2.4). Hence, two different values for α are used to calculate the cooling down during open hot box time and cooling down during closed hot box time. In the model we only use α for open hot box time, since it is very hard differentiate between open and closed time. Therefore, the used temperature distribution can be considered as 'worst case scenario'.

Lastly, the destacker and conveyor to the furnaces are omitted in the model. These processes are just short, intermediate steps to finally charge the slabs in the furnaces and hence not necessary to model. We also do not include the delving factor, since the delving factor originates in the creation of rolling schedules and composition of stacks in PE/PF hall. These processes are not included in the model.

4.3 Model Based on Stochastic Data

In this model we create slab demand and slab production by using a normal distribution. We use the same three steps as in Section 4.2: Section 4.3.1 explains how we create slab demand and how we use this to determine series length and the start of casting. Section 4.3.2 describes three slab allocation rules for the hot boxes, we use in this model. Finally, Section 4.3.3 shortly expounds on how we select and charge slabs.

4.3.1 Slab birth

For each day i we use a normal distribution to create demand $\mathrm{D_{ijk}}$ for slabs of quality j and dimension k. If on the current day $(\mathrm{i}=1)$ the demand for all slabs of quality j is larger than 0 $(\sum_{k\epsilon K}\mathrm{D_{1jk}}>0)$, then we decide to cast this quality on this day. The next step is to determine the series length per quality. For this purpose, we look in the planning horizon (day $\mathrm{i}=1..10$) and sum up demand for all slabs of quality j. We choose the largest number of days n for which the total demand does not exceed the maximum series length $\mathrm{S_{j,max}}$ for quality j, i.e., the largest n for which holds:

$$\frac{\sum_{i=1}^{n}\sum_{k=1}^{K}\left(D_{ijk}\times W_k\right)}{L}\leq S_{j,max} \tag{2}$$

With:

D_{ijk} : Demand for slabs of quality j and dimension k on day i

W_k : Weight of slab with dimension k

L : Ladle size $(=330$ ton)

$S_{j,max}$: Maximum series length for quality j (in number of ladles)

Example 4.1

Quality $123L$ has three different dimensions (so we have three SKUs), as displayed in Table 4.2. Each SKU has a demand d_{ijk}, of dimension k, quality j on day i, determined by a normal distribution (see Appendix 5). The sum over k determines the demand d_{ij} for a certain quality j on day i.

Slab specifications					Demand d(i,j,k) in # of slabs					
SKU	Quality (j)	Dimension (k)		W(k) (ton)	day (i)					
		Width (mm)	Length (mm)		day 1	day 2	day 3	day 4	day 5	day 6
1	123L	1.200	10.300	21,4	-	31	24	20	12	-
2	123L	1.400	8.000	19,4	18	-	25	17	10	35
3	123L	1.700	8.000	23,5	32	7	19	27	-	-
Total cumulative demand for quality *j* on day *i* (in tons)					1.102	1.930	3.376	4.769	5.219	5.898

Table 4.2 - Example of determining casting demand

Given the fact that $S_{123L,max}=15$, we decide to cast for 4 days $(n=4)$ ahead, since the demand until day 5 (5,577 tons) exceeds the maximum series length $(15\times 330=4{,}950$ tonnes). The excess volume of $4{,}950-4{,}769=181$ tons is omitted for the simulation. Hence, on day 1 we produce 80 slabs of SKU1, 62 slabs of SKU2 and 94 slabs of SKU3. Logically, after casting, we remove the demand of SKU 1 to 3 until day 4. On day 5 we make a new casting decision for this quality. (N.B. if there would be no demand for SKU 1, 2 and 3 on day 1, we decide not to cast on day 1 and postpone this decision until day 2).

If we cast multiple qualities per day, we always cast in the sequence of the index of the quality. So, we first cast quality 594T, then 122B, etc. (see Appendix 5).

4.3.2 Storage of a slab

In contrast to the model with historical data, we now send all slabs to the hot boxes. When arriving at the hot boxes is decided whether a slab will be placed inside or outside the hot box, using three different allocation rules (see also Figure 4.4):

- **HB rule 1:** If there is place on an existing stack of this SKU, always place slab. If a stack is full or not available yet, start a new stack for this SKU by probability 0.7 (which is derived from the fact that 30% of slabs is charged within 24 hours, so they do not require to store in a hot box)
- **HB rule 2:** For a certain SKU, sum up the casted number of slabs and the number of slabs on stock and round this down to a number of stacks (e.g. 52 slabs is rounded down to 3 stacks of 16 slabs, hence 4 slabs are placed outside the hot box)
- **HB rule 3:** If there is place, either on an existing or new stack of this SKU, always place slab

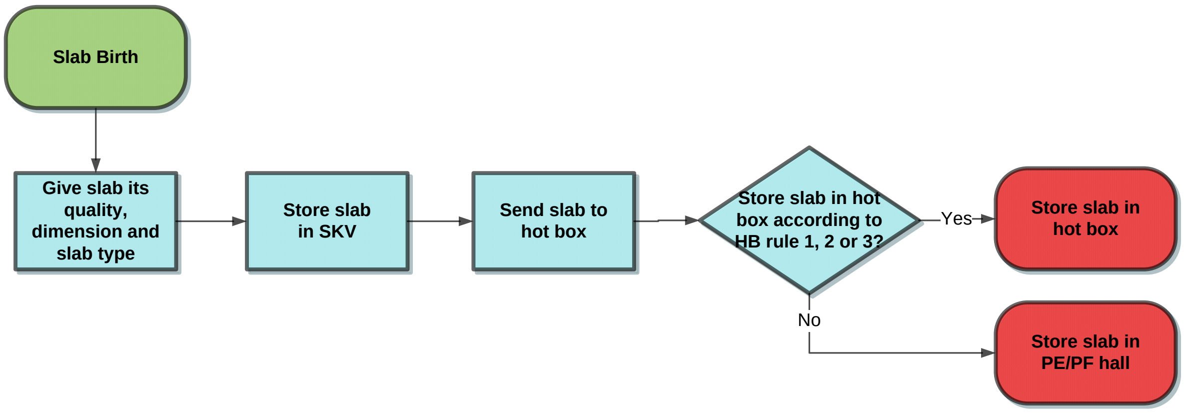


Figure 4.4 - Slab birth and storage of a slab using hot box rule 1, 2 or 3

4.3.3 Slab is requested by the WB2 and brought to the Ready Section

For charging slabs, we use the demand we have generated in Section 4.3.1. So, if we take example 4.1 again, on day 1, we charge 18 slabs of SKU2 and 32 slabs of SKU3. On day 2 we charge 31 slabs of SKU1 and 7 of SKU3, and so on. Charging on a certain day always starts 6 hours after casting the first slabs of that day and in the same sequence the slabs were casted.

4.4 Performance Measurement

To measure performance on both models, we come up with a set of key performance indicators (KPIs). Table 4.3 shows per KPI if it is applicable to only the hot box, or the entire system performance. Furthermore it shows in which simulation the KPI is used (Sim.1 is historical data simulation, Sim.2 is stochastic data simulation).

The objective of the historical data simulation is to see what increase in hot charging percentage could have been reached if the hot boxes were already in use during the simulated quarter. The purpose of the stochastic data simulation is to investigate the hot box performance under more stable conditions (i.e. only a few qualities in a more stationary pattern) and the use of different slab allocation rules. For this reason, we do not use KPI 5 and 6 in the stochastic data simulation (i.e. we cannot compare the hot charged slabs with a realistic volume).

KPI	Hot Box	Overall	Sim. 1	Sim. 2
1. Fill rate of the hot box (i.e. average occupation: percentage of maximum capacity	✓		✓	✓
2. Average throughput time in the hot box (in hours)	✓		✓	✓
3. Standard deviation of throughput time in the hot box (in hours)	✓		✓	
4. Throughput of hot boxes (average # slabs per week)	✓		✓	✓
5. Cannibalization (percentage of slabs with TPT < 24hrs, charged via the hot boxes)		✓	✓	
6. Hot charging (percentage of slabs charged within 24hrs OR through the hot boxes)		✓	✓	
7. Average temperature of the entire charged volume (in ° Celsius)		✓	✓	✓
8. Percentage within throughput time categories (see Section 3.6)		✓	✓	✓

Table 4.3 - Explanation of KPIs used in the models

Based on the KPIs that hold for both simulation models we can compare their results in Section 6.3. Furthermore, we can use KPI 8 to validate our models and check overall performance improvement based on KPI 6 and 7.

4.5 Conclusions

We have set up two different, but related, models as a basis for simulation. This means we can answer research questions 3.a to 3.c.

3.a. Which factors are important for the simulation model and which can be omitted?

Important factors for the model are:

- Since hot charging is expressed in time (see Section 3.6), the throughput time of slabs is very important. Therefore we have to model every (process) step that takes time:
    - Time for storage in SKV
    - Time for transport from SKV to AOV
    - Time the slab is stored in the AOV
    - Time the slab spends in the ready section
- Furthermore, since the throughput times vary enormously between different slab types, we have to take into account all slabs, from slabs with unusual quality or dimension to high frequent slabs.
- Physical stack composition in hot boxes
- When using hot boxes, from one SKU, slabs occur in three phases: (1) hot slab in PE/PF hall, (2) hot slab in hot box, and (3) cold slab in PE/PF hall. Because we always want to pick the hottest slab of a certain SKU, we use a prioritizing rule to search for slabs in this sequence.

We omit some factors from the model, because they not (directly) contribute to hot charging:

- Crane operations in SKV and AOV
- Physical stack composition in the PE/PF hall
- Downtime of cranes, furnaces, and other equipment

3.b. Which factors do we vary in the simulation model to test operational performance?

In the model based on historical data we use (per experiment) a fixed number of hot box destined SKUs and a fixed fraction of SKU volume that is send to the hot boxes. In this way we test different product mixes. In the model based on stochastic data, we have a more dynamic approach in which we send all SKUs to the hot box. In this way we can test the hot box performance on three different allocation rules and an increasing number of SKUs.

5 Simulation Model and Experimental Design

As explained in Chapter 4, we use two different models in this research. In this chapter, we explain how we translated both models into simulation models (Section 5.1). After that, in Section 5.2, we explain for both models how we set up a simulation study according to the principles from Chapter 2.

5.1 Translation of Both Models into Simulation Software

This section describes how we translate our 'paper' models from Chapter 4 to simulation software. We use a discrete event simulation software package, called Tecnomatix Plant Simulation (version 8.2), which is developed by Siemens. First, we describe the translation of the model based on historical data (Section 5.1.1). Then, we describe the translation of the model based on stochastic data in Section 5.1.2.

5.1.1 Creating a Simulation Model Based on Historical Data

Figure 5.1 depicts the main screen of the simulation model for historical data. Slabs are casted in the *OSF2* section, stored in the *AOV* section (where the hot boxes are located), and finally charged in the *WB2* section.

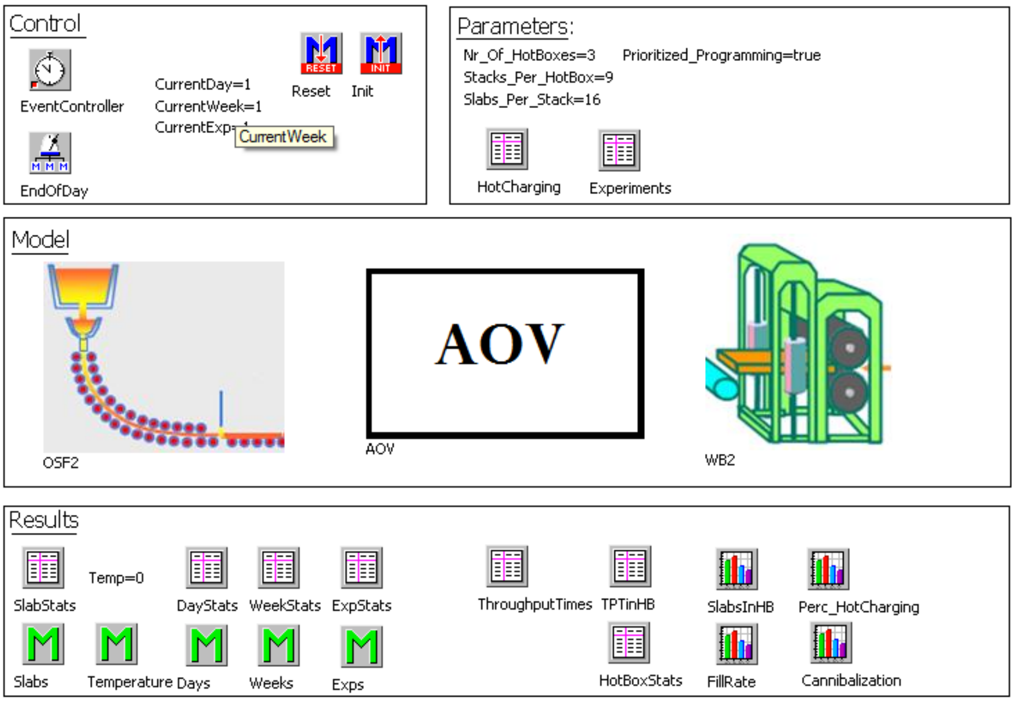


Figure 5.1 - Overview of simulation model for historical data

Furthermore, Figure 5.1 shows four frames. These frames have the following function:

- ***Control***: with the *EventController* the simulation can be started, interrupted, or stopped. The variables (e.g. *CurrentDay*) show (during a run) which day of the week and which week of the quarter it is in the simulation. Furthermore, *EndOfDay* triggers the model, such that statistics are made up every day at 0:00.

- ***Parameters***: in this frame, hot box specifications are defined. Furthermore, the table *Experiments* contains detailed information of the various experiments. The table *HotCharging* consists of a list of SKUs that are chosen or obliged hot charging. Section 5.2.1.1. explains this is more detail.
- ***Model***: this is our actual model, as described in Section 4.2. The three sections (*OSF2*, *AOV*, and *WB2*) respectively represent the models explained in the Sections 4.2.1, 4.2.2, and 4.2.3. In Sections 5.1.1.1, 5.1.1.2, and 5.1.1.3 respectively, we describe these models in more detail.
- ***Results***: in this frame, we keep statistics to determine hot box- and system performance. At the end of every day, week, and experiment, statistics are drawn on a set of KPIs that we described in Section 4.4.

5.1.1.1 OSF2 Section

Figure 5.2 shows the (simulated) *OSF2* section at the 15th of March, 2011, 07:21 AM. Slab *R9373405* is just casted (according to the *CastingPlan*) and will now receive its specifications, such as quality, width, and length (from the data table *SlabSpecs*). The *SlabCounter* is used to keep the casting plan up to date. In the next step, the slab will move to the *SKV*, where a random, Gamma distributed number determines the slabs' waiting time in the *SKV* (see Section 4.2.1 and Appendix 3). Once the time in the SKV is over, the method *SendToAOV* is triggered. This method determines whether a slab is sent to the PH hall, PE/PF hall, or the hot boxes according to the decision process from Figure 4.1.

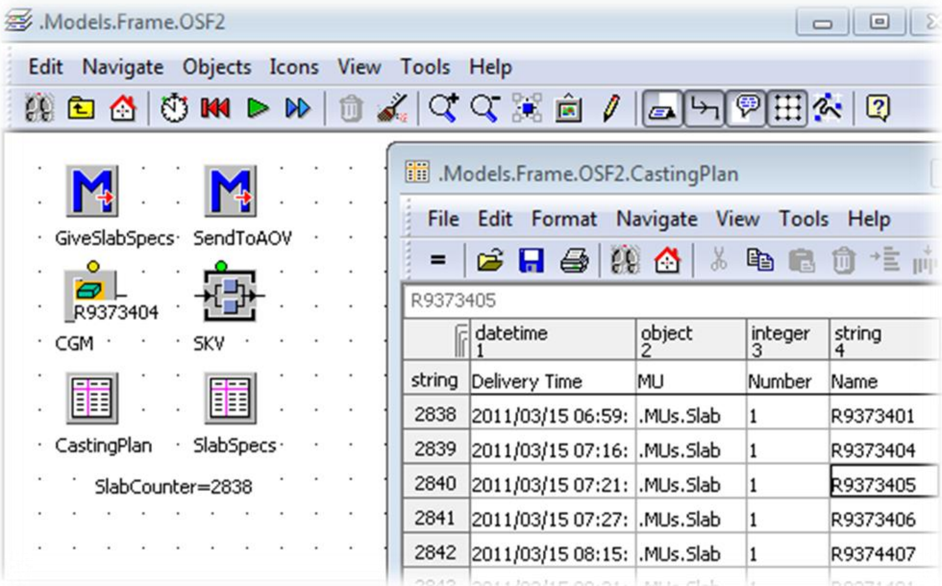


Figure 5.2 - Slab 'R9373405' is just casted at the CGM

Depending on the experiment, only a fraction of a certain SKU volume is sent to the hot boxes. For example, if in an experiment 50% of the chosen hot charging volume must be sent to the hot boxes, then for each chosen hot charging slab, we draw a randomly distributed number between 0 and 1. If this number is at most 0.5, we label the slab as 'chosen hot charging' and send it to the hot box. Otherwise, the slab is sent to PE/PF hall immediately. Section 5.2.1.1 and Appendix 4 give a more detailed overview of the fractions used per experiment.

5.1.1.2 AOV Section

Figure 5.3 shows the *AOV* section in the simulation model. There are several slabs in the *PH hall*, waiting to be inspected or adjusted. Their rework time is determined by a uniform distribution (see Section 4.2.1). Once their rework is finished, they automatically move to the *RestOfAOV* (i.e. PE/PF hall), where they are stored until they are requested by the WB2. To increase simulation speed, these slabs are not stored physically, but their specifications are saved in a stock list (i.e. *InStock*).

Furthermore, Figure 5.3 shows that one slab (i.e. *R9789103*) is just brought to the hot boxes. Based on the decision tree of Figure 4.2, the method *StoreInHotBoxes* then determines on which stack in the hot box the slab will be stored.

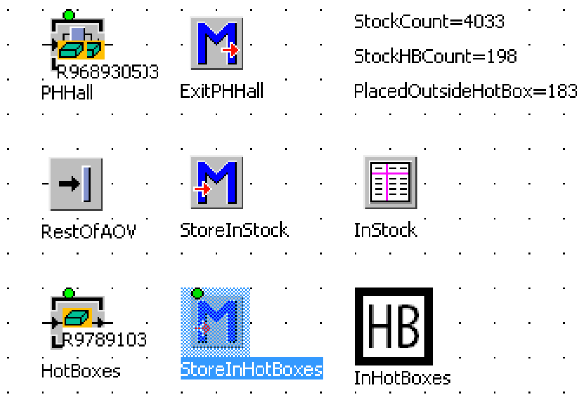


Figure 5.3 - Overview of AOV section

A few calculation steps later, slab *R9789103* is sent to *InHotBoxes* and stored in the first stack of the hot boxes (i.e. *Stack11*, see Figure 5.4). From Figure 5.3 and Figure 5.4 we see that at this moment 198 slabs (i.e. *StockHBCount*) are stored in the hot box, which means we have a fill rate of $198/432 \approx 46\%$. The number *PlacedOutsideHotBox* represents the number of slabs that (during an entire run) could not be placed in the hot boxes (e.g. because it was full or blocked for this type of SKU), whereas these slabs were hot box destined.

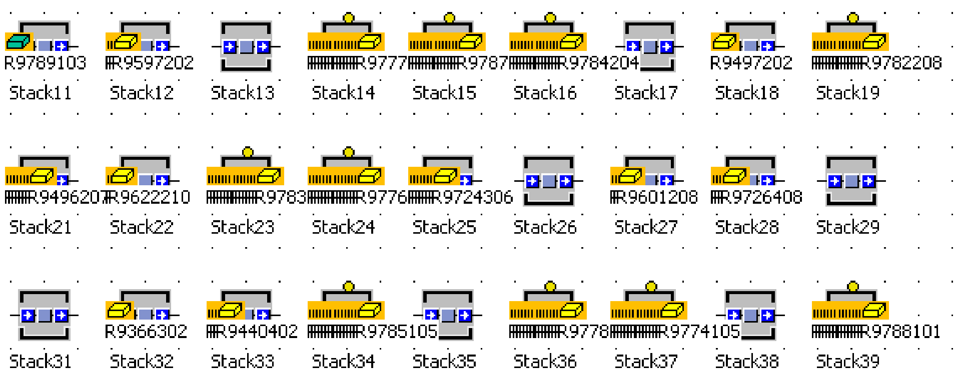


Figure 5.4 – Detailed overview of *InHotBoxes* (i.e. the three hot boxes)

5.1.1.3 WB2 section

Section 4.2.3 describes how slabs are selected once their SKU is programmed in a rolling schedule. We did, however, not explain how rolling schedules are created. Figure 5.5 shows how we create rolling schedules in the simulation model. They are created based on historical data (i.e. the table *RollingSchedules*) as well. For example, during the real quarter, schedule *P1000* was started at 2:00AM on Sunday the 20th of March, 2011, so we simulate the same starting time for this schedule in our model. The result of *P1000* is a list of SKUs that have to be picked and brought to the ready section. (N.B. a schedule consists of a list of slabs of certain quality, width, and length and not slab-ID. This means we do not pick exactly the same slabs as during the real quarter.)

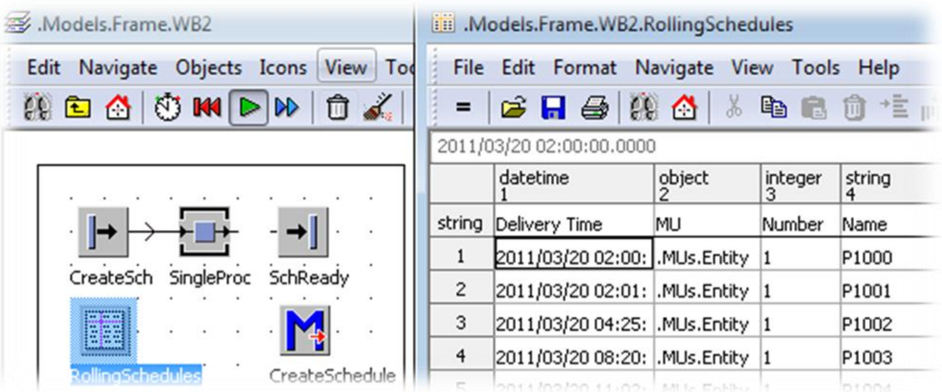


Figure 5.5 - Creating rolling schedules

Since slabs are stacked according to LIFO (i.e. Last In, First Out) principle in reality, the simulation model must always pick the youngest available slab as well. This is realized by sorting the stock list on descending casting date and time of the slabs. Hence, when the looping procedure from Section 4.2.3 starts, the youngest slabs will always be picked first, since they are on the top of the list and the list is looped from top to bottom.

After starting the schedule, the slabs are brought to the ready section in sequence of the rolling schedule. When a slab arrives at the ready section, it receives a waiting time between 2 and 5 hours, determined from a uniform distribution. Figure 5.6 depicts a set of slabs that is brought to the *ReadySection* and waiting to be charged in the *Furnaces*. The time between charging two slabs is then determined by a random number between 1.5 and 3 minutes (uniform distribution). Once the slabs have been charged, the model registers slab statistics such as quality, width, length, throughput time, temperature, and storage location (i.e. hot box or PE/PF hall).

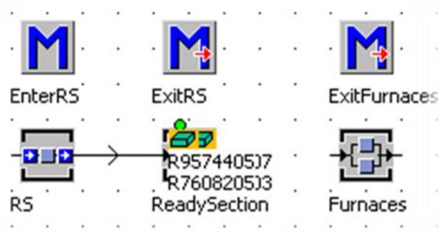


Figure 5.6 - Slabs in ready section, waiting to charge in the furnaces

5.1.2 Creating a Simulation Model Based on Stochastic Data

Figure 5.7 shows the simulation model for stochastic data. At first glance, the model looks identical to that of Figure 5.1. However, there are some major differences. We discuss these differences in the same sequence as in Section 5.1.1. First, we discuss the four frames:

- ***Control***: Compared to Figure 5.1, a few things are different. Since we are dealing with stochastic numbers in this model, we have to perform replications of each experiment and delete the warm-up data (see Sections 2.3 and 5.2). For this purpose, we added methods and variables in this frame.
- ***Parameters***: in this frame, we added a few things, such as number of replications, run length, and warm-up period (see Section 5.2) as well. Furthermore, this frame contains (stochastic) data regarding quality volume, series length, and weights of all possible dimensions.
- ***Model***: this is our actual model, as described in Section 4.3. Again, we describe the three sections (*OSF2*, *AOV*, and *WB2*) separately in Section 5.1.2.1, 5.1.2.2, and 5.1.2.3.
- ***Results***: again, statistics are registered in this frame. However, as explained in Section 4.4, performance measurement of the hot boxes is most important in this model.

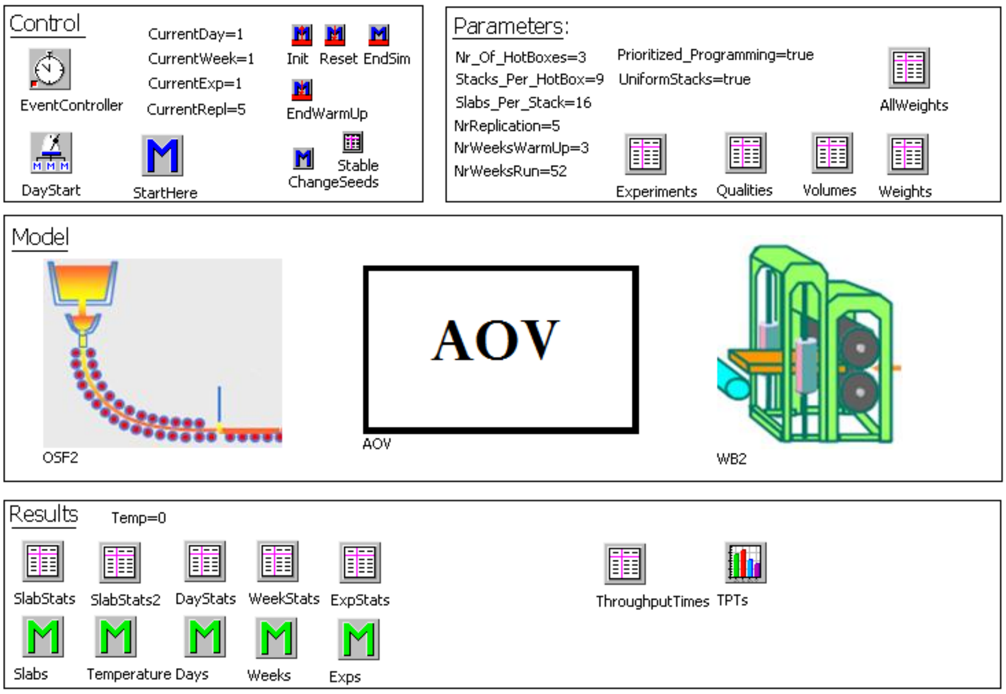


Figure 5.7 - Overview of stochastic simulation model

5.1.2.1 OSF2 Section

Since this model is based on stochastic data, the OSF2 section in Figure 5.8 is slightly different from the model in Figure 5.3.

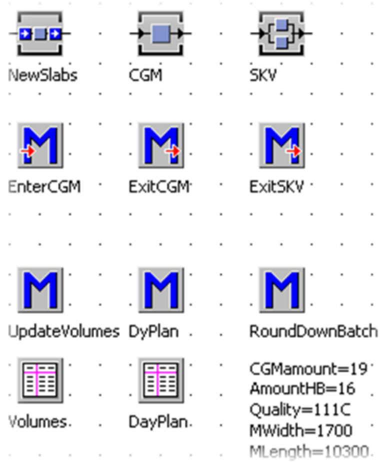


Figure 5.8 - Overview of OSF2 section in stochastic simulation model

Each day at 0:00 we create new demand at the end of the planning horizon (i.e. day 10). Again, d_{ijk} represents the demand for slabs of quality j and dimension k on day i. Then, at 0:00, we copy demand from day i to day $i-1$ and we create new demand for day 10, using a normal distribution. Each quality has a maximum number of SKUs for which demand is created that day. This ensures that we do not create too low volumes per SKU per day and that d_{ij} can become zero for certain days (as in reality).

Example 5.2

In Figure 5.9, we just copied demand from day $i+1$ to day i. Since the maximum number of SKUs of quality 594T is four, we draw a normally distributed number (for quality 594T this means $\mu = 67.1$ and $\sigma = 21.1$, see Appendix 5) four times and divide it by four. This results in a demand of 23, 16, 18 and 13 slabs for SKU 7, 8, 9 and 11 on day 10 respectively.

.Models.Frame.WB2.RollingDemand

File Edit Format Navigate View Tools Help

594T

	string 1	integer 2	integer 3	integer 4	integer 5	integer 6	integer 7	integer 8	integer 9	integer 10	integer 11	integer 12	integer 13	string 14
string	Quality	Width	Length	day1	day2	day3	day4	day5	day6	day7	day8	day9	day10	
7	594T	1200	8000	0	20	0	0	24	0	0	0	12	23	
8	594T	1200	10300	0	0	0	18	0	0	0	0	12	16	
9	594T	1600	8000	0	7	0	0	20	0	23	0	0	18	
10	594T	1600	10300	0	0	0	0	13	42	0	0	10	0	
11	594T	1800	8000	0	0	0	0	0	17	0	2	0	13	
12	594T	1800	10300	0	0	0	2	0	0	0	0	0	0	

Figure 5.9 - Example of planning horizon

As explained in Section 4.3, we only cast a certain quality if there is demand for this quality (i.e. its SKUs) on day 1. Each day at 0:00, we put all slabs for that day in *NewSlabs* (see Figure 5.8) and start casting them in sequence of the demand table. This takes two minutes per slab. The succeeding waiting time in SKV is the same as explained in Section 5.1.1.1.

5.1.2.2 AOV Section

Contrary to the historic data model, we now send all slabs to the hot boxes. When the slabs arrive at the hot boxes, we use one of the three allocation rules (see Section 4.3.2) to store them. The choice of allocation rule depends on the experiment and is programmed in the method *StoreInHotBoxes*. Hence, the AOV section has the same overview as in Figure 5.3, except that we do not have a PH hall in this model and that slabs only go to the RestOfAOV if there is no space in the hot boxes. Furthermore, we only have chosen hot charging slabs in this model, so we only allow the model to store slabs in uniform stacks in the hot box.

5.1.2.3 WB2 Section

Figure 5.10 shows an overview of the WB2 section in the stochastic simulation model. Each day at 9:00AM, we use the method *CreateSchedule* to create one rolling schedule that consist of all slabs that are demanded at day 1 of the planning horizon (see Figure 5.9). Then, every two minutes, the method *EnterRS* is recalled to perform one loop of the decision process (Figure 4.3). This means that we use the (daily) rolling schedule to bring one slab to the ready section every 2 minutes. In and after the ready section, the process is identical to the process described in Section 5.1.1.3.

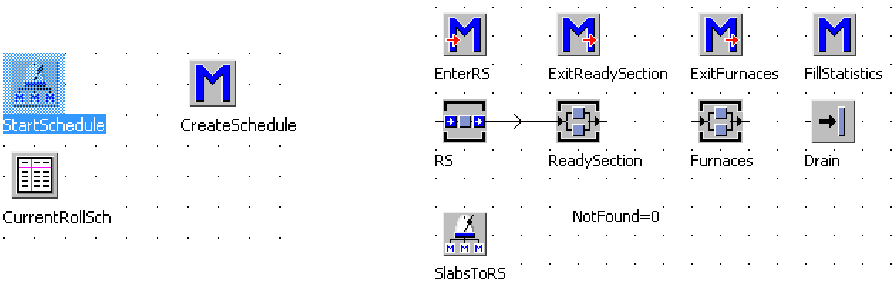


Figure 5.10 - Overview of WB2 section in stochastic simulation model

Since we have started casting slabs at midnight (in sequence of the demand table as well), the youngest slab will always have a throughput time of at least nine hours. This is comparable to the real situation, as depicted in Figure 3.18. After charging, we register slab statistics in the same way as explained in Section 5.1.1.3.

5.2 Experimental Design of Both Simulation Models

Now we have two working simulation models, we can perform various experiments to find the potential hot charging improvement. This section explains which experiments we perform in both models (Section 5.2.1). Subsequently, we describe how our simulation setup, in terms of run length, number of runs, and warm-up period in Section 5.2.2. We judge the performance of the experiments on the KPI explained in Section 4.4. The results from the various experiments follow in Chapter 6.

5.2.1 Experiments

To see what performance could have been reached during the second quarter, we run in total 13 experiments with various product mixes. In Section 5.2.1.1, we elaborate on these experiments. Section 5.2.1.2 explains how we experiment with an increasing number of SKUs and three slab allocation rules.

5.2.1.1 Experiments of Historical Data Simulation Model

In this model, we choose a number of high frequent SKUs to be 'chosen hot charging' (i.e. chosen HC). Furthermore, we have the special qualities from Table 3.2 that are 'obliged hot charging' (i.e. obliged HC). The experiments in this model consist of gradually increasing the volume of chosen HC slabs; first by increasing the volume of the 25 most frequent slabs, then by increasing the number of SKUs. Table 5.1 shows the number of SKUs and their fraction that is sent to the hot boxes per experiment. We have one base-experiment (experiment 0), in which hot boxes do not exist (i.e. this is our validation experiment to the real quarter). Subsequently we send all obliged HC slabs to the hot box and use various product mixes in experiment 1 to 13. Appendix 4 provides a more detailed overview of each experiment and example 5.1 explains a possible situation in experiment 2.

Exp.	Obliged HC	Chosen HC
0	No hot box	No hot box
1	100%	25% of volume 25 most frequent SKUs of quarter 2
2	100%	50% of volume 25 most frequent SKUs of quarter 2
3	100%	75% of volume 25 most frequent SKUs of quarter 2
4	100%	100% of volume 25 most frequent SKUs of quarter 2
5	100%	Optimal percentages of 25 most frequent SKUs of quarter 1
6	100%	Optimal percentages of quarter 2 for 25 most frequent SKUs of quarter 1
7	100%	Optimal percentages of 25 most frequent SKUs of quarter 2
8	100%	Optimal percentages of 35 most frequent SKUs of quarter 2
9	100%	Optimal percentages of 45 most frequent SKUs of quarter 2
10	100%	60% of volume of 45 most frequent SKUs of quarter 2
11	100%	70% of volume of 45 most frequent SKUs of quarter 2
12	100%	20% of volume of 80 most frequent SKUs of quarter 2
13	100%	100% of volume 25 most frequent SKUs of quarter 2, but create new stack by probability

Table 5.1 - Experiments of historical data simulation

Example 5.1

During a certain period, 200 slabs of quality 122B were casted, of which 108 of chosen HC SKU1 and 92 of chosen HC SKU2. During the same period, a short series of two ladles of the obliged HC quality 3N93 is casted at CGM22. This results in 30 slabs of 3N93, equally divided over six different dimensions (i.e. SKU3…SKU8). So, for each SKU of 3N93 we have 5 slabs. Let us now assume we are dealing with experiment 2, SKU1 and SKU2 are not available in the hot box and there are no obliged HC slabs present in the hot box yet. Experiment 5 implies that we send 50% of the 122B SKUs to the hot box and 100% of the 3N93 quality SKUs. This means $\left\lceil \frac{0.5*108}{16} \right\rceil = 4$ *stacks of SKU1,*

$\left\lceil\frac{0.5*93}{16}\right\rceil = 3$ stacks of SKU2 and $\left\lceil\frac{30}{16}\right\rceil = 2$ stacks for SKU3 until SKU8. Figure 5.11 shows how we expect one hot box is filled after this example (before charging any of those slabs).

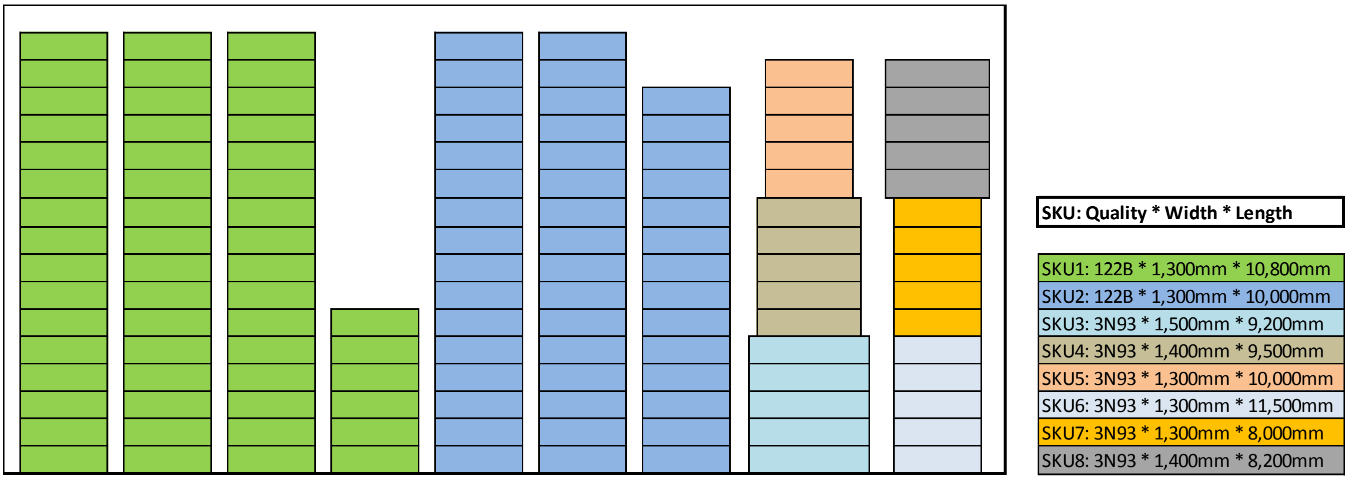


Figure 5.11 - Cross-cut view of hot box after Example 5.1

5.2.1.2 Experimental Design of Stochastic Data Simulation Model

In this simulation model we have an $m \times n$ experimental design. Here, m resembles the number of slab widths we use and n the number of hot box allocation rules. By increasing the number of widths for an experiment, we increase the number of SKUs that are sent to the hot box. Since we only allow uniform stacks in the hot box, we expect the fill rate to decrease with an increasing number of SKUs (i.e. with a higher number of SKUs, the volume per SKU will decrease, hence the probability that we can optimally use storage capacity is expected to decrease as well). By using three smart allocation rules (see Section 4.3.2), we want to optimize hot box usage in terms of fill rate and throughput.

Table 5.2 depicts the various experiments. Since we have $n = 3$ hot box allocation rules (see Section 4.3) and we use $m = 8$ different widths, we have $8 \times 3 = 24$ experiments.

# Slab	Hot Box Rule		
Widths	1	2	3
1	Exp 1	Exp 9	Exp 17
2	Exp 2	Exp 10	Exp 18
3	Exp 3	Exp 11	Exp 19
4	Exp 4	Exp 12	Exp 20
5	Exp 5	Exp 13	Exp 21
6	Exp 6	Exp 14	Exp 22
7	Exp 7	Exp 15	Exp 23
8	Exp 8	Exp 16	Exp 24

Table 5.2 - Experimental design

Slab	Slab Length		Average	Overall
Width	8.000	10.300	Weight	Average
1.400	19,4	25,0	22,2	22,2
1.300	18,0	23,2	20,6	21,4
1.500	20,8	26,7	23,8	22,2
1.200	16,6	21,4	19,0	21,4
1.600	22,2	28,5	25,3	22,2
1.800	24,9	32,1	28,5	23,2
1.100	15,2	19,6	17,4	22,4
1.700	23,5	30,3	26,9	23,0

Table 5.3 – Weight changes because of adding widths

Furthermore, we use five qualities and two different lengths. This means that in experiment 1, 9, and 17, we have at most $5 \times 2 \times 1 = 10$ different SKUs and in experiment 8, 16, and 24, we have at most $5 \times 2 \times 8 = 80$ different SKUs. Since adding slab dimensions in increasing order of slab width would yield lower average slab weights for the first experiments, we shuffled the widths in such a way that each experiment has an average slab weight of 22 to 23 tons (see Table 5.3). For example, by using widths 1,400, 1,300 and 1,500 in experiment 3, 11, and 19, we guarantee that the average slab weight is 22.2.

5.2.2 Simulation Setup

As explained in Section 4.1, the approach of both simulations is rather different. The fact that we use historical data for the first simulation means this is a so-called 'terminating simulation'; the parameters are determined by a fixed set of data and the simulation stops by a terminating event (i.e. charging the last slab of the simulated quarter). Since we have only one set of data of 13 weeks, we cannot perform any replications and the run length is fixed to 13 weeks. However, in a certain sense, there is a warm-up period. The 13 weeks of data namely resemble the period in which slabs were charged. However, some of these slabs were casted prior to the period of 13 weeks. This means we have to run the model for more than 13 weeks. In the first weeks we cast slabs for initial stock (these slabs will probably have a large throughput time), but we only measure performance over the last 13 weeks in which we actually charge slabs (see Figure 5.12).

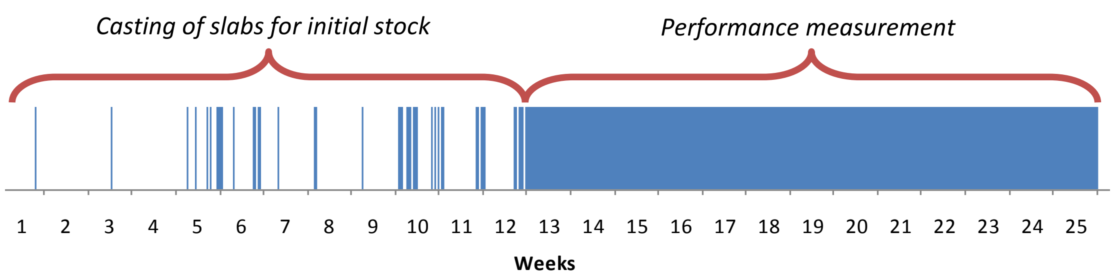


Figure 5.12 - Casting activity in historical data simulation (on behalf of warm-up period)

Whereas it was not really possible to set up the model based on historical data according to the characteristics of a thorough simulation model (see Section 2.3), this is possible for the model based on stochastic data. In this model we use several probability distributions. So, to come up with reliable performance measurement, we have to determine the run length and warm-up period (Section 5.2.2.1) and the number of replications (Section 5.2.2.2). We summarize the entire setup of the stochastic simulation model in Section 5.2.2.3.

5.2.2.1 Run Length and Warm-up Period for the Stochastic Simulation Model

From the moment we start our simulation, we create demand for the 10th day in the horizon. This means that if we start the simulation at day $i = 1$, we cast the first slabs at day $i = 10$. Furthermore, since the maximum time span for which we cast slabs is five days, this means that on day $i = 15$ we have casted each quality at least once. At day $i = 20$, we have casted each quality at least twice, meaning that we have finished at least one production cycle (casting → storage → charging) of one quality. This also means that we do not depend on initial conditions (i.e. an empty hot box) anymore. Hence, we set out warm-up period to 21 days (i.e. three weeks). Since our model does not require very long computation time, we decide to run our model for 52 weeks (i.e. the run length). Because we are able to choose such a long run length, we expect that volatility in demand levels out during the run.

5.2.2.2 Number of Replications for the Stochastic Simulation Model

To determine the number of replications, we use the sequential procedure (Law, 2006). With this procedure, we compare the confidence interval width to a relative error. We apply the procedure on the experiments with the maximum number of SKUs (i.e. experiment 8, 16, and 24), because we expect the most volatility in performance in these experiments. Appendix 6 explains the procedure in more detail. From the appendix, we conclude that, at a confidence interval of $1 - \alpha = 95\%$ and a relative error of $\gamma = 2.5\%$, only 4 replications satisfy for our model. However, since performance can differ per experiment and our model does not require long computation time, it is safer to use more replications. So, we decide to make 5 replications.

5.2.2.3 Entire Setup of Simulation Based on Stochastic Data

Now we have determined the warm-up period, run length, number of replications, and the number of experiments, we can draw a similar figure as in Section 2.3.2 (see Figure 5.13).

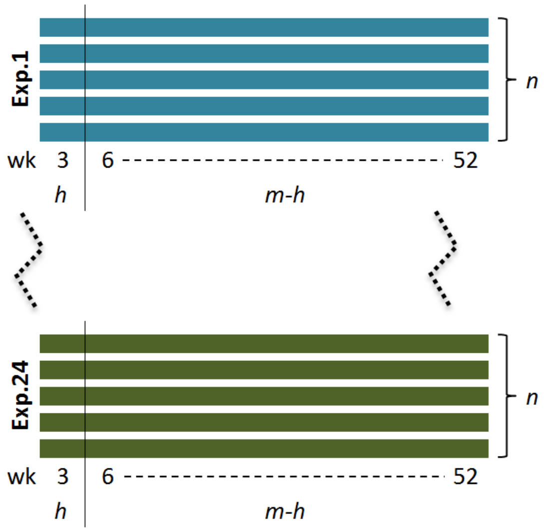


Figure 5.13 - Experimental setup of stochastic simulation model
N.B. Experiments 2 to 23 are omitted from this figure

We have $n = 5$ replications of $m = 52$ weeks. From these 52 weeks, we delete $h = 3$ weeks of warm-up period data. For each experiment, we calculate the average performance of 5 replications. This performance is explained in Section 6.2. One run (i.e. 52 weeks) takes approximately 2.5 minutes of computation time. This means that performing 5 replications of 24 experiments lasts around $5 \times 24 \times 2.5 \approx 300$ minutes or around 5 hours.

5.3 Conclusions

We explained how we translated our models from Chapter 4 to discrete event simulation software. Furthermore, we explained how we perform various experiments in both simulation models. Finally, we expounded on the experimental setup of both simulations. The results of both simulation models and the answer to research question 4 follow in Chapter 6.

6 Results

This chapter elaborates on the results of both simulation models. We explain the performance on the KPIs that we in explained in Section 4.4. In Section 6.1 we explain the results of the simulation based on historical data. In Section 6.2, we interpret the results of the simulation based on stochastic data. In Section 6.3, we combine the results of both models and explain the expected benefits of those results. Finally, in Section 6.4, we draw conclusions from the simulation results.

6.1 Results of the Simulation Model Based on Historical Data

Table 6.1 shows the performance of the simulation model based on historical data on the KPIs defined in Section 4.4. First, we validate the model with the real quarter. As explained in Section 3.2, during the second quarter 32% of all slabs was charged within 24 hours (category 1, see Figure 3.18) and nearly 70% was charged within 72 hours after casting. If we look at the throughput time categories of the benchmark experiment (i.e. Exp. 0), we see this matches the real data. Furthermore, the average charging temperature over the real second quarter was 157°C, so our model gives higher charging temperature (around 30°C). This is caused by the temperature calculation; in the model we use formula (1) (see Chapter 3) to calculate the charging temperature of a slab. For this purpose we use an average stack height of 6 slabs ($n = 6$). In reality this number appears to be very volatile, resulting in a lower average charging temperature. To judge experiments 1 to 13, we will compare them with experiment 0.

Exp.	1. Fill rate of HB	2. Average TPT in HB	3. St.Dev. of TPT in HB	4. Throughput of HB	5. Cannibali-zation	6. % Hot Charging	7. Average Temperature	8. Throughput time categories		
								≤ 24hrs	≤ 72hrs	> 72hrs
0	0,0%	-	-	-	0,0%	32,9%	190,23	32,9%	36,6%	30,5%
1	17,3%	28,99	29,42	412	9,0%	38,3%	209,39	32,6%	36,9%	30,5%
2	32,9%	31,34	32,21	700	15,4%	42,1%	223,22	32,4%	37,0%	30,6%
3	41,1%	28,67	31,11	908	24,3%	43,4%	230,02	32,2%	37,2%	30,6%
4	45,4%	26,83	31,35	1.034	32,2%	43,4%	232,07	32,1%	37,2%	30,7%
5	21,8%	27,50	26,73	565	13,7%	39,9%	216,00	32,5%	37,0%	30,5%
6	20,9%	28,50	27,53	527	11,6%	39,7%	214,76	32,5%	37,1%	30,5%
7	21,5%	29,49	28,79	512	10,5%	39,7%	214,54	32,4%	37,1%	30,5%
8	24,8%	29,82	28,45	575	11,3%	40,7%	217,93	32,4%	37,2%	30,5%
9	26,9%	30,18	28,54	612	11,8%	41,3%	220,03	32,4%	37,1%	30,5%
10	41,7%	30,29	31,78	855	20,2%	43,6%	229,72	32,3%	37,2%	30,6%
11	44,2%	29,32	31,37	921	23,5%	43,9%	231,75	32,2%	37,2%	30,5%
12	21,0%	29,77	29,12	469	9,5%	39,3%	212,86	32,6%	36,9%	30,5%
13	44,5%	36,25	34,58	946	27,4%	43,5%	230,24	32,6%	36,7%	30,7%

Table 6.1 - Results from simulation based on historical data

These are the most important conclusions we draw from Table 6.1:

- We are able to increase the percentage hot charging from 32.9% to at most 43.9%
- We can send up to 1,000 slabs per week through the hot box (Exp. 4). This equals around 20% of quarterly volume (not visual in Table 6.1).
- We can realize an average temperature increase of 40°C
- Various mixes of SKUs and volume approximate the 11%-point increase in hot charging and 40°C increase in temperature (experiments 3, 4, 10, 11 and 13)

- Allowing too many SKUs in the hot boxes (experiment 12) has a negative influence on fill rate and increase of the hot charging percentage
- Relying on throughput data of an earlier quarter (experiment 5) does not work efficiently
- Using a fixed percentage of the volume of a large set of frequent SKUs gives the best result for this static model (experiments 3, 4, 10, 11 and 13)

Knowing that (1) the average slab weight over the second quarter was 21.9 ton, (2) we have charged approximately 62,000 slabs, and (3) that each 100°C increase in charging temperature saves us XXX GJ/ton (see Section 3.4), we save XXX GJ of gas. This equals the consumption of around XXX Dutch households and would have saved Tata Steel €XXX in the second quarter of 2011.

Next to savings in gas, a higher percentage hot charging also results in capacity increase of the furnaces. Appendix 7 shows a table, set up by Van der Meulen (2009), to calculate the expected capacity increase. Our 44% hot charging consisted of approximately 15,400 direct hot charging slabs and 12,000 indirect hot charging slabs. The first had an average temperature of around 260°C, the latter an average temperature of around 450°C. This means, that on average we charged 44% of the volume hot at a temperature of $15{,}400/27{,}400 \times 260 + 12{,}000/27{,}400 \times 450 \approx 340℃$. If we interpolate these numbers in Table A7.2 (see Appendix 7), we find a capacity increase of around XXX%. Over a yearly WB2-volume of XXX kTon, this still means around XXX kTon, or a week of extra production capacity.

We proved that we could have increased the hot charging percentage by 11% if the hot boxes were available in the second quarter, even without changing planning rules and without making dynamic choices. For example, in this model we were not able to send a non-predetermined SKU to the hot box in case there was space available at a certain point in time. In other words, we might have missed opportunities to further increase the hot charging percentage. In the stochastic simulation model we diminish this phenomenon by sending all SKUs to the hot boxes. Section 6.2 explains the results of this simulation model.

6.2 Results of the Simulation Model Based on Stochastic Data

This section shows the performance of the hot boxes on (1) fill rate, (2) average throughput, and (3) average throughput time in the hot box. We use three slab allocation rules and a varying number of SKUs (i.e. per experiment we use five qualities and two lengths and add one width each experiment).

Figure 6.1 depicts the fill rate of the hot box in each of the 24 experiments. Although some differences are marginal, we see that:

- A higher number of SKUs (over the same volume) negatively affects the fill rate
- HB rule 2 (i.e. rounding the number of slabs to a multiple of maximum stack height) is least sensitive for an increasing number of SKUs
- HB rule 2 performs best with respect to hot box fill rate

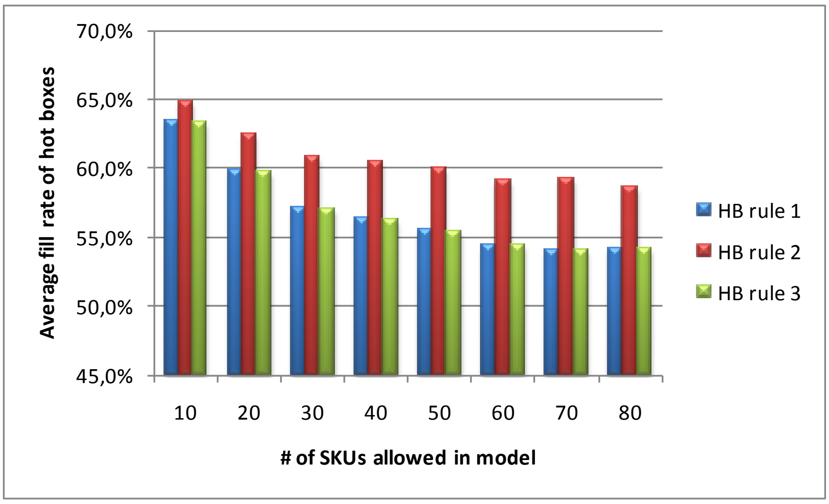


Figure 6.1 - Influence of number of SKUs on hot box fill rate per hot box allocation rule

Figure 6.2 shows the average throughput of the hot boxes in each of the 24 experiments. Again, HB rule 2 performs better than allocation rules 1 and 3, but we see high variation in the results with respect to the number of SKUs. We think this has one major reason: they way we add SKUs each experiment influences throughput times, both in the hot boxes as of the entire volume, too much (see Figure 6.3 and Figure 6.4).

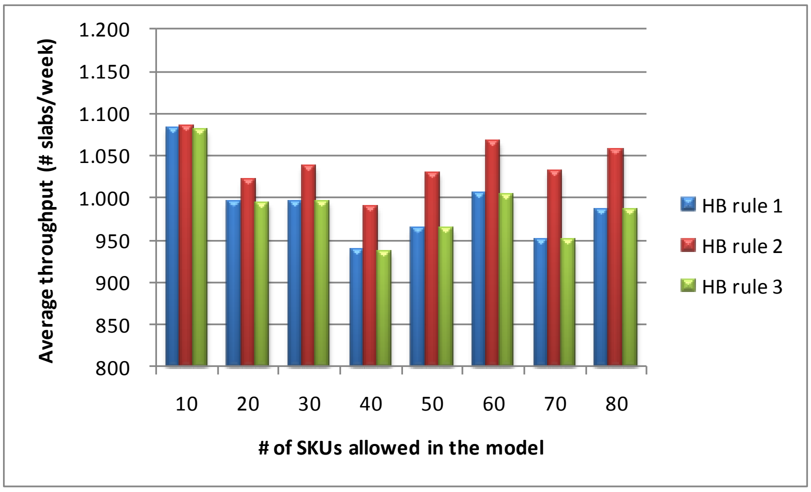


Figure 6.2 - Average throughput of hot boxes (in slabs/week)

As explained in Section 5.2.1.2, we add slab widths to the model to create more SKUs. For this purpose we shuffled the sequence of widths such that the overall average slab weight is not varying too much. However, the small range in average slab weight (21.4 to 23.2 tons, see Table 5.3) does affect the model.

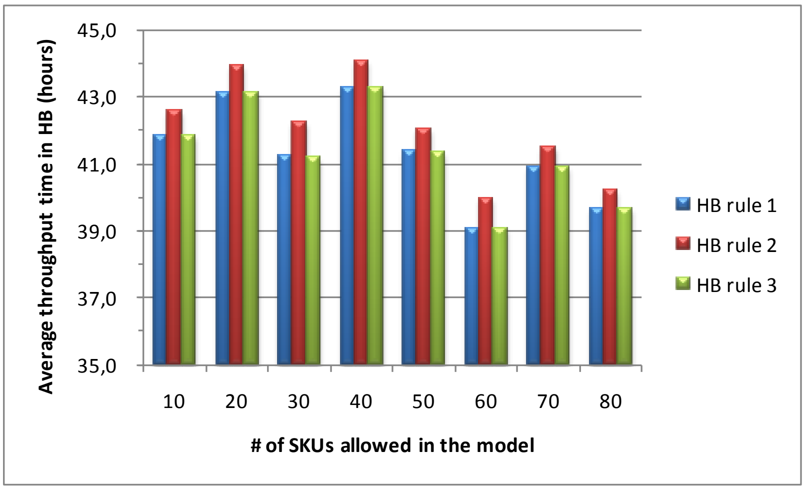


Figure 6.3 - Average throughput time in the hot box

If we compare the average slab weight per experiment (Table 5.3) to the throughput times (e.g. Figure 6.4), we see that throughput time increases if average slab weight decreases (e.g. experiments 10 and 12, i.e., 20 and 40 SKUs). The same holds for a large average slab weight (e.g. experiment 14, i.e. 60 SKUs). This phenomenon is caused by the fact that we create slab demand in number of slabs, but when deciding to cast slabs, we look at volume. For example, 10 slabs in experiment 2 will have an average weight of 214 tons, whereas 10 slabs in experiment 6 will have an average weight 232 tons. However, for both experiments we use the same maximum series length. Hence, in experiment 2 we probably cast slabs for a longer period than in experiment 6, resulting in shorter throughput times in the latter experiment.

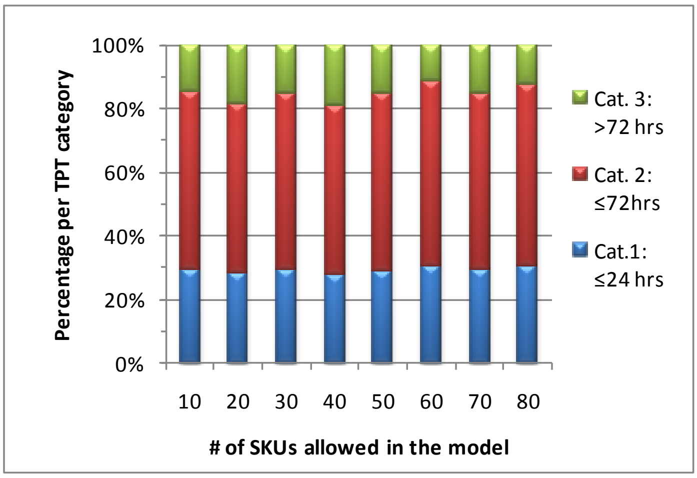


Figure 6.4 - Throughput time categories of entire volume (under hot box rule 2)

A higher throughput time in the hot box means the hot box is blocked more often for new slabs. Hence the average throughput (in number of slabs per week) goes down (related to Little's Law, see Section 2.1.4). To check whether the adding of SKUs is really causing the high variation, we performed a sensitivity analysis. Appendix 8 provides this sensitivity analysis.

6.3 Comparison and Combination of Results

Table 6.2 shows the characteristics of experiment 11 of the historical data simulation and the results of experiment 13 of the stochastic data simulation (i.e. 50 SKUs and using the second slab allocation rule for the hot boxes). If we look at the throughput times, we see that for the 45 SKUs in simulation 1, 82% was charged within three days. This is comparable to the throughput of the 50 SKUs in the second simulation. However, in the first simulation we charge a relatively large volume in the first 24 hours compared to the second simulation. This results, among other things, in a shorter throughput time in the hot boxes with a relatively large deviation. Even though the average throughput time in the hot box for the second simulation was larger – also resulting in a higher fill rate – we were able to charge on average 110 slabs per week more through the hot boxes. From this we conclude that it must be possible to reach a higher percentage of hot charging than we reached in the historical data simulation (i.e. more than 11 percentage point increase, as explained in Section 6.1).

	% Charged within			Throughput time in Hot Box		Fill rate	Average # HB
	24 hrs	48 hrs	72 hrs	μ (TPT HB)	σ (TPT HB)	Hot Box	slabs per week
45 SKUs of exp. 11 Sim. 1	41,0%	71,8%	82,0%	29,8	29,1	44,2%	920
50 SKUs of exp. 13 Sim. 2	29,0%	N/A	84,7%	42,0	N/A	60,0%	1.030

Table 6.2 - 45 SKUs of simulation 1 vs. 50 SKUs of simulation 2

In the historical data simulation we charged approximately 62,000 slabs in 13 weeks. From this volume, around 15,400 slabs were direct hot charging (i.e. without hot box usage, within 24 hours) and 12,000 slabs indirect hot charging (i.e. through the hot boxes). This resulted in a hot charging percentage of (experiment 11):

$$\frac{15{,}400 + 12{,}000}{62{,}000} \times 100\% \approx 44{,}2\%$$

In the stochastic simulation model we charged approximately 99,100 slabs in 49 weeks. From this volume, around 50,500 slabs were indirect hot charging. This means that we charged on average 1,030 slabs per week through the hot boxes.

If we now assume that we would have been able to (plan and) cast the hot box determined SKUs in a more dynamic way, then the stochastic simulation model implies that we would have been able to charge $13 \times 1{,}030 = 13{,}390$ slabs during the second quarter. This would have resulted in a hot charging percentage of:

$$\frac{15{,}400 + 13{,}390}{62{,}000} \times 100\% \approx 46{,}4\%$$

Since the 14,170 hot box slabs have an average charging temperature of 450°C and the average charging temperature of non-hot box slabs in the historic data simulation was 180°C, we can realize a temperature of:

$$\frac{13{,}390}{62{,}000} \times 450 + \frac{62{,}000 - 13{,}390}{62{,}000} \times 180 \approx 238°\mathrm{C}$$

This temperature increase of 47°C leads to energy savings of approximately € XXX and, with an average temperature of hot charged slabs of 350°C, a capacity increase of XXX% (see Appendix 7), or XXX kTon on a yearly basis.

An important remark to these results is that the large variance in SKU-frequency and SKU-volume in the historic data simulation is causing a lower hot box throughput. This variance is caused by volatility in demand, which is flattened out in the stochastic simulation. Hence, the increase of 33% (current situation) to 46% (achieved with stochastic simulation model) hot charging has to be valued with care. On the other hand, as shown in Appendix 8, the throughput time in the hot box has a major impact on the throughput of the hot box. So if we are able to increase the average throughput from 1,030 slabs per week to 1,100 (by decreasing the throughput time in the hot box), then a hot charging percentage of $(15{,}400 + 14{,}300)/62{,}000 \times 100\% \approx 48\%$ is possible.

6.4 Conclusions

The results of Sections 6.1 to 6.3 showed that a significant increase in hot charging percentage can be reached by using hot boxes. With this information we can answer research question 4:

4. What hot charging performance can be reached by the use of hot storage boxes?

We were able to reach 44% hot charging in the simulation based on historical data, which is 11 percentage points more than in the current situation. We also showed that the hot charging percentage can be further optimized to 48%, if there is a stable supply of hot box destined slabs and we can allocate slabs to the hot box in a more dynamic way (as in the simulation based on stochastic data). This results in a quarterly savings of approximately € XXX

7 Implementation

This chapter describes what changes in organization, planning, and the current way of working are necessary to gain benefit from future hot boxes. First, we describe the necessary changes in Section 7.1. Second, we expound on a pilot test of two weeks we performed at the AOV (Section 7.2). We end up with drawing conclusions from this chapter in Section 7.3.

7.1 Control Rules for Hot Boxes

In this section we expound on the necessary changes to be able to work with hot boxes. First, we describe the allowable content (Section 7.1.1). Then, we describe how slabs can be allocated to the hot boxes (Section 7.1.2). In Section 7.1.3, we describe how slab selection for a rolling schedule can be controlled. Finally, in Section 7.1.4, we explain how the hot box performance can be measured.

7.1.1 Allowable Content

Table 7.1 shows what prerequisites determine whether a slab is allowed in the hot box. If a slab meets all prerequisites, then it is in essence allowed in the hot box. Since it is on forehand not always known what part of SKU-volume will be charged between 24 and 72 hours after casting, it might be necessary to work with expected percentages. Furthermore it can occur that a slab meets all prerequisites, but the hot box is full or blocked for this SKU. In that case, the slab must be placed outside the hot box.

Prerequisite	Reason
Expected Throughput time: 24 < E[TPT] ≤ 72 hours (category 2)	Slabs younger than 24 hours are already hot and do not need to be stored in a hot box. Slabs older than 72 hours occupy hot box capacity too long.
Slab is not A-slab	A-slabs are PH hall destined
Slab is not (non-ordered) Drop quality	These slabs have an E[TPT] >> 72 hours
Slab is not B-quality	These slabs have an E[TPT] >> 72 hours
Slab has standard dimension	Non-standard slabs are low-frequent and in low volume
# slabs in hot box + # slabs casted ≥ 16	To create (large) uniform stacks

Table 7.1 - Prerequisites for hot box destined slabs
N.B. >> means 'much larger than'

7.1.2 Slab Allocation

To ensure that the right slabs are sent to the hot box, it must be possible to distinguish between hot box destined and not hot box destined slabs. For this purpose, we suggest to use the following destination labels:

- **WBH**: Chosen Hot Box slabs (because they meet hot box prerequisites)
- **WBV**: Obliged Hot Box slabs (because of quality issues)
- **WB2**: Normal WB2 destined slabs (to be stored in the PE/PF hall)
- **WBW**: slabs with expected throughput time of less than 24 hours (direct hot charging)

WBV-slabs must always be placed in the hot box, even though this means that hot box content (i.e. WBH-slabs) must be removed. This (exceptional) situation must either be programmed in POSS, or the PoCo at the AOV must clear space for the WBV-slabs, when he sees WBV-slabs are being cast.
WBH-slabs can only be stored in the hot box if there is space available. If this is the case than we suggest the following allocation rules:

- Only allow uniform stacks: adjust POSS such that for WBH-slabs only stacks of one SKU are allowed. For WBV-slabs delving is allowed.
- When placing, try to avoid creating stacks of a few slabs (e.g. suppose we have a volume of 35 slabs of one SKU. Then, rather create two stacks of 16 slabs in the hot box and three slabs outside the hot box, then creating a third (low) stack in the hot box). For this decision, it is important that POSS 'corresponds' with the OSF2 casting software, so that can be determined what volume is in the pipeline (WIP) for a certain SKU
- To keep stock 'clean' it is better to re-label WBH-slabs that could not be placed in the hot boxes, to WB2.

7.1.3 WB2-scheduling

To be able to distinguish between slabs (of the same SKU) in a hot box and slabs in the PE/PF hall, it is necessary that the prioritizing rule, as explained in Section 4.2 (Figure 4.3), is implemented. Figure 7.1 shows two options for implementing the prioritizing rule.

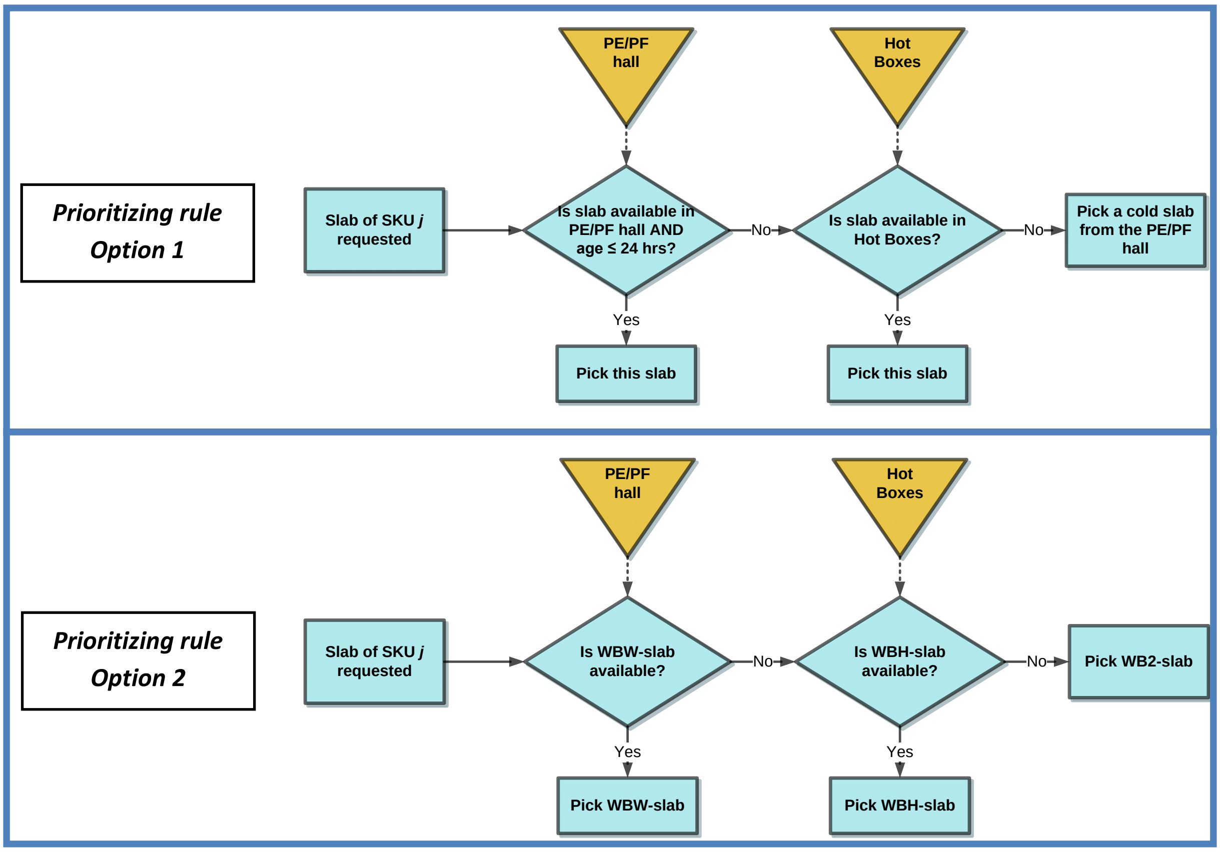


Figure 7.1 - Two options for implementing the prioritizing rule

Both options can be implemented in either POSS or the Bèta Planner (WB2). However, for option 2 it is necessary that a slabs destination label changes from WBW to WB2 if it becomes older than 24 hours. In the current situation, the prioritization rule must be implemented in the Bèta Planner, since customer orders in the rolling schedules are linked to a unique slab (i.e. slab-ID). However, based on the SKU-principle and keeping stock generic, we suggest that slabs are no longer coupled to slab-IDs, but to slab specifications. Then POSS can decide which slab to pick (using the prioritizing rule) and keep stock 'clean' more easily. The latter will solve the mixed stack problems, as depicted in Section 3.3. The frequency types (i.e. Wl, Wh, Vl and Vh) can then be reduced to 'low-frequent' and 'high-frequent'.

7.1.4 Performance Measurement

To evaluate the performance of the hot boxes we suggest the following set of key performance indicators (KPIs):

- Fill rate of hot box: percentage of maximum hot box capacity used during a week
- Throughput: number of slabs charged out of hot box per week
- Throughput time in the hot box: time each slab was stored in the hot box (N.B. this is something else than the general throughput time between casting and charging, since it excludes transportation time from and to the hot box)
- Delving factor in the hot box (not included in the simulation models, but in reality necessary to check whether uniform stacks are created)

7.2 Pilot: Virtual Hot Boxes

Since the simulation models are mainly focused on the (maximum) content of the hot boxes and not on operational rules, we set up a pilot of two weeks to test the logistical behavior of the production chain as if the hot boxes were already present. During these two weeks:

- We labeled all standard slabs of a fixed number of order qualities as WBW (N.B. WBH was not available yet). All other slabs, even obliged hot charging, were labeled WB2 or else
- We marked three sections as hot boxes in the PF hall (i.e. virtual hot boxes, see Figure 7.2)
- We programmed POSS, such that it only stored WBW-slabs in the virtual hot boxes
- We asked the SKV-personnel to load trains with as much as possible WBW-slabs
- We asked the PoCo at the AOV to receive WBW-trains at the PF hall
- We programmed a delving factor calculation for WBW-slabs in POSS

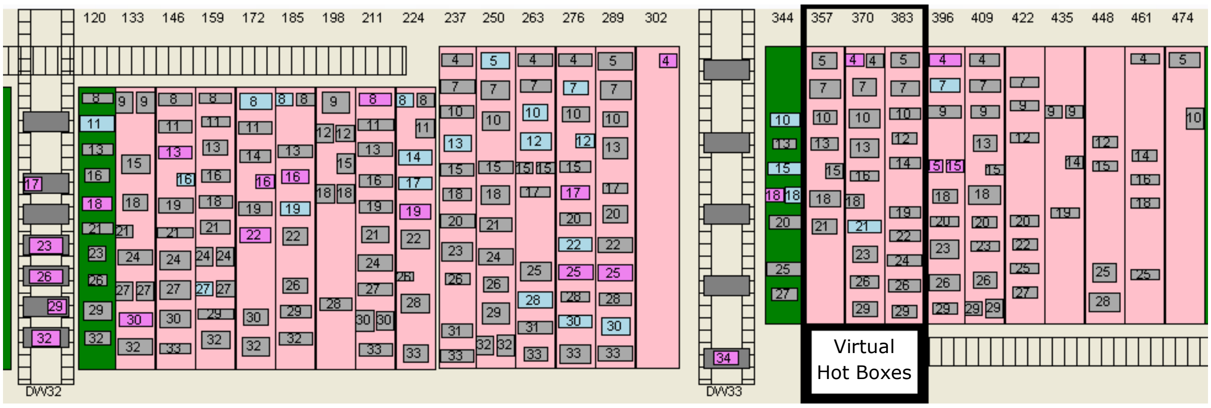


Figure 7.2 - Virtual hot boxes in the PF hall

Goal of the pilot was to test the logistical performance, and examine throughput times and delving factor of all WBW slabs. With the pilot, we wanted to answer the following pilot questions:

1. *Are all expected WBW-slabs actually labeled 'WBW'?*
2. *Are all WBW-slabs loaded on the same train(s)?*
3. *Are all WBW-trains sent to the PF-hall?*
4. *Are uniform stacks formed in the virtual hot boxes?*
5. *Are the throughput times of WBW-slabs comparable to (normal) WB2-slabs?*
6. *What is the delving factor in our virtual hot boxes?*

We will not discuss the entire pilot in detail, since many things went wrong. The result was that a thorough (data) analysis was not possible. However, we can still learn from the following observations:

I. A planned and expected series of a WBW-quality suddenly became VRD-G (tactical stock), because of demand changes downstream the supply chain
   - **Result**: our virtual hot boxes remained empty

II. Once a train with WBW-slabs was formed, the PoCo inattentively sent the train to the PE hall, where subsequently the WBW-slabs were stored
   - **Result**: our virtual hot boxes remained empty

III. Again, a train with WBW-slabs was formed, but this time the cranes in the PF hall were in maintenance. Hence, the PoCo was forced to sent the train to the PE hall
   - **Result**: our virtual hot boxes remained empty

IV. When casting a WBW-quality, its corresponding drop-qualities also became WBW. In many cases this was only a small volume
   - **Result**: these small volumes disrupted the creation of uniform stacks

V. Once WBW-slabs in the virtual hot boxes became order-coupled or programmed in a rolling schedule, the destination code changed to WB2
   - **Result 1**: in our hot boxes unnecessary delving occurs, because of the phenomenon explained in Section 3.3 (Figure 3.12).
   - **Result 2**: our delving factor calculation for WBW-slabs was an empty data sheet

VI. Since OSF2 planning was not instructed to take the hot boxes into account, the planning and length of series was not adjusted to hot box usage
   - **Result:** at a certain period in time, the hot boxes were overloaded with WBW-slabs, whereas at another moment in time, the hot boxes remained empty

With these observations we are still able to answer most of the pilot questions:

1. *Are all expected WBW-slabs actually labeled WBW?*
   No, due to adjustments in planning downstream, but also in OSF2-planning, not all expected WBW-slabs actually received destination label WBW
2. *Are all WBW-slabs loaded on the same train(s)?*
   Mostly, yes. The SKV-personnel proved to be able to compose trains with (mainly) WBW-slabs
3. *Are all WBW-trains sent to the PF-hall?*
   No, because of human acting and maintenance (planning) (see observation II and III)
4. *Are uniform stacks formed in the virtual hot boxes?*

Mostly, yes. However, some stacks became mixed stacks because of order coupling or presence of drop-quality slabs

5. *Are the throughput times of WBW-slabs comparable to (normal) WB2-slabs?*
   Since we did not analyze the data, we are not able to give a solid answer to this question
6. *What is the delving factor in our virtual hot boxes?*
   Since the destination code of programmed slabs changed to WB2, our delving factor calculation did not work. However, we can say that there is being delved in the hot boxes concluding from observation V

7.3 Conclusions

Now we have translated the simulation model back to reality and performed a pilot, we can answer the last research question, i.e. research question 5:

5. How can the findings from this research study be translated into an operational concept?

To send slabs, which meet the hot box requirements, to the hot boxes we suggest that different destination labels are used. This makes it easier to distinguish between hot box and non-hot box slabs and between obliged hot charging and chosen hot charging slabs.

Furthermore, we suggest that only uniform stacks (of one SKU) are allowed in the hot boxes. This will prevent delving and, hence, unnecessary ‘open’ time of the hot box. An exception can be made for obliged hot charging slabs, since they often arrive in a small quantity.

Third, it is important to distinguish between a hot slab in the hot box and a hot slab in the PE/PF hall. For this purpose, we suggest to implement the following prioritization rule:

1) If available, pick a hot slab (slab age $\leq$ 24 hours) from the PE/PF hall
2) If 1) is not available, then pick a hot slab from the hot box
3) If 1) and 2) are not available, then pick a cold slab from the PE/PF hall

Finally, we conclude from the pilot that these operational rules do not work properly in the current situation yet. The two main problems were: unexpected changes in production planning and human intervention during transport of slabs to the virtual hot box. We also conclude that the mixed stack problem, as explained in Section 3.3.3, occurs at the virtual hot box as well, resulting in unnecessary delving.

8 Conclusions and Recommendations

In this research we analyzed how future hot boxes can contribute to an increase in the percentage of hot charged slabs at Tata Steel IJmuiden. We started with positioning the research in a theoretic framework. This was followed by a thorough description of the current situation. Then, we described how we used two different simulation models to determine a good product mix and a desirable fill rate for the hot boxes. Finally we carried out a pilot to test logistical performance. This chapter finalizes the research by drawing conclusions from the research (Section 8.1) and giving recommendations for implementation (Section 8.2). We end up with some suggestions for further research (Section 8.3).

8.1 Conclusions

The conclusions are split up in conclusions drawn from the simulation models (Section 8.1.1) and conclusions drawn from the pilot and, hence, the analysis of the current way of working (Section 8.1.2). Conclusions from the simulation models are mainly concerning hot box content. The conclusions from the pilot and current situation are mainly concerning operational control rules (i.e. well designed supply and removal of slabs). With these conclusions we can answer the main research question in Section 8.1.3.

8.1.1 Conclusions from the Simulation Study

Under the assumption of creating uniform stacks and based on the first simulation, we are able to increase the percentage hot charging with at least 11%. Thereupon, based on the results of the second simulation, we conclude that the hot boxes were not used optimally in the first simulation and that the percentage hot charging can be further increased up to 15%. The difference between the two simulations originates in several facts:

- The first simulation is a static model with a fixed number of chosen slab types
- The second simulation is more dynamic and can anticipate on production in the short future
- The first simulation is based on real data and hence taking into account the (large) daily volatility in production, demand and slab availability
- In the second simulation volatility is mostly flattened out. The result is a more stable production environment, but with the same throughput characteristics as the first simulation model

The benefits of both simulations are depicted in Table 8.1. (N.B. capacity increase calculations have not been validated enough to draw solid conclusions).

	% Hot Charging	Total Average Temperature	Annual Energy Savings	Annual Capacity Increase
Current situation[1)]	33%	170°C		
1st Simulation	44%	231°C[2)]		
2nd Simulation	46%	238°C[2)]		

Table 8.1 - Benefits from increasing hot charging due to the use of hot boxes

1) Current situation is based on second quarter of 2011

2) Temperature calculation in the simulation models is approximately 20°C higher than reality. Hence, savings are calculated based on respectively 41°C and 48°C increase to the current situation

These benefits were reached by storing all obliged hot charging slabs and a set of chosen hot box slabs with the following characteristics (both are hot box destined slabs):

- Cycle stock, so only slabs that currently have destination label WB2
- Common order qualities, so no drop- or B-qualities or rare order qualities
- Standard dimensions as depicted in Table 3.1.
- Expected throughput time: $E[TPT] > 24$ hours
- Considerably large volume to create uniform stacks (1 stack consists of 16 slabs)

The way slabs were stored in the hot boxes, and the way they are picked from the hot boxes fulfilled the following requirements:

- All hot box destined slabs were loaded on PF hall destined trains
- Chosen hot charging slabs were stored in uniform (of one SKU) stacks in the hot boxes
- Obliged hot charging slabs were stored in mixed stacks, because of their small volume
- Best results were reached, when the arriving volume of a certain SKU was rounded down to a multiple of stack height
- Obliged hot charging slabs were always stored in the hot boxes, even though this meant removing other slabs from the hot boxes
- When selecting slabs for a rolling schedule, a prioritization rule was used in order to give precedence to hot slabs:
    1) If available, pick a hot slab (slab age $\leq$ 24 hours) from the PE/PF hall
    2) If 1) is not available, then pick a hot slab from the hot box
    3) If 1) and 2) are not available, then pick a cold slab from the PE/PF hall

8.1.2 Conclusions from both Pilot and Analysis of Current Situation

The pilot had a length of two weeks. During this period a selected number of qualities received a unique destination label (i.e. WBW). In the PF hall, in the sections where the future hot boxes will be built, an area was created (i.e. the virtual hot boxes) in which only slabs with this unique destination label were allowed.

Since many things went wrong, we are unfortunately not able to draw conclusions from a data analysis. However, we can draw conclusions from observations:

- The route of bringing slabs to the hot boxes can be easily disturbed by human inattention
- Making a fixed number of qualities hot box destined causes emptiness or overload of the hot boxes at certain moments (the same as in the historic data simulation)
- The phenomenon of wrongly composed stacks (Section 3.3) also occurs in the virtual hot boxes
- This was mainly the result of coupling customer orders to specific slabs

8.1.3 Answer to Main Research Question

Now we have drawn the most important conclusions and answered the research questions in the previous chapters, we can answer the main research question:

"What factors are influencing hot charging through hot boxes and how to deal with these factors to maximize the overall average slab temperature using hot boxes?"

The most important factors influencing hot charging through hot boxes are:

- Allowable content for the hot boxes
- Allocation of slabs, both to and in the hot box
- Throughput time of slabs
- Distinction between hot slabs in the hot box and hot slabs in the PE/PF hall

In this research we cope with these factors by using the following rules and solutions:

- We send all obliged hot charging SKUs to the hot boxes
- We use a set of fast moving SKUs as 'chosen hot charging'
- From these SKUs, we send a fraction of the volume to the hot boxes by using different destination labels
- In the hot box, we create uniform stacks for chosen hot charging slabs and mixed stacks for obliged hot charging slabs
- We round the batch size down to a multiple of stack height
- When selecting slabs for a rolling schedule, we use a prioritization rule to distinguish between a hot slab in the PE/PF hall and a hot slab in the hot box

With these rules we are able to increase the hot charging percentage from 33% to 46%, resulting in an overall temperature increase of almost 50°C and an annual saving of approximately € XXX.

8.2 Recommendations

In order to gain maximum benefits from the future hot boxes, we recommend a couple of actions to be taken before the hot boxes are built:

- Stop coupling customer orders to physical stock. This holds for the entire stock. A motive for this is that slabs of the same SKUs are interchangeable. Hence, customer orders must be coupled to SKUs instead of specific slabs
- Use the following slab destination labels to distinguish between hot and cold slabs:
  - **WBV**: Obliged Hot Box slabs (because of quality issues)
  - **WBH**: Chosen Hot Box slabs (because they meet slab requirements, as explained in Section 8.1)
  - **WBW**: slabs with expected throughput time of less than 24 hours (direct hot charging)
  - **WB2**: Normal WB2 destined slabs (to be stored in the PE/PF hall)
- Computerize that WBV- and WBH-slabs are put on the same train and brought to the PF hall. Intermediate solution might be to build in a pop-up/warning system to prompt personnel that they are working with hot box destined slabs
- Computerize in the BètaPlanner, or in POSS if physical order coupling is relinquished, the prioritization rule to distinguish between hot slabs in the halls, hot slabs in the hot box and cold slabs
- Investigate the possibilities to better link OSF2-planning to WB2-planning (see Section 8.3)

8.3 Future Research

During the research we came across a couple of matters that were out of scope or noticed too late to take action. In this section, we recommend to carry out further research to two important issues.

First, an extensive research to the scheduling requirements of the OSF2 can be performed. The general expectation is that the hot charging percentage can be increased by aligning the OSF2 planning with the WB2 planning. Further research can expose how changes in OSF2 planning affect hot charging and what is this (financial) effect downstream the supply chain.

Second, we recommend a warehousing research to explore whether stock handling at the AOV can be improved in terms of allocating and prioritizing slabs and keeping stock clean.

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List of Common Used Abbreviations and Terms

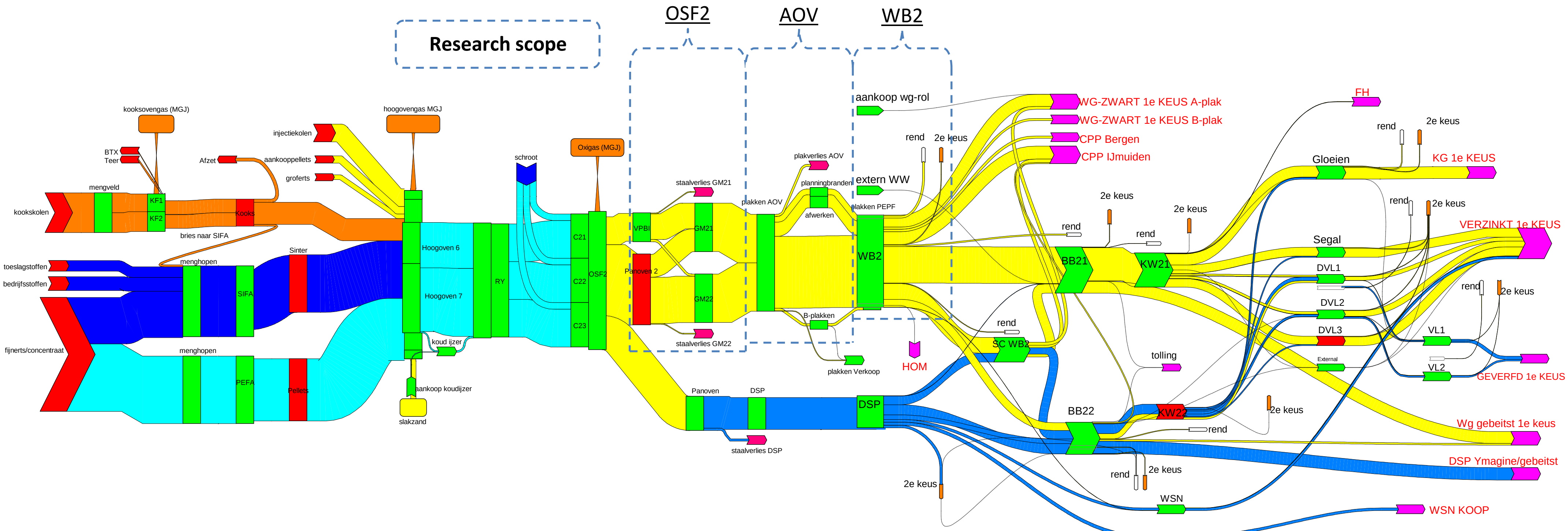
8.3.1 Abbreviations

	English	Dutch
AOV	Rework, Storage & Dispatch (slab yard, section of OSF2)	Afwerken, Opslag & Verzenden (plakopslag, afdeling van OSF2)
CGM	Continuous Casting Machine	Continue Giet Machine
CODP	Customer Order Decoupling Point	Klantorderontkoppelpunt (KOOP)
DSP	Direct Sheet Plant	Giet-wals installatie
HO 6/7	Blast Furnace 6/7	Hoogovens 6/7
KPI	Key Performance Indicator	Kritieke Prestatie Indicatoren
OSF2	Oxygen Steel Plant 2	Oxy Staal Fabriek 2
POCO	AOV-operator	Plakken Opslag Coordinator (AOV)
POSS	AOV-operating system	Plak Opslag Sturing Systeem (AOV)
S&OP	Sales & Operational Planning	Sales & Operational Planning
SKU	Stock Keeping Unit (unique slab in terms of quality, width & length)	Stock Keeping Unit (unieke plak op basis van kwaliteit, lengte & breedte)
SKV	Cutting, Classifying & Shipping (section of OSF2)	Snijden, Klasseren & Verladen (afdeling van OSF2)
STO	Steel Ordering	Steel Ordering (afdeling staal bestellen)
TSSPIJ	Tata Steel Strip Products IJmuiden	Tata Steel Strip Products IJmuiden
WB2	Hot Strip Mill 2	Warmbandwalserij 2
WI	Hot Charging	Warme Inzet

8.3.2 Terms

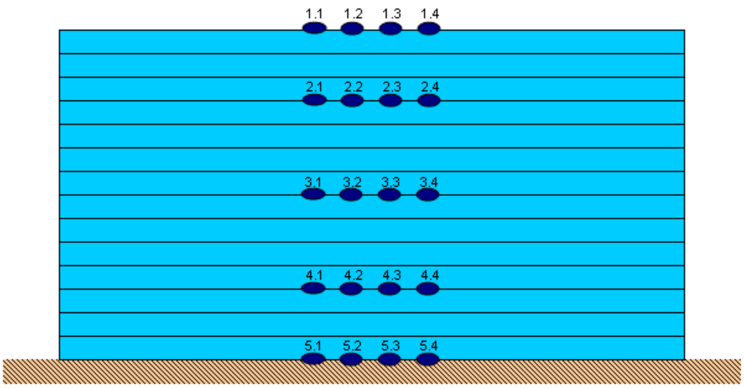
	English	Dutch
Debur	Remove the burr, which is created from cutting a slab from the CGM-string	Ontbaarden; verwijderen van de baard, die ontstaat bij het afsnijden van een plak
Pig Iron	Liquid iron	Ruwijzer
Tundish	Storage bin (buffer) to divide the liquid steel over the two strings of a CGM	Verdeelbak om het vloeibare staal over de 2 strengen van de CGM te verdelen
Obliged HC	Obliged Hot Charging: obligatory storage in hot box, because of quality issues	Verplicht warme inzet. Deze plakken moeten altijd opgeslagen worden in de wamhoudbox vanwege kwalitatieve eisen.
Chosen HC	Chosen Hot Charging: assigned hot box storage, because of expected (short) throughput time	Gekozen warme inzet. Deze plakken worden in de warmhoudbox opgeslagen omdat ze een bepaalde doorlooptijdverwachting hebben

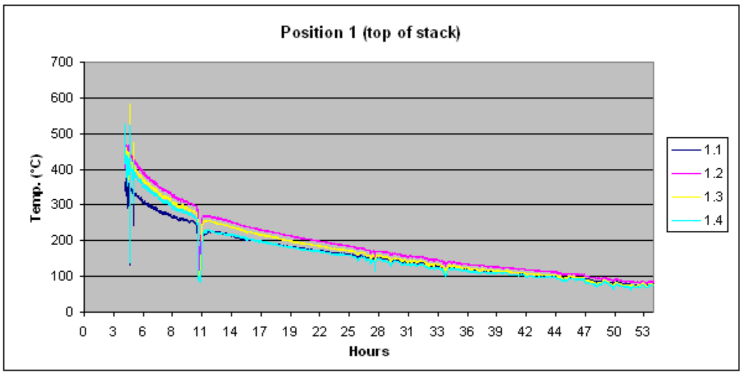
Appendix 1: Flowchart of Tata Steel IJmuiden

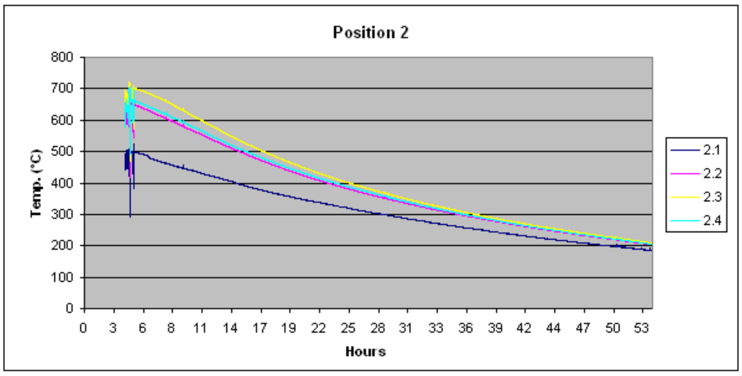


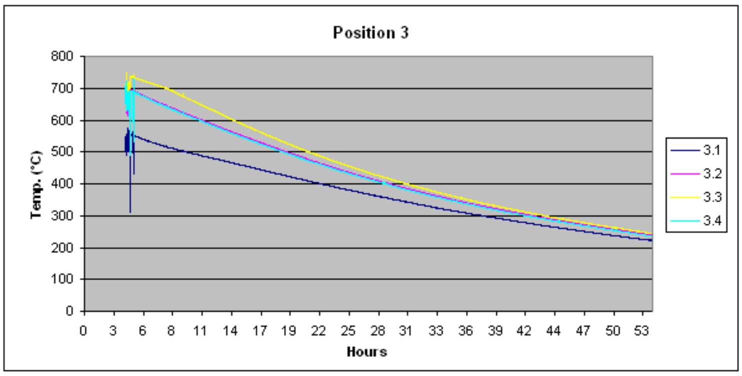
Appendix 2: Cooling Down Curves of Slabs

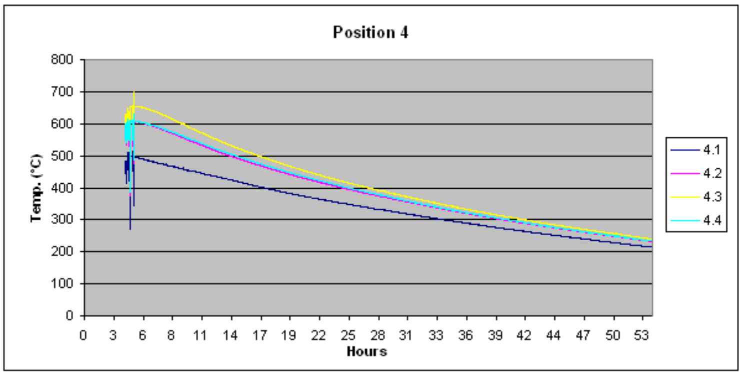
Tata Steel's R&D department has made some test on cooling down times. For this purpose, they placed 20 thermocouples on five different places in a stack of 14 slabs (see upper left figure). The results can be seen in the five remaining figures.

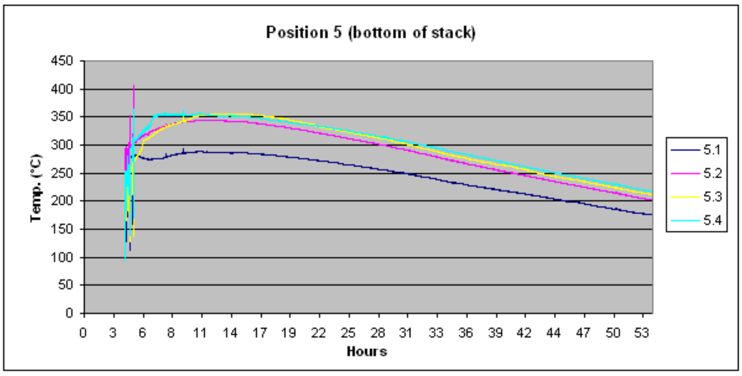












Appendix 3: Probability Distribution for SKV and Transportation Time

To analyze the time slabs spend in SKV and on the train (transportation to AOV), we take 55,177 observations. For these observations we calculate $T_{SKV+Transport}$:

$$T_{SKV+Transport} = T_{Storage\ at\ AOV} - T_{slab\ birth}$$

After calculating the median, the 25%-percentile and the 75%-percentile (see Table A3.1), we are able to draw the box plot of Figure A3.1

Hours in SKV and transportation	
# observations	55.177
min	0,58
1,5 * interquartile	0,58
1st quartile	2,43
median	3,35
3rd quartile	5,37
1,5 * interquartile	9,77
max	5.765,58
Outliers (> 9,77)	10.750

Table A3.1 – Statistics of $T_{SKV+Transport}$

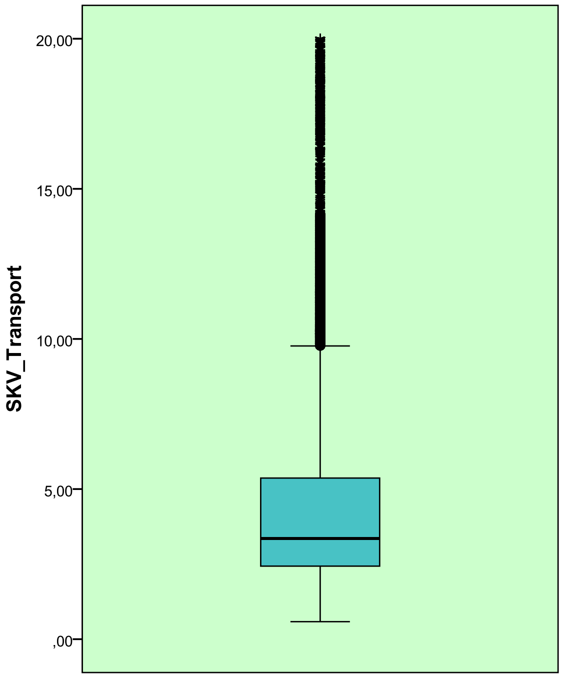


Figure A3.1 – Box plot of $T_{SKV+Transport}$

As depicted in Table A3.1, we have 10,750 outliers. For the remaining 44,427 observations, we draw a histogram with 20 bins (see Figure A3.2). So, for example, over 18% had a $T_{SKV+Transport}$ between 2.5 and 3 hours. Since we have some skewness to the left, we expect the Gamma distribution to have the best fit with the data.

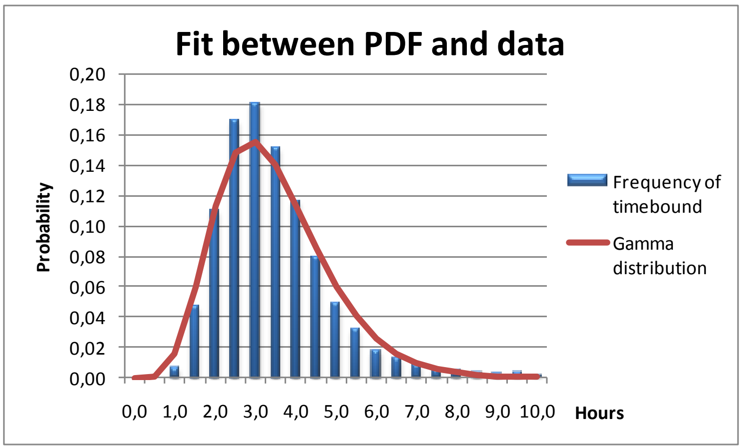


Figure A3.2 – Histogram of $T_{SKV+Transport}$

To test if the data is really Gamma distributed, we use Pearson's Chi Square Test. For the parameters of the Gamma distribution, we use the following estimations:

$$\alpha = \left(\frac{\bar{x}}{s}\right)^2 \qquad \text{and} \qquad \beta = \frac{s^2}{\bar{x}}$$

Where $\bar{x}$ and s denote respectively the mean and standard deviation of $T_{SKV+Transport}$. For the remaining 44,427 observations, we calculate this mean and standard deviation (see Table A3.2). This results in α = 5.45 and β = 0.59.

Descriptive statistics remaining obs.	
Mean	3,21
Standard Error	0,01
Median	2,97
Mode	2,52
Standard Deviation	1,38
Sample Variance	1,90
Kurtosis	2,94
Skewness	1,37
Range	9,18
Minimum	0,58
Maximum	9,77
Count	44.428

Table A3.2 – Statistics of the remaining $T_{SKV+Transport}$

For the Chi Square Test we use Sturger's rule to determine the number of bins:

$$\#\ of\ bins = 1 + \log_2(\#\ observations)$$

This means we have: $\lfloor 1 + \log_2 44{,}428 \rfloor = 16$ bins.

The hypothesis we state is:

H$_0$: $T_{SKV+Transport}$ is Gamma distributed
H$_\alpha$: $T_{SKV+Transport}$ is not Gamma distributed

We reject the hypothesis if $\chi^2 > \chi^2_{15,0.05}$

The 44,428 remaining observations are divided over the 16 bins equally. Furthermore we count the true number of observations within each bin. The Chi Square value is calculated for each bin and the Chi Square test value is:

$$\chi^2 = \sum_{i=1}^{16} \frac{(True\ \#\ obs_i - Expected\ \#\ obs_i)^2}{Expected\ \#\ obs_i}$$

Sturger's rule:		16	classes			
i	i/16	L-Bound	R-Bound	Exp # Obs.	True # Obs.	Chi
1	0,063	-	1,41	2.776,75	1714	406,75
2	0,125	1,41	1,74	2.776,75	2609	10,13
3	0,188	1,74	1,99	2.776,75	2839	1,40
4	0,250	1,99	2,21	2.776,75	3042	25,34
5	0,313	2,21	2,42	2.776,75	3107	39,28
6	0,375	2,42	2,62	2.776,75	3140	47,52
7	0,438	2,62	2,82	2.776,75	3213	68,54
8	0,500	2,82	3,02	2.776,75	3364	124,20
9	0,563	3,02	3,23	2.776,75	2973	13,87
10	0,625	3,23	3,46	2.776,75	3022	21,66
11	0,688	3,46	3,72	2.776,75	2842	1,53
12	0,750	3,72	4,01	2.776,75	2833	1,14
13	0,813	4,01	4,36	2.776,75	2552	18,19
14	0,875	4,36	4,82	2.776,75	2331	71,56
15	0,938	4,82	5,54	2.776,75	2183	126,96
16	1,000	5,54	19,16	2.776,75	2664	4,58
						982,64

Table A3.3 – Chi Sqaure Test for $T_{SKV+Transport}$

Since the critical Chi Square value (df=15 at 95%) is 7.26 < 982.64, we have to reject H(0). We have enough evidence to say that the time in SKV and during transportation is not Gamma distributed.

However, since no other distribution gives a good fit with the data, and the graph in Figure A3.1 seems to give a good fit, we will still use a gamma distribution to simulate time in SKV and transportation, with α = 5.45 and β = 0.59.

Appendix 4: Experiments Used in the Historical Data Model

Table A4.1 shows the SKUs we use for the simulation model based on historical data. The numbers in the fifth column indicate the percentage of category 2 slabs (see Section 3.2). So, for example, for SKU1, in reality 47% of the volume was charged between 24 and 72 hours after casting. If we look at SKU82, for example, then the number 0.46 indicates that on average 46% of all SKU82 slabs was charged between 24 and 72 hours after casting during the quarter <u>prior</u> to the simulated quarter.

SKUs simulated quarter				
SKU	**Quality**	**Width**	**Length**	**Opt. %**
1	184K	1300	10000	47%
2	122B	1300	10800	48%
3	182B	1300	5800	28%
4	126L	1300	10800	25%
5	594T	1700	8000	44%
6	186C	1300	10000	39%
7	123L	1000	9200	31%
8	122B	1300	10000	36%
9	123L	1100	8250	32%
10	594T	1800	5800	22%
11	123L	1100	8350	13%
12	111C	1300	5800	54%
13	594T	1500	9200	38%
14	126C	1000	9200	39%
15	122B	1300	9200	44%
16	111C	1400	5800	45%
17	122B	1200	8000	44%
18	114K	1900	9500	53%
19	182B	1300	8000	35%
20	126C	1100	8000	44%
21	182B	1200	8000	46%
22	590Z	1800	5800	32%
23	594T	1900	5800	27%
24	3N93	1600	8000	49%
25	594T	1300	10800	45%
26	594T	1800	8000	44%
27	126C	1100	8350	21%
28	126C	1000	8250	36%
29	590Z	1700	8000	38%
30	1T84	1600	8000	41%
31	187L	1300	10800	53%
32	122B	1300	8000	73%
33	112L	1500	8000	52%
34	594T	1400	8000	40%
35	184L	1000	8250	26%
36	186C	1300	9200	36%
37	186C	1300	10800	30%
38	594T	1500	8000	46%
39	125C	1000	9200	30%
40	594T	1600	8000	28%
41	1T84	1300	10800	58%
42	126C	1000	11800	40%
43	186C	1300	8000	24%
44	594T	1400	9200	41%
45	125C	1100	8350	9%
46	187L	1500	11500	51%
47	122B	1300	5800	71%
48	187L	1500	10300	44%
49	111C	1000	9200	44%
50	129L	1000	11800	78%
51	1N86	2050	9000	47%
52	1N83	1600	8000	27%
53	110E	1300	8000	15%
54	125C	1100	8250	26%
55	126C	1100	10300	44%
56	111C	1500	8000	53%
57	123L	1100	9200	22%
58	111C	1600	10300	43%
59	184L	1300	10000	42%
60	1N99	1600	8000	42%
61	1N99	1900	9200	52%
62	594T	1600	10300	23%
63	3N93	1900	8000	30%
64	1N86	1600	8000	64%
65	184K	1300	8000	48%
66	1N83	1400	9200	48%
67	1T86	1600	8000	40%
68	594T	1300	11500	19%
69	594T	1100	10300	38%
70	123L	1600	8000	12%
71	594T	1400	11500	33%
72	1S38	1500	9200	29%
73	180N	1500	9200	42%
74	110F	1300	10000	22%
75	594T	1600	11500	35%
76	110F	1250	10700	0%
77	594T	1300	8000	37%
78	1S38	1600	8000	44%
79	1T84	1900	9200	58%
80	186C	1700	8000	44%

SKUs previous quarter				
SKU	**Quality**	**Width**	**Length**	**Opt. %**
81	126L	1300	10800	25%
82	122B	1300	10800	46%
83	123L	1100	8250	26%
84	182B	1300	5800	38%
85	111C	1400	5800	63%
86	123L	1000	8250	2%
87	126C	1000	9200	25%
88	184K	1300	10000	58%
89	594T	1800	5800	43%
90	122B	1300	10000	51%
91	594T	1700	8000	46%
92	594T	1600	8000	50%
93	125C	1100	8250	22%
94	126C	1100	8000	41%
95	186C	1300	10800	33%
96	122B	1300	9200	20%
97	110F	1250	10700	0%
98	123L	1000	5800	32%
99	594T	1900	5800	36%
100	114K	1900	9500	25%
101	184L	1000	8250	34%
102	594T	1500	8000	62%
103	594T	1800	8000	41%
104	182B	1300	9200	26%
105	187L	1600	10300	64%

Table A4.1 – SKUs used for the simulation model based on historical data

Table A4.2 shows how we used the SKUs from Table A4.1 to set up experiments with different product mixes. We have one base-experiment (experiment 0), in which hot boxes do not exist (i.e. this is our validation experiment to the real quarter). For experiment 1 to 4, we send 100% of obliged HC slabs to the hot box and increase the percentage of the 25 most frequent SKUs of the simulated quarter. For experiment 5, we pick the 25 most frequent SKUs of the previous quarter and see if their optimal percentages give a good result for the quarter we simulate. In experiment 6 we use the same SKUs as in experiment 5, but take the optimal percentages of the quarter we simulate. In experiment 7 we take 25 most frequent SKUs (same as in exp. 1-4) and their optimal percentages from Table A4.1. In experiment 8 and 9, we do the same but then increase the number of most frequent SKUs.

	Experiment													
SKU	0	1	2	3	4	5	6	7	8	9	10	11	12	13
1	-	0,25	0,50	0,75	1,00	-	-	0,47	0,47	0,47	0,60	0,70	0,20	1,00
2	-	0,25	0,50	0,75	1,00	-	-	0,48	0,48	0,48	0,60	0,70	0,20	1,00
3	-	0,25	0,50	0,75	1,00	-	-	0,28	0,28	0,28	0,60	0,70	0,20	1,00
4	-	0,25	0,50	0,75	1,00	-	-	0,25	0,25	0,25	0,60	0,70	0,20	1,00
5	-	0,25	0,50	0,75	1,00	-	-	0,44	0,44	0,44	0,60	0,70	0,20	1,00
6	-	0,25	0,50	0,75	1,00	-	-	0,39	0,39	0,39	0,60	0,70	0,20	1,00
7	-	0,25	0,50	0,75	1,00	-	-	0,31	0,31	0,31	0,60	0,70	0,20	1,00
8	-	0,25	0,50	0,75	1,00	-	-	0,36	0,36	0,36	0,60	0,70	0,20	1,00
9	-	0,25	0,50	0,75	1,00	-	-	0,32	0,32	0,32	0,60	0,70	0,20	1,00
10	-	0,25	0,50	0,75	1,00	-	-	0,22	0,22	0,22	0,60	0,70	0,20	1,00
11	-	0,25	0,50	0,75	1,00	-	-	0,13	0,13	0,13	0,60	0,70	0,20	1,00
12	-	0,25	0,50	0,75	1,00	-	-	0,54	0,54	0,54	0,60	0,70	0,20	1,00
13	-	0,25	0,50	0,75	1,00	-	-	0,38	0,38	0,38	0,60	0,70	0,20	1,00
14	-	0,25	0,50	0,75	1,00	-	-	0,39	0,39	0,39	0,60	0,70	0,20	1,00
15	-	0,25	0,50	0,75	1,00	-	-	0,44	0,44	0,44	0,60	0,70	0,20	1,00
16	-	0,25	0,50	0,75	1,00	-	-	0,45	0,45	0,45	0,60	0,70	0,20	1,00
17	-	0,25	0,50	0,75	1,00	-	-	0,44	0,44	0,44	0,60	0,70	0,20	1,00
18	-	0,25	0,50	0,75	1,00	-	-	0,53	0,53	0,53	0,60	0,70	0,20	1,00
19	-	0,25	0,50	0,75	1,00	-	-	0,35	0,35	0,35	0,60	0,70	0,20	1,00
20	-	0,25	0,50	0,75	1,00	-	-	0,44	0,44	0,44	0,60	0,70	0,20	1,00
21	-	0,25	0,50	0,75	1,00	-	-	0,46	0,46	0,46	0,60	0,70	0,20	1,00
22	-	0,25	0,50	0,75	1,00	-	-	0,32	0,32	0,32	0,60	0,70	0,20	1,00
23	-	0,25	0,50	0,75	1,00	-	-	0,27	0,27	0,27	0,60	0,70	0,20	1,00
24	-	0,25	0,50	0,75	1,00	-	-	0,49	0,49	0,49	0,60	0,70	0,20	1,00
25	-	0,25	0,50	0,75	1,00	-	-	0,45	0,45	0,45	0,60	0,70	0,20	1,00
26	-	-	-	-	-	-	-	-	0,44	0,44	0,60	0,70	0,20	-
27	-	-	-	-	-	-	-	-	0,21	0,21	0,60	0,70	0,20	-
28	-	-	-	-	-	-	-	-	0,36	0,36	0,60	0,70	0,20	-
29	-	-	-	-	-	-	-	-	0,38	0,38	0,60	0,70	0,20	-
30	-	-	-	-	-	-	-	-	0,41	0,41	0,60	0,70	0,20	-
31	-	-	-	-	-	-	-	-	0,53	0,53	0,60	0,70	0,20	-
32	-	-	-	-	-	-	-	-	0,73	0,73	0,60	0,70	0,20	-
33	-	-	-	-	-	-	-	-	0,52	0,52	0,60	0,70	0,20	-
34	-	-	-	-	-	-	-	-	0,40	0,40	0,60	0,70	0,20	-
35	-	-	-	-	-	-	-	-	0,26	0,26	0,60	0,70	0,20	-
36	-	-	-	-	-	-	-	-	-	0,36	0,60	0,70	0,20	-
37	-	-	-	-	-	-	-	-	-	0,30	0,60	0,70	0,20	-
38	-	-	-	-	-	-	-	-	-	0,46	0,60	0,70	0,20	-
39	-	-	-	-	-	-	-	-	-	0,30	0,60	0,70	0,20	-
40	-	-	-	-	-	-	-	-	-	0,28	0,60	0,70	0,20	-

	Experiment													
SKU	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
41	-	-	-	-	-	-	-	-	-	0,58	0,60	0,70	0,20	-
42	-	-	-	-	-	-	-	-	-	0,40	0,60	0,70	0,20	-
43	-	-	-	-	-	-	-	-	-	0,24	0,60	0,70	0,20	-
44	-	-	-	-	-	-	-	-	-	0,41	0,60	0,70	0,20	-
45	-	-	-	-	-	-	-	-	-	0,09	0,60	0,70	0,20	-
46	-	-	-	-	-	-	-	-	-	-	-	-	0,20	-
47	-	-	-	-	-	-	-	-	-	-	-	-	0,20	-
48	-	-	-	-	-	-	-	-	-	-	-	-	0,20	-
49	-	-	-	-	-	-	-	-	-	-	-	-	0,20	-
50	-	-	-	-	-	-	-	-	-	-	-	-	0,20	-
51	-	-	-	-	-	-	-	-	-	-	-	-	0,20	-
52	-	-	-	-	-	-	-	-	-	-	-	-	0,20	-
53	-	-	-	-	-	-	-	-	-	-	-	-	0,20	-
54	-	-	-	-	-	-	-	-	-	-	-	-	0,20	-
55	-	-	-	-	-	-	-	-	-	-	-	-	0,20	-
75	-	-	-	-	-	-	-	-	-	-	-	-	0,20	-
76	-	-	-	-	-	-	-	-	-	-	-	-	0,20	-
77	-	-	-	-	-	-	-	-	-	-	-	-	0,20	-
78	-	-	-	-	-	-	-	-	-	-	-	-	0,20	-
79	-	-	-	-	-	-	-	-	-	-	-	-	0,20	-
80	-	-	-	-	-	-	-	-	-	-	-	-	0,20	-
81	-	-	-	-	-	0,25	0,25	-	-	-	-	-	-	-
82	-	-	-	-	-	0,46	0,48	-	-	-	-	-	-	-
83	-	-	-	-	-	0,26	0,31	-	-	-	-	-	-	-
84	-	-	-	-	-	0,38	0,28	-	-	-	-	-	-	-
85	-	-	-	-	-	0,63	0,45	-	-	-	-	-	-	-
86	-	-	-	-	-	0,02	-	-	-	-	-	-	-	-
87	-	-	-	-	-	0,25	0,39	-	-	-	-	-	-	-
88	-	-	-	-	-	0,58	0,47	-	-	-	-	-	-	-
89	-	-	-	-	-	0,43	0,22	-	-	-	-	-	-	-
90	-	-	-	-	-	0,51	0,36	-	-	-	-	-	-	-
91	-	-	-	-	-	0,46	0,44	-	-	-	-	-	-	-
92	-	-	-	-	-	0,50	0,46	-	-	-	-	-	-	-
93	-	-	-	-	-	0,22	-	-	-	-	-	-	-	-
94	-	-	-	-	-	0,41	0,44	-	-	-	-	-	-	-
95	-	-	-	-	-	0,33	0,30	-	-	-	-	-	-	-
96	-	-	-	-	-	0,20	0,44	-	-	-	-	-	-	-
97	-	-	-	-	-	-	-	-	-	-	-	-	-	-
98	-	-	-	-	-	0,32	-	-	-	-	-	-	-	-
99	-	-	-	-	-	0,36	0,27	-	-	-	-	-	-	-
100	-	-	-	-	-	0,25	0,53	-	-	-	-	-	-	-
101	-	-	-	-	-	0,34	0,26	-	-	-	-	-	-	-
102	-	-	-	-	-	0,62	0,46	-	-	-	-	-	-	-
103	-	-	-	-	-	0,41	0,44	-	-	-	-	-	-	-
104	-	-	-	-	-	0,26	-	-	-	-	-	-	-	-
105	-	-	-	-	-	0,64	0,53	-	-	-	-	-	-	-

Table A4.2 – Various product mixes per experiment
N.B. in experiment 1-13 we send all obliged HC slabs to the hot box

In experiment 10 and 11 we increase the volume of the 45 most frequent SKUs. In experiment 12 we choose 80 frequent SKUs and take a small percentage of their volume (20%).

One major issue with experiments 1 to 12 is that dedicated percentages can lead to missed hot storage opportunities (e.g. suppose the hot boxes are almost empty and we are running the fourth – 25% chosen HC volume – experiment, then we probably could have stored a large part of the remaining 75% as well, since there is enough free space). Therefore we took another approach for the 13th experiment: we use the optimal percentages of experiment 7 to create a probability p_j to start a stack for a certain SKU j. Hence, we send 100% of each of the 25 SKUs to the hot box, but when a slab arrives we check whether it will be stored or not:

- If a stack with the same specifications (SKU) as the arriving slab is present and it is not full (i.e. smaller than 16 slabs), then we always store the arriving slab on that stack
- If a stack with the same specifications (SKU) as the arriving slab is full or not available, then we start a new stack with probability p_j

With this method we will always optimally use the full height of a stack and starting a new stack for a certain SKU depends on the available empty stack positions in the hot boxes. Example A4.1 depicts a situation in this experiment. To create p_j, we use the optimal percentages of experiment 7 by the following steps:

- We normalize the percentages of the chosen HC slabs so that the sum of the fractions per SKU is 1
- These fractions represent the values of an empirical distribution
- Per free stack in the hot box, we draw a number from this empirical distribution
- This number represents the row in the table (i.e. Table A4.2)
- If the SKU in this row is the same as the arriving SKU, we start a new stack. If not, then we continue with the next empty stacks
- If a SKU was not 'hit' by this method, then no stack will be created and hence, the slab will be stored outside the hot box

Example A4.1

Assume we have 6 free stack positions in the hot box and the arriving slab is of type SKU5. This means we draw (at most) 6 empirical distributed numbers from Table A4.3.

SKU	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	**SUM**
Emp. Distr.	0,02	0,05	0,02	0,04	0,07	-	0,02	0,06	0,05	0,06	0,05	0,06	0,02	0,05	0,04	0,02	-	0,04	0,04	0,02	0,07	0,04	0,05	0,02	0,07	**1,00**

Table A4.3 – Empirical distribution for SKU 1-25, based on 'optimal' percentages from experiment 9

The first empirical number has a result column 2 (i.e. SKU2). This SKU is not equal to the arriving slab, so we continue to the second empirical number. This number has as a result column 11 (i.e. SKU11), hence we continue to the third empirical number. This number has a result column 5 (i.e. SKU5). We have a 'hit'. Since this SKU is the same as the arriving slab, we may start a new stack and can stop iterating here. (N.B.1: if there would be no 'hit' until the sixth empirical number, we do not start a new stack and the slab is placed outside the hot box. N.B.2: SKU 6 and 17 will never be 'hit', since their probability is 0.)

Appendix 5: Analysis of Volumes for the Stochastic Simulation Model

In Table A5.1 the volumes of five different qualities are depicted; in blue, the actual volumes in kTon; in green, the 2-week moving average, since it can occur that for example a quality is casted on Monday and Saturday and not in the subsequent week.

Week	Quality				
	594T	122B	186C	111C	123L
51	15,4	1,7	3,5	5,4	2,4
52	10,8	4,6	2,7	2,6	5,5
1	10,9	9,2	5,6	5,7	5,5
2	1,9	0,4	1,2	1,1	1,6
3	4,7	4,4	5,6	9,5	4,3
4	7,2	1,6	3,5	11,3	4,4
5	10,8	4,9	4,0	3,5	3,7
6	11,2	2,0	6,4	7,3	6,1
7	14,4	6,4	4,0	12,4	4,5
8	15,1	7,3	5,6	6,1	5,1
9	2,1	4,0	11,1	8,0	1,5
10	14,7	7,3	7,5	3,6	6,4
11	15,6	4,8	4,2	1,4	5,3
12	8,5	9,5	8,4	0,3	5,5
13	14,6	7,6	4,1	5,4	3,0
14	9,9	0,4	5,8	10,9	7,8
15	5,3	12,4	5,8	7,6	5,0
16	9,3	8,7	4,4	2,2	7,1
17	14,2	7,1	4,0	9,4	1,9
18	9,5	4,2	6,6	7,4	7,4
19	10,9	10,2	4,2	3,7	2,4
20	8,3	5,5	4,3	2,6	8,2
21	9,7	7,3	4,3	5,1	1,9
22	18,8	0,2	3,9	1,2	6,1
23	18,5	3,2	5,0	4,1	2,2
24	12,3	9,8	14,9	1,1	2,2

	594T	122B	186C	111C	123L
Mean	10,9	5,6	5,4	5,3	4,5
StDev.	4,5	3,3	2,7	3,5	2,1
Min	1,9	0,2	1,2	0,3	1,5
Max	18,8	12,4	14,9	12,4	8,2

Week	Quality				
	594T	122B	186C	111C	123L
51	-	-	-	-	-
52	13,1	3,2	3,1	4,0	4,0
1	10,9	6,9	4,1	4,1	5,5
2	6,4	4,8	3,4	3,4	3,5
3	3,3	2,4	3,4	5,3	3,0
4	6,0	3,0	4,5	10,4	4,4
5	9,0	3,3	3,7	7,4	4,0
6	11,0	3,5	5,2	5,4	4,9
7	12,8	4,2	5,2	9,8	5,3
8	14,7	6,8	4,8	9,2	4,8
9	8,6	5,6	8,4	7,0	3,3
10	8,4	5,6	9,3	5,8	4,0
11	15,1	6,1	5,9	2,5	5,9
12	12,0	7,2	6,3	0,8	5,4
13	11,5	8,5	6,3	2,8	4,2
14	12,2	4,0	5,0	8,2	5,4
15	7,6	6,4	5,8	9,3	6,4
16	7,3	10,5	5,1	4,9	6,1
17	11,8	7,9	4,2	5,8	4,5
18	11,8	5,7	5,3	8,4	4,6
19	10,2	7,2	5,4	5,5	4,9
20	9,6	7,8	4,2	3,1	5,3
21	9,0	6,4	4,3	3,8	5,1
22	14,2	3,7	4,1	3,2	4,0
23	18,6	1,7	4,4	2,7	4,1
24	15,4	6,5	9,9	2,6	2,2

	594T	122B	186C	111C	123L
Mean	10,8	5,6	5,3	5,4	4,6
StDev.	3,4	2,2	1,7	2,7	1,0
Min	3,3	1,7	3,1	0,8	2,2
Max	18,6	10,5	9,9	10,4	6,4

Table A5.1 – Half year volumes charged at WB2 of five different qualities
N.B.: Left: the actual volumes. Right: the 2-week moving average

We use the mean, standard deviation, minimum and maximum volumes from the two-week moving average to create slab demand. Since we have an average slab weight of 23 tons, we expect for example $\frac{10.8 \times 1000}{23} \approx 470$ slabs of quality 594T per week. This equals on average 67 slabs per day. Depending on the experiment, this volume is divided equally over a certain amount of dimensions (i.e. SKUs).

Appendix 6: Number of Replications

To determine the number of replications for the model based on stochastic data, we use the sequential procedure (see Law, 2006, Section 9.4). We decide to apply the sequential procedure on the experiments with the highest number of SKUs (i.e. experiment 8, 16, and 24), because we expect the highest volatility in these experiments. With the sequential procedure we find the number of replications n for which the half of the confidence interval width compared to the mean is below a certain allowed error γ:

$$\frac{t_{i-1,1-\alpha/2} \times \sqrt{S_n^2/i}}{|\bar{X}_n|} \leq \frac{\gamma}{1+\gamma}$$

With:

X_i	:	Independent observations $i = 1..n$
$\bar{X}_n = \frac{1}{n}\sum_{j=1}^{n} X_j$	:	Sample mean of X_i
$S_n^2 = \frac{1}{n-1}\sum_{j=1}^{n}\left(X_j - \bar{X}_n\right)^2$	:	Sample variance of X_i

For the confidence interval we choose $\alpha = 0.05$ (i.e. $1 - \alpha = 95\%$). As relative error we use $\gamma = 0.025$, resulting in an corrected target value $\gamma' = \gamma/(1+\gamma) = 0.0244$.

Table A6.1 shows the results of the sequential procedure on the two most important KPIs; fill rate and throughput of the hot boxes. Based on the KPI throughput, we can conclude that we need at least 4 replications (Exp. 8).

KPI Fill rate (Exp. 8: HB1, 80 SKUs)							
n	Fill rate	Avg(n)	StDev(n)	Tinv	½ width	Error	≤ϒ' ?
1	0,539	0,539	-	-	-	-	
2	0,548	0,543	0,007	12,706	0,060	0,111	✗
3	0,546	0,544	0,005	4,303	0,012	0,023	✓
4	0,539	0,543	0,005	3,182	0,008	0,014	✓
5	0,538	0,542	0,005	2,776	0,006	0,011	✓

KPI throughput (Hot box slabs per week) (Exp. 8: HB1, 80 SKUs)							
n	Throughput	Avg(n)	StDev(n)	Tinv	½ width	Error	≤ϒ' ?
1	971	971	-	-	-	-	
2	1.001	986	21,242	12,706	190,852	0,194	✗
3	992	988	15,381	4,303	38,209	0,039	✗
4	989	988	12,565	3,182	19,994	0,020	✓
5	973	985	12,834	2,776	15,935	0,016	✓

KPI Fill rate (Exp. 16: HB2, 80 SKUs)							
n	Fill rate	Avg(n)	StDev(n)	Tinv	½ width	Error	≤ϒ' ?
1	0,586	0,586	-	-	-	-	
2	0,589	0,587	0,002	12,706	0,018	0,030	✗
3	0,582	0,585	0,003	4,303	0,009	0,015	✓
4	0,587	0,586	0,003	3,182	0,005	0,008	✓
5	0,588	0,586	0,003	2,776	0,003	0,006	✓

KPI throughput (Hot box slabs per week) (Exp. 16: HB2, 80 SKUs							
n	Throughput	Avg(n)	StDev(n)	Tinv	½ width	Error	≤ϒ' ?
1	1.048	1.048	-	-	-	-	
2	1.060	1.054	8,601	12,706	77,274	0,073	✗
3	1.053	1.053	6,086	4,303	15,119	0,014	✓
4	1.067	1.057	8,269	3,182	13,157	0,012	✓
5	1.055	1.056	7,211	2,776	8,954	0,008	✓

KPI Fill rate (Exp. 24: HB3, 80 SKUs)							
n	Fill rate	Avg(n)	StDev(n)	Tinv	½ width	Error	≤ϒ' ?
1	0,547	0,547	-	-	-	-	
2	0,547	0,547	0,001	12,706	0,006	0,010	✓
3	0,546	0,547	0,001	4,303	0,002	0,004	✓
4	0,540	0,545	0,004	3,182	0,006	0,010	✓
5	0,539	0,544	0,004	2,776	0,005	0,009	✓

KPI throughput (Hot box slabs per week) (Exp. 24: HB3, 80 SKUs							
n	Throughput	Avg(n)	StDev(n)	Tinv	½ width	Error	≤ϒ' ?
1	1.006	1.006	-	-	-	-	
2	1.002	1.004	2,814	12,706	25,283	0,025	✗
3	992	1.000	7,180	4,303	17,836	0,018	✓
4	990	998	7,609	3,182	12,107	0,012	✓
5	974	993	12,404	2,776	15,402	0,016	✓

Table A6.1 – Sequential procedure to determine number of replications

Appendix 7: Capacity Increase as a Result of Hot Charging

Van der Meulen & Pesschier (2010) carried out some calculations to determine the capacity increase of the furnaces as a result of a higher percentage hot charging as well as a higher average charging temperature. Table A7.1 depicts the theoretic capacity increase as a result of hot charging. The first line in this table means that if we have 0% hot charging over the entire volume, we have a capacity of 100% (i.e. this equals 5.2 MTon per year for the WB2). For example, if we charge 30% of the entire volume at a temperature of 300°C, we will reach a capacity of 103,6%, or in other words, a capacity increase of 3,6%. This calculation, however, is based on the fact that we first charge 30% hot followed by 70% cold. In practice, hot and cold slabs are mixed in the furnaces. Hence, a so-called bunch factor is used. A bunch factor of $\eta = 1.0$ indicates that all hot slabs are bunched in the furnaces.

	Bunched	Charging temperature						
% HC	**η**	**100**	**200**	**300**	**400**	**500**	**600**	**700**
0	0	100,0	100,0	100,0	100,0	100,0	100,0	100,0
10	1,00	100,4	100,8	101,2	101,6	102,0	102,4	102,8
20	1,00	100,7	101,5	102,4	103,2	104,0	104,8	105,6
30	1,00	101,1	102,3	103,6	104,8	106,0	107,2	108,3
40	1,00	101,4	103,1	104,8	106,4	108,0	109,6	111,1
50	1,00	101,8	103,9	106,0	108,0	110,0	112,0	113,9
60	1,00	102,1	104,6	107,1	109,6	112,0	114,3	116,7
70	1,00	102,5	105,4	108,3	111,2	114,0	116,7	119,5
80	1,00	102,8	106,2	109,5	112,8	116,0	119,1	122,2
90	1,00	103,2	106,9	110,7	114,4	118,0	121,5	125,0
100	1,00	103,5	107,7	111,9	116,0	120,0	123,9	127,8

Table A7.1 – Theoretic effect of hot charging on capacity increase

Table A7.2 shows the same capacity increase calculation, but now corrected for a realistic bunch factor. Logically, the bunch factor increases with an increasing percentage of hot charging. Although increases seem marginal, we remark that 1% of 5.2 MTon capacity is still 52 kTon increase in yearly capacity.

	Bunched	Charging temperature						
% HC	**η**	**100**	**200**	**300**	**400**	**500**	**600**	**700**
0	0	100,0	100,0	100,0	100,0	100,0	100,0	100,0
10	0,30	100,1	100,1	100,2	100,2	100,3	100,3	100,4
20	0,32	100,1	100,3	100,4	100,5	100,6	100,7	100,8
30	0,46	100,3	100,6	100,9	101,1	101,4	101,5	101,7
40	0,56	100,5	101,0	101,5	101,9	102,2	102,5	102,7
50	0,60	100,6	101,4	102,0	102,5	102,9	103,3	103,6
60	0,75	100,9	102,0	103,0	103,7	104,4	105,0	105,4
70	0,86	101,3	102,7	104,0	105,0	105,9	106,6	107,2
80	0,94	101,6	103,4	105,0	106,2	107,4	108,3	109,0
90	0,98	101,9	104,0	105,9	107,3	108,6	109,7	110,6
100	1,00	102,1	104,5	106,7	108,3	109,8	111,0	112,0

Table A7.2 – Expected capacity increase due to bunched hot charging

Appendix 8: Sensitivity Analysis of Stochastic Simulation Model

In this appendix we perform a sensitivity analysis on some of the variables in the model based on stochastic data. First, our model appeared to be very sensitive for the used slab weights. Figure A8.1 until A8.6 show the effect of slab weight on the performance. On the left side we see the performance under varying slab weight (as in Table 5.3). On the right side we see the performance if we take the same slab weight (i.e. 22 tons) for all width/length combinations.

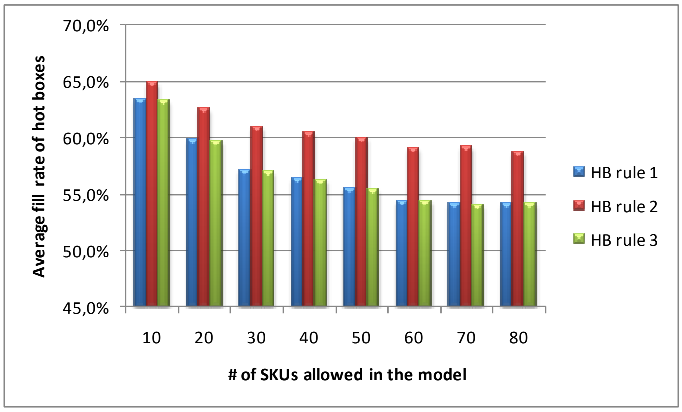


Figure A8.1 – Hot box fill rate

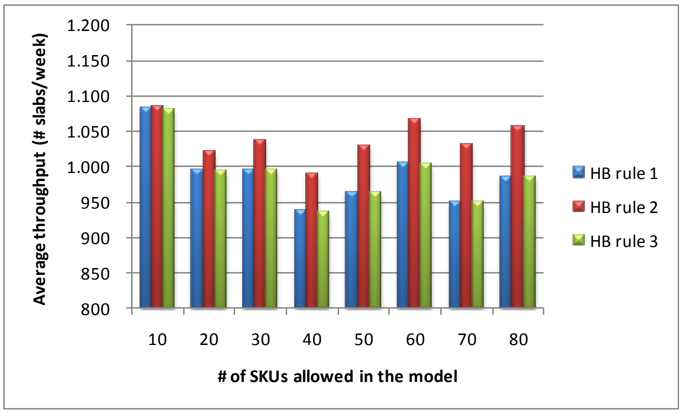


Figure A8.2 – Average hot box throughput

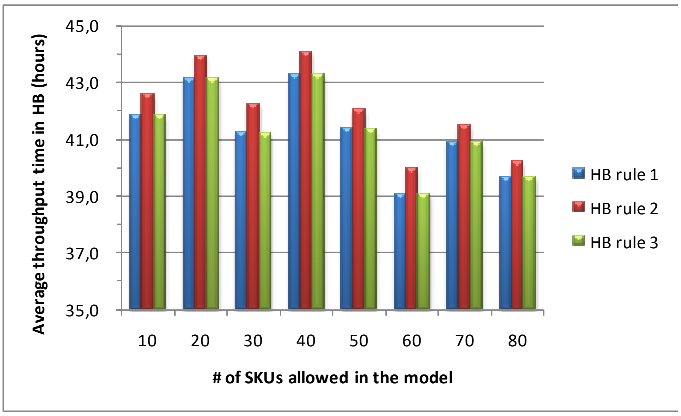


Figure A8.3 – Average throughput time in hot box

Varying slab weight

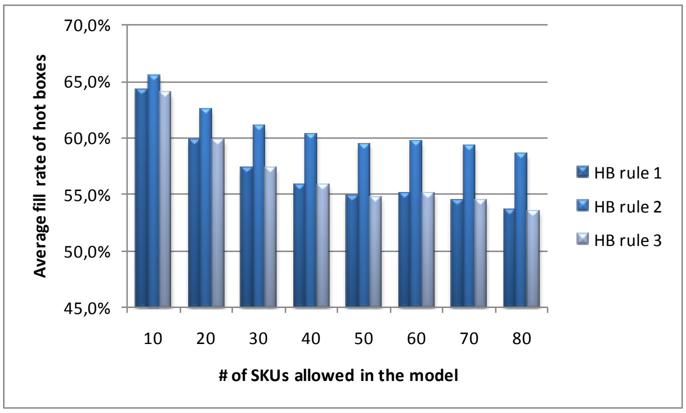


Figure A8.4 – Hot box fill rate

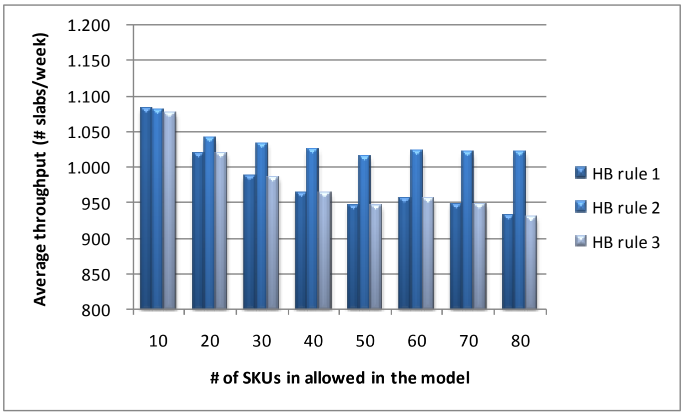


Figure A8.5 – Average hot box throughput

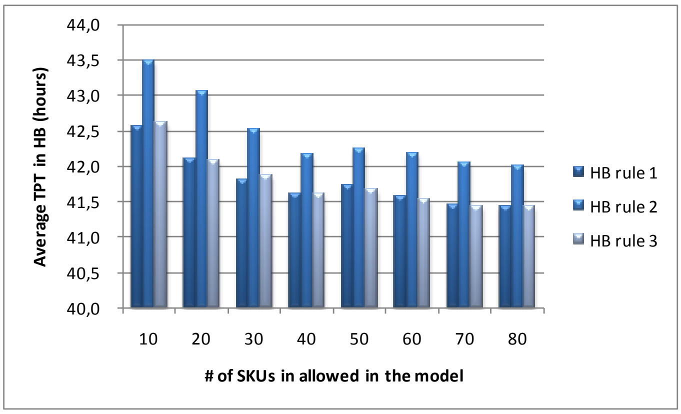


Figure A8.6 – Average throughput time in hot box

Equal slab weight

We see that throughput times are much more stable if we use equal weights. This is because series length and, hence, the period for which we cast ahead, depends on the average slab weight (i.e. the average slab weight varies per experiment, whereas the series length remains the same).

Second, we tested the performance of the model on adding a sixth quality. This does not only mean we have more volume in the model, but also more SKUs (i.e. at most 96 SKUs in experiment 8, 16, and 24). For this instance we also checked the difference between varying and equal slab weight (see Figure A8.7 until A8.10).

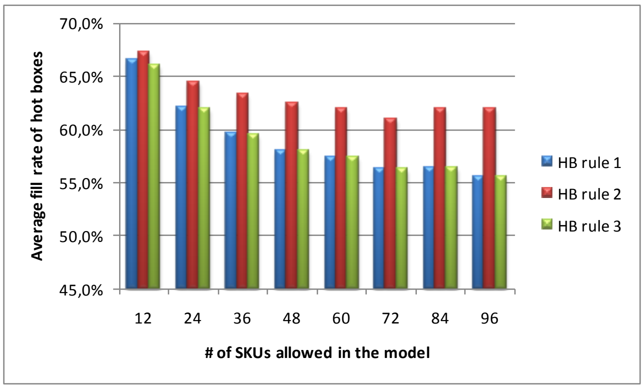


Figure A8.7 – Hot box fill rate

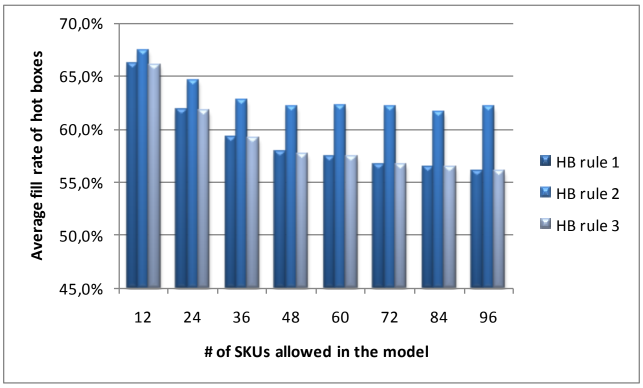


Figure A8.9 – Hot box fill rate

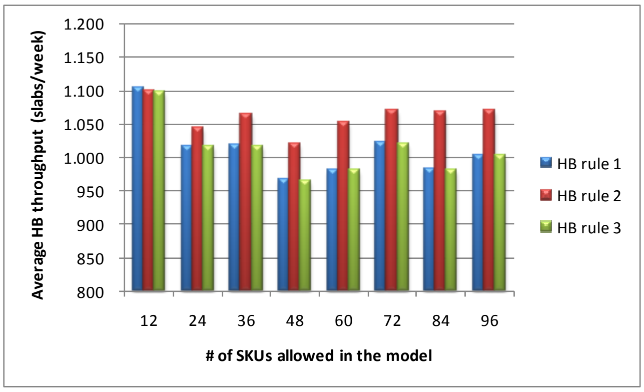


Figure A8.8 – Average throughput of hot box

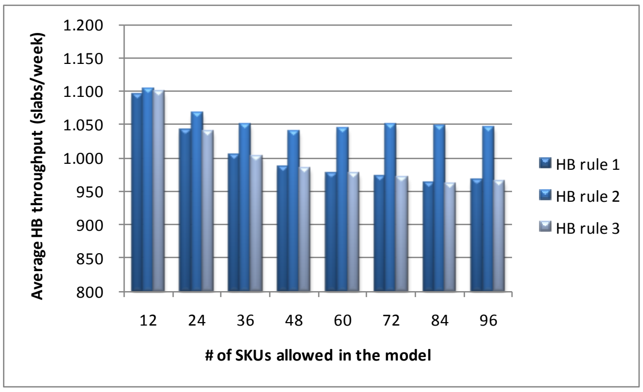


Figure A8.10 – Average throughput of hot box

6 qualities, varying slab weight

6 qualities, equal slab weight

We see that the same phenomenon, with respect to slab weight variance, occurs. Furthermore, we see that fill rate and throughput have increased a little compared to the experiments with 5 qualities. However, this is not in proportion to the volume we added to the model (around 10% more volume).