Methods to Generate the Yearly Shutdown-Schedule of a Basic Oxygen Steel Plant

Master Assignment Industrial Engineering and Management

by Michiel Bel

UNIVERSITEIT TWENTE.

TATA STEEL

Date and Place:
August 2013, Velsen-Noord

Author:
Michiel Bel

Supervisors:
Dr. Ir. J.M.J. Schutten, Universiteit Twente
Dr. Ir. M.R.K. Mes, Universiteit Twente
R. Broers, Tata Steel

Commissioned by:
Tata Steel's Basic Oxygen Steel Plant 2

Management Summary

Tata Steel's Basic Oxygen Steel Plant in IJmuiden converts pig iron into sheets of steel, which requires several installations. These installations all require different maintenance jobs, which are specified in the SAP system where the job's cycle time, duration, priority, start date, etc. are stored. Currently, Tata Steel bases the Yearly Shutdown-Schedule (YSS) too much on the maintenance needs of installations, instead of on the jobs that have to be performed on these installations. Furthermore, Tata Steel generates the YSS based on manual processes, without a formal methodology. Hence, the research question of this research is:

How can the current method of developing the yearly shutdown-schedule at the Basic Oxygen Steel Plant of Tata Steel be improved, such that the restrictions are met and are clear, and that all iron produced by the Blast-Furnaces is processed?

Method

In the literature, our problem is called the 'Maintenance Scheduling Problem' (MSP) and the problem is solved in the literature by applying a local search heuristic, because the problem is too complex to be solved to optimality. Our MSP is even more complex, mainly due to the high amount of possible routes through the Basic Oxygen Steel Plant. In order to create a transparent and subjective method to generate a YSS, we formulated the MSP as a Mixed-Integer Program, which includes the restrictions on shutting down an installation. The method contains four ranked objectives, in which a lower ranked objective can never by improved at the cost of a higher ranked objective:

1. Minimize the overflow of pig iron (deregulating the Blast-Furnaces and dumping at Harsco).
2. Minimize working in overtime (during the weekends and on working days before 7am and after 3pm).
3. Minimize deviating from the job's cycle time.
4. Maximize the spreading of jobs.

In order to solve the MSP, we applied a Simulated Annealing (SA) heuristic that uses four runs to subsequently optimize each objective.

Results

The analysis of the results of our four-run SA approach clearly shows the correctness of the approach with respect to clustering jobs in order to minimize the overflow: our approach causes a decrease in the objective value of 89% with respect to the initial schedule, as Table 1 shows. In Table 1, the 'initial' column shows the values of the four objectives if every job is scheduled at its start date in SAP.

Table 1 - Results of our SA approach

	Initial	After SA	Decrease
Objective	653,066.4	74,291	-89%
Overflow	651,066.4	72,067	-89%
Overtime	2,000	2,155	+8 %
Deviation (/1000)	0	69,662	- %
Spread (/1000)	5.03	4.149	-18%

Additionally, we applied two Iterative Improvement approaches, a one-run SA approach, and a combined approach to the same MSP. From this analysis, we conclude that both our four-run SA and the one-run SA outperform the Iterative Improvement approaches and the combined approach. Although it did not out- or underperform the method in the small experiment that we performed, we expect our four-run SA approach to outperform the one-run SA approach on the long run, because the one-run SA approach finds a bad local optimum relatively quickly.

Furthermore, the analysis shows that not all rules of thumb that Tata Steel currently applies to generate the YSS remain valid from an overflow point of view, whereas we are unable to conclude on the validity of the rules of thumb from any other point of view, such as safety. Although not all of these rules of thumb remain valid, the current YSS seems to outperform our YSS. However, 55% of the jobs do not fit to the shutdowns in the YSS as Tata Steel generated it. This is mainly due to our usage of tight bounds on the allowed deviation from the cycle time: we expect that our approach outperforms the current manual approach if it is based on the same restrictions.

Conclusions and Recommendations

As mentioned in the previous section, the currently applied restrictions differ from the restrictions as we applied them, which is mainly due to the incorrectness or unavailability of the job's duration, the priority, and cycle time. We propose determining the correct parameters for every job in SAP, such that the YSS is based on these data, which improves the objectivity of the restrictions and the trust in the output. Furthermore, we recommend clustering jobs in order to decrease the runtime of the SA approach. Especially clustering the jobs on the casting installations decreases the problem size without decreasing the quality of the method and the YSS.

Finally, the main advantages of our method over the current method to generate the YSS are mainly due to the scheduling of jobs instead of installations (as Tata Steel currently does) and due to the computerized approach instead of a manual approach. The main advantages are:

- Sections have more insight in and a better overview of the maintenance to perform during the year.
- The method to generate the YSS is neither based on experience, nor a manual process.
- Less additional maintenance jobs appear during the year, because the schedule includes every job. This leads to less rescheduling and more time to prepare a shutdown.
- The method takes four objectives into account for each and every job.
- The consequences of rescheduling can be analyzed quickly and comprehensively.
- The restrictions of the YSS are clear. Hence, the reasoning behind the scheduling itself is clear.

Preface

By means of this report, I finish my master Industrial Engineering and Management at the University of Twente. This report contains my research towards an improved method to generate the yearly shutdown-schedule at the Basic Oxygen Steel Plant of Tata Steel IJmuiden. This master assignment offered me the opportunity to work on both maintenance concepts and complex schedules within a plant with an impressive production process, which is part of a chain of complex and interesting processes at the Tata Steel IJmuiden site.

For providing me this opportunity, the offered supervision, and shown interest from the initial contact until handing in this report, I would like to thank Tata Steel. I would especially thank my Tata Steel-supervisor Randy Broers for providing me with useful feedback and introducing me in a complex plant and system. I enjoyed using the workplace next to you.

Furthermore, I would like to thank Marco Schutten and Martijn Mes, my supervisors from the University of Twente. The useful feedback that I received while carrying out my research was full of clear content and often helped me obtaining new insights in my research. Especially the different and complementary types of feedback helped me obtaining these.

I would like to thank my parents for their interest in this assignment and for their financial support during my studies. Finally, I would like to thank Sandra for moving to Enschede during her studies, to join me during my years in Enschede.

Michiel Bel

Table of Contents

1. Introduction 6
1.1 Background and Motive 6
1.2 Core Problem and Research Questions 8
1.3 Approach and Outline 10
2. Current Situation 11
2.1 Flows through the Plant 12
2.2 Process of Generating and Applying the Yearly Shutdown-Schedule 15
2.3 Complications 17
2.4 Cycle Time Defined 19
2.5 Restrictions to Scheduling Maintenance 20
3. Literature Review 23
3.1 Position in the Literature 23
3.2 Approaches to Comparable Problems 26
3.3 Options to Improve the Process 26
3.4 Concluding Remarks 31
4. Model of the Maintenance Scheduling Problem at Tata Steel 32
4.1 Evaluation of the Modeling Techniques 32
4.2 Mathematical Model of the Maintenance Scheduling Problem 32
4.3 Implementing the Local Search Technique 38
4.4 Concluding Remarks 44
5. Analysis and Discussion of the Results 45
5.1 Initial Solution 45
5.2 Performance of Simulated Annealing 45
5.3 The Generated YSS 56
5.4 Computation Time 63
5.5 Summarizing the Results 65
6. Conclusions and Recommendations 66
6.1 Conclusions 66
6.2 Further Research 69
Bibliography 72
Appendices 77
A Translation of Terms 77
B Maps the Basic Oxygen Steel Plant and the IJmuiden Site 79
C Defining the Minimum and Maximum Differences between Neighboring Solutions 81

1. Introduction

This research focusses on the scheduling of installation shutdowns to perform maintenance at Tata Steel's Basic Oxygen Steel Plant 2[1] in IJmuiden. Figure 1 shows a part of the Tata Steel IJmuiden site, and Appendix B contains a map of both the IJmuiden site and the Basic Oxygen Steel Plant. Tata Steel IJmuiden employs approximately 9,000 people, of which 1,000 are employed by the Basic Oxygen Steel Plant. The Basic Oxygen Steel Plant converts liquid iron – produced by two blast furnaces – into sheets of steel, which are further processed by the Direct Sheet Plant and the Hot Strip Mill. Section 1.1 explains the motive and importance of this research for both Tata Steel and the scientific research; Section 1.2 derives the research question and this chapter finishes with the outline of this research in Section 1.3.

1.1 Background and Motive

Every manufacturing organization faces the breakdowns of machines at unexpected and unwanted moments. All these organizations use some kind of approach to perform maintenance, based on the balance between costs, time, and safety. Maintenance is often seen as a cost function only, instead of a way to save money and time during breakdowns and for a company such as Tata Steel – with a continuous process and expensive installations – the call for maintenance often comes at an inopportune moment. Still, maintenance is more and more accepted as needed to increase the total amount of output and the output's quality, and Tata Steel recognizes that the planning of maintenance should be improved. Figure 2 shows a simplified flowchart of the continuous process, in which some installations are more critical to the flow than other installations. Currently, the yearly process of planning the shutdown of an installation aims to attain a high flow through the plant, by scheduling the shutdowns of these installations in a finely tuned way. Note that we add more installations to this flow in Chapter 2.

Figure 1 - A view over a part of the IJmuiden Tata Steel Site

[1] Appendix A contains a translation of several terms from English to Dutch

The relevance of this research for Tata Steel is especially in acquiring new insights in maintenance scheduling as well as in a method to schedule maintenance. This research is also relevant to other organizations, because every organization with a continuous process that does not have the possibility to change the flow of goods via spare machines needs to cut the flow by shutdowns, in order to maintain the installations. All these organizations can use new insights in the process and methods of developing a shutdown schedule. Next to the relevance to organizations, this research's relevance to science lies in the fact that maintenance scheduling is mostly researched in the power generating industry, where simpler flows are considered. Dekker (1996) recognizes an increasing trend from the late 1980s to the early 1990s of research in the field of maintenance optimization and since that time, more and more literature has become available on the maintenance scheduling topic, although its focus remains on the power generating industry. Furthermore, the relevance to science lies in the fact that maintenance scheduling is not highlighted in basic scheduling books, such as Pinedo (2009), while there is a clear link between maintenance and scheduling. He does discuss the differences between manufacturing and service industries and from that discussion we conclude that maintenance is somewhere in between these two types of industries and should be dealt with on the interface of manufacturing and services, making maintenance planning and scheduling an even more interesting topic. So, maintenance becomes an important research topic in the scientific literature, and Tata Steel improves its maintenance policy and process, to attain high uptime and more output.

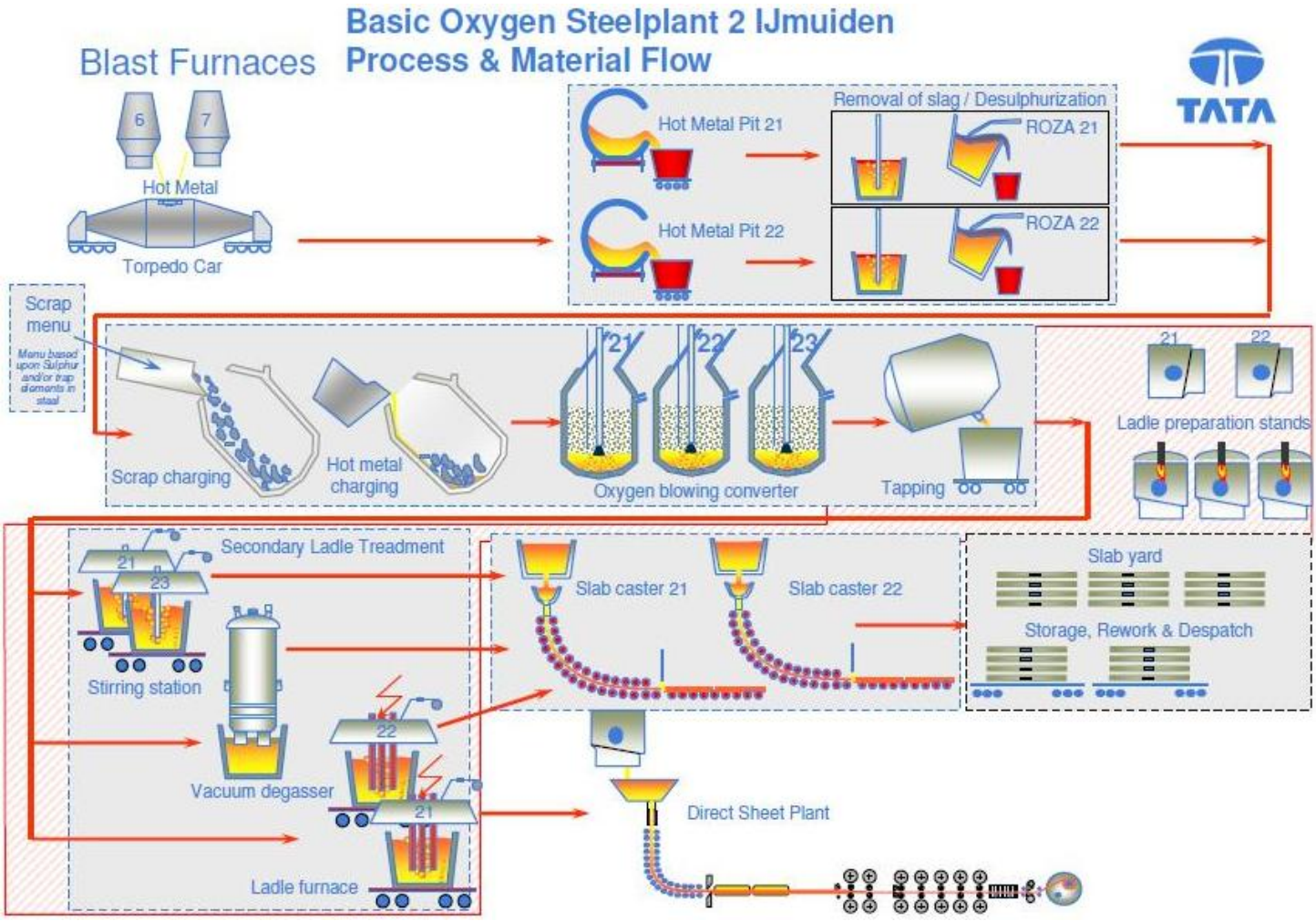


Figure 2 - Simplified flowchart of the process from the Blast Furnaces via the Basic Oxygen Steel Plant to the Direct Sheet Plant and the Slab Yard

1.2 Core Problem and Research Questions

To perform planned maintenance at the Basic Oxygen Steel Plant, several installations need to be taken out of service. Every installation has several maintenance jobs attached to it (lubricating, replacement of parts, etc.) and these jobs all have a cycle time[2], which is defined by a maintenance engineer. These cycle times are combined to schedule the shutdown of an installation and these shutdowns are combined to a yearly shutdown-schedule (YSS), which shows the moments of a shutdown.

The shutdown moments are set such that the flow through the plant is guaranteed and every installation is maintained. Actually, the most important aim is to guarantee a flow through the plant that is high enough to process the pig iron processed by the Blast-Furnaces. The scheduling is based on human knowledge about restrictions with respect to taking different installations together out of service and these are not clear to everybody, such that convincing others about its correctness is hard. Moreover, the scheduling is based on rules of thumb that have proven their usability in the past, but it is unclear whether each of these rules is needed to set up the schedule. Still, most of these rules are based on cycle times through the plant. The scheduling process of setting up a shutdown schedule for the installations in the Basic Oxygen Steel Plant repeats itself every year and the YSS needs to be revised several times before it is accepted and frozen. Another disadvantage of the unclear process and the rescheduling before freezing the YSS, is the decreasing trust in the developed YSS. Part of the process is the method of deducting the YSS from the different maintenance needs, which currently holds that the different installation engineers define the installation cycle time, without really basing this on the cycle times of maintenance jobs that are stored in SAP. Therefore, this process is too much based on experience and human knowledge. That is why Tata Steel recognizes a possibility to increase the clarity and understandability of the YSS. Finally, because of the manual approach to define and combine the cycle times of installations, we question the correctness of the resulting schedule.

So far, we have mentioned several problems in the current process of generating the YSS: the process is based on human knowledge, the method is based on a manual approach, the process is unclear and incomprehensible, rescheduling is required, and the outcome has a questionable quality. While the process basically covers three steps – the determination of the cycle times, the generation of the schedule, and the implementation of the schedule – we only focus on the generation itself, because most problems appear there (rules of thumb, outcome, manual approach). Although the focus is on the method to generate the schedule, we do recognize the importance of the other two steps. Now, the main problem with respect to maintenance scheduling at the Basic Oxygen Steel Plant is:

> *The current method of generating the yearly shutdown-schedule is unclear, does not lead to the best schedule, and is too much based on human knowledge, manual processes, and rules of thumb.*

To improve the method, a manual process should be prevented, the trust and understandability should be higher, and the outcome should not be questionable anymore. So, a model should be developed that clarifies the restrictions, such that the trust in the correctness of the YSS increases.

[2] The cycle time of maintenance is the time between two identical and subsequent maintenance jobs. In practice, this time varies between two bounds (e.g., a cycle time of 10 weeks means that the job should be repeated after at least 9 and at most 11 weeks).

Hence, the model should have high *face validity* (or logical validity), which means that the process seems logical. So, if the process is composed of understandable steps and restrictions, the YSS (the result of the process) should be intuitively understandable. Notice that high face validity only means that the process looks like it obtains good solutions, rather than that it finds good solutions. Recall that we only focus on the method of generating a YSS, so we improve the method of generating a YSS given the cycle times and maintenance needs of installations, while leaving out the process of determining these values (e.g., determining the cycle times, determining the maintenance needs, changing the way of approaching the YSS).

Furthermore, the main task of maintenance management is to guarantee availability (Moghaddam, 2008), which equals – for this research – guaranteeing the flow of steel through the plant or making sure that all iron produced by the Blast-Furnaces, is processed by the Basic Oxygen Steel Plant. While there are hardly any buffers in the plant, the iron is only processed if the cycle time through the different areas of the plant is at most the Blast-Furnaces' cycle time. Section 2.4 elaborates on this topic. In addition to that main task of guaranteeing availability, maintenance management should guarantee some repeatability and predictability of maintenance moments, such that scheduling is possible and everybody expects the shutdown of an installation. So, in order to make sure that a new method is accepted, the capacity of the Basic Oxygen Steel Plant should be high enough to process the iron supplied by the Blast-Furnaces, while the maintenance cycles are repeating.

Both the problem and the explanation above lead to the following research question:

> *How can the current method of developing the yearly shutdown-schedule at the Basic Oxygen Steel Plant of Tata Steel be improved, such that the restrictions are met and are clear, and that all iron produced by the Blast-Furnaces is processed?*

In order to answer this question, we first need to have a better insight in the current process of developing the YSS, which results in the first sub-question:

1. How is the yearly shutdown-schedule currently developed at the Basic Oxygen Steel Plant?
    a. What are the current steps to generate the YSS?
    b. What are the *restrictions* of the YSS?
    c. How should the *cycle time* be defined?

Based on the first question, we are able to position this research in the literature and we are able to derive useful insights for this research from that literature. So, our second sub-question is:

2. How should this research be positioned in the literature?
    a. How is the problem described in the literature?
    b. What can we learn from the literature to improve the current method of scheduling maintenance at the Basic Oxygen Steel Plant?
    c. Which methods are applied in the literature?

After answering these questions, we can develop a new method to generate the YSS:

3. What is the most suitable option to improve the current method of scheduling shutdowns, taking into account the method's clarity and understandability, such that the flow is guaranteed and the restrictions are met?
    a. What option discussed in the literature suits best to our problem?
    b. How can we adapt that option to make it fit to our problem?
    c. How should this option be implemented?

Finally, we have to reflect on the selected method and evaluate the results:

4. What are the results of applying the selected method?
    a. What is the improvement in the flow?
    b. What is the improvement in clarity and understandability?
    c. How bad/well is the current method (i.e., are the rules of thumb useful)?

1.3 Approach and Outline

In Chapter 2, we answer the first question by interviewing schedulers, by analyzing the map of the plant, and by analyzing existing reports. Chapter 3 positions this research in the literature and translates the literature to insights applicable to the current situation of the problem. Chapter 3 is solely based on a literature review. Chapter 4 answers sub-question 3 based on both the literature research in Chapter 3 and our own insights. Chapter 5 describes and discusses the results of implementing the options chosen in Chapter 4. Chapter 6 contains our conclusions and recommendations.

2. Current Situation

This chapter explains the current situation – with respect to planned maintenance – at the Basic Oxygen Steel Plant. This chapter comprises a part on the flows of steel through the plant and a part on the developing of the yearly shutdown-schedule (YSS). We explain the current flow of iron, scrap, steel, and slag through the Basic Oxygen Steel Plant in Section 2.1, before we explain the current process of developing the YSS in Section 2.2. Section 2.3 explains the complications in the current process, and Section 2.4 and Section 2.5 clarifies the terms: *cycle time* and *restrictions*.

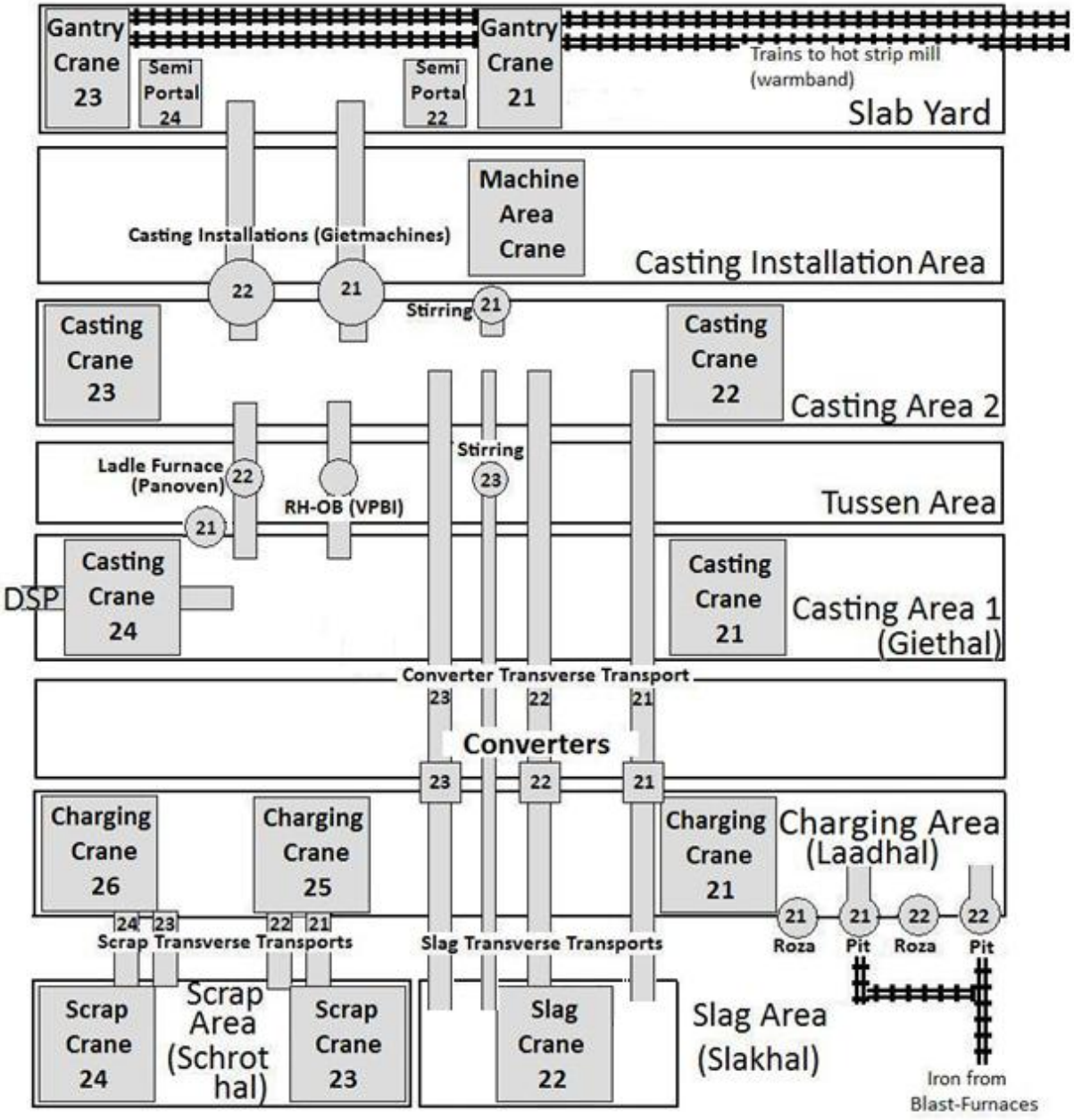


Figure 3 - Simplified lay-out of the Basic Oxygen Steel Plant

This figure shows the different installations we consider in this research. Every Transverse Transport contains one unit moving along the transport. The flow is as follows: liquid iron arrives at the Pits; there, the iron is tapped into a pig iron ladle and a Charging Crane moves the ladle to a Roza. From the Roza, the Charging Crane takes the ladle to a Converter, where the scrap is added by a Charging Crane. The steel moves, via a Converter Transport and a Casting Crane, in a steel-ladle to one of the Ladle Furnaces, one of the Stirring Stations, or the RH-OB installation. Then it either moves to the Direct Sheet Plant (DSP), or via the Casting Installations, Gantry Cranes and the Slab Yard to the Hot Strip Mill (HSM).

2.1 Flows through the Plant

The Tata Steel IJmuiden site is made up of several separate plants that together manufacture sheets and roles of steel (Appendix B.1 contains a map of the site). The relevant plants for this research are the two Blast-Furnaces, (especially) the Basic Oxygen Steel Plant, and – although less relevant – the Direct Sheet Plant and the Hot Strip Mill. The Blast-Furnaces produce pig iron (liquid iron), which is transported by hot metal cars to the Basic Oxygen Steel Plant. As the name implies, this steel plant converts the iron into steel: either sheets or roles. Finally, the sheets and roles are transported to the Direct Sheet Plant (DSP) and the Hot Strip Mill respectively, where they are prepared for the customer and further operations, such as galvanizing and cold rolling. This research's focus is on the maintenance scheduling of the Basic Oxygen Steel Plant, which is influenced by the supply of iron of the predecessors (Blast-Furnaces) and the capacity and the demand for steel of the succeeding DSP, because the DSP is directly attached to the Basic Oxygen Steel Plant, whereas the Hot Strip Mill has the possibility to store the sheets of steel before handling these. The only way to buffer between the Blast-Furnaces and the Basic Oxygen Steel Plant, is by means of filling the hot metal cars, but this type of buffering is obviously limited.

Figure 3 contains a simplified map of the Basic Oxygen Steel Plant and only shows the installations that we consider in this research. Recall that Appendix B.2 contains a more detailed map of the plant and that hot metal cars (Figure 4) transport pig iron to the pits. From Figure 3, we derive Figure 5 that contains the flows through the plant from the Blast-Furnaces, via the hot metal cars and the Basic Oxygen Steel Plant to the DSP and train to the Hot Strip Mill. As mentioned before, the shutdown of a Blast-Furnace means that the supply of pig iron decreases and installations are out of supply. On the other hand, shutting down an installation while both Blast-Furnaces produce pig iron, may lead to the need to deregulate the Blast-Furnaces to lower the amount of iron processed by the Blast-Furnaces and so the amount of iron to be processed by the Basic Oxygen Steel Plant. Whether or not deregulation of the Blast-Furnaces is required depends on the impact of shutting down that installation on the capacity of the Basic Oxygen Steel Plant, because there may be the possibility to use another flow (e.g., Converter 21 instead of Converter 22) and pig iron may be dumped and reused as scrap. Figure 6 and Figure 7 show the charging of respectively pig iron and scrap into the Converter by a Loading Crane.

Figure 4 – hot metal car, transports the pig iron from the Blast-Furnaces to the Basic Oxygen Steel Plant (RolandRail.net, 2005)

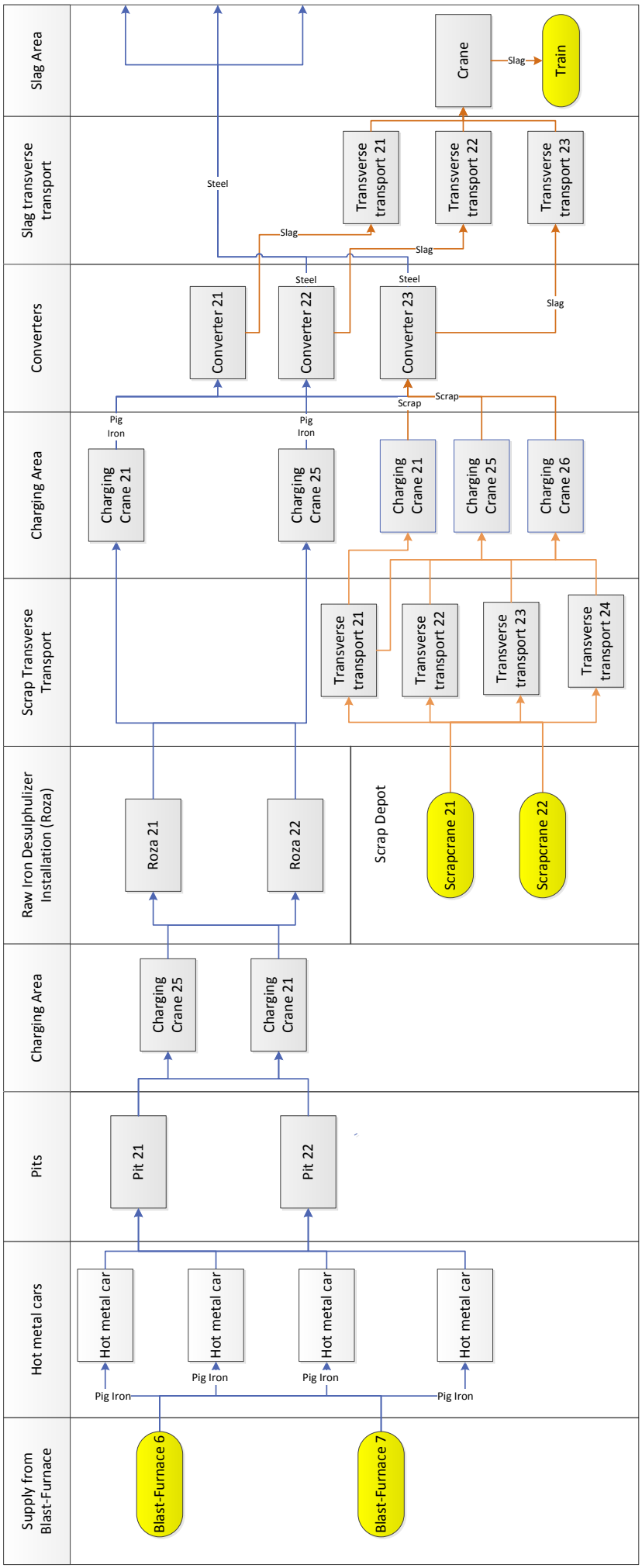


Figure 5a - Flow through the Basic Oxygen Steel Plant

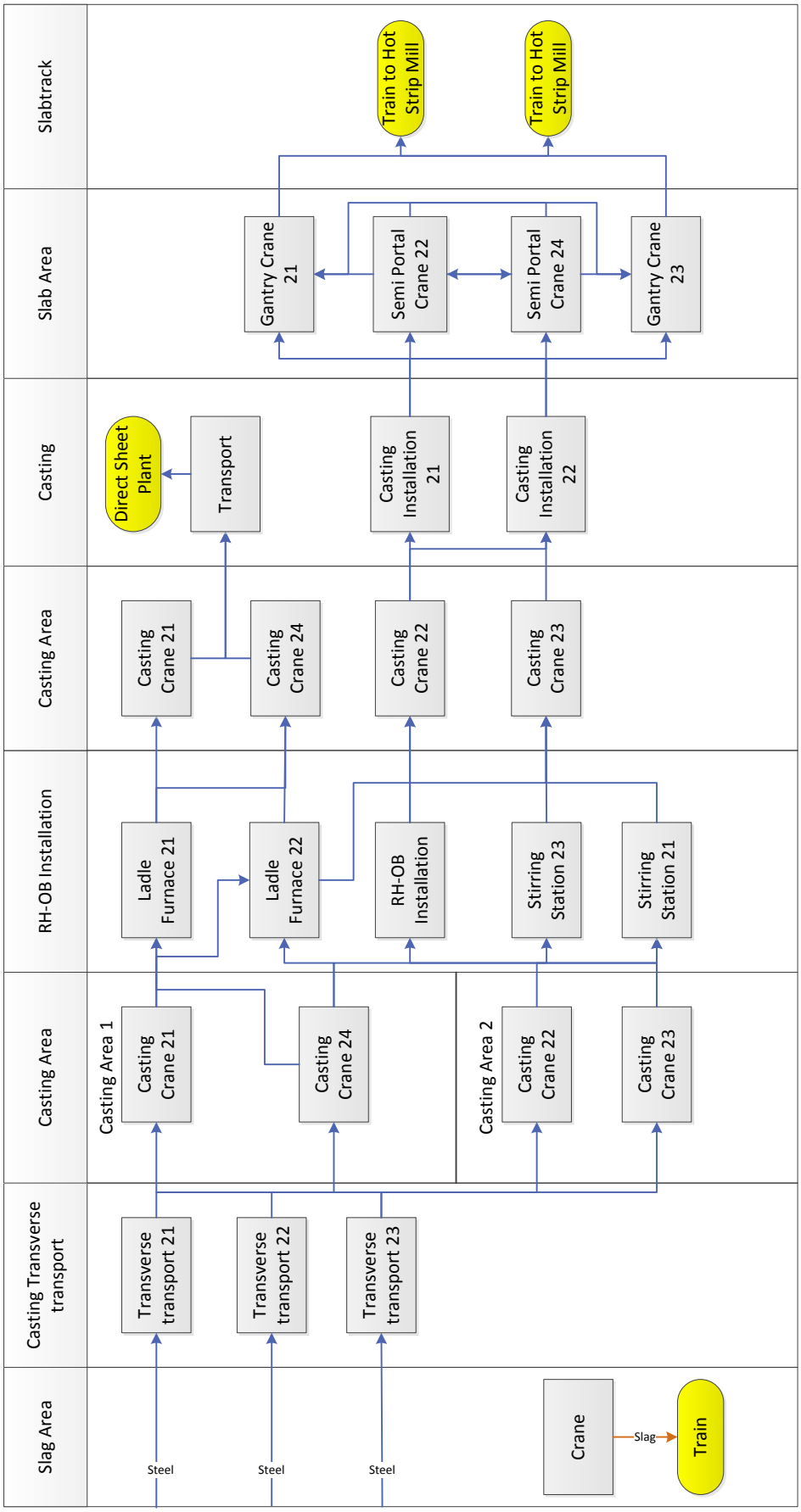


Figure 5b - Flow through the Basic Oxygen Steel Plant

Finally, a shutdown of one of the cranes pictured in Figure 3 may mean that an installation is locked out of possible supply and may also lead to locking another crane. For example, the shutdown of Charging Crane 25 in the Charging Area means that the crane is put as far as possible to the left side of the picture. Now, Charging Crane 26 cannot be used because it is isolated and for the same reason Scrap Transverse Transports 22, 23, and 24 cannot be used either. Consequently, Charging Crane 21 should take the pig iron ladle from the Pits to the Rozas and further to the Converters, but also put scrap from Scrap Transverse Transport 21 into a converter, which obviously has its impact on the cycle time in the Charging Area. In practice, some routes shown in the figure are not used for practical reasons and we return to that point in Section 2.5. Notice that Figure 5 shows both the Charging Area and the Casting Area two times, meaning that these cranes have more tasks. For example, the Charging Cranes charge pig iron into the converters, but also charge scrap into the same converter.

2.2 Process of Generating and Applying the Yearly Shutdown-Schedule

In the current situation, Tata Steel develops the YSS for the next fiscal year (April to March) between May and October and bases it solely on planned maintenance. The development can be divided into four phases, which Figure 8 depicts. During Phase 1, the installation engineers belonging to the section[3] that manages the installation define the maintenance needs of the different installations and store these needs and the corresponding cycle times in PO-plans[4] in SAP. As a reminder for the job, SAP shows a pop-up of the PO-plan a preset number of weeks before the maintenance has to be performed.

Figure 6 - Charging of pig iron into a converter

Figure 7 - Charging of scrap into a converter

[3] The 'Basic Oxygen Steel Plant 2' is made up of 5 sections that are all responsible for a set of installations.
[4] PO-plan stands for the Dutch term 'periodiek onderhoud'-plan, which means 'periodical maintenance'-plan, and is a function in SAP. These plans are used to store maintenance jobs and its corresponding cycle times. PO-plans pop-up a preset number of weeks before the maintenance is actually performed.

During the determination of the cycle times of the installations, the engineers assume that their maintenance suits best in the schedule if the plant is down: they know that one of the Blast-Furnaces is down every ten weeks, and assign a cycle time of ten weeks to their installation. Despite of their good intentions, to keep the shutdown controllable, there should be the least maintenance as possible during a shutdown, so only the maintenance that really requires a shutdown should be scheduled during a shutdown (Blok et al., 2012). Presently, Tata Steel tries to make the engineers aware of the need to define their needs from a maintenance point of view, meaning that they really define the maintenance needs of the installation. Besides planned maintenance, installations need to be shut down due to additional needs, called projects. These projects are also proposed during Phase 1. Hereafter, the maintenance schedulers combine these needs to cluster jobs and to schedule shutdowns, such that production is the highest possible: *they* should add the production point of view, rather than the installation engineer, who adapts the cycle time of the installation to the cycle time of the Blast-Furnaces in the current method.

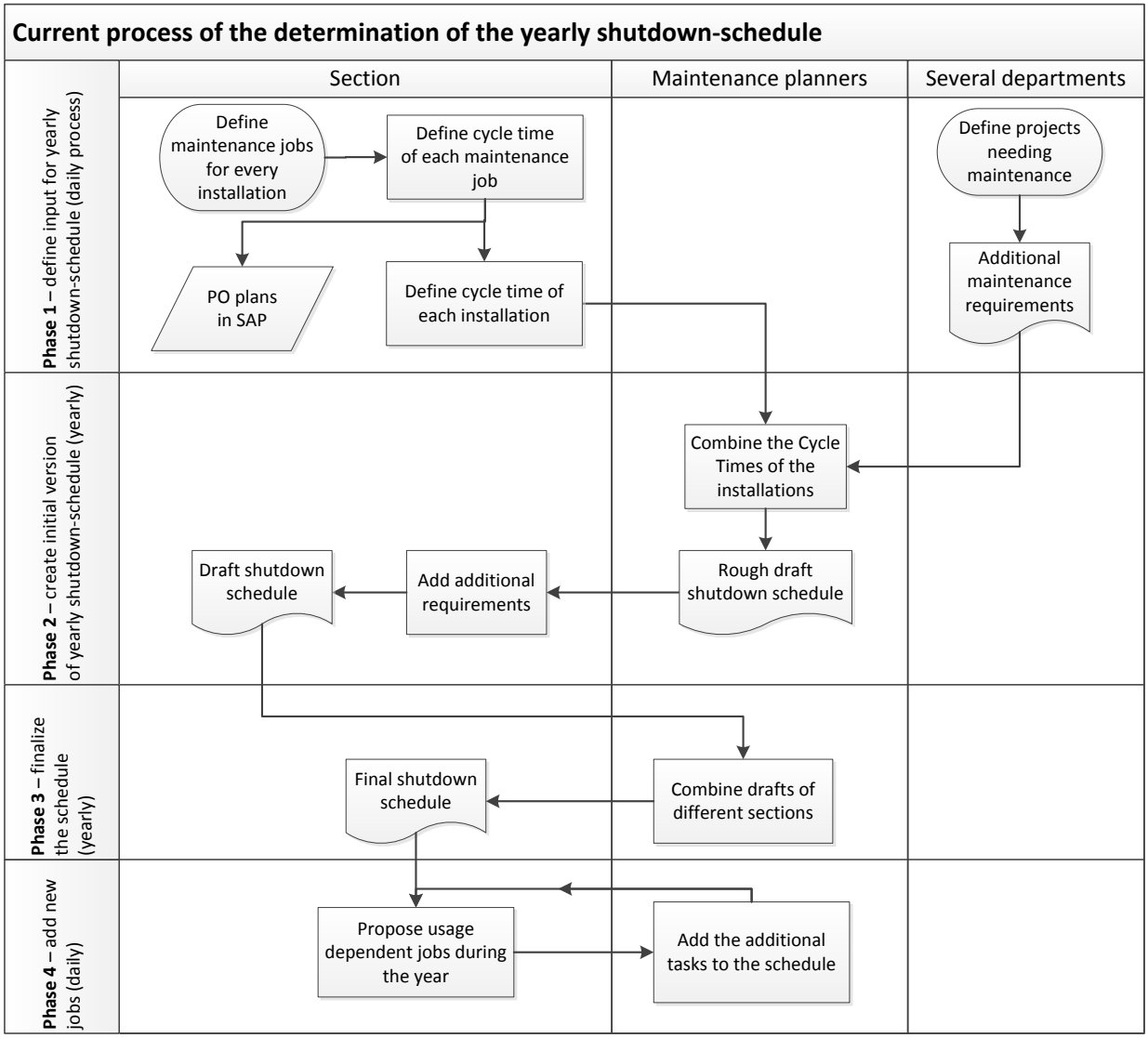


Figure 8 - Procedure for developing the yearly shutdown-schedule

Currently, the defined jobs and their cycle times are stored in SAP, but to generate the YSS during Phase 2, these PO-plans are hardly used and the process is mostly based on discussions and consultation with the responsible sections and installation engineers, after which the needs are combined with the needs of the Blast-Furnaces and the Direct Sheet Plant (DSP). During the development, several restrictions appear, especially due to the continuous production of steel, meaning that the production speed of the Blast-Furnaces should be adjusted if certain installations in the process are shut down too long, which may result from an uncertain duration of the maintenance job. Because an overflow of steel is unwanted, the uncertain jobs are scheduled with more slack. This makes the whole YSS-procedure a deterministic process: the amount of shutdowns, the time windows, etc. Furthermore, to take care of the restrictions to the flow, Tata Steel uses rules of thumb instead of scientific and objective measures. Note that some shutdowns of installations do not affect the flow of steel, because the plant has some buffers – such as ladles – in which transport takes place and iron and steel can flow on different routes through the plant. Still, these shutdowns are scheduled in the YSS.

The resulting YSS contains two axes: the horizontal axis contains the different installations in the plant and the vertical axis contains the time in weeks. The YSS gives per installation, the day and time to be down – Figure 9 shows a simplified view. Note that the current schedule contains 41 installations and 52 weeks, which are divided in days. In order to add the production view to the maintenance jobs, the schedulers search for ways to cluster different maintenance jobs, such that no crane or installation is unreachable without being maintained, so no crane is unreachable while it is available for production. In Phase 3, the different sections propose adaptions to the schedule and the planner changes the schedule. The process remains in that cycle of adapting and proposing adaptions until the schedule fits best to the needs of the sections, such that after Phase 3 the YSS is finished and the shutdowns of the plant are scheduled. Finally, in Phase 4, additional maintenance jobs are defined and added to the schedule, which is done throughout the year. These jobs vary from unexpected shutdowns, to additional maintenance requirements of an installation.

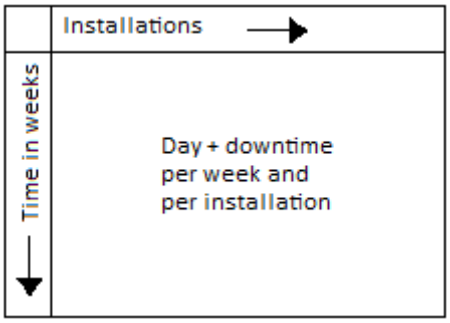


Figure 9 - Simplified Lay-Out of the Current YSS

After scheduling the shutdowns (i.e., after Phase 4), the actual jobs to be performed during a shutdown still have to be determined. As mentioned before, the different maintenance jobs are stored in PO-plans and pop up a few weeks before the maintenance has to be performed and based on the pop-up and the YSS, the section sets a date and time for the task, depending on the availability of personnel, materials, and time (as scheduled in the YSS). Notice that not every job exactly fits in the YSS, because jobs have different theoretical cycle times, but are combined by the planners.

2.3 Complications

This section clarifies the link between Chapter 1 and 2 by shortly concluding on Section 2.1 and Section 2.2.

The main complication of generating the YSS, is the current manual method, including the fact that the schedule is based on experience to set the cycle times of installations and on human knowledge

about the schedule's restrictions, such as rules of thumb. Due to this manual method, Tata Steel is not sure about the performance of the current method with respect to total flow, but Tata Steel is also not sure about the correctness of the rules of thumb. A negative side-effect of the manual method is the difficulty to adapt the schedule when new information is present and it makes it hard to convince others about the schedule. Besides these topics, the engineers who define the cycle times during Phase 1 do not define the cycle times from a maintenance point of view, but rather from a production point of view. This process should be the other way around: the engineers define the optimal maintenance cycle times of jobs and the schedulers compose the YSS based on these optimal cycle times. By defining the cycle times from a maintenance point of view, the installation engineers only focus on the availability of their installation and the requirements of their jobs, whereas the shutdown manager adapts these cycle times such that the jobs fit in the schedule. So, the shutdown manager adds the production point of view based on the cycle times defined by the installation engineers, such that the YSS guarantees the highest availability of the whole plant, given certain restrictions (safety, supervising workforce, etc.).

The scope of this research does not include this problem of determining the cycle times (i.e., Phase 1), because the current, non-optimal cycle times can be used as input for the process of generating a YSS and besides that, Tata Steel is dealing with a better determination of the maintenance needs by means of implementing new software based on *Failure Mode, Effects, and Criticality Analysis* (FMECA). Although we do not focus on defining the cycle times of jobs, we do use the cycle times of installations as input. We obtain the maintenance jobs and the corresponding cycle times by generating all PO-plans in SAP, to obtain every job that has to be performed during the upcoming year. Hence, we link Phase 1 to Phase 2 by using Phase 1's output as input for Phase 2. By generating these PO-plans, we already circumvent one 'human knowledge'-problem, because the current cycles in the YSS are based on discussions with the different sections instead of on the cycle times that are defined for the jobs. Furthermore, we initially leave out Phase 4 of this research because of time restrictions, but we aim to recommend on the implementation and addition of Phase 4 to the method we deliver, because robustness of the YSS makes sure that rescheduling is prevented as much as possible, which leads to an increase in trust and the willingness to accept the schedule. Figure 10 shows a brief summary of the current situation: cycle times of different jobs are available (Phase 1), the jobs are combined, and the YSS is generated. In this research, we focus on the generation of the YSS (Phase 2 and Phase 3 of Figure 8), hence the frame in Figure 10: we develop a method to generate the YSS, given the cycle times of maintenance jobs.

We cannot set a target on the output of the process, because there is no benchmark value available, so the current performance is not comparable. Besides that, the current method does not necessarily cover every job; neither necessarily uses the correct cycle time.

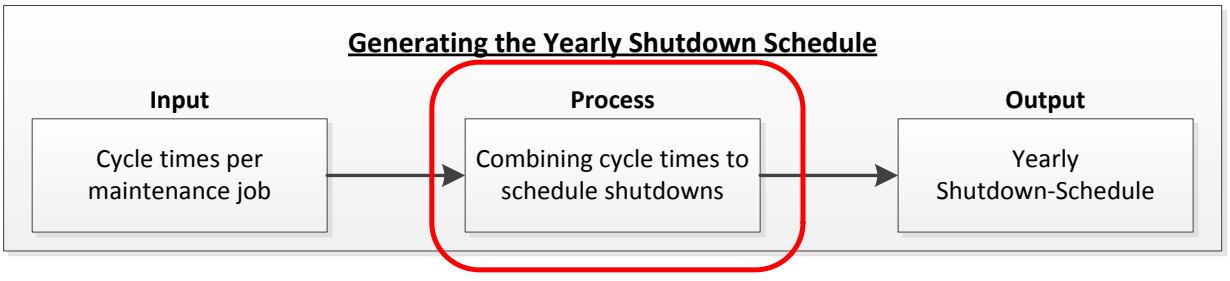


Figure 10 - Summary of the research's scope

2.4 Cycle Time Defined

The previous sections already briefly indicated that, when the Basic Oxygen Steel Plant cannot handle all the iron produced by the Blast-Furnaces, either the Blast-Furnaces have to be deregulated or pig iron has be dumped. This section elaborates on the in- and decrease of the cycle time of the Basic Oxygen Steel Plant *due to planned maintenance*, such that it is clearer how the Blast-Furnaces and the Basic Oxygen Steel Plant influence each other. Again, this section only considers the cycle time due to planned maintenance, so it does not include deviations due to corrective maintenance. Furthermore, it only considers the theoretical cycle time, as if all other factors are not restrictive: plenty of steel, enough demand, etc.

Recall that there is a small capacity to buffer pig iron (in hot metal cars) between the Blast-Furnaces and the Basic Oxygen Steel Plant. So, in order to process all iron produced by the Blast-Furnaces at a certain moment, the capacity of the Basic Oxygen Steel Plant should be at least the output of the Blast-Furnaces minus the available capacity of the buffer. The Basic Oxygen Steel Plant is made up of several areas (see Figure 3 for the different areas and Figure 11 for a view in one of these areas) that all have their own capacity, but these areas can only produce what the successor can handle or the predecessor supplies, due to the continuous process and the – for a yearly schedule – negligible buffers between the areas. Moreover, only the capacity of the bottleneck area influences the amount of iron that the Basic Oxygen Steel Plant can handle. Here we assume that it is not possible to use the non-bottleneck installations as a small buffer (work in process), such that the installation that is maintained can be fully occupied when it is taken into service again (when it is taken into service the bottleneck shifts to another installation, such that it is not fully occupied). Due to this assumption, the simplicity of the model increases, while it does not influence the representativeness much, because an installation needs some time to be back on full operational capacity after maintenance.

Figure 11 - A view in the Charging Area

Now, the cycle time in the bottleneck area depends on the shutdown of (a set of) installations in that area. For example, if Charging Crane 21 is down, the cycle time of a load in the Charging Area is 25 minutes instead of 18 minutes. This means that the cycle time of the same amount of iron at the Blast-Furnaces may not be less than 25 minutes, if the buffer has reached its capacity. Because Tata Steel has data about the cycle time in an area if a certain set of installations is taken out of service, we define the bottleneck cycle time $CT_{bottleneck}$ as the maximum cycle time through an area, resulting from shutting down combination c ($Down_c = 1$).

Formula 2.1

$$CT_{bottleneck} = \max_{1 \le c \le C} \{CT_c * Down_c\}$$

$CT_{bottleneck}$ is the bottleneck cycle time of one load,
c is the index of a combination. c = 1…C,
CT_c is the cycle time if combination c is down,
$Down_c$ is a binary variable indicating whether combination c is down. If c is down, $Down_c = 1$.

Note that an installation may be present in more than one combination and that the formula only searches for the highest cycle time without indicating which combination leads to the highest cycle time, although it can be found in a recursive manner. Finally, we recognize that maintenance scheduling is not just about maintaining the capacity of installations and that other aspects such as costs and manpower, need to be considered as well. We assume that costs are closely related to reductions in the capacity and that the cycle times determined by the installation engineers are among others based on costs of maintenance.

2.5 Restrictions to Scheduling Maintenance

The current process of scheduling maintenance is subject to several constraining dependencies between installations (the combinations of Section 2.4). This section states and explains the different constraints that Tata Steel currently applies to the scheduling process in Section 2.5.1. These restrictions focus on organizational requirements. Then, Section 2.5.2 discusses the currently used rules of thumb to generate the YSS.

2.5.1 Currently Applied Restrictions

To schedule the shutdowns, several organizational requirements have to be met. These organizational restrictions are:

1. During an installation shutdown, only the jobs that really require the shutdown of that installation should be performed. Other jobs should be performed during production, in order to keep the jobs during the shutdown manageable.
2. Plant shutdowns are preferred outside holiday periods and outside the winter period, because of weather restrictions, such as frost.
3. If maintenance is started it should be finished without interruption. So, if an installation is shut down for maintenance, it is not allowed to take it back into service without finishing the job. Furthermore, most jobs that last longer than 8 hours are performed during several days between 7:00 and 15:00. This means that jobs with a duration of twelve hours take one full day and a day from 07:00 till 11:00, so the installation is down for more than one day. There

are jobs, on the other hand, that should be finished quicker (require more hours per day) if they affect the flow too much. A distinction between jobs should be made here.

4. The Basic Oxygen Steel Plant should adapt its shutdown schedule to the amount of pig iron produced by the Blast-Furnaces. If one of the Blast-Furnaces is shut down (every 10 weeks), the Basic Oxygen Steel Plant receives less iron and is partly down too. If the Blast-Furnace that is still up produces more iron than the Basic Oxygen Steel Plant can handle, the buffer increases. The schedule should take care of this finite buffer: pig iron is storable in a pre-specified amount of hot metal cars. If this finite buffer is fully occupied, pig iron can be dumped at Harsco (company on the IJmuiden site), where the iron solidifies. Hereafter the solid iron can be reused as scrap, which obviously has a lower value than the liquid iron as it left the Blast-Furnaces, because it not desulfurized and has to become liquid again. The final option is to deregulate the Blast-Furnaces, which is highly unwanted and only scheduled in the YSS if one maintenance task takes a long time, such that it cannot be prevented.
5. The converters are maintained based on the number of loads they processed, instead of on a number of weeks, so the cycle times may differ when the loads per period differ. After a certain amount of loads on a converter, that particular converter is maintained during 2 x 168 hours (two weeks). The amount of loads is uncertain and a converter may require maintenance because of a breakdown, so indicating when the converter should be maintained is subject to uncertainty and Tata Steel does not include the converters in the YSS. Furthermore, if the steam-system is down, Converter 21 and Converter 22 are also down and finally, all three converters are down if the secondary dust exhausting system is down. The secondary dust exhausting system is scheduled in the YSS.
6. There is no restriction on the maintenance of Scrap Cranes, as long as a mobile spare scrap crane is available. This availability is to be determined at the operational level and is not relevant for this research. So, we assume that one of the two Scrap Cranes can always be maintained. On the other hand, if Charging Crane 25 is maintained and still scrap has to be added to the converter, Scrap Transverse Transport 21 needs to be in use. The flowchart in Figure 3 and Figure 5 nicely show the logic behind that: Charging Crane 21 can only reach Scrap Transverse Transport 21, meaning that if Charging Crane 25 is out of service while still scrap has to be added to the converters, Scrap Transverse Transport 21 needs to be in use. Furthermore, if Charging Crane 26 is maintained above Scrap Transverse Transports 23 and 24, then Scrap Transverse Transports 21 and 22 should be available.

2.5.2 Rules of Thumb

This section discusses the rules of thumb on which the current method of generating the YSS is based, such that we can compare these rules of thumb with the outcomes of the method we propose in Chapter 4. We discuss the rules of thumb in order of appearance in the process, so we start with the Charging Area and end with the trains to the Hot Strip Mill and the Direct Sheet Plant. Again we refer to Figure 3 for a better understanding of these rules of thumb, which are basically based on not disturbing the flow in the plant.

Charging Related

Taking more than one installation in the Charging Area out of service at the same time is not allowed, unless the whole plant is down. An exception is that Charging Crane 25 and Charging Crane 26 may be down together, especially because taking Charging Crane 25 out of service, leads to the unreachability of Charging Crane 26. Furthermore, during plant shutdowns, there should be at least two Charging Cranes, one Roza, and one Pit available after 8 hours of downtime, such that production can continue.

Loads without scrap can only be produced for 10 hours. Production of loads without scrap happens when both Charging Crane 26 and Charging Crane 25 are out of service. Recall that the shutdown of Charging Crane 25 leads to the unreachability of Charging Crane 26. This rule of thumb is based on a buffer overflow after 10 hours.

Slag Related

To transport slag away from the converters, either the Slag Area or Casting Area 1 should be used. The Slag Area consists of three transverse transports and a Slag Crane. These can be taken out of service as long as Casting Area 1 is available, so as long as either Casting Crane 21 or Casting Crane 24 is available. This rule is derived from Figure 5, which indicates the disruption of the flow.

Scrap Related

If Charging Crane 25 is maintained and still scrap has to be added to the converter, Scrap Transverse Transport 21 needs to be in use. The flowchart in Figure 5 shows the logic behind that: Charging Crane 21 can only reach Scrap Transverse Transport 21, meaning that if Charging Crane 25 is out of service while still scrap has to be added to the converter, Scrap Transverse Transport 21 needs to be in use. Furthermore, if Charging Crane 26 is maintained above the Scrap Transverse Transports 23 and 24, then Scrap Transverse Transports 21 and 22 should be available.

Converter Related

Besides the restriction mentioned in Section 2.5.1, there are no rules of thumb for the converters.

Casting Areas

This paragraph discusses Casting Area 1, Casting Area 2, and the area in between these. These areas contain Casting Crane 21, 22, 23, and 24, Casting Installation 21 and 22, RH-OB installation, Stirring Station 21, Stirring Station 23, Ladle Furnace 21, and Ladle Furnace 22. At most two of the latter five installations are allowed to be down during a plant shutdown and it is not allowed to take both Ladle Furnace 21 and Ladle Furnace 22 out of service. Outside a plant shutdown, at least two of the ladle furnaces and RH-OB installation should be available. So, it is never allowed to take all five installations out of service, neither during conventional production, nor during a plant shutdown. Furthermore, the RH-OB installation also requires the steam system, which means that the RH-OB installation is down if the steam system is down. Additionally, Stirring Station 21 is a spare installation and Tata Steel prefers to keep this installation as a spare installation. Furthermore, both Ladle Furnace 22 and the RH-OB installation have to be available if the Direct Sheet Plant is down. Finally, Casting installation 21 and the RH-OB installation should be down together.

3. Literature Review

This chapter answers question 2 *How should this research be positioned in the literature?,* by first giving a general overview of the literature in Section 3.1. Section 3.2 explains why existing exact methods and heuristics do not fit to the problem that Tata Steel faces, although these suit to seemingly comparable problems. Section 3.3 explains how the previous research models and solves comparable maintenance scheduling problems and Section 3.4 contains some concluding remarks on the literature review.

3.1 Position in the Literature

The process we consider in this research distinguishes itself by being a continuous process without buffers (the only buffers are outside the Basic Oxygen Steel Plant and are relatively small, compared to the production speed). Continuous processes are distinguished from other types of processes by high volume and low variety in the production process (Slack et al., 2007). The lack of buffers in the continuous process at organizations such as Tata Steel is what makes the topic of maintenance scheduling difficult and this difficulty makes it an appreciated subject of research as it turns out in the upcoming paragraphs.

A major part of the literature on maintenance comprises terms such as 'availability' (Sherbrooke, 2004), 'mean time to repair' (Sherbrooke, 2004), 'failure statistics' (Aven and Jensen, 1999), and 'corrective and preventive maintenance' (Gertsbakh, 2005). These concepts influence the length of a maintenance cycle calculated by the engineers of every installation and although this influences the YSS, the determination is outside the scope of this research. Still, this determination is interesting and it may be important to search for possibilities to in- or decrease the cycle time, because as Van Dijkhuizen and Van Harten (1997) and Gits (1992) state, changing the cycle time may lead to a better clustering of maintenance jobs. A better clustering makes that the total costs decrease, because installations can be maintained in parallel, which leads to lower set-up costs. Considering our research, clustering maintenance jobs is especially relevant if a whole branch of the flow of steel is unreachable, after shutting down one installation, because all these installations can be maintained and clustered.

The concepts mentioned in the previous paragraph all influence the type of maintenance we consider: planned and preventive maintenance (Deshpande and Modak, 2002). Another important characteristic of this research is the deterministic nature of the scheduling problem. We already touched upon the deterministic nature of this problem in Section 2.2, but because of its importance we elaborate on this topic here. Based on Winston (2004), we define a deterministic problem as 'a problem that does not consider any randomness', whereas a stochastic problem is 'a problem that contains variables that fluctuate randomly'. The definition of deterministic problems corresponds to the research situation, because the only variables that contain uncertainty are the duration of a maintenance job and the cycle time between jobs, which we both take as given, because the maintenance engineers include the uncertainty in the duration, and the randomness is added when the actual job is planned a few weeks in advance. Moreover, the YSS is set up a year in advance and it is a common approach to leave out uncertainty at this stage. Furthermore, the determinations of the cycle times incorporate the uncertainty in the lifetime of equipment, such that we take the calculated cycle time as optimal. Yamayee's literature review in 1982 states that most maintenance scheduling is performed on deterministic simplified problems, but we found that since that time more and more authors performed research on stochastic maintenance scheduling by the addition of

for example fuzzy integer programming. So, the literature discusses deterministic as well as stochastic maintenance scheduling problems.

Previous research classifies our problem as a 'Maintenance Scheduling Problem', and we add the term 'deterministic' to that formulation, because the literature belonging to that term does not explicitly focus on deterministic problems, but on both stochastic and deterministic problems. For the Maintenance Scheduling Problem, there is an exhaustive base of literature available that focusses especially on power systems, as mentioned by Kralj and Petrovic (1995). Since that time the subject of maintenance scheduling is still especially researched in the electric power utilities. We highlight the relevant and important literature on the power generating units in this paragraph. One of the researches is performed by Huang et al. (1992), who use fuzzy dynamic programming to solve a generator Maintenance Scheduling Problem at the Taiwan Power Company. Another example of maintenance scheduling in power systems can be found in Volkanovski et al. (2008), who schedule maintenance for generating units of a Macedonian power system by minimizing the loss of load expectation. Such an objective is comparable to ours, because we aim to minimize the loss of pig iron. Besides Volkanoviski et al. and Huang et al., Chattopadhyay et al. (1995) research the maintenance of generating units, but they combine this with the production schedule, which makes the approach a more integrated one. Berrichi et al. (2010) also combine the scheduling of production and maintenance, in order to obtain an integrated schedule. These approaches are less applicable to our problem, because both the maintenance and the production schedule are not that detailed a year in advance. Kralj and Petrović (1988) performed a review of papers published between 1973 and 1988 that focus on the optimization techniques used in preventive maintenance scheduling for energy supplying organizations. Although the authors focus on the energy supply, the insights they summarize (objectives, constraints) are interesting and comparable to other industries. El-Sharkh and El-Keib (2003) apply an evolutionary programming-based technique to the problem of maintenance scheduling of power generation and transmission systems, by means of a search method that finds local optima and an additional method to move from an infeasible solution to a feasible solution. They define the Maintenance Scheduling Problem as "determining the optimal starting time for each preventive maintenance outage in a weekly period for one year in advance, while satisfying the system constraints and maintaining system reliability", which more or less corresponds to the problem central in our research. Mohanta et al. (2007) uses a combination of genetic algorithms and simulated annealing to schedule maintenance at a power plant by developing a model that is applicable to other power-intensive industries, but the focus is much on the power industry and may not be extendable to the steel manufacturing industry.

The reason for this focus on power systems probably is the continuous process and fluctuating demand without the possibility to store the power supplied. Although Tata Steel and the Basic Oxygen Steel Plant can store its steel, the process itself is much more complex than the power industry. Unfortunately, the Maintenance Scheduling Problem in other industries than the power industry is less researched. This paragraph discusses the researches in these other industries where possible. Deshpande and Modak (2002) apply reliability centered maintenance to a specific installation of a steel plant in India, namely to the vacuum degassing/vacuum oxygen decarburizing installation. Aissani et al. (2009) focus on the dynamic – real-time – control of manufacturing systems at an oil refinery in Algeria. They take the production planning as given and establish to schedule the maintenance around it. They apply reinforcement learning to find the best maintenance schedule and include a part on on-line scheduling of maintenance, meaning that they include corrective and

short-term preventive maintenance in their model. This corresponds to Phase 4 in this research and their approach is interesting for the Basic Oxygen Steel Plant if Tata Steel decides to extend the static YSS to a more dynamic YSS with a rolling horizon that includes medium-term scheduling. Escudero (1981) develops a mixed integer linear program that is applicable to a broad range of Maintenance Scheduling Problems, because of his broad definitions of variables. A negative side-effect of this broad definition is the low direct usability, but a positive effect is the fact that it is applicable as a first way of thinking. With respect to maintenance scheduling, the most comparable industry that the literature discusses is the railway industry, which deals with several flows and a rather continuous process (continuous enough to restrict maintenance durations) and both small routine jobs and larger projects have to be performed. Umiliacchi et al. (2011) research the requirements to implement predictive maintenance to the railway system, ranging from trains to the infrastructure. Their approach is rather theoretical and based on the linking of different installation states, but their ideas about the rather new view of maintenance – predictive maintenance – are worth mentioning here, because predictive maintenance may be of use for Tata Steel. Peng et al. (2011) also focus on the railroad track maintenance problem, but especially emphasize on the personnel constraints. Such constraints are not useful for our problem, but their heuristic approach to solve the problem shows the simplicity to quickly find a solution. This heuristic is based on clustering jobs and the probability that the cluster violates a mutually exclusive constraint. These clusters are scheduled first. Budai et al. (2004) discuss other heuristics for solving the Maintenance Scheduling Problem for the Dutch railway system. Alkhamis and Yellen (1995) use Integer Programming to solve the Maintenance Scheduling Problem at a refinery in Kuwait, which is part of an interesting and highly comparable industry because of the continuous process, storable goods, and dependent installations. However, their problem is less complex, because they have fewer flows and fewer dependencies among the different installations. Still, their setting is comparable to ours and they also recognize that it is impossible to know the quality of the current schedule: “Also with manual methods it is impossible to know how well the maintenance schedule is and how far we are from the optimal schedule” (Alkhamis and Yellen, 1995, p544).

Other authors researched other types of scheduling that also interacts to our problem scope. For example Pinedo (2009), who discusses several planning and scheduling principles that definitely have ground in common with maintenance scheduling, such as planning in a job shop and scheduling with time windows and slack. The principles mentioned in Pinedo (2009) and other literature seems not to be applicable to the Maintenance Scheduling Problem, which is probably the reason why the authors mentioned in the previous paragraph did not use such heuristics. For example, the flow-shop and job-shop problem focus on the assignment of jobs to machines, which is decision making on an operational level. Another example is the project scheduling problem that focusses on the sequencing of jobs, which is applicable at Tata Steel to sequence jobs during a shutdown of an installation, so after Phase 4 when the jobs are scheduled with much more detail. That sequencing should be based on the YSS that indicates the duration of a shutdown. Lima et al. (2011) discuss another example of non-maintenance scheduling that is comparable to our research. They apply a mixed integer linear programming (MILP) based scheduling method to a long term scheduling problem at a glass manufacturer with a continuous process. Although they do not focus on maintenance, they do use a rolling horizon to adjust the medium term scheduling of operations. Such a rolling horizon approach can be used to improve Phase 4 in Figure 8 and Lima et al. (2011) show that in their case the safety stock is fully used at the end of the cycle, such that rebuy is not required. In our case, this would mean that a rolling horizon makes sure that for the last weeks, the YSS is

allowed to postpone certain jobs to the next year if it suits better in the schedule. Obviously, such a rolling horizon has a positive impact on the solution instead of a negative impact in Lima's case.

None of the above mentioned authors focuses on minimizing the impact on the successors of the process, on the total flow of the plant, or on the flow through different areas. We do focus on these aspects and the reason for this apparently non-conventional objective is, as mentioned before, the fact that the Basic Oxygen Steel Plant has different flows through the plant, whereas the energy generating plants do not have such flows. Besides that, in a continuous process such as Tata Steel's process, maximizing the flow equals maximizing availability, uptime, output, and revenues. Some researches aim to the same output of the model as the YSS we propose to develop, for example Saraiva et al. (2011), who schedule maintenance for a year discretized in weeks. However, their objective is to minimize the costs for a generating plant, which is a slightly different objective.

We conclude that finding an optimal solution with respect to any objective is almost impossible, but near-optimal solutions are attainable. This conclusion is based on the fact that most authors used a local search heuristic to find a near-optimal solution to their problem, because the problem was too complex to solve to optimality, whereas our problem is even more complex than most of these problems. Section 3.3 returns to this topic and discusses the literature that applies local search heuristics. Furthermore, this research contains more complexity than previously performed research. Still, we understand that the deterministic aspect in this research reduces the complexity and possibly leads to an easier achievable optimum. Whether or not we are able to find an optimal solution to this deterministic problem depends on the definition of the objective and the set of restrictions. Finally, the literature only contains problems without pre-specified cycle times, whereas we have to deal with those cycles specified by maintenance engineers. This decreases the model's mathematical complexity, but increases the difficulty of combining maintenance jobs based on time-windows.

3.2 Approaches to Comparable Problems

This section discusses problems that seem to be comparable to the Maintenance Scheduling Problem and for which there are methods to quickly find a good or optimal solution. At first sight, the Maintenance Scheduling Problem looks comparable to the *project scheduling problem,* which is a scheduling problem with precedence constraints where multiple resources are required, while the make-span has to be minimized. In our problem, the make-span does not have to be minimized, which makes the problem quite different from the project scheduling problem, so techniques to solve the project scheduling problem do not apply to our problem. Nevertheless, the scheduling *during* a shutdown is comparable or even equal to a project scheduling problem and the heuristics may be applicable after Phase 4 in Figure 8 on page 16, during the operational level scheduling of the shutdown where multiple jobs have to be performed as quick as possible, hence aiming to minimize the make-span. Furthermore, the problem seems comparable to the *flow-shop problem* and the *job-shop problem* (Pinedo, 2009), which are special cases of the project scheduling problem and are consequently applicable after Phase 4, but are not applicable to our problem.

3.3 Options to Improve the Process

Section 3.2 explains why heuristics that apply to other scheduling problems do not apply to the Maintenance Schedule Problem and this section outlines several methods that do appear in the literature about maintenance and shutdown scheduling, such that we can answer sub-question 2.c *Which methods are applied in the literature?* The options are solely made up of models that are

solved by computers, in contrast with Tata Steel's current manual method. The need for computers to schedule maintenance is already set forth in Christiaanse and Palmer (1971), who state that automated techniques increase system reliability, reduce cost, allow planners to reschedule quickly, and require less manpower to set up the schedule. Especially for more complex Maintenance Scheduling Problems, manually developed schedules do perform worse on these aspects. Computers probably do not find the optimum either, but the probability of finding a good solution with a computer model is higher and automated planning methods save a lot of time for the human planners. First, Section 3.3.1 discusses techniques to model the Maintenance Scheduling Problem as they appear in the literature and Section 3.3.2 discusses search techniques to obtain good solutions based on these models. Table 2 shows the different techniques that Section 3.3.1 and 3.3.2 discuss. More techniques appear in the literature (e.g., Ant Colony Optimization), but those are comparable to or even derived from these techniques and in our view too complex to be applied to our problem.

Table 2 - Overview of the methods used by different authors

Type	Method	Authors
Problem Formulations	Linear Programming Formulations	Escudero (1981); Chattopadhyay (1998).
	(Mixed) Integer Programming Formulations	Dopazo and Merill (1975); Alkhamis and Yellen (1995); Fetanat and Shafipour (2011); Dahal and Chakpitak (2007); Satoh and Nara (1991); Lima (2011); Escudero (1981); Muckstadt and Wilson (1968); Chattopadhyay, et al. (1995).
Search Techniques	Genetic Algorithm	Burke and Smith (2000); Volkonovski (2007); Mohanta (2007); Dahal et al. (1999); Baskar (2003); Wang and Hanschin (2000); Dahal and Chakpitak (2007); Huang (1998).
	Simulated Annealing	Satoh and Nara (1991); Mohanta (2007); Saraiva et al. (2011); Dahal and Chakpitak (2007).
	Tabu Search	Burke and Smith (2000); El-Amin et al. (2000); Gopalakrishnan et al. (2001).

3.3.1 Problem Formulations

This section discusses the main formulations to model the Maintenance Scheduling Problem that appear in the literature. For every problem formulation in Table 2, this section briefly explains the characteristics and the way previous research applies the type of formulation. Section 3.3.2 explains techniques to solve the models, such as the ones that this section discusses.

A Linear Programming (LP) formulation is a mathematical modeling technique that assumes no dependencies among decision variables[5], hence the techniques is called linear. If the variables are allowed to have fractional values, the model is called an LP and if the variables should be integers, the model is called an Integer LP (ILP). The major advantage of an LP is the existence of efficient techniques to find an optimal solution, which is harder for ILPs. However, the literature on the Maintenance Scheduling Problem does not widely describe LPs to model the Maintenance Scheduling Problem as Table 2 indicates, probably because a job either starts or does not start (variable is 0 or 1 - ILP), and it cannot start for 70% (variable is 0.7 - LP). Chattopadhyay (1998), on

[5] Decision Variable: "The variables whose values are under our control and influence the performance of the system" (Winston, 2004, p2). So, in our case this may be the variable that indicates when a job is started, which actually is the decision to be taken and changed by the computer.

the other hand, states that an LP formulation simplifies the method of finding an exact moment (e.g., after 9.7 days) to start maintenance instead of during a specific period (at day 10). Escudero (1981) models the Maintenance Scheduling Problem with integer variables, but solves the problem as if the variables are continuous, so he relaxes the problem. As mentioned before, the LP that is left can be solved quickly and the solution obtained from that relaxation is a lower bound to the solution of the actual problem.

An important requirement to efficiently solve the modeled problem is the need to have continuous variables and the need to have a formulation that is linear. Both requirements are major difficulties of the Maintenance Scheduling Problem: usually the problem can neither be formulated as a linear program, nor with solely continuous variables. Pinedo (2010) also recognizes this difficulty and states that for continuous manufacturing, such as steel mills, mixed integer programming is the most suitable way to model the problem. Mixed integer programming means that the model uses both continuous and integer variables and is not linear. As mentioned before, several other authors require integer variables to formulate the Maintenance Scheduling Problem, because an integer program formulation suits better to select a specific moment, as Dopazo and Merril (1975) show. Another useful idea is the use of time intervals to make sure that the maintenance is performed on a given day and the use of penalties in case maintenance is performed too early or too late, as Dopazo and Merril (1975) propose. By starting maintenance too early, as they state it, 'we are throwing away some of the twelve months of operation purchased the last time maintenance was performed'. Alkhamis and Yellen (1995) apply integer programming to schedule maintenance at a refinery in Kuwait, which is a comparable industry to the steel industry and Alkhamis and Yellen (1995) use comparable constraints. They admit that a large and complex problem is not solvable to optimality and we conclude that the approach should use a local search method, because other heuristics do not apply to the Maintenance Scheduling Problem as Section 3.2 explains. Section 3.3.2 discusses the main local search techniques. Marwali and Shahidehpour (1998) and Muckstadt and Wilson (1968) use 'Benders decomposition' (Benders, 1962) to solve the Mixed Integer *Linear* Program of a maintenace scheduling problem with network constraints. Benders decomposition is based on a master scheduling problem – a relaxation of the original problem – that is decomposed into several smaller sub-problems. If one of the sub-problems is infeasible, an infeasibility-cut is generated. At each iteration, an upper and lower bound to the main problem is generated, such that the different feasible solutions converge to the optimum. However, the practical use of this method is rather low.

3.3.2 Search Techniques

If the models that Section 3.3.1 discusses are too complex to solve to optimality within reasonable time, search heuristics or other heuristics can be used to find an acceptable solution within the given time range. For example, the constraints of a linear programming formulation are – as its name implies – linear and it is rather easy to find the best solution, because the problem has an easily analyzable solution space. On the other hand, more complex problems have more complex solution spaces and require more complex solving methods. Figure 12 shows an example of such a solution space, where the horizontal axes show the decision variables and the vertical axis shows the solution value. Notice that the solution values are the highest at the top of the hills. In case of a maximization problem, every top of a hill is a local optimum and the highest top is the global optimum. The methods that this section discusses are all based on hill climbing with the addition that they are able to step to other hills, so the methods all start with an initial solution from which they search for better neighboring solutions (hill climbing) or solutions on other hills: local and global search respectively. Besides the need for an initial solution, there is the need for a method to generate neighboring solutions and the need for a procedure to accept these neighbors. Clearly, if the heuristic only accepts neighbors with a higher solution, the probability of moving to another hill is lower than in case it also accepts neighbors with a lower solution value. So far, the fundamentals of the local search techniques are clear and the remainder of this section discusses three techniques that use a different way to generate neighbors and have their own procedure to accept neighbors. These heuristics are the main heuristics to solve the Maintenance Scheduling Problem, according to our literature review.

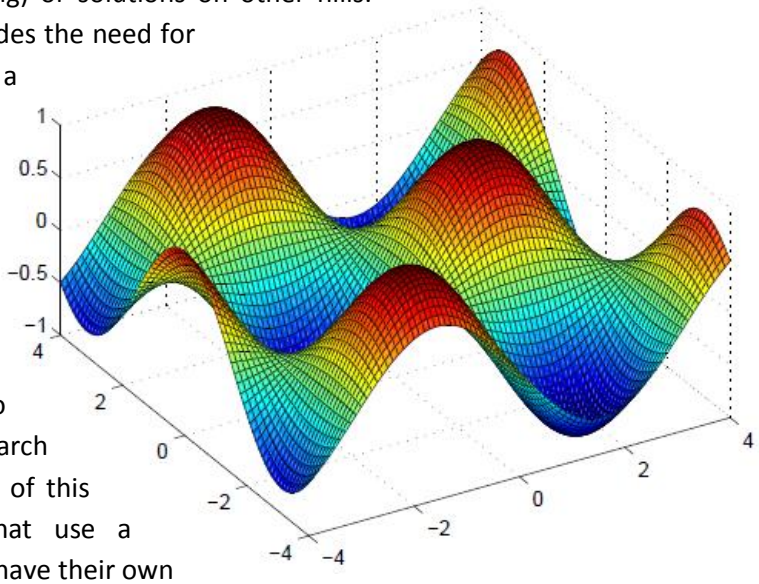


Figure 12 - Possible solution space

Genetic Algorithm

Holland developed the Genetic Algorithm (GA) approach in the mid-sixties and based GAs on natural evolution and survival of the fittest (Coley, 2003). In case of maximizing the solution value, the fittest solutions are the solutions at the top of the hills. GA searches for the fittest solutions, by creating so called parents and offspring in regions that seems to be near the top of a hill. The process is, like the other search algorithms, on creating new solutions from the available solutions: creating offspring by matching good parents. This matching based on the fittest parents is called *selection* and combining the parents to create offspring is called *crossover*. In addition, there is way to create new solutions by changing variables without crossover, which is called *mutation* and is meant to step to other local optima in order to search for the global optimum. Finally, GA creates a new generation and deletes generations with the least fit. The process starts over again as long as it does not exceed a preset number of generations to be created and as long as it does not attain a preset solution value. For a more detailed discussion on Genetic Algorithms, we refer to Coley (2003) and Holland (1992).

Baskar et al. (2003) apply GA to the Maintenance Scheduling Problem, but they only use it for small instances and they adapt the approach to make it suitable to their problem. Wang and Hanschin (2000) also apply and adapt the GA to suit to their Maintenance Scheduling Problem, such that the storage space and decoding time decrease. Due to these decreases, the computation time becomes shorter, which may be of use for our research.

Tabu Search

This explanation on Tabu Search (TS) is based on Hertz et al. (2003) and Glover et al. (1993). TS uses a memory (the tabu list), not only to compare the values of the current objective and best objective, but also to compare the values of variables and objectives of earlier steps. Every step in searching for a new solution starts with evaluating all neighboring solutions (change the variables), followed by choosing the best of these solutions that is not on the tabu list. Instead of complete solutions, the tabu list may also contain characteristics of solutions that are not allowed. Several mechanisms can be chosen to make the algorithm stop, for example if every neighboring solution is on the tabu list or a certain time window has passed. Of course, there are many approaches to this broad explanation of tabu search.

The literature does not discuss many approaches to the Maintenance Scheduling Problem that solely uses TS, because usually researchers combine it with other approaches. Burke and Smith (2000) for example apply a memetic approach (to start a genetic algorithm with good initial solutions) that employs TS in order to improve the found schedule. They state that this method is applicable to large-scale problems, whereas other models, such as the model of Satoh and Nara (1991) are solely applicable to small-scale problems. On the other hand, El-Amin et al. (2000) apply only TS to solve a MILP of the Maintenance Scheduling Problem in the power industry. Their conclusion is that the TS approach is good and promising for further usage based on a comparison with an enumeration method, but they do not compare it with other search techniques. Gopalakrishnan et al. (2001) also add a tabu search heuristic to previously performed research and decrease the optimality gap from 2.26% to 0.60%. Again, they do not compare their results with the results of other search heuristics.

Simulated Annealing

We discuss Simulated Annealing (SA) more extensively than TS and GA, because Chapter 4 concludes that this is the most suitable approach to our problem. Kirkpatrick et al. (1983) developed the SA method and based it on the Metropolis algorithm (Metropolis et al., 1953). The latter method shows that natural systems can be used to search for rather good solutions. They take N imaginary particles, put them in a random structure and calculate the energy of the whole system. Then they rearrange one particle, again calculate the energy of the system, and compare it with the energy before the change. If this energy is lower, the algorithm accepts the new structure, otherwise a new change is proposed based on the previous structure (with the lowest energy).

Now, Kirkpatrick et al. (1983) worked out this idea by comparing it to the annealing of materials, so melting the material and then slowly let the temperature decrease such that the pattern becomes more and more fixed. For every decrease in temperature, the pattern changes in order to attain a steady state and finally – if the temperature is at a preset point – the structure is fixed and changes are impossible. To apply this idea to find solutions for an optimization problem, Kirkpatrick et al. (1983) start with a high temperature in which the algorithm moves through the whole solution space by accepting worse solutions. If the temperature decreases, the search becomes more local (the solution space is more fixed), meaning that the acceptance of a solution is more and more based on

its solution value and less on a random probability, until the temperature is low enough to make the search algorithm a local search where it only accepts improvements. Kirkpatrick et al. (1983) conclude that performing SA to a problem requires four aspects:

1) A concise description of a configuration of the system.
2) A random generator of "moves" or rearrangements of the elements in a configuration.
3) A quantitative objective function containing the trade-offs that have to be made.
4) An annealing schedule of the temperatures and length of times for which the system is to be evolved.

For a much more elaborated overview of SA with explanations of different cooling schedules we refer to Aarts et al. (1997).

The literature widely describes the use of SA to solve the Maintenance Scheduling Problem, for example Mohanta et al. (2007) use a combination of a GA and SA to solve the Maintenance Scheduling Problem. They distinguish between a stochastic and deterministic objective, where obviously the deterministic function is most comparable to our situation. Satoh and Nara (1991) research the Maintenance Scheduling Problem for thermal generator maintenance and formulate the problem as a mixed integer linear programming (MILP) model, which they solve by using SA. They use penalty functions on some tight restrictions in order to make sure that a feasible solution will be found, while the deviation from the initial model is the smallest possible. Finally, Saraiva et al. (2011) formulate the generator Maintenance Scheduling Problem as a mixed-integer problem and use SA to solve it. They conclude that SA performs very well with a short computation time, but they do not compare their results with the results attained by enumeration or other search methods.

3.4 Concluding Remarks

To conclude, throughout the literature the most applied technique to model the Maintenance Scheduling Problem is a Mixed Integer Programming technique, whereas the Linear Programming approach is the least applied technique. Probably because of the usage of non-linear models, most literature describes a search heuristic to obtain an acceptable solution and the majority of these researches use Simulated Annealing. Several researches apply Genetic Algorithms and some use Tabu Search. Combinations of these three local search heuristics are hardly used. Which approach to apply depends on the specific problem and Chapter 4 continues on this discussion with respect to Tata Steel's Maintenance Scheduling Problem. Finally, a search algorithm requires an initial solution, a neighborhood structure, an acceptance criterion, and a way to measure the quality of the solution.

4. Model of the Maintenance Scheduling Problem at Tata Steel

This chapter answers the third sub-question of this research: *What is the most suitable option to improve the current method of scheduling shutdowns, taking into account the method's clarity and understandability, such that the flow is guaranteed and the restrictions are met?* In order to answer this question, we described several ways to formulate and solve the problem in Chapter 3, which have to be compared with each other in order to select the most suitable option for scheduling maintenance at Tata Steel. Section 4.1 covers the analysis and comparison of the different options to formulate the problem; Section 4.2 formulates the model and compares the formulation with the formulations in the literature. Section 4.3 selects and describes the local search heuristic to solve the problem and Section 4.4 contains a conclusion on this chapter.

4.1 Evaluation of the Modeling Techniques

This section evaluates the modeling techniques that Section 3.3 discusses and selects the most suitable option to mathematically model the scheduling problem that Tata Steel faces.

Our problem, as Section 4.2 explains, requires integer variables to set for example the start times of the jobs and to check whether or not a combination is down. Besides these integer variables, we do require continuous variables as well to formulate the problem properly, for example to calculate the overflow of pig iron. Furthermore, the more complex problems that the literature discusses all require a search technique to obtain good solutions. Our problem is characterized by a high complexity and, as appears in Section 4.2, linearity cannot be attained. To conclude, we model the problem as a Mixed Integer Program (MIP), which corresponds to the most used modeling technique applied in the literature, as Table 2 shows.

4.2 Mathematical Model of the Maintenance Scheduling Problem

This section covers the development of the model that can be used to generate the YSS. In order to model the problem, Section 4.2.1 explains the input and required output, and then Section 4.2.2 stepwise develops the model, based on the requirements.

4.2.1 Model's Input and Output

This section briefly explains the available input and the required output. Section 4.2.2 develops the model by explaining the objective and the different constraints step by step.

Input

Currently, Tata Steel generates the YSS based on discussions with the representative sections that maintain the installations, instead of based on the PO-plans in SAP, which contain the section's jobs. Our model uses these PO-plans, because it decreases the subjectivity (i.e., the clarity and understandability increase) and speeds up the process of searching for required jobs. Moreover, by using the PO-plans, the jobs instead of the installations are scheduled, which increases the understandability and the adaptability of the YSS, because it supports the possibility to check when a specific job is scheduled. In addition, by scheduling the jobs that are stored in SAP instead of the installations, every job is scheduled, whereas the current approach does not schedule every job. Hence, by using the jobs as input, the sections do not require additional requests for performing a job that does not fit in the schedule with installations.

#Job	Description	Installation	Cycle Time	Upper Bound	Lower Bound	Duration	First Start
1	37184	Ruwijzerput 21	1.680	420	420	5	20-5-2013
2	37183	Ruwijzerput 21	4.368	1092	1092	9	8-4-2013
3	38949	Ruwijzerput 21	17.472	1680	1680	4	29-6-2013
4	41367	Ruwijzerput 22	1.680	420	420	5	21-5-2013

Blast-Furnaces are		
Scheduled in:	BF 1	BF 2
Output (T/period)	333	437
Period	698	1874
Period	699	1875
Period	700	1876

Figure 13 - Format of input requirements

Although the PO-plans have entries for all required data to schedule the maintenance properly, the duration and priority of a job usually lack. Obviously, we need the duration of the jobs to schedule the maintenance, so Tata Steel has to estimate the non-available durations and we require the priorities to determine the allowed deviation of the cycle time and assign a standard range of [cycle time - 10%; cycle time + 10%] to the jobs, unless the priority is specified. Finally, Tata Steel bases the YSS on the downtimes of the Blast-Furnaces and the Direct Sheet Plant (DSP), so these downtimes function as input. Figure 13 shows the format of the input to the model.

In order to formulate the problem in a mathematical model, we require the following terms:

- Decision variables: Variables that change due to decisions made. In our case, the only decision variable is the moment to start maintenance on an installation.
- Parameters: Constant numbers that do not change during scheduling the shutdowns. An example of a parameter in our case is the amount of Blast-Furnaces.
- Auxiliary variables: Variables that change during the solving of the problem. For example, whether or not an installation is down at time t is a variable, because this is a value that changes due to decisions on the decision variable (if it is decided that a job will be performed at time t, the installation corresponding to that job will be down at time t).

Desired Output

In the current lay-out of the YSS, the horizontal axis shows the installations and the vertical axis shows the time in weeks. From a site-wide point of view, a mirrored lay-out is preferred: the installations on the vertical axis and the time on the horizontal axis. Besides that preference from a site-wide point of view, the only additional requirement of the Basic Oxygen Steel Plant is their preference to a schedule based on hours. Furthermore, the model should represent the problem of scheduling jobs, in which four objectives appear, which have a different importance ranking and the next three paragraphs discuss these.

The primary objective of scheduling the shutdowns is to prevent dumping at Harsco or deregulating the Blast-Furnaces, which consequently is the primary objective of the method we develop. This corresponds to the objective of minimizing the 'Loss of Load Expectation' (LOLE), which frequently appears in the literature, see among others Suresh and Kumarappan (2012). The method does not have to distinguish between dumping at Harsco and deregulating the Blast-Furnaces, because a year in advance it is not possible to determine which option to select.

The secondary objective is to prevent working in overtime, which is performing maintenance between 7am and 3pm or during the weekends. The tertiary objective is to prevent deviating from the cycle time, so if a job has a cycle time of ten weeks, the objective should be to stay as close to

these ten weeks as possible. Finally, in contradiction with the aim to prevent deviating from the cycle time of jobs, the quaternary objective is to spread the jobs as much as possible.

The relation between these objectives is the requirement to firstly fulfill the objectives with a higher ranking, before even considering the objectives with a lower ranking. In order to attain this ranking, the increase in the objective value due to an overflow should be substantially larger than the value of increasing one of the other three aspects, the value of working an extra hour in overtime should be substantially larger than the value of deviating more from the cycle time or spreading the jobs a little less, etc. For the problem we consider, we calculate the quaternary objective – the spread – by measuring it as the standard deviation of the number of jobs performed in a period. We select this indicator, because it *punishes* extreme values heavier than a lot of small deviations. Other indicators (e.g., mean absolute deviation) also strongly punish these extreme values, but not as heavily as the standard deviation does.

4.2.2 MIP-formulation of Tata Steel's Maintenance Scheduling Problem

This section formulates Tata Steel's Maintenance Scheduling Problem as an MIP and starts with expressing the objective in mathematical terms. From that objective this section continues to the constraints on that objective and the relations between different variables and parameters. The only decision variable that the model contains is $Start_{jt}$ and indicates whether or not a job j starts at time t. Based on the discussion in Section 4.2.1, we formulate the objective as:

Formula 4.1

$$\boldsymbol{Minimize} \left\{ \begin{array}{c} \sum_{t=1}^{T} Overflow_t * PenaltyOverflow + \\ \sum_{t=1}^{T} Overtime_t * PenaltyOvertime + \\ \sum_{j=1}^{J} DeviationCycleTime_j * PenaltyDeviating + \\ Spread * PenaltySpread \end{array} \right\}$$

In Formula 4.1:

- i, t, j are the indices of the installation ($i = 1 \dots I$), the time ($t = 1 \dots T$), and the jobs ($j = 1 \dots J$) respectively.
- $Overflow_t$ is the amount of iron to dump at Harsco or to be not produced by the Blast-Furnaces at time t.
- $DeviationCycleTime_j$ is the number of periods that the start moments of job j deviate from the cycle time.
- $Overtime_t$ is the number of jobs in overtime at time t.
- $Spread$ is measured as the standard deviation of the number of jobs in a period.
- $PenaltyOverflow$, $PenaltyDeviating$, $PenaltyOvertime$, and $PenaltySpread$ are values indicating the importance of an overflow, deviating from the cycle time, etc.

The explanation of the model continues in the intuitively logical way of starting with explaining how the decisicion variable relates to other variables, such that the model expands until the model explains every term in the objective function (Formual 4.1). Note that every formula applies for every job, installation, and time, unless we explicitly state something else.

As Section 4.2.1 mentions, the decision variable is whether or not to start performing a job j at time t: $Start_{jt}$. $Start_{jt}$ is the only factor that influences $DeviationCycleTime_j$, which indicates how much a job deviates from the start time that SAP proposes ($StartProposed_{jt}$: the best start time from an installation point of view). So, the deviation is the absolute value of the difference between the proposed start moment and the actual start moment:

$$DeviationCycleTime_j = \left|Start_{jt} - StartProposed_{jt}\right| \tag{4.1}$$

This relation between the actual start moment and the proposed start moment is not complex, because SAP generates the proposed start moment independent of the actual start moment of the previous job: in other words, SAP just adds up the cycle time to the proposed start moment and does not take into account that the start time of the job delayed the previous time.

Furthermore, $Start_{jt}$ is the only factor that influences the variable that indicates if a job j is performed at time t: $Perform_{jt}$. If a job either starts in this period or started less than the job's duration (d_j) ago, the job is currently performed. The duration of a job is a pre-defined value and the job should be finished without interruption. So, if job j starts at time 4 and takes 3 time units, the job should be finished at the end of period 6. The constraint that represents this statement is:

$$Perform_{jt} = \sum_{t'=t-d_j+1}^{t} Start_{jt'} \tag{4.2}$$

$Perform_{jt}$ influences the $Overtime_t$ that Formula 4.1 requires to calculate the objective. The relation is in the moment of performing the job: every job that is performed during the weekend or outside the range [7am, 3pm] influences the overtime. Otherwise the overtime is 0:

$$Overtime_t = \begin{cases} 0, & t \in T' \\ \sum_{j=1}^{J} Perform_{jt}, & else \end{cases} \tag{4.3}$$

In Formula 4.3 T' represents the time periods that are both between 7am and 3pm and outside the weekends. For example, $t = 32$ is withtin T', whereas $t = 152$ is not in T', because it is in the weekend, although it represents a moment between 7am and 3pm.

$Perform_{jt}$ is also the only factor that influences the spread of jobs over the time horizon: $Spread$. The spread indicates the equality of the amount of jobs that have to be performed in a period. As Section 4.2.1 mentions, we measure $Spread$ by means of the standard deviation, which is the square root of the variance. In our case the formula of the variance depends on the amount of jobs at period t. The spread equals the square root of the variance and we analyze the entire population:

$$Spread = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}\left(\sum_{j=1}^{J} Perform_{jt} - \frac{1}{T}\sum_{t=1}^{T}\sum_{j=1}^{J} Perform_{jt}\right)^2} \qquad (4.4)$$

So far, the model explains three of the four parts that form the objective value. The rest of this section models the relationship between the height of the overflow at time t ($Overflow_t$) and the moments to perform a job ($Perform_{jt}$).

First, an installation i is down at time t ($InstDown_{it}$) if a job is performed on that installation at time t. So, $InstDown_{it}$ is 1, if $Perform_{jt}$ is 1 for one of the jobs on installation i. In Formula 4.5 J_i represents the set of all jobs j that require installation i, such that $j \in J_i$ means for every job in the set of jobs on installation i.

$$InstDown_{it} = \max_{j \in J_i}\{Perform_{jt}\} \qquad (4.5)$$

Section 2.4 explains the influence of the down-being of an installation on the cycle time and concludes that the cycle time through the Basic Oxygen Steel Plant at time t ($CycleTimeBOS_t$) depends on the down-being of certain combinations of installations. A combination c of installations is down at time t ($Down_{ct} = 1$), if $InstDown_{it}$ is 1 for every installation in that combination at time t. If $Down_{ct}$ is 1, the cycle time through the Basic Oxygen Steel plant is at least a pre-defined cycle time that corresponds to that combination (CT_c). Obviously, only the maximum cycle time applies:

$$CycleTimeBOS_t = \max_{1 \le c \le C}\{CT_c * Down_{ct}\} \qquad (4.6)$$

Based on this cycle time, we know the capacity of the Basic Oxygen Steel Plant at time t:

$$CapacityBOS_t = \frac{1}{CycleTimeBOS_t} \qquad (4.7)$$

Besides the capacity of the Basic Oxygen Steel Plant, the model requires the input of pig iron from the Blast-Furnaces and the input of pig iron from the hot metal cars to calculate the overflow. The output of the Blast-Furnaces at time t ($OutputFurnaces_t$) is made up of two parameters: the production speed of Blast-Furnace F at time t ($BFProdSpeed_{Ft}$) and whether or not Blast-Furnace F is up at time t ($BFUp_{Ft}$). Now, the total output of the Blast-Furnaces at time t equals:

$$OutputFurnaces_t = \sum_{F=1}^{\#BFs} BFUp_{Ft} * BFProdSpeed_{Ft} \qquad (4.8)$$

The input at the Basic Oxygen Steel Plant at time t ($InputBOS_t$) depends on the available pig iron (the height of the buffer in hot metal cars that is left from the previous period ($BufferHMC_{t-1}$) plus output of the Blast-Furnaces) and the capacity of the Basic Oxygen Steel Plant. Moreover, the input equals the minimum of these two values, because we assume that the amount in the hot metal cars decreases as quick as possible, to keep the temperature as high as possible:

$$InputBOS_t = \min\begin{Bmatrix} OutputFurnaces_t + BufferHMC_{t-1} \\ CapacityBOS_t \end{Bmatrix} \quad (4.9)$$

The amount of iron in the hot metal cars ($BufferHMC_t$) at the end of time t depends on the amount of iron in the hot metal cars in the previous period and the change in the of amount pig iron in the current period ($BufferChangeHMC_t$):

$$BufferHMC_t = BufferHMC_{t-1} + BufferChangeHMC_t \quad (4.10)$$

The change in the buffer depends on the difference between the output of the Blast-Furnaces and the input at the Basic Oxygen Steel Plant, but may never be more than the difference between the capacity of the hot metal cars ($CapacityHMC$) and the buffer in the previous period ($BufferHMC_{t-1}$):

$$BufferChangeHMC_t = Min\begin{Bmatrix} CapacityHMC - BufferHMC_{t-1} \\ OutputFurnaces_t - InputBOS_t \end{Bmatrix} \quad (4.11)$$

Clearly, the output of the Blast-Furnaces that can neither be stored in hot metal cars, nor be processed by the Basic Oxygen Steel Plant, is the overflow of pig iron ($Overflow_t$):

$$Overflow_t = OutputFurnaces_t - InputBOS_t - BufferChangeHMC_t \quad (4.12)$$

Finally:

$$Down_{ct} = \{0,1\}$$

$$InstDown_{it} = \{0,1\}$$

$$Perform_{jt} = \{0,1\}$$

$$Start_{jt} = \{0,1\}$$

$$BufferChangeHMC_t \text{ is unrestricted in sign}$$

$$All\ other\ variables \geq 0$$

4.2.3 Differences with Literature

The model that we obtain from Section 4.2.2 is neither linear nor using solely continuous variables, so we typify the model as a Mixed Integer Programming (MIP) formulation of the Maintenance Scheduling Problem, which is the main technique applied in the literature, as Table 2 shows.

The main difference with the models in the literature is in the complexity of the objective function. Although Kralj and Petrović (1988) discuss that the Maintenance Scheduling Problem has multiple objectives, they conclude from their literature review that most authors optimize the problem based on only one objective. Most authors use the costs as the only objective (e.g., Saraiva (2011)), whereas we add the availability of personnel, the optimality of the previously defined cycle times,

and the manageability of maintenance to the objective. On the other hand, some authors (e.g., Chattopadhyay et al. (1995) and Berrichi (2009)) combine the scheduling of maintenance with the production schedule, which increases the complexity of the restrictions and the solving method. Nevertheless, such an approach compares to the inclusion of the cycle times in our MIP formulation. These cycle times represent the production, which is a continuous process, such that minimizing the total cycle time equals to maximizing the output of steel.

The main similarities with the literature are our usage of both integer and continuous variables and the non-linearity of the model. According to Kralj and Petrović (1988) and based on our own literature research in Chapter 3, most problems require integer variables to set the start moment of a job and most models are non-linear.

4.3 Implementing the Local Search Technique

We are not able to solve the problem by exact methods, because we use an MIP formulation, such that we require a heuristic approach to solve the Maintenance Scheduling Problem. This section starts with an analysis of the local search heuristics that Chapter 3 discusses and analyzes the suitability of the several heuristics to Tata Steel's Maintenance Scheduling Problem in Section 4.3.1. Section 4.3.2 continues by explaining how we implement the heuristic that we select and Section 4.3.3 explains how we deal with the ranking in the objectives. Finally, Section 4.3.4 explains some additional approaches that we apply to solve the Maintenance Scheduling Problem.

4.3.1 Analysis of Search Techniques

We only discuss search heuristics in this section, because the Maintenance Scheduling Problem does not compare to problems for which useful and good heuristics exist, as Section 3.2 explains. Probably, that is why previous research does not discuss approaches that use non-search heuristics.

Section 3.2.3 discusses three search algorithms that show their use to the Maintenance Scheduling Problem in the literature: Genetic Algorithms (GA), Tabu Search (TS), and Simulated Annealing (SA). In order to select the most suitable search algorithm for our problem, this paragraph discusses the advantages and disadvantages of these algorithms, but first and above all we state that the selected option heavily depends on the model's specificities, such that this approach is not per definition the most suitable approach for comparable problems. Burke et al. (1997) compare SA, TS, GA, and a combination of the first two methods for a simplified and broadly defined Maintenance Scheduling Problem and conclude that GA is the worst performing algorithm for larger feasible solution spaces, but it performs better than SA for smaller solution spaces. Our solution space is very large, especially because of the high amount of jobs that have to be scheduled.

Besides the large number of jobs, Tata Steel prefers to use a large amount of periods, which makes the problem's solution space even larger. The amount of neighboring solutions negatively influences the suitability of Tabu Search, because TS requires that every neighbor is analyzed and selects the best (non-tabu) option as the new solution. Clearly, the amount of neighbors depends on the neighborhood structure, but TS analyzes every neighbor before moving to another solution. This requires a lot of computation time to compare the different solutions before moving through the solution space. Still, Burke et al. (1997) conclude that TS outperforms the other approaches, whereas Ruiz et al. (2007) conclude the contradictory idea about their flow-shop problem. So, again the most suitable option heavily depends on the analyzed problem.

The GAs have a high computation time, due to the complicated decoding computations and the heavy fitness evaluations in each generation, according to Wang and Hanschin (1999). So, both GAs and TS spend a lot of time on evaluating the solution, while this computation time should be used to generate improvements in the solutions. Our problem requires that the algorithm quickly moves through the solution space because of the high amount of solutions with the same objective value, which indicates that Tabu Search does not suit the problem.

On the other hand, Simulated Annealing quickly analyzes a lot of different solutions and moves through the solution space with a speed corresponding to the time/temperature the method runs. Another positive point of SA is the clear convergence towards a local optimum after – as we expect – having searched most hills. Additionally, SA does not require a good initial solution, because it finds high quality solutions which do not strongly depend on this initial solution (Aarts & Korst, 1989). Based on the discussion above and the model we develop in Section 4.2, we conclude that Simulated Annealing suits best to the Maintenance Scheduling Problem that Tata Steel faces.

In our view the most important disadvantages are the amount of feasible solutions and the fact that the solution space contains many local optima. The local optima are not necessarily global optima, because SA creates clusters which are not necessarily scheduled during a plant-shutdown. Section 4.3.3 explains difficulties with local optima and explains how our method deals with this difficulty. Another important disadvantage is the required fine-tuning of the parameters in SA (initial temperature, decrease factor, stop criterion), which has to be repeated when the problem changes. Section 4.3.2 explains how to determine these parameters.

To conclude, we solve the Maintenance Scheduling Problem, which we formulate in Section 4.2.2 as Mixed Integer Program, by using Simulated Annealing. Section 4.3.2 explains how we apply SA to the scheduling problem of Tata Steel.

4.3.2 Implementing Simulated Annealing

As Section 4.3.1 shows, we require Simulated Annealing to solve the Maintenance Scheduling Problem of Tata Steel. This section explains the implementation of Simulated Annealing and the determination of the variables to apply SA. Section 3.3.2 mentions four requirements to apply SA, namely:

1 A concise description of a configuration of the system.
2 A random generator of "moves" or rearrangements of the elements in a configuration.
3 A quantitative objective function containing the trade-offs that have to be made.
4 An annealing schedule of the temperatures and length of times for which the system is to be evolved.

Section 4.2 covers the first requirement by expressing the problem in an MIP-formulation, which describes the problem and the embedded relations between the variables. The third requirement corresponds to the objective of the model (Formula 4.1) that Section 4.2 explains, together with the representativeness of this objective and the corresponding dilemma in it. Both requirement 2 and 4 comprise the actual local search procedure of SA. The remainder of this section discusses these requirements.

Neighborhood Structure

The second requirement encompasses the determination of the neighborhood structure, as Chapter 3 explains. In order to adapt a schedule, SA requires an initial schedule and, as Section 3.3.2 mentions, an advantage of SA is the robustness and effectiveness, such that it does not necessarily require a good initial solution. Hence, we set the start moment of a job to 7am on the date it should be performed according to its PO-plan, because this reduces the overtime value and deviation from the cycle time value in the objective function.

Based on the previous solution, it is allowed for SA to reschedule the jobs within certain bounds, which we based on the priority of a job as indicated in SAP. Usually the priority is equal to its initial value of 1 (highest priority: the job has to be performed close to the proposed start moment), which means that the sections did not change the priority of the jobs. We assigned both a lower bound and an upper bound of 10% of its cycle time to these jobs with priority 1: the bounds of a job equal to the proposed start moment plus and minus 10% of the job's cycle time. This results in 2,460,853 possible start moments for 2287 jobs (on average approximately 1076 moments to start a job). With each step, SA randomly selects a job out of the 2287 jobs and assigns a new start moment to that job, which it randomly selects out of the allowed start moments of the job.

The primary objective is to attain a minimum overflow, which probably means that several jobs should be performed when the buffer does not contain any steel. Of course, we recognize these jobs on some characteristics (high duration, an installation that influences the cycle time). Hence, we admit that every year's schedule contains jobs with certain characteristics on which smarter moves can be based, but these characteristics are that specific and different for every job and depend on other installations that are down (combinations influence the cycle time). In order to create an understandable approach that requires the least adaptions as possible when a new YSS has to be created, we apply the completely random generator of moves.

Annealing Schedule

The annealing schedule aims to start searching globally for new schedules and to finish searching locally for new schedules. In order to comply to this requirement, the procedure does not only accept a neighbor if the objective value of the neighbor is better than the current configuration's objective value (the hill-climbing idea, Figure 12), but also accepts neighbors with a worse objective value with a certain probability. This probability equals to $\exp\left(\frac{Objective_{Current} - Objective_{Neighbor}}{Temperature}\right)$, where the temperature needs to be specified by a cooling scheme. For SA to search globally when the procedure starts, the algorithm should initially accept almost every solution, such that the acceptance ratio (hence the probability) needs to be very close to 1. When time passes, the procedure should search more locally, so the search space should become smaller and the acceptance ratio has to approach 0 at the end of the algorithm. In order to obtain this evolvement of the acceptance ratio, initially the temperature should be very high compared to the difference in the objective value and the temperature should be relatively low at the end of the procedure.

The differences between the objectives of two neighboring schedules depend both on the value that we assign to the penalty of the corresponding objective and on the increase of the objective value. The penalties indicate when Tata Steel is indifferent between a decrease of one objective at the cost of an increase of another objective. For example, if the penalties for the overflow, overtime, deviating from the cycle time, and spread are 100, 10, 1, and 0.1 respectively, Tata Steel is indifferent between a decrease in the overflow of 1 ton or working 10 hours less in overtime. However, we are

not able to select the real points of indifference, because it requires too much time and it is not needed for the development of the method (Tata Steel can add the correct penalties if these are available). As Section 4.2.1 explains, we assume that the objectives are strictly ranked, which means that a lower ranked objective never decreases at the cost of a higher ranked objective. We solely set the penalties based on that requirement and Appendix C concludes that the penalties for the overflow, overtime, deviation from the cycle time, and spreading of jobs equal to 1, 1, 0.001, and 0.001 respectively. We admit that these penalties are subjective and do not reflect the actual importance ranking between the different parts of the objective and we admit that 1 ton overflow of steel does not correspond to an hour more in overtime, but the approach of SA holds that an increase in overflow always corresponds to an increase of at least 65 tonnes and because SA only considers one job per move, SA never accepts a rescheduling move in which the overtime decreases and the overflow increases. Again, Tata Steel should re-define these penalties for an optimal use of the method. Section 4.3.3 continues on the usage of the penalties.

4.3.3 Dealing with the Ranked Objectives

For our specific problem with four strictly ranked objectives, SA needs an adaption, because a standard SA procedure does not correctly optimize the problem. First, this section discusses an example of incorrect optimization and this section finishes with a better approach.

Figure 14 shows a possible YSS of a situation in which the plant consists of only one Blast-Furnace and two casting installations. Some jobs require only one casting installation and other jobs require both casting installations. In Figure 14, the crosses indicate that an installation is down during the corresponding period. During the shutdown of the Blast-Furnace, there is no supply of pig iron and no overflow, whereas the overflow during the shutdown of a casting installation equals to 5 tonnes and if both casting installations are down, the overflow equals to 2 x 5 tonnes. Furthermore, in Figure 14's YSS every job is performed on its proposed moment, the overtime is 6 periods (only the jobs during period 6 and 16 affect the overtime), and the spread is 1.58. So, the total objective equals to 10 + 6 + 0/1000 + 1.58/1000 = 16.00158.

Intuitively, maintaining both casting installations should be done during a plant-shutdown, because it heavily influences the cycle time (from 18 minutes to 90 minutes). However, an SA procedure that analyzes all objectives at once does not accept any change of a casting installation in this schedule: for example, if it moves a job from period 12 to start in period 6, the overflow of ten remains the same (still both casting installations are down), the overtime of 6 remains 6, the deviation of the cycle time increases to 7 – which should be divided by 1000 – and the spread increases to 1.87 – which should be divided by 1000. So, the new objective value becomes 10 + 6 + 7/1000 + 1.87/1000 = 16.88. SA does not accept any move in Figure 14, if it approaches the lower bound on the temperature (i.e., the solution is a local optimum). Hence, optimizing all objectives at once leads to a bad local optimum.

In order to prevent this problem, we first run the SA procedure with just minimizing the overflow as objective, then if this procedure finishes, we take the best schedule so far and recalculate the objective with the addition of the secondary objective. Based on the new objective and the same schedule, we start SA again and repeat this until the SA procedure contains every objective. By using this four-run SA approach, the configuration in Figure 14 is not a local optimum, because every job may be moved to the upper half of Figure 14 during the first run. These moves decrease the objective, such that the first run only ends if all jobs are moved to the upper half.

YSS	Installation			
Period	BF 1	Casting Installation 21	Casting Installation 22	Casting Installation 21 + 22
1	X			
2	X			
3	X			
4	X			
5	X			
6	X	X	X	X
7	X	X	X	X
8	X	X	X	X
9	X	X	X	X
10	X	X	X	X
11				
12		X	X	X
13		X	X	X
14		X	X	X
15		X	X	X
16		X	X	X
17				
18				
19				
20				

Figure 14 - A part of a possible YSS

The four-run SA requires four start temperatures and four stop criterions – both for every run. Table 3 shows these temperatures, which we calculated based on the explanation in Appendix C. We used the following computations to calculate the temperatures:

In order to make sure that SA accepts every neighboring schedule when the procedure starts, $\exp\left(\frac{Objective_{Current}-Objective_{Neighbor}}{Temperature}\right)$ should approach one and $e^0 = 1$. So, the current objective minus the neighboring objective should be substantially smaller than the temperature. The maximum difference between the objectives in the first run equals to 6160, as Appendix C shows. In order to attain a starting probability of 0.98, the temperature should equal:

$$\exp\left(\frac{-6160}{Temperature}\right) = 0.98 \rightarrow \frac{-6160}{Temperature} = \ln 0.98 \rightarrow Temperature = 304{,}910$$

The minimum difference in the first run equals to 68 and the probability of accepting a worse solution should be equal to 0.01, such that the final temperature should be equal to:

$$\exp\left(\frac{-68}{Temperature}\right) = 0.01 \rightarrow \frac{-68}{Temperature} = \ln 0.01 \rightarrow Temperature = 14$$

We understand that these temperatures lead acceptance ratios of more than 98% and less than 1%, because most neighboring objectives do not differ with a value of 6185 and 68 respectively. Still, we use this approach to make the determination of these parameters easier to repeat for Tata Steel. For determining better temperatures, we should use the actual acceptance ratios after a run.

Table 3 - Start and final temperatures of the four different runs of SA

Objective/Run:	Overflow/1	Overtime/2	Deviation CT/3	Spread/4
Maximum Difference	6160	8	1680/1000 = 1.68	0.15/1000 = 0.00015
Minimum Difference	68	1	1/1000 = 0.0001	0.01/1000 = 0.00001
Start Temperature	304910	396	84	0,007
Final Temperature	14	0.22	$2.2*10^{-5}$	$2.2*10^{-6}$

In order to use the values in Table 3, every chain should finish in a local optimum, such that the next run solely focusses on the last added objective. By using this adapted SA version, Figure 14's bad local optimum does not appear anymore.

Finally, we require the right balance between the length of the markov chain and the speed of decreasing the temperature. First, to make the procedure not too complex and keep the procedure understandable for Tata Steel, we set an equal decreasing factor and chain length to each of the four runs. Furthermore, we prefer SA to put most of its effort in local search, so we set the decreasing factor very high compared to the markov chain length. Another possibility or addition is to make the markov chains increase with a decrease in the temperature, but this unnecessarily increases the complexity of the method. We set the decreasing factor to 0.99975, such that SA analyzes

$$\frac{\log\left({}^{14}/_{304910}\right)}{\log 0.99975} + \frac{\log\left({}^{0.22}/_{396}\right)}{\log 0.99975} + \frac{\log\left({}^{2.2*10^{-5}}/_{84}\right)}{\log 0.99975} + \frac{\log\left({}^{2.2*10^{-6}}/_{0.007}\right)}{\log 0.99975}$$
$$= 39{,}950 + 29{,}978 + 60{,}614 + 32{,}257 = 162{,}799\ chains.$$

In order to analyze the results in Excel, we set the decreasing factor to 0.99975, because Excel 2003 can deal with at most 65,000 rows. This means that the maximum chain length – run 3: 60,614 – influences the decreasing factor and based on the number of chains and the computation time, we set the markov chain length equal to 100. By selecting a higher value to the decreasing factor and a lower value to the chain length, the time that SA spends in searching locally increases. So, setting the decreasing factor equal to 0.9999975 and the chain length equal to 1 results in the same amount of solutions, but also makes sure that SA spends more time searching locally. However, these differences do not significantly influence the result.

4.3.4 Additional Approaches to the Maintenance Scheduling Problem

This section discusses alternatives for searching for a local optimum. In order to compare the different methods, we select the parameters that characterize the approaches such that the runtimes of the different approaches are equal.

For the four-run SA we set the four start and four stop temperatures equal to the temperatures that Section 4.3.3 discusses, but we set the decreasing factor to 0.999, because this improves the usability and comparability of the results. In order to attain an equal computation time for every heuristic, the four-run SA uses a markov chain length of 3.

Besides the four-run SA approach, we also apply Simulated Annealing with only one run to obtain a YSS. This conventional SA approach optimizes all four parts of the objective together and we expect that this approach finds a local optimum in relatively short computation time, as Section 4.3.3 explains. Hence, we expect that this approach outperforms the four-run SA method in the experiment, but it should also show that the four-run SA did not find a local optimum when the

experiment ends. Finally, we set the start temperature equal to the start temperature of the first run of the four-run SA method and the lower bound on the temperature equal to the lower bound on the temperature in the final run of the four-run SA method, because the possible increase in the maximum difference in the objective value between two neighboring solution is negligible. We set the decreasing factor equal to 0.999 – to compare it with the four-run SA – and the chain length equal to 8, such that the runtime equals the runtime of the other alternatives.

Next to the SA approaches, we evaluate an iterative improvement method – in the remainder of this chapter called IIM – to obtain a solution to the problem. This method takes into account the overtime by rescheduling the start moment of a job such that it starts on another day at 7am. This heuristic starts by analyzing the solution if the first job is scheduled 24 hours later and continues with this job until it analyzed every start moment of this job as long as the job starts at 7am and within the allowed bounds. After analyzing the first job, the heuristic continues with the next job, until it analyzed every job. Finally, this procedure repeats for a preset number of iterations. Our decision to start at 7am and not to analyze every possible start moment is especially based on the decrease in the solution space by 96%. To comply with the runtime restriction, this IIM iterates 15 times over all jobs. In addition, we apply the same IIM heuristic that changes the start time with 8 hours instead of 24 hours and which iterates 5 times instead of 15 times over all jobs.

Finally, we implement a combination of SA with one run and IIM. This combined approach starts with SA and finishes with IIM, based on the solution obtained with SA. We dedicate the first 50% of the runtime to the SA approach and the last 50% of the runtime to the IIM part, which means that it starts with the same cooling scheme as the approaches that solely use SA, but the markov chain length decreases to 3 and it ends with an IIM with 7 iterations over all jobs, with the same approach as the heuristic that solely uses iterative improvement with steps of 24 hours.

We admit that several other approaches seem to be worth analyzing, such as another neighborhood structure, another search heuristic, or other combinations of and parameters in the heuristics that the previous paragraphs explain. However, the options we select clarify the potential of the type of heuristics.

4.4 Concluding Remarks

To conclude, we modeled Tata Steel's Maintenance Scheduling Problem in Mixed-Integer Programming formulation, which we solve in four steps of Simulated Annealing (SA). The SA selects a neighboring solution by randomly selecting a job and subsequently randomly selecting a new moment to start that job. The four steps comprise a SA procedure that solely optimizes the overflow objective, until it reaches a local optimum. Based on that schedule, the objective enlarges with the overtime and a new SA procedure starts. These steps continue until the objective contains the overflow, the overtime, the deviation from the cycle time, and the spread. Besides this four-run SA approach, Chapter 5 contains an analysis and comparison of four relatively simple alternative approaches to solve the Maintenance Scheduling Problem.

5. Analysis and Discussion of the Results

This chapter answers the fourth research question: *What are the results of applying the selected method?* First, Section 5.1 describes the initial solution we used. Section 5.2 analyzes the performance of the SA heuristic that we applied and the performance of alternative heuristics. Section 5.3 reflects on the rules of thumb, contains an analysis of the results, discusses the appearing shortcomings of the approach, and sets forth possible improvements to prevent the shortcomings. Furthermore, Section 5.3 compares the schedule we obtained with the YSS as Tata Steel generated it. Section 5.4 reflects on the computation time and Section 5.5 briefly summarizes the analysis.

5.1 Initial Solution

The initial solution holds that every job is scheduled on the start date in its PO-plan, so the deviation from the cycle time equals zero in the initial objective value. Furthermore, the jobs start at 7am, which means that the overtime is rather low in the initial solution, but jobs in the weekends have an impact on the overtime objective. On the other hand, jobs and – especially – the installations are not clustered in the initial solution, so we expect an increase in both the overtime and the deviation from the cycle time and a decrease in both the overflow and the spread, due to the clustering of jobs. The initial solution has an objective value of 653,066 and is made up of the values in Table 4.

Table 4 - Objective values of the initial solutions

	Initial solution
Objective	653,066.4
Overflow	651,066.4
Overtime	2,000
Deviation from CT	0 (/1000)
Spread	5.03 (/1000)

5.2 Performance of Simulated Annealing

This section discusses the performance of the four-run Simulated Annealing heuristic that we apply to the Maintenance Scheduling Problem as well as the performance of the other heuristics (IIM, SA, combination). First, Section 5.2.1 discusses the performance of the four-run SA heuristic, then Section 5.2.2 shortly discusses and compares the other four heuristics with each other and with the four-run SA approach.

5.2.1 Simulated Annealing

As Chapter 4 discusses and Table 3 shows, SA analyzed the solution space in four runs. We expect that after a run, which is after adding a part of the objective, the higher ranked objectives can never increase due to the decrease of the new objective. On the other hand, the overall objective increases, because a new part is added to the objective value. Figure 15 shows the simplified expected flow of the fictitious objective value: after the first run SA reaches a local optimum and adds the second objective, such that the objective value increases. Again, SA reaches a local optimum, which has a higher corresponding objective value than the local optimum after the first run, because this value contains objective two. This process continues until the objective contains all four parts and ends up in a local optimum. Furthermore, higher ranked objectives are not able to in- or decrease when the overall objective includes a lower ranked objective, unless the run did not end in a local optimum.

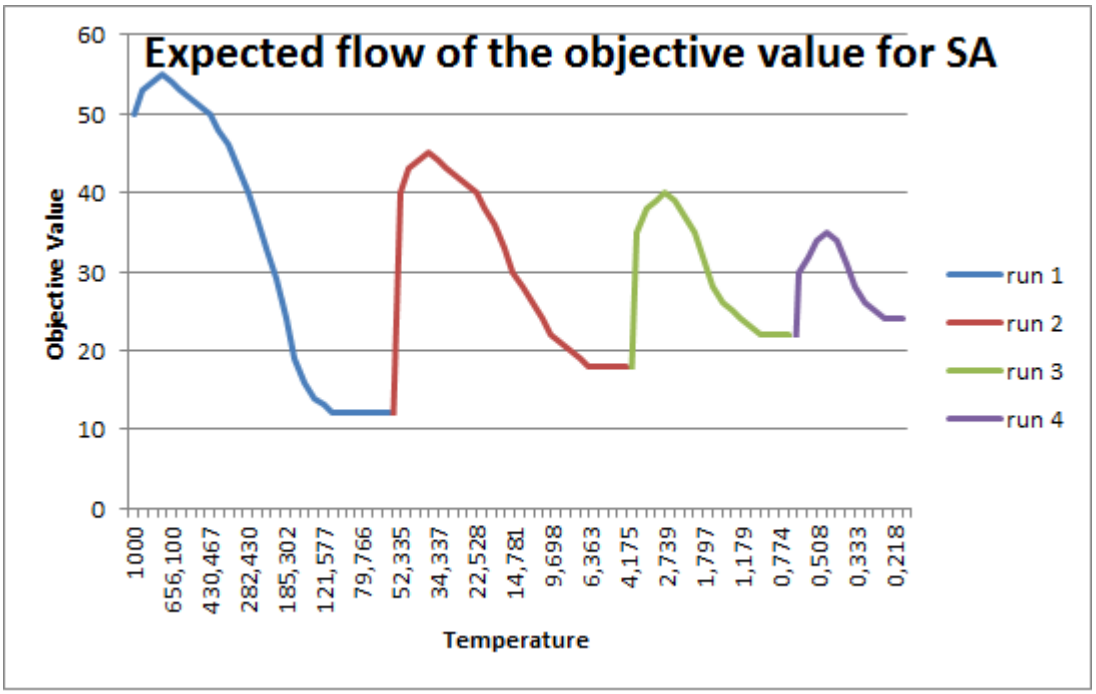


Figure 15 - Expected flow of the objective value

Table 5 shows the actual values of the objectives after the four runs finished, and specifies the values that influence the overall objective. In Table 5, only the black colored values influence the objective value, because the values in red italics are left out of the objective in the corresponding run. Table 5 shows that the decrease in the objective value is mainly due to the decrease in the overflow at the expense of working a little more in overtime and deviating much more from the cycle time. The small overtime increase of only 8% indicates that jobs are moved out of the weekend and that only a few jobs are scheduled during evenings or nights. As the previous paragraph mentions, a part of the objective cannot change if the overall objective contains a lower ranked objective. However, Table 5 clearly shows a decrease in the overflow, overtime, and deviation from the cycle time in every run in which it is optimized. This means that none of the runs ended in a local optimum, which either means that the acceptance ratio is significantly larger than zero, or that the SA method still finds better solutions. Figure 16 to Figure 19 show the acceptance ratios of the four runs and show that each run ends with an acceptance ratio of approximately 0%, so the reason for not reaching a local optimum after a run should be the fact that still better direct neighbors exist. Figure 20 to 23 show the flow of the objective value in each run and confirms the previous statement. This section continues with a discussion on the acceptance ratio and the decrease of the objective value.

Table 5 - The flow of the objective values.

	Initial	1st run	2nd run	3rd run	4th run	Decrease
Objective	653,066.4	110,689	86,648	81,152	74,291	-89%
Overflow	651,066.4	110,689	84,153	78,843	72,067	-89%
Overtime	2,000	*11,307*	2,495	2,227	2,155	+8 %
Deviation (/1000)	0	*603,015*	*619,900*	81,947	69,662	- %
Spread (/1000)	5.03	*2.757*	*3.099*	*3.995*	4.149	-18%

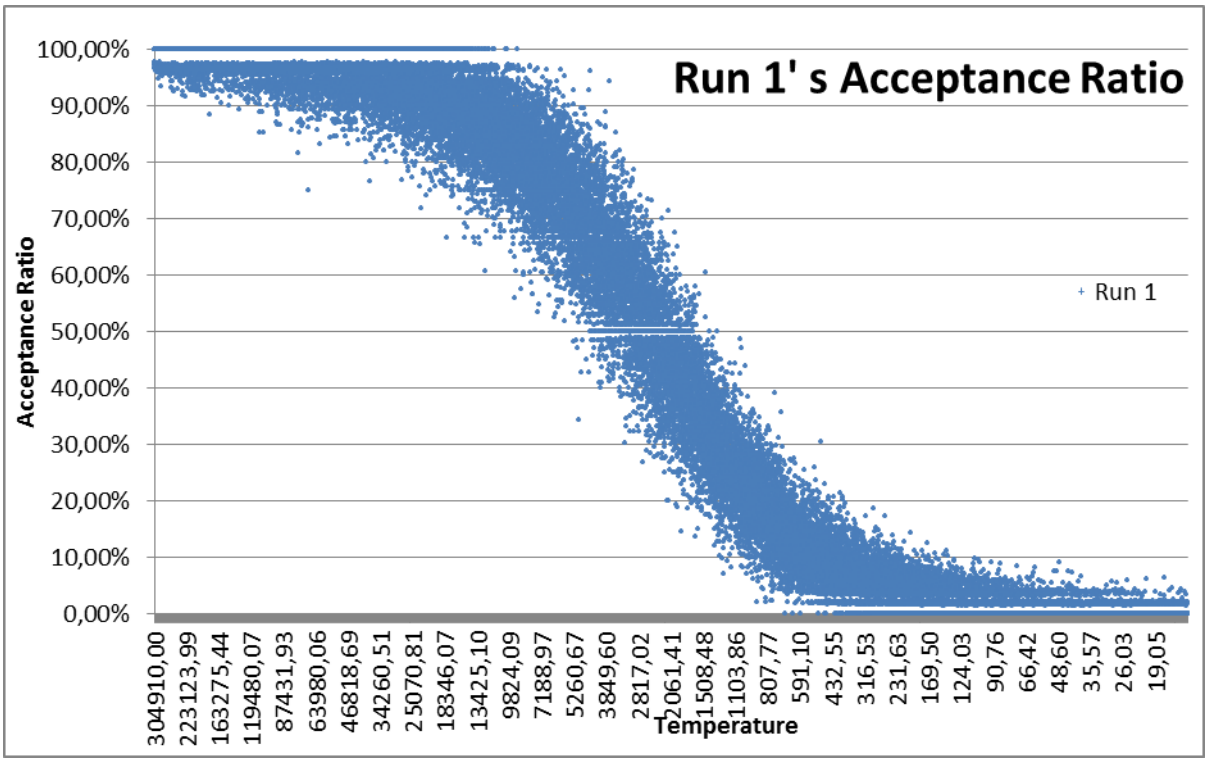


Figure 16 - Acceptance ratio of Run 1 of Simulated Annealing

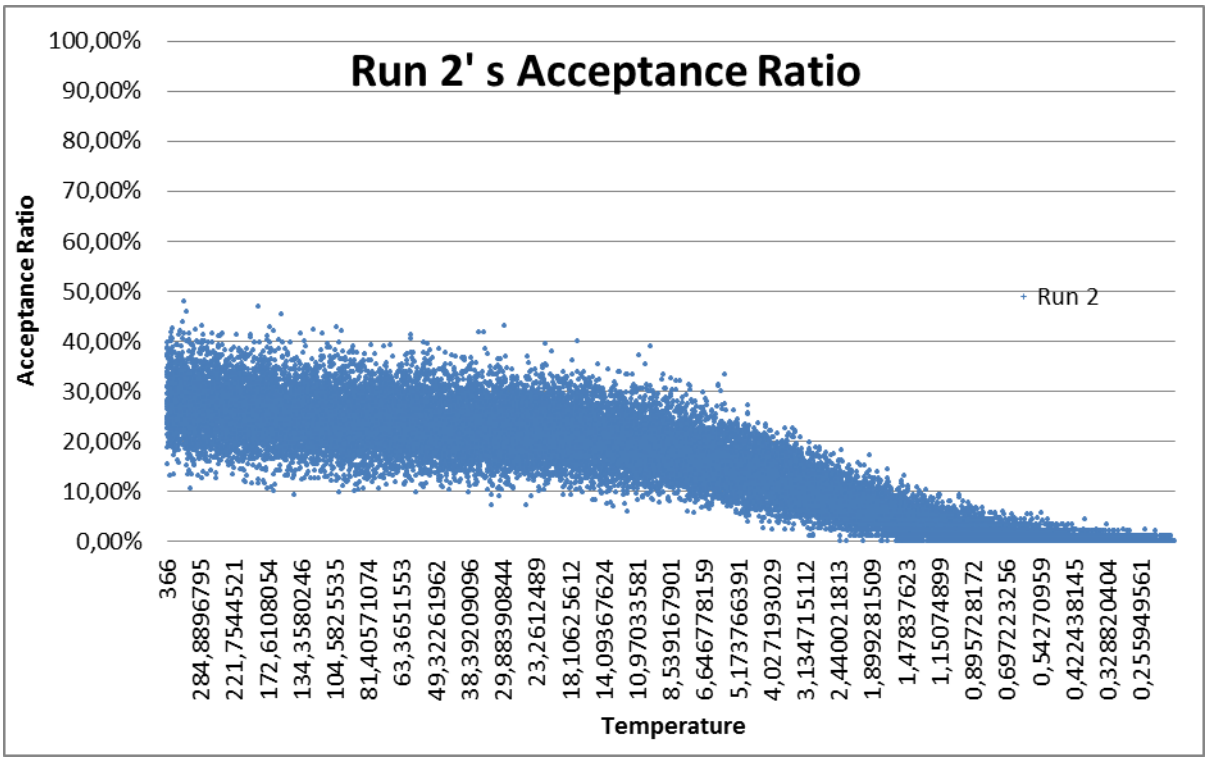


Figure 17 - Acceptance ratio of Run 2 of Simulated Annealing

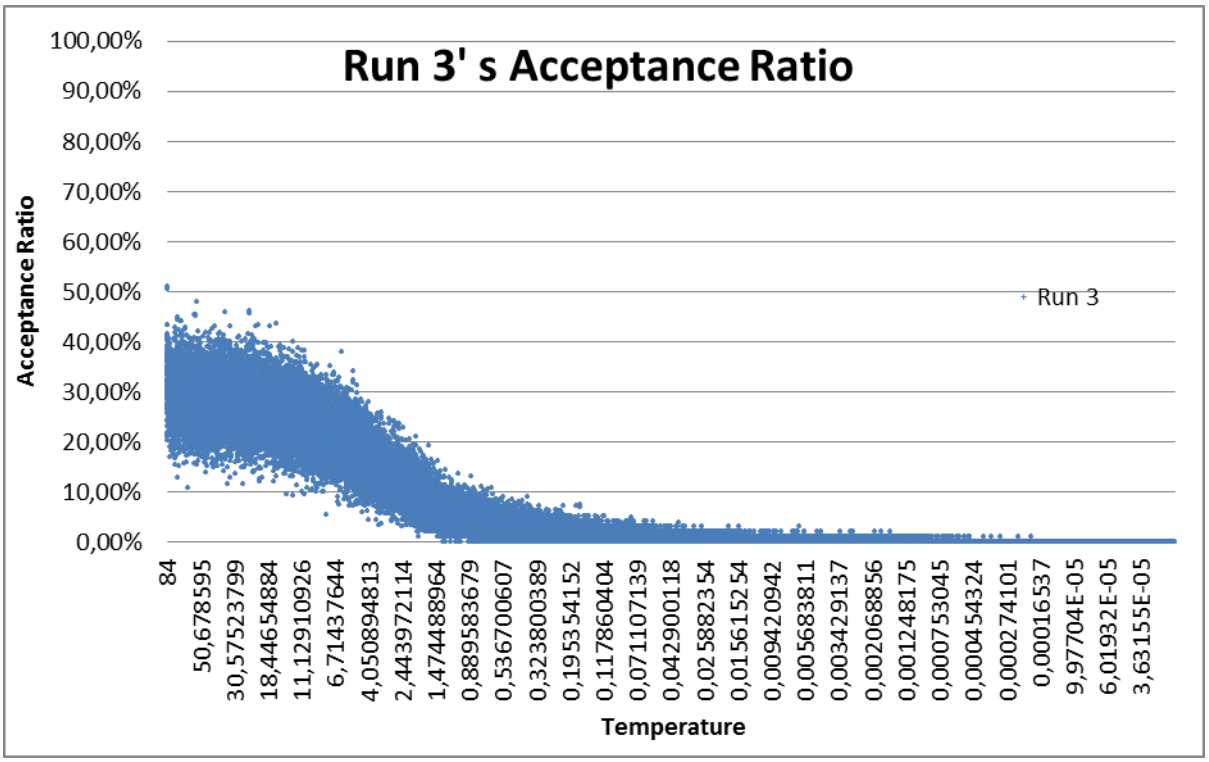


Figure 18 - Acceptance ratio of Run 3 of Simulated Annealing

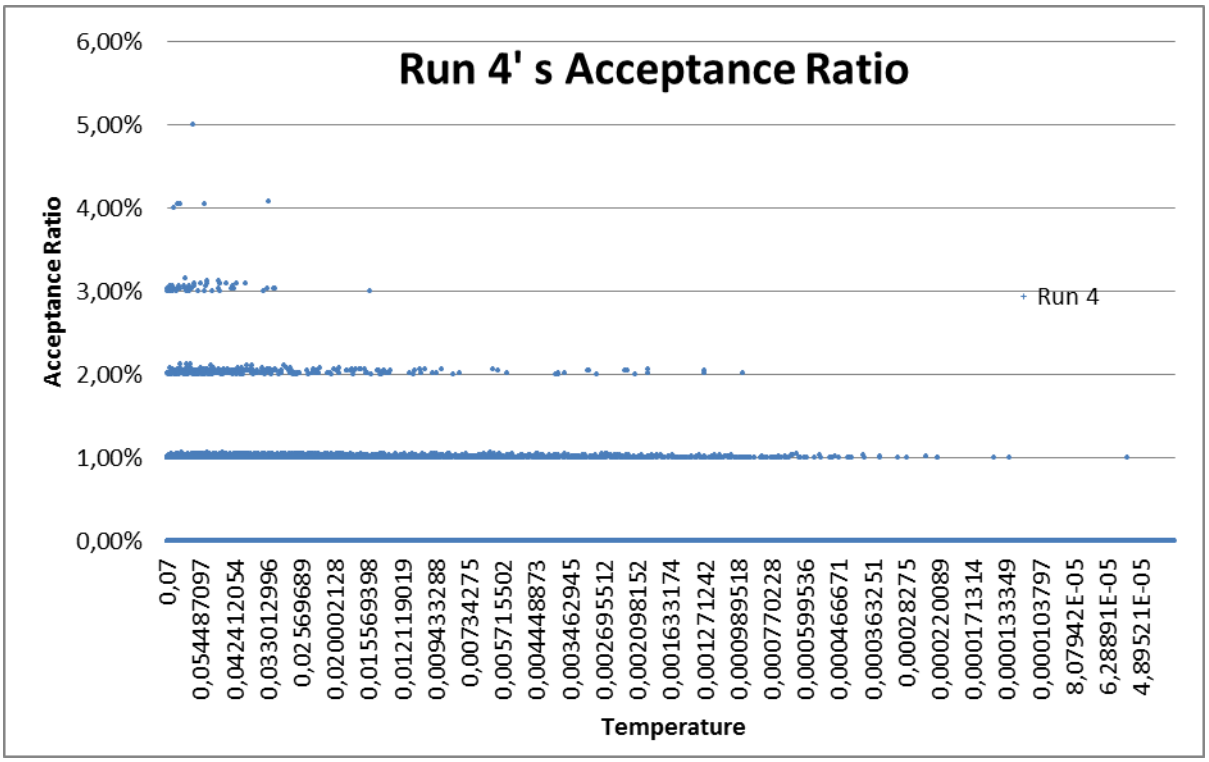


Figure 19 - Acceptance ratio of Run 4 of Simulated Annealing

Acceptance Ratio

As Chapter 4 discusses, the acceptance ratio should start close to 100% and end at almost 0%. This means that SA accepts almost all deteriorations of the objective value when SA starts and that SA does not accept any significant deterioration of the objective value at the end of the procedure. Figure 16 to Figure 19 show the ratio of worse solutions that SA accepted. As the previous paragraph mentions, all four acceptance ratios end at 0%, which means that SA only accepts improvements and we do not discuss this any further, because it confirms Chapter 4's discussion.

On the other hand, the initial acceptance ratios of run two, three, and four do not confirm the explanation in Chapter 4. The reasoning is rather straightforward: The acceptance ratio of run two (and run three) starts between 20% and 40%, which means that SA accepts approximately 30% of the deteriorations in the first stage of the procedure. Hence, 70% does not fit to the evolvement of the acceptance probabilities calculated by $\exp\left(\frac{Objective_{Current} - Objective_{Neighbor}}{Temperature}\right)$, which means that 70% of all deteriorations is too high with respect to the temperature to be accepted by SA. So, we either determined the initial temperature in the wrong way, or the differences in the objective value are higher than we expected. Besides the influence of not reaching a local optimum after the first run, the main reason for the low initial acceptance ratio in the second run is the fact that SA rejects most neighbors because it increases the first objective (i.e., the overflow). So, approximately 60% of the neighbors make the overflow to increase, such that SA does not accept these neighbors. To conclude, the strange starting acceptance ratios in run two and run three are as they should be and the ending acceptance ratios make it possible for SA to reach a local optimum.

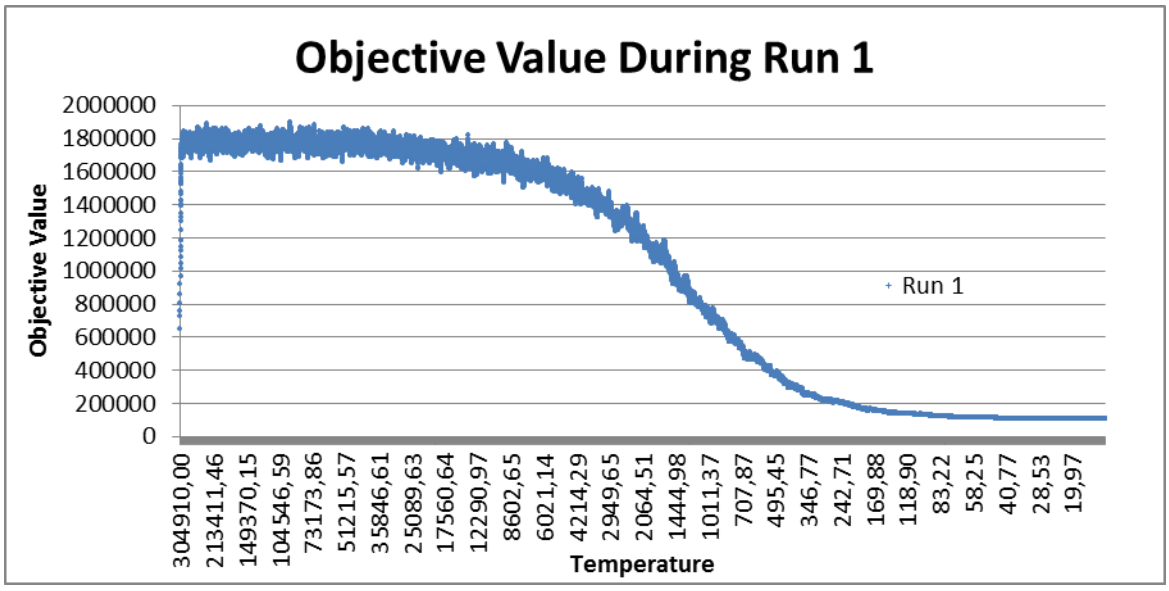


Figure 20 - Objective value during the first run

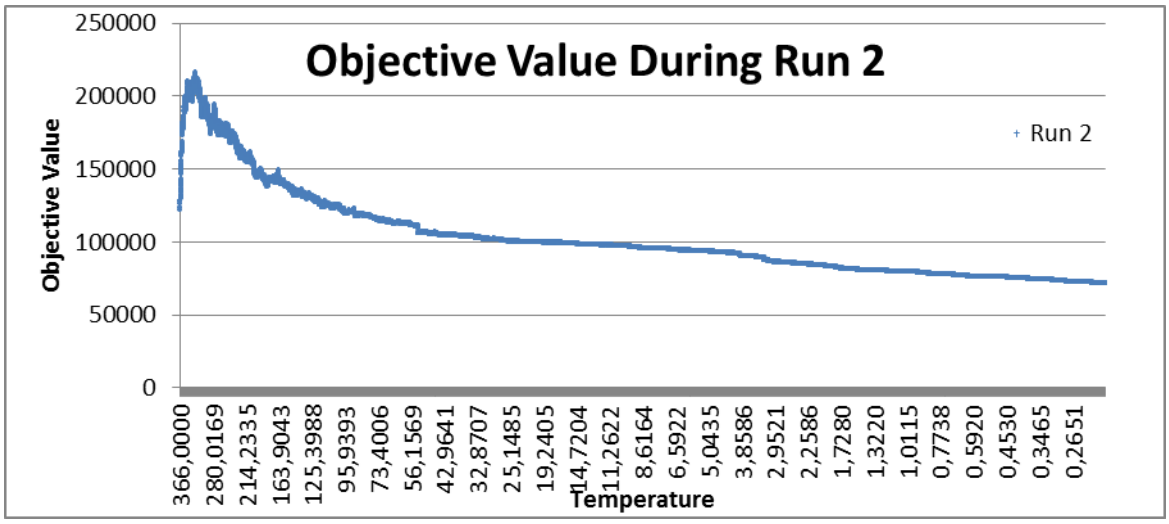


Figure 21 - Objective value during the second run

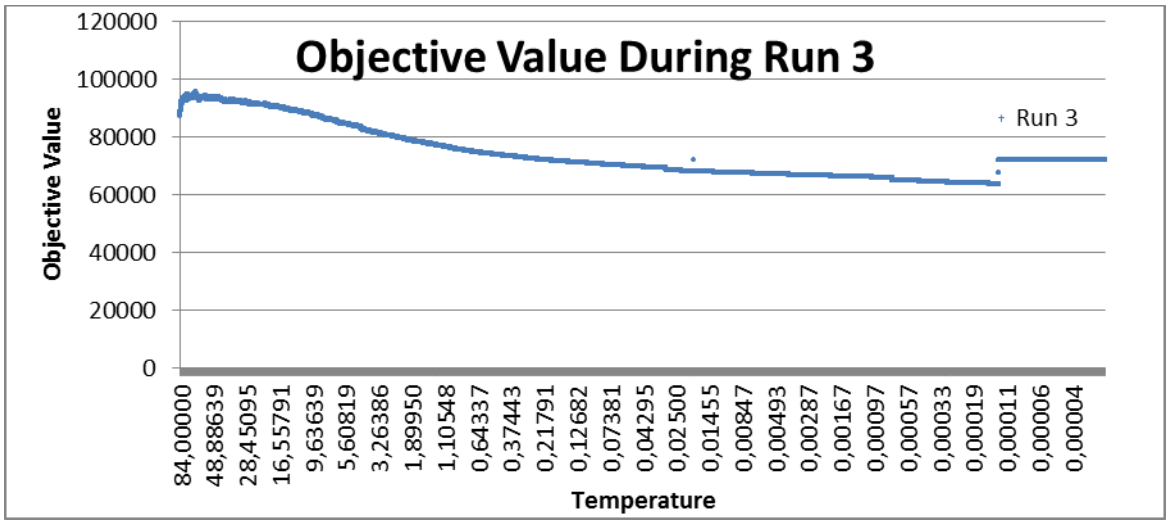


Figure 22 - Objective value during the third run

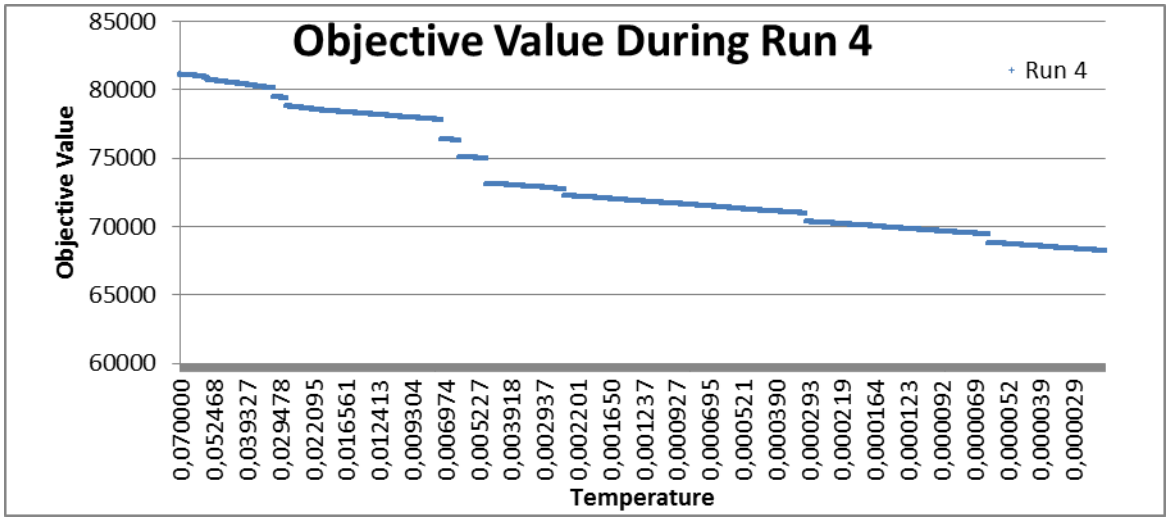


Figure 23 - Objective value during the fourth run

Objective Values

As Figure 15 shows, we expected to obtain four pictures such as Figure 20 shows. However, with each subsequent run the similarity disappears until Figure 23's evolvement of the objective value does not show any relevant similarity anymore. This section discusses the differences between Figure 15 and Figure 20, 21, 22 and 23.

First, Figure 15 shows that – optimally – the objective value after a run cannot be lower than the objective value after the previous run. Table 5 shows that the objective value decreases after every run and we conclude based on this observation that SA does not reach a local optimum during any of the runs. Another conclusion that we draw based on Table 5 is that SA clearly minimizes a new objective after its addition to the overall objective, as the red italics and the first black values in Table 5 indicate. The next paragraphs compare the different runs with the corresponding parts in Figure 15.

Figure 15 indicates that a new run should start with a small increase in the objective value, followed by a drop in the objective value until it reaches a local optimum in which the objective value does not change anymore. The evolvement of the objective value in the first run seems to comply to this statement, but if we zoom-in on the last part of Figure 20, we obtain a surprising evolvement of the objective value as Figure 24 shows. Chapter 4 explains that the minimum difference between two neighboring solutions in the first run equals to 64, but Figure 24 clearly shows smaller increases. These increases should be due to varying occupations of hot metal cars and this should be included in the future, such that the lower bound on the temperature equals 0.22 (based on a minimum difference of the objective value of one). Due to this shortcoming in the objective, it is possible for SA to outweigh an increase in the overflow by a decrease in the overtime during the second run.

Due to the fact that the first run does not end in a local optimum, Figure 21 does not show the correct evolvement of the objective value, because the deviaton in the overflow still influences the objective value. First, the increase in the left-hand side of Figure 21 corresponds to our expectations, which Figure 15 shows. However, the objective value keeps decreasing in the tail of the second run and never reaches a local optimum and the objective value drops lower than the final objective value or the first run.

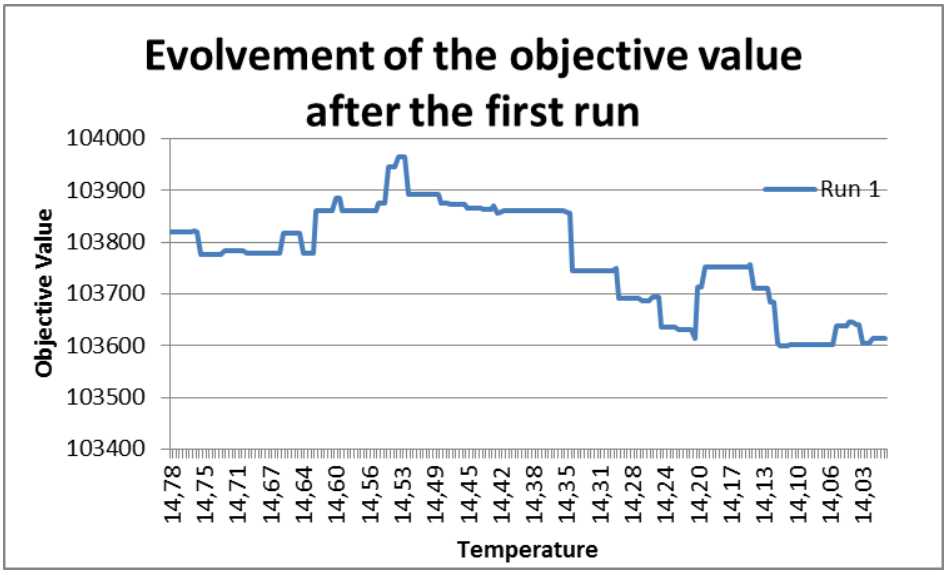


Figure 24 - Final part the evolvement of the objective value during Run 1

The third run still shows a small increase in the objective value in its first stage, but run four's Figure 23 does not show this increase anymore. The dissimilarity between the figures and Figure 15 is mainly because SA did not reach a local optimum in the first run, such that it is not able to reach a local optimum in the subsequent runs.

Another issue with respect to the objective value is – although it does not appear in the figures – the temperature overlap of the different runs. Run three starts with a temperature in which the acceptance ratio in the previous run was between 40% and 20%. This means that in these runs, the objective of the previous run is not fixed. Hence, we propose to redefine the start tempertures, which means that we propose to redefine the penalties. In order to prevent any overlap in the temperatures and to include the new minimum difference of the overflow we propose using the penalties to influence the maximum and mininum differences between the objective values of neighboring solutions. Table 6 shows the resulting penalties and bounds on the temperatures. We obtained these by using the formulas in Chapter 4. As Chapter 4 mentions, these penalties do not have to reflect the importance with respect to another objective, but have to influence the temperatures.

An issue that seems to appear in the figures and Table 5, is the fact that small changes in the spreading of the jobs appear. Although we did expect small changes in the value for spreading, if the third run would have reached a local optimum the differences in the spreading would be even smaller. This is simply because a change in the spreading of jobs always affects the devation in the cycle time or the amount of overtime. The only option in which it does not influence the overtime, neither the devation of the cycle time is to reschedule a job exactly the same amount of hours to the other side of its bound: job j is scheduled at time 40 (not in overtime) and the proposed start moment is 50, which is a local optimum after the third run. Now, the only option to reschedule job j, while not changing the deviation of the cycle time and while changing the spread is to reschedule job j to time 60 (not in overtime). Hence, SA hardly influences the spreading of jobs.

Finally, the difference between the overtime and the deviation of the cycle time in the different runs may seem odd. These differences are due to the huge increase in the deviation of the cycle time in the first run at the expense of a decrease in the overflow. During the fourth and espeically during the third run, the deviaton of the cycle time decreases with a larger value than the decrease in the overtime. However, this higher decrease is the sum of a lot of small decreases (i.e., a lot of smaller decreases for the deviation of the cycle time).

5.2.2 Other Approaches

This section analyzes the alternatives for searching for a local optimum, which Chapter 4 explains. Recall that the alternative heuristics are two Iterative Improvement Methods (IIMs), an SA method, and a combination of these two methods. These heuristics optimize the four objectives in parallel instead of subsequently (as the four-run SA does) and we used a short runtime.

Table 6 - Improved temperatures

Run / Objective	Penalty	Start Temperature	Lower Bound on Temperature
1 / overflow	1	304,910	0.20
2 / overtime	5×10^{-4}	0.20	1.08×10^{-4}
3 / deviation from CT	1×10^{-9}	8.3×10^{-5}	2.1×10^{-10}
4 / spreading of jobs	2×10^{-11}	1.5×10^{-10}	4.3×10^{-14}

Table 7 – Results after applying different heuristics

Approach	Overflow	Overtime	Deviation from CT	Spread	Objective value
SA - 4 runs	232,155	4,692	400,952	3.025	237,248
SA - 1 run	221,540	3,818	378,234	3.293	225,736
IIM – 24 hours	302,122	1,760	11,040	5.153	303,893
IIM – 8 hours	321,640	1,768	10,472	5.108	323,419
SA/IIM-combination	287,072	4,984	277,957	2.968	292,334

We compare the different alternative heuristics based on both the overall objective and the four parts of the objective, because we expect to recognize the influence of the different parts on each other. This means that we expect to recognize a clear difference in the speed of finding a local optimum and in the quality of the corresponding solution. Due to time restrictions, we are only able to apply a small experiment with short runtimes. Hence, we expect the four-run SA method to not reach a local optimum in this experiment. The next sections discuss the different heuristics and propose improvements to these heuristics.

Iterative Improvement

Table 7 shows the results after applying the before mentioned heuristics. Apparently, SA outperforms IIM and the combined approach. This is mainly because the 'IIM – 24 hours' already reaches a local optimum after seven iterations, as Figure 25 shows and 'IIM – 8 hours' just iterates too little. By changing the neighborhood structure that we programmed, probably the IIM attains much better results. In the current settings, the IIM changes the start moment of a job with 24 and 8 hours, whereas lowering this value with every new iteration probably leads to better results. For example, starting with 24 hours and decreasing it with 1 hour during every chain. In order to keep the runtime acceptable, the bounds to search within should also decrease with every iteration. We expect that such an improved IIM attains promising results, because this simple IIM already leads to a decrease of 53%.

As Chapter 4 explains, the IIM acquires low values for overtime and deviating from the cycle times. Table 7 confirms this expectation and shows that IIM even decreases the overtime for both settings (i.e., moves jobs out of the weekends). Table 8 shows that this evolvement of these parts of the objectives happens during the whole procedure.

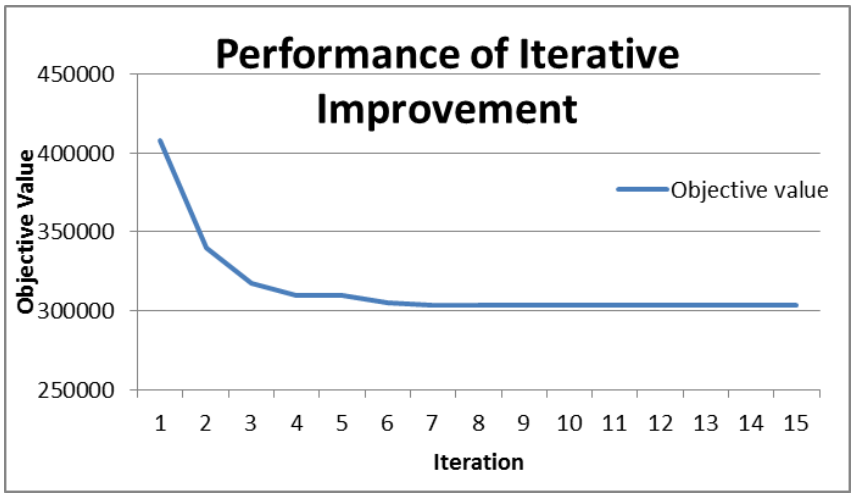


Figure 25 - Evolvement of the objective value for the IIM

Table 8 - Intermediate results of Iterative Improvement. After iteration 5, the values did not change anymore

Iteration	1	2	3	4	5
Objective	407,744	339,583	317,666	310,081	309,582
Overflow	405,692	337,700	315,841	308,287	307,810
Overtime	2,024	1,857	1,808	1,782	1,760
Devation	28,224	22,800	17,136	12,000	11,616
Spread	5.061	5.100	5.123	5.141	5.139

Simulated Annealing - Iterative Improvement Combination

The combination of SA and IIM shows the same evolvement of the objective value as the approach that only uses IIM, as Figure 26 shows. Note that both IIM and SA used half of the computation time. The SA part ends with an objective value of 330,158, which the IIM heuristic approached after two iterations (at 4/15th of the runtime of SA). So, we propose to adapt this method in the same way as we propose to adapt the IIM: reducing the amount of periods with which the solution changes in the IIM part, because the IIM part does influence the objective value by only 13% of the total decrease.

Simulated Annealing – 1 run

Figure 27 shows the objective values and acceptance ratios of the SA heuristic that minimizes the objective values at once, so without distinguishing between the different objectives by means of different runs. Figure 27 shows that this SA procedure approaches a local optimum and shows a decreasing acceptance ratio. Moreover, in this experiment it performs better than any of the other four heuristics, which is conform our expectations which Chapter 4 discusses. Chapter 4 explains that we expect this SA approach to find a local optimum quicker, but also explains that we expect that his local optimum has a lower quality than the local optimum that a four-run SA obtains. Still, this one-run SA approach performs better on each part of the objective, besides the spread. We think that this is due to the low runtime during the first run of the four-run SA procedure, but conclude that Tata Steel could use the one-run SA to obtain a quick – but promising – solution.

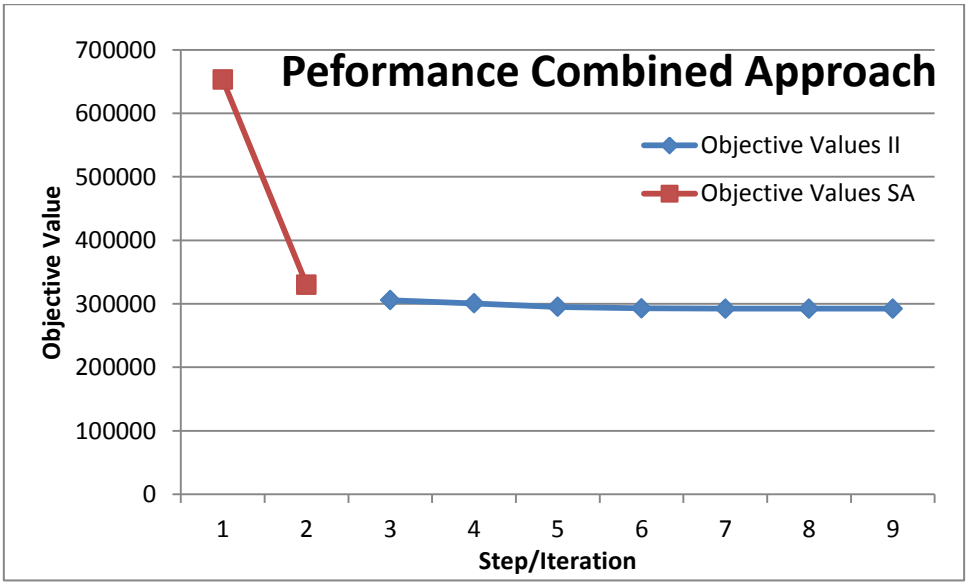


Figure 26 - Evolvement of the objective value for the SA/IIM combination

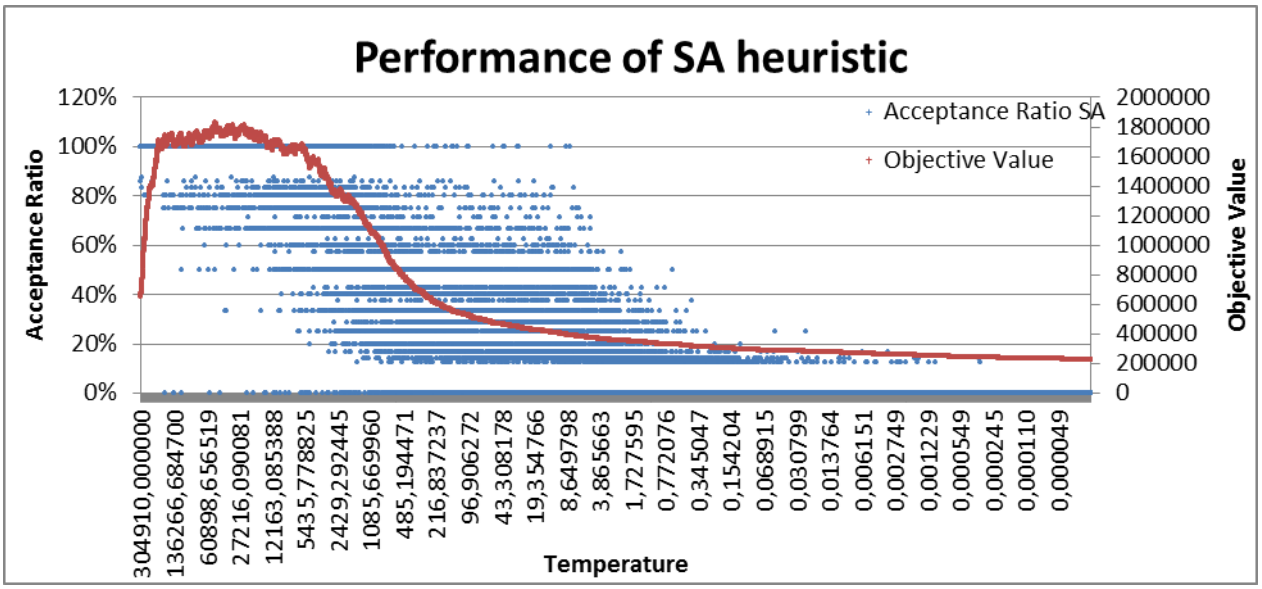


Figure 27 - Evolvement of both the objective value and the acceptance ratio for the SA heuristic

Simulated Annealing – 4 runs

Table 9 shows the results of applying the four-run SA approach to the same problem. As Table 9 shows, neither of the runs reached a local optimum, such that this approach is comparable to the one-run SA approach, whereas that approach minimizes all values together. For such a short runtime, the one-run approach suits better to solve the problem, as Chapter 4 and the previous paragraph already discuss. However, the results of the different SA approaches are very comparable to each other.

Concluding Remarks on the Alternative Approaches

This section shows the potential of Iterative Improvement, although we still face the difficulty of the four ranked objectives. This difficulty should be dealt with by a four run approach, such as our implementation. Based on the objective values in Table 7, SA outperforms IIM, but we do not agree on that statement for other problems or other settings, because IIM seems to get stuck near a local optimum very quick, such that this approach is more useful as a first start or as a finishing heuristic within another heuristic. Due to time restrictions, we are not able to implement and analyze the IIM/SA approach with a decreasing factor in the neighborhood structure definition of IIM, but we propose analyzing this option if Tata Steel requires a method that quickly finds a promising solution.

Table 9 - Intermediate results of the four-run SA

	Run 1	Run 2	Run 3	Run 4
Objective	589,332	387,323	262,866	237,248
Overflow	589,332	379,663	257,133	232,155
Overtime	106,63	7,660	5,290	4,692
Deviation	608,201	613,376	443,311	400,952
Spread	2.219	2.615	2.943	3.025

5.3 The Generated YSS

Section 5.2.1 already discusses the objective values and the quality of the SA approach. This section analyzes the rules of thumb in Section 5.3.1 and analyzes the generated clusters in Section 5.3.2. Finally, Section 5.3.3 compares the generated YSS with the YSS that Tata Steel generated. Due to the high amount of jobs and periods, we are unable to add the generated YSS, whereas adding a week based schedule does not make sense for the aim of showing it: the clustering of jobs.

5.3.1 Rules of Thumb and Other Issues in the New Method

This section evaluates every rule of thumb that Section 2.5.2 discusses. Each of the next four sections discusses one area in the plant and starts with a short repetition of the rules of thumb in that area. Recall that the SA procedure did not find an optimum yet, such that illogical parts still exist in the YSS. Furthermore, we reflect on the rules of thumb from an overflow point of view and do not take any other issues – such as safety issues – into account.

Charging Area

The only rule of thumb for the Charging Area is that outside a plant-shutdown, two installations in this area may never be down together and the only exception on this rule is that Charging Crane 25 and 26 are allowed to be down together.

The rule should intuitively hold for taking down two installations of the same type (two rozas, pits or Charging Crane 21 and 25), because in that case no flow through the Charging Area is possible, such that the optimal schedule does not contain any of these combinations, unless maintenance has to be performed on for example the power supply. Our YSS does not contain any moment in which two pits are down together, neither any moment in which the two cranes are down together, but it does contain eleven periods in which both rozas are down together. However, in none of these eleven periods the overflow increases, which is mainly due to the fact that these eleven periods are divided over the year and the maximum adjacent periods that the rozas are down is three periods. These three periods are scheduled during a plant-shutdown, such that the overflow does not increase. Figure 28 shows a part of the initial solution with the rozas being down together and the same part of the generated YSS with the rozas being down together for only two periods. If we manually reschedule these three jobs back to their initial period in the generated YSS in order to analyze the result of the move that SA performed, the deviation of the cycle time obviously decreases, but – as Table 10 shows – the overflow increases. Hence, the SA method obtained a better solution. However, in the generated YSS there are two hours without any steel, which Tata Steel does not want from a production point of view and possibly spreading the jobs should be more important for jobs on the same type of installation (both rozas, both pits) than not deviating from the cycle time.

Table 10 - Result of rescheduling the Rozas

	After Change	Before Change
Objective	75,433	74,292
Deviation of cycle time	69618	69,622
Buffer Harsco	73,209	72,067
Spread	4.149	4.149
Overtime	2,155	2,155

Job	24	25	26	27	44	45	46
Period Number	ROZA 21	ROZA 21	ROZA 21	ROZA 21	ROZA 22	ROZA 22	ROZA 22
4709							
4710							
4711		1	1			1	
4712		1	1			1	
4713		1	1			1	
4714		1	1			1	
4715							
4716							
4717							
4718							
4719							
4720							

Job	24	25	26	27	44	45	46
Period Number	ROZA 21	ROZA 21	ROZA 21	ROZA 21	ROZA 22	ROZA 22	ROZA 22
4709							
4710							
4711			1				
4712		1	1				
4713		1	1				
4714		1	1			1	
4715		1				1	
4716						1	
4717						1	
4718							
4719							
4720							

Figure 28 - A part of the initial solution (upper half) and the generated solution (lower half)

Although the pits themselves are not down together and taking down the rozas does not increase the overflow, the Rijpo requires both pits and the Rofi requires both rozas, such that during performing a job on the Rijpo or Rofi, the Basic Oxygen Steel Plant cannot process any pig iron. In the input of jobs, the start moments of these jobs are already equalized, such that the impact on the overflow is the lowest possible. Still, the SA procedure should schedule these jobs during a plant-shutdown if they take longer than four hours (Blast-Furnaces produce 770 t/h and the capacity of the hot metal cars equals 3300). Figure 29 shows the result of performing the jobs on the Rijpo and Rofi outside a plant-shutdown.

The rule of thumb also applies to installations of a different type. In the generated schedule, for fifteen times the YSS contains at least one job on more than two installations in the Charging Area. These fifteen times have a different duration and are not scheduled during a plant-shutdown or together with the Rijpo or Rofi. In none of these periods there is an overflow of pig iron.

To conclude, performing maintenance on two installations of the same type outside a plant-shutdown is only possible for less than 4 hours, if the hot metal cars do not contain any iron. Only 1% of the jobs in the Charging Area require less than 4 hours and in practice the hot metal cars always contain some pig iron, so we conclude that the rule of thumb holds for performing maintenance on the same installations. On the other hand, performing jobs on two different installations in the Charging Area is allowed from an overflow point of view.

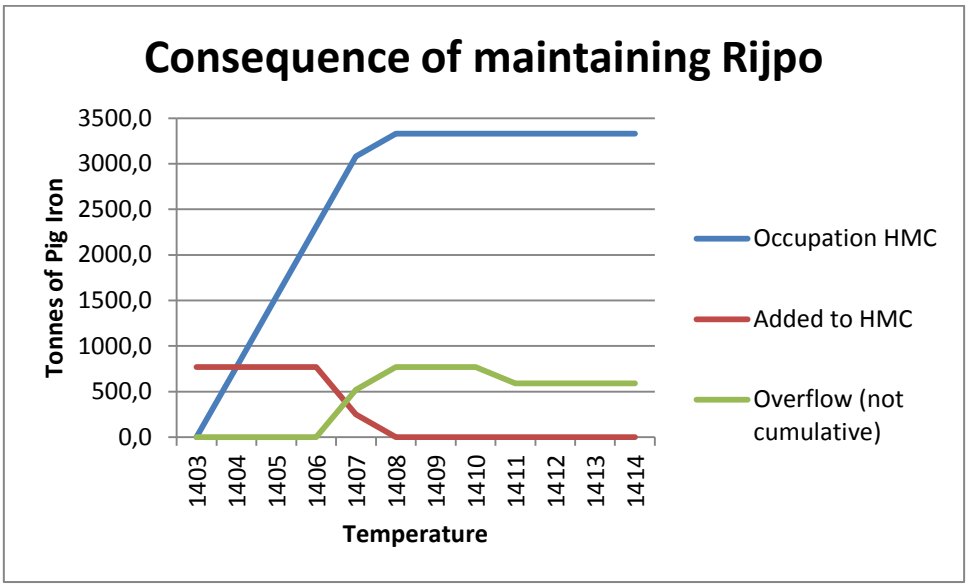


Figure 29 - Overview of the buffer and overflow if the Rijpo is down during 1403-1410

Slag Area

The only rule of thumb for the Slag Area is that either the Slag Crane or one crane in Casting Area 1 should be up. This rule of thumb does not require any analysis, because we already took the rule into account while defining the restrictions on the cycle time of the Slag Area. We included this in the cycle times, because there is no flow possible if the slag cannot be transported, such that the rule of thumb is more of a requirement.

Scrap Area

Tata Steel uses two rules of thumb for the Scrap Area, namely that Transverse Transport 21 should be up if Charging Crane 25 is down and that Transverse Transport 21 and 22 should be up if Charging Crane 26 is down. Again, we are not able to evaluate these rules of thumb, because the resulting cycle time of taking Charging Crane 25 and Scrap Transverse Transport 21 together out of service, depends on the operational level decision of producing loads without scrap. The second rule remains valid in our analysis, again due to the fact that we included this in the cycle times that function as input.

Casting Areas

Finally, the Casting Areas encompass several rules of thumb:

- If the Direct Sheet Plant (DSP) is down, Ladle Furnace 22 and the RH-OB installation should be up.
- Casting Installation 21 and the RH-OB installation should be down together.
- At least two installations of the following three installations should be up: Ladle Furnace 21, Ladle Furnace 22, and the RH-OB installation.

Neither of these rules hold after analyzing the generated YSS, in which every combination mentioned in the rules appear. A possible reason for the incorrectness of the rules is that the rules are not based on cycle times, but are to be taken into account because of other reasons, such as safety issues. Another possible reason for the incorrectness is that we did not include the correct cycle times in the SA method.

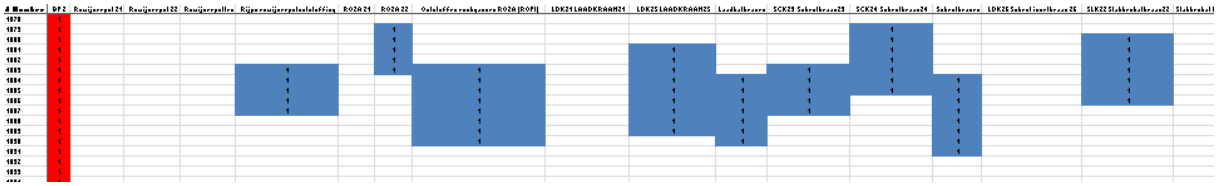


Figure 30 - An overview of clustering installations during a plant-shutdown

Tata Steel can deal with the first possibility by setting the cycle times to 1000 in the input. SA reads this as if there is no flow through the plant, such that it prevents scheduling these installations together. Tata Steel can deal with the second possibility by adding the correct cycle times to the input and finally, there is the possibility that the rules of thumb just do not hold.

Conclusion on the Rules of Thumb

Based on the analysis in this section, we conclude that most rules of thumb do not hold after analyzing the resulting YSS. However, we admit that the cycle times that function as input may be incorrect and we recognize that some rules of thumb are to be considered because of other reasons than overflow. So, we propose to check the cycle times in the input table, to check the reasons for the rules of thumb, and to reconsider the rules of thumb.

5.3.2 Performance of the Four Objectives

This section analyzes the performance of the SA approach, with respect to the different objectives: overflow, overtime, deviation from the cycle time, and spreading of jobs. The next sections discusses these in the mentioned order.

Overflow

As Section 5.2 mentions, none of the runs in the SA procedure reached a local optimum, which is partly due to the incorrect bounds on the temperature in the first run and due to the short runtime. However, we are able to search for improvements in the generated YSS' overflow. The most important aim is to analyze whether the generated YSS contains intuitively illogical parts.

Figure 30 shows a very high level overview of a cluster of jobs during a plant-shutdown. The figure shows that the SA procedure did search for the best moments (the vertical axis) to perform maintenance on critical installations (the horizontal axis). Note that Figure 30 only shows a few installations and that more than one job can be performed on each of these installations. During this plant shutdown of 24 hours, 207 jobs are scheduled of which 176 in only ten periods. Such clusters should contain jobs that require the most critical installations, such as the Rijpo or all cranes in an area. The cluster in Figure 30 contains at least one job on the Rijpo, Rofi, all charging cranes, both scrap cranes, the only crane in the Slag Area, both casting installations, and all scrap transverse transports. Hence, the clustering is intuitively logical.

Figure 31 shows a cluster of jobs that is less intuitively logic, because the DSP and the casting installations are down together. This means that no steel can be casted, such that the flow through the plant equals zero. Due to the high duration of the jobs, we expect an overflow somewhere between period 7596 and 7608. Figure 32 confirms this expectation and shows a red bar at period 7603 until period 7608. However, during these periods, six jobs on Casting Installation 22 are scheduled and another six jobs that require both casting installations are scheduled, which SA should reschedule to a better moment one by one.

Installation	31	32	33	34	35	36	37	
Period Number	CGM-Gietmachine 21	CGM-Gietmachine 22	Gietmachines	Plakkenhal kranen	SchrotKranen	DSP	MHK22	SCH
7589								
7590		1						
7591		1				1		
7592		1				1		
7593		1				1		
7594		1				1		
7595		1				1		
7596		1	1			1		
7597		1	1			1		
7598		1	1			1		
7599		1	1			1		
7600		1	1			1		
7601		1	1			1		
7602		1	1			1		
7603			1			1		
7604			1			1		
7605			1			1		
7606			1			1		
7607			1			1		
7608			1			1		
7609						1		
7610						1		
7611						1		
7612						1		
7613						1		

Figure 31 - An illogical part in the generated YSS

SA should finish this rescheduling before the first run ends, as Chapter 4 explains. After the second run, rescheduling such jobs does not happen anymore, because the tertiary objective always prevents deviating from the cycle time without improving the overtime or the overflow. Improving the overflow is impossible with rescheduling one job, because the overflow still exists due to the jobs left, whereas improving the overtime is possible in this specific part of the schedule. Based on the possibility to decrease the overtime, we conclude that the SA heuristic just did not have enough time to consider all these options during the first two runs. However, if the SA heuristic contains the optimal settings, clusters of installations such as Figure 31 shows are already rescheduled in the first run. We tried to manually reschedule the whole cluster several times and with every change the overflow and the objective increased.

Overtime

During 2,155 hours in the generated schedule, maintenance should be performed in overtime, which is an increase of only 7.75% with respect to the initial schedule in which each job starts at 7am. We expect that the schedule is near optimal with respect to this objective, because the third and fourth run still optimized this objective and – due to wrong determination of the minimum difference of the overflow – this overtime prohibits several changes although the overflow decreases.

This near optimality is supported by the fact that we could not achieve major decreases in the overtime. On the other hand, we still found jobs in overtime that do not have to be performed in overtime, which again should be due to the short runtime. An example of reducing the overtime is moving a job on Casting Installation 22 in Figure 31 to 7am.

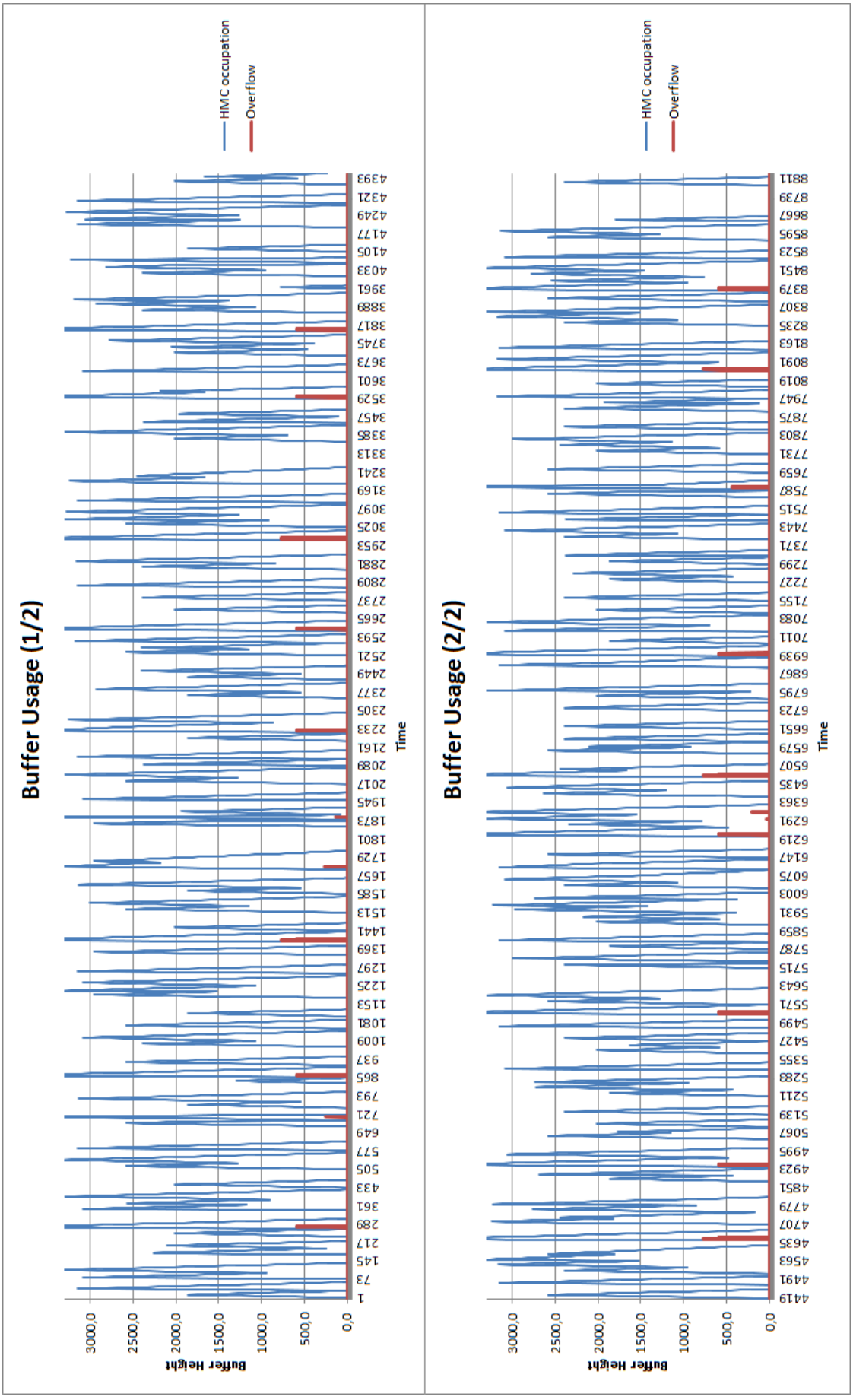


Figure 32 - Flow of the occupation of Hot Metal Cars and - as a consequence - the moments and amount of the overflow

Deviation from the Cycle Time

Clustering jobs leads to deviating from the cycle time, such that – as Table 5 shows – the SA procedure initially makes the deviation to increase very fast (603,015 in only one run), but after including this objective in the overall objective, the deviation could still be reduced with 87%. Nevertheless, the generated YSS seems to be non-optimal with respect to the deviation from the cycle time as a tertiary objective, because the third run did not reach a local optimum. On the other hand, this could also be a consequence of not reaching a local optimum in the previous runs.

Spreading of Jobs

We expected that the clustering of jobs would mainly (negatively) influence the spreading of jobs, which we included in Chapter 4's model as the standard deviation of the total amount of jobs in a period. Our analysis of the spread throughout the SA method does not confirm these expectations, because – as Table 5 – shows, the spread equals 5.03 in the initial solution, whereas it equals 2.757 after the first run. That is exactly the run that should cluster the jobs in order to reduce the overflow. Apparently, the SA method reschedules jobs to clusters at moments other jobs are not scheduled yet. As expected, after adding the overtime and the deviation from the cycle time in the objective, the spread increases, because these aim to schedule the jobs in only 8 hours and on their initial date – with the high initial standard deviation – respectively. Surprisingly, during the last run (i.e., the only run that focusses on the spread) the spread keeps increasing and again, the only explanation for this increase is that the previous runs did not reach a local optimum yet.

Figure 33 shows the division of the jobs over the year. Especially the peak at 2500, the peak at 4220, and the peak at 7550 stand out. The one in the middle is due to a cluster of 25 jobs on Casting Installation 22, the one on the left is due to a cluster of 26 jobs on Casting Installation 21, and the peak on the right is due to 21 jobs on Casting Installation 21. Shutting down a casting installation increases the cycle time from 18 minutes to 26 minutes and the jobs all require 12 hours, such that these large clusters are optimal from an overflow point of view. Finally, note that there is a small peak of 18 jobs in the last period. These jobs are scheduled in the last period, because starting a job in that period means that it does not finish during the horizon of the YSS and the installation is down for only one period. In the initial solution, no job is scheduled in the last period, because we added 100 hours to the year.

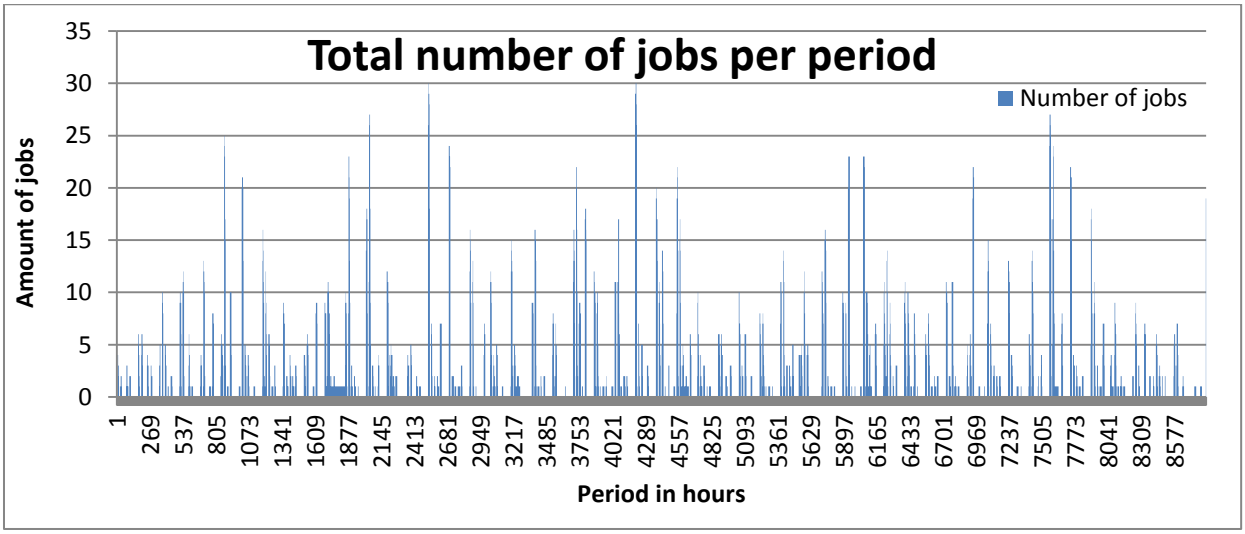


Figure 33 - Indication of the number of jobs per period

To circumvent this problem, Tata Steel should just cut-off these 100 hours and reschedule these in the YSS of the next year. Still, we propose adapting the SA, such that every job finishes in the last period of the YSS (a year + 100 hours). By means of this adaption, SA will search for a better period on the YSS, which may be in the last 100 hours, but may also be in the relevant year.

5.3.3 The Generated and the Current YSS

This section compares the YSS of 2013/14 that we generated with the YSS that Tata Steel generated and uses. We are not able to compare the schedules based on the overtime, deviation from the cycle time, and the spreading of jobs, because Tata Steel's YSS solely shows the installations, whereas these indicators require the specific jobs. Hence, this section solely focusses on the overflow of pig iron.

Tata Steel's YSS obtains only 4 times an overflow, of which 3 times are during a plant-shutdown and which equals to a total overflow of 24,641. Our YSS obtains 23 times an overflow, of which only 3 times during a plant-shutdown and which equals to a total overflow of 72,067. So, our method generates a YSS that seems to be three times worse than the YSS that the current method generates. In order to compare the result if we use the same moments for maintaining the (bottleneck) casting installations, we scheduled these installations in our YSS on the moments Tata Steel schedules these. We obtained a result of 60,744, which is quite a decrease, but still 2.5 times higher than the overflow of the current YSS.

The main reason for the gap between the two overflows is in the differences in the bounds on the start moment of the jobs. We linked the bounds to the priority of a job in SAP, although most of these priorities are equal to the initial high priority, such that most jobs have a tight bound. We analyzed whether or not our jobs fit in the YSS as Tata Steel generated it and we conclude that 810 of the 1483 jobs do not fit to the YSS due to the tight bounds. This 55% difference explains the increase in moments of overflow in our YSS. Moreover, we did not even include the jobs on highly restricting installations (e.g., Rijpo, Rofi, all loading cranes, all scrap transverse transports) in these 1483 jobs, because these are not clearly recognizable in Tata Steel's YSS.

Another reason for the gap between the overflows in the two schedules may be the long durations in our YSS, which is also due to the lack of data on the durations in SAP. Again, most entries for the durations in SAP are empty or equal to zero, such that the shutdown manager had to estimate these for 644 jobs on 61 installations. We are not able to analyze this reason, because the jobs cannot be directly linked to a moment in Tata Steel's YSS, as the previous paragraph explains.

Finally, a reason is the short runtime of the SA procedure, such that it did not obtain a local optimum. This mainly influences the bad scheduling of the bottleneck casting installations on which 42% of all jobs have to be performed, as Section 5.4 explains.

5.4 Computation Time

Due to the size of the problem space (2287 jobs and on average 1076 possible start moments per job), the computation time of the program is very high, such that we are not able to perform the adaptations to the method we propose throughout this chapter. However, we recognize several possibilities to decrease the runtime, which all aim to decrease the problem size or aim to improve the local search heuristic. Section 5.2.2 already discusses options to improve the local search heuristic. This section explains options to decrease the problem size together with the options' strengths and weaknesses.

The problem size is made up of both the number of periods and the number of jobs and this section discusses possibilities to decrease these vectors. This section first discusses how to decrease the problem size by decreasing the number of periods and finishes with a discussion on decreasing the amount of jobs.

An option to decrease the amount of periods is to decrease the days from 24 hours to 16 hours, which is the longest duration of a job in the current setting. Of course, a job that is not finished at the end of the day jumps – together with the time – 8 hours. This means that the job finishes the next morning, even if the job only requires less than 8 hours when the night starts. Such a 33%-decrease in the amount of periods causes a 33%-decrease in the problem size. However, if a job still requires only 1 hour when the night starts, the cycle time remains low during the 8-hour-night, although the job finishes after 1 hour. Hence, this approach does affect the representativeness of the model and probably has a high impact on the objective value.

Another option to decrease the amount of periods is to decompose the year into semesters or even quartiles. The main advantage of this decomposition method is that the local search heuristic finds a local optimum quicker. However, it should find more local optima to capture the whole year. Again, decomposing the year in smaller periods decreases the optimality of the YSS, but by reconsidering the last part (e.g., 20%) of the previous YSS and rescheduling these jobs, we expect that the resulting YSS is rather comparable to the YSS as the current yearly method generates it. Another advantage of this method is the fact that the current program we built is able to deal with smaller horizons and that all jobs that have to be performed during the year can still be used as input; the program recognizes that the job should start after the horizon.

For this research, we already decreased the number of jobs by clustering jobs that clearly belong together (taking an installation out service, maintaining the installation, put the installation back to service), but the literature discusses several other options to cluster jobs based on for example the cycle times (e.g., Van Dijkhuizen and Van Harten (1997) and Gits (1992)). These options are time consuming and require several additional parameters. Still, we can think of several clusters ourselves without applying any theory: for the current research we used 122 jobs on Casting Installation 21, 110 jobs on Casting Installation 22, and another 42 jobs that require both casting installations. So, the jobs on the casting installations count for 42% of the total amount of jobs. Several jobs in these three sets start at the same moment, have the same duration, and have the same cycle time as another job in that set, and – as Section 5.3.2 shows – are in a cluster in the generated YSS. As a consequence, we propose to cluster these jobs. Furthermore, by analyzing previously generated yearly shutdown-schedules, clusters of jobs that have to be performed together in every schedule appear. In next years, Tata Steel should use these clusters instead of separate jobs.

These ways to decrease the amount of jobs contradicts with one of the reasons for performing this research: let the model instead of the user cluster the jobs. On the other hand, some jobs should definitely form a cluster, such that clustering does not affect the representativeness. We strongly recommend keep using this way of decreasing the problem size *before* the heuristic starts, but we recommend not to cluster the jobs if the jobs do not form an obvious cluster.

5.5 Summarizing the Results

The four-run SA procedure reduced the objective value of the initial YSS by approximately 89%, mainly due to the decrease in the overflow. An important disadvantage of the four-run method is the required local optimum at the end of each run, which our experiment did attain in none of the four runs. Still, we recognize that the method did solve the problem and generated a YSS in the correct way, that it influenced the correct objectives, and that it behaved as expected. A major, but easily preventable, shortcoming of our method is the wrong lower bound on the temperature, such that the first run did not end in a local optimum. Section 5.2.1 already shows the improved temperatures and corresponding penalties.

Most rules of thumb as formulated by Tata Steel appear to be unnecessary, although some of these may have other reasons than just decreasing the overflow. Hence, we recommend reconsidering these, such that these can either be added to the input of the model, or be left out of the generation of the YSS.

Although these rules of thumb are not required, the manual method of Tata Steel outperformed our method on the total overflow during the year. The main reasons for the 65% difference between our YSS and the current YSS, are the short runtime in our method, the tight bounds on the jobs' start moments (55% of the jobs has too tight bounds to fit in the current YSS), and the high durations in our method.

Our analysis of alternative heuristics to solve the Maintenance Scheduling Problem did neither result in much better results, nor did these option end up in a local optimum. Moreover, we do not expect these options to outperform our four-run SA method, although a combination with Iterative Improvement seems to have a high potential.

Finally, this chapter discussed several options to decrease the problem size by decreasing the number of periods or the number of jobs. Especially decreasing the number of jobs seems to be rather promising and can be attained by clustering jobs that have an equal cycle time, an equal duration, require the same installation, and have the same start date, such as several jobs on the casting installations.

6. Conclusions and Recommendations

This chapter covers both the conclusions and the recommendations of this research. First, Section 6.1 contains the conclusions of this research and recommendations based on this research. Section 6.2 contains topics for further research.

6.1 Conclusions

This section concludes on our research and explains how we solved the problem of Tata Steel's Basic Oxygen Steel Plant with respect to scheduling shutdowns. In Chapter 1 we defined the research question as: *How can the current method of developing the yearly shutdown-schedule at the Basic Oxygen Steel Plant of Tata Steel be improved, such that the restrictions are met and are clear, and that all iron produced by the Blast-Furnaces is processed?* We answer this question by concluding on our method in Section 6.1.1. Section 6.1.2 explains the advantages and disadvantages of the method we propose and Section 6.1.3 covers additional recommendations, which are of direct influence to the usability of the method.

6.1.1 The Improved Method

Currently, Tata Steel applies a manual method to generate the Yearly Shutdown-Schedule (YSS), which is based on experience and smart rules of thumb. The literature on the other hand, solely discusses mathematical and automated methods to solve the Maintenance Scheduling Problem. Previously performed research solely solves the problem with a single objective, whereas our approach generates a YSS that aims to meet the following four ranked restrictions:

1. Process as much of the pig iron that the Blast-Furnaces produce as possible.
2. Perform the least jobs as possible in overtime.
3. Deviate the least from the proposed cycle times as possible.
4. Spread the jobs as much as possible.

In order to generate a YSS that complies with these objectives, we modeled the problem in a Mixed-Integer Programming (MIP) formulation that requires the moment to start a job as decision variable and uses a penalty for each of the objectives in order to distinguish between the importance of each objective. We defined the penalties such that there is a strict ranking in the objectives: an objective can never decrease at the cost of an increase in a higher ranked objective.

Besides the penalties, the MIP requires the duration, the cycle time, and the priority of every job that has to be performed during the relevant year. We used the MIP to evaluate schedules, which a Simulated Annealing (SA) procedure generates. The SA procedure first optimizes the primary objective and if it finds a high quality YSS based on the overflow (i.e., it finds a local optimum), it adds the secondary objective until it finds a high quality YSS based on both objectives. This process continues until the SA optimized the YSS on all four objectives. The SA procedure outperformed three out of the four other local search techniques that we applied and only an SA procedure that solved the four objectives in parallel slightly outperformed our approach. However, if we dedicate more time to running the heuristics, our four-run SA will outperform the other heuristics.

6.1.2 Advantages and Disadvantage of the Method

Currently, Tata Steel manually generates the YSS based on discussions with the installation engineers and several rules of thumb. Our method uses an automated approach to create the YSS. Although the method requires some manual preparation, our automated approach reduces the hours spent on generating the YSS.

Furthermore, Tata Steel schedules installations instead of jobs, although all jobs are stored in SAP. Our method uses these jobs to generate the YSS, because these actually have to be performed throughout the year. By using these jobs, the method is more transparent than the current method and consequently generates a more transparent schedule. Another advantage of scheduling jobs is the possibility for the installation engineers to recognize their own jobs in the YSS instead of their installation, such that the YSS is better understandable. Hence, the installation engineers probably propose better adaptions. After the proposed adaptions, adapting the YSS also becomes easier and clearer, because changing the start moment of a job in the schedule becomes easier. The results of these adaptions become better analyzable, because the KPIs of the YSS after rescheduling a job can be calculated easily (our implementation contains the possibility to calculate the KPIs based on a schedule). Tata Steel should use these KPIs to decide whether or not to accept the rescheduling of the job.

Furthermore, the inclusion of the jobs and the data in SAP that belong to that job (cycle time, duration, priority, etc.) decreases the subjectivity of the schedule. Still, the installation engineers define the duration, the cycle time, and the priority of the jobs, such that the method contains some subjectivity, but the new method circumvents the major part of this subjectivity in the generation of the schedule. The fact that the YSS is mainly based on the input of the section increases the trust in the schedule.

By gathering the correct information and including the jobs, not only the scheduling of moments to shut down the plant becomes faster, more reliable, and more useful, also the scheduling of a shutdown itself becomes more reliable and more transparent (a heuristic such as project scheduling requires the same data and increases the quality of the operational schedule).

The main disadvantage of our approach is the requirement to gather data about each and every job, which is a time consuming and, as a consequence, an expensive task. However, as Section 6.2 discusses, these data can be used to obtain new insights in the process and jobs and can be used to improve the scheduling during a shutdown. Furthermore, it increases the understanding of the jobs and the understanding of the process of defining maintenance needs.

6.1.3 Additional Recommendations

Section 6.1.2 discusses several recommendations between the lines, such as the recommendation to recalculate the KPIs after manually rescheduling a job. This section does not discuss these recommendations again, but focusses on recommendations that Section 6.1.2 does not discuss.

Currently, most of the required input parameters are incorrect or are lacking in SAP and we recommend determining the values of especially the duration and the priority on the short term, because our implementation generates a near optimal schedule that applies to the input. So, if the input is incorrect, the outcome will be incorrect. Hence, determining the correct durations, cycle times, and priorities of the jobs is a requirement for using our method. In order to convince the sections to spend time on determining the correct data, we advise to show the results after

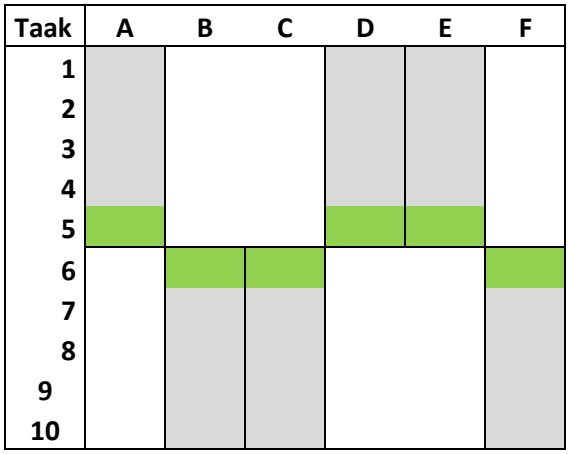


Figure 34 - An example of jobs that are scheduled on their bounds

generating a YSS based on different types of input (e.g., bad input values, acceptable input, and correct input). Especially the lack of the job's duration and the inaccuracy of the available durations influence the quality of the YSS that our method generates, because the overflow of pig iron heavily depends on the (in)correctness of the durations of the jobs. Besides the unavailability of the durations, the lack of priorities in SAP influences the method in the freedom to schedule clusters in each other's *shadow*: currently every job with a lacking priority has tight bounds on the moment to be scheduled, whereas several jobs actually have loose bounds instead.

Even if this data is correct, we advise to analyze the jobs that are scheduled close to their bounds, because these may be right after or right before another cluster of jobs, which is just outside the bounds of the job, as Figure 34 shows. In Figure 34, A-F are jobs that have to be scheduled during the periods that correspond to the grey areas (i.e., the grey areas are the bounds of the job). The green areas show the actual moment that the job is scheduled. Clearly, rescheduling job A, D and E to period 6 is worth considering. Tata Steel should perform this rescheduling step manually and we propose to use the KPIs to calculate the quality of the YSS after this rescheduling step, as Section 6.1.2 mentions.

We added 100 hours at the end of the year, such that jobs with an upper bound that reaches over the YSS's horizon are allowed to be scheduled after the last period of the year. Note that the jobs should finish during the last period instead of start during the last period. We advise to keep using this way of determining the jobs that have to be maintained the next year. Tata Steel should just cut-off the final part of the schedule and should add these jobs to the input of next year's YSS.

Finally, we recommend using the Excel-module that indicates the values of the temperatures, based on the differences between objectives. This module does exactly the same as Chapter 4 explains. However, we recommend adapting the penalties to make these temperatures unequal. Section 5.2.1 explains the procedure to obtain the penalties and shows which values apply to the current problem. Note that the penalties may change every year, until the optimal penalties are available, as the final paragraph of Section 6.2 discusses.

6.2 Further Research

This chapter sets forth possibilities and requirements for further research and starts with the most important requirements for further research.

Before applying the model, Tata Steel should determine the correct input data: the cycle times of the jobs, the priorities of these jobs, and the duration of these jobs. Defining the correct duration of a job is rather easy, because Tata Steel can easily obtain these data during the upcoming year and improve it during the subsequent years. The priorities are also rather easy to determine, because the installation engineers will have this knowledge. Moreover, Tata Steel already puts more effort in determining these values.

However, engineers may store wrong values to SAP (e.g., a long duration), such that they have more time to finish their task. In order to deal with these kinds of errors, we propose to perform some research on the possibility to store the actual durations of the jobs and take yearly averages. Based on these values, comparisons can be made with the actual performance. There are other ways to deal with these kinds of errors and we propose performing more research on this subject.

Improving the cycle time of a job is more complex than improving the duration and the priority of a job. The current cycle times of maintenance are adapted to the cycle times that were used for the previous yearly shutdown-schedules and Grall et al. (2002) propose an interesting and seemingly useful model to include the correct cycle times of the jobs. They recognize that the preventive replacement decision should be jointly optimised with the inspection dates, instead of using these as input variables. The model they propose schedules predictive maintenance for a detoriating system and they use continuous time and a continuous state of the system. Their model only focusses on a single unit, probably because – as they state – "the price for this higher efficiency is the requirement of a mathematical model for the stochastic deterioration process of the maintained system … Usually, the task of deriving such a mathematical model is more complicated than just statistically describing the binary transition from a good state to a failed state". Additionally, we refer to Duarte et al. (2006), Sherbrooke (2004), Aven and Jensen (1999), and Gertsbakh (2005) for a discussion on how to attain the optimal cycle time.

In our opinion, the complexity of the model heavily increases after the addition of these kinds of stochastic models, but the model definitely becomes more reliable. The increase in reliability is in the fact that the model is able to calculate the expected costs of in- or decreasing the cycle time. The increase in complexity is due to the amount of additional parameters that are required, such as the costs of corrective and preventive maintenance and the mean time to repair. These concepts are widely discussed in the literature, as Chapter 3 mentions, so adding the correct formulas to the model will not be too difficult. On the other hand, determining the required input functions requires a lot of data on for example mean time to repair and mean time to failure. One way to add minimal complexity, while profiting as much as possible, is to start with adding the complex functions for the maintenance-bottlenecks.

Additionally, if the cycle times can be expressed in a mathematical function that expresses the costs of maintenance after delaying it, the model can in- or decrease the cycle times based on these costs. The current method is not able to deal with these complex functions and equally penalizes every hour of deviation. A method that uses these functions does not need bounds on maximum deviations from the cycle time anymore. Still, we expect that the addition of these complex functions to the

model does not pay-off the time spend on adding these complex functions. Hence, we propose defining the optimal cycle times based on these functions and assigning these cycle times to the jobs. Here another advantage of the method that we propose appears: in the current method of generating the YSS, it is hard to combine maintenance if every job has a different cycle time. The automated approach that we propose, deals with these different cycle times as easy as it deals with equal cycle times. Furthermore, Deshpande and Modak (2002) discuss the result of applying Reliability Centered Maintenance to a specific installation of a steel plant in India. Their result is that for several parts of the installation the cycle time of preventive maintenance could be improved from one month to two months; that is an increase of 100%. Such an increase may also be more cost efficient at several installations of the Basic Oxygen Steel Plant of Tata Steel. So, there are several possibilies to improve the determination of the cycle times of the jobs and we advise to perform more research on this subject, such that the YSS can be optimized.

Chapter 5 recommends on ways to cluster jobs, but for an optimal use of clusters we recommend to apply models such as Van Dijkhuizen and Van Harten (1997) and Gits (1992) discuss. They discuss methods that lead to a better clustering of jobs. For these methods, it would pay-off if installations just show their optimal preventive maintenance cycle time, such that our approach combines these to an optimimal YSS. With respect to the clustering of jobs, we used in our analysis 122 jobs on Casting Installation 21, 110 jobs on Casting Installation 22, and another 42 jobs that require both casting installations and a lot of these jobs have the same duration, cycle times, and priorities. Hence, we propose clustering the jobs on the casting installations or redefining the jobs on the casting installations, because the casting installations heavily influences the cycle time through the plant.

We propose reconsidering the cycle times that belong to taking certain combinations of installations out of service. Chapter 5 explains that we do not confirm all currently applied rules of thumb, either because these are not based on the overflow restrictions or because the cycle times behind these rules of thumb are incorrect. Hence, it requires some further research which rules of thumb to translate to a cycle time (e.g., based on safety issues) and which rules of thumb to reconsider. Furthermore, Tata Steel can obtain new rules of thumb from the YSS that the method generates. These rules can be used for quick decisions and short-term scheduling.

As mentioned before, we recommend to apply our method to reschedule the shutdowns when additional jobs (e.g., projects) appear during the year. In such cases, rescheduling the shutdowns may have an impact on the objective value. On the other hand, rescheduling the shutdowns possibly affects the face validity of the method and the generated YSS, because a major change in the YSS due to a small change in the requirements of a section is an unintuitive consequence. Hence, we advise to be careful with adapting the YSS if it does not significantly decrease the objective value (i.e., if it does not significantly decreae the overflow). A possiblity to adapt the schedule based on only one job is an Iterative Improvement heuristic that solely takes that specific job into account and starts searching near the current start moment for a new start moment. We advise to perform more research on analyzing the robustness of our method and advise to perform more research on the Iterative Improvement heuristic. If the robustness is high or can easily be improved, Tata Steel can repeat the scheduling process more often, such there is always a schedule available for the upcoming year (i.e., a rolling horizon is used).

Finally, we used penalties in order to make sure that an objective does not influence a lower ranked objective. Optimally, these penalties represent the benefit of decreasing an objective at the expense of increasing another objective and more research is required to correctly determine these penalties. Additionally, we recommend performing more research on the ranking of the different objectives: is minimizing the deviation from the cycle time more important than spreading the jobs? This ranking may lead to periods without any steel, such that another ranking may suit better to the problem. However, another way to prevent periods without any steel may suit better to the needs of Tata Steel. These considerations have to be analyzed to correctly define the penalties.

Bibliography

thefreedictionary. (2013). Retrieved February 2, 2013, from thefreedictionary: http://www.thefreedictionary.com/stochastic

Aarts, E. H., & Korst, J. (1989). Chapter 1 - Combinatiorial Optimization. In E. H. Aarts, & J. Korst, *Simulated Annealing and Boltzmann Machines* (p. ??). Wiley.

Aarts, E. H., Korst, J. H., & van Laarhoven, P. J. (1997). Simulated Annealing. In J. K. Lenstra, *Local Search in Combinatorial Optimization* (pp. 91-120). New York: Wiley & Sons Ltd.

Aissani, N., Beldjilal, B., & Trentesaux, D. (2009). Dynamic scheduling of maintenance tasks in the petroleum industry: A reinforcemen tapproach. *Engineering Applications of Artificial Intelligence 22*, 1089–1103.

Aissani, N., Beldjilal, B., & Trentesaux, D. (2009). Dynamic scheduling of maintenance tasks in the petroleum industry: A reinforcement approach. *Engineering Applications of Artificial Intelligence 22*, 1089–1103.

Alkhamis, T. M., & Yellen, J. (1995). Refinery units maintenance scheduling using integer programming. *Applied Mathematical Modelling, Vol. 19, September*, 544-549.

Aven, T., & Jensen, U. (1999). Chapter 1 + 2. In *Stochatic Models in Reliability* (pp. 1-44). New York: Springer.

Baskar, S., Subbarai, P., Rao, M., & Tamilselvi, S. (2003). Genetic algorithms solution to generator maintenance scheduling with modified genetic operators. *IEEE Proceedings-Generation, Transmission and Distribution, Vol. 150, No. 1*, 56-60.

Benders, J. F. (1962). Partitioning Procedures for solving mixed-variable linear programming problems. *Numerische Matematik*, 238-252.

Berrichi, A., Yalaoui, F., Amodeo, L., & Mezghiche, M. (2010). Bi-Objective Ant Colony Optimization approach to optimize production and maintenance scheduling. *Computers & Operations Research*, 1584–1596.

Blok, J., Castelijn, P., Hoekstra, S., & Kokkeler, F. (2012). *Scope Management of Shutdowns - Invloedsfactoren & Strategieen.* Enschede: Universiteit Twente.

Budai, G., Huisman, D., & Dekker, R. (2004). Scheduling Preventive Railway Maintenance Activities. *Econometric Institute Report EI 2004-41*, 1-15.

Burke, E. K., & Smith, A. J. (2000). Hybrid Evolutionary Techniques for the Maintenance Scheduling Problem. *IEEE Transactions on Power Systems, Vol. 15*, 122-128.

Burke, E. K., Clark, J. A., & Smith, A. J. (1997). Four Methods for Maintenance Scheduling. *Proceedings of the International Conference on Artificial Neural Networks and Genetic Algorithms*, 264–269.

Chattopadhyay, D. (1998). A Practical Maintenance Scheduling Program: Mathematical Model and Case-Study. *IEEE Transactions on Power Systems, Vol 13, No. 4*, 1475-1480.

Chattopadhyay, D., Bhattacharya, K., & Parikh, J. (1995). A Systems Approach to Least-Cost Maintenance Scheduling for an Interconnected Power System. *IEEE Transactions on Power Systems, Vol. 10, No. 4*, 2002-2007.

Coley, D. A. (1999). *An Introduction to Genetic Algorithms for Scientists and Engineers.* Singapore: World Scientific Publishing Co. Pte. Ltd.

Dahal, K. P., & Chakpitak, N. (2007). Generator maintenance scheduling in power systems using metaheuristic-based hybrid approaches. *Electric Power Systems Research 77*, 771–779.

Dahal, K. P., Aldridge, C., & McDonald, J. (1999). Generator maintenance scheduling using a genetic algorithm with a fuzzy evaluation function. *Fuzzy Sets and Systems 102*, 21-29.

Dekker, R. (1996). Applications of maintenance optimization models: a review and analysis. *Reliability Engineering and System Safety 51*, 229-240.

Deshpande, V. S., & Modak, J. P. (2002). Application of RCM for safety considerations in a steel plant. *Reliability Engineering and System Safety 78*, 325–334.

Dopazo, J. F., & Merrill, H. M. (1975). Optimal Generator Maintenance Scheduling Using Integer Programming. *IEEE Transactions on Power Apparatus and Systems, Vol. PAS-94, no. 5*, 1573-1545.

El Moudan, W., & Mora-Camino, F. (200). A dynamic approach for aircraft assignment and maintenance scheduling by airlines. *Journal of Air Transport Management 6*, 233-237.

El-Amin, I., Duffuaa, S., & Abbas, M. (2000). A Tabu search algorithm for maintenance scheduling of generating units. *Electric Power Systems Research 54*, 91–99.

El-Sharkh, M. Y., & El-Keib, A. A. (2003). An evolutionary programming-based solution methodology for power generation and transmission maintenance scheduling. *Electric Power Systems Research 65*, 35-40.

Escudero, L. F. (1982). On maintenance scheduling of production units . *European Journal of Operational Research 9*, 264-274.

Fetanat, A., & Shafipour, G. (2011). Generation maintenance scheduling in power systems using ant colony optimization for continuous domains based 0–1 integer programming. *Expert Systems with Applications 38*, 9729–9735.

Gertsbakh, I. (2005). Preventive Maintenance Models Based on the Lifetime Distribution. In *Reliability Theory with Applicants to Preventive Maintenance* (pp. 67-102). Berlin: Springer.

Gits, C. W. (1992). Design of Maintenance Concepts. *International Journal of Production Economics, 24*, 217-226.

Glover, F., Taillard, E., & de Werra, D. (1993). A user's guide to tabu search. *Annals of Operations Research 41*, 3-28.

Gopalakrishnan, M., Mohan, S., & He, Z. (2001). A tabu search heuristic for preventive maintenance scheduling. *Computers and Industrial Engineering 40*, 149-160.

Grall, A., Dieulle, L., & Béreng, C. (2002). Continuous-Time Predictive-Maintenance Scheduling for a Deteriorating System. *IEEE Transactions on Reliability, Vol. 51, No. 2*, 141-150.

Heerkens, H. (2004). Managerial Problem-Solving Method.

Hertz, A., Taillard, E., & de Werra, D. (2003). Chapter 5, Tabu Search. In E. Aarts, & K. Lenstra, *Local Search in combinatorial optimization* (pp. 121-136). Oxfordshire: Princeton University Press.

Holland, J. H. (1992). Genetic Alghorithms. *Scientific American*, 66-72.

Huang, C. J., Lin, C. E., & Huang, C. E. (1992). Fuzzy approach for generator maintenance scheduling . *Electric Power Systems Research, 24*, 31-38.

Huang, C. J., Lin, C. E., & Huang, C. E. (1992). Fuzzy approach for generator maintenance scheduling. *Electric Power Systems Research, 24*, 31-38.

Huang, S.-J. (1998). A genetic-evolved fuzzy system for maintenance scheduling of generating units. *lectrical Power & Energy Systems, Vol. 20, No. 3*, 191-195.

Inuiguchi, M., & Ramík, J. (2000). Possibilistic linear programming: a brief review of fuzzy mathematical programming and a comparison with stochastic programming in portfolio selection problem. *Fuzzy Sets and Systems 111*, 3-28.

Kirkpatrick, S., Gelatt, C. D., & Vecchi, M. P. (1983). Optimization by Simulated Annealing. *Science, New Series, Vol. 220, No. 4598*, 671-680.

Kralj, B. L., & Petrović, R. (1988). Optimal preventive maintenance scheduling of thermal generating units in power systems - A survey of problem formulations and solution methods. *European Journal of Operational Research 35*, 1-15.

Kralj, B., & Petrovic, R. (1995). A multiobjective optimization approach to thermal generating units maintenance scheduling. *European Journal of Operational Research 84*, 481-493.

Lima, R. M., Grossmann, I. E., & Jiao, Y. (2011). Long-term scheduling of a single-unit multi-product continuous process to manufacture high performance glass. *Computers and Chemical Engineering 35*, 554–574.

Marwali, M. K., & Shahidehpour , S. M. (1998). Integrated generation and transmission maintenance scheduling with network constraints. *IEEETransactions on Power Systems, Vol.13, No.3*, 1063-1068.

Metropolis, N., Rosenbluth, A. W., Rosenbluth, M. N., Teller, A. H., & Teller, E. (1953). Equation of State Calculations by Fast Computing Machines. *The Journal of Chemical Physics, vol. 21, no. 6*, 1087-1092.

Moghaddam, K. S. (2008). *Preventive Maintenance and Replacement Scheduling: Models and Algorithms.* Lousivile: University of Louisville.

Mohanta, D. K., Sadhu, P. K., & Chakrabarti, R. (2007). Deterministic and stochastic approach for safety and reliability optimization of captive power plant maintenance scheduling using

GA/SA-based hybrid techniques: A comparison of results. *Reliability Engineering and System Safety 92*, 187–199.

Muckstadt, J. A., & Wilson, R. C. (1968). An Application of Mixed-Integer Programming Duality to Scheduling Thermal Generating Systems. *IEEE Transactions on Power Apparatus and Systems*, 1968-1978.

Peng, F., Kang, S., Li, X., Ouya, Y., Somani, K., & Acharya, D. (2011). A Heuristic Approach to the Railroad Track Maintenance Scheduling Problem. *Computer-Aided Civil and Infrastructure Engineering 26*, 129–145.

Perquin, S. (2005). *Cargo Nieuws Pagina.* Retrieved April 12, 2013, from Rolandrail.net: www.rolandrail.net/nieuws/fotopag_00676.htm

Pinedo, M. L. (2009). *Planning and Scheduling in Manufacturing and Services 2nd edition.* New York: Springer.

Ruiz, R., García-Díaz, J. C., & Maroto, C. (2007). Considering scheduling and preventive maintenance in the flowshop sequencing problem. *Computers & Operations Research 34*, 3314 – 3330.

Saraiva, J. T., Pereira, M. L., Mendes, V. T., & Sousa, J. C. (2011). A Simulated Annealing based approach to solve the generator maintenance scheduling problem. *Electric Power Systems Research 81*, 1283–1291.

Satoh, T., & Nara, K. (1991). Maintenance Scheduling By Using Simulated Annealing Method. *IEEE Power Engineering Society*, 859-857.

Sherbrooke, C. C. (2004). Optimal Inventory Modeling of Systems, 2nd edition. Boston: Kluwer Academic Publishers.

Slack, N., Chambers, S., & Johnston, R. (2007). *Operations Management.* Essex: Pearson Education Limited.

Soh, S. S., Nor, R. H., & Haron, H. (2012). Review on Scheduling Techniques of Preventive Maintenance Activities of Railway. *Fourth International Conference on Computational Intelligence, Modelling and Simulation.* IEEE Computer Society.

Suresh, K., & Kumarappan, N. (2012). Hybrid Improved Binary Particle Swarm Optimization Approach for Generation Maintenance Scheduling Problem. *Swarm and Evolutionary Computation*, Article in Press.

Umiliacchi, P., Lane, D., & Romano, F. (2011). redictive maintenance of Railway Subsystems Using An Ontology Based Modelling Approach. *9th World Conference on Railway Research*, (pp. 1-10). Lille, France.

Van Dijkhuizen, G., & Van Harten, A. (1997). Reliability Theory with Applicants to Preventive Maintenance. *European Journal of Operational Reserach 99*, 552-564.

Volkanovski, A., Mavko, B., Boševski, T., Čauševski, A., & Čepin, M. (2008). Genetic algorithm optimisation of the maintenance scheduling of generating units in a power system. *Reliability Engineering and System Safety 93*, 757–767.

Wang, Y., & Handschin, E. (2000). A new genetic algorithm for preventive unit maintenance scheduling of power systems. *Electrical Power and Energy Systems 22*, 343–348.

Winston, W. L. (2004). *Operations Research - applications and algorithms 4th edition.* Belmont: Thomson Learning.

Yamayee, Z. A. (1982). Maintenance Scheudling: Description, Literature Survey, and Intervace with Overall Operations Scheduling. *IEEE Transactions on Power Apparatus and Systems, Vol. PAS-101, No. 8*, 2270-2279.

Zürn, H. H., & Quintana, V. (1975). Generator Maintenance Scheduling Via Successive Approximations Dynamic Programming. *IEEE Transactions on Power Apparatus and Systems, vol. PAS-94, no. 2*, 665-671.

Appendices

A Translation of Terms

This appendix contains a translation of several terms used throughout the report. This appendix only contains the translation from English to Dutch.

B	
basic oxygen steel plant	oxystaalfabriek
blast-furnace	hoogoven

C	
casting crane	gietkraan
casting installation	gietinstallatie
charging crane	laadkraan
converter	converter

D	
dust exhaustion	stofafzuiging

E	
exhaust fan	afzuigventilator
exhaust system	afzuiginstallatie

H	
hot metal car	ruwijzer menger
hot strip mill	warmbandwals

G	
gantry crane	bovenloop kraan

L	
ladle furnace	panoven
ladle transport (car, wagon)	dwarstransportwagen
ladle transport VPBI	dwarstransport VPBI
loading crane	laadkraan

O	
overhead travelling crane	bovenloopkraan

P	
pit	put
pig iron	ruwijzer

R	
refractory	vuurvast
raw iron desulphizer installation (ROZA)	ruw ijzer ontzwavelings installatie (ROZA)
RH-OB installation	vacuüumpanbehandelingsinstallatie (VPBI)

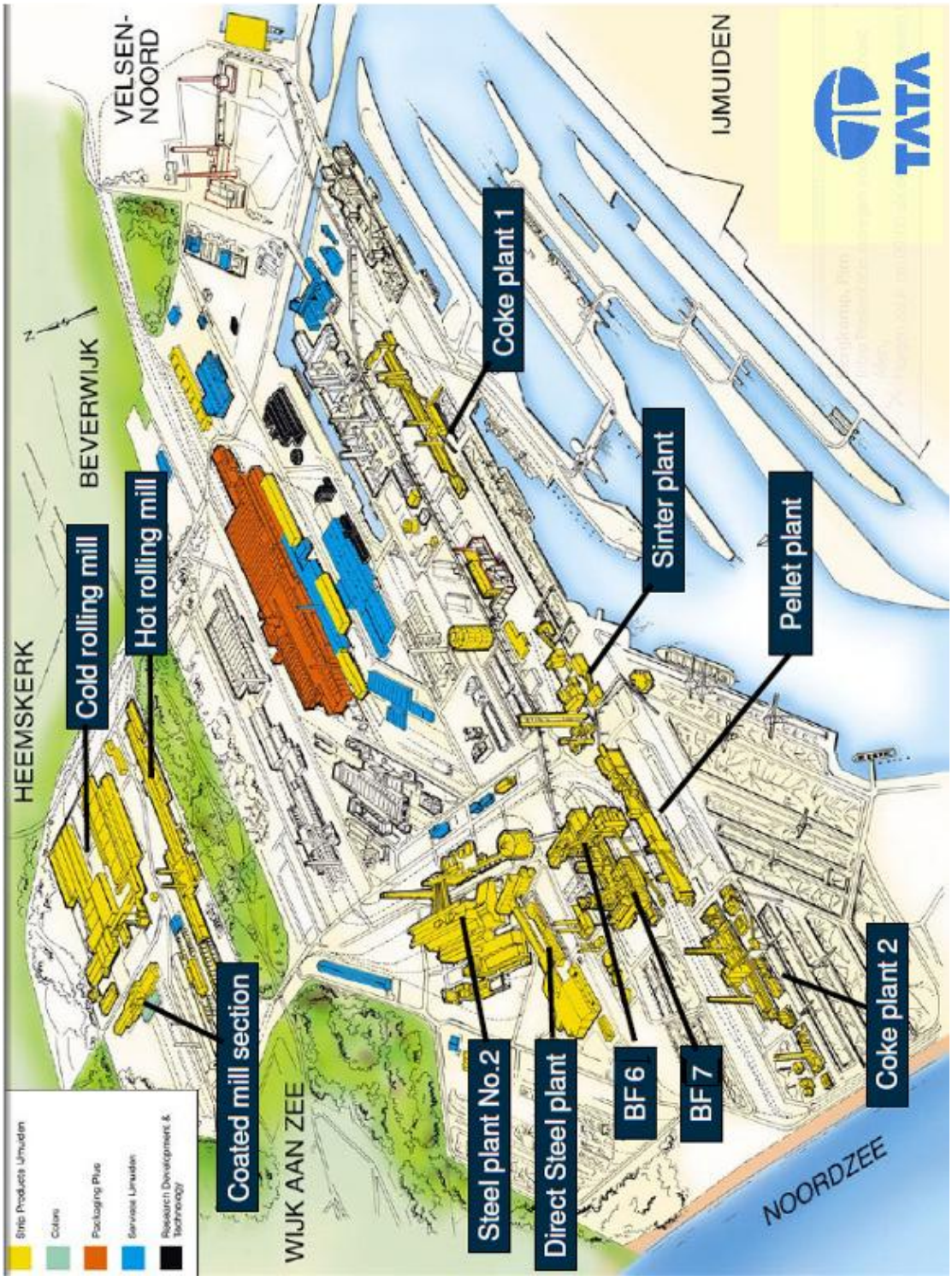
S	
scrap	schrot
slab area	plakkenhal
slag	slak
stirring station	spoelstand
semi portal	halfportaal kraan

T	
transverse transport	dwarstransport

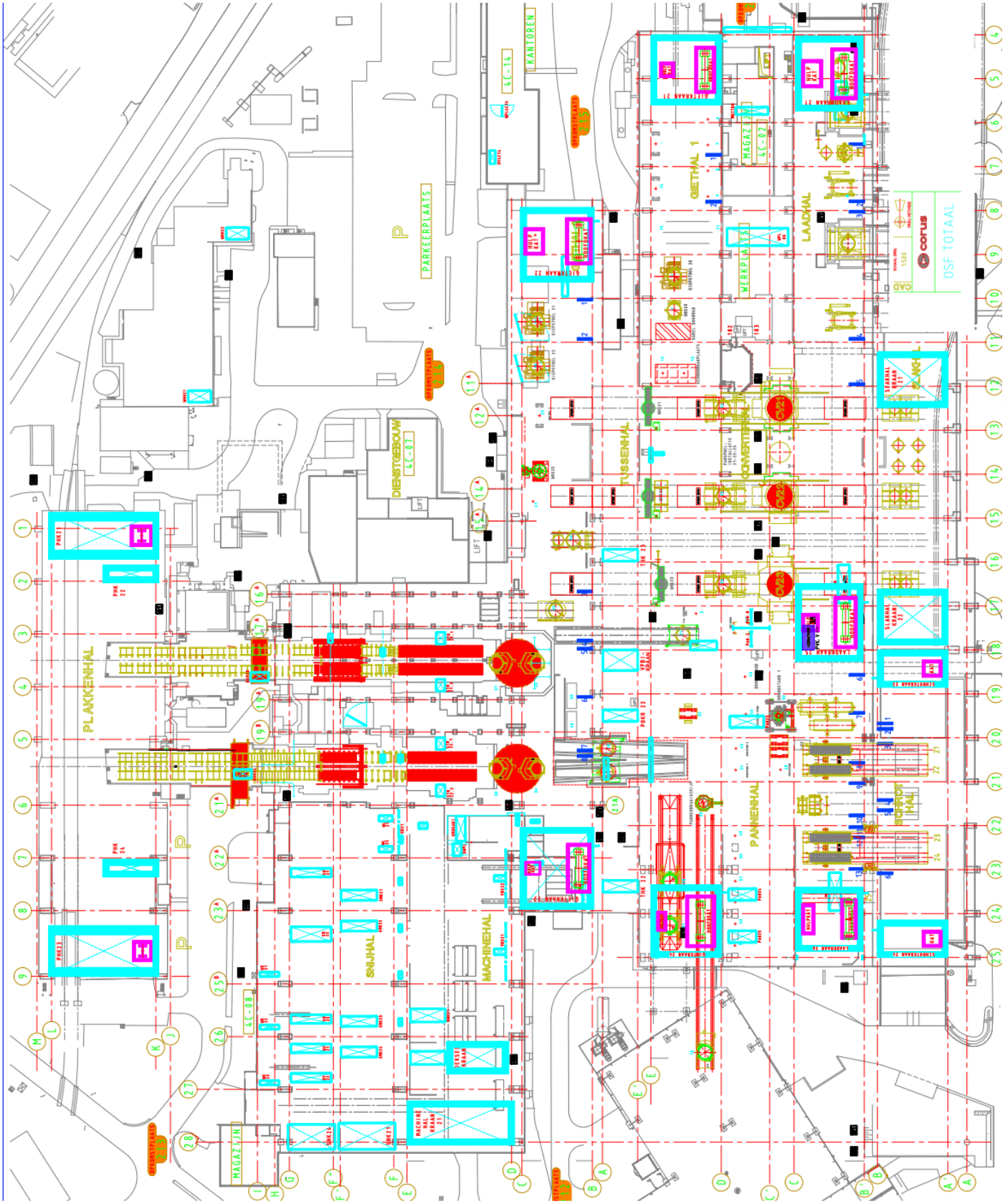
B Maps the Basic Oxygen Steel Plant and the IJmuiden Site

This appendix includes a map of the IJmuiden Tata Steel Site (B.1) and the Basic Oxygen Steel Plant (B.2). Please combine these maps with the flowchart in Figure 5, which indicates the different flows of iron, steel, slag, and scrap through the plant.

B.1 IJmuiden Tata Steel Site



B.2 Map of the Basic Oxygen Steel Plant



C Defining the Minimum and Maximum Differences between Neighboring Solutions

To define the minimum and maximum difference between two solutions, we analyze the maximum difference per part of the total objective value.

Overflow

A rescheduling-move can make the capacity of the Basic Oxygen Steel Plant to decrease from 933.33 tonnes per hour (cycle time is 18 minutes, load of 280 tonnes) to 0 t/h. However, the overflow can only increase with 770 t/h, because the Blast-Furnaces produce at most 770 t/h. The maximum duration of a job that is able to influence the cycle time from optimality to infinity is 8 hours and hence the maximum difference in overflow due to one move corresponds to $8h * 770t/h = 6160t$. Notice that other jobs take more than 8 hours, but these jobs only influence the cycle time if a certain set of other combination is also down. In these cases, the required set of installations already influences the cycle time such that the new schedule's overflow does not reach an increase of 6160 t.

The minimum increase in the overflow equals to 68 tonnes, which corresponds to an increase of one minute in the cycle time for one hour.

Overtime

The maximum increase in overtime equals to 8 hours, because only the hours that were performed during the day in the previous schedule can be additional overtime in the neighboring schedule.

The minimum increase in the overtime equals to one hour.

Deviation from the Cycle Time

The maximum increase in deviating from the cycle time equals to 1680 hours (10 weeks) and the minimum increase in the deviation from the cycle time equals to 1 hour.

Spread

The maximum difference in the standard deviation is about 0.15, due to high amount of periods (8836) we consider and the small changes in the values in these periods – at most 32 of these periods change with one point.

The minimum difference is approximately 0.01, if one job changes when the previous standard deviation equals to 0.

Penalties

The different objectives require a strict ranking. Hence, if there is a decrease in the overflow value, this decrease should always be more than an increase in any other objective. Hence, we set the penalties for overflow, overtime, deviation from the cycle time, and spreading of jobs equal to 1, 1, 0.001, and 0.001 respectively.

Conclusion

Based on the differences between the partly objectives and the penalties, the maximum difference of the total objective value equals to 6160 + 8 + 1680/1000 + 0.15/1000 = 6184.95 and the minimum difference equals to 0 + 0 + 0 + 0.01/1000 = 0.00001.