# OPTIMIZATION OF THE PRODUCTION PROCESS AT TENCATE

## Master thesis Industrial Engineering and Management

**Author**
Sven Duwe

**Supervisors University of Twente**
W.J.A. van Heeswijk
D.R.J. Prak

**Supervisor TenCate**
F. Alink

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TENCATE GRASS

UNIVERSITY OF TWENTE.

# Management summary

### Context

TenCate Grass Components Europe is a leading company in the production of artificial turf systems. Currently, the output of the production process is lacking behind due to a bad tactical planning, which causes a high reduction in production output. Their production process is split up in extrusion and twining, with each process having multiple production lines. Extrusion is the process in which the artificial grass fibers are produced. Twining is the production step directly after extrusion, in which the yarns are twisted (twined) for a stronger and more durable product. The twine lines have an available capacity to which the extrusion process must be adjusted or the speed of the extrusion lines will be reduced (less output). However, the planning department does not utilize the available knowledge about the capacity of the twine lines in combination with the characteristics of the products on the extrusion lines. Hence, within this research we focus on the resulting problem, lower production output, which we aim to solve.

In our research we solve the problem of lower production output by focusing on the planning of the extrusion lines. Since the production process is continuous (24/7) with a direct flow between the two stages, extrusion and twining, we are dealing with a no-wait two stage flexible flow shop problem. In our research we use simulation to solve the problem. We conduct our research to answer the following question:

*"How can a new tactical planning tool, based on a simulation heuristic, be designed to increase the output of the production process by taking the twine line capacities into account within the planning tool?"*

### Method

We have developed a model to plan the extrusion process on a tactical level. We have found multiple models in literature which provided a method to solve no-wait two-stage flexible flow shop problems. Within this research, we have multiple objectives to take into account which we want to weigh evenly. Therefore, we conducted research into multi objective optimization methods. We selected the normalized weighted simulated annealing algorithm from Jolai et al. (2013) and developed a simulation model including the selected algorithm of Jolai et al. (2013). We developed a multi-objective model to optimize three objectives (die changes, due date and standard deviation of the twine lines) to improve the current tactical planning (less human error) and improve the output of the production process (improved production planning).

### Results

In our simulation model, we created the normalized weighted simulated annealing model with constraints and empty dummy batches. The empty dummy batches realize the spread of the workload by including empty batches within the simulation. We used this model to compare with the planning of the planning department. The empty dummy batches were added to spread the workload taking the computational time into account. With the use of our simulation model compared to the current planning of TenCate, we achieve an average decrease of 27% in die changes, due date and standard deviation of the twine lines equally weighted.

Using empty dummy batches within the model of Jolai et al. (2013) resulted in a positive effect in the planning and output of the production process. Also, taking the second stage of the production (twining) into account induced the improvement we achieved within this research.

## Conclusion

Our simulation model takes into account the capacity of the twine lines by spreading the workload across the production lines and adjust the planning of the extrusion lines. The use of empty dummy batches creates simplicity in our simulation model and spreads the workload of the extrusion lines, taking the next stage twining into account.

Concluding, we recommend TenCate to implement our developed optimization model with the parameter settings from our research. In addition, we recommend TenCate to update their internal systems. Multiple differences appeared between internal systems in terms of product or production line characteristics. To achieve the best planning with our optimization model, validity must be guaranteed. Therefore, we recommend TenCate to check the product and production line data within our optimization model and keep up-to date with their internal systems.

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## List of abbreviations

| Abbreviation | Definition |
|---|---|
| PP | Propylene |
| PE | Polyethene |
| MF | Monofilament |
| R&D | Research and Development |
| ERP | Enterprise Resource Planning |
| KPI | Key Performance Indicator |
| SA | Simulated Annealing |
| SQ | Sub question |
| ON | Order number |
| FTE | Full time employee |
| SPC | Statistical Process Control |
| OPT | Optimized Production Technology |
| DBR | Drum-Buffer-Rope |
| TOC | Theory of Constraints |
| HFS | Hybrid flow shop |
| NWTSFFS | No-wait two-stage flexible flow shop |
| ICA | Imperialist competitive algorithm |
| FSA | Fuzzy simulated annealing |
| NWSA | Normalized weighted simulated annealing |

# 1. Introduction

This chapter introduces the aim of the study at TenCate Grass Components Europe. First, Section 1.1 provides a brief description of the company, followed by the motivation to conduct this research in Section 1.2. Section 1.3 specifies the introduction to the processes of this research. Thereafter, Section 1.4 introduces the problem, based on the first interviews with the company. Section 1.5 elaborates on the setup of the research and specifies the structure of this research. In addition, Section 1.6 represents the deliverables of the study. Lastly, Section 1.7 provides an overview of the outline of this research.

## 1.1. Company description

TenCate Grass Components Europe is a leading company in the development, production and supply of innovative components for artificial turf systems (e.g. football fields), with a strong focus on quality, durability and sustainability. TenCate offers a wide range of products for football, hockey and landscape purposes. The artificial turf systems include all components of a field such as the backing system (bottom layer), yarns and fibers.

TenCate has multiple plants across the Netherlands and the world. The focal point of this research is the plant in Nijverdal, where the production is split into three plants: yarns, backing and 3D weaving. Within this research, the continuous production processes of the yarns plant are studied, where production occurs 24/7. TenCate has five teams of 25 employees each working in the production plant and this plant produces tons of yarns every day.

## 1.2. Research motivation

Within the last couple of years, TenCate has strongly digitalized their processes. For this purpose, they already installed two software programs, Aprol and AlisQI, to better monitor the output and performance. Aprol is used as a data cloud to register all variables within the production processes. An expansion of monitoring the real-time performance is the live alarm. The live alarm will go off when a certain variable, for instance the temperature of a machine, lies outside the set boundaries. AlisQI is a Quality Management System that enables TenCate to streamline their production processes.

In addition to the developments in the past years, TenCate wants to improve the efficiency of their production process as much as possible. Due to the extensive number of various products they produce, it is a hard job to fully optimize all production processes. Hence, the focus of this research is on the processes in which TenCate encounters most problems, extrusion and twining. Extrusion is the process in which the artificial grass fibers are produced. Twining is the production step directly after extrusion, in which the yarns are twisted (twined) for a stronger and more durable product. For the twine process, there cannot be a buffer in front of the twine lines, which means that the extrusion and twine process need to be streamlined and batches will go directly onto the twine lines. Within these two processes, several problems keep returning. The capacity of the twine lines in combination with the speed of the extrusion lines is often causing a less efficient production process. The speed of extrusion lines is often reduced to be able to process the batches on the twine lines. The planning department plays a big role in these problems, since they schedule the production processes and do not take twine capacity of the subsequent process (twining) into account. The next section introduces extrusion and twining, and the corresponding problems are discussed in Section 1.4.

## 1.3. Introduction to extrusion and twining

Before describing all the processes in more detail and the plan of approach in Chapter 2, we provide a brief description of the main processes in this research in this section. The two main processes are extrusion and twining. Extrusion has three primary sub-processes in which granulate made of polypropylene (PP) or polyethene (PE) is either forced through a die with little shaped holes, is texturized or cut into “tape” yarns, see Figure 1 for the three products. The sub-process with the die is used to produce monofilament (MF) products. MF products are products which consist of multiple yarns twined together. The second process, with the tape yarns, is used to produce the Tape products. The last process discussed in this research is the texturization process, in which the yarns are texturized and get a frayed profile. Within all these three extrusion processes, the material is heated, stretched, cooled and eventually rolled on to a flange, in which the MF and tape products are then transferred to the twine process.


*Figure 1: Example of MF, Texture and Tape products*

When the flanges with MF and Tape arrive at the twine lines, the material is twisted (twined) to form a stronger, more durable product. Each twine line has a certain number of positions. On these positions, a flange can be placed. This flange is then twined and rolled onto a bobbin. When all flanges are twined and rolled onto a bobbin, the bobbins are placed on a pallet.

The raw materials in specific silos are connected to specific extrusion lines, which are also connected to the twine lines. Every extrusion line is most of the time linked to a specific twine line for simplicity for the operators moving the batches from extrusion to twining. They are not directly connected, but it is a managerial decision to keep the flow as simple as possible for the operators. Problems like broken lines and twine positions are also occurring on daily basis. When these problems occur, operators go to the Planning department to inform them of the broken line or positions. The Planning department will reschedule the current batches and the Technical Department will schedule their maintenance. Hence, the problems in this and the previous paragraph are the main subjects of our study, as introduced in the next section.

## 1.4. Introduction of the problem

In this section, three steps are taken to identify the core problem. First, we gather all problems faced by TenCate in the problem identification phase. Thereafter, in Section 1.4.2, we create a problem cluster to visualize the causal relationships between the problems. Lastly, we identify the core problem based on the problem cluster created in Section 1.4.2 using the four rules of thumb (Heerkens, 2017) in Section 1.4.3.

### 1.4.1. Problem identification

The problems within the processes of TenCate are derived from several interviews with employees from different departments. The departments interviewed are R&D, production and planning. We mapped all the problems in Section 1.4.2 in the problem cluster. An action problem as defined by Heerkens and Van Winden (2017) is “A discrepancy between the norm and reality, as perceived by the problem owner”.

The **action problem** perceived by TenCate is:

*“The variable throughput times cause either batch leftovers or a reduced number of produced products”*

Every product has a so-called “stamkaart”, from now on referred to as “unit card”. On this unit card all sorts of information are provided. On the unit card, information such as settings for extrusion and twine lines, weight of the product, dtex (measure of linear density), etc. is present as input for production. When production starts at a certain extrusion line, the unit card is used. With the use of the unit cards, the operational production operators within the plant know all settings for the machines. However, the operators sometimes reduce the speed of the extrusion lines mentioned on the unit card, due to a number of problems within the process from extrusion to twining. For instance, the twine lines have a certain number of positions in which the output of the extrusion can be twined. However, operators often know there will be insufficient positions on the successive twine line for the output of the extrusion line, and they will reduce the speed of the extrusion line (see Figure 2). This reduction is needed due to the inefficient planning of the planning department.

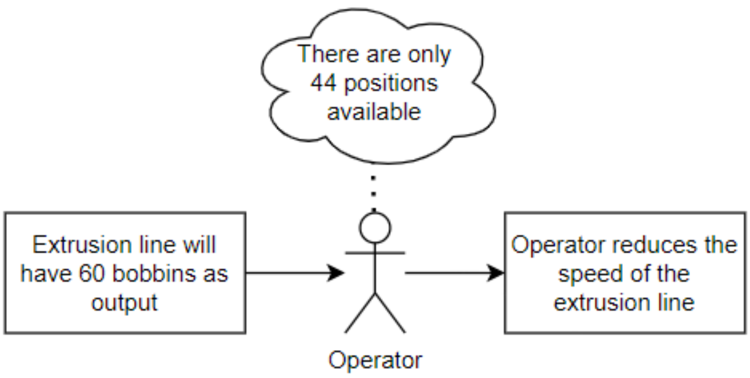


*Figure 2: Problem of the operator*

Specific extrusion lines are now often linked to specific twine lines, while other twine lines remain idle and could have been used. This is causing a less efficient flow from extrusion to twining and a reduced output. Furthermore, when the speed of the extrusion process is not constant, the moment to stop the production is hard to determine, which results in either batch leftovers (unusable batches/products) or an insufficient number of produced products (not enough produced to meet customer demands). This and more problems are further depicted in the problem cluster in Section 1.4.2.

### 1.4.2. Problem cluster

In this section we derive the core problem by creating a problem cluster. Within the problem cluster in Figure 3, four types of problems can be defined (Heerkens and van Winden, 2017), the action problem, the causal relationship (C’s) and the (potential) core problem (A’s). The action problem has already been discussed in Section 1.4.1. The action problem is caused by multiple other problems.

When a problem has no underlying cause that can be resolved, it is a (potential) core problem. Between the action problem and the potential core problems, multiple causes arise. These are here defined as the causal relationships.

Through interviews with employees of TenCate and field research, five underlying causes (A1, A2, C1, C2 and C3 in Figure 3) of the action problem discussed in Section 1.4.1 are identified, of which two are potential core problems (A1 and A2). These two are the broken production lines/twine positions and quality issues of the produced products. The first one is an insurmountable problem within manufacturing plants. The latter one is due to differentiations in the output of the production. Multiple sensors are checking the quality of the bobbins and when a bobbin is not within the set margins, the whole pallet is removed from the process and needs to be checked by R&D since they deal with all quality issues. The other three causes of the action problem have underlying causes (so no core problem) and these causes are: the frequency of batch leftovers, reduction in extrusion line speed and efficiency, and the connection between the extrusion and twine lines.

First, the batch leftovers (C3), are caused by the production operators who sometimes push the stop button too late during a batch run (C6). When too much is produced, a number of pallets remain in the warehouse. Due to changes in raw material, the characteristics of a batch of a certain product now differentiate from a batch of the same product in one year from now and is not considered the same. When a customer would use a product from a batch now and one year ago in one field, color differences would be visible. Often, only a few pallets remain, which is too little to cover one football field. Hence, eventually, these batch leftovers will be considered waste and are discarded. These batch leftovers are caused by the operators who end the run too late due to a discrepancy between the ERP system (Navision) and the physical pallet list that is tracked at the end of the process and because the operators often do not know when exactly to stop production (C8). The discrepancy between the ERP system and the pallet list is simply because the system is not used to its full potential (A3). The problem that operators do not stop the production in time is because they often do not know when to stop the production. Since the process has a high variability in throughput times, it makes it hard to determine when to stop the production. This high variability is caused by the reduction in extrusion line speed by the operators within the plant.

Furthermore, the planning department creates the daily planning for production on a tactical level (one or a few months in advance). However, because the planning department sometimes schedules various products that cannot be produced together at the same time due to needed twine positions, production is forced to lower the speed of the extrusion lines because of a lack in capacity at the twine lines. Hence, the tactical planning is lacking efficiency (C7). This less efficient planning in turn has three causes.

- Not using full potential of the ERP system (A3)
- Limited tactical planning tool in Excel (C9)
- Decision to keep it as simple as possible for the operators (A4)

The first cause is already mentioned, the not fully optimized ERP system. For instance, product data within the ERP system is incoherent and does not match the same product data on another place within the ERP system. With this incoherence no source of truth can be determined. As mentioned, TenCate did already improve the ERP system a lot, but it has not yet reached its full potential. The second cause is the limited planning tool in Excel. This is a planning sheet in which the planning is created manually with colors representing the batches to produce. There is no smart code behind it that is checking certain aspects like products that cannot be produced together and can therefore not really be called a tool. This Excel sheet is then used for the operators in the plant and all departments involved in the production process (Sales, R&D, Technical services and production). Management had decided to keep everything as simple as possible for the (temporary) production operators within the plant, which also causes a sub-optimal planning leading to the reduction in speed of the extrusion lines and reduced output.

Last, the lack of knowledge/information by the planning department (A5) is the cause of the limited planning tool. The Planning department has for instance no knowledge about the available number of twine positions on every twine line and they are therefore not planning the successive twine lines. The information is available, but not known or used by the Planning department. In addition, it may be the case that certain products cannot be produced at the same time, due to capacity limitations. When the knowledge is available at the planning department, a better tool can be created.

When highlighting all problems which have no underlying cause, five potential core problems remain of which two are selected as the core problems of this research:

- The lack of knowledge of the planning department on available resources and production constraints
- The decision to link a specific twine line to a specific extrusion line to keep it as simple as possible for the operators

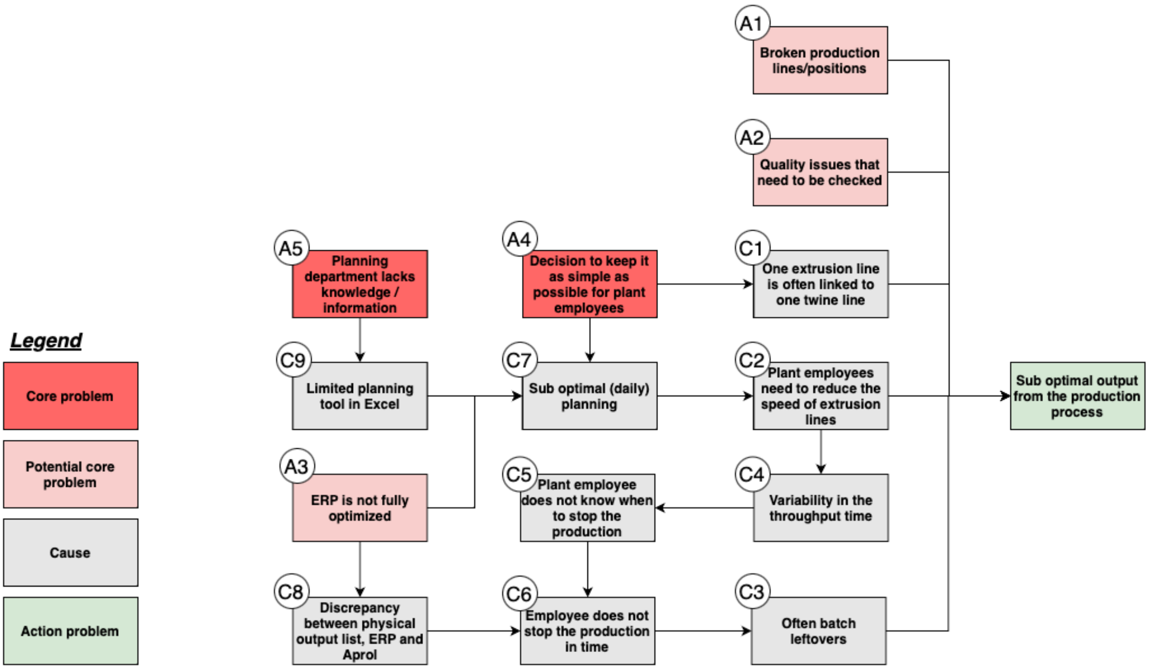


*Figure 3: The problem cluster determining the core problem of TenCate*

### 1.4.3. Core problem

In the previous section, Section 1.4.2, all the problems related to the action problem are mapped in a problem cluster. From this, five potential core problems were identified of which two core problems are selected based on the definition of a core problem described by Heerkens (2017). The core problem is identified from this problem cluster by using a few rules of thumb from Heerkens (2017).

### *Identifying the core problem*

When we discussed the two remaining core problems within TenCate, both problems are determined equally relevant by the company. After more discussions with the domain experts, we decided to conduct research into both core problems, one as the primary core problem and the other as a second core problem. Hence, the **primary core problem** is identified as:

*"Lacking insights of the production process within the planning department"*

The lack of insights within this primary core problem is mainly about the available resources and production constraints within the production process. This includes knowing how many twine positions there are available at each twine line, which products can and cannot be produced at the same time etc. This information is available, but not used within the planning department due to the sometimes-technical information needed like twine line speed, cone weight and output bobbins per hour. Therefore, the planning department often neglects the twine capacities after extrusion. In order to generalize this information, adding production process information in a tactical planning tool is helpful to optimize the planning. In this way, the planning department does not need to memorize this information, but simply run the planning tool.

The **second core problem** is identified as:

*"The decision to link a specific twine line to a specific extrusion line to keep it as simple as possible for the operators"*

The current planning of TenCate is hard to optimize, since there are limited possible solutions due to the second core problem. Neglecting this decision enlarges the solution space and enables the chance to implement possible optimization methods. Optimization of for instance planning can be achieved by different simulation models, machine learning algorithms, exact algorithms and heuristics. Machine learning techniques are used to provide new opportunities to make intelligent decisions based on data (Cadavid et al., 2019). As mentioned by Sobottka et al. (2019), the current machine learning methods offer performance improvements, but models with real-life applications with a high complexity are still lacking. Within this research, a high number of dependencies (malfunctions, human errors, etc.) and parameters, which will be further explained in Section 4.2.1, are present which increases the complexity. Furthermore, the performance of a Machine Learning model is dependent on the quality of the data (Jain et al., 2020), which is deficient within this research. Due to the lack of (historical) data and data quality of the production process, Machine Learning does not seem suitable for the core problem.

We decided not to use exact algorithms since, at this point, the exact complexity of the problem is unknown. Other possibilities are optimization algorithms or heuristics. An example of an optimization heuristic is a simulation heuristic, which is an optimization model in combination with simulation in which you optimize through simulation. The benefits of simulation and specifically simulation heuristics are elaborated below.

- With a simulation heuristic, a lot of KPIs can be studied which is much harder with other types of models (e.g. queuing theory).
- The experimental conditions can be controlled and simulations are able to model variability in various parameters including its effects (Robinson, 2014).
- The level of detail can be very high, which is helpful to convince managers about certain decisions.
    - In addition, operators within the plant look at the same planning which requires a high level of detail within the planning.

A simulation heuristic is also interesting for the second core problem, the managerial decision to keep it as simple as possible for the operators. Here, we want to study what happens when we let go of the simplifying assumption in the second core problem.

To tackle both core problems, a simulation heuristic incorporated in a tactical planning tool is a possible solution. In addition, the planning of TenCate has multiple objectives (tardiness, makespan, minimizing die changes and minimizing workload) which need to be taken into account. In a new tactical planning tool we include an optimization algorithm which takes the twine line capacities into account within the planning of the batches for the extrusion lines, while minimizing the mentioned objectives. In this way, we can tackle the lack of knowledge with a tactical planning tool. Furthermore, a limited planning tool was a cause (C9), which we can then solve as well. As an additional benefit, the knowledge within the planning tool will always be available and does not need to be transferred to a new employee. Furthermore, after the first interviews with TenCate, it is decided to develop the planning tool within Excel since they use Excel across the whole organization and want to have their planning in a known program.

Concluding, we conduct research to two core problems within this thesis. We tackle both core problems with a simulation heuristic integrated within a tactical planning tool, in which the second core problem is tackled by including the twine line capacities.

## 1.5. Research design

To tackle the core problems defined in the previous section, the main research question needs to be answered. This **main research question** is formulated as follows:

*"How can a new tactical planning tool, based on a simulation heuristic, be designed to increase the output of the production process by taking the twine line capacities into account within the planning tool?"*

To fully answer the main research question, several sub research questions need to be answered. These sub questions are defined below.

***SQ1**. What do the extrusion and twine process of TenCate look like and how is this production process currently planned?*

To know how the production processes fully work and where improvements are necessary, an overview of the current situation of the complete production process needs to be made. In this current situation, R&D, planning and production departments within the internal logistics are mapped by flow charts. In this way, a clear and proper understanding will be available to provide useful solutions. Furthermore, we conduct interviews with the planning department on their current planning methods.

***SQ2**. Which production line optimization methodologies are present in literature and how are they applied within a production plant?*

Within this research question, we study the production line optimization methodologies and concepts within literature. We conduct a literature study into different methodologies to answer the sub question.

***SQ3**. Which optimization simulation heuristics are present in literature and how are they applied within a production plant?*

To get insights into the effect on the planning when neglecting the decision of the second core problem, heuristics for assigning consecutive production lines will be studied. Furthermore, it is important to know how these heuristics are applied within manufacturing plants. This sub question is answered by means of a literature study.

***SQ4***. *How to design the tactical planning tool with a simulation heuristic for the planning of the yarns plant incorporating realistic constraints?*

Within this sub question, a planning tool is created within Excel with an optimization model that optimizes the current planning of the current situation from SQ1. The simulation model will be developed in cooperation with employees from production and planning to represent reality. Also, within this sub question, we discuss with the production department which aspects and constraints to consider and which not.

***SQ5***. *Which simulation heuristic from SQ3 performs best for the yarns plant?*

Heuristics from literature are compared to see which one has the best performance. We compare the performance of heuristics based on statistical performance measures and one heuristic is selected for the remainder of the research.

***SQ6***. *How to implement the new tactical planning tool within the current work process of TenCate?*

This last sub question incorporates an implementation meeting with TenCate to implement the tactical planning tool within the Planning Department. Furthermore, daily activities need to be changed and the current work processes need to be revised.

## 1.6. Deliverables

There are two deliverables within this research. First, we create a tactical planning tool for the planning department in which an optimization heuristic is implemented within a new tactical planning tool. Second, insights will be gathered when taking the twine line capacities into account, which results in a recommendation whether taking the twine line capacities into account would be beneficial. In conclusion, the two deliverables are:

- A tactical planning tool incorporating an optimization heuristic
- Recommendation about incorporating the twine line capacities within the planning tool

## 1.7. Thesis outline

The remainder of this thesis is structured as follows. In Chapter 2, we describe the current situation. Chapter 3 contains the literature study performed with SQ2 and SQ3 as research questions. In Chapter 4, a planning tool is created. Chapter 5 addresses the best heuristic to implement in the planning tool. Chapter 6 provides insight into the planning of the twine lines. Lastly, the conclusions and recommendations are discussed in Chapter 7.

# 2. Current situation

Within Chapter 2, we analyze the current situation at TenCate. In this section, we conduct a current situation analysis by means of interviews and field research and answering the first research question:

***SQ1**. What do the extrusion and twine process of TenCate look like and how is this production process currently planned?*

Section 2.1 provides an overview of the total process. Sections 2.2, 2.3 and 2.4 provide insights into the different departments.

## 2.1. Overview of the total process

Within the internal logistics process, multiple departments are involved. Whenever an order is placed, the sales department puts the order with the details into the ERP system. Through this ERP system, the planning department can see which orders need to be planned on short term and what the needs and forecasts are for the term. Subsequently, the planning department incorporates the orders within the planning with possible extended runs based on the needs and forecasts for the future (make to stock). Every morning several departments (Planning, Production, etc.) have a meeting to discuss last day's performance and the planning and particularities for the current day. Every Thursday, the departments have a meeting to discuss the planning for next week. Here, production evaluates the feasibility of the planning. When the planning is discussed and found feasible, it is sent to the production department and they are informed on the planning for the coming week. After the production has finished, quality issues could have raised which are then handed over to the R&D department. The flow chart in Figure 4 gives a high-level overview of the total process.

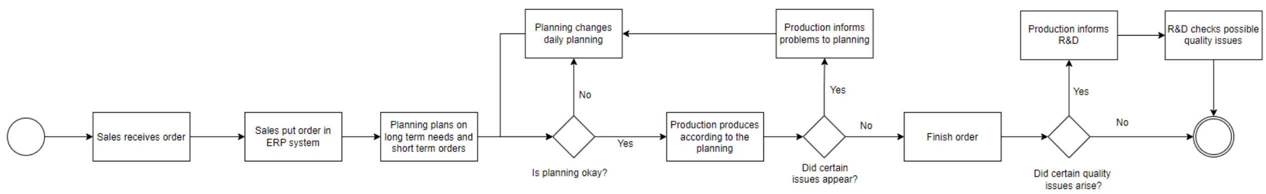


*Figure 4: A high level overview of the total process*

## 2.2. The planning department

The planning department is responsible for the planning of the extrusion lines and the inventory of the raw materials. As can be seen in Figure 4, the planning department creates a short- and long-term planning for the production based on incoming orders and forecasts. Now, the planners only plan the extrusion lines for the production. For the short-term planning, the planning department observes the orders from customers in the ERP system. Whenever the planning department includes the order in the planning, they create a batch code. This batch code is made up of a few variables like type of material and color. If no batch codes would be created and customers receive products from different batches, color differences are noticeable when the artificial grass is placed at the customer site. These color differences are due to the raw materials that change over the years and different batches can therefore not be combined in one order. This is one of the reasons that TenCate has a lot of batch leftovers, since they cannot use a batch from last year for a new order this year.

The planning department plans the production in Excel. Ideally, the planning tool would take into account for example the number of twine positions, but currently the planning department is planning based on experience. The planners only color the cells manually without automated checks (ran by code) in Excel. The shifts are split in three: early, late and night shifts. For the planning, the length of the run is being calculated and the order number is depicted. As can be seen, a lot of human errors can occur within the process of planning by doing everything manually.

## 2.3. The production department and process

Sections 2.3.1 and 2.3.2 delve into comprehensive explanations of the extrusion and twine processes, providing a thorough understanding of their individual intricacies. Moreover, in Section 2.3.3, we not only elucidate the specific connections between the extrusion and twine lines but also explore their synergistic effects on the overall manufacturing process, offering a holistic perspective on the interplay between these crucial elements in our study.

### 2.3.1. Extrusion

To provide the needed knowledge, a basic explanation of the extrusion process is elaborated within this section. Extrusion is a manufacturing process that produces a continuous length of yarns by forcing molten plastic material through certain (small) openings of various shapes and sizes. After this, the yarns are cooled and solidified. This extrusion process offers great control over the properties, such as strength, thickness and color. All the products have a specific unit card in which all specifications are mentioned for the production operators. This includes speeds for the machines, weights etc. These unit cards are therefore the basis of the production.

*MF*

The first type of product is a monofilament product. The extrusion machines get granulate from raw material silos and the granulate is then forced under high pressure through a die. The produced shapes depend on the type of product that is asked from the customer. The shapes are exceedingly small but give a certain structure to the artificial yarns.

*Tape*

The Tape product is one bigger yarn which looks like tape. In the beginning of the extrusion process, instead of using a die, one big foil is cut into lanes depending on the extrusion line. These yarns are then extruded the same way as the yarns of the MF products. Hence, after the flanges are produced, twining is the next step in the production process.

*Texturize*

The texturing product is another type of product produced by TenCate. The texturing production process gives the yarns a little curl. The difference between this structure is shown in Figure 1 of Section 1.3.

*Knitting*

The fourth type of product is somewhat the same as the texturing product. With the knitting process, one big sleeve of yarns is produced. This process results in the same structure as of the texturing product, but the production process is slightly more comprehensive.

### 2.3.2. Twining

After the extrusion, all products of MF and Tape are twined. All normal twine lines are either used for MF or Tape and cannot be used for the other type. All twine lines have a number of spots available in which flanges can be twined. When the twine capacity is not enough, either a spare twine line is used, or the speed of the extrusion line is reduced to be able to twine twice as fast the extrusion process. In this way, one extrusion process can be twined in two parts.

With MF, the number of yarns of the product are twisted together to create a stronger and more durable product. Within the twining of the tape products, little cuts are made in the tape first whereafter the product is twisted which makes it more durable.

### 2.3.3. Connection extrusion- and twine lines

It was decided by the management to make it as easy as possible for the production operators in the plant at the extrusion and twine lines. Therefore, management decided to link specific extrusion and twine lines. This is not most efficient, but is a decision from the management. However, obtained from interviews with the managers, the management is interested whether their decision results in a reduction in output.

## 2.4. R&D

The R&D department has two main jobs within the production process. First, when quality issues appear, R&D needs to check the rejected pallet to check the issues. Second, as the name of the department suggests, R&D is constantly developing new combinations for new products. These tests need to be planned within the normal planning. These tests are requested to the planning department, who will schedule the tests in the current planning. Furthermore, sometimes additional raw materials are added to the production process of already existing products to check whether the quality of the product would differ. Concluding, R&D needs to be taken into account within this research, since they are frequently involved within the production process and tests must be included in the planning. Within this research, they will provide the needed information about the current process of incorporating tests in the planning. However, since the goal of this research is to create a tactical planning tool, R&D is limited taken into account.

## 2.5. Conclusion

This chapter provided descriptions and explanations of the current production process of TenCate. Currently, the flow between the extrusion and twine lines is fixed. Furthermore, the capacity of the twine lines is not taken into account and the planning is made by hand in Excel. Concluding, we strive to optimize the current planning by:

- Planning extrusion and twine lines more dynamically
- Including the available twine positions into the planning tool
- Automate the planning, taking away the human error

In this chapter, we provided information to obtain better understanding of the production processes and its complexities. In the next chapter, we will conduct literature studies into the optimization of production processes.

# 3. Literature study

In this chapter, we answer the following two research questions:

*SQ2. Which production line optimization methodologies are present in literature and how are they applied within a production plant?*

*SQ3. Which optimization simulation heuristics are present in literature and how are they applied within a production plant?*

In Section 3.1, we answer SQ2 with a literature study to the methodology and concepts of production line optimization to gain knowledge on existing production line methodologies. In Section 3.2, we answer SQ3 also with the use of a literature study to the optimization heuristics for the planning. Here, we strive for practical heuristics to apply in this research. We will search for techniques and heuristics to take into account the bottleneck of the production plant of TenCate, which is twining. With the knowledge gained in this chapter, we are able to develop a solution for TenCate.

## 3.1. Methodologies of production line optimization

First, in Section 3.1.1, we conduct a short literature study into the most used methodologies within production line optimization. In Section 3.1.2 until Section 3.1.5, we conduct more literature studies on these findings. The goal of these sections is to provide an overview of several available methodologies and concepts applied within the optimization of production processes.

### 3.1.1. Most common methodologies and concepts

In literature, several methodologies and concepts are present that optimize the production lines within a manufacturing plant including bottlenecks. The first methodology is the Theory of Constraints (TOC). The TOC is an iterative management approach that concentrates on recognizing and enhancing the limitations that restrict an organization from achieving its objectives (Goldratt & Cox, 1986). A second concept is the Statistical Process Control (SPC), in which statistical tools control quality of the production process (Qiu, 2013). Through data analysis, SPC can help to optimize certain processes within production. Third, the Optimized Production Technology (OPT), is a comprehensive methodology within manufacturing planning based on the TOC of Goldratt, that aims to maximize the throughput (Billatos & Wolffarth, 1999). The OPT is based on strategically placing buffers on key points within the production process. The last concept, Drum-Buffer-Rope (DBR) is based on the TOC and OPT. The DBR concept helps to determine where the control of the process needs to occur (Slack, Chambers & Johnston, 2007, p. 310).

In the subsequent sections, we are going to conduct literature studies to these four methodologies and concepts to get more information about the optimization of production lines with a bottleneck. In Section 3.1.2, we conduct a literature study to the TOC. In Section 3.1.3, we elaborate on the SPC. The last two sections, Section 3.1.4 and 3.1.5, we address the OPT and DBR concepts respectively.

### 3.1.2. Theory of Constraints

Within TOC, every system has at least one limitation that prevents it from performing optimally. TOC suggests that by concentrating on the most significant constraints, organizations can optimize their output and efficiency (Goldratt & Cox, 1986). In the case of manufacturing systems, TOC identifies the constraint resources, which are categorized as physical constraints and policy constraints (Huang, 2002). The physical constraints are the machines, usable resources and facilities. The policy constraints include managerial decisions, employee mood and the organization of the system. Huang (2002) addresses nine principles of TOC and OPT, of which we selected the most applicable principles, corresponding with the core problem, for this research.

- *Balance flow, not capacity*

Planning is always based on the capacity of the constrained resource. In this case, planning should be based on the capacity of the twine lines. However, in the production of TenCate, the planning is only based on the extrusion lines and not on the twine lines, which form the bottleneck.

- *An hour lost at the bottleneck is an hour lost forever*

When the output is depending on the capacity of the bottleneck, it is fundamental to always run full capacity at the bottleneck. The entire production depends on the bottleneck, meaning when losing one hour at the bottleneck, the whole production process loses one hour. In this research, the bottleneck is not running at full capacity, which makes this principle important to consider.

- *An hour saved at non-bottleneck stations is just a mirage*

Saving an hour at a non-bottleneck process is only causing an increase in system's cost and increases the Work In Progress (WIP). This saved hour will not be seen in the output of the total production process. Therefore, the focus should be on planning the twine lines best way possible to maximize its capacity.

- *Schedules should be established by looking at all of the constraints simultaneously*

The bottlenecks and constraints of the resources can constantly change and the schedule should therefore be established by considering all constraints simultaneously. This principle of taking all constraints into account is also important during this research.

### 3.1.3. Statistical Process Control

Statistical Process Control (SPC) focuses on the quality of the products during production. The SPC is used for the control and monitoring of the whole system quality. The value of SPC is not only in checking single samples, but monitoring results of the whole production over a long period of time (Slack, Chambers & Johnston, 2007, p. 552). Within SPC, control charts are used to check whether the production process performs according to the set standards. In case of this research, as introduced in Section 1.2, TenCate implemented the monitoring programs Aprol and AlisQI to check variables (runtime, temperature of machines, etc.) during the production process. In literature of case studies in which SPC is applied within the industry of Tegegne et al. (2022), SPC played a significant role in the optimization of the production process. Within these case studies, several techniques of SPC are used for the optimization of the production processes. An example is the case study of Afkhami et al. (2015), in which the Cumulative Sum Control Chart technique is used to map historical changes to assess the performance. Concluding, as we found in literature, SPC is commonly used as a quality control measure with several techniques that can be applied to optimize the quality.

### 3.1.4. Optimized Production Technology

The optimized production technology (OPT) is an approach based on the TOC and its principles. OPT is a technique which is computer-based and helps to schedule bottlenecks within production processes (Slack et al., 2007, p. 456). They state that bottlenecks are dynamic and are constantly changing. In production, when the least efficient machine is replaced by a new one, a new bottleneck appears at another machine (newest least efficient). Furthermore, batch sizes also change, which alters the throughput of the production plant. This latter statement is also the case within the production process at TenCate. Furthermore, Lundrigan (1986) determines the goal of OPT as to model the real-world manufacturing plant and realize realistic schedules based on the bottlenecks. A part of the OPT is the Drum-Buffer-Rope concept, which we will discuss in the next section.

### 3.1.5. Drum-Buffer-Rope

As mentioned in Section 3.1.1, the Drum-Buffer-Rope (DBR) concept, is a part of the OPT and TOC concepts. DBR is an idea to control the process at the bottleneck (Slack, Chambers & Johnston, 2007, p. 310). The initial idea of controlling the process at the bottleneck originated from Goldratt (1986). The DBR concept follows the principle *"An hour lost at the bottleneck is an hour lost for forever",* mentioned in Section 3.1.2. This principle initiates that the flow of the whole process is depending on the speed and output of the bottleneck. Hence, the bottleneck should be working all the time. To maximize the utilization of the bottleneck, a buffer should be kept in front of the bottleneck to always have something to work on, which is not always possible (e.g. in this research with the twine lines). The last concept, the rope, is the communication between the input and the bottleneck to ensure that the buffer will not be overloaded. There are two ropes: the first rope is used to determine the planning at the bottleneck (Schragenheim and Ronen, 1990); the second rope subordinates the system to the bottleneck. A depiction of the DBR concept by Thürer et al. (2017) is shown in Figure 5. Concluding, the DBR concept ensures that the bottleneck is always busy which maximizes the utilization of the bottleneck process.

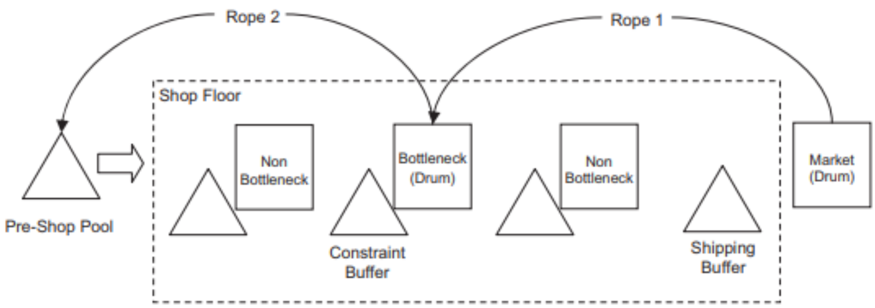


*Figure 5: The Drum-Buffer-Rope concept (Thürer et al., 2017)*

### 3.1.6. Conclusion methodologies and concepts

Concluding Section 3.1, we conducted research to four concepts: TOC, OPT, SPT and DBR. First, we did not select SPT for this research, since this concept focuses on the quality of the products and processes which is not the core problem of this study. Hence, we do not study SPT further within this research. Second, the concept of DBR, encompasses the use of buffers in front of the bottleneck. Within TenCate's production process, however, there is no space for these buffers. Hence, we will also not study DBR further within this thesis. Third, the OPT concept schedules the bottleneck which is the goal in this research, planning the twine lines. Therefore, we will search for techniques and heuristics for planning the bottleneck. Last, TOC is also an important concept within this research since the production processes include a lot of constraints. Hence, it is important to conduct research into planning techniques and heuristics which include constraints. We will conduct more research into these heuristics in the subsequent section.

## 3.2. Heuristics for optimizing the planning of production lines

In this section, we discuss heuristics and algorithms applied within the methodologies mentioned in the previous section, Section 3.1.6. First, we define the problem found in literature in Section 3.2.1. We discuss the approaches to the defined problem in Section 3.2.2.

### 3.2.1. Theory definition of the problem

The production process at TenCate exists of two main processes, extrusion and twining. These two processes are two stages within production. A production process in manufacturing is often called a hybrid flow shop (HFS). A HFS is generally defined as a production process in which materials flow in one direction (Tsubone et al., 1993). Linn and Zhang (1999) describe a HFS as a process in which a number of $n$ jobs in a series of $m$ production stages of which each stage has multiple machines operate in parallel. In case of TenCate, the number of production stages is two. The product flow between the machines of the two processes is flexible, which means that the same product can go from machine 1 to machine 4 on one day, and to machine 5 on another day. Hence TenCate's production process can be seen as a two-stage flexible flow shop. Furthermore, it is a continuous process (24/7 production) which makes it a no-wait two-stage flexible flow shop (NWTSFFS) with multiple objectives (tardiness, makespan, etc.). Due to multiple measures of the quality of the planning (lateness of orders, output and workload for operators) we discuss multi-objective NWTSFFS problems in the subsequent section.

### 3.2.2. Approaches for NWTSFFS problems

In this section, we discuss approaches for NWTSFFS problems as described in Section 3.2.1. First, Nikzad et al. (2015) suggests the use of the imperialist competitive algorithm (ICA). The ICA is a novel population-based evolutionary algorithm to solve optimization problems. The basis of the algorithm is to simulate three sociopolitical processes: imperialistic behavior, imperialistic competition and independence (Atashpaz-Gargari and Lucas, 2007). ICA starts with imperialistic behavior in which an initial population is created. The individuals of a population are called countries, which are divided into two types: imperialists and colonies. These countries (imperialists and colonies) are solutions to the optimization problem and together form an empire. In this research, a country represents a possible planning (solution) for the production of TenCate. Multiple countries are created, where imperialists are produced with simulated annealing and colonies produced at random. Here, the idea is that the imperialist penetrates the colony and tries to assimilate its colonies by making them more like itself. In the next step, imperialistic competition, the different empires try to take over the colonies of other empires. In this way, the best solution to the optimization problem remains. Khalili and Naderi (2014) developed a bi-objective ICA to solve a bi-objective NWTSFFS problem, defined as the problem in this research in Section 3.2.1.

Jolai et al. (2013) mention three simulated annealing (SA) algorithms for NWTSFFS multi-objective approaches: classic weighted, normalized weighted and fuzzy simulated annealing. Simulated annealing is a stochastic meta-heuristic to find near global optimum solutions for optimization problems. Within the beginning of the algorithm of SA, worse solutions are accepted by a high probability. In this way, a larger search space is explored to find a global optimum instead of a (worse) local optimum. SA is highly used in optimization models for a flexible flow shop as in this research. Furthermore, the paper of Jolai et al. (2013) addresses a multi-objective approach, which indicates that the paper is highly applicable within this research. One objective is to minimize the lateness of the orders. Multiple other objectives are for instance to maximize the run length of the batches, minimize the number of switches on every machine between different products, maximize the throughput, etc. The determination of the objectives used in this research are elaborated in Chapter 4. The conclusion of Jolai et al. (2013) is that the normalized weighted (scaling the KPIs) and the fuzzy (concept of partial truth instead of Boolean values true or not true) simulated annealing outperforms the classic weighted simulated annealing in six out of the seven measured metrics. Hence, this research includes the normalized weighted simulated annealing (NWSA) and an explanation of the fuzzy simulated annealing (FSA). We discuss the basic concepts of NWSA and FSA in the next two paragraphs.

*Normalized weighted simulated annealing*

In order to obtain the best solution of two objectives with different values, for instance the lateness in days and the output in kg, the normalized weighted simulated annealing is applied. Here, the maximum and minimum of both objective functions are calculated in order to measure the span of the objectives. Hence within NWSA, four values are calculated: the minimum and maximum of objective one and the minimum and maximum of objective two. By calculating the span of both objectives, one fitness function incorporating both objectives can be described.

*Fuzzy simulated annealing*

The fuzzy theory was first introduced by Bellman and Zadeh (1970). The theory is used in multi-objective linear programming problems. Within the fuzzy approach a multi-objective problem is being solved in several steps. First, only one objective is considered and maximized. Then in the second step, each objective is solely minimized. Third, all maximized and minimized models are defined as a membership function with a range covering the interval of all possible values. Last, the model is changed using fuzzy logic (partial truth) to a model in which the goal is to find the maximum value of an unknown parameter $\lambda$. Maximizing this $\lambda$ solves the presented multi-objective problem with a fuzzy approach.

In the research of Jolai et al. (2013) the normalized weighted simulated annealing outperformed the fuzzy simulated annealing. Furthermore, the approach of NWSA is less time consuming in terms of runtime and we decided to exclude the fuzzy simulated annealing. Considering the ICA and NWSA, we selected the NWSA for the remainder of this thesis. Given the complex problem of TenCate due to the different products and its extra dimension (MF and Tape), we determined to continue with the NWSA within this research. In the production process of TenCate, MF products cannot be twined on a tape twine line. Applying ICA within this research requires two separate ICAs, since ICA is used for one flow from a set of machines in the first stage to a set of machines in the second stage.

### 3.2.3. Conclusion optimization heuristics

Concluding Section 3.2, the Normalized Weighted Simulated Annealing (NWSA) algorithm is most applicable for the problem of TenCate. This optimization heuristic performed best and is used within NWTSFFS problems. As a contribution to literature, we include realistic constraints within the heuristic. In the next chapter, the simulated annealing heuristic is explained with certain number of realistic constraints which represent the situation at TenCate best.

# 4. Method

Within this chapter, we discuss the method used within this research. In Section 4.1, we elaborate on the assumptions that we made within the model and for this research. In Section 4.2, we design a model of the environment. Lastly, in Section 4.3 we present the simulated annealing model used for the optimization of the planning.

## 4.1. Assumptions

In this section, we discuss five assumptions of the simulation model. The first two assumptions are due to the tactical level of this simulation model. When an extrusion line or twine position breaks on a day, operational planning is needed. Malfunctions on extrusion and twine lines are not predictable and occur infrequently and are therefore ignored in the tactical planning. The purpose of this planning tool with a simulation model is to plan on a tactical level in which, the tactical planning tool is used once a month by the planning department. Hence, we simplify the model by removing the operational problems. The third assumption, is about the storage space between extrusion and twining, which can be seen as a limitation. Hence, we decided to include the storage as an assumption. The last two assumptions are for the simplicity of the simulation model and include the linkage of the twine lines and the production orders.

1. *Broken production lines*

In the simulation model, one assumption is that broken production lines are not taken into account within the tactical planning. This means that the simulation does not consider any potential disruptions or malfunctions occurring in the production lines, either known up front or breakdowns during production. The model assumes a continuous and uninterrupted flow of production without accounting for any downtime or delays caused by broken production lines.

2. *Broken twine positions*

Another assumption made in the simulation model is that the positions of broken twine lines are not considered. The model assumes that there is a certain percentage of positions constantly available and does not account for any instances of damaged or unusable twine positions. Hence, to simplify the simulation, the twine positions are considered available, without taking into account potential losses or constraints resulting from twine breakage.

3. *Storage between extrusion and twining*

We assumed in the simulation model that there is no storage between the extrusion and twining stages. This means that the model assumes a direct transfer of the extruded material from the extrusion process to the twining process without any intermediate storage or buffering. By omitting storage considerations, the simulation focuses on the immediate flow of materials and simplifies the analysis of the production process.

4. *Twine lines are not linked*

The simulation model assumes that there is no specific link established between the twine lines and the extrusion process. It assumes that any twine line can be assigned to any extrusion batch without any predefined or preferred allocation. This assumption allows for greater flexibility in the simulation, treating the twine lines as interchangeable resources that can be allocated as needed during the simulation runs.

5. *Orders cannot be produced half*

Lastly, the assumption in the simulation model is that no fraction of orders can be produced. This means that the model does not allow for partial fulfillment of orders. Each order is assumed to be processed in its entirety without considering the option of producing smaller batch sizes or fulfilling partial demand. This simplifying assumption streamlines the simulation by focusing solely on complete order processing.

## 4.2. Simulation model

The simulation model creates a tactical optimized planning. The basic simulation model starts with creating an initial "greedy" planning and a one-time import from the ERP system with the orders and information to produce. This information consists of possible twine lines to produce on, twine speed, extrusion speed, color etc. All information is stored and used later on in the optimization model. In the subsequent sections, we describe the input and start of the model in Section 4.2.1. Furthermore, we describe the flow of the model in Section 4.2.2 with the use of flow charts. Lastly, we discuss the optimization objectives in Section 4.2.3.

### 4.2.1. Input of the model

The input of a simulation model serves as the foundation for the optimization and output of the model. The input consists of several sets, parameters and variables. We discuss the input sets, parameters and variables in tables 1, 2, 3 and 4.

*Sets*

The sets $K$ and $Q$ represent the different extrusion and twine lines within the production process of TenCate. Set $I$ is a variable set representing the number of orders to be planned. The last set, set $S$, represents a full year of shifts. There are three shifts in one day and therefore 1095 shifts in one year.

*Table 1: Sets for the simulation model*

| Sets | Explanation |
|---|---|
| $K = \{1, 2, \dots, lastExtrLine\}$ | The different extrusion lines k |
| $Q = \{1, 2, \dots, lastTwineLine\}$ | The different twine lines q |
| $I = \{1, 2, \dots, lastRow\}$ | The batches i planned on an extrusion line |
| $S = \{1, 2, \dots, 1095\}$ | Shift number in a year (365 * 3 shifts a day) s |
| $\boldsymbol{O = \{Die\ changes, Tardiness, max\ st. dev. of\ the\ twinelines\}}$ | The different objectives that can be optimized: die changes, tardiness and max. st. dev. of the twinelines |

*Parameters*

The parameters below mostly represent attributes of a batch. Since the planning is created per extrusion line, the parameters are dependent on line $k$ and batch $i$. So, the begin time of a batch is noted as the parameter $beginTime_{ki}$, which is for instance used in the model as $beginTime_{1,3}$ for the begin time of batch 3 from extrusion line 1.

*Table 2: Parameters for the simulation model*

| Parameters | Explanation |
|---|---|
| $lastRow \in \mathbb{N}$ | The total number of batches to be planned |
| $maxTwineLines \in \mathbb{N}$ | The maximum number of twine lines to be used |
| $planFrom \in S$ | The shift number from when needs to be planned |
| $runTime_{ki} \in \mathbb{N}$ | The run time of batch i on line k |
| $productionOrder_{ki} \in \mathbb{N}$ | The production order number of batch i on line k |
| $quantity_{ki} \in \mathbb{N}$ | The quantity to produce of batch i on line k |
| $name_{ki}$ | The name of the product of batch i on line k |
| $dueDate_{ki} \in S$ | The due date of batch i on line k |
| $extrusionLine_{ki} \in K$ | The extrusion line to produce on of batch i on line k |
| $output_{ki} \in \mathbb{R}$ | The output of the extrusion line for batch i on line k |
| $coneWeight_{ki} \in \mathbb{R}$ | The cone weight of batch i on line k |
| $bobbines_{ki} \in \mathbb{N}$ | The bobbins produced every extrusion run of batch i on line k |
| $speedExtrBobPerHour_{ki} \in \mathbb{R}$ | The speed of extrusion line k of batch i |
| $runBobijnen_{ki} \in \mathbb{N}$ | The number of bobbins produced in one hour of batch i on line k |
| $twineTime_{ki} \in \mathbb{R}$ | The time to twine a run of batch i on line k |
| $twineLinesMF_{ki} \in \mathbb{N}$ | The number of MF twine lines needed for one extrusion run of batch i on line k |
| $twineLinesTape_{ki} \in \mathbb{N}$ | The number of Tape twine lines needed for one extrusion run of batch i on line k |

| | |
|---|---|
| $weight1 \in \mathbb{R}$ | The weight given to objective 1 |
| $weight2 \in \mathbb{R}$ | The weight given to objective 2 |
| $weight3 \in \mathbb{R}$ | The weight given to objective 3 |
| $\alpha \in \mathbb{R}$ | Alpha used in the value function of NWSA |

*Variables*

The different variables are mentioned in the table below. The $startTimeLine$ is used to store the first moment a batch can start on an extrusion line. This is extracted from the current planning up until the day you want to plan. The variables $z_k$ and $p_k$ are used as a counter for the number of batches on an extrusion line. The two variables $twinePositionsMF$ and $twinePositionsTape$ are used to keep track of the number of twine lines occupied in a shift. This is needed to fulfill the constraint of maximum number of twine positions. The last variable $dieCounter$ is used for the objective to minimize the number of die changes.

*Table 3: Variables for the simulation model*

| **Variables** | **Explanation** |
|---|---|
| $startTimeLine_k$ | The time from when can be started with the planning for every line k |
| $beginTime_{ki}$ | The begin time of batch i on line k |
| $endTime_{ki}$ | The end time of batch i on line k |
| $p_k$ | The number of planned batches in line k **without** die changes included |
| $z_k$ | The number of planned batches in line k **with** die changes included |
| $twinePositionsMF_s$ | The MF twine lines needed on shift s |
| $twinePositionsTape_s$ | The Tape twine lines needed on shift s |
| $dieCounter$ | The number of die changes |

*Decision variable*

The decision variable of the model is $planningPerLine$, which stores the batches to produce on the different extrusion lines. These batches consist of the characteristics mentioned in the parameters table including begin and end times of the batch, the time to twine the batch, the due date of the batch etc.

Table 4: The decision variable for our simulation model

| Decision Variable | Explanation |
|---|---|
| $planningPerLine_k = \{x_1, x_2, x_3 \ldots x_n\}$ | The sequence or planning of batches to produce on extrusion line $k \in K$, where $x_1$ is the first batch within the planning of line k and $x_1, x_2 \ldots x_n \in I$ |

*Objective functions*

With the use of the normalized weighed simulated annealing algorithm, multiple objectives are evaluated. We evaluate three different objective functions within this thesis, which are mentioned below.

1. Minimize the number of die changes

In order to maximize the number of produced batches, the idle time of the machines need to be minimized. Therefore, we included the objective of minimizing the die changes by counting the die changes with the following algorithm.

$$
\begin{array}{l}
For\ all\ batches\ for\ line\ k \\
\quad if\ planning(k,i).die <> planning(k,i+1)\ then \\
\qquad\qquad dieCounter = dieCounter + 1 \\
\quad end\ if \\
Next\ batch
\end{array}
$$

2. Minimize tardiness

Every order that needs to be planned has a due date. TenCate has as an objective to minimize the lateness of the orders. Furthermore, they want to plan the orders as early as possible with respect to the due date. Hence, we added the begin time of the order and the due date to the lateness to calculate the total tardiness. With the begin time added, we ensured that all orders are planned as early as possible. We determined the following lines of code to calculate the minimum tardiness.

$$
\begin{array}{l}
For\ all\ batches\ for\ line\ k \\
\quad tardiness = tardiness + planning(k,i).endTime - planning(k,i).dueDate \\
\qquad\qquad + planning(k,i).beginTime \\
Next\ batch
\end{array}
$$

3. Minimize the maximum standard deviation of twine lines occupied in a shift

The last objective is to minimize the maximum standard deviation of the number of twine lines occupied in a shift during the planned period. With this method, the utilization of the twine lines will be divided over the period instead of planning everything on the same time, which is not possible due to capacity limitations. Therefore, we created another procedure to determine this last objective. Here, for every shift we calculate how many twine lines are needed. After this, we calculate the standard deviation of the twine lines (which is not shown in the snippet below).

$$For\ all\ batches\ for\ line\ k$$

$$For\ x = planning(k,i).beginTime\ To\ planning(k,i).endTime$$

$$twinePositionsMF(x) = twinePositionsMF(x) + planning(k,i).twineLineMF$$

$$twinePositionsTape(x) = twinePositionsTape(x) + planning(k,i).twineLineTape$$

$$Next\ x$$

$$Next\ batch$$

### 4.2.2. Constraints

As part of the contribution to literature, we add several realistic constraints to the model. These constraints are case-specific, but some are also general constraints that can be applied across multiple manufacturing industries. Within this research, we define three main constraints, which we implemented in the model.

1. *Man power*

The first constraint is the limited man power TenCate has. Including this constraint means that not all extrusion lines can run at the same time. The amount of man power needed when using all the extrusion lines exceeds the maximum capacity of man power available. Hence, we included this as a soft constraint within the model. So, we take the peak of man power needed into account by minimizing the standard deviation of the used twine lines. This spreads the workload and man power needed to lower the peak demand of man power needed for production.

2. *Second stage capacity*

The second constraint is the capacity of the second stage, which is in this case twining. As mentioned earlier in this research as one of the main planning problems, the number of twine lines/positions is often less than the output of the extrusion lines. As an example, when an extrusion line produces 60 bobbins per hour and the twine line can handle 42 bobbins per hour, a buffer needs to be created which is not possible. Hence, in this case two twine lines are needed for the output. Since TenCate is currently not taking into account the capacity of the twine lines, we included the capacity as a constraint in the model by tracking the number of twine lines needed at any point in time. Spreading the workload on the twine lines, lowers the peak of twine lines needed. In this way, TenCate ensures that twine lines are evenly used in time and can handle all batches on the twine lines without lowering the extrusion line speed.

3. *Due date*

The last constraint we included is the due date of the order. Since the due date is a hard constraint and TenCate wants production as fast as possible, we decided to add the due date not only as a hard constraint, but also as an objective. This means that we always need to fulfill the given due date, but want to produce as fast as possible to take into account for instance possible malfunctions. It often occurs that there are malfunctions during a day and batches need to be shifted to a later date. Hence, after discussions within TenCate, we decided to include the due date as both hard constraint and objective.

### 4.2.3. Input for the simulation model

To provide a clear overview of the simulation model, we created flow charts to visualize the first input processes within the simulation model. First, we elaborate on the input of the start times. Next, we explain in more detail how the orders are loaded into the model. With the start times and the orders loaded into the model, we elaborate on the creation an initial planning. Last, we elaborate on the die changes within the planning.

**Input start times**

As an input, the planning department can enter from which moment they want to plan all batches. So when they want to plan 10 batches, all 10 batches will be planned from the starting date onwards. Furthermore, the model will derive the first start moment from the current planning and will store this in $startTimeLine_k$. In this way, we can either start planning from the input $planFrom$ or $startTimeLine_k$. In the flow chart in Figure 6, we show the code schematically.

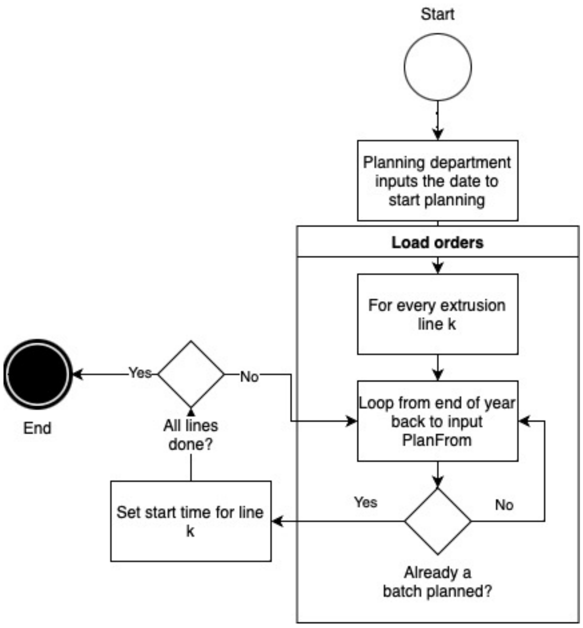


*Figure 6: Input algorithm for determining the start times of the batches either starting from the input start time or the end time of a currently planned batch*

**Load orders**

After we established the start times, we import the orders from the ERP system when the planning department wants to use the tactical planning tool. Then, the model will extract the information of the orders and load it into the parameters. We decided to randomly load the orders into the planning tool in order to shuffle the orders loaded into the system. The flow chart in Figure 7 represents this process.

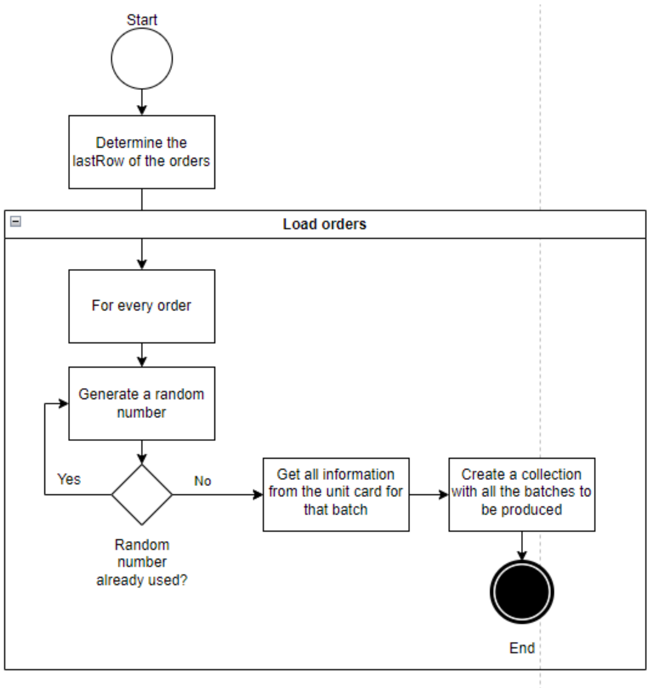


*Figure 7: Algorithm to load orders into the tactical planning tool*

**Create greedy initial planning**

First, when creating a greedy initial planning for the model, we create two counters. One counter is for the number of batches with die changes included (see Table 2, parameter z), and the second counter (see Table 2, parameter p) for the planning without the die changes included. We did this in order to easily swap batches within a planning without having the troubles of also removing die changes, which makes it more complex.

When creating the initial planning, we calculate first all the runtimes, the number of bobbins coming from the extrusion lines and the number of twine lines needed after extrusion mentioned as 'needed information' in Figure 8. Then, we create an initial planning. In Figure 8, we created an overview of this process.

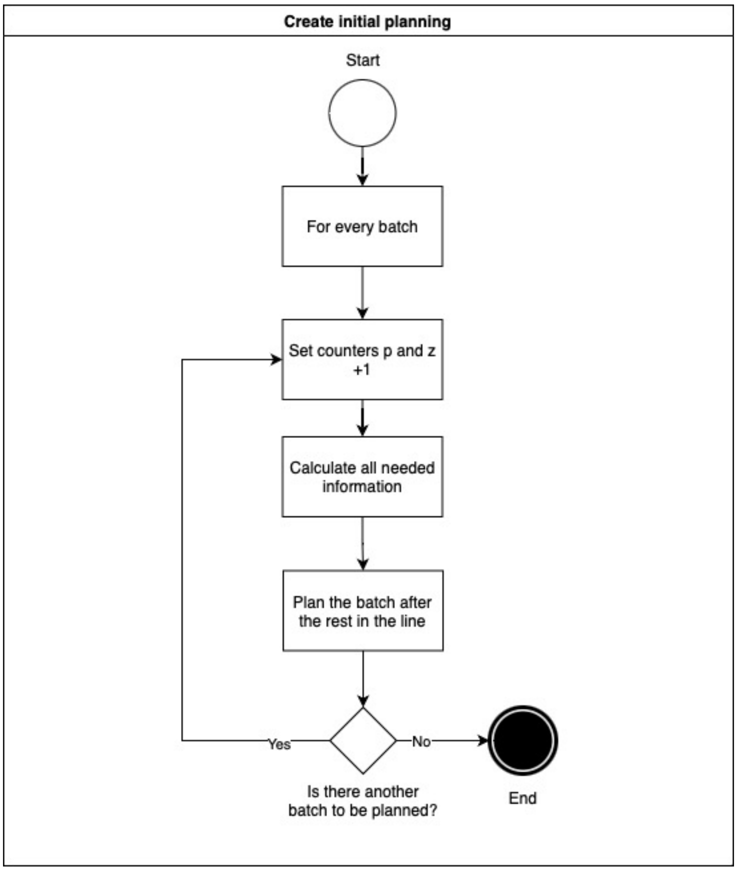


*Figure 8: Create initial planning*

### Add die changes

After we created the initial planning, the die changes are identified. This is checked by going through the planning of every extrusion line and check if the used die of two subsequent batches is the same. The flow chart below in Figure 9 describes this process.

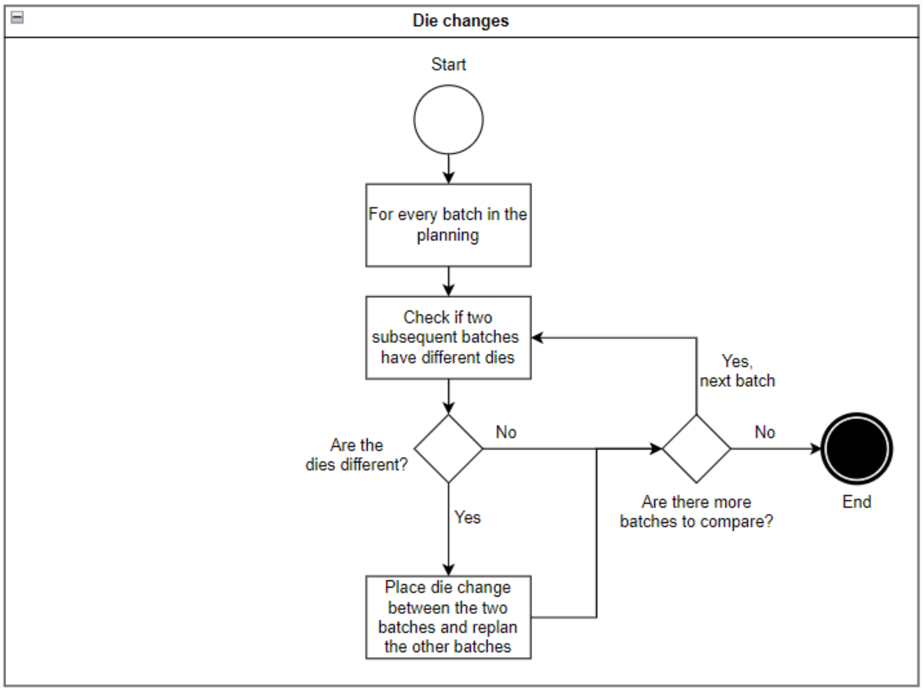


*Figure 9: Die changes*

## 4.3. Normalized weighted simulated annealing model

In Chapter 3, we found the study of Jolai et al. (2013) in which normalized simulated annealing was used for the optimization of NWTSFFS problems. We implemented this technique into the basic model from Section 4.2. In Sections 4.3.1, 4.3.2 and 4.3.3 we elaborate on the implementation of the NWSA model.

### 4.3.1. The NWSA model

Now that we modelled the environment of the simulation model, the optimization technique from Jolai et al. (2013) NWSA is a multi-objective simulated annealing model. Within this research, we defined three main objective functions as mentioned in Section 4.1.1: Minimize die changes, minimize tardiness and minimize the maximum standard deviation of the number of twine lines in use. The purpose of NWSA is to optimize objectives by normalizing the results of the multiple objectives and assign weights to each objective function. For the normalization, we first calculate the minimum and maximum values of every objective function. In this way, objectives such as twine line usage (normally between 0 and 6) and tardiness (which could be 200 shifts) are normalized by scaling them with the minimum and maximum values.

NWSA consists of two steps:

1. Calculate the minimum value and maximum value of all objective functions with the use of classic simulated annealing.
2. Run the NWSA model with a weighted value function using the results of step 1

The first step is to calculate the minimum and maximum values of the objective functions. We did this by creating a classic simulated annealing model, which will either minimize or maximize the objective function for a single objective. The classic simulated annealing model and the NWSA both use the same setup within the algorithm. The algorithms start with an initial solution ("Create initial planning" in Figure 8) and iterative swaps two batches on an extrusion line until a stopping criterion is met. When the swap results in a better planning, the new solution is stored as the best solution. When the swap results in a worse planning, it will only be accepted with a certain probability to explore more solutions in the beginning of the algorithm. The algorithm is stopped when a decreasing parameter (temperature) is below a certain threshold.

After the classic simulated annealing algorithm provided the objective values, we can continue to step 2. Within step 2 we run the NWSA model. We created an overview of the NWSA model in Figure 10.

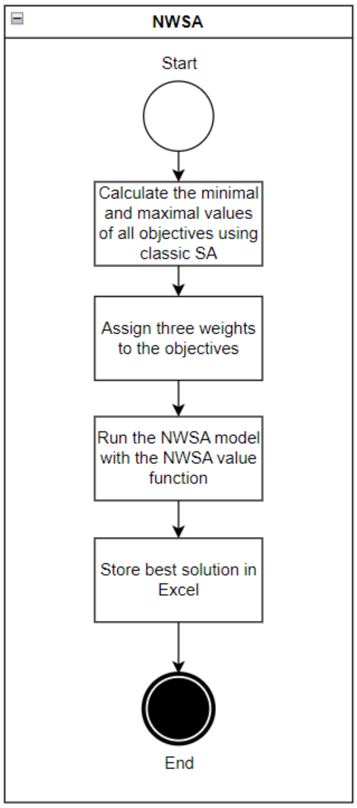


*Figure 10: A concise overview of the NWSA model*

### 4.3.2. Addition to the model

To create a more realistic model for TenCate we added two concepts to the study of Jolai et al. (2013): empty dummy batches and realistic constraints. We explain both implementations below.

*Empty dummy batches*

As an addition to the NWSA model, we created empty dummy batches with a random size which are added to the initial planning. There are two goals of adding empty dummy batches: avoid long running times and spread the workload. With a maximum of 1095 possible shifts in a year to start producing a batch, it is very time consuming to continuously move batches only one shift to check if the planning improved. Therefore, we create empty dummy batches with a random length of shifts (runtime). Now, in the simulation model, we can swap empty dummy batches with real batches to check for improvement. This is less time consuming since we only need to swap the small number of empty dummy batches with the real batches instead of moving a batch 1095 shifts and check 1095 times which planning is best. With the use of empty dummy batches, we can simply apply the already existing simulated annealing model and swap a real batch with an empty dummy batch in order to see whether this benefits for instance the spread of twine line usage. In addition, using empty dummy batches to spread the extrusion and twine line workload, contributes to the objective to lower the standard deviation of the twine lines.

*Realistic constraints in NWSA*

As already mentioned in Section 4.2, the model contains several constraints. Since Jolai et al. (2013) did not include realistic constraints into their model and stated this as a contribution to research, we included the realistic constraints into the model. To ensure these constraints are complied with, we created a check which returns whether the planning is valid or not. If no feasible solution returned, it will still create a tactical planning but will indicate that the solution is not feasible. The function checks the following two constraints and are checked for every batch in the planning accepting intermediate infeasible solutions to escape local optima:

1. $endTime_{ki} \leq dueDate_{ki}$
2. $highestTwineUsage \leq maxTwineUsage$

# 5. Results

In Chapter 5, we discuss the parameter tuning and the results from three different planning strategies within the simulation model. First, in Section 5.1 we briefly discuss the standard settings used in the greedy planning and the NWSA model. In Section 5.2 we discuss the results of the tactical planning for September 2023 created by the planning department of TenCate as a case study and elaborate on the results of the greedy initial planning based on priority. In Section 5.3 we analyze the impact of different settings using multiple sensitivity analyses. Last, in Section 5.4, we evaluate the different results from Section 5.2 and Section 5.3.

## 5.1. Parameter tuning

We determined the parameter settings based on the study of Jolai et al. (2013) and Brusco (2014). The parameters that we determined are: the Markov Chain length, the alpha within NWSA, the cooling rate, initial temperature, stopping temperature, number of empty dummy batches, length of the empty dummy batches and the weights. We choose to conduct tests on the case study and test the whole tactical planning tool generally. We elaborate on the determined settings and provide an explanation below.

*The Markov Chain length*

The Markov chain determines how many neighbor solutions are examined for a single temperature. Increasing the Markov length results in longer run times, but increases the chance of finding a better solution. In this research, approximately three batches are planned per line. Including a number of seven empty dummy batches (elaborated later in this section) per line, results in ten batches to plan for every extrusion line. Hence, the total number of possible solutions is:

$$10!\,(sequences\ per\ line) * 8\,(unique\ extrusion\ lines) = 29{,}030{,}400$$

Aarts et al. (2005) mention that the length of Markov chains may be related to the size of the neighborhoods. As Javidrad et al. (2018) state, in most available SA algorithms, the Markov length is determined experimentally. We see in the equation above that the solution space is extensive. To examine the solution space, we set the Markov Chain length to 1000. We found that with a Markov length of 1000, the model has a run time of approximately six hours, which is acceptable for TenCate as a tactical planning tool which needs to be ran every other month. Hence, we set the Markov length to 1000.

*Alpha within NWSA*

Since the maximum and minimal values obtained from the classic simulated annealing model have a probability of an error, Jolai et al. (2013) added an error rate (alpha) to the NWSA model. In this way, the upper and lower bounds loosen to reduce the probability of a result not including the minimum and maximum values obtained from the classic simulated annealing algorithm. Jolai et al. (2013) considered 18 problems with different number of jobs, machines in stage one and stage two. To initially represent the case of TenCate best, which has 13 machines in stage one and 9 in stage two, we selected the alpha of 0.136471 (see Figure 11) from Jolai et al. (2013). We use this error rate as an initial setting which we will alternate in Section 5.3 if the error rate makes a difference in this specific case study. Furthermore, the number of jobs is more closely to 24 than to 80. Hence, we run a sensitivity analysis for alpha in Section 5.3.

Table 3: Error ratio for normalized weighted simulated annealing.

| Problem number | No. jobs | No. machines in stage one | No. machines in stage two | $\alpha$ |
|---|---|---|---|---|
| 1 | 8 | 2 | 2 | 0.02 |
| 2 | 8 | 3 | 2 | 0.030588 |
| 3 | 8 | 3 | 4 | 0.041176 |
| 4 | 16 | 2 | 2 | 0.051765 |
| 5 | 16 | 3 | 2 | 0.062353 |
| 6 | 16 | 3 | 4 | 0.072941 |
| 7 | 24 | 2 | 2 | 0.083529 |
| 8 | 24 | 3 | 2 | 0.094118 |
| 9 | 24 | 3 | 4 | 0.104706 |
| 10 | 80 | 8 | 10 | 0.115294 |
| 11 | 80 | 10 | 10 | 0.125882 |
| 12 | 80 | 12 | 10 | 0.136471 |
| 13 | 100 | 8 | 10 | 0.147059 |
| 14 | 100 | 10 | 10 | 0.157647 |
| 15 | 100 | 12 | 10 | 0.168235 |
| 16 | 120 | 8 | 10 | 0.178824 |
| 17 | 120 | 10 | 10 | 0.189412 |
| 18 | 120 | 12 | 10 | 0.2 |

*Figure 11: Alpha table of Jolai et al. (2013)*

*The cooling rate, initial temperature and stopping temperature*

A cooling schedule is specified by an initial temperature, a decrement function (cooling rate), stop criterion (stopping temperature) and the Markov chain length determined in the first paragraph of Section 5.1. In this research, we use a static cooling schedule instead of for instance a logarithmic cooling schedule due to the computational benefits of a static cooling schedule (Mahdi et al., 2017), in which the parameters are fixed and not changed during the execution of the algorithm. Following the early work of Kirkpatrick et al. (1983), we choose the initial temperature to be the maximum difference of the value function between any two neighboring solutions. Since we develop a multi objective simulated annealing model and we calculate the exact maximum difference, we can also use simple estimates (Javidrad et al., 2018). We estimate a maximum difference of 1000 on average of the three objectives ($die\ changes\ \approx 4, due\ date \approx 2800\ and\ st.dev \approx 2$). Hence, we set the initial temperature at 1000. The stopping temperature is fixed at a small value, which is related to the smallest possible difference between two neighboring solutions. We calculated this difference to be approximately 0.001 (for the standard deviation of the capacity of the twine lines).

For the cooling rate, Brusco (2014) mentions a computation by the following formula in which $c$ is the cooling rate, $T(Q)$ the stopping temperature, $T(1)$ the initial temperature and $Q$ the Markov length:

$$c = \exp\left(\frac{log\big(T(Q)\big) - log\big(T(1)\big)}{Q-1}\right)$$

Completing this formula results in the following cooling rate:

$$= \exp\left(\frac{\log(0.001) - \log(1000)}{1000-1}\right) \approx 0.99$$

After running initial simulations, we determined to reduce the cooling rate to 0.98 in order to lower the run times.

*Number and length of empty dummy batches*

Since we extended the NWSA algorithm with empty dummy batches which is not used before in NWSA algorithms, no information is available about the average use of empty dummy batches. Hence, we determined the length and number of empty dummy batches based on initial simulations. The empty dummy batches are used to spread the workload and reduce run times. To achieve these goals, the number of empty dummy batches need to be rather low. On average, for a tactical planning, three to six batches need to be planned per line. Based on initial simulation runs of the number of empty dummy batches varying from 1 till 15, we determined the number of empty dummy batches to be seven and the length between one and five shifts (almost two days).

*Objective weights*

Initially, we set the weights of the three objectives to be equal at 0.3333. In addition, we analyze the differences in output when one objective weigh more than another in Section 5.3. Also, the planning department is able to fill in the weights by themselves if they want to focus more on a specific objective.

## 5.2. Result analysis

In this section, we discuss the current situation by analyzing the planning form the planning department. They provided us a test set of 28 batches, which we used in our simulation model to compare the results with the planning from the planning department (current situation). Thereafter, we discuss an initial greedy planning which is based on the priority (determined by the planning department) of the orders. Last, we discuss the results of our NWSA model and compare all results.

*Planning of the planning department*

In order to compare the created optimization model with the current situation, we asked the planning department to create a tactical planning as usual, described in Section 2.2. They planned the test set of orders by hand. The results of the objectives of this planning are shown in Table 5. We set these objective values as the current situation and compare the results in the next paragraph.

*Table 5: Results planning from the planning department*

| *Planning from Planning department* | *Objective values* |
|---|---|
| *Die changes* | 14 |
| *Due date* | 1164 |
| *Max StDev twining* | 3.601 |

*Initial greedy planning*

The initial greedy planning is based on the priority of the orders. We plan the order with the highest priority first and the order with the least priority last without including empty dummy batches. In Table 6, we provide the results of the greedy planning.

*Table 6: Results initial greedy planning*

| *Initial greedy planning* | *Objective values* | *Improvement compared to Planning department* |
|---|---|---|
| *Die changes* | 12 | 14.29% |
| *Due date* | 442 | 62.03% |
| *Max StDev twining* | 3.835 | -6.50% |

From Table 6, we conclude that the greedy algorithm performs better than the planning of the planning department in two objectives, namely die changes and due date. We expected a better due date objective, but a random result for the objective of die changes, since the greedy algorithm merely optimizes the due date. We see that the die changes improved about 14%, but this depends only on having batches with the same die in the sequence of priority. However, the fact that the greedy planning did outperform the planning of the planning department, shows the lack of a good planning tool. The standard deviation is worse than the planning of the planning department with -6.5%. Within the greedy planning, all planned batches are scheduled in the beginning resulting in a higher maximum standard deviation of the twine lines. Comparing the results with the planning of the Planning department, an average increase of 23% is achieved. Although the objective of standard deviation is slightly worse, the due date objective has an improvement of 62%, which results in an average, with an improvement of 14% on the die changes, of 23%.

*The NWSA model*

With the data of the orders provided by the planning department, we can run our NWSA model. We ran the model with the parameter settings defined in Section 5.1. We can see the results of our NWSA model in Table 7. We compare the results of the NWSA model with the planning of the planning department to analyze the improvement with our model. With the NWSA model, we achieved an average improvement of 27.62%. We expected all objectives to improve evenly due to the set weights of 0.333 to all objectives. As we can see from Table 7, the range of improvement is small with a difference of 2.3% between the biggest and smallest improvement, which supports our expectation. These first results seem promising and we will conduct a sensitivity analysis in the next section, to analyze the differences in results with different parameter settings.

*Table 7: Results of the NWSA model*

| | *NWSA* | *Improvement compared to Planning department* |
|---|---|---|
| *Die changes* | 10 | 28.57% |
| *Due date* | 838 | 28.01% |
| *Max StDev twining* | 2.655 | 26.27% |

## 5.3. Sensitivity analyses

To give insights into the different settings of the parameters, we provide a sensitivity analysis in this section. Furthermore, we test the sensitivity of assumptions and inputs and explore boundaries. We conducted a sensitivity analysis on four parameters: empty dummy batch size, number of empty dummy batches, the weights of the objectives and the alpha. We decided on the empty dummy batch size and number of empty dummy batches, since this is not used before within NWSA models. Changing the weights can be interesting to analyze the relation between the weight and the results. Also, we conduct a sensitivity analysis on the provided alpha by Jolai et al. (2013), since the corresponding number of jobs and machines were not equal within this research. Below the results of the sensitivity analyses can be seen in Table 8.

*Table 8: Results sensitivity analysis*

| NWSA | Number of empty dummy batches | | Batch size | | Weights | | | Alpha | |
|---|---|---|---|---|---|---|---|---|---|
| | 5 | 9 | 1-3 | 1-10 | 0.25, 0.25, 0.5 | 0.25, 0.5, 0.25 | 0.5, 0.25, 0.25 | 0.08 | 0.19 |
| *Setting* | *1* | *2* | *3* | *4* | *5* | *6* | *7* | *8* | *9* |
| *Die changes* | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 |
| *Due date* | 702 | 1226 | 1008 | 1540 | 1044 | 786 | 1140 | 894 | 884 |
| *Max StDev twining* | 2.801 | 2.569 | 2.817 | 2.733 | 2.672 | 2.908 | 2.805 | 2.618 | 2.612 |

The first aspect that we noticed when analyzing the results of the sensitivity analysis in Table 8, is that it does not matter if you give a weight of 0.25, 0.33 or 0.50 to the die changes objective, the result is in all cases 10. Analyzing the other two objectives, we can see that setting 1 and 9 perform best besides the NWSA model with the standard parameter settings. We analyze the best results in the remainder of this section. We can see an overview of the best results in Table 9.

*Table 9: Best results of the sensitivity analysis of the NWSA model*

| Results of the three best settings | *NWSA*<br>*Standard settings* | *Number of empty dummy batches*<br>*Set to: 5* | *Alpha*<br>*Set to: 0.19* |
|---|---|---|---|
| *Die changes* | 10 | 10 | 10 |
| *Due date* | 838 | 702 | 884 |
| *Max StDev twining* | 2.655 | 2.801 | 2.612 |

The results of the standard settings and the settings with an alpha of 0.19 are almost equal. The due date objective is a bit lower with the standard settings, but the standard deviation of twining is a bit higher. Hence, no distinction can be made between these two settings when determining a better setting. Analyzing the settings with five empty dummy batches, a much lower due date objective is achieved, which makes sense since the number of batches planned (including empty dummy batches) is lower than with the standard setting of seven empty dummy batches. However, the standard deviation is a bit higher due to the more compact planning.

### 5.4. Concluding current situation and the NWSA model

When comparing the best results of the NWSA model with the planning from the planning department in the current situation, an improvement is achieved with all three objectives. As we can see in Table 10, at least an improvement of 20% is achieved for all objectives with one of the three settings. In total an average improvement is achieved in models with the NWSA standard settings, number of empty dummy batches set to 5 and an alpha set to 0.19, of respectively 27.62%, 30.16% and 26.70%. From these results, we can conclude that our developed NWSA model performs better than the planning of the planning department in the current situation. The biggest improvement is achieved for the due date objective. This is due to the planning department of TenCate, since they do consider the due date but on a human level. They only think about it and are not able to optimize multiple objectives in their heads. Removing the human aspect within the tactical planning ensures a more consistent and improved planning.

*Table 10: Evaluation of the current situation*

| | *Current situation* | *Improvement NWSA-model* | | |
|---|---|---|---|---|
| | *Planning from the planning department* | *NWSA Standard settings* | *Number of empty dummy batches 5* | *Alpha 0.19* |
| *Die changes* | *14* | 28.57% | 28.57% | 28.57% |
| *Due date* | *1164* | 28.01% | 39.69% | 24.05% |
| *Max StDev twining* | *3.601* | 26.27% | 22.22% | 27.46% |

# 6. Conclusions & recommendations

This chapter concludes our thesis. In Section 6.1 we conclude the thesis by answering our research question: *"How can a new tactical planning tool, based on a simulation heuristic, be designed to incease the output of the production process by taking the twine line capacities into account within the planning tool?"*. Next to that, we discuss the limitations and recommendations of our research in Section 6.2 and 6.3 respectively. Furthermore, in Section 6.4, we discuss the opportunities for future research.

## 6.1. Conclusion

Within this research we tried to improve the output of the production process of TenCate by developing a new tactical planning tool. We developed a new planning tool, based on a simulation heuristic to improve the current tactical planning of the planning department. We decided to use a simulation heuristic due to the poor data quality present and high complexity involved in the production process at TenCate. The production process of TenCate is best described by a no-wait-two-stage flexible flow shop (NWTSFFS). As a simulation heuristic, we found the research of Jolai et al. (2013) in which they mention a Normalized Weighted Simulated Annealing (NWSA) algorithm for a NWTSFFS process. This research lacked the implementation of realistic constraints. We contributed to this research by integrating realistic constraints (to make the tool useful in practice) and empty dummy batches (for simplicity of the model and spread of production). With the simulated annealing algorithm of Jolai et al. (2013), we were able to improve the current planning with on average more than 28% (after conducting a sensitivity analysis) on three evenly weighted objectives: number of die changes, due date (in combination with start as early as possible) and the maximum standard deviation of the capacity of the twine lines. The number of die changes are the number of times production has to switch the die. The due date is combined with the start of the production of a batch to ensure batches are produced as early as possible to incorporate some room for malfunctions, less man power, etc. Last, the maximum standard deviation is minimized to spread the workload as much as possible.

Next, we continued our research by first creating a greedy initial model based on priority. This greedy solution already improved the current planning from the planning department with 23%. However, the improvement of 23% is not evenly spread across the three objectives (14.29%, 65.02% and -6.50%), which is not desirable for TenCate and does not take into account constraints. Second, with the use of the model of Jolai et al. (2013), we integrated realistic constraints and empty dummy batches and developed a new NWSA model. The results of this model were an improvement compared to both the planning from the planning department as the greedy solution. Not only does the new planning tool have a quantitative benefit with an evenly weighted improvement of 27% (28.57%, 28.01% and 26.27%), the NWSA model also incorporates realistic constraints (due date and max twine usage) which cannot be seen from quantitative results. Overall, the NWSA model with defined standard settings performed roughly 27% better than the planning in the current situation.

Next, we conducted a sensitivity analysis with different settings of parameters. We selected the three best settings of the sensitivity analysis. From this we concluded that the NWSA model outperformed the planning of the current situation most with the standard settings, five empty dummy batches and an alpha of 0.19. The setting with only five empty dummy batches resulted in the best overall outcome and improved the current planning on average by 28% instead of 27% with the standard settings. Concluding, lowering the number of empty dummy batches from seven to five did yield a small improvement. We conclude that the developed model with the following parameter settings is best to implement:

- Markov chain length = 1000

- Start temperature = 1000
- End temperature = 0.001
- Cooling rate = 0.98
- Alpha = 0.136
- Number of empty dummy batches = 5
- Length of an empty dummy batch = [1, 5]
- Weights = (0.333, 0.333, 0.333)

Within this model, we contributed to theory by adding realistic constraints and empty dummy batches. We developed a generic model in which constraints can be altered and empty dummy batches are integrated. Implementing the above-mentioned parameter settings for the developed NWSA model used in our case study, resulted in an average improvement of 28% of the case study planning of TenCate in three objectives: number of die changes, due date (in combination with start as early as possible) and the maximum standard deviation of the capacity of the twine lines.

## 6.2. Limitations

In this section we discuss four main limitations of this research.

*Internal systems are not up to date*

A problem we encountered during this research is that the internal systems of TenCate are not up to date. The planning tool in Excel is created in a way that the planning department only needs to import the orders and put them into our planning tool. However, not all products with their unit card are in the system yet. Hence, the planning tool is currently missing important information (speed on the extrusion and twine lines, etc.) to plan the batches. This information is key to determine run length on the production lines and the number of twine lines the batch needs. When all internal systems are up to date, an update to the planning tool needs to be made to ensure that all products to be planned are within the tool. If this is done, the planning tool works best.

*Specific twine lines are not planned*

We developed the planning tool to schedule the extrusion of the batches. Furthermore, we improved the current planning by spreading the workload for the twine lines by minimizing the standard deviation of the needed twine lines. However, the specific twine lines subsequent to the extrusion lines are not planned. Therefore, the Planning department and the operators will still need to plan the batches on a twine line. Nevertheless, the workload of the twine lines is spread more, which results in better management and less overload of the twine lines.

*Man power schedules are not implemented*

We encountered during interviews with employees that man power is a limitation in the current situation. We spread the workload of the twine lines, but did not include schedules of man power within the planning tool. Hence, overall, the workload is spread but not adapted to the schedule of the employees.

*Long run time*

Running the new planning tool will cost around 6 to 7 hours. The runs were made on a HP zbook laptop with an i7 processor from 2018, indicating that the run time on a better and more modern computer of TenCate would result in a reduction of run times. We did run the planning tool with fewer iterations than we now used within this research as discussed in Section 5.1, but this resulted in worse results.

## 6.3. Recommendations

In this section we provide recommendations to TenCate, based on our findings during this research.

*Update internal systems*

Overall, we recommend to update all internal systems with the right products and specifications. Now, different systems sometimes have different specifications like cone weight for the same product. This causes mismatches when planning the batches of these products. Furthermore, when the information of for instance the speed of the production lines for a specific product is unreliable, the planning will become unreliable. Mismatches between the planning and the real production will appear and the planning will become useless.

*Use our developed tactical planning tool*

As the main recommendation of this research, TenCate should use this planning tool with the NWSA model. TenCate is excited to implement this new tool to spend less time on the tactical planning. We showed in this research that our developed NWSA model with 5 empty dummy batches performed best and is able to improve the current planning by 28% on average. For the implementation, TenCate needs to update their internal systems and implement all correct information and specifications of their products into the planning tool.

*Continuous improvement*

The planning tool does not perform at best, TenCate should keep improving the developed tool we created. We recommend to extend the tool with possibly simulating the twine lines. In addition, we tested the new planning tool with one data set. Our recommendation is to test the tool with more data sets to keep improving and finetuning the current tool. For instance, TenCate could use historical data and test every months orders and compare the planning tool with the used planning.

## 6.4. Future research

This section addresses three possibilities for further research.

*Man power schedules*

Since we encountered the importance of man power availability, further research should be conducted to the integration of man power schedules within NWSA models and the current planning tool. The research should be conducted to the integration of man power schedules into NWSA models and the optimization of man power schedules joint with the optimization of the current objectives. The first suggestion for research is focused on how a fixed man power schedule can be integrated within the planning tool. The second suggestion for research is focused on optimizing both the planning and man power schedule.

*Planning specific twine lines*

We developed the current planning tool solely for the extrusion process. In future research, we recommend to conduct research on the possibilities with planning the second stage (twining). When next to extrusion, the twine process is also optimized and planned, more improvements can be made. The current planning tool is only taking into account the capacity of the twine lines, but it would be better to plan the batches to specific twine lines for a more realistic view on the twine line capacities. This would spread the workload even more on the twine lines and lower the peaks in man power needed.

*Add more real-life constraints and objectives*

In future research more real-life constraints and objectives should be added to make the planning represent reality even more than it does now. The current planning tool has a high representation of reality with all production specifications integrated, but this could be extended by for instance man power schedules as mentioned in the first suggestion. We suggest to conduct more research on extra constraints and objectives and the impact of a larger number of constraints and objectives on a NWSA model then we currently modelled.

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