MASTER

Production scheduling in a multi-recipe ink plant

Appeldoorn, V.

Award date:
2020

Department of Industrial Engineering & Innovation Sciences
Operations Planning Accounting & Control Research Group

Production scheduling in a multi-recipe ink plant

Master Thesis

Viktor Appeldoorn

Supervisors:
dr. L.P. (Luuk) Veelenturf, TU/e, OPAC
dr.ir. N.P. (Nico) Dellaert, TU/e, OPAC
dr.ir. R.A.C.M. (Rob) Broekmeulen, TU/e, OPAC
S.P.M. (Sebastiaan) Houben, Canon Production Printing

Public Version

Eindhoven, May 2020

Abstract

Due to increasing demands, Canon Production Printing is building a new plant for the production of latex ink. Because the production environment in the new plant will be different than the current production environment, the current production scheduling model cannot be used for the new plant. Therefore, a new production scheduling model needs to be developed. This research presents a mixed integer linear programming (MILP) model in the form of an extension of the Flexible Job Shop Scheduling Problem (FJSP), which minimizes the sum of changeover costs and labour costs. Because the FJSP is a NP-hard problem, the MILP model only finds an optimal solution within reasonable time for small problem instances. Therefore, a hybrid heuristic model is proposed which combines a congruence based heuristic with tabu search. Furthermore, a business case has been performed in order to calculate the optimal production cycle length. The optimal production cycle length has been calculated by making a trade-off between production costs and inventory holding costs using an adjusted EOQ method.

Executive summary

Problem description and research objective

Canon Production Printing (CPP) is a global leader in digital imaging and industrial printing. Besides printers, CPP also provides consumables for the printers. Ink is one of these consumables. This research focuses in particular on the latex ink. Latex ink is a relatively new product for CPP. The ink is currently being produced in the pilot plant which has been in operation since 2016. Due to growing demand, CPP is currently building a new master plant. This plant will have a bigger production capacity than the current pilot plant.

Latex ink is being produced by dosing raw materials into a mixing vessel using dosing lines. The pilot plant currently has one mixing vessel. The new master plant will have two mixing vessels, with the possibility to install a third and fourth mixing vessel. There are currently 22 different latex ink types, called recipes. Each recipe consist out of several steps. In every step one or more raw materials need to be dosed into the mixing vessel. There are more raw materials than dosing lines. When a dosing line needs to switch from raw material, a changeover needs to happen. A changeover takes time and brings along costs. Therefore the amount of changeover needs to be kept as low as possible.

The current production planning model works based on the principle of a fixed sequence. This production planning model only works for a production environment with a single mixing vessel. A situation with two mixing vessels could cause a conflict between dosing lines and mixing vessels. Therefore, a new production scheduling model needs to be developed. The aim of this research is to develop a method for determining a cost efficient production planning for the latex ink. This production planning consists out of two elements. The length of the production cycle needs to be determined. The second element is a decision support tool for the sequencing of the recipes within the production cycle. The model will allocate the raw materials to the dosing lines in order to minimize the operational costs. The operational costs consist out of changeover costs and labour costs. Aligned with the challenges and requirements, the following main research question has been formulated:

"What is the optimal production planning for the latex ink that minimizes operational costs and end product inventory?"

Production scheduling model

A literature review has been conducted to select the most appropriate method to answer the research question. From relevant literature can be concluded that the latex ink production scheduling problem for can be seen as a Flexible Job Shop Scheduling Problem (FJSP) with parallel operations and sequence dependent setup times. A mixed integer linear programming (MILP) model is proposed to solve the scheduling problem. However, due to the NP-hard nature of the FJSP the MILP model can only find the optimal production schedule for problem instances with 4 or less recipes within reasonable time. To solve problem instances with 5 or more recipes, a hybrid heuristic model is proposed.

The hybrid heuristic model combines a global and a local search heuristic. The global search heuristic focuses on finding the sequence of the recipes on the mixing vessels. The local search heuristic focuses on allocating operations to dosing lines and the sequencing of the operations on these allocated dosing lines. A congruence based heuristic is used as global search technique. A tabu search is used as local search technique. The tabu search optimizes the operation allocations and the sequencing of the operations on these allocated dosing lines given the recipe sequence obtained from the global heuristic.

Production cycle length

In order to find an optimal production cycle length, a trade-off between the production costs and the inventory costs has been made. The production costs are calculated using the proposed hybrid heuristic model. The inventory costs are calculated based on the production cycle length. The longer the production cycle, the higher the inventory level. The inventory costs are calculated as a percentage of the average stock value. From the cost trade-off can be concluded that a production cycle length of 1 week is the optimal length. An optimal distribution of the products into production cycles has been provided based on demand predictions for the year 2023.

Scenario testing

The proposed hybrid heuristic model has been used to test the effects of a changing production environment. For the situation in the master plant with 2 mixing vessels and 19 dosing lines, installing a new dosing line of type G yields the highest cost savings. However, the ROI of this dosing is 5.33 years. Because CPP requires its investments to have a ROI of lower than 3 years, it is not recommended to invest in a new dosing line. Furthermore, the capacity of the master plant has been tested for situations with 1, 2 and 3 mixing vessels. From these tests can be concluded that the demand for the years 2020 until 2022 can be met with a production environment with 1 mixing vessel. To meet the demand for the year 2023, a second mixing vessel needs to be installed. Therefore it is recommended to install the second mixing vessel in the year 2023.

The expectation is that new recipes containing new raw materials will be introduced in the coming years. Therefore, the model is used to test the effects of new recipes and new raw materials. From these tests can be concluded that the number of changeovers, as well as the production costs increase when new recipes enter the production environment. If a type D1 line is added to the problem instance, the number of changeovers and the production costs are reduced. However, the ROI of this new type D1 dosing line is 8.14 years. Therefore, the advice is not to invest in a new dosing line.

Preface

This thesis is the result of my graduation project performed in order to receive a master's degree in Operations Management & Logistics at Eindhoven University of Technology. This research project has been carried out at Canon Production Printing (hereafter referred to as CPP).

First, I would like to thank my company supervisor Sebastiaan Houben for the opportunity to conduct my graduation project at CPP. Sebastiaan has been guiding me throughout the project. He always helped me with his resourceful ideas whenever I got stuck. Furthermore, I would like to thank Emiel van de Rijt who has been of great help when developing the model proposed in this research. I would also like to express my gratitude to Sjors op het Veld and John Joosten who helped me gather the information required to perform my research. I also thank all my colleagues from the Production Engineering department who have contributed to a great time at CPP.

Second, I would like to thank my mentor from the TU/e, Luuk Veelenturf. I am grateful for his regular feedback and helpful suggestions which improved the quality of my research project. I would also like to thank my second supervisor Nico Dellaert, who provided me with his feedback and thoughts on the developments throughout the project. Furthermore, I would like to thank Rob Broekmeulen for being the third assessor for this project.

Last but not least, I would like to thank my family and friends for supporting me during my time at Eindhoven University of Technology.

Viktor Appeldoorn

Eindhoven, April 2020

Contents

Contents v

List of Abbreviations viii

List of Figures ix

List of Tables xi

1 Introduction 1

1.1 Company background . . . 1
1.2 Problem context . . . 1
1.3 Research objective . . . 3
1.4 Research questions . . . 4
1.5 Project scope . . . 4
1.6 Project relevance . . . 5
1.6.1 Scientific relevance . . . 5
1.6.2 Practical relevance . . . 5
1.7 Confidentiality . . . 5
1.8 Thesis outline . . . 5

2 Production and scheduling process 6

2.1 Production process . . . 6
2.2 Production environment . . . 7
2.2.1 Recipes and raw materials . . . 7
2.2.2 Dosing lines . . . 9
2.2.3 Mixing vessels . . . 10
2.3 Production planning . . . 10
2.3.1 Production with multiple mixing vessels . . . 11

2.3.2 Additional requirements . . . 13
2.4 Production costs . . . 13

3 Literature **15**
3.1 Production scheduling . . . 15
3.2 Job shop scheduling . . . 16
3.2.1 The flexible JSP . . . 16
3.2.2 JSP with setup times . . . 17
3.2.3 FJSP with parallel operations . . . 17
3.2.4 The latex ink JSP . . . 18
3.3 Solution methods for the JSP . . . 18
3.3.1 Exact algorithms . . . 18
3.3.2 Heuristics . . . 18
3.3.3 FJSP with parallel operations . . . 20
3.4 Conclusion . . . 20

4 Production planning optimization **21**
4.1 MILP model . . . 21
4.1.1 Job shop scheduling problem . . . 21
4.1.2 Model notation and assumptions . . . 22
4.1.3 Model formulation . . . 23
4.1.4 Computational results . . . 25
4.2 Heuristic approach . . . 26
4.2.1 Recipe sequencing heuristic . . . 26
4.2.2 Raw material allocation heuristic . . . 29
4.2.3 Testing the model . . . 35

5 Lot sizing **39**
5.1 Concept of lot sizing . . . 39
5.2 Costs of inventory . . . 39
5.3 Production costs . . . 41
5.4 Costs trade off . . . 42
5.5 Distribution of products per cycle . . . 43

6 Changing parameters **45**

6.1 Mixing vessels and dosing lines 45
6.1.1 Adding a dosing line 45
6.1.2 Adding a mixing vessel 46
6.2 Recipes and raw materials 47

7 Conclusions, limitations and future research 50
7.1 Conclusion 50
7.2 Recommendations 51
7.3 Discussion 52
7.3.1 Limitations 52
7.3.2 Future research 53

References 54

Appendix 57

A Production schedule 58

B Product distribution per cycle 60

List of Abbreviations

CIP	Cleaning In Place
CPP	Canon Production Printing
DAG	Direct acyclic graph
EFJSP	Extended Flexible Job Shop Scheduling Problem
EOQ	Economic order quantity
EPEx	Every Product Every x
FJSP	Flexible Job shop scheduling problem
F&P	Filling & Packing
IBC	Intermediate Bulk Container
ICA	Imperialist Competitive Algorithm
JSP	Job shop scheduling problem
MILP	Mixed Integer Linear Programming
MS string	Machine selection string
MV	Mixing vessel
no.	number
OEE	Overall equipment effect
R&D	Research & Development
RAW	Raw material
ROI	Return on investments
RQ	Research Question
WIP	Work-in-Progress

List of Figures

1.1 Visual representation of the latex ink production process 2
1.2 The dosing lines and mixing vessels in the three phases 3

2.1 Schematic model of the latex ink production process 6
2.2 Recipe portfolio 7
2.3 Graphical representation of recipe C4 8
2.4 Sample production wheel 10
2.5 Effects of reducing time between production runs on average stock level 11
2.6 Process flow of phase 3 12
2.7 Example solution for the latex ink planning problem 13

3.1 (a) A representation of a G-job. (b) A representation of a Y-job (Birgin et al., 2013) 17

4.1 Graphical representation of recipe C4 including dummy operations 21
4.2 Decomposition of the operations set into subsets 22
4.3 MILP model solution for problem instance with 4 recipes 26
4.4 Flowchart of the hybrid heuristic 26
4.5 Best objective function value found at global iteration 27
4.6 Workflow of the recipe sequencing heuristic 29
4.7 Workflow of the raw material allocation heuristic (X. Li & Gao, 2016) 30
4.8 Testing results of the iteration parameters for the tabu search heuristic for 20 different recipe sequences 31
4.9 Testing results of maxTabuSize parameter 32
4.10 Example of a MS string based on the jobs explained in Table 4.5 33
4.11 Flowchart of the generation of the initial solution for the raw material allocation heuristic 33
4.12 Application of the initial solution generation on the current set of raw materials and dosing lines 34

4.13 Results of the recipe sequencing heuristic vs a random recipe sequence 36
4.14 Results of the raw material allocation heuristic vs a random method for the same recipe sequence 37

5.1 Inventory costs vs operational costs per cycle length (in weeks) 43

A.1 Production schedule for problem instance with 22 recipes 59

List of Tables

2.1 Processing steps of recipe C4 8
2.2 Descriptive statistics of the recipe types 8
2.3 Occurrence rate of the raw materials in the total number of recipes 9
2.4 Dosing line types 9
2.5 Specification of changeover costs 14

4.1 Computational results 25
4.2 Problem instance used to calculate the congruence matrix of Table 4.3 28
4.3 Congruence matrix based on the problem instance of Table 4.2 28
4.4 Parameter values of the raw material allocation heuristic 31
4.5 Job description used to explain the MS string in Figure 4.10 32
4.6 Probabilities of destruction operators 35
4.7 Probabilities of construction operators 35
4.8 Computational results heuristic 36

5.1 Three factors of inventory costs 40
5.2 Inventory costs per cycle length 40
5.3 Number of products per cycle length 41
5.4 Production costs per cycle length 42
5.5 Inventory and production costs per cycle length 42
5.6 Products to be produced per month 44

6.1 Number of changeovers per dosing line type 45
6.2 Effects of adding dosing lines on the production costs 46
6.3 Effects of adding dosing lines on the number of changeovers per dosing line type . . 46
6.4 Production costs for the scenarios with 1, 2 and 3 mixing vessels 47
6.5 Total production capacity per year for the scenarios with 1, 2 and 3 mixing vessels 47

6.6 Demand in batches for the years 2020-2023 47
6.7 Production costs for the original problem instance versus a scenario with four new recipes 48
6.8 Effects of adding dosing lines on the number of changeovers per dosing line type for a situation with four new recipes 48
6.9 Effects of adding dosing lines on the production costs for the problem instance with four new recipes 49

Chapter 1

Introduction

This research project is related to the production planning of latex ink. Throughout this introductory chapter, the main problem is briefly introduced and the project details are presented through a description of the project goal, the research questions and the relevance from both the academic and practical perspective.

1.1 Company background

Canon Production Printing (in that time called Océ) is founded in 1877 by Lodewijk van der Grinten. The company started as a butter coloring plant. Since then, Océ grew out to be a global leader in digital imaging, industrial printing and collaborative business services (Canon Production Printing, 2020). The company is headquartered in Venlo and has several locations in Europe, Asia and Australia.

In 2010, Océ joined the Canon Group of companies with headquarters in Tokyo, Japan. Canon is a global leader in consumer and professional imaging. It develops, manufactures and markets printers, cameras, optical and other products that meet a diverse range of customer needs. In 2020, Océ changed its name to Canon Production Printing (CPP).

CPP develops, manufactures and sells printing and copying hardware and related software. It is focused on accelerating digital imaging technologies and developing high-tech printing products and services (Canon Europe, 2019). CPP is focused on printers for the corporate market. These are large printers for massive print volumes and fast, high quality results in full color or black and white. Their customers are active in markets varying from printing books to printing blueprints used in construction. Therefore, CPP delivers printers with different specifications specific for the demands of a market.

1.2 Problem context

Besides printers, CPP also provides consumables for the printers. Ink is one of these consumables. For most printers they sell, they also produce their own inks. As different printers have their specific purposes and specifications, they also use different inks. This research focuses on the latex ink. Latex ink is an eco-conscious water-based ink where pigments are dissolved by resins in water instead of using solvents.

Latex ink is a relatively new product for CPP. The ink is currently being produced in the pilot plant which has been in operation since 2016. Because more and more new generation CPP printers use latex ink, the demand is expected to grow. The pilot plant was build with the purpose to produce small volumes and test the production process. The lessons learned from the tests will be implemented in the design of the master plant. The master plant will take over production from the pilot plant when the demand exceeds the capacity of the pilot plant. The master plant is currently under construction and is expected to take over production in the summer of 2021.

There are five steps in the latex ink production process (see Figure 1.1). These steps will be explained in further detail in Chapter 2. This research focuses on the Dosing & Mixing step. In this step, liquid raw materials are dosed into a mixing vessel and are then mixed which results in latex ink. After the Dosing & Mixing step, the ink needs to be filtered to improve the quality. After filtering, cans are filled with the ink and are then packed in boxes.

Figure 1.1: Visual representation of the latex ink production process

Different kind of printers also use different kinds of latex ink. These different kind of inks have different raw materials. Each ink is produced in four different colors: cyan, magenta, yellow and black. When mixing these four colours, almost every colour can be created. Each ink with a given type and color is called a recipe. There are also liquids for cleaning and quality enhancement which are being produced in the same pilot factory. These liquids are also defined as recipes. There are currently 22 different recipes being produced in the pilot factory. As all these recipes have a different bill of material, there are currently 29 different raw materials used for the latex ink production. The Research & Development department of CPP keeps introducing new recipes with new raw materials. This means that the number of recipes and raw materials is expected to grow in the coming years.

The raw materials are dosed into the mixing vessel through dosing lines. These dosing lines ensure that exactly the right amount of raw material is dosed into the mixing vessel. Because of the high investment costs for dosing lines there are more raw materials than dosing lines. This means that multiple raw materials utilise the same dosing line. When a raw material on a dosing line needs to be switched, the dosing line needs to be cleaned. This cleaning process takes time and brings along costs. The switching of a raw material on a dosing line is called a changeover.

The master plant was planned to completely take over the production of the pilot plant. Due to cut investment budget, the master plant is being built in phases (see Figure 1.2). The first phase is the current situation. In this phase the latex ink is produced in the pilot plant. The pilot plant has a set of dosing lines and one mixing vessel. In phase 2 the latex ink will be produced simultaneously in the pilot plant and the master plant. Phase 2 is expected to start in 2021. Only part of the initially planned mixing vessels and dosing lines for the master plant will be installed in this phase. As a result, the pilot and master plant will both have to be in operation to meet the demand. In this phase there are two separate plants which means that there are also two separate sets of dosing lines and two separate mixing vessels. In phase 3, more equipment will be installed in the master plant to increase the capacity enough to meet the demand. This phase is expected to start in 2023. When the master plant can handle the demand, the production in the pilot plant can be shut down. The capacity will be increased by adding (a) mixing vessel(s) and dosing lines. This means that there will be only one set of dosing lines which is utilised by two or more mixing vessels. Because phase 2 is only a temporary situation, the focus of this research is on phase 3.

The current production planning divides the total demand into so called production cycles. Every recipe is produced at least once in a cycle. The decision to be made is how many batches of each recipe will be produced in a cycle. Taking changeover costs into consideration, it is more

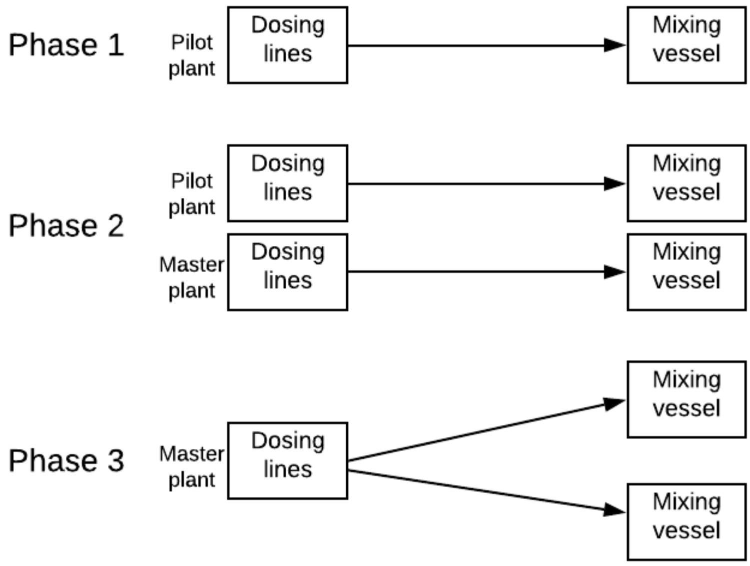


Figure 1.2: The dosing lines and mixing vessels in the three phases

cost efficient to produce as many batches of one recipe as possible in one cycle as it minimizes the amount of changeovers. However, this affects the end product inventory. If the length of the production cycle is longer, there is more time between two replenishments. This means that inventory needs to be higher to cover this time. There are however costs tied to inventory (see chapter 2 for a detailed description of the inventory costs). If inventory increases, the inventory costs will also increase. Therefore a trade off has to be made between the changeover costs and the inventory costs to determine the length of the production cycle.

The current production planning works on the principle of a fixed sequence (see Chapter 2 for a more elaborate description). Because there is only one mixing vessel, there is no conflict within the set of dosing lines. The transition from one to two or more mixing vessels causes that the mixing vessels use the same set of dosing lines. This could cause a conflict between the two mixing vessels if both mixing vessels need to use the same dosing line simultaneously. This means that the current way of production planning is not longer possible in the new situation. Therefore, a new way of making the production planning needs to be investigated. This and the fact that a trade off between the changeover costs and the inventory costs has to be made, makes the production planning a challenge.

The R&D department of CPP is constantly doing research on improving the quality of the inks. As a result, the number of recipes will increase in the future. With the number of recipes increasing, the number of raw materials will also increase. There are currently 22 recipes being produced in the pilot plant by using 37 raw materials. The expectation is that the number of recipes will grow to 45 in 2021 and the number of raw materials will grow to 50. This will make the production planning more complex as the number of possible allocations of raw materials to dosing lines will increase.

1.3 Research objective

The aim of this research is to develop a method for determining a cost efficient production planning for the latex ink. This production planning consists out of two elements. First the length of the production cycle needs to be determined. The second element is a decision support tool for the sequencing of the recipes within the production cycle. The model will also allocate the raw materials to the dosing lines in order to minimize the operational costs.

1.4 Research questions

To reach the objective of this research, the following main research question has been formulated:

"What is the optimal production planning for the latex ink that minimizes operational costs and end product inventory?"

To answer this question fully, the main research question is divided into several sub research questions:

1. *What does the production environment look like for phase 1 and 3?*

   The first step is to map the production environment. The steps in the latex ink production process are defined and the current production planning is explained. Factors which could have an influence on the ink processing and thus the planning of the ink processing will be analysed. The difference between phase 1 and 3 concerning the production planning will be highlighted and the parameters of the production scheduling problem for phase 3 are described in detail.

2. *How can the production planning be optimized for phase 3?*

   After the current situation is clearly described, a literature review will be performed on production scheduling. The theoretical problem has to be adjusted to be applicable to the latex ink processing scheduling problem. Furthermore, several methods for solving the problem will be compared to investigate which one will solve the problem the best. After the right model and solution method are chosen, the model will be build in Python.

3. *What is the optimal production cycle?*

   The optimal length of the production cycle will be determined regarding inventory holding costs and production costs. Because of demand variations among different recipes, not all production cycles will be the same. It is possible that a recipe only occurs once every four cycles. An optimal distribution of the products into cycles has to be found.

4. *What is the effect on the production planning if a mixing vessel or dosing line is added to the model?*

   When the model of question 2 has been developed, an analysis will be performed on the effects of adding or removing a mixing vessel or dosing lines. The effects of these changes on the operational costs will be compared to the costs of adding or removing a mixing vessel or dosing line. Also the effect on the capacity will be analysed. An advice will be given on whether or not dosing lines and / or mixing vessels should be added or removed in order to increase operational efficiency.

5. *What is the effect on the production planning if raw materials and recipes are added to the model?*

   The model of question 2 will be used to test the effects of future expansion of the product range. New recipes bring along new raw materials. The effects of adding these to the model will be analysed to see what the effects are in the future.

1.5 Project scope

To narrow down the scope of this research project, several restrictions are used. This research focuses only on the Dosing & Mixing step of the latex ink production process (see Figure 1.1). All other steps will be out of scope. This also means that we assume that there are always enough raw materials on stock to start the processing of the ink. Furthermore, the scope of this research is narrowed down to phase 3 described in Figure 1.2. Phase 1 is the current phase and phase 2 will be a temporary phase. These two phases will therefore be out of scope.

1.6 Project relevance

This project involves two stakeholders: Eindhoven University of Technology (TU/e) and Canon Production Printing. The relevance for both parties is hereafter described in further detail.

1.6.1 Scientific relevance

This research project aims to contribute academically by performing a case study on how to implement the job shop scheduling model in practice. The model optimizes recipe sequencing on two or more mixing vessels with an allocation of raw materials to dosing lines. Factors taken into account are the flexibility of raw materials on dosing lines, sequence dependent setup times and minimizing operational costs. Furthermore, a MILP model and a hybrid heuristic will be compared to address the NP-hard nature of the job shop scheduling problem.

1.6.2 Practical relevance

There are two practical objectives to be reached. The first objective is to minimize the operational costs concerned with the production of the latex ink. The operational costs consist out of changeover costs and operator costs (labour costs). Currently the production of the latex ink is scheduled using gut feeling. This research will result in a decision support tool which replaces the gut feeling with logic and minimizes the production costs.

The second objective is to optimize the production cycle length to reduce the end product stock. A trade off between production costs and inventory holding costs has to be made.

1.7 Confidentiality

For confidentiality reasons, exact information regarding costs, demand data, recipes and raw materials have been modified in this public version of the report. These modifications do not affect the conclusions and recommendations provided in this report.

1.8 Thesis outline

The remainder of this report is structured as follows. In Chapter 2, the production environment of the latex ink is described in detail. Chapter 3 presents a brief overview of relevant literature regarding production scheduling. In Chapter 4, a MILP model and a hybrid heuristic approach are proposed to solve the latex ink production scheduling problem. Chapter 5 addresses the lot-sizing problem related to the production cycle length. An analyses of the effect of adding or removing mixing vessels, dosing lines, recipes, and raw materials is presented in Chapter 6. Finally, the conclusions, recommendations and suggestions for further research are provided in Chapter 7.

Chapter 2

Production and scheduling process

2.1 Production process

As explained in Chapter 1 the production process of latex ink consists out of five steps. A detailed schematic view of the entire production process of the latex ink can be found in Figure 2.1. This figure shows the current production process with only one mixing vessel in the pilot plant.

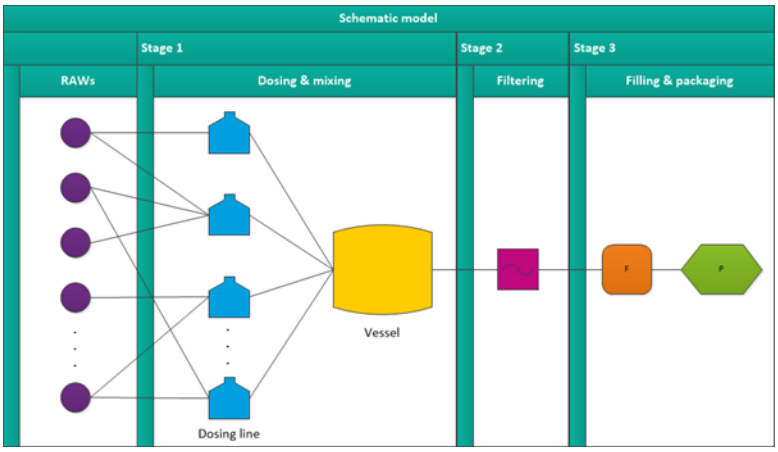


Figure 2.1: Schematic model of the latex ink production process

CPP uses different raw materials from all over the world. To guarantee good quality CPP only uses raw materials of the best quality. Some raw materials must first be preprocessed before they can be used in production. There are two different preprocesses. A certain type of raw material is delivered to CPP in powders. These powders cannot be dosed in the dosing lines. Therefore, the powders will first be dissolved in water before they can be used in production. The second preprocess is filtering a specific raw material. These raw materials are delivered in liquids but are not yet of the right quality. The liquids first have to be filtered before they can be used in production.

After preprocessing the raw materials go to the pilot plant where they can be used in production. In the pilot plant there is a room where the raw materials are connected to the dosing lines. The dosing lines are connected to the mixing vessel. The dosing lines dose the raw materials in the right amounts and in the right sequence to the mixing vessel. The sequence of the raw materials is very important in this process. The raw materials are added while being stirred in the mixing vessel. The mixing time of the ink varies per recipe. This process is called Dosing & Mixing and will hereafter be referred to as "processing". If a batch is finished, the mixing vessel will be cleaned and the ink will be stored in Intermediate Bulk Containers (IBCs). The batches are always the same size (full mixing vessel). This is considered Work-in-Progress (WIP) stock. The IBCs then go the Filling & Packing (F&P) room.

Before the filling process begins, the ink is filtered to remove impurities. After filtering the ink is filled in 5 or 9.5 kg cans depending on the ink type. These cans are then packed in boxes and stacked on pallets. This happened manually before the introduction of a fully automated Filling & Packing line by the end of 2019. This new F&P line is located in the master plant. Before the introduction of the fully automated F&P line, the F&P line was the bottleneck. Now the new F&P line is in operation, the processing of the ink is the bottleneck. The pallets with the end products are shipped to the logistic service provider Seacon. Seacon provides the distribution of the end products to the customers.

2.2 Production environment

2.2.1 Recipes and raw materials

As mentioned in Chapter 1, CPP currently produces 16 ink recipes and 6 primer recipes which brings the total number of recipes to 22. The total recipe portfolio can be found in Figure 2.2. For confidentiality reasons, the names of the ink types are replaced with the numbers 4 through 7. The letters C, M, Y and K correspond to the colors cyan, magenta, yellow and key (black).

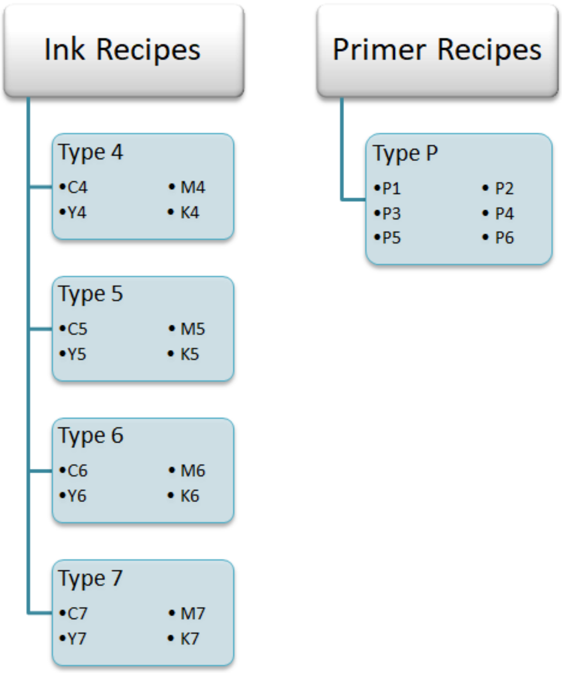


Figure 2.2: Recipe portfolio

A recipe consists out of several steps. In each step one or more raw materials are dosed into the mixing vessel via the dosing lines. In most cases, the recipe has to be mixed inside the mixing vessels between two steps but that is not always the case. The mixing inside the mixing vessel is also considered as a processing step. To give insight in how a recipe is build up, an example is shown in Table 2.1. In Figure 2.3 a graphical representation from the same recipe is shown to clarify the precedence constraint.

Operation	Step	RAW	Duration (minutes)
1	1	RAW1	21
2	1	RAW2	17
3	2	RAW3	7
4	3	MIX	3
5	4	RAW4	18
6	4	RAW5	24
7	4	RAW6	36
8	4	RAW7	35
9	4	RAW8	46
10	5	MIX	3
11	6	RAW9	20
12	7	MIX	5
13	8	RAW10	21
14	9	MIX	5

Table 2.1: Processing steps of recipe C4

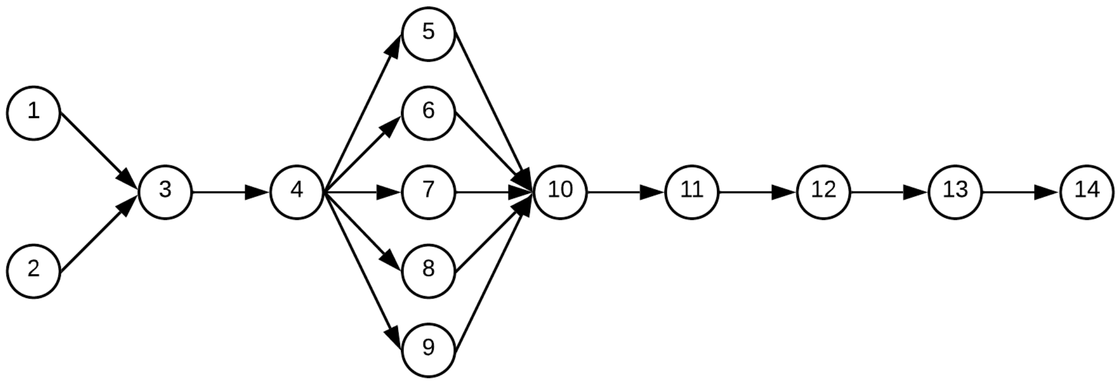


Figure 2.3: Graphical representation of recipe C4
The numbers correspond to the operation numbers in Table 2.1

The recipe types differ in the number of raw materials, the processing times and the number of processing steps. Table 2.2 gives an overview of these characteristics per recipe type.

Recipes	Average no. RAWs	Average minimum processing time (minutes)	Average no. processing steps
Type 4	10	136,25	10
Type 5	10,5	181,75	15
Type 6	9,5	217,25	15,5
Type 7	12	163,75	13
Primers	5	153	7,83

Table 2.2: Descriptive statistics of the recipe types

The 22 recipes are composed of a total of 29 different raw materials. Some of these raw materials are used in almost every recipe while other raw materials are used in only a few recipes (as shown in Table 2.3). From Table 2.3 can be concluded that four raw materials are used in almost all recipes while 17 raw materials are only used in less than 20% of the recipes. The four raw materials which are used in almost every recipe all have their own dedicated dosing line.

No. RAWs	Occurrence rate
4	80% - 100%
8	20% - 80%
17	0% - 20%

Table 2.3: Occurrence rate of the raw materials in the total number of recipes

Because latex ink is a water based ink, the main ingredient is demineralised water (demiwater). Demineralised water is water of which the minerals or salts are removed. Demiwater is used in every recipe and therefore belongs to the four raw materials having their own dedicated dosing line. Demiwater is also used to clean dosing lines and mixing vessels. This will be described in the next section.

2.2.2 Dosing lines

As mentioned in Chapter 1 the raw materials are dosed into the mixing vessels using dosing lines. The dosing lines make sure that exactly the right amount of raw material is added to the mixing vessel. Because of the chemical characteristics of the raw materials, not every dosing line can handle every raw material. Based on these chemical characteristics and the occurrence rate of the raw materials, CPP decided to install 18 dosing lines in the new master plant. The dosing lines are divided into different types and every type can handle specific raw materials. Table 2.4 shows the dosing line types and how many raw materials can be handled by a specific type. Dosing line type D is a special case. Type D1 can facilitate 8 raw materials. Type D2 can handle the same 8 raw materials as type D1 plus an extra raw material. Dosing line type D3 can facilitate the same 8 raw materials as type D1 plus two extra raw materials. Dosing line types A, B and C are dedicated dosing lines. These dosing lines can only facilitate one raw material either because of the chemical characteristics of the raw material or because of the high occurrence rate. There is also a dosing line which can only facilitate the dosing of demiwater.

Dosing line type	number of dosing lines	number of RAWs
A	1	1
B	1	1
C	1	1
D1	3	8
D2	1	9
D3	2	10
E	1	1
F	4	14
G	4	12
DEMI	1	1

Table 2.4: Dosing line types

When a dosing line needs to switch from one raw material to another, the dosing line has to be cleaned. This is called a changeover. There are two types of changeovers. A hard changeover occurs when processing stops in order to clean the dosing line (downtime). A soft changeover occurs when the dosing line can be cleaned during processing. This happens when the process does not have to be stopped in order to clean the dosing line.

For some raw materials, cleaning the dosing line with demiwater is good enough. For other raw materials cleaning with only demiwater is not enough. The dosing lines are then cleaned with a combination of demiwater and detergents. This process takes more time and brings along more costs than cleaning with only demiwater. More information about the changeover costs can be found in Section 2.4.

2.2.3 Mixing vessels

The current pilot plant uses only one mixing vessel in the production of latex ink. The new master plant will have two mixing vessels. If the demand for latex ink will keep growing, there is also the possibility to install a third and fourth mixing vessel. The dosing lines can only dose a raw material into one mixing vessel at a time. So if a specific raw material needs to be dosed into two mixing vessels simultaneously, either one mixing vessel has to wait until the other mixing vessel is finished or the raw material needs to be connected to two dosing lines.

When a mixing vessel is finished with the processing of a recipe, the mixing vessel needs to be cleaned. This will take approximately half an hour. There is one exception when the mixing vessel does not have to be cleaned. This is when the mixing vessel will process two identical recipes successively.

2.3 Production planning

The production of the latex ink is currently being scheduled by using the so called production wheel. The production wheel is a sequence of recipes. The ink production must always be performed in this sequence. For every cycle of the wheel, the number of batches per recipe can be different as long as the sequence stays the same. A sample production wheel can be found in Figure 2.4. The production wheel has been created with two purposes: minimizing stock and minimizing changeovers. Before the production wheel was used, the production planning was done manually. The logistics department would send an order with the amounts of ink they wanted and then the production planner would start planning. This resulted in a high amount of batches per recipe in a row because the planner wanted to minimize changeovers. As a result, the end product stock was very high. To save costs on inventory, CPP decided to apply an Every Product Every x (EPEx) policy. This means that every product is produced at least once in a period of x. CPP produced every product on average every 8 weeks. They want to go to every product every week (EPEW) to minimize stocks.

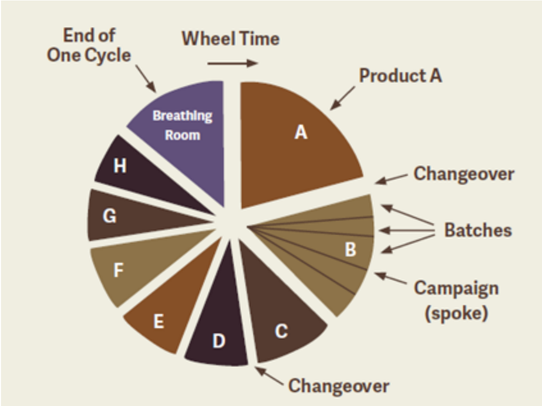


Figure 2.4: Sample production wheel

The stock consists out of a safety stock and a part which covers the time between two production runs. If every product is produced in a shorter time period, the part which covers the time between two production runs will be smaller. This results in a reduction of the average stock level and therefore a reduction of the costs associated with stock. The effects of reducing the time between production runs on the average stock level can be seen in Figure 2.5. Here can be seen that the average stock drops when reducing the time between production runs from 8 to 4 weeks.

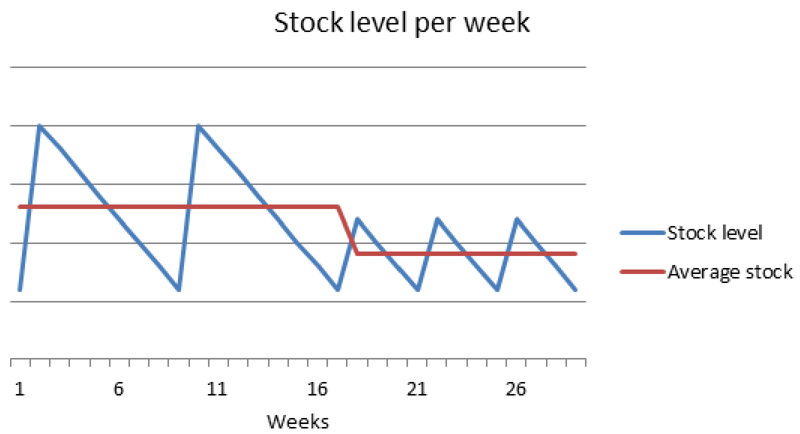


Figure 2.5: Effects of reducing time between production runs on average stock level

Producing every product more frequent decreases the end product stock but it increases the number of changeovers in production. This is because the number of changeovers are fixed within one production cycle because of the fixed sequence. This means that changeover costs will increase when the production cycle is shortened while the stock costs decrease. Therefore a trade off has to be made to find the optimal cycle length which minimizes the total costs.

Manual planning is difficult because there are too many variables. Therefore a model has been built to minimize the number of changeovers (Athanasiadou, 2018). This model has been modified by CPP employee Emiel van de Rijt. The output of this model is a sequence. This sequence is the production wheel that is now used in practice. This sequence minimizes the number of changeovers in ink processing.

If every ink will be processed once, the optimal production wheel sequence has a duration of approximately two weeks. Because the demands of different inks vary, the production wheel needs to be flexible. There must be a possibility to produce multiple batches of a single ink within a cycle of the production wheel. To provide this flexibility, one cycle of the production wheel is determined to last a maximum of three weeks. This will create flexibility but will also keep stock to a minimum. All batches that will be produced are always the same size (full mixing vessel). Approximately a total of 51 batches can be produced in three weeks (17 per week). The logistics department has the freedom to vary the number of batches per ink per production wheel cycle as long as every product will be produced at least once and the total number of batches will not exceed 51. The implementation of the production wheel has caused a transition from an Every Product Every 8 Weeks (EPE8W) situation to an Every Product Every 3 Weeks (EPE3W) situation.

2.3.1 Production with multiple mixing vessels

The current production wheel model is only applicable for the situation with one set of dosing lines and one mixing vessel (phase 1). In phase 2 there are two sets of dosing lines each connected with one mixing vessel. The current production wheel model could be used in this situation if the recipes are allocated to a specific plant. Then the problem could be solved by using the model for both plants. Phase 3 is a very different situation compared to phase 1 and 2. In phase 3 there is one set of dosing lines connected to two (or more) mixing vessels. Working with sequences will then cause a problem as each recipe has a different processing time. It could then happen that one mixing vessel is finished processing a batch and can continue with the next one while the other mixing vessel is still processing. Then the first mixing vessel cannot use a dosing line which is utilised by the second mixing vessel. This means that the concept of a fixed production wheel is not optimal anymore because variation in the number of batches will cause problems.

Because phase 3 is the focus of this research, the process flow of this phase has been visualized in Figure 2.6. The dosing lines are not occupied for the whole process time of a recipe. The raw materials are dosed into the mixing vessel in a specific sequence. Therefore, a dosing line can be used on a different mixing vessel if the dosing for the first mixing vessel is already done but the mixing vessel is still mixing that batch. After some steps mixing needs to happen before the next raw material can be dosed.

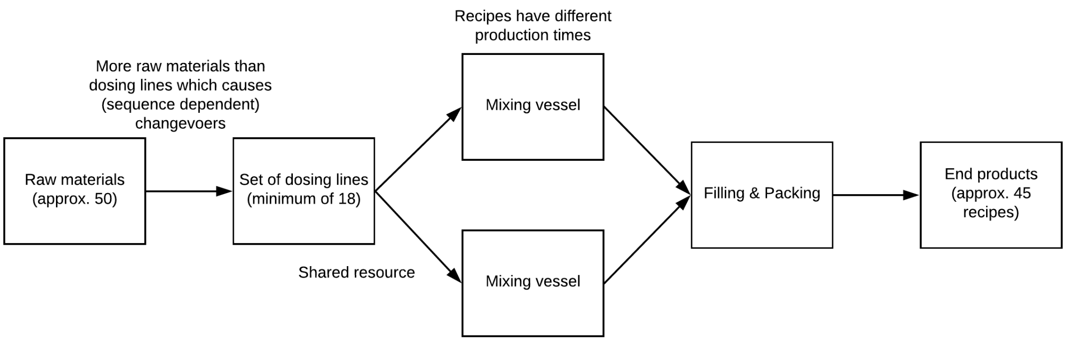


Figure 2.6: Process flow of phase 3

There are a number of decisions to be made to come to a solution for the planning problem. First of all the sequencing of the recipes on the mixing vessels needs to be decided. Another decision to be made is which dosing line will dose the raw materials at what time. In Figure 2.7 an example solution can be found. This example solution contains six dosing lines, two mixing vessels, 11 raw materials and four recipes. The figure shows a visualization of the solution. The solution shows which recipe is processed when and which dosing lines dose the raw materials. A recipe cannot be interrupted by another recipe because a recipe in a mixing vessel needs to be finished before another recipe can start. There are a maximum of two recipes being processed simultaneously. This is because there are only two mixing vessels in this example.

When producing ink in two mixing vessels simultaneously, it can happen that one vessel has to wait until a dosing line is available during production. The effect of this waiting time on the ink is not yet known. Because the current production environment has only one mixing vessel, this effect has not yet been tested. However, it is expected that the waiting time does not affect the quality of the ink.

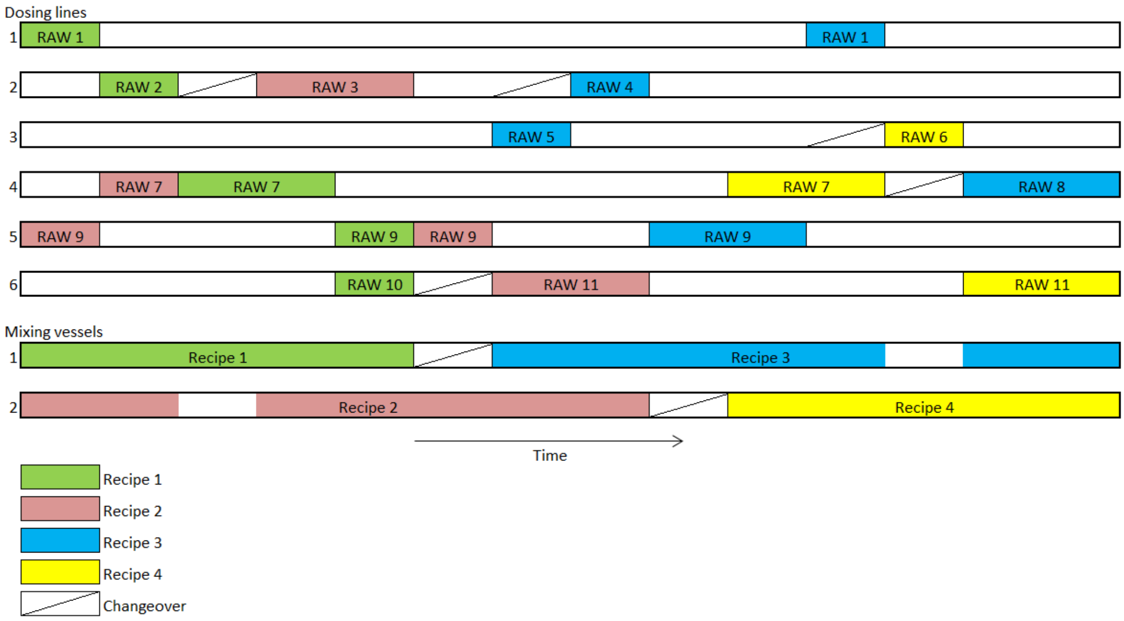


Figure 2.7: Example solution for the latex ink planning problem

2.3.2 Additional requirements

The proposed decision support model should meet the following additional requirements:

- The model should be easy to use for the operators. They only have to set the recipe frequencies per production cycle as input and get a production schedule as output solution.
- The model should be robust. This means that it should be easy to add or remove dosing lines, recipes, raw materials and mixing vessels. This is necessary to see the effect of future changes on the production planning. At the end of this project, the model will be transferred to the Production Engineering department of CPP. Therefore, the model should be easy to use, understand and transfer.

2.4 Production costs

There are two costs associated with the production of the latex ink:

- Labour costs
- Changeover costs

There are currently working three operators per shift on the production of the latex ink. An assumption has been made that the number of operators per shift in phase 3 is also three. The labour costs are determined by the number of hours worked by the operators. To determine the labour costs, the total length of the production cycle is multiplied by the number of operators to get the total number of hours worked by the operators. These hours are then multiplied by the labour cost per hour to get the total labour costs. For confidentiality reasons, the labour cost per hour is not stated in this public version of the report.

The latex ink department currently works with three shifts. One morning shift, one afternoon shift and one night shift. This means that there are 112 production hours per week. There is also a possibility to shift to different shift systems. The two shift system has 80 production hours per week. The labour costs per hour are higher for the three shift system than for the two shift system. This means that the labour cost per hour depend on the shift system. Due to time constraints, the dependence of the labour costs on the shift system is not taken into account when calculating the labour costs in this research. However, this is something to consider for future research (see Chapter 7).

There are several costs associated with changeovers: demiwater costs, detergent costs, wastewater costs, and costs of disposing raw material. As explained earlier in this chapter, there are two ways of cleaning a dosing line. A dosing line can be cleaned with only demiwater or a dosing line must be cleaned with a combination of demiwater and detergents. When a dosing line has to be cleaned with detergents it is called Cleaning In Place (CIP). Therefore, the detergents will be referred to as CIP in this report.

The demiwater and the detergents that are used for cleaning the dosing lines generate costs. Furthermore, cleaning dosing lines generates wastewater. There are costs tied to the disposal of wastewater (Waste 950). A fourth cost tied to changeovers is the waste of raw material. The raw material which is still in the dosing line has to be disposed (Waste OO). Because of the chemical composition of the raw materials, the costs of disposal are higher than the costs of disposing wastewater. A specification of the changeover costs can be found in Table 2.5.

		Changeover with CIP	Changeover only DEMI
DEMI	Liters	175	100
	Cost per KG	€ 0.02	€ 0.02
	Costs	€ 3.50	€ 2.00
CIP	Liters	45	0
	Cost per KG	€ 0.05	€ 0.05
	Costs	€ 2.25	€ 0
Waste 950	Liters	120	45
	Cost per KG	€ 0.35	€ 0.35
	Costs	€ 42.00	€ 15.75
Waste OO	Liters	3	3
	Cost per KG	€ 0.70	€ 0.70
	Costs	€ 2.10	€ 2.10
Total	Costs	€ 49.85	€ 19.85

Table 2.5: Specification of changeover costs

Chapter 3

Literature

The aim of this chapter is to provide a brief overview regarding the existing literature in production scheduling. Different types and variations within the field of production scheduling are investigated to find the variations which can be applied to the latex ink production scheduling problem. Thereafter, several solution techniques for solving the production scheduling problem are explored.

3.1 Production scheduling

Before diving directly into types and variations of production scheduling that can be applied to the latex ink production scheduling problem, the concept of production scheduling needs to be introduced. During the last decades, a lot of research has been performed on scheduling problems. Johnson (1954) was one of the first to address the scheduling problem. He introduced a problem where a collection of items are to be produced on two machines. Each machine can handle only one item at a time and each item must be processed through the first machine and then through the second machine.

In the years that followed, research on production scheduling expanded and different types and variations were investigated. According to Graves (1981), production scheduling can be defined as the allocation of available production resources over time to best satisfy some set of criteria. Rodammer and White (1988) state that production scheduling concerns the efficient allocation of resources over time for the manufacture of goods. Whenever a common set of resources (labor, materials, and equipment) must be used to make a variety of different products during the same period of time, scheduling problems arise. The objective of scheduling is to find a way to assign and sequence the use of these shared resources such that production constraints are satisfied and production costs are minimized.

From these two definitions can be concluded that the main concept of production scheduling is to allocate resources over time to best satisfy some set of criteria. There are many types and variations of production scheduling which are all based on this main concept.

Graves (1981) introduced a classification scheme for production scheduling problems. The classification scheme categorizes the production scheduling problems using five dimensions: requirements generation, processing complexity, scheduling criteria, nature of the requirement specification (parameter variability) and scheduling environment. J. Zhang, Ding, Zou, Qin and Fu (2017) added two dimensions to this classification based on the work of Lin, Hao, Gen and Jo (2012). These dimensions are the plant characteristics and resource constraints.

This classification scheme is used to describe the latex ink production scheduling problem. For the latex ink, all orders are being serviced from inventory. This means that all production orders are a result of replenishment decisions. Therefore this is a closed shop production scheduling problem. Because there are multiple machines in this problem and every product has a unique precedence ordering, the latex ink problem is a job shop scheduling problem. The focus lies on reducing the production costs. To reduce the complexity of the problem, it has been decided that all parameters are deterministic and there is a static environment. The latex ink production problem has only one plant and there is only one resource (the dosing lines) at a time needed for the production.

3.2 Job shop scheduling

As mentioned in Section 3.1 the latex ink production scheduling problem is a job shop scheduling problem (JSP). In this chapter the definition of job shop scheduling is given and different types of job shop scheduling problems are highlighted.

In a classical job shop scheduling problem, n jobs $J_1, ..., J_n$ have to be processed on m machines $M_1, ..., M_m$. Job J_i consists out of n_i operations $O_{i1}, ..., O_{in_i}$ which have to be processed in this order. At any time each machine can process at most one operation, and for each operation O_{ij} a processing time $p_{ij} > 0$ and a machine μ_{ij}, on which operation O_{ij} must be processed, are known in advance (Brucker & Neyer, 1998). Pre-emption is not permitted, which means that the processing of an operation cannot be interrupted and removed before the processing is completed. The decisions to be made are the sequencing of the operations on each one of the machines. For the latex ink scheduling problem, the recipes which have to be processed can be compared to the jobs of the JSP. Each recipe consists out of a number of raw materials which have to be dosed into the mixing vessel. These dosing of the raw materials are the operations of each job. The operations of a job have to be performed on machines. These machines are the dosing lines in this case. The classical JSP cannot be applied on the latex ink problem without some necessary adjustments. The ink production planning problem is more complicated than the classical JSP. The most common types and variation of the JSP are elaborated in this section.

3.2.1 The flexible JSP

In the industry there are many complex manufacturing systems. This resulted for research to expand the focus to different applications of the JSP. Brucker and Schlie (1990) were the first to address the JSP with multi-purpose machines. This problem became later known as the flexible job shop scheduling problem (FJSP). The FJSP is a generalization of the classical JSP in which a set of machines is associated with each operation of a job. The operation can be processed on any of the machines in this set. The FJSP consists out of a routing sub problem and a scheduling sub problem. The routing sub problem is allocating each operation to a machine. The scheduling sub problem is the sequencing of the operations on each machines. There are two approaches available to solve this problem. The hierarchical approach solves these two sub problems separately to reduce complexity. The concurrent (or integrated) approach solves these problems simultaneously (Brandimarte, 1993).

Recent research has focused mainly on solution techniques for solving the NP-hard JSP. Chaudhry and Khan (2015) and Xie, Gao, Peng, Li and Li (2019) provided reviews on flexible job shop scheduling which focuses mainly on the many existing solution methods for the problem in the recent literature.

3.2.2 JSP with setup times

Setup time is the time which is required to prepare the necessary resources such as machines to perform a task. A setup operation often occurs while shifting from one operation to another. In practical situations this often means that required machine tools have to be changed, work in process materials have to be positioned, machines have to be cleaned or materials need to be inspected.

Several researchers have provided comprehensive reviews of the literature on job shop scheduling with setup times (Allahverdi, Ng, Cheng & Kovalyov, 2008; Sharma & Jain, 2015). They classify setup time into two categories: sequence-independent setup time and sequence-dependent setup time. Sequence-independent setup time depends solely on the current task regardless of its previous task. Sequence-dependent setup time depends on both the current and the preceding task. This means that a setup time occurs when changing from one specific task to another specific task. Furthermore, setup times can occur in two modes: non-batch (job) setup times and batch setup times. Non-batch (job) setup times occur when shifting from one job to another. Batch setup times occur when job types are grouped into batches and setup time is incurred while shifting from one batch to another.

Sharma and Jain (2015) claim that there is a growing interest among researchers in the field of job shop scheduling with setup times. Most research is focused on job shop scheduling with sequence-dependent non-batch (job) setup times because this type occurs most in the industry. Özgüven, Yavuz and Özbakir (2012) make a distinction between separable and non-separable setup times. In the non-separable approach the setup times are included in the processing times. In the separable approach the setups can be performed when the previous operation is still in process.

3.2.3 FJSP with parallel operations

Birgin et al. (2013) introduced the concept of a flexible JSP with parallel operations. This type of problem is also referred to as the extended flexible job shop scheduling problem (EFJSP) by Lunardi and Voos (2018) or the flexible JSP with sequencing flexibility (Birgin, Ferreira & Ronconi, 2015). In the classical JSP, each job consists of a sequence of operations to be processed in a given order (so called path-jobs). However, in the industry it is common to have jobs with operations that can be performed simultaneously. Mutually independent sequences of operations may feed into an “assembling” operation. Similarly, there may be “disassembling” operations which split the sequences of subsequent operations into two or more mutually independent sequences. A job may consist of two independent sequences of operations followed an assembling operation connecting to a third sequence. This is called a Y-job (see Figure 3.1(b)). Figure 3.1(a) represents a more general type of job (so called G-job). In Figure 3.1 each node represents an operation. The arcs represent precedence constraints and all arcs are directed from left to right. The black nodes are assembling operations and the gray nodes are disassembling operations.

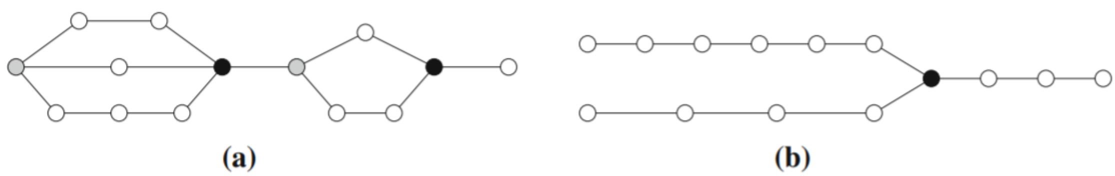


Figure 3.1: (a) A representation of a G-job. (b) A representation of a Y-job (Birgin et al., 2013)

3.2.4 The latex ink JSP

The latex ink production scheduling problem is a practical problem for which multiple JSP variations are applicable. Because the raw materials (operations) can be dosed into the mixing vessel by more than one dosing line (machine), this is a flexible JSP. A choice has to be made for each operation to which machine it will be allocated before the operation sequencing problem can be solved.

The JSP with setup times is also applicable to the problem. When there is a changeover of raw materials on a dosing line, it takes time to clean the dosing line. These are the setup times. The costs incurred with a changeover are the setup costs.

The order of the operations is a fixed sequence in in the latex ink problem. There it is not an advanced JSP. However, the fixed order jobs are not path-jobs. There are operations which can be processed simultaneously. Therefore it is a FJSP with parallel operation. This means that the latex ink production scheduling problem is a flexible JSP with setup times and parallel operations.

3.3 Solution methods for the JSP

The JSP is a very computationally intractable combinatorial problem (Arisha, Young & El Baradie, 2001). Garey, Johnson and Sethi (1976) proved that the classical JSP is NP-complete for every problems with more than two machines and that the flexible JSP is NP-hard. A small example with 10 jobs and 10 machines was posed by Muth and Thompson (1963). This problem remained open for more than 15 years until it was solved by Carlier and Pinson (1989). According to Hoitomt, Luh and Pattipati (1993) the JSP has a maximum of $(n!)^m$ different solutions to a problem instance, where n is the number of jobs and m is the number of machines. This means the JSP can only be solved with exact methods for very small instances. For larger instances, heuristics have to be applied to come to a solution within reasonable computation time.

Since Brucker and Schlie (1990) introduced the flexible JSP in 1990, many different methods and algorithms have been developed to solve this problem. Many research surveys focusing on flexible job shop scheduling techniques have been provided (Chaudhry & Khan, 2015; Jones, Rabelo & Sharawi, 1999; Türkyılmaz, Senvar, Ünal & Bulkan, 2020; Xie et al., 2019; J. Zhang et al., 2017). The solution methods can be divided into two groups: exact algorithms and heuristics.

3.3.1 Exact algorithms

Due to the NP-hard nature of the FJSP problem, exact approaches such as mathematical programming typically only find optimal solutions for small size problems within reasonable time (Birgin et al., 2013; Gomes, 2013; Mousakhani, 2013; Özgüven, Yavuz & Özbakir, 2010, 2012; Roshanaei, Azab & ElMaraghy, 2013). Most exact algorithms are formulated by integer linear programming (ILP) or mixed integer linear programming (MILP) models. An integer linear programming model is a mathematical optimization program in which some or all of the variables are restricted to integers.

3.3.2 Heuristics

Over the last decades, a lot of research has been conducted on solving the FJSP using a wide variety of heuristics. Chaudhry and Khan (2015) published a review of 192 journal articles on flexible job shop scheduling. They found that most papers used Hybrid Algorithms (35%), Evolutionary Algorithms (24%), Tabu Search (6%) and Integer Linear Programming (5%) were the most commonly studied techniques for solving the FJSP.

Evolutionary Algorithms

Evolutionary algorithms generally involve techniques inspired by biological evolution, such as reproduction, mutation, recombination and selection (Chaudhry & Khan, 2015). An evolutionary algorithm generally starts with an initial population. This population consists out of several candidate solutions (or individuals). A population is therefore a collection of solutions. After the initial population has been generated, the evolutionary algorithm repeats a number of steps until a certain termination criterion has been satisfied. The quality of the individuals in the population is determined by a fitness function. The fittest individuals are selected for reproduction. They are called the parents. These parents breed new individuals through crossover and mutation operations to give birth to the offspring. The new individuals are evaluated and least-fit individuals of the population are replaced with with new individuals. Evolutionary Algorithms are popular amongst researchers for solving the FJSP (De Giovanni & Pezzella, 2010; Lu, Wu, Tan, Peng & Chen, 2018; Moradi, Ghomi & Zandieh, 2011; Piroozfard, Wong & Wong, 2018; G. Zhang, Gao & Shi, 2011; G. Zhang, Zhang, Song, Wang & Zhou, 2019).

Tabu search

Tabu search is a meta-heuristic method originally proposed by Glover (1986). It has been successfully applied in various combinatorial optimization problems including several scheduling problems and has emerged as one of the most efficient local search strategies for scheduling problems. Tabu search allows the searching process to explore solutions with a worse objective function value, given that these solution are not declared tabu (forbidden). Tabu search keeps track of the most recent found solution and looks for a new solution in the neighborhood structure which is not tabu.

Brandimarte (1993) was the first to apply tabu search in solving the flexible job shop scheduling problem. He split the FJSP in a a routing and a job shop scheduling subproblem. Both problems are tackled by tabu search. Hurink, Jurisch and Thole (1994) and Mastrolilli and Gambardella (2000) published further research in the application of tabu search on job shop scheduling problems. More recent research has been performed by Vilcot and Billaut (2011) and Jia and Hu (2014). However in most recent publications, tabu search is applied as local search heuristic in hybrid algorithms.

Hybrid Algorithms

Hybrid solution techniques have become more popular amongst researchers as compared to pure heuristics and meta-heuristics (Karthikeyan, Asokan, Nickolas & Page, 2015; J. Q. Li, Pan & Tasgetiren, 2014; X. Li & Gao, 2016; Z. C. Li, Qian, Hu, Chang & Yang, 2019; Moslehi & Mahnam, 2011; Shao, Liu, Liu & Zhang, 2013; Yuan, Xu & Yang, 2013). A hybrid technique combines multiple heuristics or meta-heuristics to take advantage of the strengths of each (meta-)heuristic. In most research publications, a global search heuristic and a local search heuristic are combined. The strength of a global search heuristic is to make big jumps within the solution space while a local search heuristic is strong in finding local optima. By combining these two, the chance of getting closer to the global optimum increases.

3.3.3 FJSP with parallel operations

The flexible JSP with parallel operations has been less popular amongst researchers. However, there are several papers published by a small group of researchers on this topic.

Birgin et al. (2013) proposed a MILP which proved to be very better than an extended version of the MILP model proposed by Özgüven et al. (2010). However, the MILP model can only solve small instances in reasonable time. Birgin et al. (2013) also created instances for the FJSP with parallel operations which were later used by several researchers to compare the quality of heuristic solution methods. Birgin et al. (2015) tried to solve the problem using a beam search method. Lunardi and Voos (2018) compared the Genetic Algorithm with a Firefly Algorithm and found that the Firefly Algorithm achieved better results when tested on the instanced created by Birgin et al. (2013). Lunardi, Voos and Cherri (2018a) proposed a new MILP and applied the Firefly Algorithm on the FJSP with parallel operation and availability constraints.

Lunardi, Voos and Cherri (2018b) proposed an Imperialist Competitive Algorithm (ICA) which achieved better results than the Firefly Algorithm and the Genetic Algorithm on the instances of Birgin et al. (2013). A hybrid algorithm was proposed by Lunardi, Voos and Cherri (2019) which applies the ICA for global search and Tabu Search for local search. This hybrid algorithm proved to better than all other heuristics proposed for the FJSP with parallel operations.

3.4 Conclusion

Because the flexible JSP is a NP-hard combinatorial problem, only small instances can be solved exact by integer linear programming models. Therefore several heuristics have been elaborated. It was found that a majority of the research focuses on hybrid algorithms. These hybrid algorithms combine a global search heuristic and a local search heuristic. The strength of a global search heuristic is to make big jumps within the solution space while a local search heuristic is strong in finding local optima. By combining these two, the chance of getting closer to the global optimum increases. Tabu search is by far the most commonly applied local search heuristic. For the global search heuristic Evolutionary Algorithms are the most popular among researchers.

Chapter 4

Production planning optimization

The aim of this research is to find an optimal production schedule in which the production costs are minimized. A production schedule is defined by the sequence of recipes on the mixing vessels and the allocation of raw materials to dosing lines. In this chapter, an MILP model and a heuristic method are developed and tested to find the best production schedule.

4.1 MILP model

4.1.1 Job shop scheduling problem

As mentioned in Chapter 3, the latex ink production scheduling problem shares characteristics with the Flexible Job Shop Scheduling Problem (FJSP). We can translate the latex ink production scheduling problem to a FJSP. The recipes are the jobs which have to be processed. A job consists of a number of operations which in this case are the raw materials which have to be dosed into the mixing vessel. The raw materials have to dosed into the mixing vessel by a dosing line. The dosing lines and the mixing vessels are the machines in the FJSP.

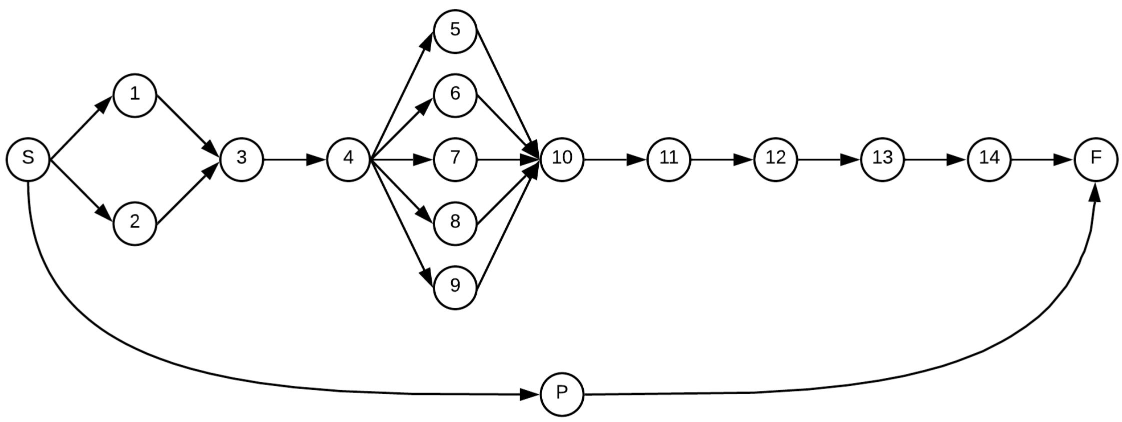


Figure 4.1: Graphical representation of recipe C4 including dummy operations
The numbers correspond to the operation numbers in Table 2.1, S: start dummy, F: finish dummy, P: processing dummy

To include the mixing vessels into the model, three dummy operations are added to every job.

One start operation, one process operation and one finish operation. The adjusted graphical representation of recipe C4 can be found in Figure 4.1.

4.1.2 Model notation and assumptions

The MILP model explained in this chapter is based on the model of Birgin et al. (2013). This model is developed for the flexible JSP with precedence flexibility. The model has been adjusted to fit the additional requirements of the latex ink production scheduling problem. From this point on the terms "jobs", "operations" and "machines" will be used instead of "recipes", "raw materials" and "dosing lines" to be in line with the literature on Job Shop Scheduling.

The precedence relations between operations are given by an arbitrary direct acyclic graph (DAG). Let V, A be the directed acyclic graph. The vertices of the DAG represent the operations and the arcs (A) represent the precedence constraints. An example of this DAG can be found in Figure 4.1.

Let V be a set of all operations. To implement certain constraints, dummy operations have to be added to the model. Therefore, V consists of a set of processing operations ($V(o)$) and a set of dummy operations ($V(d)$). The processing operations set consists of a set of dosing processing operations ($V(od)$) and a set of mixing processing operations ($V(om)$). Within the set of dummy operations there is a distinction between job dummy operations ($V(dj)$) and machine dummy operations ($V(dm)$). The set of job dummy operations ($V(dj)$) is split up in a set with start and finish job dummy operations ($V(djsf)$) and process job dummy operations ($V(djp)$). Finally, the machine dummy operations set $V(dm)$ is split up in start machine dummy operations ($V(dms)$) and finish machine dummy operations ($V(dmf)$). To make this more clear, a visual decomposition of V into subsets can be found in Figure 4.2.

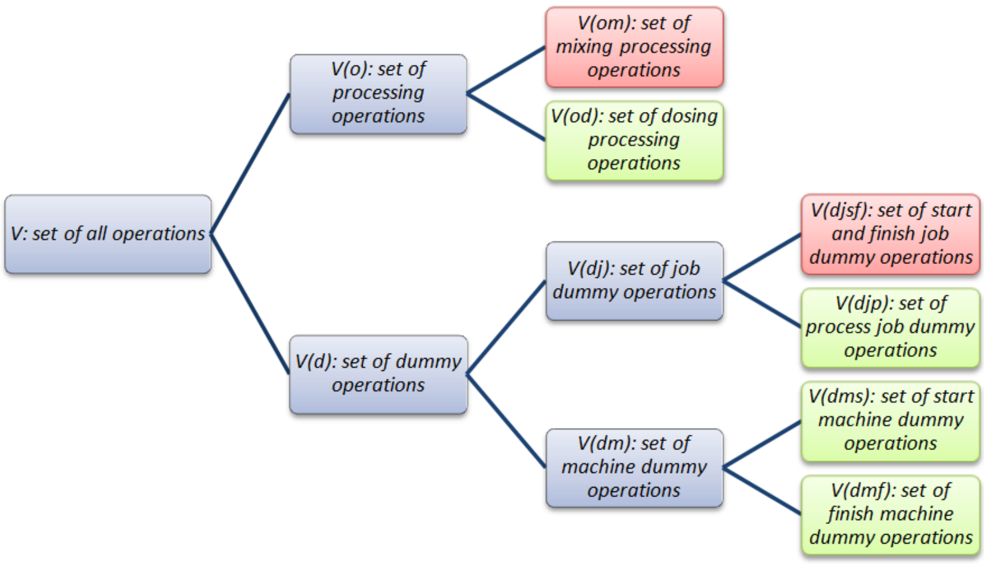


Figure 4.2: Decomposition of the operations set into subsets
The green operation subsets have to be assigned to a machine while the red operation subsets do not have to be assigned to a machine (see Section 4.1.3 for the subset descriptions)

In this model not all operations have to be assigned to a machine. To simplify the presentation of the model, let $V(a)$ denote the set of operations which has to be assigned to a machine and let $V(na)$ be a set of operations which does not have to be assigned to a machine. The mixing operations and the start and finish job dummy operations do not have to be assigned to a machine.

This results in the following: $V(na) = V(om) \cup V(djsf)$ (see the red colored sets in Figure 4.2). All other operations do have to be assigned to machines which results in: $V(a) = V(od) \cup V(djp) \cup V(dms) \cup V(dmf)$ (see the green colored sets in Figure 4.2).

Let A be a set of all precedence relations which consists of two subsets. $A(o)$ is a set of all precedence constraint for all operations in $V(o) \cup V(djsf)$. These are the precedence relations between all processing operations and the start and finish job dummy operations. Let $A(d)$ be a set of precedence constraint for all process job dummy operations in $V(djp)$.

Given is a set M of machines. A machine represents either a dosing line or a mixing vessel. For each to be assigned operation $v \in V(a)$, let M_v be the set of machines which can process operation v. For each to be assigned dosing processing operation $v \in (V(od))$ and each machine k in M_v, a positive rational number $p_{v,k}$ representing the processing time of operation v on machine k is given. For the to be assigned process job dummy operations $v \in (V(djp))$ and machine dummy operations $v \in (V(dm))$, $p_{v,k} = 0$. For these operations which have to be assigned to a machine p'_v is a decision variable representing the processing time of operation v on the assigned machine. For the operations which do not have to be assigned to a machine $(V(na))$, p'_v is a given parameter.

For each machine $k \in M$, let V_k be the set of operations that can be processed on machine k, that is, $V_k = \{v \in V : k \in M_v\}$. Let B_k be the set of all ordered pairs of distinct elements of V_k. The pairs (v, w) in B_k are designed to prevent v and w from using machine k at the same time. Let B denote the union of all B_k for all $k \in M$.

To include the setup times and costs in the model, there are two setup parameters used in the model. $st_{v,w}$ is the setup time incurred when operation w is sequenced immediately after v and $sc_{v,w}$ is the setup cost incurred when operations w is sequenced immediately after v. The labour cost per minute is denoted as lc.

An upper bound L on the makespan is needed in the model. This upperbound functions as the Big M in the MILP model. The upper bound is calculated globally by taking the sum of all the processing times of the operations:

$$L = \sum_{v \in V(a)} max_{k \in M_v}\, p_{v,k} + \sum_{v \in V(na)} p'_v$$

The formula above gives the sum of processing times of all operations. If all operations would be performed consecutively, this would be the makespan. Because operations can be processed simultaneously, the makespan for a given schedule will always be lower than the sum of all processing times.

4.1.3 Model formulation

This section explains the mathematical model for flexible job shop scheduling problem with sequence flexibility. The model is based on the model of Birgin et al. (2013).

Parameters:

V	= Set of all operations
$V(o)$	= Set of processing operations
$V(om)$	= Set of mixing processing operations
$V(od)$	= Set of dosing processing operations
$V(d)$	= Set of dummy operations
$V(dj)$	= Set of job dummy operations
$V(djsf)$	= Set of start and finish job dummy operations

$V(djp)$ = Set of process job dummy operations
$V(dm)$ = Set of machine dummy operations
$V(dms)$ = Set of start machine dummy operations
$V(dmf)$ = Set of finish machine dummy operations
$V(a)$ = Set of operations which have to be assigned to a machine
$V(na)$ = Set of operations which do not have to be assigned to a machine
V_k = Set of operations that can be processed on machine k
A = Set of all precedence constraints
$A(o)$ = Set of precedence constraints for all operations in $V(o) \cup V(djsf)$
$A(d)$ = Set of precedence constraints for all operations in $V(dj)$
M = Set of all machines
M_v = Set of machines which can process operation v
$p_{v,k}$ = Processing time of operation v on machine k
p'_v = Processing time of operation v for all v in $V(na)$
B_k = Set of all ordered pairs of distinct elements of V_k
B = Union of all B_k
$st_{v,w}$ = Setup time incurred when operation w is sequenced immediately after v
$sc_{v,w}$ = Setup costs incurred when operation w is sequenced immediately after v
lc = Labour cost per minute
L = Upper bound

Decision variables:

$$x_{v,k} \quad \forall\, v \in V(a) \text{ and } \forall k \in M_v \quad = \begin{cases} 1, & \text{if operation } v \text{ is assigned to machine } k \\ 0, & \text{otherwise} \end{cases}$$

$$y^k_{v,w} \quad \forall (v,w) \in B \text{ and } \forall k \in (M_v \cap M_w) \quad = \begin{cases} 1, & \text{if operation } v \text{ is sequenced immediately before } w \text{ on machine } k \\ 0, & \text{otherwise} \end{cases}$$

$$s_v \quad \forall v \in V \quad = \text{starting time of operation } v$$

$$e_v \quad \forall v \in V \quad = \text{finishing time of operation } v$$

$$p'_v \quad \forall\, v \in V(a) \quad = \text{processing time of operation } v$$

$$C_{max} \quad = \text{makespan}$$

Minimize: $\left(\sum_{\forall (v,w) \in B \text{ and } \forall k \in (M_v \cap M_w)} y^k_{v,w} * sc_{v,w}\right) + C_{max} * lc$

Subject to:

$$e_v \leq C_{max} \qquad \forall\, v \in V, \tag{1}$$

$$\sum_{k \in M_v} x_{v,k} = 1 \qquad \forall\, v \in V(a), \tag{2}$$

$$p'_v = \sum_{k \in M_v} p_{v,k} x_{v,k} \qquad \forall\, v \in V(a) \tag{3}$$

$$\sum_{v \in V_k \wedge v \neq w} y^k_{v,w} = x_{w,k} \qquad \forall\, w (w \in V(a) \wedge w \notin V(dms)) \text{ and } \forall k \in M_w, \tag{4}$$

$$\sum_{w \in V_k \wedge w \neq v} y^k_{v,w} = x_{v,k} \qquad \forall\, v(v \in (V(a) \wedge v \notin V(dmf)) \text{ and } \forall k \in M_v, \tag{5}$$

$$e_v \leq s_w \qquad \forall\,(v,w) \in A(o), \tag{6}$$

$$e_v = s_w \qquad \forall\,(v,w) \in A(d), \tag{7}$$

$$s_v \geq 0 \qquad \forall\, v \in V, \tag{8}$$

$$e_v = s_v + {p'}_v \qquad \forall\, v(v \in V \wedge v \notin V(djp)), \tag{9}$$

$$e_v + (st_{v,w} * \sum_{k \in (M_v \cap M_w)} y^k_{v,w}) - (1 - \sum_{k \in (M_v \cap M_w)} y^k_{v,w})L \leq s_w \qquad \forall (v,w) \in B, \tag{10}$$

The objective function minimizes the total costs which consists of the changeover costs and the labour costs. Constraint (1) makes sure C_{max} is the makespan of the schedule. As x is binary, constraint (2) ensures that exactly one machine is assigned to every operation which has to be assigned to a machine. Constraint (3) makes array p' represent the processing times of the operations. In fact, p' is an intermediate value, not a decision variable, that helps to simplify the presentation of the model.

Constraint (4) makes sure that all operations that have to be assigned to a machine (except the start machine dummy operations) have a predecessor operation on the assigned machine while constraint (5) ensures that all the to be assigned operations (except the finish machine dummy operations) have a successor operation on the assigned machine.

Constraints (6) and (7) ensure that the precedence relations are not violated. Constraint (8) ensures that the starting times of all operations are non-negative. The finishing time of the operations are defined by constraint (9).

Constraint (10) stipulates that if operation v and w are assigned to the same machine k and operation v is sequenced immediately before w, operation w can only start after operation v is finished. This constraint also includes the setup time between operations v and w.

4.1.4 Computational results

The MILP model is applied to several small instances and the results are compared. Because of the NP-hardness of the FJSP the computation time drastically increases when adding more recipes to the instances. The production schedule for the problem instance with four recipes can be found in Figure4.3.

Number of recipes	Recipe types	Computation times (hh:mm:ss)	Objective function value
1	C4	00:00:03	255.06
2	C4, M5	00:00:04	301.78
3	C4, M5, Y6	00:00:07	576.32
4	C4, M5, Y6, K7	02:58:39	698.58
5	C4, M5, M6, Y6, K7	> 10:00:00	-

Table 4.1: Computational results

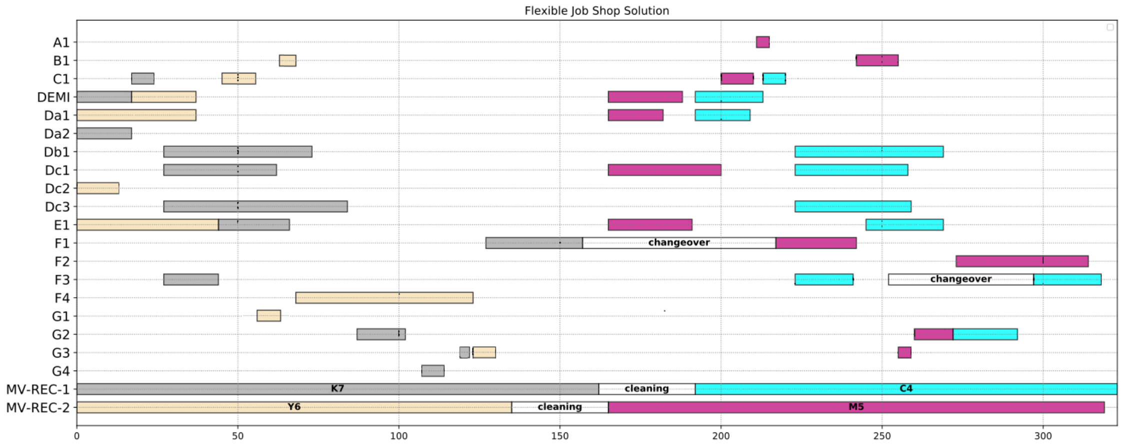


Figure 4.3: MILP model solution for problem instance with 4 recipes
The raw material names have been removed in this public version of the report

4.2 Heuristic approach

The computational results described in Section 4.1.4 showed that the computation time exceeds 10 hours when five or more recipes have to be scheduled. Therefore, a heuristic approach is presented to solve the latex ink production scheduling problem within reasonable time. As found in the literature, the majority of researchers tries to solve the flexible job shop scheduling problem by combining a global search heuristic and a local search heuristic (see Chapter 3). This is called a hybrid heuristic. The hybrid heuristic proposed in this research also combines a global and a local search heuristic. The global search heuristic focuses on finding the sequence of the recipes on the mixing vessels. The local search heuristic focuses on allocating operations (raw materials) to dosing lines and the sequencing of the operations on these allocated dosing lines. A congruence based heuristic is used as global search technique. A tabu search is used as local search technique. The tabu search optimizes the operation allocations and the sequencing of the operations on these allocated dosing lines given the recipe sequence obtained from the global heuristic. The workflow of the hybrid heuristic can be found in Figure 4.4.

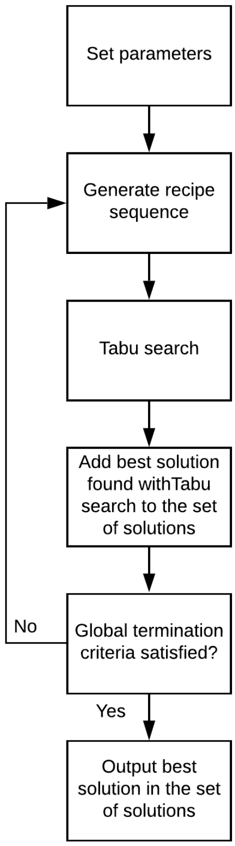


Figure 4.4: Flowchart of the hybrid heuristic

4.2.1 Recipe sequencing heuristic

A global search heuristic is used to find a sequence of the recipes on the mixing vessels. This recipe sequence is used as input for the local search heuristic (raw material allocation heuristic) to find the best possible operation allocation and sequencing corresponding to this recipe sequence.

Because the number of possible recipe sequencing drastically rises when the problem instance gets bigger, it is not possible to investigate all recipe sequences. Therefore, a heuristic method is used which looks for potential good recipe sequencing using the congruence between recipes. The heuristic assures in this way that only the part of the solution space with the highest potential will be searched. This causes the computation time to decrease. The recipe sequencing heuristic will repeat itself until the termination criteria has been satisfied. The model will output the best found solution.

The termination criterion is a maximum amount of iterations. To determine the value of this parameter, the model has been run 10 times on a problem instance with 1 batch of each of the 22 recipes. The results can be found in Figure 4.5. From the figure can be concluded that most improvements are made within the first 100 iterations. After 200 iterations there are only a few improvements. Therefore the maximum number of iterations is set to 200.

Congruence

Before the heuristic starts, the congruence between recipes is calculated. The congruence indicates the similarities between recipes concerning the raw materials. The higher the percentage of common raw materials between recipes, the higher the congruence. The congruence is a number between 0 and 1 and is calculated by dividing the intersection of the sets of raw materials of two recipes by the union of the sets. See below for the mathematical description.

$$
\begin{aligned}
R1 &= \text{Recipe 1} \\
R2 &= \text{Recipe 2} \\
R1_{raw} &= \text{Set of all raw materials of recipe 1} \\
R2_{raw} &= \text{Set of all raw materials of recipe 2}
\end{aligned}
$$

$$
congruence_{R1,R2} = \frac{|R1_{raw} \cap R2_{raw}|}{|R1_{raw} \cup R2_{raw}|}
$$

A matrix is created using these formula to calculate the congruence numbers of all recipes in the problem instance. An example congruence matrix is shown in Table 4.3 based on the problem instance displayed in Table 4.2.

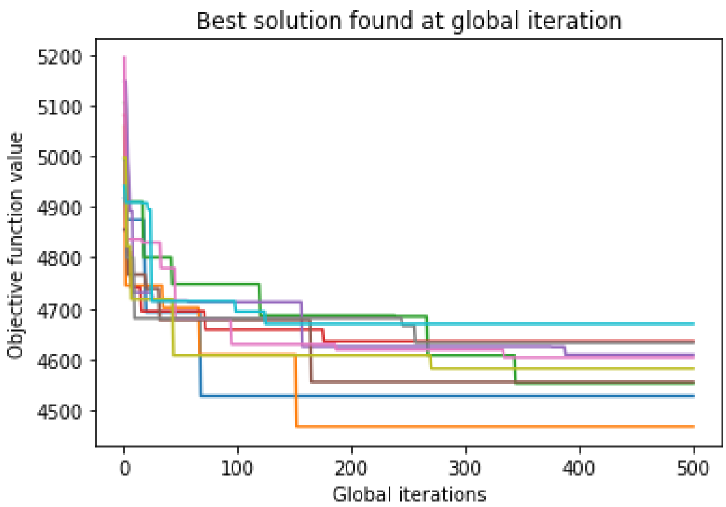


Figure 4.5: Best objective function value found at global iteration
Tested on a problem instance with 1 batch of each of the 22 recipes

Recipe	Raw materials
C4	1 - 2 - 4 - 5 - 8 - 9 - 11 - 12 - 14 - 17
M5	1 - 2 - 3 - 6 - 7 - 8 - 9 - 11 - 14 - 16 - 19
Y6	1 - 2 - 6 - 8 - 10 - 13 - 14 - 15- 20
K7	1 - 2 - 4 - 5 - 8 - 9 - 11 - 12 - 14 - 15 - 16 - 18

Table 4.2: Problem instance used to calculate the congruence matrix of Table 4.3

Recipe	C4	M5	Y6	K7
C4	1.0	0.4	0.267	0.692
M5	6/15	1.0	0.429	0.438
Y6	4/15	6/14	1.0	0.313
K7	9/13	7/16	5/16	1.0

Table 4.3: Congruence matrix based on the problem instance of Table 4.2
The lower left half of the matrix presents the fractional congruence values, while the upper right half presents the decimal congruence values.

The heuristic workflow

The workflow of the recipe sequencing heuristic can be found in Figure 4.6 The heuristic starts with a set of non-allocated recipes. All recipes in the problem instances are added to this set. For each of the mixing vessels in the problem instance, a random recipe is selected from the set of non-allocated recipes. Because the main focus of this research is on the problem instance with two mixing vessels, the heuristic will be explained in this chapter using two mixing vessels. These recipes are the starting recipe for each mixing vessel. These recipes are then removed from the set of non-allocated recipes. The next step is to check if all recipes are allocated. If all recipes are allocated, the recipe sequence solution is complete and will be used as input for the tabu search heuristic (see Section 4.2.2). If not all recipes are allocated, the heuristic continues with the next step.

For every recipe in the problem instance there is a given minimum processing time (see Section 2.2.1). For every mixing vessel, the sum of the minimum processing times of all recipes allocated to that mixing vessel is calculated. The mixing vessel with the lowest sum of processing times is then selected. The last recipe in the recipe sequence of the selected mixing vessel determines the next recipe. If there is an identical recipe in the set of non-allocated recipes to the last recipe, this identical recipe is selected to be the next recipe on the selected mixing vessel.

If there is no identical recipe in the set of non-allocated recipes, the next recipe is selected based on probabilities. A probability is calculated for each recipe in the set of non-allocated recipes based on the congruence level. The congruence level for between the last recipe and all recipes in the set of non-allocated recipes are retrieved from the congruence matrix. All these congruence levels are added to get the sum of congruence levels. The probability for each recipe is calculated by dividing the congruence level by the sum of congruence levels. See below for the mathematical description.

$$
\begin{aligned}
R &= \text{Set of non-allocated recipes} \\
l &= \text{Last recipe} \\
C_{l,r} &= \text{Congruence level between recipe } l \text{ and } r \\
p_r &= \text{Probability recipe } r \text{ is selected}
\end{aligned}
$$

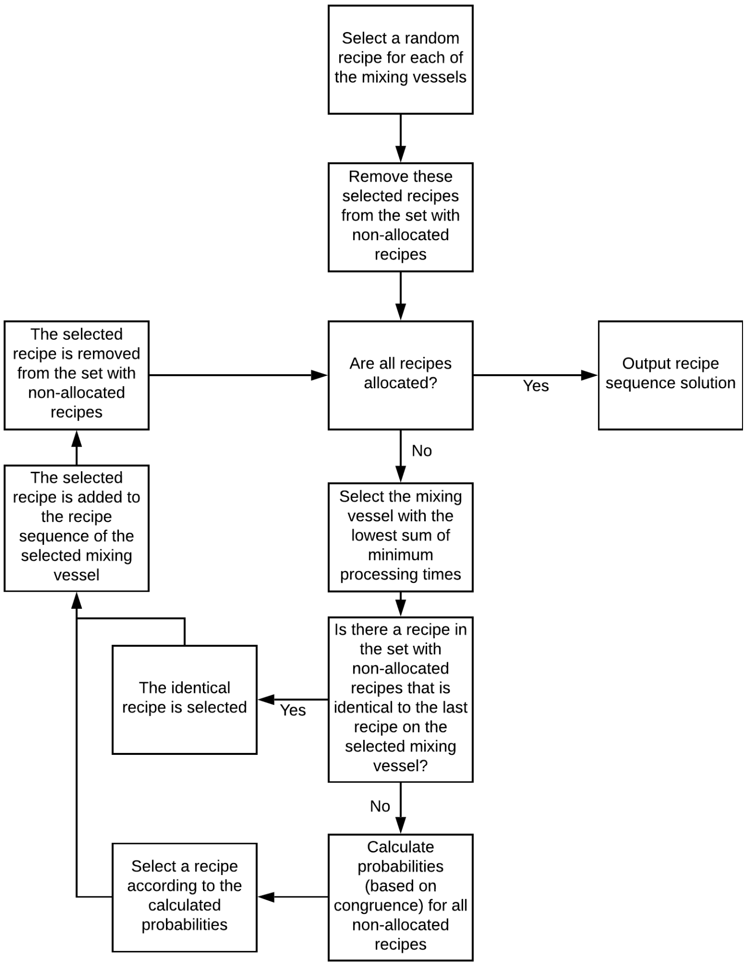


Figure 4.6: Workflow of the recipe sequencing heuristic

$$p_r = \frac{C_{l,r}}{\sum_{\forall r \in R} C_{l,r}} \qquad \forall\, r \in R$$

The heuristic then selects one of the recipes from the set of non-allocated recipes by using the probabilities. The selected recipe is then added to the recipe sequence of the selected mixing vessel and removed from the set of non-allocated recipes. The heuristic continues these steps until all recipes are allocated.

4.2.2 Raw material allocation heuristic

In this research project, a tabu search heuristic has been adopted as local search heuristic in the proposed hybrid algorithm. Tabu search is a meta-heuristic method originally proposed by Glover (1986). It has been successfully applied in various combinatorial optimization problems including several scheduling problems and has emerged as one of the most efficient local search strategies for scheduling problems. Tabu search allows the searching process to explore solutions with a worse objective function value, given that these solution are not declared tabu (forbidden). The workflow of the raw material allocation heuristic is shown in Figure 4.7. The overall procedure is described in the following steps, adopted from X. Li and Gao (2016):

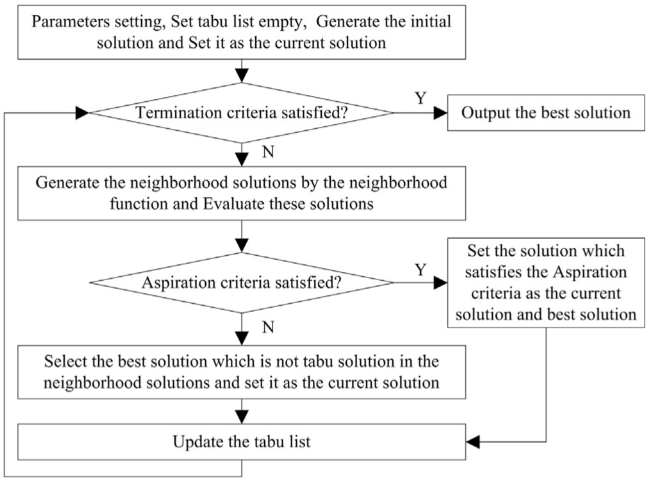


Figure 4.7: Workflow of the raw material allocation heuristic (X. Li & Gao, 2016)

1. Set the parameters of the tabu search, set the tabu list empty, generate the initial solution and set it as the current solution.
2. Is the termination criterion satisfied? If yes, go to step 8. Else, go to step 3.
3. Generate the new neighborhood solutions by the neighborhood function and evaluate these solutions.
4. Is there a better solution in the neighborhood space which is better than the current best found solution (aspiration criterion)? If yes, go to step 6. Else, go to step 5.
5. Select the best solution in the neighborhood solutions which is not tabu and set it as the current solution. Go to step 7.
6. Set the best solution in the neighborhood space as the current solution and best solution. Go to step 7.
7. Update the tabu list and go to step 2.
8. Output the best solution.

The recipe sequence obtained from the global search engine is used as input for the raw material allocation heuristic. There are still two problems which have to be solved within the raw material allocation heuristic. The first problem is the allocation of the operations to the machines. The second problem is the scheduling of these operations on their allocated machines.

Tabu search parameters

There are several parameters which need to be set in order to start the tabu search based raw material allocation heuristic. First of all, the termination criteria need to be set. There are two termination criteria. The first termination criterion is the maximum number of iterations and the second criterion is the number of iterations since there has been any improvement in the best found solution. The tabu search algorithm stops when one of these criteria is satisfied. The aspiration criterion is set to be satisfied when a newly found solution in the neighborhood structure is a better solution than the current best solution. The newly found solution than becomes the current best solution. The last parameter to be set is the size of the tabu list. If a new solution is found, the solution is added to the tabu list. If the size of the tabu list exceeds the maximum tabu list size, the oldest solution in the tabu list is deleted. The values of the parameters used in this research project are shown in Table 4.4.

Parameter	Value
The maximum number of iterations (*maxIter*)	500
The permitted maximum number of iterations without improvement (*maxStagnantIter*)	200
Length of the tabu list (*maxTabuSize*)	2

Table 4.4: Parameter values of the raw material allocation heuristic

To determine the value of the parameters, the raw material allocation heuristic has been tested with 20 different recipe sequences on a problem instance with 1 batch of each of the 22 recipes. Each sequence has been tested with 1000 local iterations. The results can be seen in Figure 4.8. From the figure can be concluded that most improvements are made within the first 200 iterations. After 500 iterations there are almost no improvements anymore. Therefore the maximum number of iterations is set to 500. From the figure can also be concluded that if there have not been any improvements for 200 iterations, the chance that another improvement will occur is very small. Therefore the maximum number of iterations without improvements is set to 200.

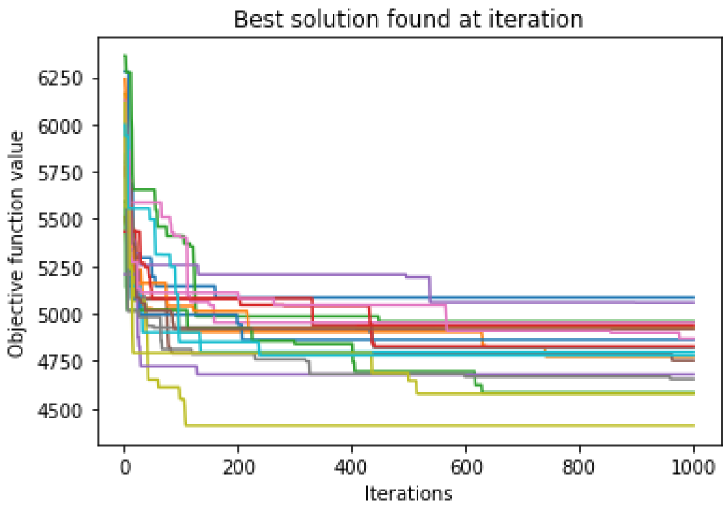
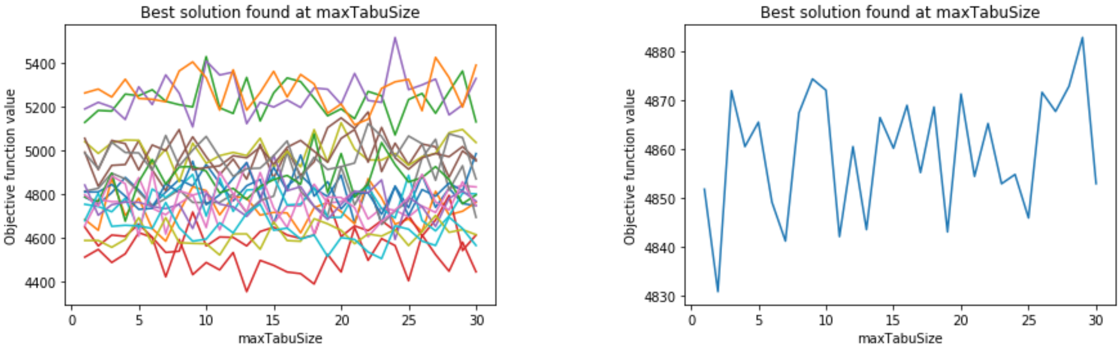


Figure 4.8: Testing results of the iteration parameters for the raw material allocation heuristic for 20 different recipe sequences
Tested on a problem instance with 1 batch of each of the 22 recipes

To determine the optimal size of the tabu list, the model has been tested on tabu list sizes ranging from 1 to 30. In Figure 4.9b (a), the results of 20 different recipes sequences can be found. The average objective function value of these 20 recipe sequencing per tabu list size can be found in Figure 4.9b (b). From these graphs can be derived that the differences between the tabu list sizes are very small. The tabu list size with the best average objective function value is a tabu size of 2 with an average objective function value of 4830.73. The worst results are achieved with a tabu size of 29 with an average objective function value of 4882.75. This is only a difference of 1.07%. From this test can be concluded that the tabu list size does not have a lot of influence. Because the tabu list size of 2 has slightly better results, a tabu list size of 2 is used as standard in this research.

The tabu list size of 2 is very small. Sarmady (2012) has tested the effect of tabu sizes on the objective function value and found that smaller tabu list sizes achieved better results than big tabu



(a) Best solution found at tabu list size for 20 different recipe sequences

(b) Average of 20 best found solutions at tabu list size

Figure 4.9: Testing results of maxTabuSize parameter
Tested on a problem instance with 1 batch of each of the 22 recipes

list sizes. However, Nababan, Sitompul and Sianturi (2019) concluded that small tabu list size do not produce optimal makespan values in Job Shop Scheduling for large-scale problem instances (50 or more jobs). These two research findings do not prove that a tabu list size of 2 is too small for the production scheduling problem in this research project.

Initial operation allocation

The raw material allocation heuristic first allocates the operations to the machines and will try to improve this initial solution. An initial allocation solution has to be generated in the first step of the raw material allocation heuristic.

The operation allocation problem is represented by the MS (Machine Selection) string adopted from Gao et al. (2016). The MS consists of n parts, where n is the number of jobs. Each part consists of n_i elements, where n_i is the number of operations of job i. This means that every element in the MS string corresponds to an operation. Every operation has a set of machine possibilities. Every element in the MS string is an index corresponding to a machine in this set of machine possibilities. An example of a MS string can be found in Figure 4.10. In this simplified example, there are three jobs with each three operations (see Table 4.5).

Job	Operation	No. of possible machines	Example index for MS string
J_1	O_{11}	1	1
	O_{12}	4	3
	O_{13}	3	3
J_2	O_{21}	2	2
	O_{22}	4	4
	O_{23}	3	1
J_3	O_{31}	4	2
	O_{32}	6	5
	O_{33}	2	2

Table 4.5: Job description used to explain the MS string in Figure 4.10

The indices in the MS string can be selected randomly to create the initial solution. However, the randomly generated initial solution is not a very good solution (high objective value). Therefore

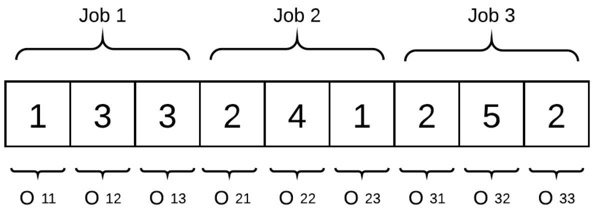


Figure 4.10: Example of a MS string based on the jobs explained in Table 4.5

the initial solution will not be generated randomly. To create a better initial solution, two steps have to be applied. In the first step, all operations are divided in groups based on the raw material of the operation. The second step is to allocate the raw materials to the machines. All operations with the same raw material are allocated to the same machine in order to minimize changeovers.

In order to reduce changeovers in the initial solution, it is important that the number of raw materials per dosing line are as low as possible. This means that the raw materials need to be balanced over the dosing lines. The raw materials are ordered based on the number of dosing lines they can be allocated to. To create an optimal balance, the raw materials are allocated to the dosing lines in this order. The raw material is then allocated to the dosing line which has the least amount of raw materials already allocated to it in the set of possible machines belonging to that specific raw material.

A flowchart of the generation of the initial solution can be found in Figure 4.11. The application of the initial solution generation on the current set of raw materials and dosing lines can be found in Figure 4.12.

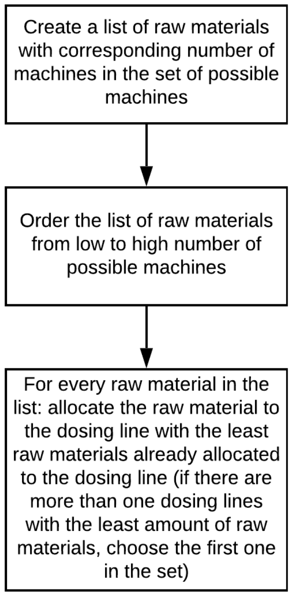


Figure 4.11: Flowchart of the generation of the initial solution for the raw material allocation heuristic

Operation scheduling

Now that the MS string of the initial solution has been generated, the operations need to be scheduled on their allocated machines. Because the recipe sequence and the operation allocation are both known at this time, there is not much variability left. Therefore the operation sequencing will be performed using a fixed method. This method will be applied to every new MS string generated within the raw material allocation heuristic to create a feasible schedule.

The operation sequencing method handles one job at a time. The method starts with the first job of the first mixing vessel in the recipe sequence and then continues with an alternating order through the jobs of the mixing vessels. For example in a situation with two mixing vessels, the operation sequencing method starts with the first job of mixing vessel 1, then continues with the first job of mixing vessel 2, then continues with the second job of mixing vessel 1 and continues in this way until all jobs have been scheduled.

For every operation of the job (starting with the first operation and ending at the last operation), the operation will be planned as early as possible on the machine it is allocated to. The earliest possible time the operation can start depends on two factors: the ending time of the preceding operation on the mixing vessel and the operations already planned on the machine. The preceding operation on the mixing vessel can be the last operation from the preceding job on the mixing vessel or the preceding operation of the current job. The preceding operation has to be finished before the current operation can start.

To plan the operation on the machine, the operation cannot have any conflict with operations already planned on the machine. This means that the operation has to start after the end time plus the changeover time and before the start time minus the changeover time of any operation already planned on the machine.

RAW	Machine set
1	15 16 17 18
2	4 5 6 7 8 9
3	4 5
4	3
5	10
6	1
7	11 12 13 14 15 16 17 18
8	4 5 6 7 8 9
9	2
10	11 12 13 14 15 16 17 18
11	15 16 17 18
12	15 16 17 18
13	11 12 13 14
14	11 12 13 14
15	11 12 13 14
16	11 12 13 14
17	11 12 13 14
18	11 12 13 14
19	11 12 13 14
20	4 5 6 7 8 9
21	6
22	4 5 6 7 8 9
23	4 5 6 7 8 9
24	4 5 6 7 8 9
25	4 5
26	15 16 17 18
27	15 16 17 18
28	15 16 17 18
29	19

Ordering the raw materials based on machine set size

RAW	Machine set
4	3
5	10
6	1
9	2
21	6
29	19
3	4 5
25	4 5
1	15 16 17 18
11	15 16 17 18
12	15 16 17 18
13	11 12 13 14
14	11 12 13 14
15	11 12 13 14
16	11 12 13 14
17	11 12 13 14
18	11 12 13 14
19	11 12 13 14
26	15 16 17 18
27	15 16 17 18
28	15 16 17 18
2	4 5 6 7 8 9
8	4 5 6 7 8 9
20	4 5 6 7 8 9
22	4 5 6 7 8 9
23	4 5 6 7 8 9
24	4 5 6 7 8 9
7	11 12 13 14 15 16 17 18
10	11 12 13 14 15 16 17 18

Allocate raw material to machine with the least allocated raw materials

RAW	Allocated machine
4	3
5	10
6	1
9	2
21	6
29	19
3	4
25	5
1	15
11	16
12	17
13	11
14	12
15	13
16	14
17	11
18	12
19	13
26	18
27	15
28	16
2	7
8	8
20	9
22	4
23	5
24	6
7	14
10	17

Display the allocated raw materials per machine

Machine	Allocated RAW
1	6
2	9
3	4
4	3 22
5	25 23
6	21 24
7	2
8	8
9	20
10	5
11	13 17
12	14 18
13	15 19
14	16 7
15	1 27
16	11 28
17	12 10
18	26
19	29

Figure 4.12: Application of the initial solution generation on the current set of raw materials and dosing lines

Evaluating the solutions

After applying the operation scheduling method, a feasible schedule has been created. The solution has to be evaluated by calculating the objective function value in order to compare it to other solutions.

The hybrid algorithm uses the same objective function as the MILP model explained in Section 4.1. The objective is to minimize the production costs which consist of the changeover costs and the labour costs. A detailed desciption on how these costs are calculated can be found in Section 2.4.

Neighborhood function

The initial solution has now been generated. The next step in the raw material allocation heuristic is to generate the neighborhood solutions by applying the neighborhood function. The neighborhood function generates the neighborhood solutions by destroying the current solution (destruction) and creating new solutions from the destroyed solution (construction). to destroy the current solution, one or more operations in the solution will be selected and taken out of the solution. To create a new solution, the operation(s) will be put back into the solution on a different machine. This means that the index of the selected operation(s) will be changed in the MS string. The operation scheduling method will be applied to the newly generated MS strings to generate a feasible schedule.

There are three destruction operators which all have a probability to be selected (see Table 4.6). The first destruction operator selects a random operation from the current solution. The size of the set with possible machines corresponding to the operation must be bigger than one, in order to create a solution which is different from the current solution.

The second destruction operator searches for changeovers in the schedule of the current solution and selects one of the changeovers at random. The operation right before the changeover is selected and taken out of the current solution. The criterion that the size of the set with possible machines corresponding to the operation must be bigger than one also applies here. The third destruction works the same as the second destruction operator except that not the operation before the changeover is selected, but the operation right after the changeover.

Destruction operator	Probability
Random operation	0.2
Operation before changeover	0.4
Operations after changeover	0.4

Table 4.6: Probabilities of destruction operators

After an operation is selected by one of the destruction operators, one or more solutions need to be generated to create the neighborhood structure. There are two construction operators with corresponding probabilities (see Table 4.7). The first construction operator generates a new solution for every machine in the set of possible machines of the selected operation (except the machine which is used in the current solution). This means that for all possible machines a new MS string is created by replacing the index of the selected operation. The operation sequencing method is then applied to generate a feasible schedule and calculate the objective function.

The second construction operator selects all operations in the current solution which contain the same raw material as the selected operation. For every machine in the set of possible machines of the selected operation (except the machine which is used in the current solution) a new solution is generated. This means that for all possible machines a new MS string is created by replacing the index of all the selected operation.

Construction operator	Probability
Selected operation	0.5
All operations with the same raw material as the selected operation	0.5

Table 4.7: Probabilities of construction operators

All new solutions generated by one of the construction operators together form the neighborhood structure. The best solution which is not tabu is selected to be the current solution. If this solution is better than the best solution found so far, the solution also becomes the best solution. The current solution is then added to the tabu list.

4.2.3 Testing the model

To test the quality of the hybrid heuristic model, some tests have been performed. First, the results of the hybrid heuristic are compared to results of the MILP model. The hybrid heuristic is also compared to a random heuristic to show the effect of the proposed hybrid heuristic. Furthermore, the tabu search operators are compared totally random operators. Finally, the proposed hybrid heuristic is compared to the current production wheel model of phase 1.

MILP model versus the heuristic model

The hybrid heuristic model is tested on the same five instances as the MILP model is tested on. The results can be found in Table 4.8. The hybrid heuristic achieves the same result for the problem instances with 1, 2 and 3 recipes. For the problem instance with 4 recipes, there is a gap of 5.53%.

Number of recipes	Recipe types	Computation time (hh:mm:ss)	Objective function value (heuristic)	Objective function value (MILP)
1	C4	00:00:02	255.06	255.06
2	C4, M5	00:00:11	301.78	301.78
3	C4, M5, Y6	00:00:30	576.32	576.32
4	C4, M5, Y6, K7	00:01:41	739.46	698.58
5	C4, M5, M6, Y6, K7,	00:08:33	1012.41	-

Table 4.8: Computational results heuristic

Combining the recipe sequencing heuristic with the MILP model

It is possible to combine the recipe sequencing heuristic with the MILP model. The recipe sequencing heuristic is then used as global search technique while the MILP model is used as local search technique. This ensures that the optimal local solution is found for the selected recipe sequence. The computation time of the MILP model is reduced because the recipe sequence variables are fixed. However, for problem instances with 6 or more recipes, the computation time of the MILP model (with the given recipe sequence) is more than 10 hours. Therefore, the combination of the recipe sequencing heuristic and the MILP model does not reduce the computation time enough.

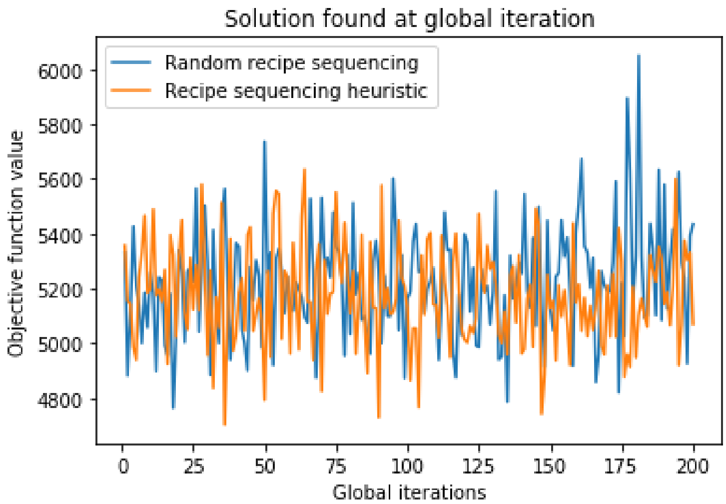


Figure 4.13: Results of the recipe sequencing heuristic vs a random recipe sequence
Tested on a problem instance with 1 batch of each of the 22 recipes

Recipe sequencing heuristic

The recipe sequencing heuristic is compared to a model with a random recipe sequencing method. The tabu search proposed in this chapter is used with both tests. Both methods are tested on a problem instance with 1 batch of each of the 22 recipes. The results can be found in Figure 4.13. From the graph can be concluded that the recipe sequencing heuristic is not significantly better than a random recipe sequencing heuristic. However, the recipe sequencing heuristic generates a slightly better solution than the random recipe sequencing method. The objective function value of the best found solution with the recipe sequencing heuristic is 4703.50 while the objective function of the best found solution with the random recipe sequencing method is 4764.70. This is only a difference of 1.28%.

Raw material allocation heuristic

The proposed raw material allocation heuristic is compared to a raw material allocation heuristic with only random operators. This means that only the "Random operator" destruction operator (see Table 4.6) and the "Selected operation" construction operator (see Table 4.7) are used. Both heuristics are tested on a problem instance with 1 batch of each of the 22 recipes. Both methods are tested on the same recipe sequence (this is the recipe sequence of the best found solution in Figure 4.13). The results of the tests can be found in Figure 4.14. From the graph can be concluded that the proposed raw material allocation heuristic achieves better results than the raw material allocation method with random destruction and construction operators. The solution found with the raw material allocation heuristic is 23.45% better than the best solution found with the random raw material allocation method. From the graph can also be concluded that the random raw material allocation heuristic did not find any better results than the initial solution.

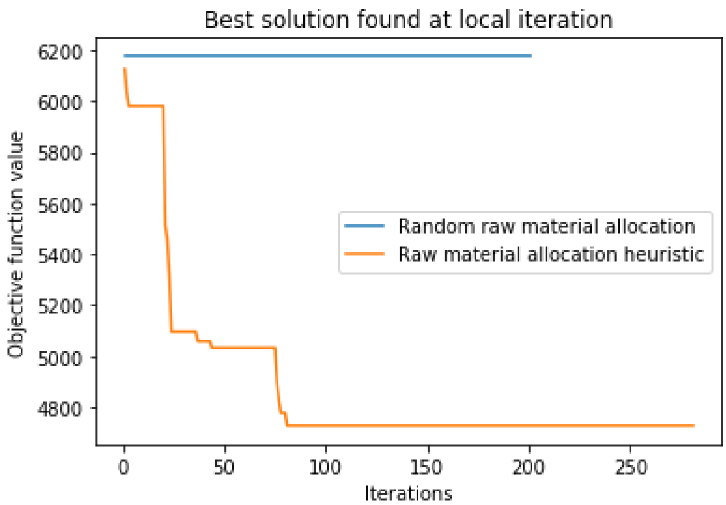


Figure 4.14: Results of the raw material allocation heuristic vs a random method for the same recipe sequence
Tested on a problem instance with 1 batch of each of the 22 recipes

Both the recipe sequencing heuristic and the raw material allocation heuristic have been tested against a random heuristic. The production schedule of the best solution found solution can be found in Appendix A. From Figure 4.13 and Figure 4.14 can be concluded that the recipe sequencing heuristic is only slightly better than a random recipe sequencing heuristic while the raw material allocation heuristic is significantly better than a random raw material allocation method.

Heuristic model versus current production wheel

The heuristic model has also been tested on the production environment of phase 1 to test the quality of the model. The current production wheel model used to schedule the production for the pilot plant in phase 1 (described in Section 2.3) only optimizes based on changeovers. The labour costs are not taken into account in this model.

This model works a little different than the model proposed in this report. However, the two models can be compared to indicate the quality of the proposed model. Both models are tested on the same problem instance (production environment of phase 1 with 22 recipes). The current production wheel model generates a production schedule with 24 changeovers. The proposed hybrid heuristic model generates a production schedule with 20 changeovers. This means that the proposed hybrid heuristic model has found a solution with 4 less changeovers. However the two models work a little different, the results from these tests can be interpreted in a away that the proposed hybrid heuristic model is better than the current production wheel model.

Chapter 5

Lot sizing

The goal of this research is to optimize the production scheduling of the latex ink in order to minimize the production costs and the costs tied to inventory. The latex ink is currently being produced in production cycles. The current production cycle (called the production wheel) has a length of three weeks. A shorter cycle length will cause less inventory costs but operational costs will increase. On the other hand, a longer cycle length will cause more inventory costs but will also reduce the operational costs. Therefore, an optimal cycle length has to be found for the latex ink production. A trade-off between the production costs and the costs of inventory has to be made.

As described in Chapter 1, the focus of this research is on phase 3. In this phase all production activities will take place in the master plant by using two mixing vessels. Phase 3 is expected to start in 2023. Therefore the expected demand for latex ink for 2023 is used to determine the length of the production cycle in this chapter.

5.1 Concept of lot sizing

In the lot-sizing problem, there is a forecast of product demand over a relevant time horizon. There is a setup cost incurred for each production order and there is an inventory holding cost per item per period. The problem is how many units to produce now to minimize the sum of setup cost and inventory cost. The lot-sizing problem is often related to the well-known economic order quantity (EOQ) formula. However, the EOQ formula is mostly applied to a single-item lot-sizing problem. In the latex ink lot-sizing problem there are multiple products per production cycle.

While determining the length of the production cycle, there are three important factors. The first factor is the demand. The demand forecast for 2023 is approximately 1740 batches of latex ink. Each product has a percentage forecast of the total demand (see Section 5.3 for a detailed description).

5.2 Costs of inventory

There are three factors which determine the costs of inventory. These factors are: storage space costs, cost of capital and inventory risk costs. These cost factors can be found in Table 5.1.

The storage space costs are all costs of storage and handling and costs involved with having or renting the facility. CPP has outsourced warehousing activities. This means that all transportation

Cost factor	Costs
Storage space costs	1.73 per pallet per week
Cost of capital	8% of average stock value per year
Inventory risk costs	22.5% of average stock value per year

Table 5.1: Three factors of inventory costs

and warehousing is performed by a Logistics Service Provider partner. The costs for these activities are €1.73 per pallet per week.

The cost of capital are the costs related to the fact that you need to invest first in order to have the working capital or that the money can't be used by the company to invest somewhere else (opportunity). The cost of capital is company wide used percentage of 8%. This means 8% of the average stock value.

The inventory risk costs the costs related to the risk of obsolete inventory. Because the latex ink has a determined shelf life, the products can expire. These costs also involve the risk of spoilage or losing products during transportation and warehousing activities. The inventory risk costs for the latex ink products has been set at 22.5% by CPP.

Cycle length (weeks)	0.5	1	1.5	2	2.5	3
Cycles per year	98	49	32.67	24.5	19.6	16.33
Average stock (weeks)	0.25	0.5	0.75	1	1.25	1.5
Average stock value	€XXXX*	€XXXX*	€XXXX*	€XXXX*	€XXXX*	€XXXX*
Average number of pallets on stock	12.65	25.29	37.94	50.58	63.23	75.87
Average storage costs (week)	€21.88	€43.75	€65.63	€87.51	€109.39	€131.26
Cost of capital	€XXXX*	€XXXX*	€XXXX*	€XXXX*	€XXXX*	€XXXX*
Cost of risk	€XXXX*	€XXXX*	€XXXX*	€XXXX*	€XXXX*	€XXXX*
Total costs	100%**	200%**	300%**	400%**	500%**	600%**

Table 5.2: Inventory costs per cycle length
*The actual costs have been left out of this public version of the report
**The total costs are represented as a percentage of the total costs of a cycle length of 0.5 weeks

The current length of the production cycle is 3 weeks. The current production environment (phase 1) is not able to handle production cycles shorter than 3 weeks. However, when the master plant will be in operation, the production cycle can be shortened. Therefore, different cycle lengths will be investigated in this chapter. An overview of the inventory costs per cycle length can be found in Table 5.2. The cycle lengths that have been investigated range from 0.5 to 3 weeks. In Table 5.2 one can see that the total inventory costs have a linear relation because it is a percentage of the average stock value.

5.3 Production costs

The production costs consist out of the changeover costs and the labour costs (see Section 2.4). To determine the optimal length of the production cycle, the production costs are calculated for production cycles ranging from 0.5 to 3 weeks. The cost per cycle are calculated using the model described in Chapter 4. To compare the production costs to the inventory costs, the production costs per cycle are multiplied with the amount of cycles per year to get the yearly production costs.

The demand forecast for 2023 is approximately 1740 production batches. The latex ink is in operation for 49 weeks per year. This means that approximately 37 batches have to be produced per week. The different products all have a forecasted percentage of the total demand. The contents of the production cycles have been determined by using the cycle length and demand percentage. The products per production cycle can be found in Table 5.3.

		Cycle length (weeks)	0,5	1	1,5	2	2,5	3
Product*	% of total demand	Products per cycle	18	37	52	72	89	107
1	2.39%		0	1	1	2	2	3
2	3.65%		1	1	2	3	3	4
3	5.10%		1	2	3	4	5	5
4	2.08%		0	1	1	1	2	2
5	2.49%		0	1	1	2	2	3
6	5.37%		1	2	3	4	5	6
7	5.19%		1	2	3	4	5	6
8	2.63%		1	1	1	2	2	3
9	1.95%		0	1	1	1	2	2
10	3.82%		1	1	2	3	3	4
11	4.32%		1	2	2	3	4	5
12	2.26%		0	1	1	2	2	2
13	7.82%		2	3	4	6	7	8
14	6.00%		1	2	3	4	5	6
15	22.37%		4	8	12	16	20	24
16	4.88%		1	2	3	3	4	5
17	0.01%		0	0	0	0	0	0
18	2.83%		1	1	2	2	3	3
19	0.34%		0	0	0	0	0	0
20	0.69%		0	0	0	0	1	1
21	11.30%		2	4	6	8	10	12
22	2.49%		0	1	1	2	2	3

Table 5.3: Number of products per cycle length
*The product names are replaced with numbers in this public version of the report

The model from Chapter 4 calculates the best possible schedule for a given number of products. However, one production cycle continues where the previous cycle has stopped. Therefore the model is adjusted to make sure that the schedule ends with the same raw material on a dosing line as it starts with. The production costs per cycle length can be found in Table 5.4.

Cycle length	0.5	1	1.5	2	2.5	3
Products per cycle	18	37	52	72	89	107
Cycles per year	98	49	32.67	24.5	19.6	16.33
Production cost per cycle	€XXXX*	€XXXX*	€XXXX*	€XXXX*	€XXXX*	€XXXX*
Production cost per year	100.00%**	82.56%**	73.17%**	72.75%**	69.97%**	69.55%**

Table 5.4: Production costs per cycle length
*The actual costs have been left out of this public version of the report
**The total costs are represented as a percentage of the total costs of a cycle length of 0.5 weeks

5.4 Costs trade off

The inventory costs and the production costs per cycle length have now been calculated. The optimal cycle length is where the sum of these costs is the lowest. The total costs incurred per cycle length can be found in Table 5.5 and have been plotted into a graph in Figure 5.1. From Table 5.5 and Figure 5.1 can be concluded that a production cycle length of 1 week is the optimal length.

Cycle length	Production cost per year	Inventory cost per year*	Total costs**
0.5	€424,316.81	€XXXX	100.00%
1	€350,319.09	€XXXX	96.31%
1.5	€310,452.44	€XXXX	99.73%
2	€308,704.10	€XXXX	111.08%
2.5	€296,892.11	€XXXX	120.33%
3	€295,104.22	€XXXX	131.67%

Table 5.5: Inventory and production costs per cycle length
*The actual costs have been left out of this public version of the report
**The total costs are represented as a percentage of the total costs of a cycle length of 0.5 weeks

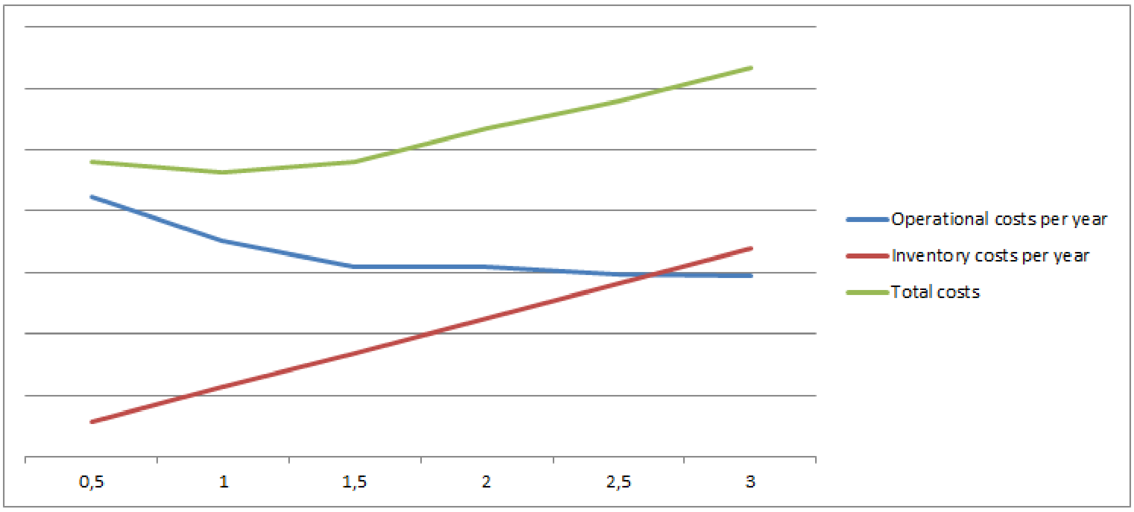


Figure 5.1: Inventory costs vs operational costs per cycle length (in weeks)
*The Y axis labels have been removed in this public version of the report

5.5 Distribution of products per cycle

The production costs of the production cycles with different cycle lengths are determined by the model of Chapter 4. The products that were used as input for the model are given in Table 5.3. Because of varying demand over the year, not every cycle will be the same. However, the cycle length will be the same for every cycle (1 week) to keep the inventory as low as possible.

Because of varying demand of the products over the year, a detailed production scheme per month has been developed. This detailed production scheme can be found in Table 5.6. This table shows how many batches of each product have to be produced per month. The products that have to be produced in a specific month have to be split into 4 production cycles to get the products that have to be produced in a specific week. A detailed overview of the distribution of the products per production cycle can be found in Appendix B.

From the Table 5.6 can be concluded that in July and October the production is much higher than in the other months. To test if the capacity in these two months is enough, the hybrid heuristic has been used to schedule the production for the first week of July. With 52 batches, this week has the highest production demand of the year (see Appendix B). The makespan of the schedule is 4,193 minutes.

There are 112 production hours per week. CPP works with an Overall Equipment Effectiveness (OEE) of 0.8. This OEE is based on machine availability, operator performance and quality (fraction of approved products). When multiplying the OEE with the number of production hours per week gives a quantity of 89.6 effective production hours per week. This can be converted to 5,376 effective production minutes per week. The makespan of the production schedule of the first week of July is 4,193 minutes (78% of the max capacity). This means that even the week with the highest production demand can be handled easily with the current capacity.

Product	Batches per year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1	42	5	4	1	6	2	3	5	4	5	3	3	1
2	64	8	3	2	4	3	4	10	4	3	13	6	4
3	89	10	4	6	4	9	5	16	11	5	11	4	4
4	37	2	2	2	3	2	3	3	5	3	4	3	5
5	44	4	4	0	7	4	4	5	6	4	3	2	1
6	94	6	10	4	3	6	7	10	7	3	17	16	5
7	91	5	4	9	4	9	5	13	14	8	10	4	6
8	46	2	3	2	2	4	5	4	7	3	4	4	6
9	35	3	2	1	5	3	3	6	3	3	4	1	1
10	67	6	11	1	4	3	6	10	5	4	8	6	3
11	76	5	4	6	4	8	6	14	7	3	9	5	5
12	40	1	4	3	1	3	4	3	6	3	3	5	4
13	137	13	7	11	8	17	10	14	5	6	12	17	17
14	105	9	11	4	7	6	7	10	7	8	14	16	6
15	390	28	23	44	23	16	25	44	31	26	43	33	54
16	85	4	4	7	5	7	6	7	9	9	8	8	11
17	1	0	0	0	1	0	0	0	0	0	0	0	0
18	50	4	4	4	5	4	4	4	4	5	4	4	4
19	6	0	1	0	1	0	1	0	1	1	0	0	1
20	12	1	1	1	1	1	1	1	1	1	1	1	1
21	197	14	21	7	11	9	16	24	13	14	28	19	21
22	44	3	4	3	2	4	3	4	4	3	4	7	3
Total	1752	133	131	118	111	120	128	207	154	120	203	164	163

Table 5.6: Products to be produced per month
*The product names are replaced with numbers in this public version of the report

Chapter 6

Changing parameters

The hybrid heuristic model proposed in Chapter 4 is used to analyse the effect of a changing production environment. What is the effect of installing an extra dosing line or mixing vessel? What is the effect on the production schedule if new recipes with new raw materials are introduced? These questions will be answered in this chapter.

6.1 Mixing vessels and dosing lines

The effects of adding a dosing line on the operational costs will be compared to the costs of installing a new dosing line. Also the effect on the capacity of installing a new mixing vessel will be analysed. An advice will be given on whether or not dosing lines and / or mixing vessels should be added or removed in order to increase operational efficiency.

6.1.1 Adding a dosing line

The production environment described in Chapter 2 with two mixing vessels and 19 dosing lines is referred to as the "original problem instance" in this chapter. For testing what the effects of adding dosing lines are, the production cycle of 1 week with 37 batches is used (see Figure 5.3 for the detailed product distribution).

The number of changeovers per dosing line type in the original problem instance can be found in Table 6.1. From this table can be concluded that most changeovers occur on the dosing lines of type F (41%) and G (32%). Therefore, an analysis has been performed on the effects of adding a F dosing line and the effects of adding a G dosing line. The effects on the production costs can be found in Table 6.2 and the effects on the number of changeovers per dosing line type can be found in Table 6.3.

Dosing line type	Number of changeovers
A	0
B	0
C	0
D1	4
D2	0
D3	2
E	0
F	9
G	7
DEMI	0

Table 6.1: Number of changeovers per dosing line type

From Table 6.2 can be concluded that adding a F dosing line generates a production cost saving of €153.12 per production cycle. The production cost savings of adding a G dosing line are €306.51 per production cycle. This means that is more cost efficient to add a G dosing line

Problem instance	Original	Extra dosing line F	Extra dosing line G
Makespan (minutes) *	100%	100.78%	99.55%
Changeover CIP	20	14	14
Changeover DEMI	2	7	3
Total costs	€7,031.41	€6,878.29	€6,724.90

Table 6.2: Effects of adding dosing lines on the production costs
*The makespan is expressed as a percentage of the first tested scenario to eliminate the possibility to retrieve the hourly labour cost

Dosing line type	Original	Extra dosing line F	Extra dosing line G
A	0	0	0
B	0	0	0
C	0	0	0
D1	4	2	2
D2	0	4	2
D3	2	3	2
E	0	0	0
F	9	9	4
G	7	5	6
DEMI	0	0	0
Total	22	21	17

Table 6.3: Effects of adding dosing lines on the number of changeovers per dosing line type

instead of a F dosing line. Because there are 49 effective production weeks per year, the yearly savings of adding a G dosing line are €15,018.99. CPP wants a return on investments (ROI) of 3 years or less for the investment of new production equipment. This means that the cost savings over 3 year should be higher than the investment costs. In this report the cost savings are calculated linearly. This means that the cost savings are assumed to be the same for every year. In reality the cost savings are expected to increase as demand also increases. The investment costs for installing a new G dosing line are €80,000. The ROI for the dosing line is calculated as follows:

$$ROI = \frac{80,000}{15,018.99} = 5.33\, years$$

The ROI of 5.33 years is higher than the maximum of 3 years set by CPP. This means that is not cost efficient to invest in a new dosing line.

6.1.2 Adding a mixing vessel

What is the effect on the total production capacity if a mixing vessel is added or removed? In this section, three scenarios will be analysed. The first scenario is a situation with 1 mixing vessel, the second scenario is a situation with two mixing vessels (the original problem instance of phase 3) and the third scenario is a situation with 3 mixing vessels. All three scenarios are tested on the production cycle of 1 week with 37 batches (see Figure 5.3 for the detailed product distribution). The results can be found in Table 6.4.

CPP produces 49 weeks per year. There are 112 production hours per week. This means that there are 5,488 production hours per year. CPP works with an Overall Equipment Effectiveness (OEE)

Problem instance	1 MV	2 MV's	3 MV's
Makespan (minutes)	5861	3079	2374
Changeover CIP	17	20	16
Changeover DEMI	2	2	6
Total changeovers	19	22	22
Total costs*	100%	57.17%	45.04%

Table 6.4: Production costs for the scenarios with 1, 2 and 3 mixing vessels
*The total costs are expressed as a percentage of the first tested scenario to eliminate the possibility to retrieve the hourly labour cost

Problem instance	1 MV	2 MV's	3 MV's
Makespan (minutes)	5,861	3,079	2,374
Effective production time per year (minutes)	263,424	263,424	263,424
Total production cycles per year	44.95	85.56	110.96
Total production capacity per year (in batches)	1,663	3,165	4,105

Table 6.5: Total production capacity per year for the scenarios with 1, 2 and 3 mixing vessels

of 0.8. This OEE is based on machine availability, operator performance and quality (fraction of approved products). When multiplying the OEE with the number of production hours per year gives a quantity of 4,390.4 effective production hours per year. This can be converted to 263,424 effective production minutes per year. The total number of possible production cycles per year for each scenario can be calculated by dividing the number of effective production minutes per year by the makespan of 1 production cycle. The number of possible production cycles per year is multiplied by 37. This gives the total production capacity per year in batches. See Table 6.5 for a detailed calculation for each scenario.

The demand per year (in production batches) for the years 2020 until 2023 can be found in Table 6.6. From Table 6.5 and Table 6.6 can be concluded that the scenario with 1 mixing vessel can meet the demand for the years 2020, 2021 and 2022. To meet the demand for 2023, a scenario with 2 mixing vessels is necessary. For the year 2022 there is not much room for slack. Approximately 91% of the capacity will be used in this year. Therefore, the second mixing vessel should be installed halfway the year 2022. In this way there is room for slack in 2022 and in 2023 there will be more than enough capacity.

Year	Demand (in batches)
2020	783
2021	1183
2022	1517
2023	1742

Table 6.6: Demand in batches for the years 2020-2023

6.2 Recipes and raw materials

The R&D department of CPP is constantly doing research on improving the quality of the inks. As a result, the number of recipes will increase in the future. With the number of recipes increasing, the number of raw materials will also increase. This will make the production planning more complex as the number of possible allocations of raw materials to dosing lines will increase.

To test the effect of the introduction of new recipes and new raw materials, four new fictional recipes have been added to the model. All four recipes consist two new raw materials. One of these raw materials can be allocated to the dosing lines of type D1, D2 and D3. The other raw material can be allocated to the dosing lines of type G. To test the effects of the new recipes on the production schedule, the hybrid heuristic model is applied to the original situation with 2 mixing vessels with a production cycle of 41 recipes (the 37 original recipes plus one of each of the four new recipes).

The production costs of the original problem instance (plus 4 current recipes) are compared to the production costs of the problem instance with the four new recipes. Both problem instances consist of 41 recipes. The results can be found in Table 6.7. From this Table can be concluded that the number of changeovers drastically increases when the new recipes and raw materials are added to the model.

Dosing line type	Original	New recipes
Makespan (minutes)*	100%	105.34%
Changeover CIP	23	30
Changeover DEMI	3	4
Total changeovers	26	34
Total costs	€ 7,691.45	€ 8,406.81

Table 6.7: Production costs for the original problem instance versus a scenario with four new recipes
*The makespan is expressed as a percentage of the first tested scenario to eliminate the possibility to retrieve the hourly labour cost

To reduce the number of changeovers, three new scenarios will be tested. Each scenario will add a dosing line of a different type to the model. The dosing line types which have been added in the three scenarios are type D1, type F, and type G. The number of changeovers per dosing line type for the three different scenarios can be found in Table 6.8. The production costs for each of the three scenarios can be found in Table 6.9.

Dosing line type	New recipes	Extra dosing line F	Extra dosing line G	Extra dosing line D1
A	0	0	0	0
B	0	0	0	0
C	0	0	0	0
D1	4	8	3	5
D2	2	0	0	0
D3	2	4	3	0
E	0	0	0	0
F	16	15	10	15
G	10	6	14	6
DEMI	0	0	0	0
Total	34	33	30	26

Table 6.8: Effects of adding dosing lines on the number of changeovers per dosing line type for a situation with four new recipes

From Table 6.8 and Table 6.9 can be concluded that adding a D1 dosing line generates the most cost savings and the highest reduction of changeovers. The cost savings are € 200.57 per production cycle. Because there are 49 effective production weeks per year, the yearly savings of adding a D1 dosing line are € 9,827.93. AS mentioned before, CPP wants a return on investments (ROI) of 3 years or less for the investment of new production equipment. The investment costs for installing a new D1 dosing line are €80,000. The ROI for the dosing line is calculated as follows:

$$ROI = \frac{80,000}{9,827.93} = 8.14\, years$$

The ROI of 8.14 years is higher than the maximum of 3 years set by CPP. This means that is not attractive enough to invest in a new dosing line, even if new recipes are entering the production environment.

Dosing line type	New recipes	Extra dosing line F	Extra dosing line G	Extra dosing line D1
Makespan (minutes)*	100%	96.21%	101.48%	102.02%
Changeover CIP	30	29	24	24
Changeover DEMI	4	4	6	2
Total changeovers	34	33	30	26
Total costs	€8,406.81	€8,098.01	€8,248.65	€8,206.24

Table 6.9: Effects of adding dosing lines on the production costs for the problem instance with four new recipes
*The makespan is expressed as a percentage of the first tested scenario to eliminate the possibility to retrieve the hourly labour cost

Chapter 7

Conclusions, limitations and future research

In this chapter, the main findings of this research are presented. Section 7.1 presents the conclusions drawn based on the formulated research questions. Section 7.2 provides recommendations for company purposes. A discussion of the results is presented in Section 7.3 by addressing the limitations of this research and suggesting directions for future research.

7.1 Conclusion

In this section, the conclusions of this research project are presented. First the research questions will be answered shortly. Furthermore, an overall conclusion will be given.

1. *What does the production environment look like for phase 1 and 3?*

   The production of the latex ink is currently being scheduled by using the so called production wheel. The production wheel is a sequence of recipes. The ink production must always be performed in this sequence. For every cycle of the wheel, the number of batches per recipe can be different as long as the sequence stays the same. The current production wheel model is only applicable for the situation with one set of dosing lines and one mixing vessel (phase 1). In phase 3 there is one set of dosing lines connected to two (or more) mixing vessels. Working with sequences will then cause a problem as each recipe has a different processing time. It could then happen that one mixing vessel is finished processing a batch and can continue with the next one while the other mixing vessel is still processing. Then the first mixing vessel cannot use a dosing line which is utilised by the second mixing vessel. This means that the concept of a fixed production wheel is not optimal anymore because variation in the number of batches will cause problems.

2. *How can the production planning be optimized for phase 3?*

   From relevant literature can be concluded that the latex ink production scheduling problem for phase 3 can be seen as a Flexible Job Shop Scheduling Problem with parallel operations and sequence dependent setup times. For small instances, the problem can be solved by a mixed integer linear programming model. For larger problem instances with 5 recipes or more, a hybrid heuristic model is proposed to solve the production planning problem. The hybrid heuristic model combines a congruence based heuristic for the recipe sequencing problem and a tabu search heuristic for the dosing line allocation problem.

3. *What is the optimal production cycle?*

   The optimal length of the production cycle is 1 week. Because of demand variations among recipes, not all production cycles will be the same. An optimal distribution of the products into production cycles has been proposed for every production cycle in 2023 based on demand variations per product and demand variations per month.

4. *What is the effect on the production planning if a mixing vessel or dosing line is added to the model?*

   The proposed hybrid heuristic model is used to test the effects of adding a type F dosing line and a type G dosing line. From these tests can be concluded that it is more cost efficient to install a new type G dosing line. The ROI for this new dosing line is 5.33 years. CPP requires a new investment to have a ROI of 3 years or less. Therefore, the advice is not to invest in a new dosing line.

   The total production capacity has been calculated for a scenario with 1, 2 and 3 mixing vessels using the hybrid heuristic model. From these tests can be concluded that the scenario with 1 mixing vessel can meet the demand for the years 2020, 2021 and 2022. To meet the demand for 2023, a scenario with 2 mixing vessels is necessary. For the year 2022 there is not much room for slack. Therefore, the second mixing vessel should be installed halfway the year 2022. In this way there is room for slack in 2022 and in 2023 there will be more than enough capacity.

5. *What is the effect on the production planning if raw materials and recipes are added to the model?*

   The proposed hybrid heuristic model is used to test the effects of new recipes containing new raw materials. From these tests can be concluded that the number of changeovers, as well as the production costs increase when new recipes enter the production environment. If a type D1 line is added to the problem instance, the number of changeovers and the production costs are reduced. However, the ROI of this new type D1 dosing line is 8.14 years.

This research project has been focused on phase 3. In this phase the current pilot plant is not in operation anymore. All production activities will take place in the new master plant. This research has provided a hybrid heuristic production scheduling model which will be used for the production planning in the master plant. This is an entire new situation. There was no tool for the production scheduling in the new master plant. This research has solved that problem by providing this new tool, which means that the main goal of this research has been successfully reached.

7.2 Recommendations

The goal of this research is to develop a cost efficient production planning for the latex ink. The proposed MILP model finds an optimal production schedule for a given input of recipes. However, the model is not able to find the optimal solution for problem instances of 5 or more recipes. Therefore a hybrid heuristic model is proposed. This model does not find the optimal solution. However, the model finds a good solution within reasonable computation time. The hybrid heuristic model can be used in practice to develop a production schedule for a production cycle. Both models optimize the production schedule by minimizing the sum of changeover costs and labour costs. The model has been designed to be easy to use. The following input parameters for the model can be easily changed to see the effect on the production schedule:

- The raw material composition of the recipes

- The frequency of each recipe in the production cycle
- The frequency of each dosing line type
- The possible dosing lines for every raw material
- The number of mixing vessels
- The labour costs
- The changeover costs
- The changeover times
- The parameters for the global and local search techniques

In order to find an optimal production cycle length, a trade-off between the production costs and the inventory costs has been made. The optimal production cycle length is one week. An optimal distribution of the products into production cycles has been calculated based on demand predictions for the year 2023. These recommended production cycles can be found in Appendix B.

The proposed hybrid heuristic production scheduling tool calculates the optimal production schedule for a given cycle. Because the length of the production cycles is one week, the production scheduling tool should be used every week. Because the demand for latex ink is steady, the production cycles can be calculated on a monthly base. This means that the production plan for the entire month can be calculated in advance. If there are changes in the production demand during the month, the production cycle can be recalculated and the production schedule can be adjusted.

While making the monthly production planning, it is interesting to analyse the makespan of the production cycle. If the makespan is higher than the effective production time for that week, the production planning department can decide to work with an extra shift to increase the capacity for that week. If the makespan drops under a certain level, CPP can decide to change to a two shift system for that specific week to save on labour costs.

7.3 Discussion

The gap between theory and practice provides some boundaries. These boundaries are discussed by stating the assumptions and limitations of the proposed model. Furthermore, directions for further research are suggested.

7.3.1 Limitations

Although the research has reached its aims, there were some unavoidable limitations and things that I could have done in a different way to increase the quality of this research.

- The latex ink department currently works with three shifts. One morning shift, one afternoon shift and one night shift. This means that there are 112 production hours per week. There is also a possibility to shift to different shift systems. The two shift system has 80 production hours per week. The labour costs per hour are higher for the three shift system than for the two shift system. This research did not take the possibility to change the number of shifts into account. This can however greatly influence the labour costs. I could have used an adjusted objective function which takes these shifts into account.

- The ROI calculations in this report are calculated linearly. This means that the cost savings are assumed to be the same for every year. In reality the cost savings are expected to increase as demand also increases. As the demand forecast for the years after 2023 has not yet been performed, it is difficult to calculate the expected savings after 2023.
- The dosing time of the raw materials into the mixing vessel are assumed to be deterministic. However, in practice there is some variability in the dosing times.
- The dosing times of the raw materials are assumed to be independent of the dosing the raw material is allocated to. In practice there is some difference in dosing times between dosing lines due to the differences in width of the dosing lines.
- There raw materials are stored in IBCs. When a IBC gets empty during the dosing a raw material into the mixing vessel, the IBC needs to be replaced. The time it takes to replace the IBC is not represented in the proposed model.
- In this research, the assumption has been made that there are always three operators working per shift. The number of operators has a big effect on the labour costs.
- The model assumes that there are no restrictions on when a changeover can happen. In practice there are some restrictions which prohibit some changeovers to be performed simultaneously.

7.3.2 Future research

Based on the research conducted in this project, several suggestions for future research are identified. A future research direction could be to analyse the effect of changing the number of operators per shift. If the number of operators per shift could be reduced, the labour costs will also be reduced. This will however affect the total production capacity because of a lower OEE. Research could be performed on how many operators should be working per shift to meet the demand.

In this research, the effects of adding a dosing line, adding or removing a mixing vessel, and adding recipes and raw materials are calculated separately. Future research could focus on what the effects are if these actions are combined. What are the effects of adding both a mixing vessel and a dosing line? This would result to a more detailed analysis of the effect of a changing production environment on the production schedule.

Finally, the production cycle length and the distribution of the products over the production cycles have been calculated with a given demand. The demand for latex ink is reasonably stable, however an analysis could be performed on the effects of varying demand. What is the effect on the performance of the production schedule if the demand is more varying than expected? The effects on the cycle length and the number of changeovers within a production cycle should be analysed.

References

Allahverdi, A., Ng, C. T., Cheng, T. C. E. & Kovalyov, M. Y. (2008). A survey of scheduling problems with setup times or costs. *European Journal of Operational Research*, *187*(3), 985–1032. doi:10.1016/j.ejor.2006.06.060

Arisha, A., Young, P. & El Baradie, M. (2001). Job shop scheduling problem: An overview. In *International conference for flexible automation and intelligent manufacturing* (pp. 682–693). Dublin, Ireland.

Athanasiadou, A. (2018, November 30). *Decision support model for wastewater minimization with sequence dependent changeovers: Application on latex ink production* (Master's thesis, Eindhoven University of Technology).

Birgin, E. G., Feofiloff, P., Fernandes, C. G., de Melo, E. L., Oshiro, M. T. I. & Ronconi, D. P. (2013). A milp model for an extended version of the flexible job shop problem. *Optimization Letters*, *8*(4), 1417–1431. doi:10.1007/s11590-013-0669-7

Birgin, E. G., Ferreira, J. E. & Ronconi, D. P. (2015). List scheduling and beam search methods for the flexible job shop scheduling problem with sequencing flexibility. *European Journal of Operational Research*, *247*(2), 421–440. doi:10.1016/j.ejor.2015.06.023

Brandimarte, P. (1993). Routing and scheduling in a flexible job shop by tabu search. *Annals of Operations Research*, *41*(3), 157–183.

Brucker, P. & Neyer, J. (1998). Tabu-search for the multi-mode job-shop problem. *OR Spektrum*, *20*(1), 21–28. doi:10.1007/BF01545525

Brucker, P. & Schlie, R. (1990). Job-shop scheduling with multi-purpose machines. *Computing*, *45*(4), 369–375. doi:10.1007/BF02238804

Canon Europe. (2019). Our group companies. Retrieved from https://www.canon-europe.com/about%5C_us/group-companies/

Canon Production Printing. (2020). About canon production printing. Retrieved from https://cpp.canon/about/

Carlier, J. & Pinson, E. (1989). An algorithm for solving the job-shop problem. *Management Science*, *35*(2), 164–176. doi:10.1287/mnsc.35.2.164

Chaudhry, I. A. & Khan, A. A. (2015). A research survey: Review of flexible job shop scheduling techniques. *International Transactions in Operational Research*, *23*(3), 551–591. doi:10.1111/itor.12199

De Giovanni, L. & Pezzella, F. (2010). An improved genetic algorithm for the distributed and flexible job-shop scheduling problem. *European Journal of Operational Research*, *200*(2), 395–408. doi:10.1016/j.ejor.2009.01.008

Gao, K. Z., Suganthan, P. N., Pan, Q. K., Chua, T. J., Cai, T. X. & Chong, C. S. (2016). Discrete harmony search algorithm for flexible job shop scheduling problem with multiple objectives. *Journal of Intelligent Manufacturing*, *27*(2), 363–374. doi:10.1007/s10845-014-0869-8

Garey, M. R., Johnson, D. S. & Sethi, R. (1976). The complexity of flowshop and jobshop scheduling. *Mathematics of Operations Research*, *1*(2), 117–129. doi:10.1287/moor.1.2.117

Glover, F. (1986). Future paths for integer programming and links to artificial intelligence. *Computers operations research*, *13*(5), 533–549.

Gomes, M. C. (2013). Reactive scheduling in a make-to-order flexible job shop with re-entrant process and assembly: A mathematical programming approach. *International Journal of Production Research*, *51*(17), 5120–5141. doi:10.1080/00207543.2013.793428

Graves, S. C. (1981). A review of production scheduling. *Operations Research*, *29*(4), 646–675. doi:10.1287/opre.29.4.646

Hoitomt, D. J., Luh, P. B. & Pattipati, K. R. (1993). A practical approach to job-shop scheduling problems. *IEEE Transactions on Robotics and Automation*, *9*(1), 1–13. doi:10.1109/70.210791

Hurink, J., Jurisch, B. & Thole, M. (1994). Tabu search for the job-shop scheduling problem with multi-purpose machines. *Operations Research Spektrum*, *15*(4), 205–215. doi:10.1007/BF01719451

Jia, S. & Hu, Z. H. (2014). Path-relinking tabu search for the multi-objective flexible job shop scheduling problem. *Computers & Operations Research*, *47*, 11–26. doi:10.1016/j.cor.2014.01.010

Johnson, S. M. (1954). Optimal two- and three-stage production schedules with setup times included. *Naval Research Logistics Quarterly*, *1*(1), 61–68. doi:10.1002/nav.3800010110

Jones, A., Rabelo, L. & Sharawi, A. T. (1999). Survey of job shop scheduling techniques. *Wiley Encyclopedia of Electrical and Electronics Engineering*. doi:10.1002/047134608X.W3352

Karthikeyan, S., Asokan, P., Nickolas, S. & Page, T. (2015). A hybrid discrete firefly algorithm for solving multi-objective flexible job shop scheduling problems. *International Journal of Bio-Inspired Computation*, *7*(6), 386–401. doi:10.1504/IJBIC.2015.073165

Li, J. Q., Pan, Q. K. & Tasgetiren, M. F. (2014). A discrete artificial bee colony algorithm for the multi-objective flexible job-shop scheduling problem with maintenance activities. *Applied Mathematical Modelling*, *38*(3), 1111–1132. doi:10.1016/j.apm.2013.07.038

Li, X. & Gao, L. (2016). An effective hybrid genetic algorithm and tabu search for flexible job shop scheduling problem. *International Journal of Production Economics*, *174*, 93–110. doi:10.1016/j.ijpe.2016.01.016

Li, Z. C., Qian, B., Hu, R., Chang, L. L. & Yang, J. B. (2019). An elitist nondominated sorting hybrid algorithm for multi-objective flexible job-shop scheduling problem with sequence-dependent setups. *Knowledge-Based Systems*, *173*, 83–112. doi:10.1016/j.knosys.2019.02.027

Lin, L., Hao, X.-C., Gen, M. & Jo, J.-B. (2012). Network modeling and evolutionary optimization for scheduling in manufacturing. *Journal of Intelligent Manufacturing*, *23*(6), 2237–2253. doi:10.1007/s10845-011-0569-6

Lu, P. H., Wu, M. C., Tan, H., Peng, Y. H. & Chen, C. F. (2018). A genetic algorithm embedded with a concise chromosome representation for distributed and flexible job-shop scheduling problems. *Journal of Intelligent Manufacturing*, *29*(1), 19–34. doi:10.1007/s10845-015-1083-z

Lunardi, W. T. & Voos, H. (2018). An extended flexible job shop scheduling problem with parallel operations. *ACM SIGAPP Applied Computing Review*, *18*(2), 46–56. doi:10.1145/3243064.3243068

Lunardi, W. T., Voos, H. & Cherri, L. H. (2018a). A mathematical model and a firefly algorithm for an extended flexible job shop problem with availability constraints. In *International conference on artificial intelligence and soft computing* (pp. 548–560). doi:10.1007/978-3-319-91253-0_51

Lunardi, W. T., Voos, H. & Cherri, L. H. (2018b). An imperialist competitive algorithm for a real-world flexible job shop scheduling problem. In *23rd ieee international conference on emerging technologies and factory automation* (p. 8). Torino, Italy.

Lunardi, W. T., Voos, H. & Cherri, L. H. (2019). An effective hybrid imperialist competitive algorithm and tabu search for an extended flexible job shop scheduling problem. In *34th acm/sigapp symposium on applied computing* (p. 8). doi:10.1145/3297280.3297302

Mastrolilli, M. & Gambardella, L. M. (2000). Effective neighbourhood functions for the flexible job shop problem. *Journal of scheduling*, *3*(1), 3–20. doi:doi:10.1002/(sici)1099-1425(200001/02)3:1⟨3::aid-jos32⟩3.0.co;2-y

Moradi, E., Ghomi, S. F. & Zandieh, M. (2011). Bi-objective optimization research on integrated fixed time interval preventive maintenance and production for scheduling flexible job-shop problem. *Expert Systems with Applications*, *38*(6), 7169–7178. doi:10.1016/j.eswa.2010.12.043

Moslehi, G. & Mahnam, M. (2011). A pareto approach to multi-objective flexible job-shop scheduling problem using particle swarm optimization and local search. *International Journal of Production Economics*, *129*(1), 14–22. doi:10.1016/j.ijpe.2010.08.004

Mousakhani, M. (2013). Sequence-dependent setup time flexible job shop scheduling problem to minimise total tardiness. *International Journal of Production Research*, *51*(12), 3476–3487. doi:10.1080/00207543.2012.746480

Muth, J. F. & Thompson, G. L. (1963). *Industrial scheduling*. Englewood Cliffs, NJ: Prentice Hall.

Nababan, E., Sitompul, O. & Sianturi, J. (2019). Analysis of tabu list length on job shop scheduling problem. In *Journal of physics: Conference series* (Vol. 1235, *1*, p. 012047). IOP Publishing.

Özgüven, C., Yavuz, Y. & Özbakir, L. (2010). Mathematical models for job-shop scheduling problems with routing and process plan flexibility. *Applied Mathematical Modelling*, *34*(6), 1539–1548. doi:10.1016/j.apm.2009.09.002

Özgüven, C., Yavuz, Y. & Özbakir, L. (2012). Mixed integer goal programming models for the flexible job-shop scheduling problems with separable and non-separable sequence dependent setup times. *Applied Mathematical Modelling*, *36*(2), 846–858. doi:10.1016/j.apm.2011.07.037

Piroozfard, H., Wong, K. Y. & Wong, W. P. (2018). Minimizing total carbon footprint and total late work criterion in flexible job shop scheduling by using an improved multi-objective genetic algorithm. *Resources, Conservation and Recycling*, *128*, 267–283. doi:10.1016/j.resconrec.2016.12.001

Rodammer, F. A. & White, K. P. (1988). A recent survey of production scheduling. *IEEE Transactions on Systems, Man, and Cybernetics*, *18*(6), 841–851. doi:10.1109/21.23085

Roshanaei, V., Azab, A. & ElMaraghy, H. (2013). Mathematical modelling and a meta-heuristic for flexible job shop scheduling. *International Journal of Production Research*, *51*(20), 6247–6274. doi:10.1080/00207543.2013.827806

Sarmady, S. (2012). An investigation on tabu search parameters. *School of Computer Sciences, Universiti Sains Malaysia, 11800.*

Shao, X., Liu, W., Liu, Q. & Zhang, C. (2013). Hybrid discrete particle swarm optimization for multi-objective flexible job-shop scheduling problem. *International Journal of Advanced Manufacturing Technology*, *67*, 2885–2901. doi:10.1007/s00170-012-4701-3

Sharma, P. & Jain, A. (2015). A review on job shop scheduling with setup times. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, *230*(3), 517–533. doi:10.1177/0954405414560617

Türkyılmaz, A., Senvar, Ö., Ünal, I. & Bulkan, S. (2020). A research survey: Heuristic approaches for solving multi objective flexible job shop problems. *Journal of Intelligent Manufacturing*. doi:10.1007/s10845-020-01547-4

Vilcot, G. & Billaut, J. C. (2011). A tabu search algorithm for solving a multicriteria flexible job shop scheduling problem. *International Journal of Production Research*, *49*(23), 6963–6980. doi:10.1080/00207543.2010.526016

Xie, J., Gao, L., Peng, K., Li, X. & Li, H. (2019). Review on flexible job shop scheduling. *IET Collaborative Intelligent Manufacturing*, *1*(3), 67–77. doi:10.1049/iet-cim.2018.0009

Yuan, Y., Xu, H. & Yang, J. (2013). A hybrid harmony search algorithm for the flexible job shop scheduling problem. *Applied soft computing*, *13*(7), 3259–3272. doi:10.1016/j.asoc.2013.02.013

Zhang, G., Gao, L. & Shi, Y. (2011). An effective genetic algorithm for the flexible job-shop scheduling problem. *Expert Systems with Applications*, *38*(4), 3563–3573. doi:10.1016/j.eswa.2010.08.145

Zhang, G., Zhang, L., Song, X., Wang, Y. & Zhou, C. (2019). A variable neighborhood search based genetic algorithm for flexible job shop scheduling problem. *Cluster Computing*, *22*(5), 11561–11572. doi:10.1007/s10586-017-1420-4

Zhang, J., Ding, G., Zou, Y., Qin, S. & Fu, J. (2017). Review of job shop scheduling research and its new perspectives under industry 4.0. *Journal of Intelligent Manufacturing*. doi:10.1007/s10845-017-1350-2

Appendix A

Production schedule

The production schedule in the form of a gantt chart can be found on the next page. This production schedule is the output of the hybrid heuristic described in Chapter 4 applied on a problem instance with 22 different recipes.

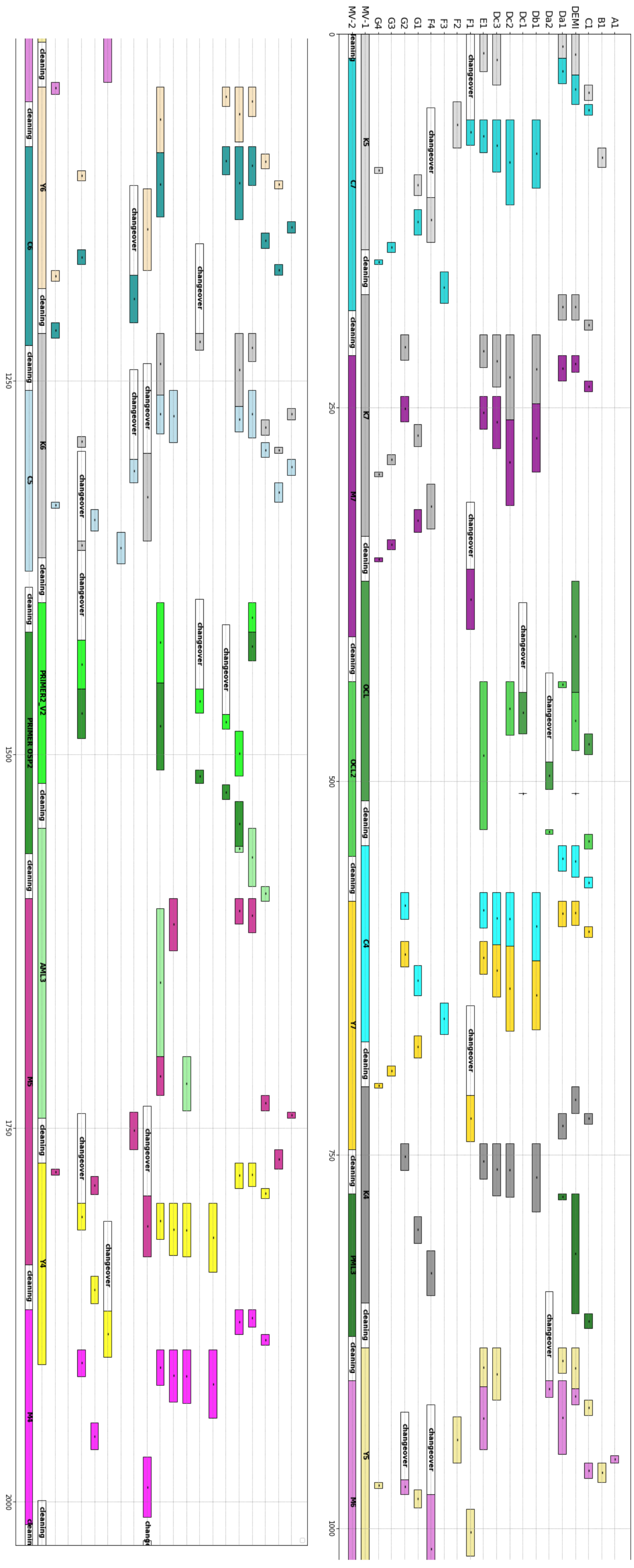


Figure A.1: Production schedule for problem instance with 22 recipes

Appendix B

Product distribution per cycle

The distribution of the products over the production cycles can be found in the table below. Every month consists out of 4 production cycles of with a length of 1 week.

Product	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	Total
Jan	**5**	**8**	**10**	**2**	**4**	**6**	**5**	**2**	**3**	**6**	**5**	**1**	**13**	**9**	**28**	**4**	**0**	**4**	**0**	**1**	**14**	**3**	**133**
Wk 1	2	2	2	1	1	1	1	1	1	1	1	1	3	2	7	1	0	1	0	0	4	1	34
Wk 2	1	2	3	0	1	2	1	0	1	2	1	0	4	2	7	1	0	1	0	0	4	0	33
Wk 3	1	2	2	1	1	1	2	1	0	1	2	0	3	3	7	1	0	1	0	0	3	1	33
Wk 4	1	2	3	0	1	2	1	0	1	2	1	0	3	2	7	1	0	1	0	1	3	1	33
Feb	**4**	**3**	**4**	**2**	**4**	**10**	**4**	**3**	**2**	**11**	**4**	**4**	**7**	**11**	**23**	**4**	**0**	**4**	**1**	**1**	**21**	**4**	**131**
Wk 1	1	1	1	0	1	3	1	1	0	3	1	1	2	2	6	1	0	1	1	0	5	1	33
Wk 2	1	1	1	1	1	2	1	0	1	3	1	1	1	3	6	1	0	1	0	1	5	1	33
Wk 3	1	1	1	0	1	3	1	1	0	3	1	1	2	3	5	1	0	1	0	0	6	1	33
Wk 4	1	0	1	1	1	2	1	1	1	2	1	1	2	3	6	1	0	1	0	0	5	1	32
Mar	**1**	**2**	**6**	**2**	**0**	**4**	**9**	**2**	**1**	**1**	**6**	**3**	**11**	**4**	**44**	**7**	**0**	**4**	**0**	**1**	**7**	**3**	**118**
Wk 1	1	0	2	0	0	1	2	1	0	0	2	1	2	1	11	2	0	1	0	0	2	1	30
Wk 2	0	1	1	1	0	1	2	0	1	0	1	1	3	1	11	2	0	1	0	0	2	0	29
Wk 3	0	0	2	0	0	1	3	1	0	0	2	0	3	1	11	2	0	1	0	0	2	1	30
Wk 4	0	1	1	1	0	1	2	0	0	1	1	1	3	1	11	1	0	1	0	1	1	1	29
Apr	**6**	**4**	**4**	**3**	**7**	**3**	**4**	**2**	**5**	**4**	**4**	**1**	**8**	**7**	**23**	**5**	1	**5**	**1**	**1**	**11**	**2**	**111**
Wk 1	2	1	1	0	2	1	1	0	2	1	1	0	2	1	6	2	0	1	0	1	3	0	28
Wk 2	1	1	1	1	2	1	1	1	1	1	1	0	2	2	6	1	0	1	0	0	3	1	28
Wk 3	2	1	1	1	1	1	1	0	1	1	1	1	2	2	5	1	1	1	0	0	3	0	27
Wk 4	1	1	1	1	2	0	1	1	1	1	1	0	2	2	6	1	0	2	1	0	2	1	28
May	**2**	**3**	**9**	**2**	**4**	**6**	**9**	**4**	**3**	**3**	**8**	**3**	**17**	**6**	**16**	**7**	**0**	**4**	**0**	**1**	**9**	**4**	**120**
Wk 1	1	0	3	0	1	2	2	1	0	1	2	1	5	1	4	1	0	1	0	1	2	1	30
Wk 2	0	1	2	1	1	1	3	1	1	1	2	0	4	2	4	2	0	1	0	0	2	1	30
Wk 3	1	1	2	0	1	2	2	1	1	0	2	1	4	1	4	2	0	1	0	0	3	1	30
Wk 4	0	1	2	1	1	1	2	1	1	1	2	1	4	2	4	2	0	1	0	0	2	1	30
Jun	**3**	**4**	**5**	**3**	**4**	**7**	**5**	**5**	**3**	**6**	**6**	**4**	**10**	**7**	**25**	**6**	**0**	**4**	**1**	**1**	**16**	**3**	**128**
Wk 1	1	1	1	1	1	1	2	1	1	1	2	1	2	2	7	1	0	1	0	1	4	0	32
Wk 2	1	1	1	1	1	2	1	1	1	2	1	1	3	1	6	2	0	1	0	0	4	1	32
Wk 3	1	1	1	1	1	2	1	1	1	1	2	1	2	2	6	1	0	1	1	0	4	1	32
Wk 4	0	1	2	0	1	2	1	2	0	2	1	1	3	2	6	2	0	1	0	0	4	1	32
Jul	**5**	**10**	**16**	**3**	**5**	**10**	**13**	**4**	**6**	**10**	**14**	**3**	**14**	**10**	**44**	**7**	**0**	**4**	**0**	**1**	**24**	**4**	**207**
Wk 1	2	2	4	0	2	3	3	1	1	3	3	1	3	3	11	2	0	1	0	0	6	1	52
Wk 2	1	3	4	1	1	2	3	1	2	2	4	1	4	2	11	1	0	1	0	1	6	1	52
Wk 3	1	2	4	1	1	3	4	1	1	3	3	1	3	3	11	2	0	1	0	0	6	1	52
Wk 4	1	3	4	1	1	2	3	1	2	2	4	0	4	2	11	2	0	1	0	0	6	1	51
Aug	**4**	**4**	**11**	**5**	**6**	**7**	**14**	**7**	**3**	**5**	**7**	**6**	**5**	**7**	**31**	**9**	**0**	**4**	**1**	**1**	**13**	**4**	**154**
Wk 1	1	1	3	1	2	2	3	1	1	2	2	1	1	2	8	2	0	1	0	1	3	1	39
Wk 2	1	1	3	1	1	2	4	2	1	1	1	2	1	2	7	3	0	1	0	0	4	1	39
Wk 3	1	1	3	1	2	1	3	2	1	1	2	1	2	2	8	2	0	1	0	0	3	1	38
Wk 4	1	1	2	2	1	2	4	2	0	1	2	2	1	1	8	2	0	1	1	0	3	1	38

Product	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	Total
Sep	**5**	**3**	**5**	**3**	**4**	**3**	**8**	**3**	**3**	**4**	**3**	**3**	**6**	**8**	**26**	**9**	**0**	**5**	**1**	**1**	**14**	**3**	**120**
Wk 1	2	0	2	0	1	1	2	1	0	1	1	1	1	2	7	2	0	2	0	1	3	0	30
Wk 2	1	1	1	1	1	1	2	0	1	1	1	1	2	2	6	2	0	1	0	0	4	1	30
Wk 3	1	1	1	1	1	1	2	1	1	1	0	1	1	2	7	2	0	1	1	0	3	1	30
Wk 4	1	1	1	1	1	0	2	1	1	1	1	0	2	2	6	3	0	1	0	0	4	1	30
Oct	**3**	**13**	**11**	**4**	**3**	**17**	**10**	**4**	**4**	**8**	**9**	**3**	**12**	**14**	**43**	**8**	**0**	**4**	**0**	**1**	**28**	**4**	**203**
Wk 1	1	3	3	1	1	4	2	1	1	2	2	1	3	4	11	2	0	1	0	0	7	1	51
Wk 2	1	3	3	1	0	5	3	1	1	2	2	1	3	3	10	2	0	1	0	1	7	1	51
Wk 3	1	3	3	1	1	4	2	1	1	2	2	1	3	4	11	2	0	1	0	0	7	1	51
Wk 4	0	4	2	1	1	4	3	1	1	2	3	0	3	3	11	2	0	1	0	0	7	1	50
Nov	**3**	**6**	**4**	**3**	**2**	**16**	**4**	**4**	**1**	**6**	**5**	**5**	**17**	**16**	**33**	**8**	**0**	**4**	**0**	**1**	**19**	**7**	**164**
Wk 1	1	1	1	1	1	4	1	1	0	1	2	1	4	4	9	2	0	1	0	0	5	1	41
Wk 2	1	2	1	0	0	4	1	1	1	2	1	1	4	4	8	2	0	1	0	1	4	2	41
Wk 3	1	1	1	1	1	4	1	1	0	1	1	1	5	4	8	2	0	1	0	0	5	2	41
Wk 4	0	2	1	1	0	4	1	1	0	2	1	2	4	4	8	2	0	1	0	0	5	2	41
Dec	**1**	**4**	**4**	**5**	**1**	**5**	**6**	**6**	**1**	**3**	**5**	**4**	**17**	**6**	**54**	**11**	**0**	**4**	**1**	**1**	**21**	**3**	**163**
Wk 1	1	1	1	1	0	1	2	1	1	0	2	1	4	1	14	3	0	1	0	0	5	1	41
Wk 2	0	1	1	1	1	1	1	2	0	1	1	1	4	2	13	3	0	1	0	1	5	1	41
Wk 3	0	1	1	2	0	1	2	1	0	1	1	1	5	1	14	2	0	1	1	0	5	1	41
Wk 4	0	1	1	1	0	2	1	2	0	1	1	1	4	2	13	3	0	1	0	0	6	0	40