Reconfiguration of a Two-Stage Production System with a Shared Pipeline Network

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Management Summary

Increasing competition and ever-changing consumer demands force manufacturers to frequently reconfigure their production system to meet the needs of numerous product groups. New fruit juices were introduced to the market by Riedel, resulting in a larger but more fragmented production volume. Since then, deteriorating performance measures have been observed regarding the efficiency of packaging and filling equipment due to increasing unplanned stops.

A problem cluster was used to identify the core problems from the central (perceived) problem. The central problem is unplanned stops in the form of internal supply problems. These situations occur when the production stages, which precede the packaging stage, cannot bring a batch of fruit juice to the packaging and filling equipment at the desired time. Two coherent core problems are identified: either the material transfer equipment collection is not being used efficiently, or the equipment collection is not adequate for current operations. The following research question was formulated to address both problem simultaneously:

What cost-effective reconfigurations, capacity expansion or improved scheduling methods, can be made in Riedel's production system to minimize unplanned stops in the packaging stage caused by resource conflicts in prior stages?

Riedel's production system can be divided into three stages: the pre-processing stage, the processing stage and the packaging stage. The pre-processing stage comprises all activities concerning the collection and transfer of ingredients. The processing stage involves all mixing and dilution operations. The packaging stage includes pasteurization, filling and packing. The processing and packaging stage are highly interdependent and decoupled from the pre-processing stage. The production rate the packaging stage affects the rate of upstream equipment in the processing stage. These stages are connected by a shared pipeline network, which means that only a limited number of juice transfers can be performed simultaneously. Shared refers to the fact that there are fewer routes by which juice can be transferred between stages than there are internal sources of fruit juice. The utilization rates of the equipment included in this network ranges from 15% to 45%. Transfers in the shared pipeline network are currently not considered by scheduling procedures. This suggests that there is room for improvement through better scheduling.

A multi-product flow shop reflects characteristics of Riedel’s production system. Of which the packaging stage in turn reflects a unrelated parallel machine scheduling problem with sequence-dependent setup times, release dates and splitting property. The processing stage is a batch process with characteristics of finite intermediate (buffer) storage and partial connectivity (caused by the shared pipeline network). Partial connectivity refers to equipment that is connected to some of the equipment and not all of the equipment in the system, which can cause internal logistical problems. The problem of scheduling lies at the operational control level, while decisions on capacity expansion concern the strategic control level. The compatibility between those levels is emphasized. Optimization techniques for scheduling problems are mathematical models and (meta-)heuristics. Rule-based scheduling approaches are available for blending plants such as the prior stages.

The proposed solution design models Riedel's production system such that improved scheduling algorithms and the effect of capacity expansions can be evaluated in an experimental setting. The objective of this model is to minimize total cost, which is a function of overtime, stops (scheduled and unscheduled), temporary workers, and economies of scale achieved through synchronizations in the processing stage. This model has specific features that are not well covered by scientific literature. The first of these is whether or not the mixing operations of different production orders should be synchronized, since they are composed of the same mixture. The splitting property must be addressed by choosing whether or not to use a second filling machine on a packaging line. To minimize the number of temporary workers, filling machines can be released at different times during the week to obtain a balanced workload that can be handled without temporary workers. A constraint for which

there is no formulation in the scientific literature concerns the time that may elapse between two Cleaning-in-Place operations, which can be at most 72 hours.

In this study, heuristic solution methods were used, since similar problems cannot be brought to an optimal solution by exact methods within a reasonable time. A framework of simulated annealing was implemented with five operators that allow the full solution space to be traversed. The processing stage, and thus shared pipeline network, is integrated by implementing a greedy equipment allocation heuristic. The feasibility of the solutions is ensured by advancing packaging orders in time in case the processing stage cannot transfer a batch of fruit juice at the desired time. Such stops are not identified by the current planning procedure and are therefore unplanned stops. Identifying these stops in advance allows schedules to be adjusted by making changes to the solution and provides a more comprehensive scheduling approach. Capacity expansions are modeled by changing parameters.

Based on experiments, improvements through explicit scheduling and only capacity expansions have been identified as shown in the table below. The most promising expansion involves two pipelines parallel to existing pipelines in the shared pipeline network. Both reconfigurations significantly reduce the duration of total stops compared to the current situation, without compromising other indicators that make up the total cost of a schedule.

	Output rate of packaging stage	**Current Situation**	**Explicit Scheduling**	**Capacity Expansion**
Total Stops [weekly]	*Deterministic*	113.84 hours	101.48 hours	102.23 hours
Total Stops [weekly]	*Stochastic*	130.80 hours	121.51 hours	121.41 hours
Cost reduction [annually]	*Deterministic*	€ 0	€ 102,880	€ 95,520
Cost reduction [annually]	*Stochastic*	€ 0	€ 77,376	€ 78,208

From this, it can be concluded that capacity expansion and improved schedules perform similarly in terms of the average number of stops, and thus in terms of the expected annual cost reduction. The performance converges further when the generated schedules are subjected to stochasticity. Convergence can be explained by the observation that lower utilization rates result from capacity expansions, reducing the likelihood of observing a system in which all equipment in the shared pipeline network is occupied. Based on the annual cost reductions and the lower investment involved in the capacity expansion, it is recommended that Riedel proceeds with the expansion. The investment associated with the extension is estimated at €15,127 based on a non-binding quote. The investment required to embed the (explicit) planning algorithm into the current planning tool is estimated to be much higher based on service-level agreements with the supplier.

Sensitivity analysis shows that expansion maintains current performance on total stops with a 30% growth in production volume. Once a 30% growth in production volume is achieved, it is recommended to resort to an explicit planning approach that is less constrained by partial connectivity at that point because capacity in the shared pipeline network has been expanded. Stochastic output rates of filling machines causes additional unplanned stops, indicating the need for robust optimization techniques and a resilient online scheduling method.

Preface

Dear reader,

I have been working on this thesis for the past 5 of months. Its completion constitutes the conclusion of my master's degree in Industrial Engineering and Management at the University of Twente and thus of my student days. Through this page I would like to express my gratitude to the people who have been directly and indirectly involved in the creation of this report.

First of all, I would like to thank the management of Riedel. Regardless of the situation we found ourselves in, the COVID-19 pandemic, Riedel did not stop hiring interns and letting them visit the production facility. I would like to thank Jan Paul Koorn and Robin Wisse for hiring me and for exchanging thoughts on the topic of this research. I would like to thank Frank Koolen and Wout van de Pavert for making contacts within the organization and providing information that was needed for the purpose of this research.

Secondly, I would like to thank Matthieu van der Heijden for being my first supervisor at the University of Twente and guiding me through the final phase of my master's program. I've always found the meetings to be enjoyable and pleasant. I would also like to thank Engin Topan for being my second supervisor at the University of Twente.

I would like to thank some individuals from my personal circle. I would like to thank my parents and other relatives, friends and my girlfriend during this time.

I sincerely hope you enjoy reading this thesis.

Jan van den Hengel

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List of Abbreviations

Abbreviation	Definition	Introduced on page
SKU	Stock-Keeping-Unit	1
COP	Combinatorial Optimization Problem	6
CO2	Carbon Dioxide	8
CIP	Cleaning-in-Place	8
T	Mixing-Tank	11
L	Pipeline	11
P	Pump	11
PA	Pasteurizer	12
R	Filling machine	12
MES	Manufacturing Execution System	13
FIS	Finite Intermediate Storage	21
SA	Simulated Annealing	23
MIP	Mixed Integer-Programming	25

| Contents

1 | Introduction

This Chapter begins with a company introduction and a brief introduction of the department where the research is being conducted in section 1.1. Next, Section 1.2 provides a rationale for the developments that created the need for this research, followed by a problem description including a problem cluster. Section 1.4 formulates the objective of the research and delineates its scope. Finally, section 1.5 introduces the research design and the research questions as well as the deliverables.

1.1 | Company introduction

Riedel produces and sells ready-to-serve fruit juices and fruit beverages in cartons. It has one production facility which is located in Ede. In 2020 Riedel sold 205 million liters of juices and beverages, of which 190 million liters was produced at its own facility. This business generates 196 million euros in revenue. It currently produces 204 distinct products or SKUs composed out of 136 blends and 8 packaging varieties.

In 1966 Riedel moved to the Veluwe because of the better quality of the available water and in 1970 the company was taken over by the Verenigde Coöperatieve Melkindustrie Coberco, which itself later became FrieslandCampina through many mergers and acquisitions. In 2017, Riedel became independent again through the sale of FrieslandCampina to Standard Investment, a Dutch investment company.

The beverage industry in which Riedel was active in the 1970s was faced with a number of negative developments, such as the introduction of excise taxes on beverages, which forced the industry to look for healthier alternatives. Thanks to the merger with Coberco (which had the necessary technology), Riedel came up with the ideal solution: a range of fruit juices packed in convenient, space-saving disposable cartons.

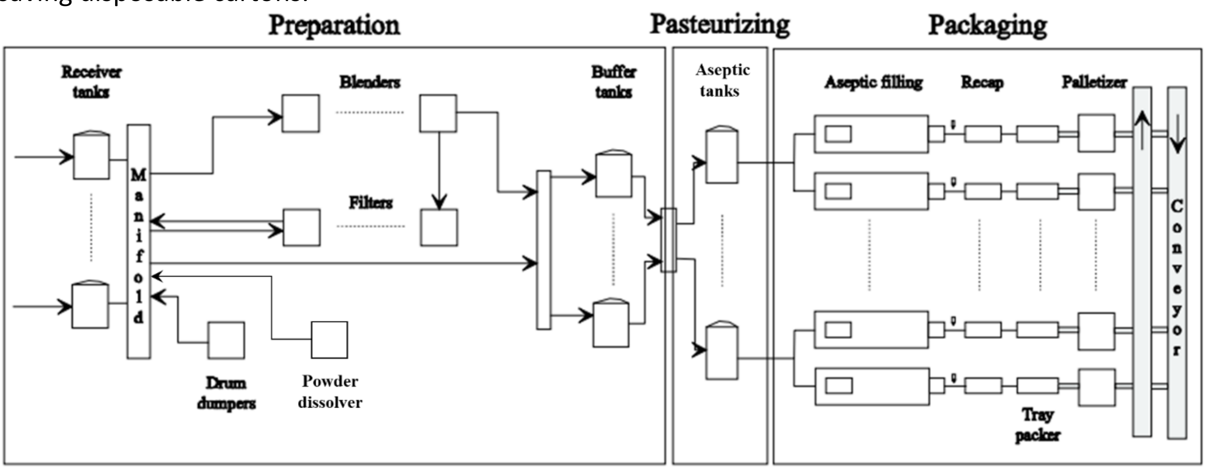

Figure 1 Simplified overview of Riedel's Fruit Juice Plant (Fey, 2002)

The production of fruit juices can be divided into three stages: pre-processing, pasteurization and packaging. These stages are shown in Figure 1 and are explained in more detail below. A more elaborate version of Figure 1 regarding the design of the production system can be found in Appendix A.

Preparation is a production stage that uses a variety of tools, such as tanks, pipes, manifolds, pumps and mixers. Ingredients are supplied from tanker trucks or in discrete forms, such as drums and bags. Production at Riedel is batch-wise. In the pre-processing stage, the ingredients are deportioned, dissolved, homogenized, mixed and diluted. Two mixing methods can be distinguished. The first method is in-tank mixing, the second is inline mixing. In the first method, all ingredients are transferred into a mixing tank, then the corresponding amount of water is added and then mixed. In the second method, the ingredients except water are transferred into a mixing tank and mixed. The appropriate amount of water is then added by a inline mixer in continuous manner

A batch of fruit juice is fed to pasteurizers. Fruit juices are pasteurized to reduce the number of bacteria and thus extend shelf life. These pasteurizers produce a continuous flow of juice to packaging lines, between which there is an aseptic buffer tank. The packaging lines use various machines to carry out operations such as filling, capping or straining, packing into trays and palletizing. The finished products are stored in Riedel's distribution center.

1.2 | Research motivation and problem statement

The issues addressed in this report have arisen as a result of developments within the organization, those developments are twofold. The first development is the corporatization of Riedel in 2017, which led to the production of private-label brands and the introduction of new products to boost brand awareness. Both developments contribute to an increasing production volume generated by a larger number of products. The second development within the organization is the pursuit of a lower Duration-of-Stay in the distribution center to prevent spoiled goods.

Increasing production volume combined with an increasing product portfolio results in a more fragmented production volume. Fragmentation has led to a greater number of production orders of smaller size. More production orders means that more changeover activities are required, which are classified as non-value-added activities and come at the expense of production capacity that could otherwise be used for value-added activities. In other words, the pressure on the capacity of the production system increases. This situation is depicted in Figure 2 and shows increased sales volume and decreasing lot size since Riedel's independence.

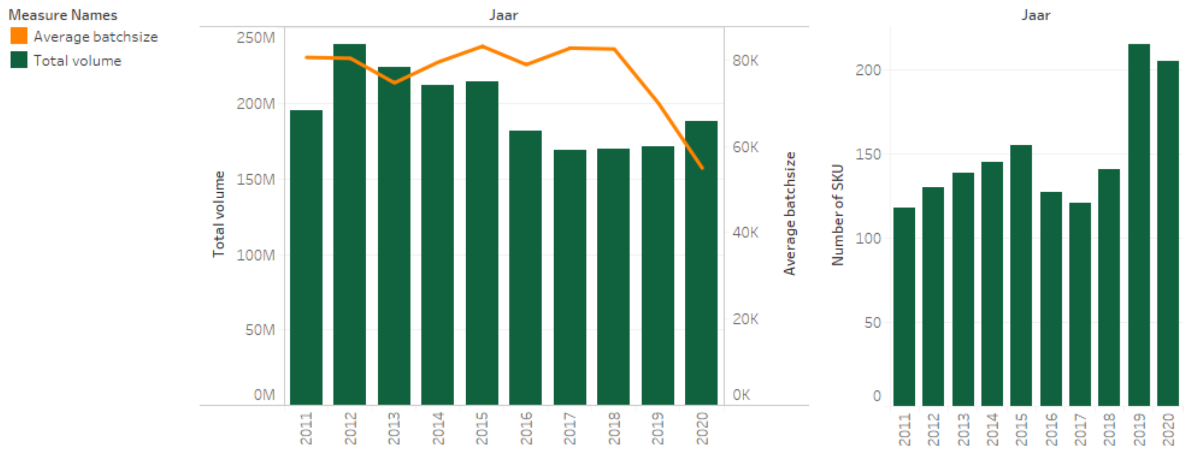

Figure 2 Development of order profiles

It is suspected that the previously mentioned developments are the cause of the degradation of some measures of overall equipment effectiveness (OEE). Figure 3 shows that juice shortages and routine interruptions, such as setup times, have degraded since the production volume and the number of different products increased. A juice shortage is defined as a material shortage that occurs when there is no flow of fruit juice from the pasteurization department to the filling machines or corresponding aseptic tanks and thus cannot start at the scheduled time. In the field of operations management, we would define this situation as *tardiness* in preceding stages.

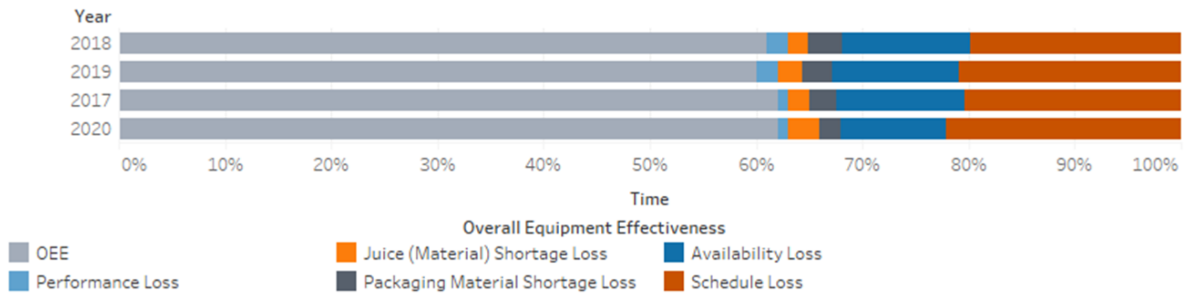

Figure 3 Packaging stage capacity losses development

In 2020, we observe a juice shortage that corresponds to an average time loss of 2.9% per filling machine. Given that there are eleven filling machines, this time loss implies that 1167 hours were left unused due to juice shortages. Given the cost of man and machine hours, this represents a loss of approximately €186,000. As a result of the increasing juice shortages, a sense of inefficiency is emerging with regard to the stages of the production system that precede the packaging stage. These stages are not considered capable of efficiently producing the current order profiles and volumes at the right time. This research addresses juice shortages caused by disruptions in stages preceding the packaging stage. Other capacity losses are not addressed since other improvement programs are in place to address those.

Core problems and problems related to the core problem can be identified and the relationships between them can be expressed in a problem cluster. Multiple core problems can be identified that in turn cause the central or perceived problem (Heerkens & van Winden, 2017). The central problem addressed in this study is juice (material) shortages from a packaging perspective. The sub-problems that relate to this central problem are incorporated into the problem cluster, shown in Figure 4. The problems are explained in more detail below.

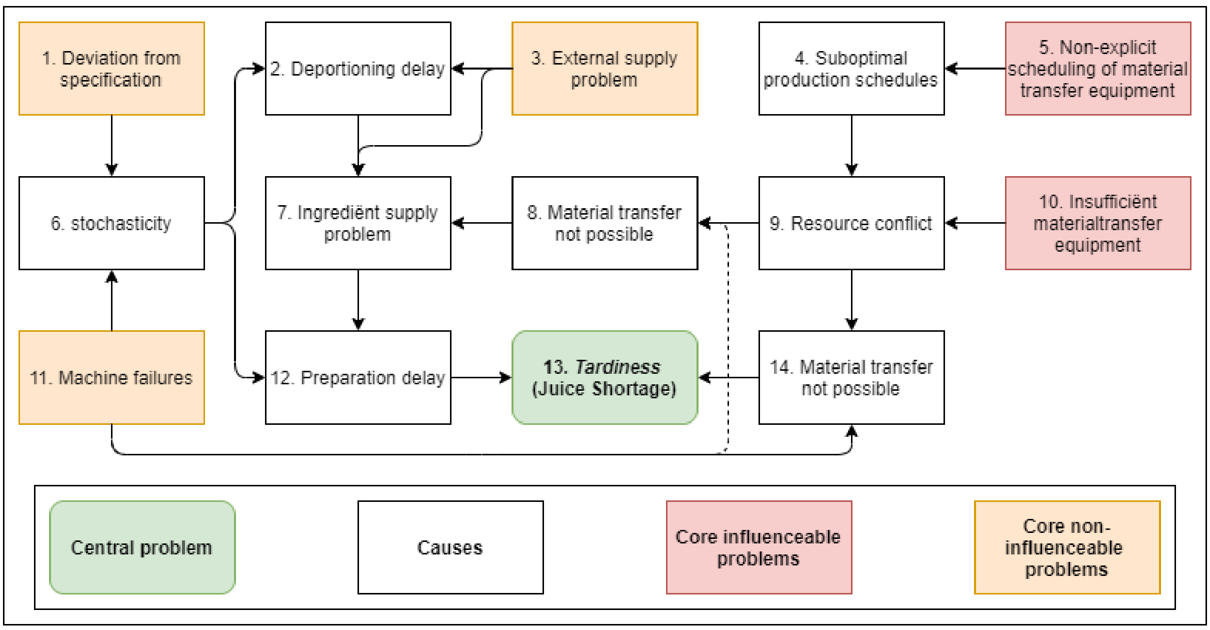

Figure 4 Problem cluster

The central problem addressed in this study is the situation where there are shortages of juice at the packaging stage (13). These situations imply that there is no juice flow to packing machines at times when packing machines were supposed to be working on a batch of juice. The previous section highlighted that in 2020, 2.9% of available packing time was lost due to juice shortages.

Tardiness of juice transfers from the processing stage to the packaging stage may occur when the preparation stage has not completed its operations at the scheduled time (12), in other words, when the preliminary activities were not completed in time. In addition, juice shortages may occur when juice cannot be transferred to the packaging stage by piping and pumping (14), even though preparation activities had been completed.

A disruption in the preparation stage (12) occurs due to a shortage of ingredients (7) and stochastic processing times (6). The latter is caused by machine breakdowns (11), which means that machines need to be repaired, or when additional mixing steps are required to make the juice meet specifications (1). Both can cause a delay. An ingredient shortage means that not all the required ingredients are present in the mixing tank that are needed to begin mixing.

Ingredient shortages are twofold. An ingredient shortage is caused by an external supply disruption (3). For example, a shipment of fruit concentrate that arrives late. Section 2.1 states that ingredients must be deportioned from bags and drums. Deportioning is the process of emptying packaging units so that the contents can be further processed. Deportioning is subject to stochasticity (6), for example, because a barrel of fruit concentrate is partially frozen. It may also be that those barrels or bags were not delivered on time (3). From the deportation stations, these ingredients must be transferred into receiving tanks; this transfer may not be possible at any given time (8).

Both ingredient transfers (8) and juice transfers (14) may be impossible at any given time. All transfers within the production systems is done through pipes and pumps. The production system has a shared pipeline network, which means that a particular combination of piping and pumps can be used for transfers with different origins and destinations. More specifically, in such a situation, there are more storage locations from and to which juice can be transferred than there are routes through which material can be transferred. This arrangement implies that *resource conflicts* arise when a resource, in this case equipment must do two or more operations on different flow units at the same time (9). In addition, pumps and pipes are also subject to machine failures (11).

The cause of resource conflicts is twofold. Resource conflicts can arise as a result of scheduling methods that do not take into account the occurrence of resource conflicts, which can result in suboptimal schedules (4). When all conflicts are taken into account and schedules are optimal for a given objective, conflicts may still arise because there are insufficient resources of a certain type (10). Riedel's current scheduling method or software package takes into account conflicts of resources for processing, such as mixing tanks, deportioning units, inline mixers, pasteurizers, and filling machines. However, it does not explicitly plan for material transfer equipment such as pumps and piping (5).

Two potential action problems arise from the problem cluster. The first potential action problem is the problem that material transfer operations are implicitly planned. In other words, the current production schedule does not reveal potential resource conflicts in the shared pipeline network consisting of pipes and pumps. Second, even if material transfer equipment were implicitly planned and included in planning methods, there may still be insufficient material transfer equipment of one type to avoid conflicts. This report addresses both action problems sequentially, since the these problems are clearly related.

1.3 | Research objective and scope

The research objective based on the previously displayed problem description can be formulated as:

To find efficient reconfigurations in Riedel's production system, either by capacity expansion or improved scheduling methods, with the goal of reducing unplanned stops in the packaging stage due to tardiness caused by resource conflicts in prior stages.

Resource conflict: A situation in which a certain equipment, e.g., a pump or pipe, is needed for several production orders at the same time. As a result, the fruit juice cannot be transferred from one stage to another at the desired time.

Reconfiguration: An intervention in the production systems that involves either physical or logical (procedural) changes.

Unplanned stops: Time during which the equipment in the packing stage cannot function because there is no juice flow transferred to the packing stage at the required time, resulting from delays in the processing stage.

Tardiness: Time that elapses between the time a packaging line is set up and the time a flow is actually established between the packaging stage and the preceding stage.

The result of this study will be findings regarding cost-effective reconfigurations of the production system. Furthermore, the effectiveness of these reconfigurations under changing conditions in terms of production volume and fragmentation will be examined.

This research focuses on reconfigurations in the production system with the goal of reducing equipment downtime in the packaging stage due to juice shortages. Several other causes of downtime were identified, which are not addressed in this thesis.

The purpose of this study is to define reconfiguration options that are the most cost-effective. Reconfigurations are either physical or logical, as will be discussed in more detail in Chapter 3. Physical reconfigurations to equipment other than the juice transfer equipment are not considered because Riedel is not willing to invest in them.

The reconfigurations will be modeled in a computer to evaluate performance under different conditions. It will assessed how the production system performs under different scenarios. The tool provided should include a module to generate problem cases that reflect reality. The changing parameters should enable Riedel to evaluate the performance of the production system under changing demand profiles. This will enable Riedel to assess the extent to which production volume and fragmentation can continue to increase while meeting demand with the current and proposed production system configuration. In short, the solution of this research must be compatible for it to be integrated in some capacity analysis tool.

Section 1.3 introduced some key problems that are not controllable, that is all uncertain events such as deviating specifications, machine failures and external supply disruptions. Reduction of downtime by reducing stochasticity in the production system is not considered as part of his research.

Reverse flows through the production system are not considered. These are small flows that do not affect forward flows. Their effect on performance is therefore considered negligible. Examples of reverse flows are dairy products that are stored in cooling tanks at the end of a week and transferred back to mixing tanks at the beginning of a week.

1.4 | Research design

The research question is formulated as:

What cost-effective reconfigurations, capacity expansion or improved scheduling methods, can be made in Riedel's production system to minimize unplanned stops in the packaging stage caused by resource conflicts in prior stages?

In order to answer this research question, the following knowledge questions are formulated:

1. **What is the current situation and configuration of production system?**

1.1 Which product groups to be produced can be distinguished and what are the production-related characteristics?
1.2 What are the characteristics of the order sets and demand distributions at the product level?
1.3 What is the current physical configuration of the production system?

1.4 What is the current logical configuration related to the scheduling of operations in the production system?
1.5 What is the current utilization of the production system with respect to resource conflicts?

The answer to question 1 allows for a further delineation of the research area. To achieve a proper delineation, it is useful to introduce the product portfolio and its production-related characteristics when answering question 1.1. The order patterns are introduced in question 1.2 for the same reason. Questions 1.3 and 1.4 deal respectively with the physical and logical configuration of the current production system. Based on observations regarding the physical configuration and the order patterns, an initial delineation can be made. Question 1.5 will address the performance of the current production system with respect to utilization rates with the goal of selecting the most promising core problem that will be addressed in the remainder of this thesis.

2. What optimization methods are available in scientific literature regarding the reconfiguration of production systems in general and for situations that reflect Riedel?
2.1 What is a good definition of production systems according to the scientific literature and what classification frameworks for production systems are proposed?
2.2 How do production systems evolve according to the scientific literature?
2.3 What frameworks are available for the classification of planning problems?
2.4 What solution methods are available in the scientific literature for combinatorial optimization problems (COP)?
2.5 Are solution methods proposed in the scientific literature for situations similar to Riedel's?

The answers to questions 2.1 and 2.2 will provide a theoretical framework related to production systems that will allow the problem at Riedel to be positioned in the scientific literature. Question 2.3 proposes theoretical frameworks to classify the solution approach resulting from Question 1 in the planning and scheduling literature. Question 2.4 in turn discusses optimization approaches for these scheduling problems. Finally, Question 2.5 discusses solution approaches discussed in the scientific literature that have proven useful.

3. **How can algorithms/heuristics, modeling approaches and optimization techniques found in the literature (and beyond) be applied to Riedel's production system?**
3.1 What is an appropriate performance measure for the packaging stage and how is it calculated taking into account juice shortages caused by prior stages?
3.2 What planning algorithm can be used to optimize the packaging stage independently of the processing stage?
3.3 Can the performance of the algorithm proposed in 3.2 be verified and validated with the current performance of the production system?
3.4 How can the algorithm of section 3.2 be extended to optimize the packaging stage while taking into account the juice shortages generated by the generated schedules?

To optimally solve a problem, a performance measure is needed. A solution must be found to address the multi-objective problem at Riedel. In the remaining section, two scheduling algorithms are proposed. The first algorithm is assumed to represent the current production system, while the second is extended to account for material shortages that may occur. It will be graphically assessed whether the algorithm generates schedules that reflect reality.

4. **What performance increase is achieved by explicitly scheduling material transfer operations in a shared pipeline network and capacity expansions?**
4.1 How can order sets be generated such that they properly represent Riedel's current order pattern for experimental purposes?
4.2 What reduction in juice supply problems is achieved by the proposed scheduling algorithm?
4.3 What are the most promising physical reconfigurations and what is its expected performance increase.

4.4 What is the most cost-effective reconfiguration?

To draw statistically valid conclusions it is required to conduct several experiments. An experiment is considered solving the scheduling problem for an arbitrary instances. These problems are solved by modeling the human scheduler and the proposed algorithm, this allows for a paired t-test. An instance generator is designed for this purpose. The second sub-question answers what reduction in juice supply problems is achieved by the proposed algorithm. The second sub-question assesses whether the improvement becomes more significant if Riedel's production volume continues to increase. The third question evaluates what material transfer equipment is most involved in resource conflicts. Physical reconfigurations are defined to relieve this equipment and expected performance is evaluated. Finally, the most cost-effective reconfiguration is determined.

5. **What is the endurance and robustness of proposed reconfiguration?**
5.1 What is the endurance of proposed reconfigurations?
5.2 What is the robustness of proposed reconfigurations to stochasticity?
5.3 What is the most cost-effective reconfiguration under changing conditions?

Finally, it examines the extent to which the proposed reconfiguration supports growth and stochasticity and whether the conclusions drawn in Chapter 4 withstand.

1.5 | Conclusions

This Chapter introduced the company and the setting in which this research took place. The company was introduced, as well as the motivation for this research. A problem statement and research questions were formulated. From this Chapter, we learned the following:

- Riedel produces and sells ready-to-use fruit juices in disposable cartons. Currently 204 SKUs are produced at its factory in Ede. The production process can be divided into three stages: preparation, pasteurization and packaging.
- This study was prompted by the observation that some capacity losses, which degrade the OEE of the production facility, are increasing despite all efforts and improvement programs. The capacity losses referred to are juice shortages that occur at Riedel when no juice is transferred from the preparation stage to the packaging stage in time. It is suspected that the increased juice shortages are the result of the increasing production volume and the fragmentation of this volume. The core-problems relating to this problems are twofold. The first core-influenceable problem addresses the observation that some equipment groups are not explicitly scheduled, potentially causing conflicts. At the second, even if it would be explicitly and optimally scheduled, situations may remain in which there is insufficient equipment of any type.
- These developments cause additional complexity and increased pressure on the production system capacity.
- The research question was formulated as follows: *What cost-effective reconfigurations, physical or logical, can be made in Riedel's production system to minimize equipment downtime in the packaging stage due to resource conflicts?* To answer this research question, a series of sub-questions are formulated. This formulation does not comment upon which core-problem is most promising to address, so a delineation was made as the research proceeded.

Chapter 2 provides information on the current situation, which allows for further delineation of the scope of this study. Scientific contributions relevant to the study are identified and discussed in Chapter 3. The various scientific contributions are combined in Chapter 4 to design a solution to the problem addressed in this study. Chapter 5 continues with the implementation of this solution and identifies the performance of the solutions compared to the current situation. It remains to be seen whether these performances hold up when subjected to a sensitivity analysis, which is described in Chapter 6. Finally, Chapter 7 provides recommendations and conclusions.

2 | Current situation

This Chapter will answer the first research question. The first research question was "*What is the current situation and configuration of production system?*". A production system is a collection of people, equipment and procedures (Groover, 2016). To give a better understanding of this system, Section 2.1 will first introduce Riedel's product range and explain the ordering pattern of these products. Section 2.2 will introduce the collection of equipment in Riedel's production facility. Based on findings in Section 2.2 and section 2.1 combined, the scope of this study will be further delineated. The current planning and scheduling methods will be introduced in Section 2.3. Finally, Section 2.4 measures the current performance of the production system with respect to resource conflict and utilization.

2.1 | Product and production order characteristics

Fruit juices and drinks are produced at Riedel's production facility in Ede. Currently, Riedel produces 204 Stock Keeping Units (SKUs), which are composed of 136 different blends and different packaging types. Some blends occur in as many as four SKUs; the concept of blends and SKUs is shown in Figure 5. Riedel uses many different ingredients, which can be categorized as follows:

- Water
- Concentrates
- Additives: *aromas, powder and carbon dioxide (CO2)*

Concentrates are concentrated substances, fruit juice concentrates are fruit juices from which most of the water component has been removed. Riedel produces fruit juices by reconstituting these concentrates with water. Additives may be added to enhance certain characteristics. Carbon dioxide is dissolved in beverages to produce a carbonated drink.

Figure 5 Example of blends in different packaging types (Riedel, 2021)

In addition to the different types of ingredients, there are other product characteristics that are important to the production system. Four other product characteristics determine sequence dependent cleaning tasks in the production system. These characteristics are:

- *Whether the product contains allergens or not;*
- *Whether the product is biobased or not;*
- *The pasteurization temperature;*
- *And the structure of the product.*

The main idea is to prevent contamination of products, and therefore two cleaning operations with different durations are distinguished: either *flushing* with water or *Cleaning-In-Place (CIP)* with caustic substances, the latter being the most extensive. The products can be classified into 14 product families that differ from each other based on at least one of these product characteristics. Thus, the matrix of setup times is asymmetric and 14x14 in size. Depending on the *carton content* and *the number of cartons per tray*, additional setup time is required to prepare the machine for the next order.

Riedel's production facility produces fruit juices to meet customer demand and replenish inventory levels at its distribution center. Weekly time buckets are used at Riedel by the demand planner. The detailed production planner is tasked with generating a detailed production schedule for the week that specifies start and end times for production orders at resources. In 2020, 191 million liters will be produced at the factory in Ede. Divided over 52 weeks, this amounts to 3.7 million liters per week. An average of 68 production orders are completed per week. The average batch size is therefore about 55,000 liters. Figure 6 shows the total production volume in liters for each week in 2020, including how this production volume fluctuates and is spread across different production orders. The production volume for a week can be thought of as a composite function of whether a product is ordered and an arbitrary order size.

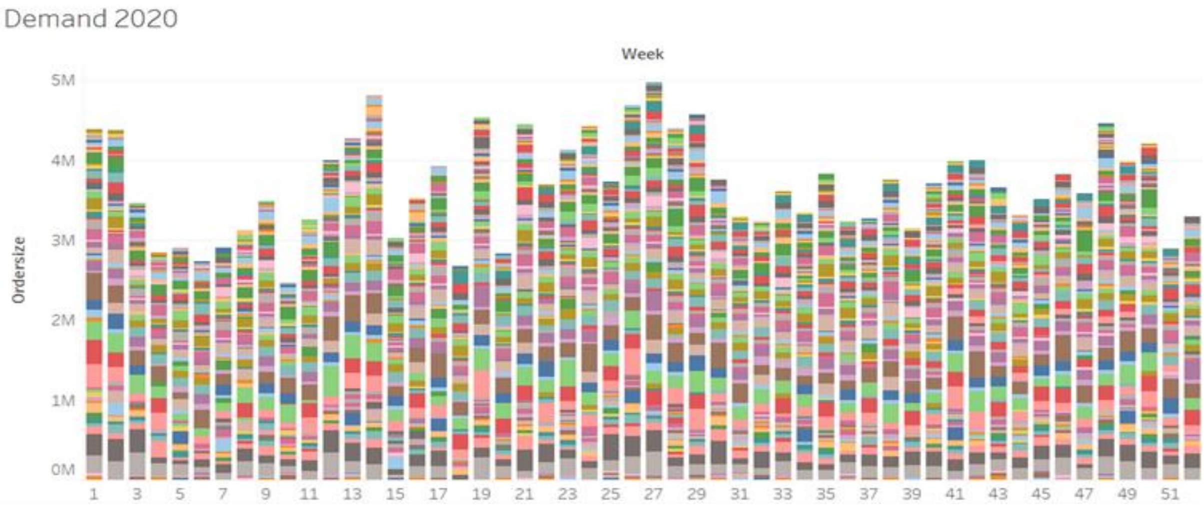

Figure 6 Production volume fluctuation and fragmentation

2.2 | Physical configuration of the production system design and demarcation

The function of a production system can be described as a transformation system that converts input to output (Attri & Grover, 2012). This section will elaborate on the physical configuration of the production system. The scope of this research will be delineated based on observations regarding dependencies within the system.

Riedel's production system transforms water, concentrates and other additives into fruit juices or beverages. Equipment such as mixing tanks, inline mixers, deportioning and dissolving equipment and packaging equipment are used for the conversion process. The transfer of ingredients, mixtures and juices between the transforming equipment is done with pumps, pipes and valves. For the purpose of this study, it is useful to distinguish three stages in the production system that differ from those described in Chapter 1. It makes sense to group the pasteurization and packaging processes into one stage, as they are interrelated. These proposed stages are:

- *Pre-processing stage*
- *Processing stage*
- *(Pasteurization and) packaging stage*

The pre-processing stage includes all operations related to concentrates and additives, except carbon dioxide. Concentrates and additives are supplied in different ways or stored in different tanks and transferred to mixing tanks. At the processing stage, the ingredients are reconstituted with water and the resulting product is transferred to the packaging and stage. This stage is responsible for these transfers and also for operating the inline mixers. The packaging stage receives a continuous flow of juice from the processing stage that is pasteurized and then packaged. The production stages are connected by a shared pipeline network, intermediate storage and a switchboard. The interaction between these stages can be illustrated by of Figure 7.

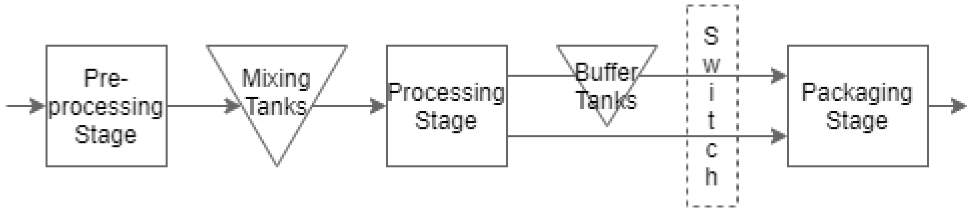

Figure 7 Stages in production system and storage between them

Once and only if all ingredients for a production order have been transferred to the mixing tank by the preprocessing stage, the processing stage can begin processing this production order. The pre-processing stage is therefore decoupled from the processing stage and from the packaging and pasteurization stage. Moreover, the capacity of the mixing tanks ranges from 50 m^3 to 155 m^3, which means that most tanks are suitable for the average batch size. However, the processing stage and the packaging and pasteurization stage are highly interactive and interdependent. All buffer tanks have a capacity of 30 m^3 liters and the capacity of the aseptic tanks in the packaging and pasteurization stage varies from 1.5 m^3 to 40 m^3. In the previous section, we found that the average size of a batch is 55 m^3. Thus, the aseptic tanks usually cannot store the whole batch. This can be explained by the fact that the function of these tanks is to reduce the oscillating output of continuous mixers and pasteurizers instead of storing it. These observations show that these two stages are highly interactive and interdependent and that production orders find themselves in both stages simultaneously.

Because of the negligible interdependence between the pre-processing stage and processing stage and the observation that resource conflicts at the processing stage directly lead to material shortages (juice) at the packing and pasteurization stage due to interdependence, we decided to exclude the pre-processing stage from the scope of this study. Therefore, the rest of this study will not address the pre-processing stage.

2.2.1 | Processing stage

The first step in the processing stage is blending of ingredients by reconstitution with water. In other words, a homogenous blend with correct product specifications is obtained. Two different blending methods are:

- In-tank mixing*: The ingredients are collected in a mixing tank. Water is added incrementally and homogenized by agitation in the tank itself until the correct specifications are obtained.*
- Inline mixing: *A continuous process that immediately produces a homogeneous product. A mixture of concentrates and additives is proportionally reconstituted with water by an inline mixer.*

The stage of packaging is reached once a flow of fruit juice is established into this stage. A route from a mixing tank to 5 five is created by switching a number of valves. A large number of routes can be created in this way. A route is formed by a mixing tank, a pump, a set of pipes and, in the case of inline mixing, a mixer and a buffer tank. Some of these pumps are specific to inline mixing or in-tank mixing, while others support both methods. Figure 8 shows all possible routes between the mixing tanks and switchboard 5. Green lines indicate route sections that can only be used for in-tank mixing, red lines for inline mixing, and black for both.

The concept of switchboards requires an introduction. A switchboard is a device that manages a set of connections between incoming and outgoing lines. A second concept that needs to be introduced is the concept of tank groups. Figure 8 shows on the left 5 formations of 4 tanks, these formations are tank groups. Tank groups share a number of pumps that there are fewer of than tanks. This is where potential resource conflicts can arise.

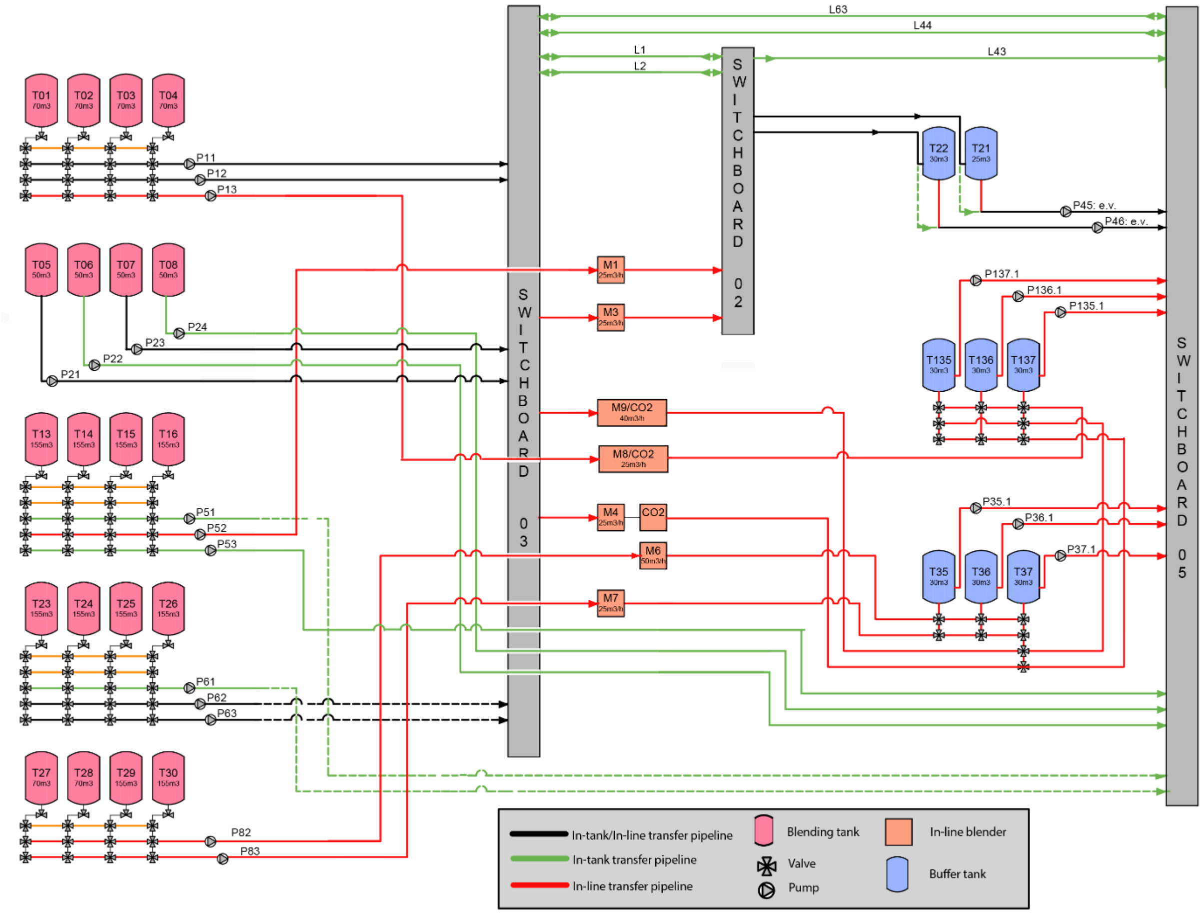

Figure 8 Physical configuration of processing stage

The current production system uses a shared pipeline network consisting of pumps, pipelines, mixers and buffer tanks. The shared pipeline network connects the processing stage to the packaging stage, but is intertwined with the processing stage. A combination of equipment is to be formed to produce a stream of juice from mixing tanks to the packaging stage through switchboard 5. Currently, there are 141 possible combinations of equipment that qualify for in-tank mixing and 296 for inline mixing, 437 in total. Thus, a production order which qualifies for both inline and in-tank blending has a solution space of 437 combinations. It is known that the packing stage is reached at the time a stream of fruit juice reaches switchboard 5. Moreover, it is likely, that the route used by the processing stage remains claimed by a production order that is pasteurized and packaged at that time. Consequently, the processing speed of the packaging lines directly determines the processing time of the equipment in the processing stage.

2.2.2 | Packaging stage

There are nine packaging lines that can be divided into five groups based on the type of packaging:

1. 0.15-0.20L cartons
2. 0.5-1.0L cartons
3. 1.0L cartons - *regular cap*
4. 1.0L cartons - *wing cap*
5. 1.5L cartons

Table 1 shows that the packaging stage has nine pasteurizers and aseptic tanks and eleven filling machines. Thus, there are nine packaging lines, two of which operate two parallel filling machines. It should be noted that if these machines work in parallel, they must necessarily work on the same production order, since the aseptic tank can only be used for the storage of one production order.

Table 1 Physical Packaging stage configuration

	Pasteurizer		Aseptic tank		Filling machine	
Type	**Name**	**Capacity (m^3/h)**	**Name**	**Capacity (m^3)**	**Name**	**Capacity (m^3/h)**
1	PA12	3.2	AT12	10	R11	2.4
1	PA21	6	AT21	1.5	R12	2.4
					R13	2.4
2	PA14	14.5	AT08	10	R20	6
2	PA22	14.5	AT22	20	R21	9
3	PA11	14.5	AT09	30	R61	8
4	PA07	20	AT11	40	R62	8
					R63	8
5	PA09	14.5	AT07	30	R90	13.5
5	PA10	14.5	AT10	30	R91	13.5
5	PA15	14.5	AT20	20	R92	13.5

The concept of multiple SKUs sharing the same mixture can be exploited by synchronizing jobs in the packaging stage. A synchronization means that jobs on different lines partially overlap on a time horizon or are sequential on the same packaging line. Enforcing a synchronization ensures that two packaging production orders are consolidated into one processing production order. The benefit of a synchronization is a reduction in production time in the processing stage. Fewer setup-time and mixing steps are needed since there is one batch to be produced rather than two.

2.3 | Current scheduling method of the production system

The logical configuration of production explains how a production system is controlled. This section explains how production orders are scheduled. A set of production orders is generated by the demand planner based on customer orders and inventory positions. The production planner schedules these orders on a one-week time horizon. All of the production orders to be scheduled are delivered by the demand planner at once rather than continuously. Some of these orders have releases due to ingredient availability. Production planning at Riedel is currently a sequential process. The production planner schedules the stages in the following order:

1. Packaging and pasteurization stage
2. Processing stage

2.3.1 | Packaging and pasteurization scheduling

Earlier we discussed the presence of nine packaging lines, some of which have the same capabilities in terms of package size and opening type. For each packaging type, a number of production orders are released that can be produced on packaging lines that support that type. The detailed production planner is charged with the task of determining the sequence and assigning the orders to the packaging lines. The following objectives are considered when creating this weekly schedule:

1. Minimize overtime
2. Minimize sequence dependence setup times
3. Maximize the number of synchronizations
4. Minimize the hours of temporary workers

The fourth objective requires an introduction. Temporary labor hours are required during periods when more than nine filling machines are operational. This has to do with the number of available operators in a shift. For this reason, the production planner shifts the workload over the week. To generate good schedules, the production planner takes into account the following constraints:

- Setup times are sequence dependent.
- Jobs should not overlap with other jobs and setup activities
- A CIP operation must be inserted into the schedule before a machine is operational for more than 72 hours.
- Some production orders cannot be scheduled in time intervals due to ingredient availability, so here are release dates or times.
- Any number of parallel filling machines can be assigned to a production order. This number must be between 1 and the number of parallel filling machines on the corresponding packaging line, i.e. either 1 or a 2.

The output of this planning process is a schedule for all filling machines with expected start and end times for all production orders. The preceding stage, the processing stage, must meet those start times to avoid material shortages. The schedules for the packaging line are thus inputs to the planning of the processing stage.

2.3.2 | Processing scheduling

The detailed production planner assigns mixing tanks and inline mixers to production orders. Processing equipment is assigned to production orders in such a way that a flow of fruit juice can be established at the required time. Schedules of this stage has no special objectives except to meet the processing requirements of the schedule for the packaging stage, and thus minimize tardiness.

A set of tanks is considered for each production based on the corresponding product characteristics and order size. Currently, the production planner takes into account some parts of the shared pipeline network when generating processing stage schedules. Tank groups that share a limited number of pumps are considered, but those pumps are considered uniform, which they are not, as shown in Figure 8. The use of pipes is not considered in any way; it is assumed that all flows can flow through the network of pipes at any time. The following constraints are considered when planning the processing stage:

- With in-tank mixing, the total production volume must not exceed the capacity of the mixing tank
- With inline mixing, the total production volume without water must not exceed the capacity of the mixing tank,
- Dissolution of carbon dioxide is only possible with inline mixers 4, 8 and 9.
- Some tanks are not compatible with some products due to product and tank characteristics.
- There are sequence-dependent setup times.
- Jobs should not overlap with other jobs and setup activities

2.4 | Equipment utilization

Two key problems were introduced in Chapter 1. The first *non-explicit scheduling of material equipment resources* and the second is *insufficient material transfer equipment*. This section introduces the utilization rates and patterns of material transfer equipment in an attempt to choose the most promising core influencing problem that will be addressed in the rest of this thesis.

Data on start and end times of equipment used by production orders are stored in a database by Riedel's manufacturing execution system (MES). Based on this data, the equipment utilization rate can be estimated and its behavior over time evaluated. Figure 9 shows the average equipment utilization rate. Equipment that has the same function in the shared pipeline network is consolidated. Capacity utilization in this context of batch processing refers to the percentage of time that fruit juice is in a (intermediate) storage area or flows through a portion of the pipeline network. The utilization rate thus indicates the percentage of time the equipment is being used for fruit juice production.

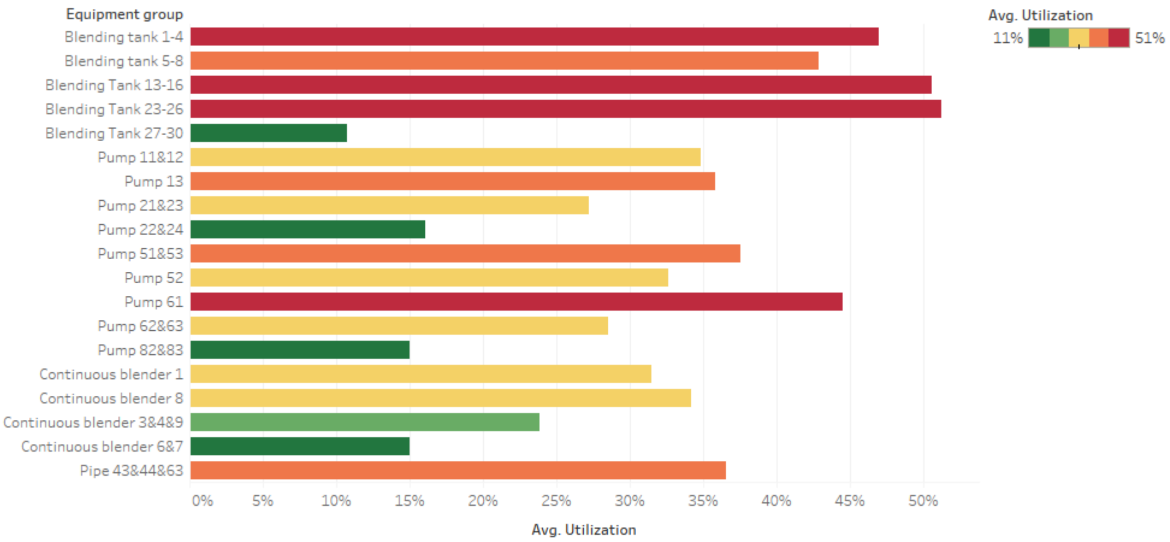

Figure 9 Consolidated Utilization Rates

The flow and utilization rates of the shared pipeline network (pipes and pumps) show no problems in the sense that the utilization rate approaches the numerical value of 1. Thus, these utilization rates reject the hypothesis that there would be insufficient resources of any kind. Somehow resource conflicts occur in this network of shared pipelines. The *flaw of averages* suggests that the assumption that average conditions will occur is usually wrong, and so it is interesting to see how these utilization rates behave over time. A closer look reveals that the consolidated utilization of parallel equipment group are approaching the numerical value 1 at some time intervals. These time intervals can lead to resource conflicts when trying to establish another stream that requires this parallel equipment. Figure 10 provides an examples of the high utilization rates at certain time intervals. It can be observed that the average utilization of L44, L62 and L43 in the time interval between February 16 and 17 approaches the numerical value 1. This is an example of a situation where the workload is not balanced and there is no room for an additional flow through this type of equipment.

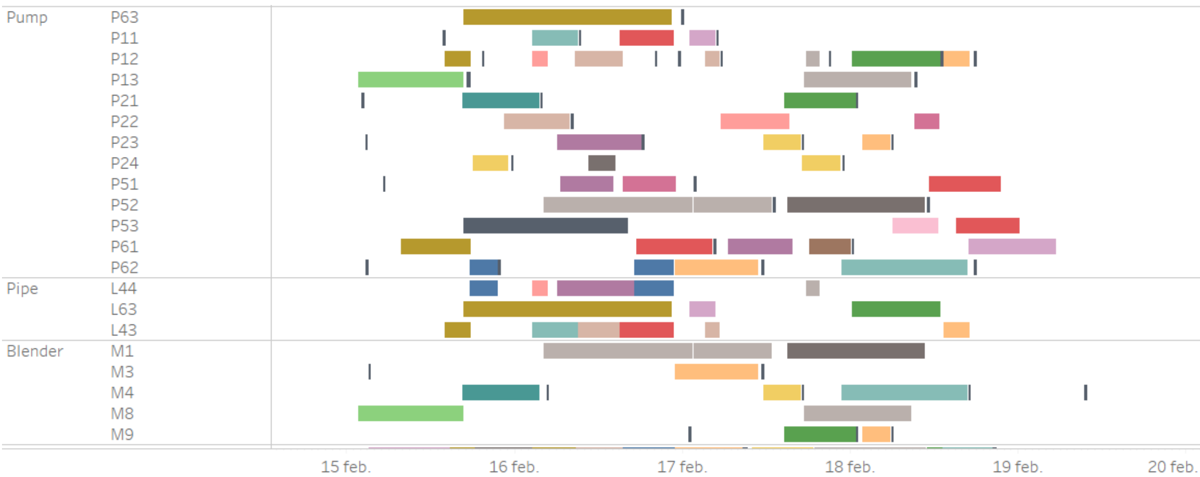

Figure 10 Gantt-Chart reconstructed from MES data

It is time-consuming to reconstruct production schedules from the data stored by MES. For this reason, we cannot quantify the current extent of material shortages due to conflicts. Current scheduling performance related to material shortages is quantified in Chapter 5 by modeling the human scheduler.

2.5 | Conclusions

This Chapter provided insight into the current setup and situation of the production system at Riedel. The product characteristics, the order patterns, the resources within the system and the transfers of goods are discussed. The following research question is answered: *What is the current situation with respect to production system and its resources?* We observe the following:

- The production process at Riedel consists of three stages. The first stage is decoupled from the subsequent stages because there is sufficient storage capacity at the decoupling point to store entire batches. This makes that an interruption in the first stage does not immediately lead to disruption in the second and third stages. For this reason, the first stage is excluded from the scope of this study. For the purposes of this study, two stages remain, the processing stage and the packaging stage, resulting in a *two-stage production process*.
- The processing stage produces 136 different blends that are further processed at the packaging stage into 204 stock-keeping unit (SKU). This allows multiple production orders at the packaging stages to be consolidated into one order at the processing stage, which is called *synchronization*.
- Another important feature of the production process is the observation that there are two packaging lines serving two parallel filling machines, which leads to a decision about the number of filling machines assigned to an order, this decision is known as job splitting.
- The processing stage connects the mixing tanks and the packaging stage through a shared piping network in which 437 combinations of equipment can be formed to produce an order.
- The most promising core-problem to be addressed is the non-explicit scheduling of material transfer equipment. This equipment is in the processing stage (and shared pipeline network) and a disruption due to a resource conflict directly results in tardiness in the packaging stage because the transfer is delayed. This situation is called a material (juice) whose total duration should be reduced through this study.
- The improved planning approach should be designed generic so that capacity expansion can also be evaluated in terms of performance, in case improvement through planning is deemed insufficient.

Chapter 3 introduces techniques, concepts and approaches to address the core problem of *non-explicit scheduling of material transfer equipment*, which is a scheduling problem.

3 | Literature review

The previous Chapter learned that the most promising influenceable core-problem is the *non-explicit scheduling of material transfer equipment*. This Chapter reviews scientific literature relevant for addressing this core problem. A theoretical framework is constructed by answering the following question, *"What optimization methods are available in scientific literature regarding the reconfiguration of production systems in general and for situations that reflect Riedel?".*

3.1 | Production systems design, classification and lifecycle

Chapter 2 described the current situation of the Riedel production system. It is therefore useful to consider the wide variety of production systems and their life cycle. Definitions of production system are given in Section 3.1.1. The types of production systems are explained in Section 3.1.2. The development of production systems in a life cycle framework is discussed in Section 3.1.3, as well as the concept of reconfigurations. This Chapter concludes with a conclusion.

3.1.1 | Production systems

Most businesses provide either products or services, or a combination of both, to make a profit. Various inputs, such as human resources, energy, raw materials, and information, are converted into finished products or services. These conversions take place through production processes. All activities related to the transformation processes are included in a production system.

For the purposes of this report, we use Groover (2016) definition of production system: "*the people, equipment and procedures that are organized for the combination of materials and processes that comprise a company's manufacturing operations*." Production systems include not only groups of machines, but also the procedures that make them work. Examples of such procedures are planning and control processes. One component of production systems is manufacturing systems. A production system is the collection of integrated equipment designed for a special purpose. These production systems are automated to varying degrees. Some are highly automated, while others are completely manually operated. A production system, in the context of a supply chain, can be defined as an assembly of production subsystems that carry the value streams of the firms and constitute the entire production flow, from raw materials or components to customers (Erlach, 2005). Houshmand and Jamshidnezhad (2002) emphasize that these subsystems operate interdependently and therefore must be designed together.

3.1.2 | Production system classification

There are many classification schemes for production systems. Hayes and Wheelwright were the first to introduce a classification scheme known as the product-process matrix (Hayes, 1979). Schmenner (1993) further developed the scheme proposed by Hayes and Wheelright. Schmenner's scheme distinguishes four major process types, which are shown in Table 2**Error! Reference source not found.** with their definitions.

Table 2 Schmenner (1993) process types

Process Type	Explanation
Continuous flow	Product Flows continuously.
Connected line flow	Used when the products have a sufficiently high volume and consist of discrete units. The product range is narrow, allowing for a continuous production system, and generally has a high degree of automation. The operations for each product are uniform.
Disconnected line flow	Use of batch processes to repeatedly make similar products. Volumes are not large enough to use a continuous production line. This type allows for a wider product range than continuous flow lines.
Jumbled flow lines	Used when products differ significantly. Operations for each product vary and allow for a high degree of customization.

Schmenner's scheme introduces the concepts of discrete units. Discrete production refers to the production of individual items such as cars, appliances, or computers (APICS, 2020). Process manufacturing refers to production that adds value by mixing, separating, forming and/or performing chemical reactions. This can be done in batch or continuous mode (APICS, 2020). According to van Dam, Gaalman, and Sierksma (1993), manufacturing companies whose at least one production stage involves homogeneous products classifies as a process industry company. Process industries have different operational characteristics according to Taylor, Seward, S F, and Heard (1981) and Taylor et al. (1981). A further distinction can be made within the process industry. Biegler, Grossmann, and Westerberg (1997) distinguish three main types of batch process plants: *single product structure; multi-product structure and multi-purpose structure*. Figure 11 visualizes *multi-product batch plants* and *multi-purpose plants*. In *multi-product* batch plants, products are very similar and the same equipment configuration or sequence of equipment is used. In *multi-purpose* batch plants, products can be produced in random sequences and equipment. Reklaitis (1990) points out that *multi-product structure*s are defined in the operations management literature as *flow shops*. In *flow shops*, there is a high degree of similarity in products and equipment is used in the same order, thus eliminating the need for rearrangement.

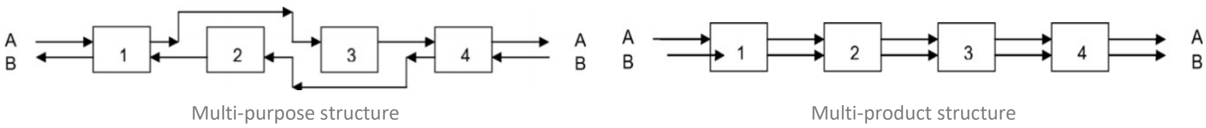

Figure 11 Process production systems (Biegler et al., 1997)

3.1.3 | Production system lifecycle

The previous sections discussed the concept of production systems and the fact that they can move along a diagonal line in the product-process matrix over time. Planning becomes a continuous process in response to rapidly changing market conditions due to globalization. In this light Kotler and Keller (2006) have proposed a product life cycle thinking framework. A product life cycle can be represented as a bell-shaped curve that distinguishes four stages: introduction, growth, maturity and decline. Market behavior is significant for manufacturing firms to design an efficient production system (Attri & Grover, 2012). Life cycle models for production systems have emerged for this reason. Most of these life cycle models recognize the fact that production systems must change over time.

Chase and Aquilano (1977) were the first to propose a life cycle model. This model had eight phases, the seventh of which is the "revision of the system" before the production system moves to the "termination of the system." Another life cycle framework, which emphasizes changes in market conditions, is proposed by Nakano, Noritake, and Ohashi (2008). Their model introduces two stages that can trigger reconfiguration. These are:

- Volume change and mix change stage
- Product change stage

ElMaraghy (2005) discusses the reconfigurability of production systems. ElMaraghy distinguishes between logical and physical reconfigurations. Logical or soft reconfigurations are inherently less costly and should always be exploited before moving on to other, more complex solutions. Some examples of reconfigurations are depicted in figure 12.

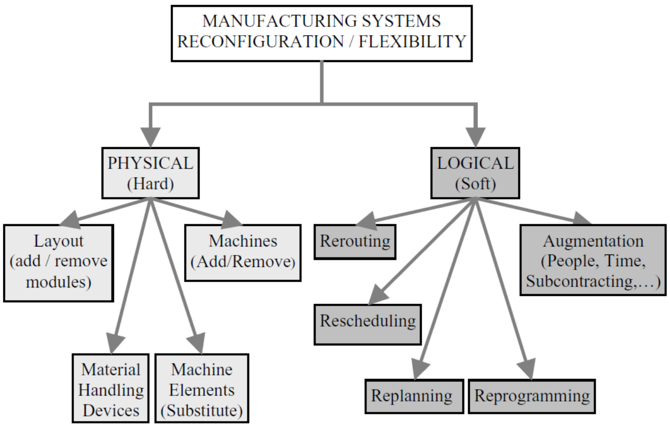

Figure 12 Manufacturing systems reconfigurations (ElMaraghy, 2005)

From this section, we learned that subsystems within a production system function interdependently. As a result, a need for joint design arises. Riedel's production systems would be classified as a disconnected line flow because the volume is insufficient to continuously produce one type of product. The production system reflects a multi-product batch plant rather than a multi-purpose plant. Most production system life cycle frameworks have some kind of reconfiguration/revision phase. In reconfiguration phases, production systems can be reconfigured either logically or physically. The choice made in Chapter 2, to first explore improvement potential through planning, could be classified as logical reconfiguration.

3.2 | Planning and Scheduling

Section 3.1 discussed the concept of production systems. It was shown that production systems include not only the physical design of the production facility, but also the procedures that enable its operation. This section will look more closely at the problems of planning and scheduling, which help positioning Riedel's problem.

A framework that classifies organizational decisions into three categories: strategic planning, tactical planning and operational control was proposed by (Anthony, 1965). (De Boer, 1998) distinguishes decisions at these three hierarchical levels, which are depicted in Figure 13, as well as their interrelationships

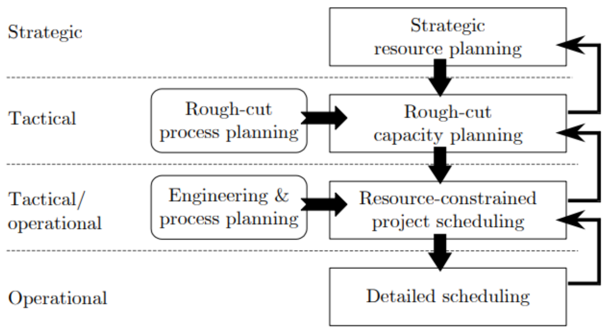

Figure 13 Hierarchical planning framework (De Boer, 1998)

De Boer (1998) emphasizes that information is passed on to the next hierarchical level. Such information generally imposes constraints on lower levels that create downward compatibility. Upward compatibility must be integrated into the framework. The time horizon at the operational level can range from one week to several weeks. According to (Spearman & Hopp, 1996), decisions at different levels of organizational control require different levels of detail, modeling assumptions, and planning frequencies. Consistency between levels is required in planning and analysis tools.

The hierarchical planning framework in the context of this thesis implies that the physical design of Riedel's manufacturing system should be taken into account when generating detailed schedules, or vice versa. Improving planning procedures to reduce material shortages is classified as achieving downward compatibility. Thus, the planning and scheduling problem addressed by this research is a detailed scheduling problem om the operational hierarchical level, therefore the next section proceeds on scheduling problems.

3.2.1 | Scheduling problems

A definition of planning proposed by Baker (1974) reads as follows: " *Scheduling is the allocation of resources over time to perform a collection of tasks*." The theory of scheduling is characterized by an almost unlimited number of problems. A schedule is an allocation of one or more time intervals for each task to one or more machine types (Brucker, 1999). Lawler, Lenstra, Kan, and Shmoys (1993) introduce the concept of sequencing and scheduling simultaneously. Their definition differs from other scientific literature by emphasizing the scarcity of resources: "*Sequencing and scheduling is concerned with the optimal allocation of scarce resources*." It is useful to provide two working definitions of scheduling and sequencing. A machine is a type of resource that performs at most one activity at a time. Jobs are activities performed by at most one machine at a time (Lawler et al., 1993). Solutions to scheduling problems are schemes that can be represented by Gant-Charts, as shown in Figure 14 *Machine-oriented* (a) and *job-oriented* (b) Gantt-Chart (Brucker, 1999).

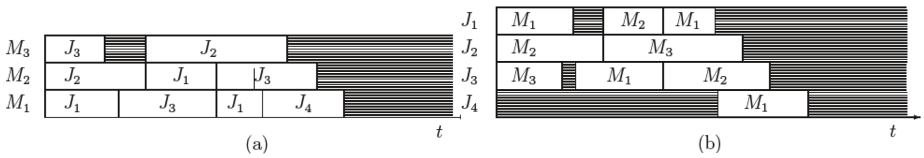

Figure 14 Machine- (a) and job-oriented (b) Gantt chart (Brucker, 1999)

3.2.2 | Classification of scheduling problems

A wide variety of planning problems can be defined, differing in complexity. Classification frameworks can provide guidance in addressing a wide range of problems. Scheduling problems are often classified with three fields α|β|γ. Where α refers to the machine environment, β to the job characteristics, and γ to the optimality criteria (Brucker, 1999). The α|β|γ classification framework was originally proposed by Graham, Lawler, Lenstra, and Kan (1979). This classification method was developed in light of the rapidly expanding field of deterministic planning theory. To use this classification scheme, one must know that each planning problem involves n tasks J_i (j=1,...,n) that must be processed on m machines M_i (i=1,...,m). To use the classification scheme of Graham et al. (1979) it must also be assumed that each machine is working on at most one task and that each task is processed by at most one machine at a time.

Machine environment

The machine environment is specified in the field α, which is a combination of α_1 and α_2. The possible values α_1 can take are (Graham et al., 1979):

$$\alpha_1 = \begin{cases} \emptyset & \text{single machine} \\ P & identical\ parallel\ machines \\ Q & uniform\ parallel\ machines \\ R & unrelated\ parallel\ machines \\ O & open\ shop \\ F & flow\ shop \\ R & job\ shop \end{cases}$$

Single machines and parallel machines refer to single-stage systems, while open, flow and job shops refer to multi-stage production systems. Parallel machines are classified as identical in the case that p_{ij} is p_j, meaning that processing times are the same on all parallel machines. Uniform refers to parallel machines whose processing time for a job is determined based on a speed factor q_i, where $p_{ij}=q_ip_j$. Unrelated parallel machines are environments where a speed factor cannot be defined, the processing times are not machine specific. Open workshops refer to machine environments in which there is no predetermined sequence of operations to follow, which can be found in flow and job shops. A flow shop has the same sequence of operations for each product, while job shop environments can have arbitrary, but predefined, sequences (Graham et al., 1979). α_1 is complemented by α_2, which has an integer value indicating the number of machines on which jobs are scheduled (Graham et al., 1979).

The packaging stage at Riedel is classified as *unrelated parallel machines* with nine parallel packaging lines. Some machines are unrelated because not all products can be produced on all machines. Within these nine unrelated parallel machines, there are some groups of identical parallel machines, but also uniform parallel machines. Nevertheless, the total packaging stage is classified as unrelated parallel machines.

Schalekamp et al. (2015) describe a job splitting property in a setting with identical parallel machines. A splitting property is generally addressed by ordinary preemption, in which feasible schedules do not allow multiple machines to work on the same order simultaneously. This constraint is dropped in Job splitting problems. In Graham notation, these formulations are indicated by *split* as job characteristics. Schutten (1996) considers parallel machine scheduling with release dates and sequence dependent setup times as job characteristics, those characteristics are denoted by r_j and s_{ij}, respectively.

The scheduling problem regarding the packaging stage can be classified as R9|r_j,s_{ij},*split*|TC. Where TC denotes a total cost function. The next section will introduce a classification scheme for batch processes specifically, which can be used to classify the processing stage at Riedel. The integral scheduling problem including the processing stage is classified as flow shop as discussed in section 3.1.1.

The assumption that each machine is working on at most one task and that each task is processed by at most one machine at a time does not hold since a batch of fruit juice may be in multiple stages simultaneously. The scheduling problem related to the packaging stage can be classified as R9|r_j,s_{ij},split|TC. Where TC is a total cost function of cost associated with each sub objective discussed in Chapter 2. The next section will introduce a classification scheme for batch processes in particular, which can be used to classify the stage at Riedel. The integral scheduling problem including the processing stage is classified as flow shop as discussed in Section 3.1.1.

3.2.3 | Classification of scheduling problems in batch processes

When developing scheduling models for batch processes, a wide variety of aspects must be taken into account. This makes it difficult to develop a general scheduling method suitable for most batch process systems (Méndez, Cerdá, Grossmann, Harjunkoski, & Fahl, 2006). The remainder of this section will present a roadmap that can be used to characterize a scheduling problem for a batch process system.

Process topology

The process layout of a batch plant and its topological characteristics have implications for the complexity of the problem. Section 3.1 already introduced the concept of single-product, multi-product and multi-product plants. Méndez et al. (2006) propose to distinguish topologies in three steps, where the first categorization can be made according to whether the operations should be sequential or random. In practice, sequential is the most common. Within sequential processes, a distinction can be made between single or multiple stages. If there are multiple stages, a distinction can be made between multiproduct (flow-shop) and multipurpose (job-shop).

Equipment assignment

Master recipes specify the equipment needed to perform the recipe procedures. In general, alternative equipment allocations are possible (Fuchino & Watanabe, 2005); in this case, the equipment allocation is considered variable. In other cases, the equipment allocation is fixed.

Equipment connectivity

Equipment connectivity can be categorized as partial (limited) or full (Méndez et al., 2006). In multi-path process structures, it is often the case that there are multiple production paths that meet the equipment requirements, but some equipment is not connected through pipes (Fuchino & Watanabe, 2005), in this case the equipment connectivity is partial.

Inventory storage policies

Wu and He (2004) present storage policies that can be divided into four classes, namely, *Unlimited Intermediate Storage* (UIS), *Non-Intermediate Storage* (NIS), *Finite Intermediate storage* (FIS) and *zero-wait* (ZW). Within the Finite Intermediate storage policy Méndez et al. (2006) make a further classification into dedicated storage units and shared storage units.

Material transfer

According to Méndez et al. (2006), material transfer operations may be instantaneous (or negligible) or time-consuming. Time-consuming material transfer operations can be further subdivided into conventional production systems, where equipment is connected by a fixed pipeline network, or pipeless batch systems where mixtures do not flow from tank to tank (Beek, Ham, & Rooda, 2002).

Changeover

Méndez et al. (2006) describe changeovers as a very important factor. Changeovers are especially critical when the setups are sequence dependent, as opposed to unit dependent switching. Thus, there can be either no changeover, unit-dependent changeover, or sequence-dependent changeover.

Time constraints

Different time constraints can affect the complexity of the scheduling problem. Méndez et al. (2006) state that working time constraints can arise due to non-work periods, for example weekends or vacations. Other time constraints are time intervals reserved for maintenance and shift work.

Degree of uncertainty

Planning problems and their solution may be subject to uncertainty or stochasticity. Thus, the degree of uncertainty of a planning problem is either deterministic, where the uncertainty is negligible, or stochastic, where uncertainty is significant (Méndez et al., 2006).

In this Chapter, several concepts have been discussed in which batch processes may differ. Regarding the process topology, we can classify the processing stage at Riedel as multi-product (flow-shop). Equipment allocation is variable, as there are many different combinations of equipment allowed for the production of one product. Finite Intermediate Storage (FIS) is the storage policy in the processing stage at Riedel, see section 2.3. Material transfer within the processing system takes place by means of a fixed, but common, pipeline network. The processing stage is subject to sequence-dependent setup times. There are non-working periods, such as weekends.

3.2.4 | Time representation

Scheduling formulations, according to Floudas and Lin (2004), can be classified into two main categories: discrete-time models and continuous-time models. Early attempts to model scheduling problems relied heavily on discrete-time models that divided the time horizon into a number of intervals of uniform length. Start and end of operations were related to the boundaries of these intervals, i.e., an operation could not start halfway through a time interval. To achieve a good approximation, it was necessary to make these time intervals sufficiently small. This led to major combinatorial problems. As a result of the complexity of the problem, science turned to the development of continuous-time models. Events, such as the beginning and end of operations, can occur at any point in the domain. The differences between these approaches are illustrated in Figure 15.

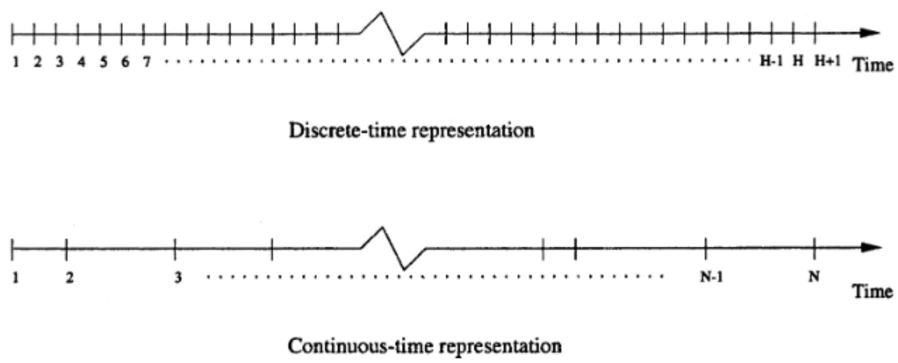

Figure 15 discrete versus continuous-time representations (Floudas & Lin, 2004)

Méndez et al. (2006) claim that using discrete-time models reduces the complexity of the problem and makes the structure simpler and easier to solve, especially when resource and inventory constraints are taken into account. However, there are two major drawbacks. The size and computational efficiency depend heavily on the number of time intervals. Moreover, infeasibilities and suboptimal solutions may result from simplification. Formulations with continuous time have the advantage of using exact times and are thus more flexible.

3.3 | Optimization techniques

Many optimization techniques are described in the scientific literature to obtain an optimal or good solution or to improve an existing solution. This Chapter discusses optimization techniques such as, mathematical models, constructive and meta-heuristic techniques, and decomposition approaches.

3.3.1 | Explicit method / exact algorithms

Scientific approaches to decision-making often involve the use of mathematical models. A mathematical model is a mathematical representation of the actual situation. These models can be used to better understand decision-making problems so that better decisions can be made. Most mathematical models used in operations research are prescriptive or optimization models. Such models prescribe decisions to the organization that will allow them to achieve their goals in the best way. A prescriptive mathematical model includes the following components (Winston & Goldberg, 2004):

- Objective function(s)
- Decision variables
- Constraints

Winston and Goldberg (2004) recognize the fact that some problems are much more difficult to solve. These situations occur when nonlinear and/or integer models are formulated. A nonlinear model refers to models in which decision variables are not multiplied and summed exclusively by constants. A model is an integer model if some decision variables must be of integer value (Winston & Goldberg, 2004). The next section will propose techniques to overcome the fact that some problems are much more difficult to solve.

3.3.2 | Approximation methods / heuristics

Optimization problems are likely to remain untraceable for exact algorithms forever, regardless of exponentially increasing computing power. Heuristics are used to solve this problem. A heuristic is defined as, "“*A form of problem solving in which results or rules have been determined by experience or intuition instead of by optimization* " (APICS, 2020). Heuristics have been used throughout human history for challenging problems.

The basic local search method is commonly called iterative improvement (Blum & Roli, 2003), but is also known as gradient or steepest descent, proposed by Cauchy (Lemaréchal, 2012). This technique performs changes in a solution only if the resulting solution is better than the current one. Once a local minimum is found, the algorithm stops. The performance of iterative improvement is usually unsatisfactory due to finding local optimums. To address this unsatisfactory performance, several algorithms are proposed in the scientific literature to escape these local optimums (Blum & Roli, 2003) for example metaheuristics.

Metaheuristics overcome the drawbacks of iterative improvement techniques, such as steepest descent. It is possible to overcome local optimality through metaheuristics. Metaheuristics are high-level strategies that use a more problem-specific heuristic to increase performance (Blum & Roli, 2003). Sörensen and Glover (2013) define a metaheuristic as, "A *high-level problem-independent algorithmic framework that provides a set of guidelines or strategies to develop heuristic optimization algorithms*."

The simulated annealing metaheuristic, originally proposed by by Kirkpatrick, Gelatt, and Vecchi (1983), was the earliest approximation method classified as a metaheuristic (Sörensen, 2015). According to Blum and Roli (2003), it was certainly one of the first algorithms to have an explicit strategy for escaping local optima. Kirkpatrick et al. (1983) describe their algorithm as composed of four ingredients:

- A concise description of a configuration of the system
- A random generator of rearrangements in the configuration
- A quantitative objective function
- An annealing schedule

The simulated annealing (SA) algorithm starts by constructing an initial solution, either random or heuristically. Then, at each iteration, a random neighbor solution is generated and accepted as the current solution with a certain probability in case it is worse. This probability is a function of the temperature, which is decreasing during the search process. Eventually, this annealing framework will evolve into a simple iterative improvement algorithm since no worse solutions are accepted once the temperature drops to zero (Blum & Roli, 2003). The advantage of Simulated Annealing is that it can deal with arbitrary optimization problems and cost functions. The structure of the algorithm is shown in Figure 16.

Input: Cooling schedule.
$s = s_0$; /* Generation of the initial solution */
$T = T_{max}$; /* Starting temperature */
Repeat
  Repeat /* At a fixed temperature */
    Generate a random neighbor s' ;
    $\Delta E = f(s') - f(s)$;
    If $\Delta E \leq 0$ **Then** $s = s'$ /* Accept the neighbor solution */
    Else Accept s' with a probability $e^{\frac{-\Delta E}{T}}$;
  Until Equilibrium condition
  /* e.g. a given number of iterations executed at each temperature T */
  $T = g(T)$; /* Temperature update */
Until Stopping criteria satisfied /* e.g. $T < T_{min}$ */
Output: Best solution found.

Figure 16 SA framework Talbi (2009)

Regarding the stopping conditions, Talbi (2009) states that the search can stop when the probability of a move being accepted is negligible. Talbi (2009) proposes three strategies for establishing a starting temperature, these are:

- Accept all: must be high enough to accept all neighbors in the initial stage
- Acceptance deviation: set starting temperature to *kσ*, where σ is the estimated difference of objective functions and *k* = −3/ln(*p*) with acceptance probability of *p*.
- Acceptance ratio: Set the starting temperature so that the acceptance ratio is greater than a predetermined value.

3.3.3 | Decomposition

Decomposition techniques are often used to address complex problems. Ovacik and Uzsoy (2012) explain decomposition of a complex problem into a number of smaller subproblems in an attempt to develop solutions that are more tractable and easier to understand. Goldratt and Cox (1986) describe that it is beneficial to solve subproblems in order of criticality, in this way a high quality solution can be found. Specific features of subproblems can be exploited to create an appropriate decomposition. Ultimately, the solutions of those subproblems are integrated into a solution to the original problem. Careful decomposition can produce good solutions to a single problem while making it easier to implement. Decomposition refers to the reduction of decision space and complexity, which improves decision making (Bertrand, Wortmann, & Wijngaard, 1990).

This section discussed optimization techniques that are highly relevant to the problem addressed in this thesis. These approaches will be combined in Chapter 4 to formulate a solution design. Decomposition will be used to reduce the problem size to improve computational efficiency. Section 3.4 will discuss optimization techniques that have been used in case studies in similar settings. Decomposition is useful to decompose a production system with multiple stages into subsystems and still obtain good solutions to a production-related problem.

3.4 | Optimization techniques for batch process systems

This paragraph will present optimization techniques for situations that reflect the situation at Riedel. The first paragraph presents a mathematical model that reflects the packaging and pasteurization stage of Riedel. The second paragraph introduces a batch scheduling heuristic for a blending plant which shares characteristics with the processing stage of Riedel.

3.4.1 | Mathematical models for parallel machine scheduling problems

Vallada and Ruiz (2011) propose an algorithm to solve the unrelated parallel machine scheduling problems with sequence dependent setup times. The goal is to minimize the maximum completion time. This mixed-integer problem (MIP) formulation for this problem is as follows:

Parameters:

$$p_{ij} = Processing\ time\ of\ job\ j, j\ \in N\ at\ machine\ i, i\ \in M$$

$$S_{ijk} = Machine\ based\ sequence\ dependent\ setup\ time\ on\ machine\ i, i \in M, when\ processing\ job\ k, k \in N, after\ having\ processed\ job\ j, j \in N.$$

The model has the following decision variables:

$$X_{ijk} = \begin{cases} 1, if\ job\ j\ precedes\ job\ k\ on\ machine\ i \\ 0, otherwise \end{cases}$$

$$C_{ij} = Completion\ time\ of\ job\ j\ at\ machine\ i$$

$$C_{max} = Maximum\ completion\ time$$

The objective function is:

$$\min C_{max} \tag{1}$$

Subject to:

$$\sum_{i \in M} \sum_{\substack{j \in \{0\} \cup N \\ j \neq k}} X_{ijk} = 1, \qquad \forall k \in N \tag{2}$$

$$\sum_{i \in M} \sum_{\substack{k \in N \\ j \neq k}} X_{ijk} \leq 1, \qquad \forall j \in N \tag{3}$$

$$\sum_{k \in N} X_{i0k} \leq 1, \qquad \forall i \in M \tag{4}$$

$$\sum_{\substack{h \in \{0\} \cup N \\ h \neq k, h \neq j}} X_{ihj} \geq X_{ijk}, \qquad \forall j, k \in N, \qquad j \neq k, \qquad \forall i \in M \tag{5}$$

$$C_{ik} + V(1 - X_{ijk}) \geq C_{ij} + S_{ijk} + p_{ik}, \qquad \forall j \in \{0\} \cup N, \forall k \in N, j \neq k, \forall i \in M \tag{6}$$

$$C_{i0} = 0, \qquad \forall i \in M \tag{7}$$

$$C_{ij} \geq 0, \qquad \forall i \in M, \qquad \forall j \in N \tag{8}$$

$$C_{max} \geq C_{ij}, \qquad \forall i \in M, \qquad \forall j \in N \tag{9}$$

$$X_{ijk} \in \{0,1\}, \qquad \forall j \in \{0\} \cup N, \qquad \forall k \in N, \qquad \forall j \neq k, \qquad \forall i \in M \tag{10}$$

The goal is to minimize the maximum completion time. According to (Yalaoui & Chu, 2003) this criteria is most studied in the scheduling literature. Constraint set (2) ensures that each job precedes some other job, including dummy jobs, on some machine. Constraint set (3) controls that each job has at most one successor. Constraint set (4) controls that each dummy job has at most one successor, such that only one jobs is the first job on some machine. The correct assignment of jobs to machines is ensured by constraint set (5), more specifically that the predecessor of a job must have a predecessor as well. This ensures that a sequence of operations is created. Completion times of jobs are controlled by constraints in set (6). In constraint set (6), *V*, represents a very large integer number. The purpose of this number is to control whether a constraint is active or not. Constraints (7) and (8) ensure that the completion times of (dummy) jobs are non-negative, while constraint (9) ensures that the maximum completion time is assigned the value of the largest completion time of any job. Finally, set (10) takes care of binary decision variables.

This mathematical problem formulation contains dummy jobs for all machines. Optimizing this mathematical problem formulation is difficult to optimize for exact algorithms. Therefore, Vallada and Ruiz (2011) propose a local search procedure used to improve solutions. The proposed operator is inter-machine insertion, which consists of inserting all jobs at every position of all machines, for all machines.

The model proposed above does not reflect the characteristics of the packaging planning problem at Riedel. This model needs to be extended in order to achieve an appropriate modeling approach. With respect to the splitting property of the packaging problem (Yilmaz Eroglu & Ozmutlu, 2014), the following limitation is proposed:

$$C_{ik} + V(1 - X_{ijk}) \geq C_{ij} + S_{ijk} + D_{ik} * Q_{ik}, \qquad \forall j \in \{0\} \cup N, \qquad \forall k \in N, \qquad \forall i \in M \qquad (11)$$

This constraint replaces constraint (6) of the mathematical problem formulation proposed by Vallada and Ruiz (2011). The constraint is that to control the completion time of job *k*, C_{ik} must be greater than the completion time of j plus the setup time and the processing time of *k*. The processing time is computed by the production quantity of job *j* on machine *i*. D_{ij} refers to the unit processing time of machine *k* for job *i* and Q_{ij} to the production quantity of job *i* scheduled on machine *k*.

Section 3.2.1 showed that the scheduling problem also had the job characteristic r_j. (Gharehgozli, Tavakkoli-Moghaddam, & Zaerpour, 2009) propose a model constraint that controls the release dates of jobs for a one-machine scheduling problem:

$$C_k + V(1 - X_{ijk}) \geq max(r_k, C_j + S_{jk}) + p_{ik}, \forall i \in \{0\} \cup N, \forall j \in N, j \neq k, \forall i \in M \qquad (12)$$

Constraint (12) guarantees that the completion time of task *i* is at least equal to the completion time of its predecessor or release date plus processing time.

(Yalaoui & Chu, 2003) dissertates heuristics for parallel machine scheduling with job splitting and sequence dependent setup times. Emphasized is the definition of splitting, which means that parts of the same job can be processed simultaneously on different machines. The dissertation shows that much work has been done on sequence independent setup times. The problem of scheduling sequence-independent jobs on identical parallel machines is NP-hard (Guinet, 1993). In light of the complexity, (Yilmaz Eroglu & Ozmutlu, 2014) found that a solver solves these problems for a 2-machine 6-jobs problem, where jobs can be split into at most 3 subjobs. For a 4-machine 6-job problem, a solver could not give the optimal solution in reasonable time.

The constraints discussed so far allow us to formulate a mathematical problem formulation for Riedel's packing scheduling problem. To our knowledge, there is no scientific literature on machine release data to balance workloads, as discussed in Section 2.4, nor literature on multi-objective values that reflect the Riedel situation. Most of the work in the scientific literature has been done on heuristics to solve the parallel machine scheduling problem with sequence dependent setup times. For this reason, a heuristic approach is considered the most promising. Especially considering that additional constraints must be added to represent Riedel's operational conditions.

3.4.2 | Scheduling for a blending plant with shared pipeline network

Hill, Cornelissens, and Sörensen (2016) propose a scheduling heuristic that can be used to solve a batch scheduling problem in a multi-product petrochemical plant. It takes into account the complex pipeline network that controls the flow of materials. This pipeline network is designed with limited end-to-end connections. By classifying this planning problem using the framework of Méndez et al.

(2006), the connectivity of this process is classified as partially connected. The proposed heuristic of by Hill et al. (2016) is one of the few scientific publications that considers partial connectivity.

The overall algorithm prioritizes orders based on a mixing priority. Since the mixing stage generally plays a central role in mixing plants and is subject to bottleneck situations. The algorithm proposed by Hill et al. (2016) precomputes transfer paths by using network techniques. Blending orders are prioritized based on a number of criteria, it is proposed to prioritize orders based on order quantity, since as the algorithm progresses it becomes more difficult to allocate scarce resources to such orders. The algorithm gradually explores the possible production paths in a greedy manner. All possible paths are enumerated using a depth-first search in the pipeline network. The proposed heuristic is suitable for short-term planning, but by its design can be integrated into tools for strategic or tactical plant layout decisions. Their approach also takes into account the Pipeline-Cleaning-System (PIG). The algorithm procedure is visualized in Figure 17 Overall scheduling algorithm for a blending plant Figure 17.

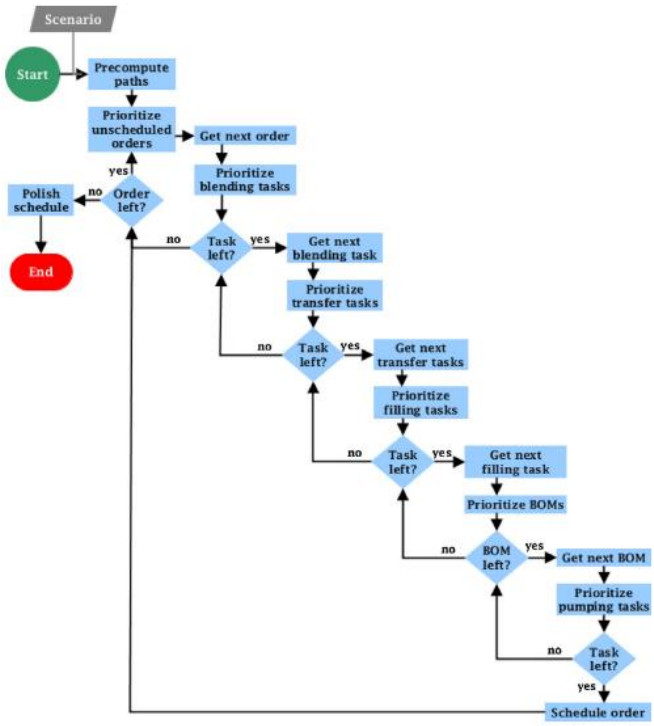

Figure 17 Overall scheduling algorithm for a blending plant

The operational conditions of the production systems considered by Hill et al. are similar to those of Riedel. The main differences are that the mixing stage is considered the most important, and not the packing/filling stage as is the case with Riedel. The proposed tool is suitable both for short-term planning and to support tactical and strategic decisions. The algorithm is useful for evaluating resource availability in blending processes including a shared pipeline network.

3.5 | Conclusions

This Chapter answered the following question "*What optimization methods are available in scientific literature regarding the reconfiguration of production systems in general and for situations that reflect Riedel?"* Findings in scientific literature and their purpose can be summarized as follows:

- The system itself is a *disconnected line flow system* or referred to in other contexts as a *multi-product batch plant* in the process industry field and as a *multi-product batch plant* in the operations management field. Systems are subject to *reconfiguration*, or change, during their life cycle.
- The planning problem addressed in this thesis is classified as a detailed planning problem at the *hierarchical level of control*. Addressing this problem is considered a *logical* reconfiguration. While *physical* reconfigurations could take place at the *strategic level of control* in the form of capacity expansion. Both require upward and downward *compatibility*.
- The packaging stage scheduling problem reflects features of an *unrelated parallel machine scheduling problem* with a property of *job splitting, sequence-dependent setup times*, and *release dates*. To our knowledge, the processing stage is not well represented by any generic model, but the contribution of Hill et al. best represents the problem by a combining different rule-based techniques.
- The unrelated parallel machine scheduling problem including the specific features cannot be solved by exact algorithms in reasonable time, since the complexity is *NP-hard*. For this reason, optimization by *heuristic approaches* and more specifically *simulated annealing* (SA) is most promising for the purpose of this study.
- The scheduling problems of both stages are to be integrated such that a *two-stage production process* scheduling problem can be solved. *Decomposition* is a useful concept for reducing complexity, where subproblems are solved in order of criticality.
- *Sim-heuristics*

This Chapter introduced concepts, techniques, and approaches to address a detailed scheduling problems, all of which are highly relevant to the problem at hand. In the next Chapter, these concepts, techniques, and approaches will be applied to the two-stage planning problem of the manufacturing process at Riedel. An integrated planning approach, which considers all equipment in the production system, identifies and avoids conflicts in weekly schedules that would otherwise not be identified in advance, while equipment in the shared pipeline network is not explicitly planned. All with the aim of reducing material shortages caused by resource conflicts.

4 | Solution design

This Chapter introduces an integral solution to the two-stage manufacturing process scheduling problem at Riedel. It answers *"How can algorithms/heuristics, modeling approaches and optimization techniques found in the literature (and beyond) be applied to Riedel's production system?"*. The solution design is constructed by combining multiple models and approaches to combinatorial optimization problems. Section 4.1 provides an outline of this Chapter and the coherence of its solution components for better guidance through this Chapter.

4.1 | Chapter outline, solution design and preliminary choices

The solution proposed in this Chapter finds a heuristic solution by combining various techniques, approaches and models as discussed in Chapter 3. The choice of a heuristic approach is motivated in Section 4.4. The design of the solution approach and the interaction between the components is visualized in Figure 18. These solution components are based on the corresponding papers, which are reviewed in chapter 3.

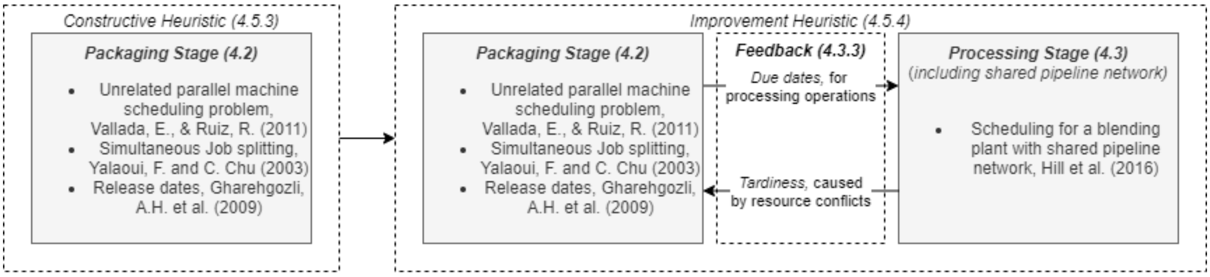

Figure 18 Solution Design

The overall design of the solution is implemented in a heuristic framework. The optimization procedure starts with a constructive heuristic that schedules the packaging stage without considering its interaction with the processing stage. The processing stage is neglected in this first phase because the packaging stage is considered more important because this stage has the most sequence-dependent setup times; moreover, this stage determines the rate of the production system (2.2). The obtained solution is further improved by a simulated annealing (SA) metaheuristic while taking into account the constraints in the processing stage. The SA algorithm is an integral approach that addresses both scheduling problems simultaneously rather than sequentially. An integral approach is established by embedding a feedback loop between the two stages.

A solution resulting from this solution approach is a production schedule, a set of production orders whose details are known, as equipment allocation and start and end times. The equipment allocation consists of the filling machines assigned to an order (and the associated pasteurizer and aseptic tank), as well as contiguous processing equipment that does not cause resource conflicts as a result of explicitly scheduling all equipment at this stage. This contiguous allocation certainly includes a mixing tank and material transfer equipment and, in the case of in-line mixing, an in-line mixer. Such information can be represented in Gantt charts (4.5). For a better understanding of the concepts concerning splitting, synchronization and release of machines, it is advisable to consult Section 4.2.1

Chapter 3 introduced two different time formulations for scheduling problems, discrete-time and continuous-time formulations. For the purpose of this solution, a continuous-time formulation is proposed. This choice is motivated by the observation that the duration of resource conflicts is short, but can have disruptive effects on the course of a schedule. The choice of a discrete-time formulation would carry the risk of oversimplification, resulting in these conflicts being ignored and not identified. The effects of oversimplification can be mitigated by making the discrete-time intervals sufficiently small, but this leads to much larger problem sizes. However, for the evaluation of some measures, the approach resorts to discretization of continuous time intervals, as they are less critical and approximation is justifiable.

4.2 | Packaging stage scheduling problem

The goal of the scheduling problem is to find production schedules for the packaging stage which are desirable in Riedel's opinion. The extent of desirability is measured by a total cost function that integrates multiple sub-objectives in order of criticality. Section 4.2.1 introduces some highly relevant properties of the scheduling problem to provide a better understanding of the remainder of this Chapter. Section 4.2.2 introduces the objectives of the scheduling. Section 4.2.4 introduces a solution structure for heuristic purposes and how this structure can be decoded into an objective function.

4.2.1 | Synchronization, splitting and machine releasing

The packaging stage scheduling problem has three highly relevant concepts which require an introduction:

Synchronizing: Processing Stage Efficiency versus Packaging Stage Efficiency

Synchronization is the concept whereby two packaging orders, consisting of the same mixture, are combined into one production order for the processing stage. The advantage of synchronization is that the pre-processing and processing steps are performed once instead of twice. As a result, fewer man and machine hours are required at the processing stage, as well as fewer setup activities at those stages. On the other hand, some less convenient production sequences must be scheduled to meet certain conditions that must be met in order for synchronization to occur. An example of a synchronization is shown in Figure 19. In this particular example, we managed to establish a synchronization between orders scheduled on packaging lines R12/R13 and R91. These packaging lines are supplied from mixing-tank T24, pump P62, in-line mixer M3 and buffer tank T22. Equipment denoted by 'PA' refers to pasteurizers of a packaging line.

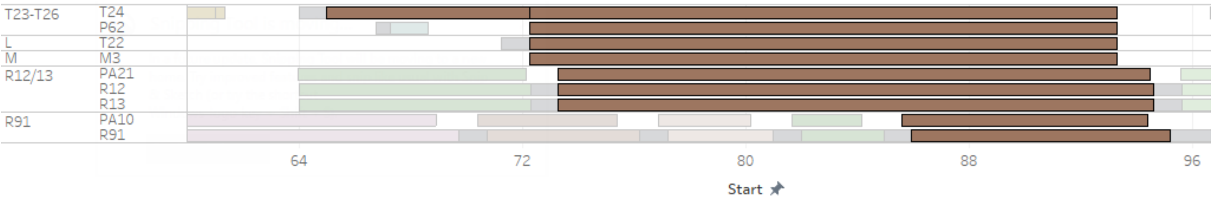

Figure 19 Synchronization

Splitting: Makespan versus Packaging Stage Efficiency

Splitting is dividing the quantity of an order into two equal portions that can be produced on different machines. Splitting concerns only the packaging lines that have two packaging machines. At these lines a choice can be made between operating one or two filling machines. One of these two machines is referred to as the primary machine and the other as secondary machine. If a packaging order is assigned to a packaging line it is always produced on the primary machine. On the lines which have two packaging machines, there is an optional decision whether or not to operate the secondary machine as well. Figure 20 shows packaging line R12/R13 with primary machine R12 and secondary machine R13. The advantage of splitting is a shorter makespan, the duration of a packaging order is reduced by half. Not splitting has the advantage of having one machine to be set up, in case of not splitting only the primary machine is required to be set up, which enhances OEE measures.

Figure 20 Splitting

***Machine releasing**: Workload balancing*

Releasing is the time at which a packaging line starts its operations on the first order. This is a concept that, to our knowledge, has not been addressed in the scientific literature, but is highly relevant to the problem at hand. By releasing machines at different times during the week, the workload can be distributed throughout the week. The goal is to comply with the soft limitation regarding the number of filling machines operating simultaneously. This restriction is imposed because Riedel can operate nine filling machines simultaneously with its own personnel. When ten or eleven machines are operated simultaneously, a charge is made. A set of decision variables is needed to control the times when machines must start or be released.

4.2.2 | Total cost objective

This study is prompted by degrading measures regarding material shortages in the packaging stage, as a result of tardiness in the processing stage. It is unwanted to merely considered this performance measure while formulating a scheduling algorithm, it would ignore other performance measures. It is suspected that other performance measures degrade while measures regarding material shortages improve, at the bottom line it would not result in an improvement. Other performance measure that are highly relevant besides material shortages are:

- *Overtime hours (minimization)*
- *Sequence-dependent setup times (minimization)*
- *Temporary worker hours (minimization)*
- *Number of synchronizations (maximization)*

All these performance measures have costs associated with them, except the number of synchronizations, which has a financial benefit associated with it. The financial benefit associated with a synchronization is established at a value which lies between the most extensive setup, not considering CIP operations, and the cost a CIP operation. This forces optimization approaches not establish a synchronization at the cost of an additional CIP operations. On the other hand, the optimization approaches may schedule more extensive flushes in exchange for a synchronization. This way schedules are generated that are considered desirable. The total cost function can be formulated as follows:

$$\begin{aligned} Total\ Cost = {} & OvertimeCost * OvertimeHours + IdleCost \\ & * (SequenceDependentSetupTime + material\ shortage\ duration) \\ & + TemporaryWorkerHours * TemporaryWorkerCost \\ & - NumberOfSynchrnozation * SynchronizationBenefit \end{aligned}$$

The time during which equipment is being set up and the time during which it is idle as result of a material shortage does both classify as idle time and are penalized similarly, as can be seen in the total cost function. Solutions can be evaluated by breaking down the overall performance into its performance measures to draw conclusions about the behavior of schedules. Section 4.4 explains how this performance measure could be optimized from a mathematical programming standpoint of view whereas 4.5 introduces a heuristic approach.

4.3 | Processing stage scheduling problem

Emphasis is placed on the importance of compatibility of production stage schedules. It should be verified that there is a schedule for the processing stage that meets the requirements resulting from a schedule for the packaging stage. More specifically, it should be verified that the due dates of the packaging stage can be met. The solution to this planning problem is an equipment allocation for each production order with minimal resource conflicts. An equipment allocation is a set of equipment assigned to a production order that can be interconnected to form a path between a mixing tank and the packaging stage through a pump, and any piping, buffer tanks and in-line mixers to the packaging stage.

4.3.1 | Constraints

The processing stage scheduling problem is subject to constraints which restrict the solution space. These constraints are formed by the following problem characteristics:

- **Mixing Tank Capacity**
  - For in-tank mixing: Order quantity may not exceed tank capacity
  - For inline mixing: The concentrates may not exceed tank capacity.
- **CO2 dissolving compatibility**: P*roducts containing CO2 can only be produced on some of the inline blenders.*
- **Blending-Tank Capabilities**: *Not all mixing tanks have the same technical capabilities. A subset of compatible mixing tanks is determined for each blend.*
- **In-Tank/Inline compatibility**: *The* mixing *method(s) that may be used for each mixture shall be indicated.*

The first constraint regarding mixing tank capacity does also apply to the consolidated production volume of synchronized orders. Even if a decision is made to synchronize orders in the packaging stage scheduling problem, this decision can be reversed once addressing the processing stage scheduling problem. The current physical configuration of the production systems results in 437 production paths that can be used. The constraints discussed in this section ensure that each order is compatible with a subset of these 437 production paths.

4.3.2 | Objective

The objective of the processing stage scheduling problem is to minimize overall tardiness so that the need and extent to advance packaging operations in time is minimized. This objective contributes to efficient scheduling of the packaging stage with minimal material shortages and minimal overtime due packaging operations that are advanced in time. These advances in time are required to enforce compatibility between the schedule for the packaging stage and processing stage.

4.3.3 | Feasibility

The goal, as discussed in 4.4.2, of minimizing overall tardiness cannot always be reduced to the numerical value 0. Any number other than 0 indicates that a conflict exists in the schedule that in turn causes material shortages in the packaging stage. To ensure feasibility, packing operations whose operations are delayed (as a result of resource conflicts) at the processing stage should be moved forward in time, i.e., the packing operation can start as soon as the processing stage can establish a juice flow to this stage. These packing operations are shifted forward in time when evaluating the objective value of an arbitrary solution. Figure 21 shows a situation where delay is not included in the planning, thus infeasible. While in Figure 22 for the same example, delay is included, and thus made feasible.

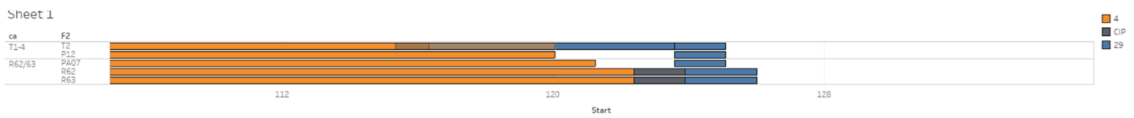

Figure 21 Schedule without feedback loop

Suppose we are forced to insert order 29, as shown in Figure 25, and in particular the order to mixing tank 2. This would cause a resource conflict as shown, order 29 and order 4 overlap for some time at mixing tank 2. This can be resolved by moving order 29 forward in time.

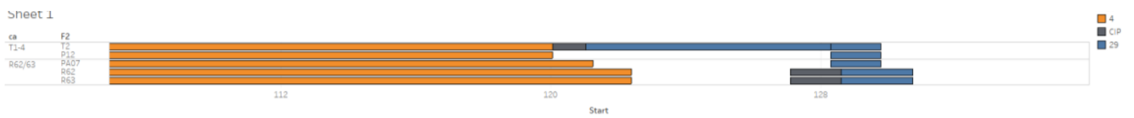

Figure 22 Schedule with feedback loop

Figure 22 shows the resolved conflict, order 29 is pushed forward in time, as a result there is a period of material shortage on filling machines R62 and R63. In this way, the feedback from the scheduling problem of the processing stage is used in the scheduling problem of the packaging. Advancing these operations in time results in capacity losses in the form of idle time, which are penalized as discussed in 4.2.2, enabling optimization approaches to address the problem of material shortages.

4.4 | Mathematical problem formulation

This chapter so far introduced the problem formulations of the scheduling problem. Section 4.1 revealed that a heuristic solution approach was chosen. In this section, we discuss the mathematical problem formulation for Riedel's packaging stage and whether it provides a useful approach for optimization purposes. It will appear that solving the problem by exact methods from a MIP formulation is not a promising solution approach. The formulation as discussed in 3.4.1 is further developed to make it suitable for Riedel's situation. This provides an overview of the complexity of the scheduling problem, as well as the constraints and dependencies in the scheduling problem. The model of Vallada and Ruiz (2011) was extended to include the following features:

- Evaluation of a total cost function considering: overtime, temporary workers, idle time and synchronization:
  - Derivation of Over Time Hours
  - Derivation of Temporary Worker Hours
  - Derivation of sequence-dependent setup times
  - Derivation of number of synchronizations
- Implementation of the splitting property
- Constraint regarding elapsed time in between CIP operations.

For the implementation of these properties we need 32 constraint sets, additional decision variables, parameters and sets. Based on the expected size of sets we can approximate the number of individual decision variables and constraints:

≈ 1,000 continuous decision variables
≈ 87,000 binary decision variables
≈ 275,000 constraints

We are left with a mathematical problem formulation whose basis was considered by the scientific literature to be untraceable and not solvable in reasonable time with exact algorithms to the optimum. The extension of this model further increases its complexity to the extent that there are approximately 275,000 constraints and 87,000 binary decision variables. For this reason, we resort to heuristic optimization approaches rather than exact algorithms, such as those established by implementing the formulation in AIMMS or CPLEX. For these reasons no attempt has been made to integrate the processing stage into mathematical formulation. Appendix I provides an overview of constraints and decisions in the packaging stage scheduling problem. The next section provides an introduction to the solution structure that can be used by heuristic approaches.

4.5 | Heuristic approach

This section describes all the components prerequisite for a heuristic solution. Returning to 4.1, it was concluded that the heuristic solution approach finds a solution by first performing a constructive heuristic which in turn is used as input to an improvement heuristic. Within the improvement heuristic, orders are assigned a production path that spans the processing and packaging stages, allowing schedules to be generated. Within the improvement heuristic, explicit decisions are made about the allocation of orders to the packaging lines, the splitting feature and sequencing. Equipment allocation in the processing stage is implicitly decided by a greedy heuristic, in this sense it is a simple adjoint problem.

Before proceeding to the actual operation of these heuristics, it is necessary to introduce a solution structure (4.5.1) that allows modified solutions to be stored. A constructive heuristic (4.5.3) is introduced to fill in an initial solution structure that can be further modified by an improvement heuristic (4.5.5) to find good solutions. In order to compare solutions, it is necessary to evaluate solutions (4.5.2). The greedy heuristic for scheduling processing activities is embedded in the improvement heuristic is introduced in (4.5.4).

4.5.1 | Solution structure

This part introduces the solution structure we propose to use for encoding a solution. Such a structure is needed for storing and modifying solutions to problems without storing excessive information such that computational performance remains satisfactorily. Figure 23 reveals the encoding structure of the main solution part. This example only features two packaging lines instead of nine for illustrative purposes.

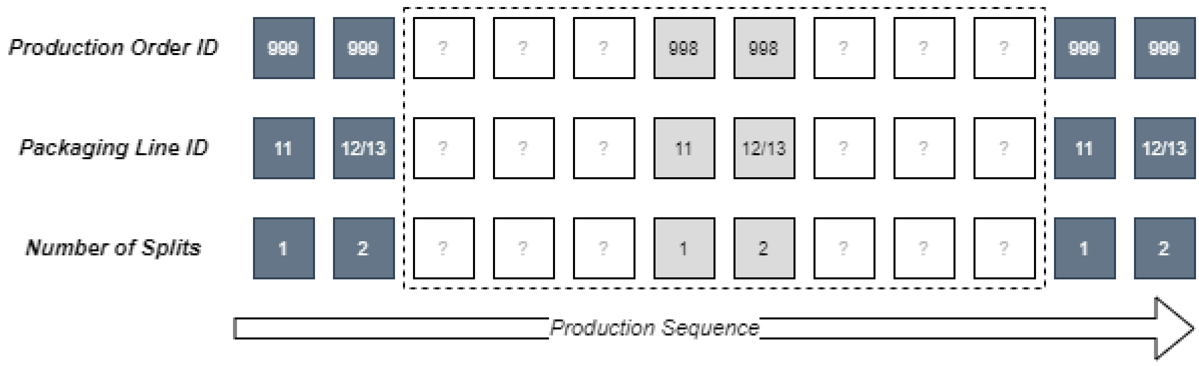

Figure 23 Solution Structure (columns represent orders)

The sequencing and scheduling problem is addressed by a solution structure as visualized in Figure 23. The columns represent production orders of type: CIP operation (Gray) or regular operation (White). These CIP operations are dummy jobs that enforce certain events that are required to reflect reality and comply with constraints. The sequence from left to right of orders in this structure represents the production sequence in the processing stage as well as the packaging stage. We can distinguish based on the second row, *Packaging Line ID*, this encodes the packaging line allocation of the production order. The filling machine assignment can be derived from the third row, which indicates whether or not an order uses the secondary filling machine (or split property). Dark gray CIP (with ID 999) operations are not eligible for repositioning in the structure, as they enforce a clean system at the beginning of the week and a clean system at the end of the week, which causes the week to end with a CIP operation. Light gray CIP (with ID 998) operations do qualify for repositioning, these can be used to satisfy the rule regarding elapsed time between CIP operations. To address the concept of machine releasing a second structure is needed that encodes the release times of machines, or times at which they are scheduled to start the first order. For this purpose, we use a vector of nine numerical values. The introduced structures supports the following decisions:

- Position of *Order ID* in sequence

- *Packaging Line ID* assigned to *Order ID*
- *Number of Splits assigned to Order ID*
- *Release Time* of *Packaging Line ID*

Whether or not to synchronize two packaging orders is now implicitly decided up on. A synchronization is enforced if two orders are sequential in this the solution structure; if the intervals at which they are scheduled to be packed partially overlap; consist of the same mixture; and if the sequential orders fit into one mixing tank. A synchronization shall not take place if there is no overlap between operations. In this way, it is an implicit decision, while the decision to be sequential is an explicit decision.

4.5.2 | Solution evaluation

The previous part of this section introduced a structure that stores decisions and the solution formed by these decisions. It is a series of data that contains the order-packaging line allocation, the splitting decision and production sequence in both the packaging and processing stage. This part introduces the procedure that evaluates the objective value associated with a solution. The procedure loops over the structure from left to right to find the associated total cost with the schedule and represent the solution graphically in terms of line and machine assignments and start and completion times of orders.

The evaluation procedure begins by initializing some information regarding the initial state of the system. It takes the decision variables regarding the release times of the machines and initializes the times when the packaging lines are available. Once the procedure is initialized, it loops through the solution structure, encountering either regular production orders or CIP orders. For each of these orders, the procedure calculates the sequence-dependent setup time and duration of the packaging operation based on the order quantities, the splitting decision, and the output rates of the machines. This information is used to add the order to the production schedule. It is checked whether the considered production order qualifies for synchronization with its predecessor in the solution structure, since they are composed of the same mixture. In addition, for synchronization to occur, packaging activities must partially overlap on a time horizon. The consolidated production volume must fit into the mixing tank previously assigned to the predecessor. It is verified that the processing equipment assigned to an order is available at the scheduled start time in the packaging stage; if not, the packaging operations are advanced in time to resolve these conflicts and therefore infeasibilities. After this information on the production order considered has been established, the information on the current state of the production system should be updated and stored. This information is needed to proceed with scheduling the next order or to determine the objective value at the end of the procedure. This information concerns the following states of the system with its objective:

- **Most recent mixture line level/system level:** The procedure updates information about the previously produced mixture on a packaging line and in the overall system. This information is needed to determine the setup time for subsequent orders.
- **Line available time:** The time when a line becomes available is set to the scheduled end of a packing order, based on the setup time, duration, and previous value of this variable.
- **Elapsed time on line:** This variable is incremented to keep track of how much time has elapsed since the last CIP command. There is a maximum time allowed to elapse between two CIP cleanings.
- **Total duration:** The total production time, excluding setup time and other capacity losses, is increased each iteration to determine the objective value.
- **Start time of filling machine:** The start time of the filling machine is updated to eventually obtain the interval in which the machine is available. For primary machines, this is always set to the minimum of the current value and the start time of the current job. For secondary, this is done only when the split decision is made.

- **Completion time of filling machine:** The completion time of the filling machine is updated to finally obtain the interval in which the machine is available. For primary machines, this is always set to the maximum of the current value and the completion time of the current order. For secondary machines, this is done only when the decision to split is made.
- **Number of synchronizations:** The number of synchronizations is incremented if the order is synchronized.
- **Remaining mixing tank capacity:** The capacity that remains after assigning one or multiple orders (in case of synchronization) must be stored for synchronization purposes.

Time intervals during which each filling machine is operational are obtained after completing the above procedure, solutions as in figure 24 as obtained.

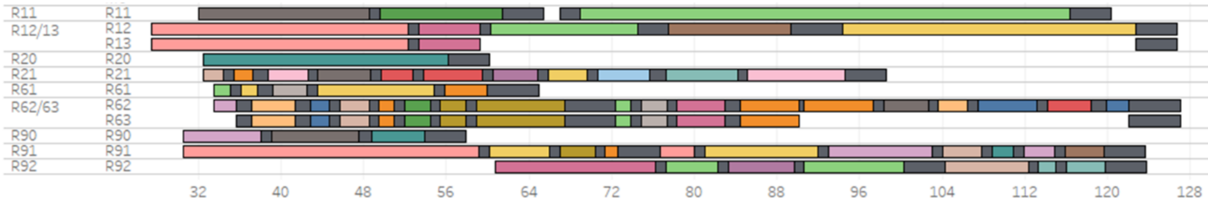

Figure 24 Solution Representation of Packaging and Pasteurization Stage

From these time intervals, the total production time can be calculated by subtracting the completion time of each machine from its start time. The difference between this numerical value and the total duration as determined by the procedure are the total capacity losses associated with a schedule that can be affected by scheduling decisions. The difference is penalized as in the objective value discussed in 4.2.2. The benefit of the number of synchronizations is easily deducted from these costs. The costs associated with temporary workers and overtime require a bit more effort. To determine these cost components, we must consider the entire time horizon in 1-hour time slices. A charge will be made if more than nine filling machines are in operation during this time slice. Overtime charges will be applied if these time intervals are in overtime, depending on the number of machines that remain operational in time intervals. The total cost associated with a solution is obtained after performing the procedure discussed in this section.

The algorithm used to evaluate a solution in terms of objectives and associated cost is visualized in a flowchart in appendix C. This section introduced a structure that encodes a solution which can be decoded or evaluated by an algorithm to obtain the objective value and detailed information regarding start and completion times of orders. The remaining Sections of this Chapter use the introduced heuristic components to solve the scheduling problem.

4.5.3 | Constructive heuristic

The constructive heuristic assigns production orders from the order set, regardless of the prioritization rules. For each production order, it assesses all the packaging lines where the order can be produced. It inserts the order at any possible position in the current solution structure, splitted, if the packaging line supports it. After all possible solutions have been evaluated, the algorithm adds the production order at the position and line that decrease the objective value the least. The maximum number of filling machines or splits on this packaging line is assigned to the solution code. The algorithm used is illustrated in a flowchart Figure 25.

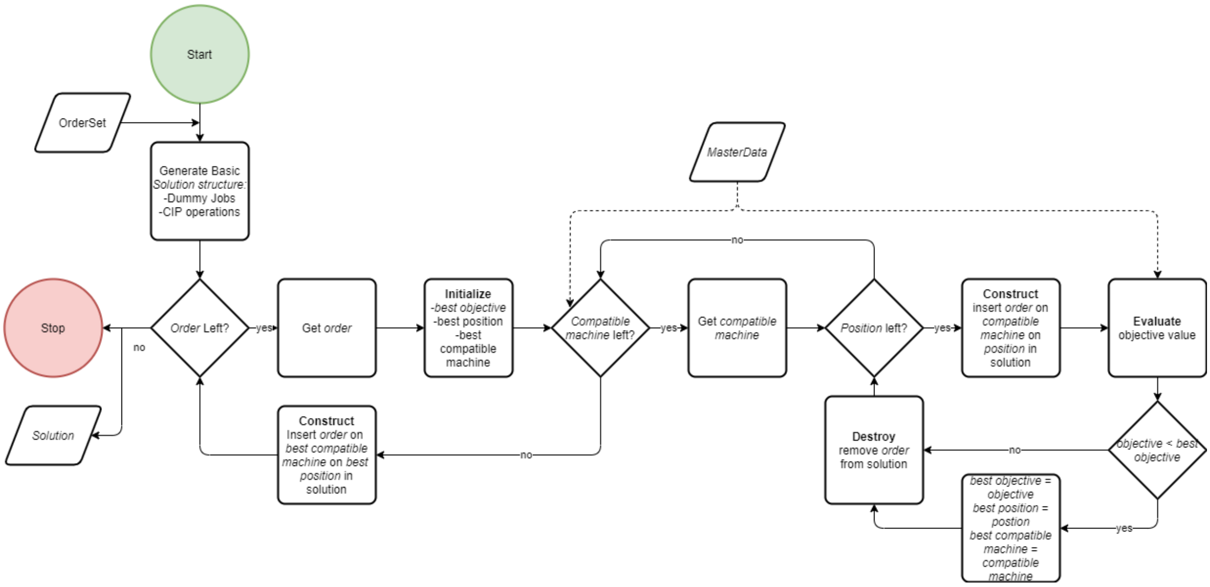

Figure 25 Constructive Heuristic

The constructive heuristic ignores the processing requirements to reduce computational complexity. In addition, the sub-objective of minimizing the number of temporary workers is not addressed. Each packing line is released at the earliest possible time and the number of splits as a decision variable is ignored. Thus, it is only about sequencing and minimizing overtime. The next section discusses the greedy heuristic for selecting processing equipment for these orders.

4.5.4 | A greedy heuristic for processing equipment allocation

A procedure is required to assign orders to processing equipment such as mixing tanks, pumps, in-line mixers, and piping, a combination of which forms a production path. Given a decision, the evaluation procedure (4.5.2) can assess the ability of the processing stage to meet the due dates of the packaging stage. If the deadline cannot be met, the operations in the packaging stage are pushed forward in time until the deadline is met. This procedure constitutes a module embedded in solution evaluation and is used in the case where objectives are evaluated for the improvement heuristic, discussed in the next section.

The decision to be made at this stage is which of the production paths to assign to a production order. It is proposed that the allocation be done in a "greedy" manner. The first production path that has a delay of 0 is chosen. The path with the least delay is allocated if no paths with a delay of 0 are found. After each allocation, three state variables are updated for devices in the chosen path:

- **Completion Time of Equipment:** *The completion time of equipment is needed to identify potential resource conflicts at preceding orders.*
- **Previous Mixture of Equipment:** *The mixture produced must be stored to enforce sequence-dependent setup times at preceding orders.*
- **Remaining tank capacity:** *The remaining space in a mixing-tank must be stored such that it can be checked whether or not there remains sufficient space for a potential synchronization.*

The allocation procedure is shown in **Error! Reference source not found.**.

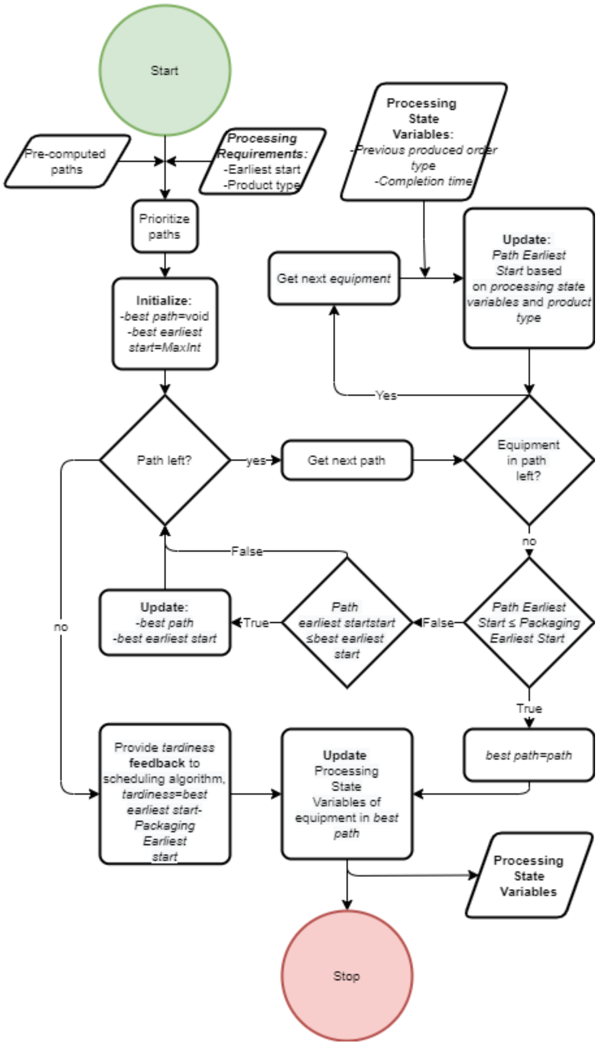

Figure 26 Processing Requirement Evaluation

The greedy procedure allows for simultaneous scheduling of production orders in the packaging and processing stages. This allows identifying which delays are penalized so that the SA framework further improves scheduling by reducing delays.

4.5.5 | Improvement heuristic

An improvement heuristic is needed to find a door or near-optimal solution from an initial solution (4.5.3) as starting point. The feedback loop between the packaging and processing stage is enabled in this improvement heuristic for integral scheduling purposes. Chapter 3 introduced the concept of meta-heuristics. For the purpose of this solution approach, a simulation-annealing framework is proposed to be implemented. Five operators are proposed to traverse the entire solution space, these are:

- **Move in sequence**: *Moves any order in the solution structure to any position.*
- **Random swap**: *Swaps any two production orders given that it does not violate packaging line compatibility.*
- **Assign packaging line**: *A random order in the solution structure is assigned a random packing line from its set of compatible machines.*
- **Random Split**: *Randomly chooses whether and order is split or not.*
- **Random start-time**: *Assigns a release datetime to any packaging line.*

Examples of the use of neighborhood operators can be seen in Appendix D. Another important aspect in formulating a simulated annealing metaheuristic are the numerical values for parameters such as: *start temperature, stop criteria, cooling schedule and markov-chain length*. Chapter 3 discusses different approaches for selecting the starting temperature. For the purpose of this solution, it is proposed to use a start temperature that accepts deteriorations of the objective value in the first Markov-chain iteration up to a certain threshold. To encourage a fast search process, a **starting temperature of 2000** is proposed. With this starting temperature, local optima can be overcome by adding a CIP operation, which temporarily degrades the objective values.

A threshold value of **0.005** is proposed for the stopping criterion. Dropping to this threshold forces the algorithm into a purely local search algorithm for some iterations of the Markov chain. A simple geometric cooling scheme is proposed:

$$T = T\alpha$$

A numerical value of 0.6 is proposed for α. A Markov-chain length of 2000 is used to minimize the execution time of the algorithm.

The numerical values for parameters of the SA framework are established empirically, as there are no rules of thumb. Experimentation with these parameters reveal that performance, as will be discussed in Chapter 5, can be slightly increased by doubling the Markov chain length. The improvement of objective values is statistically significant. Further increasing Markov chain lengths up to 8000 does not yield further improvement. Increasing the starting temperature does not yield an improvement on average.

4.6 | Representation and validation

Chapter 3 discusses the representation of scheduling problems. It is proposed that solutions of the Riedel scheduling problem are visualized in a machine-oriented Gantt chart as proposed by Floudas and Lin (2004). Machine orientation was chosen because this thesis deals with material shortages due to resource conflicts. Task-oriented Gantt Charts provide insight into production order lead times that are not relevant to the purpose of this study. The Gantt chart resulting from the scheduling algorithm is shown in Figure 27 which was visualized using *Tableau Desktop*.

Figure 27 Integral Solution Representation

A visual representation can be used to assess whether solutions to scheduling problems reflect reality. It is concluded that the scheduling algorithm reflects reality, no overlapping activities occur in the production schedule. The graphical representations show material shortages if any. White time intervals at filling machines indicate idle time.

4.7 | Conclusions

This Chapter answered the question: "*How can algorithms/heuristics, modeling approaches and optimization techniques found in literature (and beyond) be applied to the production system of Riedel?*" Approaches regarding scheduling problems and optimization approaches are combined into an integrated scheduling approach with the objective to minimize material shortages in the production schedule without deteriorating overall performance, this Chapter results in the following conclusions:

- Solving an unrelated parallel machine scheduling problem, as the packing stage, is considered untraceable for an exact algorithm and cannot be solved to optimality within a reasonable time. Extending the basic model with features such as task splitting, synchronization, and machine release data makes it more complex. Therefore, the MIP was not implemented in a solver and resorted to heuristic approaches to combinatorial optimization problems.
- A solution structure is designed that stores information about production order prioritization and packing line allocation. From the prioritization, a production sequence can be derived for both the packaging stage and processing stage. For a production order and its assigned packing line, information is stored about whether or not a split will be performed.
- A constructive and an improvement heuristic are proposed for solution generation and optimization. The constructive heuristic assigns production orders in a random order to the position in the solution structure where they degrade the objective value the least. The improvement heuristic uses five operators that allow it to travel through the full solution space.
- A heuristic procedure is defined for integrating the processing stage into the packaging stage scheduling problem. Production paths are assigned to production orders by a greedy allocation rule. The rule loops over compatible production paths and assigns the first path that does not cause a delay. If delay is unavoidable, the packaging orders are moved forward in time to make the schedule feasible.
- The solution is represented using machine-oriented Gantt charts. These charts can be generated by software packages. For the purpose of this research, *Tableau Desktop* is used. The general optimization algorithm is implemented in the open source programming language *Python*.

5 | Solution implementation

Chapter 1 taught that the problem of material shortages involves two core influential problems. The choice was made to study the core influential problem related to non-explicit scheduling of material transfer equipment, for which a solution is proposed in Chapter 4. In this Chapter, Section 5.2 will identify the performance enhancement of the solution. Section 5.1 will first introduce an instance generator for experimentation purposes and a method for modeling human schedules to form a comparison platform. The design of the solution allows for the evaluation of the impact of capacity expansions on material shortages, thus addressing the second key problem, "insufficient equipment of any type." This is examined in Section 5.3, before weighing the possible changes in Section 5.4. This Chapter answers *“What performance increase is achieved by explicitly scheduling material transfer operations in a shared pipeline network and capacity expansions?”.*

5.1 | Instance generator and human scheduler

Order sets that must be produced in a week form the problem instances for the detailed scheduling problem. The release of these production orders is simulated for experimentation. Demand data for all SKUs is collected. The probability that a SKU appears in the weekly order set is calculated based on the number of orders in 2020. In addition, for experimentation purposes an empirical distribution is used for order sizes. The required data is stored as in Table 3.

Table 3 Demand Data Format

Product ID	Product Name	Probability of Order in week	Order Sizes
4970	CB Extremely	0.692	20000,40000,20000,…,40000,40000,40000
4975	CB Mango Dream	0.730	30000,30000,15000,…,30000,30000,30000
4976	CB Passionfruit	0.826	70000,30000,30000,…,25000,30000,25000
…	…	…	…
…	…	…	…
4432	TK Sailing Strawberr	0.057	25000,15000,5000
4433	TK Thrilling Tropica	0.077	20000,15000,10000,15000
4434	TK Wild Orange	0.077	30000,20000,10000,10000

The algorithm used for instance generation runs over all "ProductID" and draws a new random number on the interval [0,1] for each product. The SKU is admitted to the order set if the "order probability" is greater than the random number. A random element is then drawn from the "Order Size" column corresponding to the current production order. In this way, order sets are generated that reflect the situation at Riedel

The problem addressed in this thesis is that material shortages occur as a result of implicit planning of the shared pipeline network. This means that the human planner ignores the resource availability constraint on the shared pipeline network. It is chosen to model the human scheduled to create a basis for comparison. Evaluation of real world schedules is time consuming and are disturbed by stochatsic elements. Futhermore, the masterdata of used for this study is based on the year 2020, whereas currently new products are introduces which would require an update of masterdata. The human planner can be modeled by relaxing the constraint related to the shared pipeline network. This allows the generation of detailed production schedules as the human planner would. These schedules perform better since the complexity of the problem is reduced by the relaxation. To create a basis for comparison, the schedules generated by the human planner must be evaluated for potential material shortages, for this purpose we use a simulation step. The human planner assigns a mixing tank, a pump, and an inline mixer. Piping is ignored. The simulation step models how the juice flows through the network of pipes, where resource conflicts may occur and cause a material shortage.

5.2 | Scheduling algorithm performance

The performance of the scheduling algorihtm is idenfied by solving 300 problem instances. The same instance are solved by modeling the human scheduler which allows to compare both situations. The results are shows in table 4.

Table 4 Improvement by logical reconfiguration

	Current Situation		Improved Scheduling	
Total Cost	**18.770**	**€**	**14.126**	**€**
Total Idle Time	113.84	Hours	101.48	Hours
• *Material Shortages*	*10.98*	*Hours*	*0.04*	*Hours*
• *Setups*	*101.23*	*Hours*	*101.44*	*Hours*
Overtime	6.77	*Hours*	3.91	*Hours*
Temporary worker	4.54	Hours	4.15	Hours
Synchronizations	10.05	Synchronizations	10.16	Synchronizations
OEE	*67.6%*		*68.6%*	

Table 4 shows a reduction in total cost due to explicit planning. The objectives that make up the total cost all improve. It can be seen that the duration of material shortages is reduced to the point where an average of 2.4 minutes of unplanned downtime per week remains. To achieve this reduction, a slight concession is made on planned standstill in the form of sequence-dependent setups. The reduction in overtime and temporary labor is explained by the reduction in distrubances that advance operations in time and might cause overtime. OEE is an appropriate performance measure for instance-by-instance comparison, as it deals with the proportionality between downtime and total production time. Figure 28 concerns OEE measurements at the instance level. It can be seen that under explicit schedules, outliers disappear. Thus, an explicit scheduling state removes the need for rescheduling, as there are fewer disruptions.

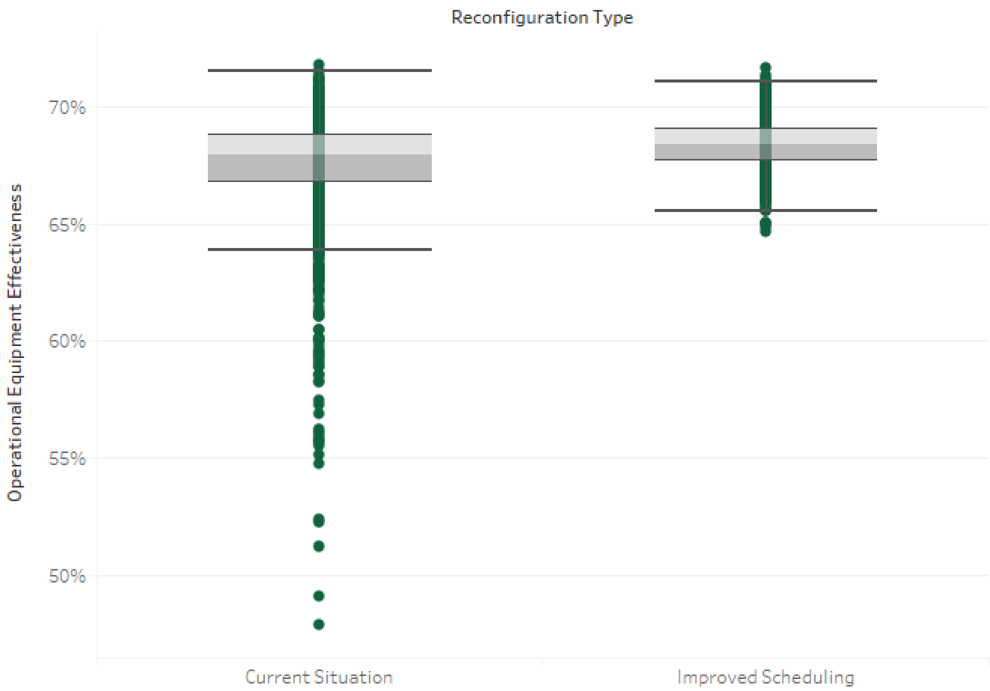

Figure 28 Logical reconfiguration improvement shown in boxplot

Computational performance and optimality gap
Lower bounds are established to assess the scheduling performance of the scheduling algorithm with respect to the total sequence-dependent setup times. For establishing the lower bound, it is assumed that no splitting occurs. Moreover, it is assumed that the number of sequence-dependent setup times, depending on the change of tray type and box content, is minimized. In this way, we find an optimality gap of 18%, corresponding to 16 hours of sequence-dependent setup times. The magnitude of this gap is explained by the observation that packaging lines with splitting characteristics must necessarily split to reduce makespan with the goal of avoiding overtime, which is a more critical objective. Earlier we explained that splitting involves twice as many sequence-dependent setup times because it is done on two machines.

The run time of the improved scheduling algorithm averages 7 minutes and 33 seconds based on 300 observations. This run time depends on the computer specification. The following processor was used for the observation: Intel(R) Core(TM) i7-9750H CPU @ 2.60GHz.

The disadvantage of the proposed planning approach is the increased planning complexity. The problem size becomes about twice as computationally complex if the number of routes increases from 80 to 190 by considering the entire shared pipeline network. The following section discusses the results if Riedel were to opt for a physical reconfiguration instead.

5.3 | Capacity expansion performance
It is interesting to investigate whether improvements can be achieved by capacity expansion rather than explicit scheduling. By extracting data from the human scheduler model, we gain insight into which equipment is most involved in resource conflicts and therefore most constraining. Figure 29 shows the average duration of material shortages per equipment type per week. From this we learn that the group of parallel pipes 43, 44, 63 is the most constraining equipment group, as well as pump 61. The observation in Chapter 1 on utilization rate showed that pump 61 was the most used pump, which is consistent with the observation in this Chapter on material conflict.

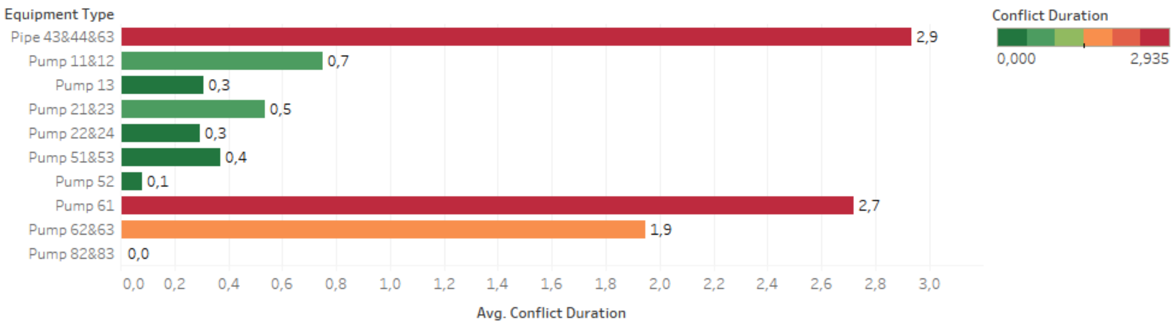

Figure 29 Resource Conflict Duration per resource type

Based on the observations from Figure 29 we can suggest the following physical reconfigurations that have the greatest potential for improvement:

- **Expansion 1**: 1 additional pipeline between switchboard 03 and 05
  This physical reconfiguration allows pumps 11, 12, 21, 23, 62 and 63 to simultaneously transfer mixtures. The reconfiguration is depicted in Appendix F.
- **Expansion 2**: 1 additional pump parallel to pump 61.
  Currently the tank formation with tanks 23, 24, 25 and 26 shares pumps 61,62 and 63. An additional pump parallel to pump 61 will allow four batches to be pumped over simultaneously instead of three. The reconfiguration is illustrated in Appendix G.

These expansions are evaluated by adding the new production paths that emerge, because of expansion, to the master data. Table 5 shows the performance of the proposed capacity expansions.

It can be seen that the expansions improve the overall performance and especially the hours of material shortages. Capacity expansion 1 performs better than capacity expansion 2 in all performance measures. Section 5.4 will ultimately decide upon the most cost-effective reconfiguration.

Table 5 Improvement by physical reconfiguration

	Current Situation		Expansion 1		Expansion 2	
Total Cost	**18.770**	**€**	**15.302**	**€**	**15.712**	**€**
Total Idle Time	113.84	Hours	102.36	Hours	103.16	Hours
• *Material Shortages*	*10.98*	*Hours*	*1.13*	*Hours*	*1.93*	*Hours*
• *Setups*	*101.23*	*Hours*	*101.23*	*Hours*	*101.23*	*Hours*
Overtime	6.77	Hours	4.90	Hours	5.18	Hours
Temporary worker	4.54	Hours	3.07	Hours	3.17	Hours
Synchronizations	10.05	Synchronizations	10.05	Synchronizations	10.05	Synchronizations
OEE	*67.6%*		*68.5%*		*68.4%*	

5.4 | Reconfiguration trade-off

The performance of reconfiguration proposals individually is identified. This section compares the performance of the proposal to the end of identifying the most cost-effective reconfiguration. Section 5.4.1 does identify the annual expected cost reduction of each reconfiguration, whereas 5.4.1 estimates the investment associated with each reconfiguration. Finally, in 5.4.3 a conclusion is drawn.

5.4.1 | Material shortage cost reduction

The previous sections (5.2 and 5.3) learned that the proposed changes to the production systems, which are either capacity expansions or an improved scheduling approach do all result in lower total cost objectives. All other sub-objectives contributing to this objective do not degrade and may even improve. This section will identify the most cost-effective reconfiguration by identifying the annual savings and the investment involved.

For the purpose of this study we will not use the total cost function reduction as basis for comparing improved scheduling and the physical capacity extensions. The total cost function parameters are set such that desirable solutions are obtained, rather than once that are actual. For this reason the overtime cost component does not reflect the actual overtime cost. For the purpose of trade-off we use the idle-time reduction for comparison purposes, since this covers material shortages which are addressed by this study. Table 6 contains the annual cost reduction of the three changes to the production system.

Table 6 Cost reduction of reconfigurations

Reconfiguration Type	Expected Annual Idle Time Reduction	Expected Annual Idle Time Cost reduction
Improved Scheduling	643 *hours*	€ 102.880
Expansion 1	597 *hours*	€ 95.520
Expansion 2	555 hours	€ 88.800

We find that the improved scheduling approach reduces the annual idle time cost the most, the first expansion proposal the second most and the second expansion proposal the least.

5.4.2 | Implementation cost

Implementation activities are needed to make the reconfigurations successful. This section estimates the cost of each reconfiguration proposal to ultimately determine the most cost-effective reconfiguration.

Improved scheduling

The described scheduling algorithm must be implemented in Riedel's current scheduling software. The current scheduling software must be modified so that the optimization approach is embedded in the tool, so that manual input is also possible. Cooperation with the supplier of this tool is required. The agreement with the supplier of the planning software includes a daily rate for assistance of €1,395 (Appendix H). Previously, a minor functional improvement was implemented for which two days of assistance were used. More specifically, this improvement concerned one conditional alert. A feature that alerts the human planner of a conflict if the condition is violated. Intuitively and based on the time spent implementing the model and scheduling algorithm in python, the vendor is expected to provide a quote of at least €41,850. Additional annual license fees will be charged as a license for the optimization module is required.

Expansion 1

A non-binding quote was received from a company specializing in welding for food grade systems. This physical reconfiguration involves two pipelines between switchboard 3 and 5, parallel to the existing pipelines L43, L44 and L63. The reconfiguration is quoted at €15,127.

Expansion 2

The cost components of physical reconfiguration 2 are known within the organization. This reconfiguration involves a pump parallel to P61. The cost is estimated at €210.000. The majority of the cost is spent on the reconfiguration of the automation that controls the pump.

5.4.3 | Trade-off

Two pareto-efficient changes to the production system remain. Extension 2 is dominated by extension 1 in terms of both cost and performance. Expansion 1 outperforms explicit scheduling reconfiguration 1 in terms of cost, but is outperformed in terms of performance. Both are "pareto efficient." Some additional characteristics of both reconfigurations are listed in Table 7.

Table 7 Benefits and disadvantages of reconfigurations

Logical Reconfiguration	**Physical Reconfiguration** 1
Best Performance	Least complex
198 production paths to evaluate	96 production paths to evaluate
Weekly recurring problem	Non-recurring problem
Annual license fee	Reduces partial connectivity

The most cost-effective change to the production system is capacity expansion 1. This change has the shortest payback period of 2 months, while embedding the scheduling algorithm has a period of 5 months. Moreover, it should be noted that taking into account the annual license fee for the embedding reduces the annual cost reduction. If this is taken into account, the performance of both pareto efficient modifications converges such that the annual cost reduction is similar. Thus, expansion 1 is pareto-efficient and the most cost-effective. The recommendation regarding the best reconfiguration for Riedel will be based on the results of the sensitivity analysis in Chapter 6. Remark, does not reflect stochastic elements.

5.5 | Conclusions

This Chapter learned the answer to the following question: *"What performance increase is achieved by explicitly scheduling material transfer operations in a shared pipeline network and capacity expansions?".* There is sufficient evidence to conclude that both explicit scheduling and capacity expansions perform better than the current situation. The following conclusions can be drawn:

- All reconfigurations perform better than the current situation.
- The improved planning approach improves all the sub-objectives that make up the total cost function, and especially the material shortages. This proves that material shortages can be reduced without affecting the objectives regarding total standstill; overtime; and temporary workers.
- Capacity expansion can also be applied to address the problem of material shortages. Experiments show that the best capacity expansion is to place additional pipes between switchboard 3 and 5. This physical reconfiguration removes some of the partial connectivity in the shared pipeline network and reduces the degree of sharedness of the shared pipeline network.
- These observations prove that the core-influenceable problems as identified in Chapter 1 cohere with the problem of material shortages.
- Comparison between this capacity expansion and the enhanced scheduling approach shows that both perform comparably in terms of annual cost reduction due to material shortages and sequence-dependent setup time. However, building the optimization approach into the current software requires twice as much investment, and involves annual license fees. Capacity expansion is the most cost-effective reconfiguration of the production system when we consider the licensing costs on top of the implementation costs of improved scheduling.
- It remains to be seen whether these conclusions will hold up if Riedel's production volume increases, as envisaged in Riedel's strategic plan. Furthermore, it is important to consider which reconfiguration proposal is the most robust to stochastic elements, which are defined as core-non-influenceable problems.

The latter is adressed in Chapter 6.

6 | Sensitivity analysis

This Chapter answers the research question "*What is the endurance and robustness of proposed reconfiguration?"* It concerns the evaluation of the robustness of the proposed reconfigurations with respect to changes in production environment. This Chapter evaluates three changes in the production system that are likely to degrade the performance of the proposed reconfigurations as discussed in Chapter 5. These three changes are:

- Increased production volume by increasing batch sizes
- Increased production volume by increasing order frequencies
- Stochastic processing times

The current average weekly production volume is 3,676 m^3, see section 2.1. The performance of the reconfigurations is evaluated up to a production volume of 4,776 m^3, a growth of 30%.

6.1 | Order frequency

The robustness to increased order frequencies is assessed by evaluating operational equipment effectiveness. The choice for this indicator is motivated by the observation that this measure is expected to remain the same if the shared pipeline network would not be a constraining factor. Increasing order frequencies is expected to increase sequence dependent setup times and actual production time proportionally. It is the most suitable indicator to compare growth scenarios. New order sets are generated with different order frequencies and re-solved using the same algorithms. The performances are visualized in Figure 30.

Figure 30 Robustness of reconfiguration against increased order frequencies

We learn that OEE measures decrease as the production volume grows as a result of increasing production volume. Capacity expansion and explicit scheduling perform similarly an the same decrease of OEE is observed at a growth of 30%. This decrease does confirm that the shared pipeline network and other processing related equipment becomes more constraining as production volume grows. The performance increase of the current situation at a growth of 10% cannot be explained. Both reconfigurations outperform the current situation at all production growth levels.

6.2 | Batch size

An increase in sales volume due to an increase in batch or order size is enforced by increasing the empirical order sizes by the increase in production volume. Some order sizes cannot be increased by 30% because these production orders cannot be assigned to a mixing tank since the capacity of the mixing tank is a constraining factor. Performance is assessed by considering the total standstill as this measure is expected to remain the same if production volume growth would involve additional complexity. Figure 31 shows results of reconfiguration and the current situation at different production volume levels.

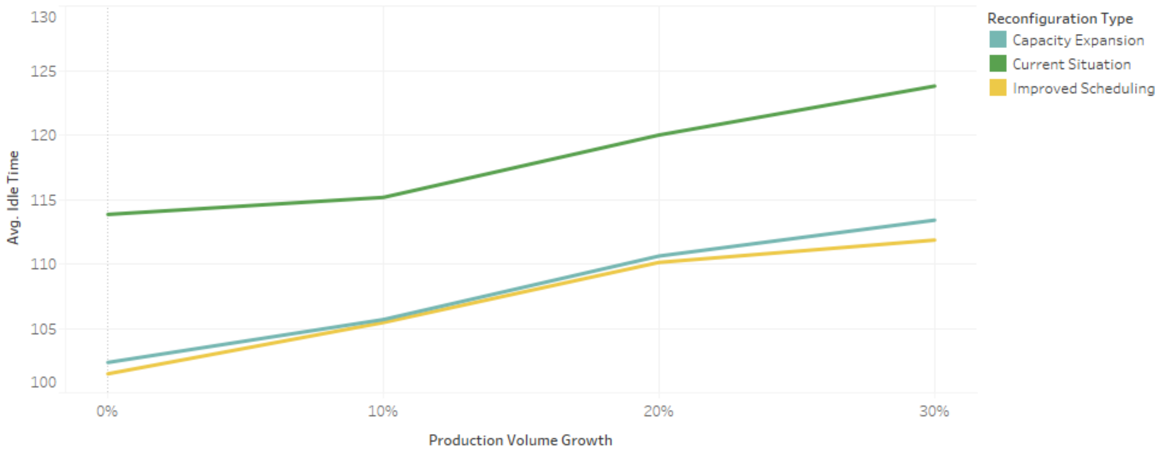

Figure 31 Robustness of reconfigurations against increased order sizes

The outcomes learn that increasing batch sizes cause additional complexity since the total standstill time increases which would not happen if the shared pipeline network would not be constraining. Either a degradation of total setup time is accepted to prevent major material shortages or minor material shortages are accepted to keep the total standstill to a minimum. The reconfiguration at a production volume growth of 30% outperforms the current situation.

6.3 | Stochastic processing times

Scheduling processes are generally simplified from stochastic combinatorial optimization problems (COP) into deterministic COPs. In the real world activities and operations do not proceed as projected in some deterministic scheduling problem. Operations are subject to stochasticity, for example as a result of machine breakdowns. This problem was identified as non-influenceable core problem in Chapter 1. It remains the question which reconfiguration copes best with matters as stochasticity. This section describes the implementation of stochasticity of the processing times of filling machines and lines. More specifically, the solutions to scheduling problems obtained in Chapter 5 and section 6.2 and 6.3 are subjected to stochastic to identify performance of these reconfiguration in situations that reflect the real world better.

A SimHeuristic approach (Juan, Faulin, Grasman, Rabe, & Figueira, 2015) is used to asses performance under stochasticity. Processing times at the packaging stage are subjected to stochasticity. The deterministic scheduling problem worked with expected processing times. This sensitivity analysis generates random processing times from a uniform distribution with a lower bound corresponding to the maximum production speed of a machine, and an expectation equal to the average production speed. Each solution is subjected to stochasticity 100 times. The same random number seed is used for each set and iteration across scenarios and reconfigurations.

Table 8 Stochasticity Sensitivity analysis, average outcomes per instance

	Reconfiguration Type					
	Current Situation		Capacity Expansion		Improved Scheduling	
Demand Scenario	Avg. Operational Equipment Effe..	Avg. Idle Time	Avg. Operational Equipment Effe..	Avg. Idle Time	Avg. Operational Equipment Effe..	Avg. Idle Time
0%	65,4%	130,8	66,2%	121,4	66,2%	121,5
30% - Frequency	64,5%	199,4	65,1%	189,5	65,2%	187,1
30% - Quanitity	68,4%	143,4	69,1%	134,0	69,1%	133,8

The most interesting observation from table 8 is converge of performance of both reconfiguration proposals. Furthermore, the performance gap between the current situation and any reconfiguration has decreased. This implies that annual benefits are expected to be less than the benefits identified in Chapter 5. These observations make, while considering the current production volume, that the capacity expansion reconfiguration is definitely the most cost effective reconfiguration after subtracting the annual license fee associated with the improved scheduling approach. It remains recommended to implement the capacity expansion as its annual benefits exceeds its associated investment. The annual expected cost reduction changes as in table 9

Table 9 Deterministic versus Stochastic cost reduction

		Current Situation	Explicit Scheduling	Capacity Expansion
Annual Cost reduction	*Deterministic*	€ 0	€ 102.880	€ 95.520
Annual Cost reduction	*Stochastic*	€ 0	€ 77.376	€ 78.208

The convergence of performance can be explained by the fact that the shared pipeline network is less restrictive after the capacity expansion. This makes it more likely that in the event of a disruption, another production path will remain available for transfers, thus eliminating the disruption. Whereas with improved scheduling, utilization rates are higher, so the likelihood of unused production paths being observed at any given time is lower.

6.4 | Conclusions

This Chapter answered the research question "*What is the endurance and robustness of proposed reconfiguration?"* Production volume grows by two growth strategies, which are to increase order frequency while remaining the same batch size, or the other way around. A hybrid growth strategy is also possible. Both are evaluated in this Chapter. We can draw the following conclusions:

- Chapter 5 showed that there are two equally efficient promising reconfigurations, logical reconfiguration and physical reconfiguration.
- The sensitivity analysis regarding an increase in sales volume shows that both reconfigurations remain pareto-efficient, i.e., one does not outperform the other on both criteria, cost and performance;
- However, when the reconfiguration is subjected to stochasticity, the performance of the reconfiguration converges such that differences on annual bases become negligible. This indicates that capacity expansion is more resilient to stochasticity. This is probably due to the fact that it has more capacity in the shared pipeline network, reducing the probability of observing a system in which all equipment is occupied.
- We conclude that improved planning has the best performance in a deterministic setting, while the performance of explicit scheduling capacity expansion is similar under stochastic conditions. Since improved scheduling requires twice as much investment in implementation, it is recommended that the proposed capacity expansion be implemented to improve the production system in terms of material shortages without affecting other measures.

7 | Conclusions and recommendations

This Chapter concludes the report by answering the main research question. The first section draws conclusions based on the findings stemming from this research. Next, recommendations are given based on the performance of alternatives identified during this research and some limitations of this research are indicated. The contribution of this study to the scientific literature is also stipulated. Finally, some directions for future research are given.

7.1 | Conclusions

This Chapter draws conclusions based on the research conducted at Riedel. This investigation addresses the central or perceived problem at Riedel. The central problem are situations where filling machines are idle due to material shortages, more specifically the lack of fruit juice at filling machines. By means of a problem cluster, two core influential problems were found:.

- Absence of explicit scheduling of the shared pipeline network;
- Insufficient material transfer equipment in the shared pipeline network.

These two core-problems are related and research objective is formulated in section 1.2 which allows to address both problems sequentially:

To find efficient reconfigurations in Riedel's production system, either by capacity expansion or improved scheduling methods, with the goal of reducing unplanned stops in the packaging stage due to tardiness caused by resource conflicts in prior stages.

Riedel's fruit juice plant is a three-stage production system, the last two stages of which are highly interconnected and interdependent. These two stages are connected by a shared pipeline network that provides partial connectivity between the equipment in both stages. The use of certain equipment in this network is not explicitly scheduled, which explains the lack of an explicit planning approach. In Chapter 2, it was observed that the utilization rates of such equipment is not close to the numerical value of 1, which would indicate the need to expand the shared pipeline network. This observation suggested the need for an explicit scheduling procedure to generate weekly schedules that are not subject to equipment conflicts in advance.

The literature review we conducted revealed that production systems are subject to change over time. Changes can be both physical (capacity expansion) and logical (improved scheduling methods). Addressing the core influential problem of insufficient resources is a physical reconfiguration and formulating an integrated scheduling procedure is a logical reconfiguration. The scheduling problem of the packaging stage can be classified as an unrelated parallel machine problem (with release dates, job splitting properties and sequence dependent setup times). General classification frameworks do not support the classification of the shared pipeline network scheduling problem in the processing stage, however, it reflects some features introduced in other classification frameworks. Various optimization models are proposed in the scientific literature, such as mathematical models and (meta-)heuristics. Several scientific contributions show that it is unlikely that a mathematical model of the packaging and pasteurization stage can be solved in reasonable time by exact algorithms alone, this led to excluding exact algorithms as solution from the scope of this research.

The proposed solution is suitable for short-term planning, but its design allows it to be integrated into tools for strategic or tactical support of decisions on physical reconfigurations of the plant layout. The scheduling algorithm is a combination of models and optimization approaches in a decomposition framework. Central to this framework is the unrelated parallel machine model. For this model, a constructive heuristic is formulated that assigns production orders to the packing line and a position in the sequence that degrades a given objective value the least. A simulated annealing metaheuristic is proposed as an optimization approach. These implementations form the scheduling algorithm for the packaging stage, whose solution are visualized in machine-oriented Gant charts. The model needs to be extended so that the processing (including the shared pipeline network) stage is also planned simultaneously. For scheduling processing, a greedy heuristic is proposed that selects the first production path, of which there are 196, zero tardiness and otherwise the least tardiness. To speed up the search process, production paths are prioritized according to certain criteria. If there is no path available that allows the start of a task in the second stage at the desired time, the algorithm provides feedback in terms of tardiness, which advances tasks in time.

Table 10 Improvement by reconfigurations

		Current Situation	**Explicit Scheduling**	**Capacity Expansion**
Total Stops	*Deterministic*	113.84	101.48	102.23
Total Stops	*Stochastic*	130.80	121.51	121.41
Annual Cost reduction	*Deterministic*	€ 0	€ 102.880	€ 95.520
Annual Cost reduction	*Stochastic*	€ 0	€ 77.376	€ 78.208
OEE	*Deterministic*	67.6 %	68.6%	68.5%
OEE	*Stochastic*	65.4 %	66.2%	66.2%

Table 10 shows the performance of the production system in the current situation, under explicit scheduling and capacity expansion. The performance increase of both reconfigurations is statistically significant. The explicit scheduling approach requires at least twice the investment of capacity expansion 1, therefore both reconfigurations are pareto-efficient. When both reconfigurations are subjected to stochasticity, the performance of both converges, in other words, the capacity expansion is more robust to stochasticity, since its deterministic performance is worse, as shown in Table 10. Based on these observations, the investment involved and the additional characteristics, a trade-off can be made between the two configuration. The OEE measurements, the deterioration of which created the need for this study, increase with both reconfigurations.

7.2 | Recommendations, limitations and scientific contribution

Since the real-world involves stochasticity we base our recommendation on performance identified during the sensitivity analysis. Both reconfiguration proposals perform the same when subjected to stochasticity. The capacity expansion reconfiguration becomes pareto-efficient as it has a lower associated investment. As a result, we recommend to implement the capacity expansion.

A limitation of this report is the expressed confidence in the ability of the human planner to generate production schedules that are near-optimal. A comparison with the current situation is based on this assumption, as the human planner is modeled using the same scheduling algorithm with some relaxed constraints.

The scientific contribution of this report lies mainly in the global design of the solution, which integrates different models and optimization algorithms. A specific feature of this design is that it allows the prioritization of production orders in two production stages simultaneously, thus enabling an integrated planning approach. Solutions, as introduced in this report, are suitable for conventional production systems where equipment is connected by a fixed pipeline network and where transfers are time consuming, and where there is finite intermediate storage. It supports situations where equipment is partially connected. Another scientific contribution is the implementation of machine releasing, which was not addressed by scientific literature to the best of our knowledge. This concept allows to start the first job on a machine somewhere on a time horizon, rather than at time 0, as is the case in all parallel machine scheduling problems. In this study, a mathematical problem formulation is proposed and introduced for a packaging and pasteurization planning problem, with specific features that have not yet been addressed in the scientific literature. Finally, the solution design was designed in such a generic way that it does not only allow to address detailed scheduling problems on an operational level of control, but also strategic resource planning by evaluating decisions on this level regarding capacity expansion by adding units of any equipment.

7.3 | Further research

In this report and by the human planner, processing times within the processing stage were thought to be SKU-dependent rather than batch size-dependent, whereas in the real world, processing times depend on both. For each batch of a SKU, the processing time of the largest possible lot is used, even if the actual lot is only a fraction of the largest lot. It will be interesting to see if scheduling performance increases when a better approximation of the actual processing time is used.

Once a logical reconfiguration has to be performed, it is interesting to reduce the decision space for production paths at the SKU level, since in practice some paths will never be assigned to a particular SKU. Reducing the decision space increases the computational performance of such a scheduling algorithm. It is interesting to consider whether such a strategy would not reduce the scheduling performance.

Sensitivity analysis learned that actual performance is affected by stochasticity. For this reason it is recommended, once resorting to scheduling approach, to consider joint design with online scheduling techniques and robust optimization. Thus, generating robust schedules up front and making resilient decisions in case of disturbances is important.

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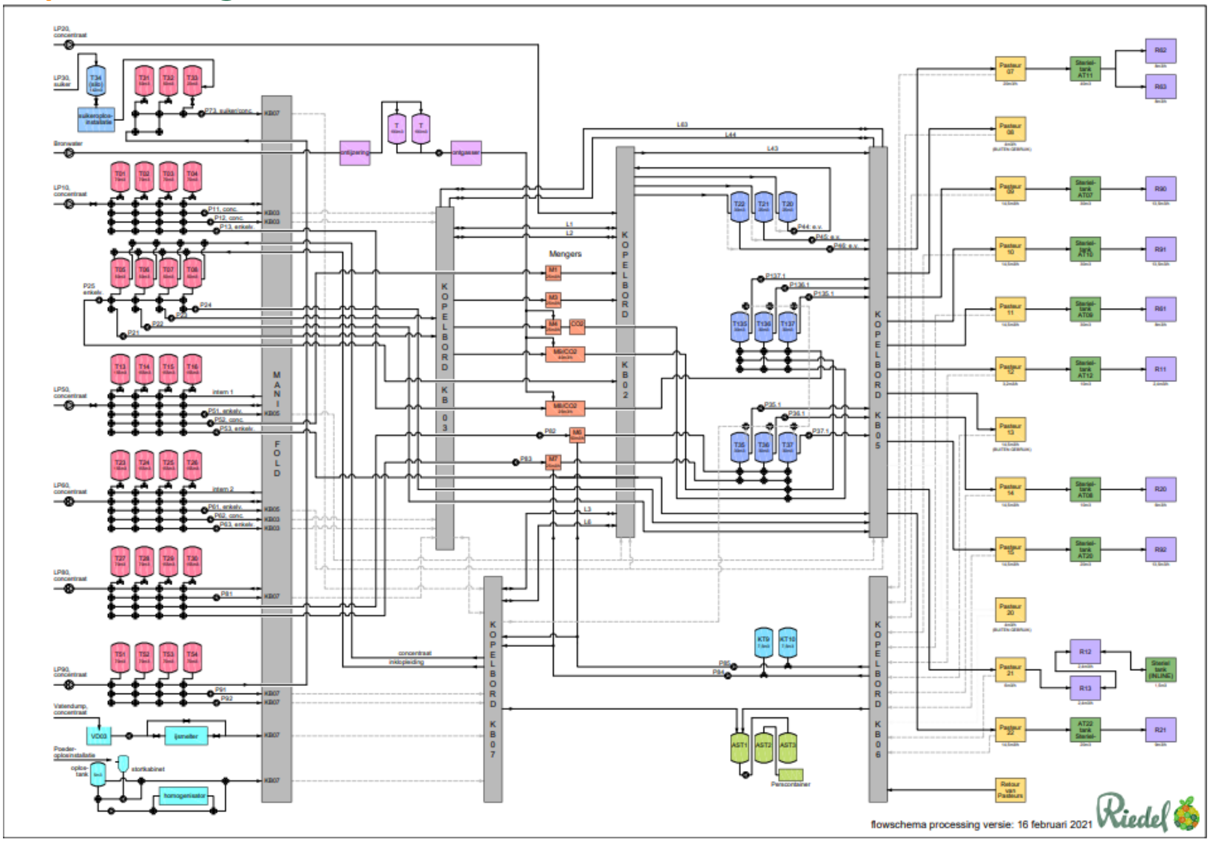
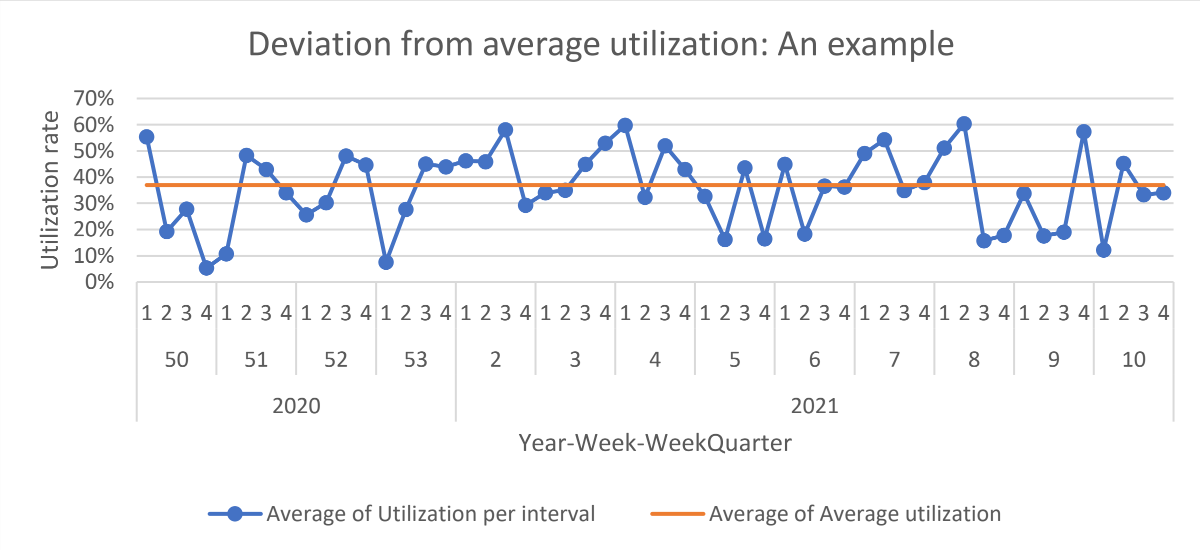
A | Flow diagram



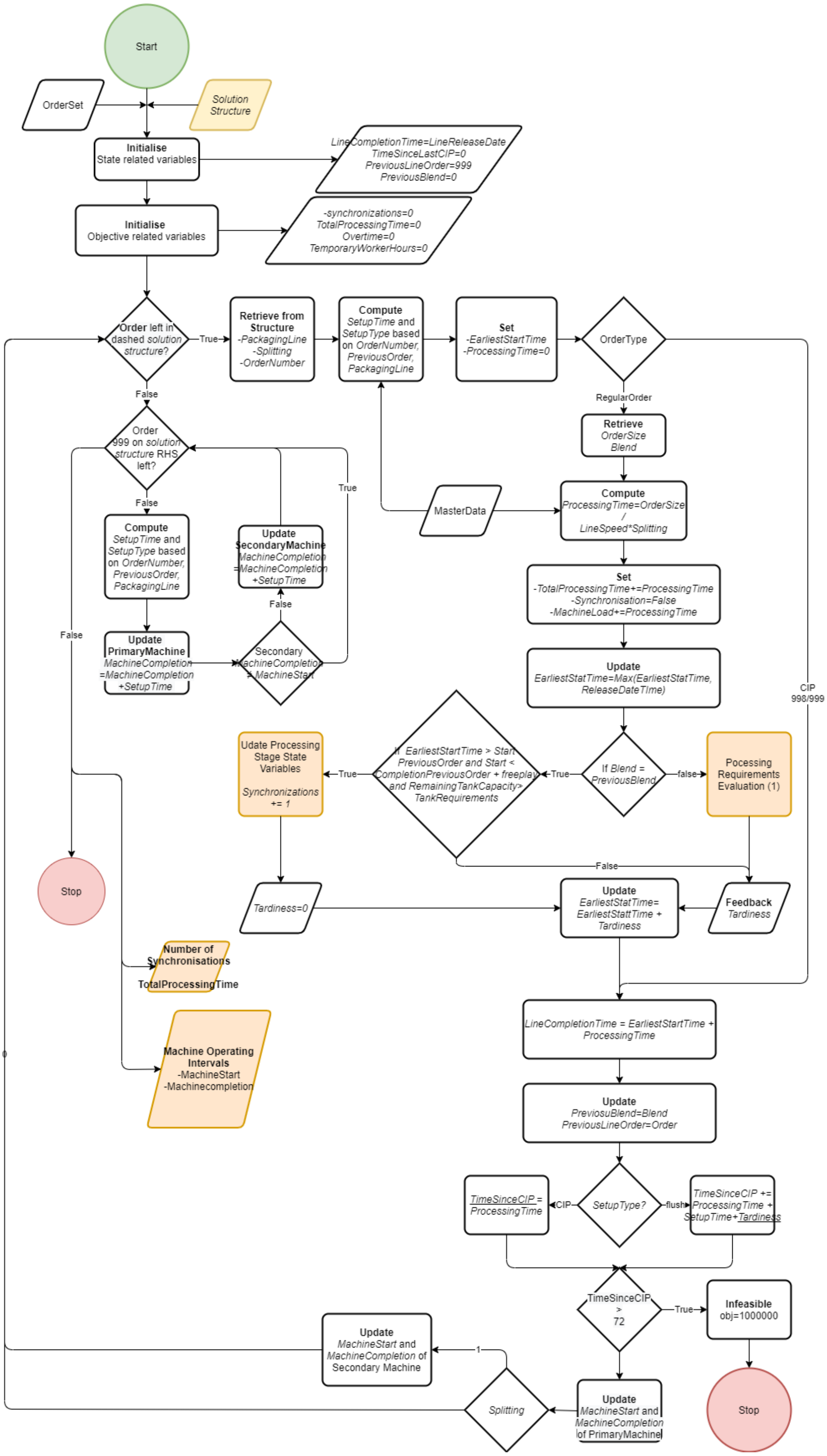
B | Equipment utilization

The figure below shows equipment occupation over a one-week time-horizon. The red cluster shows a smaller time interval of approximately 18 hours in which a utilization rate of 1 occurs for the resource cluster composed out of L44, L63 and L43.



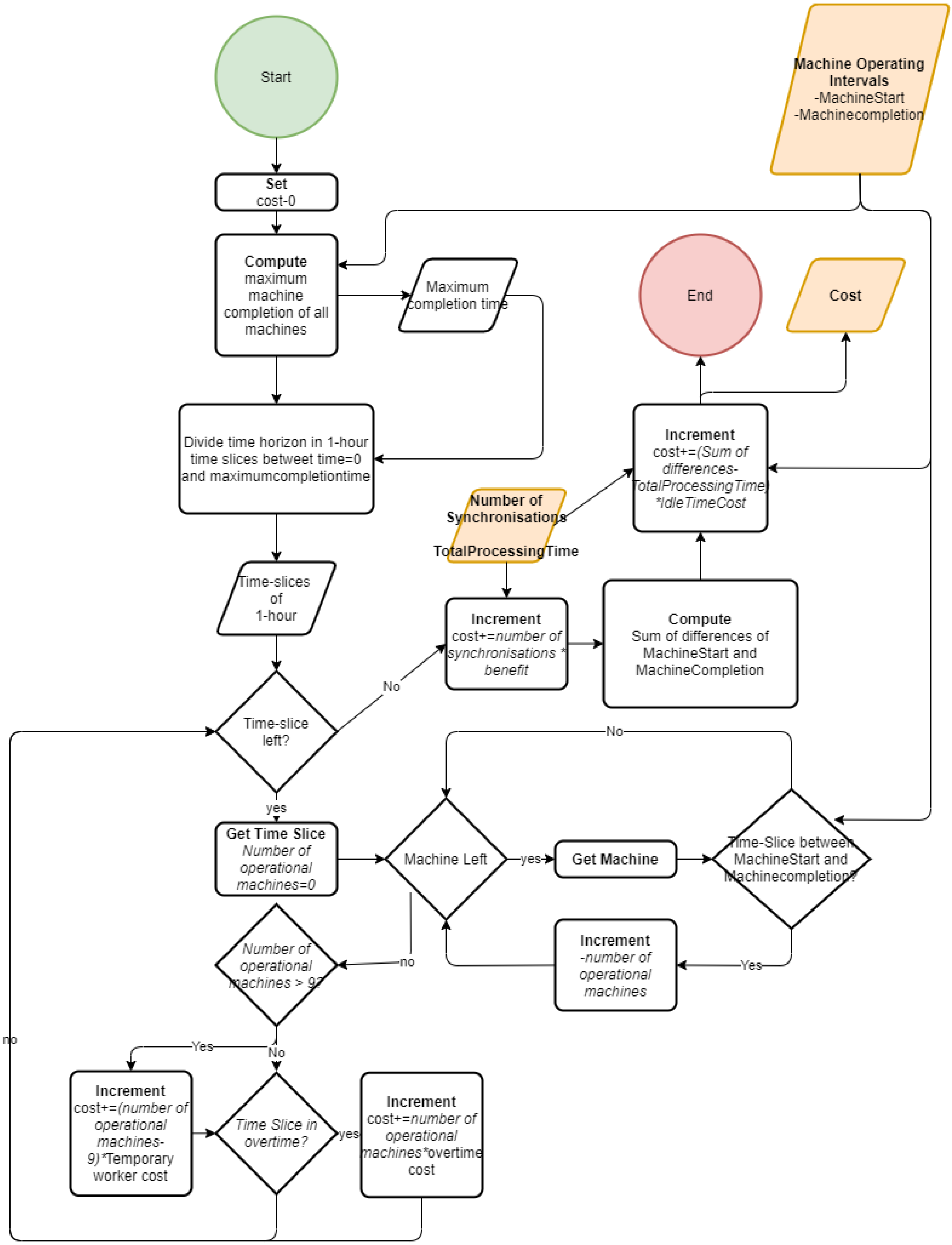
C | Cost function algorithm

The figure below shows the algorithm which identifies the performance regarding each sub objectives



Part 2

The second figure translates these sub-objectives into its associated cost.



D | Improvement heuristic operators

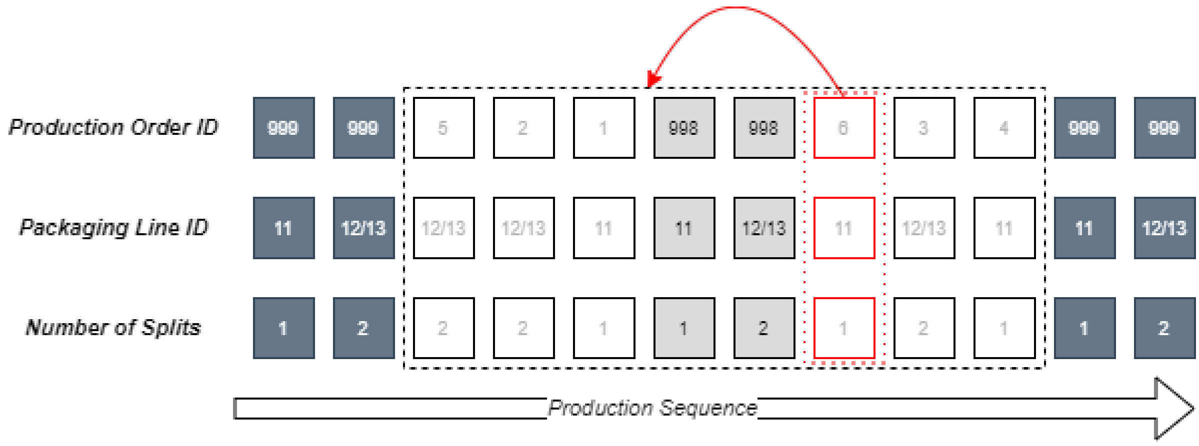
- **Move in sequence**: *Moves any element in the solution code to any position.*
- **Random swap**: Swaps any two production orders given that they have the same set of compatible packaging lines.
- **Assign packaging line**: *A random element in the solution coding is assigned a random packing line from its set of compatible machines.*
- **Number of splits**: *Randomly assigns the number of splits from the interval [1,maxsplit(machine,order)]. The upper limit of maxsplit is 2 in Riedel's production system.*
- **Random start-time**: *Assigns a release datetime to any packaging line.*

| Move in Sequence

The move operator selects an arbitrary element in the solution encoding within the dashed rectangle. In other words, all production orders are eligible for this operator except those with ID 999. The procedure is as follows:

1. Select random element in dashed rectangle,
2. Remove this element from rectangle.
3. Insert at random position in dashed rectangle.

Figure below visualizes the procedure. An arbitrary order on packaging line 11 is moved to the left and therefore earlier in the sequence. As can be seen it now precedes production order 998 on packaging line 11. More specifically, this means that it no precedes the CIP operation.

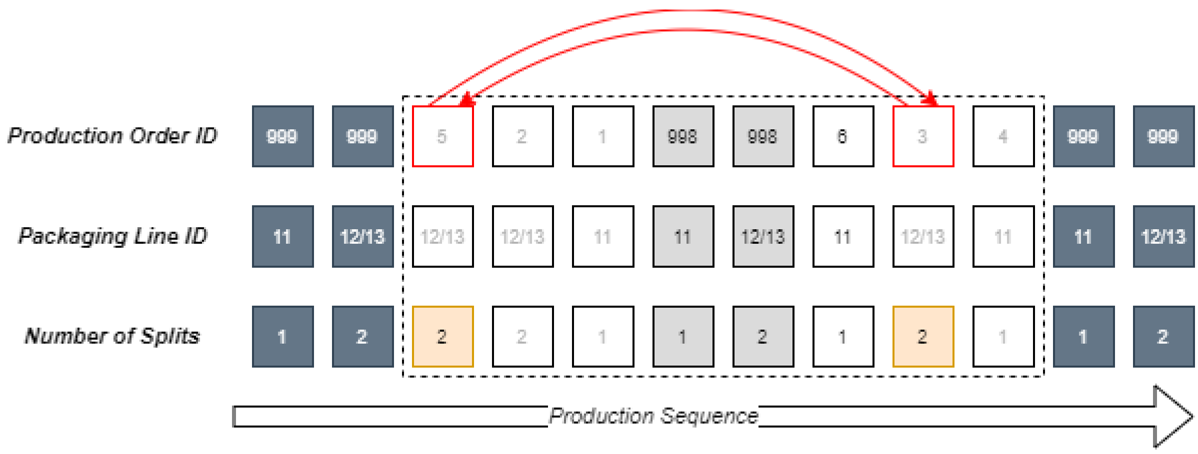


Random Swap

The swap operator swaps to production order IDs of orders that share the same set of compatible packaging lines. The number of splits remains unchanged, unless one of these products is not compatible with the number of splits. The procedure is as follows:

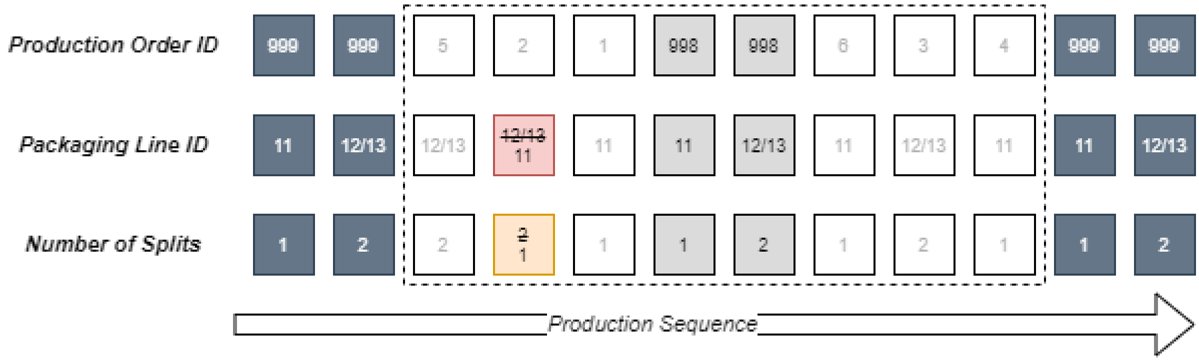
1. Select arbitrary packaging line type with at least 1 order
2. Select first arbitrary order on packaging line type
3. Select second arbitrary order on packaging line type
4. Swap production Order ID
5. Update number of splits if constraint is violated regarding product split compatibility.

The operator is illustrated in the figure below. The orange box indicates a decision variable which is updated if constraints are violated.



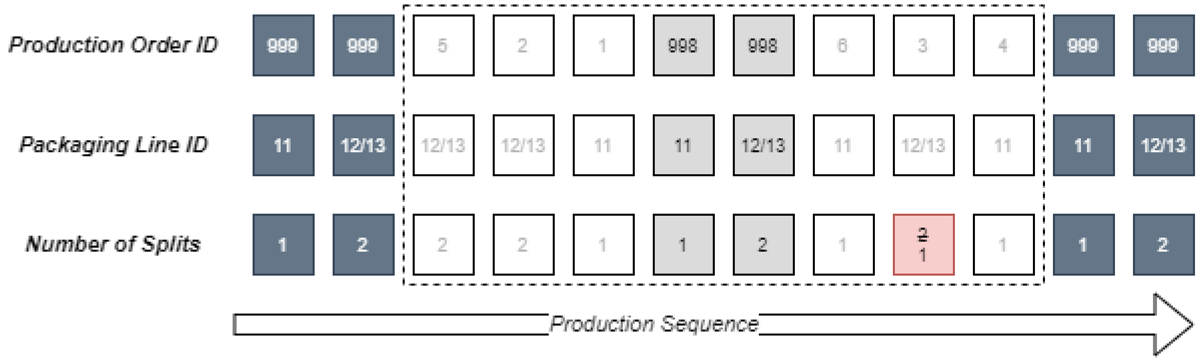
| Assign Packaging Line

This operator changes the packaging line assigned to a production order. Consider the following example in figure below. Production order *2* was previously assigned to packaging line 12/13 with 2 splits, since packaging line 12/13 has two filling machines, 12 and 13. It is re-assigned packaging line *11* which has only one filling machine, *11.* The packaging Line ID changes by means of this operator and the number of splits changes if the previous number of splits violates a constraint.



Number of splits

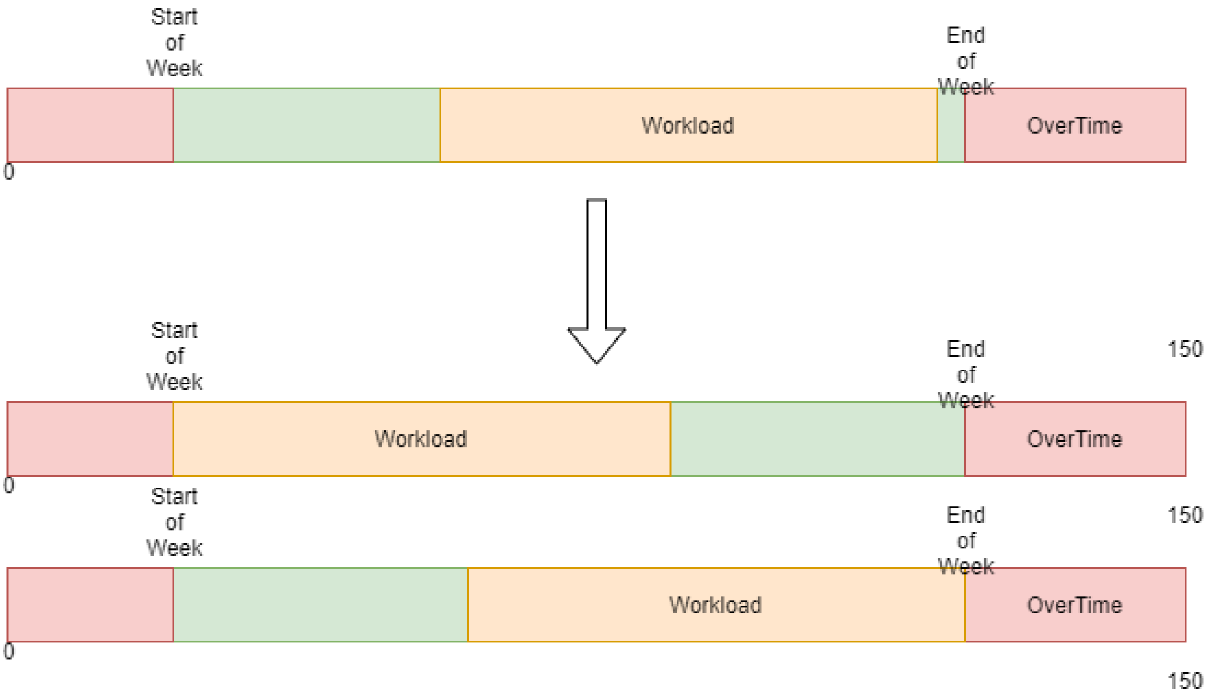
The number of splits refers to the number of machines that is scheduled to operate on a packaging line. Packaging line 12/13 has 2 filling machines, it can be chosen to operate one machine rather than two. The benefit is than only one setup activity is needed rather than two, enhancing the OEE. In the example, figure below, the number of splits is changed from 2 to 1. This operator does not affect production orders with ID 998.



Random start-time

This operator is different compared to the previous four, since these are addressed by a different solution encoding. The use of this operator is illustrated by providing an example for one packaging line.

This operator is based on the idea that the objective is necessary to minimize completion time. Furthermore, not all machines are scheduled to be operational 100% of the available production time. Consider the figure below, Suppose the first bar illustrates an original situation. The machine is currently scheduled to be release somewhere within the week rather than the beginning. The operator allows to shift the workload throughout the week, with as extreme examples the two bars below. In between those extremes all situations can be randomly generated. The main idea is that the workload is never scheduled in overtime, and never before the beginning of the week.



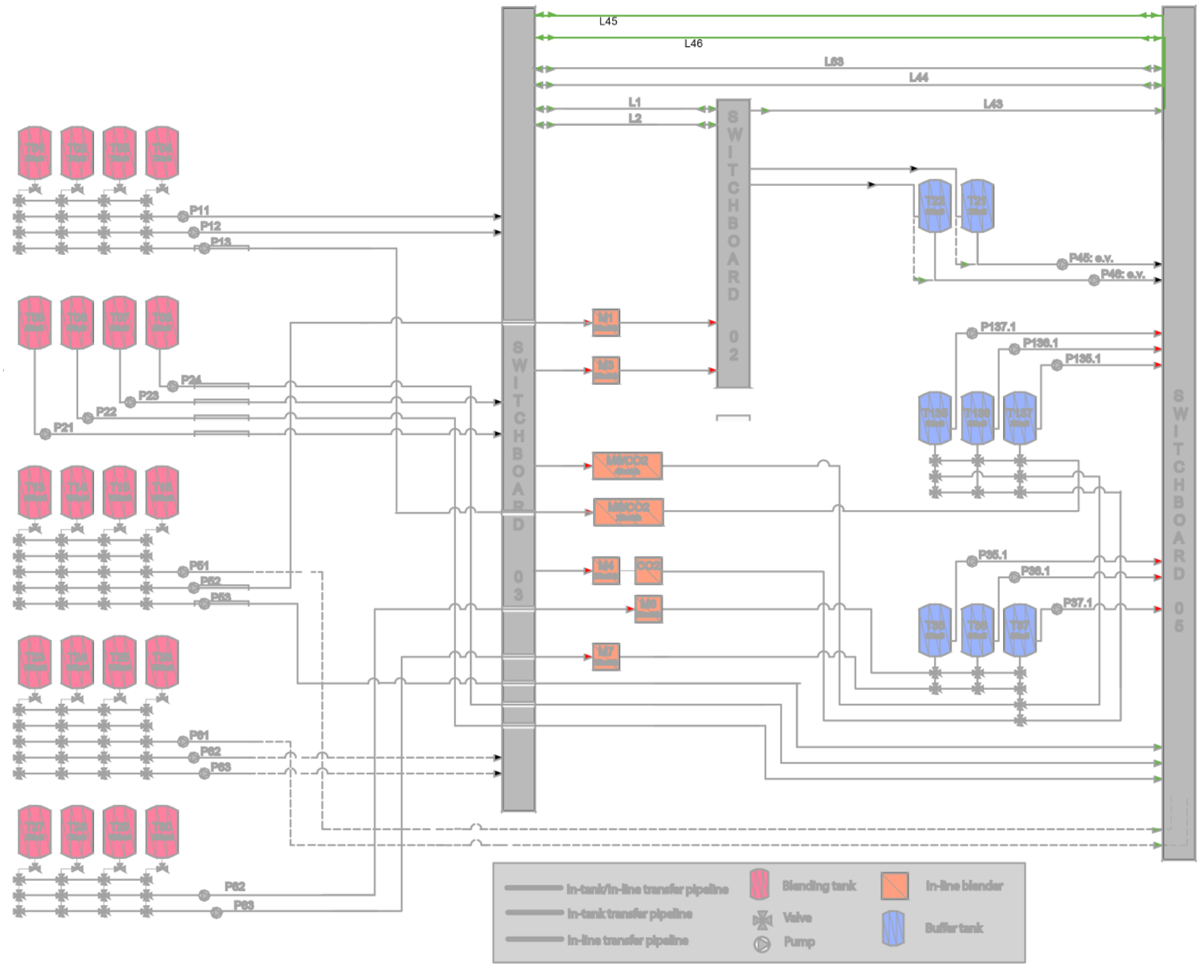
E | Statistical test regarding significancy

A statistical test is to performed to check whether there is strong evidence that the logical reconfiguration outperforms the current situation. A paired t-test is conducted. Variable 1 is the result from the no configuration situation and variable 2 the result from the logical configuration situation. The critical values are computed by the *Analysis Toolpack* plug-in of *Microsoft Excel*.

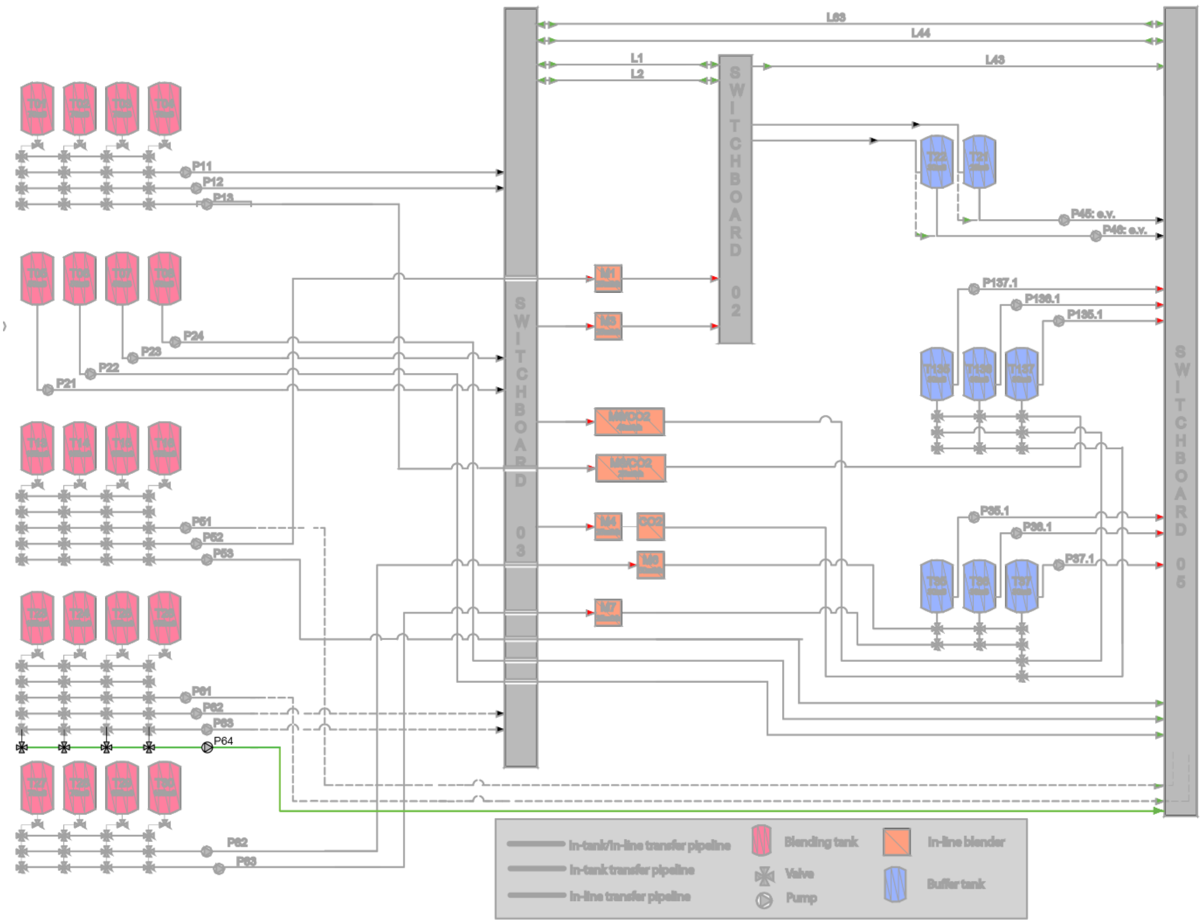
t-Test: Paired Two Sample for Means		
	Variable 1	*Variable 2*
Mean	0.67459	0.685213113
Variance	0.000782	0.000192415
Observations	300	300
Pearson Correlation	0.542666	
Hypothesized Mean Difference	0	
df	299	
t Stat	-7.82278	
P(T<=t) one-tail	4.48E-14	
t Critical one-tail	1.649966	
P(T<=t) two-tail	8.96E-14	
t Critical two-tail	1.96793	

The upper percentile of Students *t* distribution with α is 0.05 and degrees of freedom approaches infinity is 1.64 (Diem, 1962). Since one-tail p-value of the statistics test is 4.48E-14, which is less than 0.05 we conclude that the difference in means is significant, and thus a logical reconfiguration performs better.

F | Capacity expansion 1 flow diagram



G | Capacity expansion 2 flow diagram



H | Scheduling software agreement

This appendix shows an offer from the supplier of scheduling software for some small functional enhancements to the scheduling software package.

After the successful upgrade and migration of [redacted], Riedel has requested [redacted] for an offer for some small functional enhancements.

1.1 Material Imbalance Conflict

Due to mismatching volumes received from masterplanning or due to rescheduling, it may happen that scheduled volumes for finished-goods and the related semi-finished-good do not match. To assist the scheduler in finding these mismatches, a conflict is requested.

- Conflict line to be shown on phase 50 steps
- Color: black
- Conflict indication:
  - when the sum of volumes produced with phase 50 steps is not the same as the sum of volumes consumed with **interlinked steps** in phase 60.
  - Allowed margin is 1%.

1.2 Assistance

Total assistance for the above change is 2 days.

Total costs:

2 days * 1.395 EUR/day = 2.790 EUR

1.3 Timing and delivery

- Building and delivery will only start when a PO is received on this offer
- Delivery of the functionality will be to the test environment
- Only after use testing and approval, these items will be moved to the production environment

I | Mathematical problem formulation for the packaging scheduling problem

This section will introduce the mathematical problem formulation of the packaging scheduling problem at Riedel. The formulation is further build upon the MIP of ruiz et. Als as introduced in section 3.4.1. This problem formulation will provide an overview of the problem structure, constraints and model.

Sets

N	∈	$\{j/k=1,2,\ldots,N\}$	, For regular production orders
O	∈	$\{j/k=N+1,N+2,\ldots,N+9\}$	, For CIP Midweek production orders
P	∈	$\{j/k=N+10,N+11,\ldots,N+18\}$	, For CIP End of week production orders
M	∈	$\{i=1,2,\ldots,M\}$	, For packaging lines
L	∈	$\{l=1,2,\ldots,L\}f$	, For filling machines
T	∈	$\{t=0,1,\ldots,T\}$	, For time

The set of N refers to any packaging production order, each element of which refers to a fruit juice to be produced. The set N refers to CIP production orders that are dummy jobs, it is a set of 9 elements, which is 1 dummy job for each packaging line, of which there are 9. These CIP operations must be scheduled somewhere in the sequence, just like the orders in set N. The set P contains dummy jobs for each packaging line, consider it a CIP operation that forces cleaning operations at the end of the week.

$Speed_i$	=	Production capacity per hour of an individual filling machine on line *i*
S_{ijk}	=	Sequence-dependent setup time on machine *i*, when processing *k*, after having processed *j*
SP_i	=	1, if line *i* has the splitting property, 0, otherwise.
MT_l	=	1, if the filling machine type is primary 0, if secondary
ML_l	=	Packaging line corresponding to filling line *l*, $ML_l \in M$
SC_{jk}	=	1, if *j* can be synchronized with *k* (have the same mixture) 0, otherwise
R_j	=	Release date/time of *j*
Q_j	=	Order quantity of *j*
$FOCL$	=	Fixed Operator Capacity Level
OT	=	Overtime Threshold
V	=	Large Numerical Value
CO	=	Cost of overtime per hour
CTW	=	Cost of one temporary worker per hour
BS	=	Financial benefit of synchronization
CI	=	Cost of Idle time
$CipTime$	=	Duration of a CIP cleaning on a filling machine.
$Compatibility_{ik}$	=	1, if packaging line i is compatible with order k

Decision variables

X_{ijk}	=	1, if job j precedes job k on machine i 0, otherwise	=9*(69+18+1)*(69*18+1)
Y_{ij}	=	1, if order j is spitted on packaging line i	=9*(69*18+1)
C_{ij}	=	Completion time of order j at packaging line	=9*(69*18+1)
$Cmax_l$	=	Completion time of filling machine l of latest order	11
$Smin_l$	=	Start time of filling machine l of earliest order	11
JS_j	=	Start time of order j	69
JC_j	=	Completion time of order j	69

MS_i	=	Scheduled start time of packaging line i	9
$Active_{lt}$	=	1, if filling machine l is operational in between t and t+1	150*11*3
Cond1	=	1, if some start time of machine l is before t 0, otherwise	150*11*3
Cond2	=	1, if some completion time of machine l is after t 0, otherwise	150*11*3
TWH	=	Total Temporary Worker Hours	1
$Synch_{jk}$	=	1, if order k is synchronized with order j	150*11
TS	=	Total synchronizations	1
H	=	Total production time	1
EH	=	Total effective production time	1
$Overtime_l$	=	Over time on filling machine l	11
OT	=	Total Over Time	1
CIP_i	=	1, if CIP Midweek is not final CIP 0, otherwise	11

Objective

$$\min CO * OT + CTW * TWH + CI * (H - EH) - TS * BS \tag{1}$$

The objective is to minimize the total cost. The first element in this objective value concerns overtime, the second to the cost of temporary workers, the third to the cost of idle time and the final to obtained benefits as result of synchronization.

Constraints

$$\sum_{i \in M} \sum_{\substack{j \in \{0\} \cup N \\ j \neq k}} X_{ijk} = 1, \qquad \forall k \in N \cup O \cup P \tag{2}$$

$$\sum_{k \in N} X_{i0k} \leq 1, \qquad \forall i \in M \tag{3}$$

$$\sum_{i \in M} \sum_{\substack{k \in N \\ j \neq k}} X_{ijk} \leq 1, \qquad \forall j \in N \cup O \tag{4}$$

$$\sum_{i \in M} \sum_{\substack{k \in N \\ j \neq k}} X_{ijk} = 0, \qquad \forall j \in P \tag{5}$$

$$X_{ijk} \leq Compatibility_{ik}, \qquad \forall j, k \in N, \forall\, i \in M \tag{6}$$

$$\sum_{\substack{h \in \{0\} \cup N \cup O \cup P \\ h \neq k, h \neq j}} X_{ihj} \geq X_{ijk}, \qquad \forall j, k \in N \cup O \cup P, \qquad j \neq k, \qquad \forall i \in M \tag{7}$$

Constraint (2) makes that each production order is scheduled by forcing each order to be preceded by some other order. Constraint (3) enforces that the dummy job on each machine is preceded by at most one production order. Constraint (4) makes that all regular and CIP orders in the middle of the week are preceded by at most 1 order. Whereas constraint (5) makes that the CIP order concerning the end of the week is not preceded by any order. Constraint set (6) addresses the unrelatedness of parallel packaging lines. It control the packaging line assignment. Some lines are not capable of producing orders.. Constraint (7) makes that if a given job j is processed on a given machine i, a predecessor h must exist on the same machine.

$$C_{ik} + V\big(1 - X_{ijk}\big) \geq \max\left(C_{ij}, r_k\right) + S_{ijk} + \frac{Q_k}{Speed_i(1 + Y_{ik})}, \quad (8)$$
$$\forall j \in \{0\} \cup N, \forall k \in N, j \neq k, \forall i \in M$$
$$C_{i0} = MS_i, \qquad \forall i \in M \quad (9)$$

Constraint set (8) is to control completion times of order on a packaging machine level. Whereas constraint set (9) controls the start times of machines for the first order, since in this model it is proposed to make this a decision variable.

$$Y_{ik} \leq SplitProperty_i, \qquad \forall i \in M, \qquad \forall k \in N \quad (10)$$
$$Cmax_l \geq C_{ik}, \forall l \in L, \forall k \in N \cup O \cup P, \forall i \in M, if\ ML_l = i\ and\ MT_l = 1 \quad (11)$$
$$Cmax_l + V(1 - Y_{ik}) \geq C_{ik} + CIP_i * CipTime_i, \forall l \in L, \forall k \in N, \forall i \in M, if\ ML_l = i\ and\ MT_l = 0 \quad (12)$$
$$S_l \leq MS_i + V(1 - MT_l), \forall l \in L, \forall k \in N \cup O \cup P, \forall i \in M, if\ ML_l = i\ and\ MT_l = 1 \quad (13)$$
$$S_l \leq C_{ik} - \frac{Q_k}{Speed_i(1 + Y_{ik})} + V(1 - Y_{ik}) + V * MT_l, \forall l \in L, \forall k \in N, \forall i \in M, if\ ML_l = iand\ MT_l = 0 \quad (14)$$

Constraint set (10) is to control the splitting that is decided on. Splits are only allowed if the splitting property of a packaging line allows to do so. Constraints set (11), (12), (13), and (14) translates start and completion times from a packaging line level to filling machines. Set (11) sets the completion time of primary filling machines to the completion time of latest order completion. Set (12) does the same for secondary machines, based on whether orders are split or not. Constraint set (13) the start time of filling machines to the scheduled start times of the lines. For secondary filling machines this is done by reducing the completion time of the first job that is split by its processing time (14).

$$C_{ik} + V(CIP_i) + V(1 - Y_{ik}) \geq C_{ik}, \qquad \forall i \in M, \qquad \forall k \in N, \forall k \in O \quad (15)$$

Set (15) control whether the primary filling machine would need an additional CIP cleaning if it completes earlier than the primary machine. All production sequences must be finalized with a CIP. This constraint is designated for secondary filling machines. This constraint is required to make constraint (11) work,

$$t \geq S_l + V * (1 - Cond1_{lt)}, \forall t \in T, \forall l \in L \quad (16)$$
$$t + 1 \leq C_l - V * (1 - Cond2_{lt)}, \forall t \in T, \forall l \in L \quad (17)$$
$$Active_{lt} \geq Cond1_{lt} + Cond2_{lt} - 1, \forall t \in T, \forall l \in L \quad (18)$$
$$TWH \geq \sum_{t}^{T}\left(\sum_{l}^{L}(Active_{lt}) - RegularOperatorCapacity\right) \quad (19)$$

Constraint sets (16), (17), (18), and (19) relate to the temporary worker objective. Constraint set (16) forces the auxiliary decision variable $Cond1_{lt}$ to the numerical value of 1 if t is larger than t. Set (17) does the same with $Cond2_{lt}$ if t+1 is less than the completion time on a filling machine level. If both conditions are true, the $Active_{lt}$ constraint is forced to the numerical value of one (18), indicating that the machine is active in this time interval. Constraint set (19) computes the total number of temporary worker hours in the schedule.

$$JS_j - V(1 - Synch_{jk}) \leq JS_k, \qquad \forall j, k \in N, \qquad j \neq k \quad (20)$$
$$JS_j - V(1 - Synch_{jk}) \leq JS_k, \qquad \forall j, k \in N, \qquad j \neq k \quad (21)$$
$$Synch_{jk} \leq SC_{jk}, \qquad \forall j, k \in N, \qquad j \neq k \quad (22)$$

$$\sum_{k}^{N} Synch_{jk} \leq 1, \qquad \forall j \in N \tag{23}$$

$$TS = \sum_{j}^{N} \sum_{k}^{N} Synch_{jk} \tag{24}$$

Constraint sets (20) and (21) evaluate whether the start time of job k is in between the start and completion of job j. If so, the variable Synch may be set to the numerical value one, which will contribute to the minimization problem in the objective function. A synchronization is only allowed if both orders concern the same mixture, this is controlled by set (22). Set (23) controls that each job is synchronized with only one other job. The total number of synchronizations in a schedule is controlled by (24).

$$72 + V\left(1 - X_{ijk}\right) \geq C_{ij} - MS_i, \qquad \forall j \in \{0\} \cup N, \forall k \in O, \forall i \in M \tag{25}$$

$$72 \geq Cij - C_{ik}, \qquad \forall j \in \{0\} \cup N, \forall k \in O, \forall i \in M \tag{26}$$

Constraint sets (25) and (26) control that no more time elapses than some threshold between the start of a packaging line and its mid-week cleaning, and between the mid-week cleaning and the end of the week.

$$Overtime_l \geq Cmax_l - OvertimeTreshold \;\; \forall l \in L \tag{27}$$

$$OT = \sum_{l}^{L} Overtime_l \tag{28}$$

Set (27) sets the overtime hours involved in a schedule for each filling machine. Whereas constraint (28) sums these overall filling machines.

$$H = \sum_{l}^{L} Cmax_l - Smin_l \tag{29}$$

$$EH = \sum_{k}^{N} \sum_{i}^{M} \left(\left(\sum_{j}^{N} X_{ijk} \right) * \frac{Q_k}{Speed_i(1 + Y_{ik})} \right) \tag{30}$$

The hours involved in a production schedule is the difference between a lines completion and start, summed over all lines. These hours comprise all activities. The hours which these lines are actually effective is computed by (30) summing the processing times of all jobs and machines. The difference between those is idle time.

$$X_{ijk}, Y_{ik}, Active_{lt}, Synch_{jk}, Cond1_{lt}, Cond2_{lt} \in (0,1) \tag{31}$$

$$C_{ij}, CMax_l, SMin_l, JS_j, JC_j, OverTime_l \geq 0 \tag{32}$$

The final constraints in sets (31) and (32) make ensure binary and nonnegative values.