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Optimization-based planning approaches for food supply chains: impact of product and processing characteristics

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Contents

Abstract

Specific product and processing characteristics impact planning of food supply chains. These include, for example, the shelf life of the products and the cleaning requirements of the production equipment. This thesis introduces three types of optimization-based approaches for planning food supply chains at different levels. The developed approaches are applied to real-life food industry cases. At the strategic planning level, a two-stage stochastic programming model determines the selection of new product designs and processing technologies in a supply chain context. Numerical tests investigate the interdependencies between product designs and processing technologies for novel milk concentrates. Flexible technologies are selected that can produce different product designs. The tests also show that the technology selection is highly dependent on the uncertain demand characteristics of the new concentrate products. At the tactical planning level, a sustainability framework evaluates the impact of shelf life on the trade-off between economic and environmental objectives for the example of milk powders and milk concentrates. The framework includes a multi-objective optimization model and a rolling horizon scheme that captures product price uncertainty. Numerical tests show that the economic value of shelf life is not a strong argument against the substitution of powders with more environmental-friendly concentrates. At the operational planning level, a lot sizing and scheduling model for flowshops accurately represents different setup and cleaning classes that are identified through a novel classification scheme. Numerical tests investigate the impact of different setup and cleaning requirements in short-term production scheduling of cheese. In particular, the tests give insights into the extent to which a misidentification of cleanings may decrease the scheduling flexibility.

Zusammenfassung

Die Planung von Wertschöpfungsketten für Lebensmittel wird von spezifischen Produkt- und Prozesseigenschaften beeinflusst, wie beispielsweise Produkthaltbarkeiten und Reinigungsanforderungen der Produktionsanlagen. In der vorliegenden Dissertation werden drei auf mathematischer Optimierung basierende Methoden entwickelt, die sich mit der Planung von Wertschöpfungsketten für Lebensmittel auf verschiedenen Planungsebenen beschäftigen. Die Methoden werden in Fallstudien aus der Lebensmittelindustrie angewandt. Auf der strategischen Planungsebene werden die Auswahl neuer Produktdesigns und Produktionstechnologien und relevante Entscheidungen entlang der Wertschöpfungskette mittels eines zweistufigen, stochastischen Optimierungsmodells integriert. Die numerischen Tests analysieren die Interdependenzen zwischen Produktdesigns und Produktionstechnologien für neuartige Milchkonzentrate. Flexible Technologien werden ausgewählt, welche unterschiedliche Produktdesigns produzieren können. Die numerische Analyse zeigt auch, dass die Auswahl der Produktionstechnologien stark von Nachfrageunsicherheiten der neuen Konzentrate abhängt. Auf der taktischen Planungsebene bewertet ein konzeptioneller Rahmen den Einfluss der Produkthaltbarkeit auf ökonomische und ökologische Ziele in der Wertschöpfungskette von Milchpulver und -konzentraten. Bestandteile des konzeptionellen Rahmens sind ein mehrkriterielles Optimierungsmodell und ein Planungsschema mit rollierendem Zeithorizont, das unsichere Preisfluktuationen berücksichtigt. Die numerischen Tests zeigen, dass der ökonomische Wert von Produkthaltbarkeit kein starkes Argument gegen die Substitution von Pulvern durch umweltfreundlichere Konzentrate ist. Auf der operativen Planungsebene werden verschiedene Rüst- und Reinigungsvorgänge mit Hilfe eines neuartigen Klassifikationsschemas identifiziert und in ein Modell für Losgrößen- und Reihenfolgeplanung für Flowshops integriert. Die numerischen Tests analysieren die Auswirkungen von verschiedenen Rüst- und Reinigungsanforderungen auf die kurzfristige Ablaufplanung in der Käseherstellung. Die Studie zeigt insbesondere inwieweit eine Fehlidentifizierung von Reinigungen die Planungsflexibilität verringern kann.

Chapter 1. Introduction

1.1 Food supply chain planning

The food industry is an important manufacturing sector. In the European Union, for instance, the food and drink industry represents the largest manufacturing sector in terms of turnover and employment, with over €1 trillion turnover and over 4.25 million employees in 2016 (FoodDrinkEurope, 2016). In the food supply chain, many different organization are involved, like farmers, food processors, and distributors, which aim at providing final consumers with foods and drinks.

Several important challenges typify planning of food supply chains. Consumers demand high-quality food products that are safe and have sufficient shelf lives. This leads, for example, to extensive cleaning requirements at the processing plants. However, cleanings typically contribute considerably to food waste. Furthermore, consumer awareness of environmental sustainability has increased significantly over the last few years. In order to keep a competitive advantage, food producers therefore regularly introduce novel and more environmental-friendly processing technologies to their plants, which consume less resources. To cater both consumer and societal needs, new product introductions are also common in the food industry. Often there is no existing market or previous demand data for the new products resulting in various demand uncertainties that have major impacts on the food supply chain planning. Since food products are usually defined through their production processes, decisions on processing technologies and new products are highly interrelated. Also, new products and technologies often result in changes in the supply chain. Managing this nexus is therefore a key challenge in food supply chain planning.

Motivated by the aforementioned challenges, this thesis focuses on planning of food supply chains. Specific product and processing characteristics that cause complexities for supply chain planning must be accounted for. Novel and advanced decision tools are therefore necessary to achieve the overall supply chain objectives, which relate both to costs and environmental criteria. Depending on the planning tasks, decision tools at different planning levels are required. Three different planning levels are typically distinguished, i.e., long-term, mid-term, and short-term, or alternatively strategic, tactical, and operational. The scope of the planning activities, the level of aggregation, the impact of the decisions, and the planning horizon vary between the planning levels.

In the following, we first discuss the food-specific product and processing characteristics that are analyzed in this thesis. Then, we describe the food industry cases, which the developed planning approaches are applied to. Finally, we provide the research objectives, the thesis outline, and a list of the included publications.

1.2 Product and processing characteristics of food supply chains

Several product and processing characteristics typify food supply chains. In the following, we give a brief overview of the food-specific product and processing characteristics that are analyzed in this thesis. To appropriately address these different characteristics in food supply chain planning models, interdisciplinary research approaches involving e.g., product designers, food process engineers, and supply chain experts, are often required. Process manufacturing is common in production systems for food, chemicals, and pharmaceutics. These process industry sectors therefore share some common product and processing characteristics. We refer to Fransoo and Rutten (1994) for an overview of general process industry characteristics.

Shelf life. Managing perishability in production and distribution planning is a key challenge in many industries (see e.g., the review by Amorim et al., 2013b). In the food industry, shelf life is the most distinguishing product characteristic. Products are typically produced from relatively few types of raw materials and the quality of raw materials is often subject to variability. Furthermore, intermediates and final products are often subject to perishability. To control the quality degradations strict control of hygiene standards and careful handling of inventories are required throughout the entire supply chain. Controlling the storage conditions (e.g., chilled or ambient) is of importance for many types of food products, as the temperature levels are directly connected to the quality control. Modeling shelf life of perishable food products is fundamental to reduce product waste along the supply chain adding complexity to supply chain planning. Specific constraints are often required in planning models to track the quality degradation (see e.g., Rong et al., 2011). As described in Section 1.1, new environmental-friendly processing technologies are frequently introduced at food processing plants. Even though the resulting products are more environmentally sustainable, the shelf life is often reduced. In case of price fluctuations, shelf-life-reduced products may negatively affect the economic performance due to limited storage duration.

Setups and cleanings. Extensive setup and cleaning requirements typify the food sector. Setups and cleanings cause long downtimes of equipment, high consumption of energy, water, and cleaning agents, and waste of materials. This results in significant economic and environmental impacts. In planning and scheduling of food production it is therefore important to account for setups and cleanings (see e.g., Kopanos et al., 2012). Different to many other industries, setup and cleaning operations in food processing often cannot be reduced as they are essential to adhere to extensive quality and safety regulations. Furthermore, the quality and safety considerations lead to a diversity of setup and cleaning requirements and many different types of setups and cleanings that typically must be performed while production is stopped.

Resource consumption. Large amounts of resources, such as energy, water, and cleaning agents, are commonly needed in food processing and distribution. Consumer expectations for fresh high-quality food products typically result in high energy consumption, since in order to achieve high-quality products, cooling or more energy intensive processes often must be employed. Cleanings also consume large amounts of resources. Resource consumption is therefore a key cost driver that also has a strong impact on the environment. Consequently, including energy consumption (see e.g., Zanoni and Zavanella, 2012; Van der Vorst et al.; 2009), water consumption (see e.g., Ahumada and Villalobos; 2011), and consumption of cleaning agents in food supply chain models is especially important.

Product losses. Product losses are typical for food supply chains. They can occur at different stages in the supply chain, like in processing (see e.g., Waldron, 2009), storage, and transportation. Typically, large product losses result from cleanings and quality degradation. Products that are thrown away along the supply chain are very costly and they cause substantial environmental impacts. Reduction of product losses is therefore important both from economic and environmental perspectives. The food industry confederation in the European Union has, for example, made the fight against food waste one of its key priorities (FoodDrinkEurope, 2017).

1.3 Food industry cases

The planning approaches presented in this thesis are applied to real-life food industry cases that are introduced in this section. Particularly, two different cases from the dairy industry are analyzed. The dairy industry is a large sector within the food industry. In the German food and drink industry, for example, the dairy industry is the second largest industry with 13.2% share of the total turnover in 2016 after the meat industry with 24.3% share of the total turnover (Bundesvereinigung der Deutschen Ernährungsindustrie e.V., 2017).

1.3.1 Substitution of skim milk powders with concentrates

In the dairy industry, drying of powders is one of the most energy intensive processes (Ramírez et al., 2006). Dried dairy products are a popular ingredient in the processing of various food products, such as filled bakery products, ice-cream, yoghurt, and finished meals. For this purpose, milk is concentrated in large volumes and further dried to generate skim milk powders. These processes consume enormous amounts of energy. Before the final products are produced, the powders are often reconstituted by again adding the water, which was previously extracted. In these cases, omitting the energy intensive drying process and producing instead concentrates with more efficient concentration processes is an option. As a consequence, substantial amounts of powders may be substituted with concentrates leading to extensive energy savings in production.

However, the production advantage may be offset through the higher storage and transportation impacts (concentrates have smaller dry-matter content than powders and they may require chilled temperatures), and the increased perishability of the products (concentrates have a significantly lower shelf life than powders). The whole supply chain is therefore affected through the technology innovation. Furthermore, powders and concentrates can be processed with multitude of processing variants by combining different technologies. This results in numerous different product designs with different dry-matter contents and shelf lives. Finally, for these novel products, there are a number of uncertain demand characteristics.

This case focuses on the introduction of novel products and processing technologies. For the evaluation of these products and processing technologies it is important to account for many of the product and processing characteristics described in Section 1.2, like shelf life, cleanings, resource consumption, and product losses. This interdisciplinary project is carried out in cooperation with the chair of Food and Bioprocess Engineering at the Technical University of Munich as well as two German dairy companies.

1.3.2 Cleanings in cheese production

One of the major sectors in the dairy industry is the production of cheese. In this research project, key challenges in production scheduling of cheese are investigated. The aim is to develop a weekly production schedule such that production on weekends is minimized. The project focuses specifically on scheduling of setup and cleaning activities. In particular, different types and characteristics of setup and cleaning activities are analyzed. The analyzed settings are typical for various process industry applications with extensive setup and cleaning requirements.

A number of types of cheeses exist, each with its special production process, ripening process, taste, and texture. In this project, we analyze the production of soft and blue cheese. The production environment is classified as a no-wait flowshop, in which multiple products are produced sequentially on a single production line. The main production processes are analyzed, which are filling into tubs, curd preparation, filling into forms, resting, and brining. The usage of the forms, into which the cheeses are filled, is a specifically important consideration. Other important scheduling aspects include, for example, due date restrictions, precedence relations between products (e.g., requiring production of natural products before production of products with strong flavor), and heterogeneous processing times.

This case from the dairy industry focuses mainly on one of the processing characteristic mentioned in Section 1.2, i.e., setups and cleanings. However, scheduling of setups and cleanings also relates to some of the other product and processing characteristics as they are directly linked to the resource consumption and product losses of the processing system, as well as the quality of the products. This research project is carried out together with a medium-sized dairy company from Germany.

1.4 Research objectives

The overall aim of the thesis is to contribute to the knowledge on food supply chain planning. The thesis covers three topics that all develop an optimization-based planning approach considering a food-specific supply chain problem. Here, the relevant product and processing characteristics must be accounted for. We do not aim at developing optimization models that systematically accommodate all product and processing characteristics simultaneously, but rather focus on the ones that are relevant for the specific problem and planning level. Interdisciplinary collaboration is required to integrate knowledge about food processing technologies in the developed planning approaches. Although the problems studied in this thesis are typically found in food supply chains, similar issues can also be found in other settings. Therefore, some of the developed approaches are generically formulated. In the following, we discuss the aim of the thesis in more detail and formulate specific research questions.

Consumer demands for new and sustainable products necessitate the introduction of new processing technologies. Technological innovation also leads to new processing technologies that allow for new product introductions. Decisions on the selection of new products and technologies are therefore highly interrelated. Moreover, these must be embedded in suitable supply chain structures and the key demand uncertainties must be captured. This is especially relevant in the food industry, since the products are usually defined through their production processes. This brings us to the first research question in this thesis:

RQ1: How can interdependencies between the selection of new product designs and processing technologies including the characteristic uncertainties be addressed?

Shelf life is a product characteristic that typifies food supply chains. Shelf life can have an economic benefit in case of fluctuating prices as shelf-stable products allow to delay the sales until a higher price level is reached. Environmental impacts increase with longer shelf lives and longer storage durations. The shelf life therefore impacts different sustainability objectives. The dairy case on substituting skim milk powders with concentrates is very well suited to demonstrate the impact of shelf life on the trade-off between economic and environmental performance. The next research question therefore specifically considers this case:

RQ2: From an integrated economic and environmental perspective, should traditional milk powders be substituted with novel milk concentrates? Is the decision impacted by the value of shelf life?

Setups and cleanings represent an especially important processing characteristic in the food industry. Diverse setup and cleaning requirements result in different types and characteristics of setups and cleanings. Also, they are often interrelated through specific substitution relationships. An accurate representation of setups and cleanings in scheduling approaches is fundamental for an efficient use of resource. Although scheduling of setups and cleanings has received some attention in the literature, there is no systematic approach available. This leads us to the final research question in this thesis:

RQ3: How can different setup and cleaning requirements and their interrelationships be systematically addressed in scheduling approaches?

1.5 Thesis outline

The thesis is organized as a collection of three research papers that focus on the overall research objective. Optimization-based planning approaches at three different planning levels are developed, i.e., at a strategic level in Chapter 2, at a tactical level in Chapter 3, and at an operational level in Chapter 4. For each particular problem, the related literature is outlined in the respective chapter. More specifically, the thesis is organized as follows.

Chapter 2 investigates the selection of new product designs and processing technologies in a supply chain context, accounting for the characteristic demand uncertainties. The chapter therefore aims at answering research question 1. First, a design space is derived through interdisciplinary research, in which the interdependencies between products and processing technologies are mapped for different product specifications, such as shelf life requirements. Then, we introduce a novel modeling approach based on two-stage stochastic programming that covers the nexus between new product introduction, processing technologies, and supply chain. The developed approach is general and not only applicable to food supply chains. Next, we apply the approach to the selection of processing technologies and product designs for milk concentrates (see Section 1.3.1) and carry out numerical tests. These specifically analyze how the product and technology selection is affected by demand uncertainties.

In Chapter 3, a framework is developed for evaluating the impact of shelf life on the trade-off between the economic and environmental performance of milk powders and milk concentrates (see Section 1.3.1). The proposed framework includes a multi-objective optimization model, a rolling horizon scheme that deals with product price uncertainty, and a method for objective reduction. In this chapter both concentrates and powders are analyzed, as compared to only concentrates in Chapter 2. In numerical tests, we analyze the substitution of powders with concentrates from both an economic and an environmental perspective. We also particularly investigate the economic value of shelf life. This chapter therefore aims at answering research question 2.

Chapter 4 investigates setups and cleanings in lot sizing and scheduling. The chapter aims at answering research question 3. First, a novel classification scheme is developed for setups and cleanings. Then, a modeling approach is developed for lot sizing and scheduling of flowshops including a comprehensive representation of setups and cleanings, as well as their interrelationships. The developed methodology applies in general to flowshops and is not limited to food production. Finally, the developed modeling approach is applied to the cheese production case described in Section 1.3.2. Numerical tests specifically analyze the flexibility in scheduling cleanings and the heterogeneity of the processing times.

Finally, the thesis concludes with a summary of the results in Chapter 5. Possible directions for future research are also outlined.

1.6 Included publications

The chapters in this thesis are based on different publications and are all readable as individual contributions. Combined they provide optimization-based planning approaches for food supply chains, each addressing specific product and processing characteristics. The chapters have been published as listed below.

Chapter 2: Stefansdottir, B., Grunow, M., 2018. Selecting new product designs and processing technologies under uncertainty: two-stage stochastic model and application to a food supply chain. International Journal of Production Economics, 201, 89–101.

Chapter 3: Stefansdottir, B., Depping, V., Grunow, M., Kulozik, U., 2018. Impact of shelf life on the trade-off between economic and environmental objectives: a dairy case. International Journal of Production Economics, 201, 136–148.

Chapter 4: Stefansdottir, B., Grunow, M., Akkerman, R., 2017. Classifying and modeling setups and cleanings in lot sizing and scheduling. European Journal of Operational Research, 261(3), 849–865.

Chapter 2. Selection of product designs and processing technologies

This chapter is based on an article published as:

Stefansdottir, B., Grunow, M., 2018. Selecting new product designs and processing technologies under uncertainty: two-stage stochastic model and application to a food supply chain. International Journal of Production Economics, 201, 89–101.

Abstract

New product introduction frequently requires new processing technologies, and the development of new processing technologies also allows for the introduction of new products. An assessment of these new products and technologies must account for changes in the whole supply chain. This paper presents a two-stage stochastic mixed integer linear programming model that integrates the selection of new product designs and processing technologies in a supply chain context. Special attention is given to the demand uncertainties with regard to product specifications and volumes. The first stage of the model selects the processing technologies that determine the set of feasible product designs, leaving the detailed product designs and the production volumes as recourse actions to the second stage. We apply the developed approach to product designs and processing technologies in the dairy sector. Here, the substitution of milk powders through milk concentrates is currently being considered, which may lead to extensive energy savings in production. In an interdisciplinary effort, we first derive the design space encompassing the feasible dairy technologies and product designs for concentrates. Through numerical investigation we then show that flexible technologies are selected that can be used to produce different product designs. We also show that the selection of technologies is highly dependent on the uncertain demand characteristics of the new concentrate products.

2.1 Introduction

Consumer demands for new products require the introduction of new processing technologies. At the same time, technological progress leads to new processing technologies allowing product innovations. Product designs and processing technologies also need to be embedded in suitable supply chain structures. Managing this nexus between new product designs, technologies, and supply chains is the key challenge in today's economies with decreasing product and processing technology life cycles.

For instance, in a reaction to customer demands for more environmental-friendly product designs, the beverage industry introduced new packaging technologies, which results in changes to the whole supply chain. Similarly, the increased demand for electric mobility has led to the development of not only new traction batteries but also of body parts made of composite materials. This is reshaping the automotive industry as the new product designs require new manufacturing technologies as well as new supply chains.

There is substantial literature on integrating processing technology selection with supply chain decisions. This previous work assumes decisions on product design to be given. However, product designs and processing technologies are interdependent. An interdisciplinary approach involving product designers, process engineers, and supply chain experts is required to address the nexus. Each of these disciplines needs to contribute to the development of the design space, which encompasses information on the potential product specifications as well as the associated processing technologies and supply chains.

Managing the nexus is further complicated by demand uncertainties. Long before demand characteristics are known, decisions on significant investments must be made. Particularly, the adoption of new products is hard to predict. Besides total demand volume, especially the exact product specifications demanded by the customers are often unknown. However, this product mix uncertainty can be dealt with by selecting processing technologies that have the flexibility to change to other product designs.

Advances in fractionation technologies are examples of processing technology developments that offer opportunities for the introduction of new products. With the help of these new technologies, raw material can be separated more efficiently into different fractions of its constituents. One industry that strongly profits from these technological developments is the food sector. Milk, for instance, can be concentrated to different levels of dry-matter content. Different technologies may be employed and combined for concentration and heat treatment (for shelf live extension), leading to different product designs. Depending on the customer application, the concentrates can potentially substitute the traditionally used powders. A substantial reduction in energy consumption during processing results. However, this advantage may be offset by the necessity to ship larger volumes (which depends on the degree of concentration) and the necessity to cool certain types of concentrates (which depends on the previous heat treatment). Hence, the extent at which the new concentrates will substitute the powders and the most suitable product specifications for the concentrates are uncertain. The case therefore exemplifies the nexus between product designs, processing technologies, and supply chain, including the characteristic uncertainties.

The main contributions of the paper are (i) the development of a novel modeling approach that integrates the selection of new product designs into the decision making on processing technologies in a supply chain context; (ii) the comprehensive inclusion of product-specification and volume uncertainties related to new product introduction; (iii) the derivation of the design space for a case from the food industry based on extensive interdisciplinary collaboration; (iv) numerical results demonstrating the suitability of our approach and showing that under uncertainties typical for new product introduction, technologies are selected that have the flexibility to produce different products; and (v) the demonstration that technology selection in the case is highly dependent on the uncertain demand characteristics of the products, showing that managers should strive to obtain information on customer demand characteristics, especially on shelf life.

The remainder of this paper is organized as follows. In Section 2.2, the main related literature is outlined. Section 2.3 presents the proposed modeling approach. Initially, the design space is derived, in which the interdependence between products and processing technologies is mapped for the product specifications. Then, a two-stage stochastic mixed integer linear programming (MILP) model is presented. In the first stage, the processing technologies that determine the set of feasible product designs are selected. In the second stage, the product designs and their share in production volumes are determined, as well as the decisions on the supply chain operations. Section 2.4 describes the industry case on new energy efficient dairy processes and products. In Section 2.5, numerical analyses for an industry case at a German dairy company are carried out. Finally, Section 2.6 concludes the paper and presents future research opportunities.

2.2 Related literature

In the following, we first give a brief overview of deterministic and stochastic approaches that deal with selection of technologies (or process design) together with supply chain decisions. These approaches are summarized in Table 2.1. Because our approach is applied to a case from the food industry, we secondly review some interdisciplinary approaches in which quantitative operations management methods are integrated with food-specific characteristics.

Table 2.1: Overview of deterministic and stochastic approaches dealing with technology selection in a supply chain context.

Publication	Industry application	Method	Det./ Stoch.[a]	Product design	Technology selection (process design)	Supply chain decisions
Hugo and Pistikopoulos (2005)	Chemical	Mo-MILP	Det.	-	X	X
Corsano and Montagna (2011)	Batch process	MILP	Det.	-	X	X
Corsano et al. (2011)	Chemical	MINLP	Det.	-	X	X
You et al. (2012)	Chemical	Mo-MILP	Det.	-	X	X
Quaglia et al. (2012)	Food	MINLP	Det.	-	X	X
You and Grossmann (2008)	Chemical	Mo-MINLP	Stoch.	-	X	X
Guillén-Gosálbez and Grossmann (2009)	Chemical	Mo-MINLP	Stoch.	-	X	X
Guillén-Gosálbez and Grossmann (2010)	Chemical	Mo-MINLP	Stoch.	-	X	X
Gebreslassie et al. (2012)	Chemical	Mo-MILP	Stoch.	-	X	X
Kostin et al. (2012)	Chemical	Mo-MILP	Stoch.	-	X	X
Ruiz-Femenia et al. (2013)	Chemical	Mo-MILP	Stoch.	-	X	X
This paper (2018)	Food	MILP	Stoch.	X	X	X

[a] Det./Stoch.: Deterministic approach / Stochastic approach.

Five of the publications in Table 2.1 are based on deterministic approaches. Corsano and Montagna (2011) develop an approach for the simultaneous design of plants and supply chain for the batch process industry. Decisions on process design, such as allocation of storage tanks and determination of unit sizes, and planning decisions for the supply chain are integrated in a mixed integer linear programming (MILP) model. Similarly, Corsano et al. (2011) formulate a mixed integer nonlinear programming (MINLP) model in which the sustainable design of plant and supply chain is simultaneously achieved for a bioethanol supply chain. You et al. (2012) present a multi-objective mixed integer linear programming (Mo-MILP) model for the design of cellulosic ethanol supply chains. Decisions are taken on network design, technology selection, production planning, and logistics management. In addition, the model is integrated with a life cycle assessment and input-output analyses. Hugo and Pistikopoulos (2005) also develop a Mo-MILP model for the selection of processing technologies for a chemical supply chain. In their model, the net present value of capital investments is maximized while minimizing environmental impact. The only study from the food industry is presented in Quaglia et al. (2012). They develop an MINLP model for the synthesis and design of processing networks for a case study from the vegetable oil industry, considering both business aspects (such as financial criteria and supply chain) and engineering aspects (such as processing conditions and design of processing technology).

None of the reviewed deterministic studies captures the nexus between new product designs, processing technology selection, and supply chain operations. Integrated decisions on processing technologies and supply chain are addressed in all studies, but assuming that the product is given.

Supply chain planning problems under uncertainty have been widely studied. Six stochastic approaches related to the model developed in our paper are summarized in Table 2.1. You and Grossmann (2008) develop a Mo-MINLP model for the design and planning of responsive supply chains under demand uncertainty. Uncertainty is addressed by using a probabilistic model in which uncertain parameters are treated as variables with known probability distribution. The model is applied to a polystyrene supply chain. In Guillén-Gosálbez and Grossmann (2009), a stochastic Mo-MINLP model is also developed. The model deals with the design of a sustainable chemical supply chain including technology selection, with uncertainty in the life cycle inventory. This study is extended in Guillén-Gosálbez and Grossmann (2010) for uncertainty in the parameters of the environmental damage model. Also, Ruiz-Femenia et al. (2013) extend the study by Guillén-Gosálbez and Grossmann (2009) by considering demand uncertainties. Gebreslassie et al. (2012) develop a two-stage stochastic model for hydrocarbon biorefinery supply chain under supply and demand uncertainties, accounting also for risk management. Different conversion technologies are analyzed together with supply network design. In Kostin et al. (2012), bioethanol supply chain design with capacity expansion of production and storage facilities under demand uncertainty is addressed.

Like for the deterministic approaches, none of the stochastic approaches captures the nexus between product designs, processing technologies, and supply chain. In all studies, technology selection in a supply chain context is analyzed assuming a given product. All of the reviewed stochastic approaches are from the chemical industry because of the strong link between processing technologies and supply chains in this industry.

The integrated selection of product designs and processing technologies in a supply chain context requires interdisciplinary efforts involving operations management, engineering, and natural sciences. Food supply chains, however, have attracted only limited interdisciplinary work (Akkerman et al., 2010). There is some literature on modeling quality degradation in food processing and distribution (Rong and Grunow, 2010). Rong et al. (2011) integrate microbiological models with the logistic models, with the aim of determining storage and transportation duration together with setting the temperature. Zanoni and Zavanella (2012) present a model for a food supply chain determining temperature level and storage time, as related to quality preservation and energy consumption. Controlling the temperature is of importance for a variety of food products, because the temperature is directly connected to the control of food quality, as well as to the energy consumption and the waste in the chain. Van der Vorst et al. (2009) show how food quality and sustainability together with logistics processes can be embedded in simulation modeling for a pineapple supply chain, in which sustainability is modeled by relating energy use and emissions to distribution. The paper also addresses different potential locations for one type of processing technology.

The focus of the interdisciplinary food supply chain studies is on the impact of characteristics of a given product (such as quality degradation) on the supply chain. The design of the product and the selection of processing technologies are not covered.

There is a lack of quantitative approaches that include product design decisions in the integrated decisions on processing technology and supply chain operations. In our approach, we therefore first derive an integrated design space for both the product design and processing technology. This step requires an extensive interdisciplinary collaboration with process engineers for our case from the food industry. In a second step, we select the product designs and processing technologies in the supply chain context considering the key demand uncertainties.

2.3 Modeling approach for selection of product designs and processing technologies

The selection of product designs and processing technologies is complicated by demand uncertainties. We selected a decision model relying on two-stage stochastic programming to handle these uncertainties. The set of decisions are partitioned into first stage decisions, made facing the future uncertainties, and second stage decisions, made after the uncertainties have materialized. The first stage decisions on investments and capacities are more strategic, while the second stage decisions on production and transportation amounts are more operational. Such two-stage approaches are widely used, because they are declarative and can easily be adapted to changes in the problem environment. Examples are Kostin et al. (2012) and Ruiz-Femenia et al. (2013). However, they only consider process technologies and supply chain decisions. Different from our paper, they assume the product design to be given.

2.3.1 Problem definition

A supply chain with three echelons is considered, see Figure 2.1. Producers ship the raw material to processing plants where it is processed into finished products and then sent to customers. At the processing plants, a network of possible technology paths transform the raw material

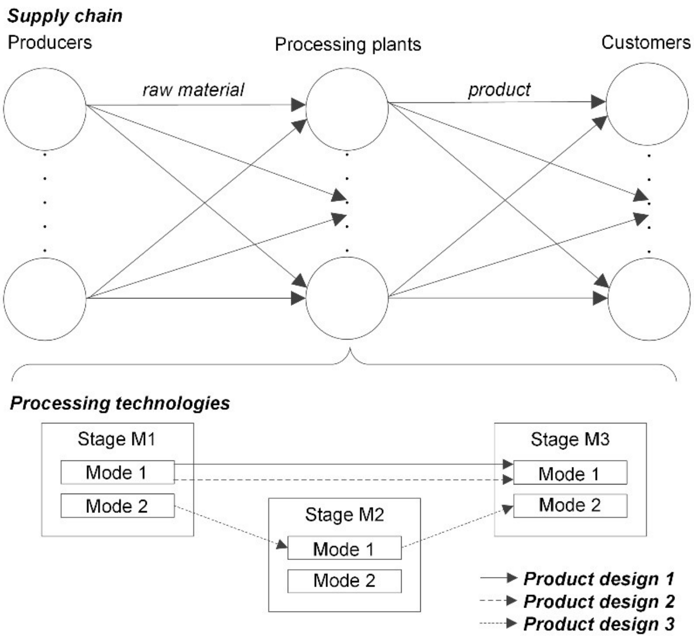

Figure 2.1: Representation of the nexus between product designs, processing technologies, and supply chain.

into finished products of distinct characteristics. This is shown in the lower part of the figure. A technology path consists of several interlinked processing stages, e.g., stages M1-M2-M3 and M1-M3 in Figure 2.1 represent two technology paths. Each technology path can produce several products by running the equipment at the processing stages in different modes, resulting in various product designs. This is illustrated, in Figure 2.1, with different arrows for the product designs.

Today's supply chain models must account for sustainability aspects, like resource consumption and waste. Therefore, we assume that at each stage the product is processed, requiring resources and also leading to waste. Detailed modeling of each stage is required, because different technology paths share stages and consequently the equipment at these stages. Additionally, waste can vary for the same type of equipment due to different characteristics of the products. Runtimes can also vary for the same type of equipment, depending on the operating mode.

The following assumptions are made to facilitate the modeling:

- Total supply of key raw material producers is fixed, e.g., due to long-term contracts.
- Additional raw material can be procured from the spot market.
- Some equipment units may be available at the processing plants, but additional equipment units with fixed capacity may be added.
- At each stage, by-products may result.
- Transportation capacities are sufficient.

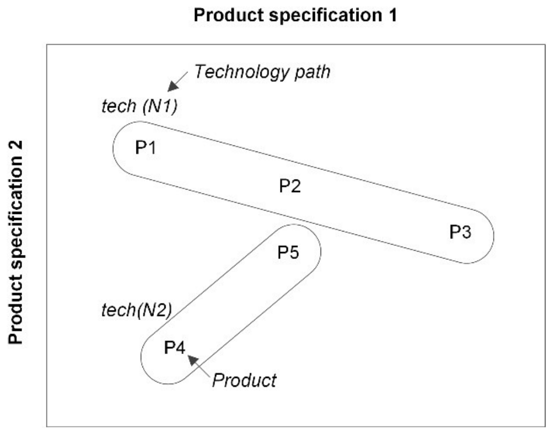

Figure 2.2: Design space for product designs and processing technologies.

- The share wasted during processing and transportation of raw material is known for each product.
- If demand is low, the products can be sent to a secondary market yielding a lower profit margin.
- The decision maker is risk-neutral.

2.3.2 Modeling of uncertainties

There is no existing market or previous demand data for the new products. The key uncertainties related to new product introduction are not only the demand volumes, but also the product specifications as demanded by the customers. A systematic representation of the interdependence of the product technology paths and the product specifications is given in the form of a design space for which an example is shown in Figure 2.2. While technology path N1 is able to span a wide range of values for product specification 1, it can only span the upper part of product specification 2. Three products with distinct combinations of values for both specifications can be produced when technology path N1 is implemented. The definition of the design space requires an interdisciplinary collaboration, in which the detailed specifications of the products and the capabilities of the technology paths are analyzed.

The uncertainties in relation to product specifications and demand volumes are handled through a two-stage stochastic programming model, in which uncertainties are represented as scenarios. The set of decisions are split into scenario-independent here-and-now decisions (first stage) and scenario-dependent wait-and-see decisions (second stage). In the first stage, the technology paths that determine the set of feasible products are selected. Furthermore, the number of invested equipment units at each processing stage is determined. In the second stage, the types of products to be produced and the production volumes of each type are determined. Therefore, depending on how uncertainties resolve, the equipment that is selected in the first stage can be operated in different modes to obtain the requested product designs. Several product designs can be chosen to fulfill customer demand. Also, decisions on production volumes and flows through the supply chain are made.

2.3.3 Model formulation

The following notation is introduced for the model:

Indices and index sets

$i \in I$	producer
$j \in J$	processing plant
$k \in K$	customer
$u \in U$	resource
$n \in N$	technology path
$m \in M$	processing stage
$p \in P$	product
$p \in tech(n)$	product belonging to technology path *n* as determined in design space
$m' \in suc_p(m)$	stage that is immediate successor of stage *m* for product *p*
$o \in O$	product specification
$t \in T$	time period
$s \in S$	scenario

Parameters

γ_s	probability of scenario *s*
ϕ	discount rate
ζ_{it}	supply of producer *i* in period *t*
ε_{ij}^{dis}	distance between producer *i* and plant *j*
ε_{jk}^{dist2}	distance between plant *j* and customer *k*
σ_{ij}^{was1}	waste fraction of raw material transported from producer *i* to plant *j*
σ_{mp}^{was}	waste fraction at stage *m* for product *p*
μ_{mp}	fraction of unconverted product at stage *m* for product *p*
α_{um}^{proc}	usage rate of resource *u* during processing at stage *m* (e.g., kW, liters/hour)
α_{um}^{set}	consumption of resource *u* over setup/cleaning cycle at stage *m* (e.g., kWh, liters)
η_m	useful lifetime of equipment unit at stage *m* (in time periods)
κ_{mj}	number of equipment units in place at stage *m* in plant *j*
θ_{mp}	capacity per equipment unit at stage *m* for incoming flow of product *p* (e.g., liters/hour)

τ	number of time units in a time period (e.g., number of hours)
λ_{mp}	runtime at stage *m* for product *p*
ξ_m	setup/cleaning time at stage *m*
δ_{op}	value for product specification *o* of product *p*
δ_{oks}^{min}	minimum value for product specification *o* requested by customer *k* for scenario *s*
δ_{oks}^{max}	maximum value for product specification *o* requested by customer *k* for scenario *s*
φ_{kts}	demand volumes for customer *k* in period *t* for scenario *s*
B_1, B_2	sufficiently large positive values
r_{pkt}^{cust}	price of product *p* sold to customer *k* in period *t*
r_{pt}^{sec}	price of product *p* sold to secondary market in period *t*
r_{mt}^{sep}	price of separated stream from stage *m* in period *t*
c_{it}^{raw1}	costs of raw material supplied from producer *i* in period *t*
c_t^{raw2}	costs of raw material supplied from spot market in period *t*
c^{trans1}	unit transportation costs of raw material
c_p^{trans}	unit transportation costs of product *p*
c_u^{res}	unit costs of resource *u*
c_n^{in1}	investment costs of technology path *n*
c_m^{in2}	investment costs per equipment unit at stage *m*
c_{mt}^{main}	maintenance costs of equipment unit at stage *m* in period *t*
v_m	scrap value of equipment unit at stage *m*

Decision variables

Here-and-now decision variables (first stage)

G_{nj}	=1 if technology path *n* is selected in plant *j* (0, otherwise)
H_{mj}	number of invested equipment units at stage *m* in plant *j*
R^{HN}	first stage revenues
C^{HN}	first stage costs

Wait-and-see decision variables (second stage)

E_{pjs}	=1 if product *p* is selected in plant *j* for scenario *s* (0, otherwise)
F_{ijts}	flow quantity of raw material from producer *i* to plant *j* in period *t* for scenario *s*
L_{jts}	amount of raw material procured from spot market for plant *j* in period *t* for scenario *s*
Z_{mpjts}^{in}	flow into stage *m* of process stream for product *p* in plant *j* in period *t* for scenario *s*

Z_{mpjts}^{out}	flow out of stage *m* of process stream for product *p* in plant *j* in period *t* for scenario *s*
Z_{mpjts}^{sep}	flow out of stage *m* of separated stream from product *p* in plant *j* in period *t* for scenario *s*
Z_{umpjts}^{res}	flow of resource *u* into stage *m* for processing product *p* in plant *j* in period *t* for scenario *s*
X_{pjts}	production quantity of product *p* in plant *j* in period *t* for scenario *s*
W_{pjts}	quantity of product *p* sold to secondary market in plant *j* in period *t* for scenario *s*
Q_{pjkts}	flow quantity of product *p* from plant *j* to customer *k* in period *t* for scenario *s*
D_{pkts}	total shipment of product *p* to customer *k* in period *t* for scenario *s*
R_s^{WS}	second stage revenues for scenario *s*
C_s^{WS}	second stage costs for scenario *s*

The two-stage stochastic model is formulated as follows:

$$Max\ R^{HN} - C^{HN} + \sum_{s\in S} \gamma_s \cdot (R_s^{WS} - C_s^{WS}) \tag{2.1}$$

subject to

$$R^{HN} = (1+\phi)^{(1-T)} \cdot \sum_{m\in M}\sum_{j\in J}\left(v_m + (c_m^{in2} - v_m)\cdot\frac{max\{\eta_m - T; 0\}}{\eta_m}\right)\cdot H_{mj} \tag{2.2}$$

$$\begin{aligned} C^{HN} = &\sum_{n\in N}\sum_{j\in J} c_n^{in1}\cdot G_{nj} + \sum_{m\in M}\sum_{j\in J} c_m^{in2}\cdot H_{mj} \\ &+ \sum_{t\in T}(1+\phi)^{(1-t)}\cdot\left(\sum_{m\in M}\sum_{j\in J} c_{mt}^{main}\cdot\left(\kappa_{mj} + H_{mj}\right)\right) \end{aligned} \tag{2.3}$$

$$\begin{aligned} R_s^{WS} = &\sum_{t\in T}(1+\phi)^{(1-t)} \\ &\cdot\left(\sum_{p\in P}\sum_{k\in K} r_{pkt}^{cust}\cdot D_{pkts} + \sum_{p\in P}\sum_{j\in J} r_{pt}^{sec}\cdot W_{pjts}\right. \\ &\left. + \sum_{m\in M}\sum_{p\in P}\sum_{j\in J} r_{mt}^{sep}\cdot Z_{mpjts}^{sep}\right) \quad \forall s\in S \end{aligned} \tag{2.4}$$

$$C_s^{WS} = \sum_{t \in T} (1+\phi)^{(1-t)} \cdot \left(\sum_{i \in I} \sum_{j \in J} c_{it}^{raw1} \cdot F_{ijts} + \sum_{j \in J} c_t^{raw2} \cdot L_{jts} + \sum_{i \in I} \sum_{j \in J} \varepsilon_{ij}^{dist1} \cdot c^{trans1} \cdot F_{ijts} + \sum_{p \in P} \sum_{j \in J} \sum_{k \in K} \varepsilon_{jk}^{dist2} \cdot c_p^{trans2} \cdot Q_{pjkts} + \sum_{u \in U} \sum_{m \in M} \sum_{p \in P} \sum_{j \in J} c_u^{res} \cdot Z_{umpjts}^{res} \right) \quad \forall s \in S \tag{2.5}$$

$$\sum_{j \in J} F_{ijts} = \zeta_{it} \quad \forall i \in I, t \in T, s \in S \tag{2.6}$$

$$\sum_{i \in I} F_{ijts} \cdot \left(1 - \sigma_{ij}^{was1}\right) + L_{jts} = \sum_{p \in P} Z_{mpjts}^{in} \quad \forall m = 1, j \in J, t \in T, s \in S \tag{2.7}$$

$$Z_{mpjts}^{out} = Z_{m'pjts}^{in} \quad \forall m \in M, m' \in suc_p(m), p \in P, j \in J, t \in T, s \in S \tag{2.8}$$

$$Z_{mpjts}^{out} = Z_{mpjts}^{in} \cdot (1 - \sigma_{mp}^{was2}) \cdot \mu_{mp} \quad \forall m \in M, p \in P, j \in J, t \in T, s \in S \tag{2.9}$$

$$Z_{mpjts}^{sep} = Z_{mpjts}^{in} \cdot (1 - \sigma_{mp}^{was2}) \cdot (1 - \mu_{mp}) \quad \forall m \in M, p \in P, j \in J, t \in T, s \in S \tag{2.10}$$

$$Z_{umpjts}^{res} = \alpha_{um}^{proc} \cdot \frac{Z_{mpjts}^{in}}{\theta_{mp}} + \alpha_{um}^{set} \cdot \frac{Z_{mpjts}^{in}}{\theta_{mp} \cdot \lambda_{mp}} \quad \forall u \in U, m \in M, p \in P, j \in J, t \in T, s \in S \tag{2.11}$$

$$Z_{mpjts}^{out} \leq B_1 \cdot E_{pjs} \quad \forall m = M, p \in P, j \in J, t \in T, s \in S \tag{2.12}$$

$$\sum_{p \in tech(n)} E_{pjs} \leq B_2 \cdot G_{nj} \quad \forall n \in N, j \in J, s \in S \tag{2.13}$$

$$\kappa_{mj} + H_{mj} \geq \left\lceil \sum_{p \in P} \frac{Z_{mpjts}^{in}}{\theta_{mp} \cdot \tau \cdot \left(1 - \frac{\xi_m}{\xi_m + \lambda_{mp}}\right)} \right\rceil \quad \forall m \in M, j \in J, t \in T, s \in S \tag{2.14}$$

$$X_{pjts} + W_{pjts} = Z_{mpjts}^{out} \quad \forall m = M, p \in P, j \in J, t \in T, s \in S \tag{2.15}$$

$$X_{pjts} = \sum_{k \in K} Q_{pjkts} \quad \forall p \in P, j \in J, t \in T, s \in S \tag{2.16}$$

$$\sum_{j \in J} Q_{pjkts} = D_{pkts} \quad \forall p \in P, k \in K, t \in T, s \in S \tag{2.17}$$

$$D_{pkts} \cdot \delta_{oks}^{min} \leq D_{pkts} \cdot \delta_{op} \leq D_{pkts} \cdot \delta_{oks}^{max} \quad \forall o \in O, p \in P, k \in K, t \in T, s \in S \tag{2.18}$$

$$\sum_{p \in P} D_{pkts} \leq \varphi_{kts} \quad \forall k \in K, t \in T, s \in S \tag{2.19}$$

$$G_{nj} \in \{0,1\} \quad \forall n \in N, j \in J \tag{2.20}$$

$$H_{mj} \geq 0 \; and \; integer \quad \forall m \in M, j \in J \tag{2.21}$$

$$R^{HN} \geq 0, C^{HN} \geq 0 \tag{2.22}$$

$$E_{pjs} \in \{0,1\} \quad \forall p \in P, j \in J, s \in S \tag{2.23}$$

$$F_{ijts} \geq 0 \quad \forall i \in I, j \in J, t \in T, s \in S \tag{2.24}$$

$$L_{jts} \geq 0 \quad \forall j \in J, t \in T, s \in S \tag{2.25}$$

$$Z^{in}_{mpjts} \geq 0, \; Z^{out}_{mpjts} \geq 0, \; Z^{sep}_{mpjts} \geq 0 \quad \forall m \in M, p \in P, j \in J, t \in T, s \in S \tag{2.26}$$

$$Z^{res}_{umpjts} \geq 0 \quad \forall u \in U, m \in M, p \in P, j \in J, t \in T, s \in S \tag{2.27}$$

$$X_{pjts} \geq 0, W_{pjts} \geq 0 \quad \forall p \in P, j \in J, t \in T, s \in S \tag{2.28}$$

$$Q_{pjkts} \geq 0 \quad \forall p \in P, j \in J, k \in K, t \in T, s \in S \tag{2.29}$$

$$D_{pkts} \geq 0 \quad \forall p \in P, k \in K, t \in T, s \in S \tag{2.30}$$

$$R^{WS}_{s} \geq 0, C^{WS}_{s} \geq 0 \quad \forall s \in S \tag{2.31}$$

In the above formulation, the objective function (2.1) aims to maximize the expected profit. The profit comprises the revenues and costs of the first stage, as well as the expected revenues and expected costs of the second stage. In constraints (2.2–2.5), the net present value of the costs and revenues are calculated. First stage revenues (2.2) include the salvage value and residual value of the investments. Residual value is allocated according to the time horizon considered and the lifetime of the equipment, assuming a straight-line depreciation. No salvage or residual value is assumed for investments in technology paths. First stage costs (2.3) include the investment and maintenance costs. Investment costs are determined by the selection of technology paths, e.g., for a material handling system, and number of equipment units at each stage. Second stage revenues (2.4) include the revenues of products sold to customers and to secondary market, as well as revenues for separated stream. Second stage costs (2.5) include costs for raw material supplied from producers and spot market, transportation costs, and resource costs.

Constraints (2.6) ensure that total supplies of producers are sent to plants, due to long term contracts between producers and plants. Raw material from producers and spot market flows into the first stage at the plant, assuming a specific waste fraction for the transportation of raw material (2.7). Constraints (2.8) reflect the material flow between consecutive stages. At each stage the product is processed (2.9) and therefore the quantity of material flow out of the stage changes. Product waste due to processing and setup/cleaning activities at each stage is also accounted for. Constraints (2.10) track the flow of separated streams (by-products).

Amount of required resources are modeled with constraints (2.11). First resource consumption for processing is considered and secondly resource consumption over setup/cleaning cycle is multiplied by the number of required setup/cleaning cycles for the processed quantity. Constraints (2.12) link the continuous flow variables to the binary variables regarding selection of product designs. Note that even though investment decisions are made in the first stage, it is decided in the second stage which product designs are produced. Constraints (2.13) enforce the selection of technology paths. A set of products can be produced with the same technology path. Constraints (2.14) reflect the total number of equipment units at each stage, considering equipment units in place as well as invested equipment units in the first stage. Material flow is thereby connected to the number of required equipment units, accounting for capacity reduction due to downtime of equipment resulting from setups/cleanings.

The flow out of the last stage is equal to the total production available for customers plus the quantity sent to secondary market (2.15). Constraints (2.16) connect the production quantity available for the customers to the customer shipments. Constraints (2.17) aggregate the total shipments to customers. Only products that fulfill the minimum and maximum level of each customer product specification are shipped out (2.18), by forcing the shipment variable to zero if the product specifications are not met. Demand can be fulfilled with several products, introducing flexible product substitution to the developed approach (2.19). Finally, constraints (2.20–2.31) define the variable domains of the decision variables.

The developed model comprehensively covers the integrated selection of product designs and processing technologies. The set of feasible product designs, depending on the selected technology, is restricted with constraints (2.13). With regard to product designs, different product specifications for the new product introduction are met with constraints (2.18). It is especially important to capture waste and resource consumption in today's supply chain models. Waste is accounted for in constraints (2.7, 2.9) and flow of resources is determined in constraints (2.11). Additionally, the number of invested equipment units is calculated in constraints (2.14) considering also capacity reduction due to equipment downtime resulting from setups/cleanings.

2.4 Case: New energy efficient dairy processes and products

2.4.1 Case introduction

Milk powders are a popular ingredient in the processing of various food products, such as ice cream blends, yoghurts, and elements for meals served in canteens and other settings. Milk powders are currently produced in two sequential process steps, first by concentrating to a dry-

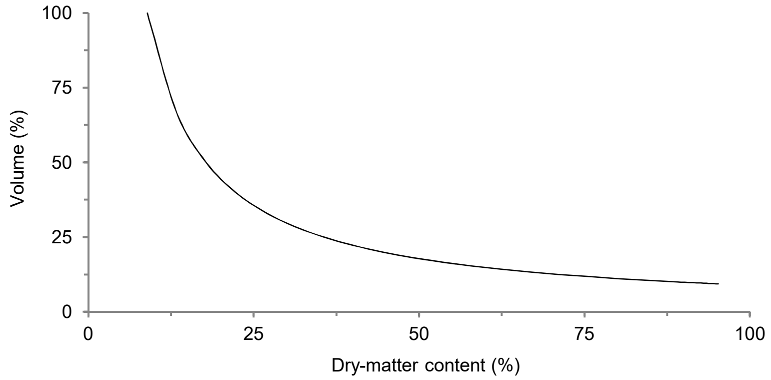

Figure 2.3: Volume reduction of skim milk.

matter content (DMC) of approximately 45% and then by drying (usually by spray drying) to a dry-matter content of 95–97%. For the processing of powders, concentration is accountable for around 45% of the primary energy demand and drying for around 51% (Ramírez et al., 2006). In this paper, we investigate the implications of an omission of the energy intensive drying process for milk powders. Instead milk concentrates are produced with new and more efficient concentration processes. A similar technology innovation is also possible for whey concentrates. The necessity to ship larger volumes because concentrates have smaller dry-matter content than powders must be taken into account in the supply context. For the example of Germany, this new technology for milk/whey concentrates has the potential of reducing energy consumption in processing by around 12% in this country alone.

Furthermore, powders are often reconstituted before the production of the final products at the customer site by again adding the water, which was previously extracted. From the customer perspective, concentrates are hence functionally superior as they are ready for use and frequent problems related to reconstitution are eliminated, such as clumping and foam development.

2.4.2 Product designs and processing technologies

Concentration and heat treatments are applied to produce concentrates. For the concentration stage, water is removed by evaporation, reverse osmosis (RO), or by applying reverse osmosis as a pre-concentration before evaporation. By running the concentration technologies in different modes, various product designs are reached. This leads to different dry-matter content of the product, defined as the total content of all substances except water (Walstra et al., 2006). Figure 2.3 shows the volume reduction of skim milk assuming an ingoing dry-matter content of 8.9% for skim milk. Obtainable dry-matter content of concentrates depends on the concentration technologies, for example, after reaching a dry-matter content of 37% it is not feasible to further apply reverse osmosis.

Table 2.2: Key characteristics and trade-offs of concentration technologies.

	Reverse osmosis (RO)	**Evaporation (EV)**	**Reverse osmosis and evaporation (Combi)**
Investment costs	↓ Typically significantly lower for RO than evaporation due to compact foot print of equipment (Jevons and Awe, 2010)	→ Two times higher for evaporation equipment based on mechanical vapor recompression than for RO (Jevons and Awe, 2010)	↑ Invest in both RO and evaporation units
Maintenance costs	↑ Lifetime of membranes typically around 1.5 years	↓ Negligible	→ Longer lifetime of membranes
Energy consumption	↓ Specific primary energy of 45–90 kJ/kg H_2O (Kessler, 2002)	↑ Specific primary energy of 200–1000 kJ/kg H_2O for triple-effect evaporator with mechanical or thermal recompression (Kessler, 2002)	→ Possibility of 33% reduction in energy consumption as compared to evaporation (Madaeni and Zereshki, 2010)
Cleaning consumption	↑ Cleaning introduces unique challenges with sequence of necessary steps (Kessler, 2002)	→ Cleaning-in-place (CIP) procedure depends on type of application (Kessler, 2002)	↑ Combination of RO and evaporation cleaning requirements
Obtainable dry- matter content (DMC)	→ 20–37%	↑ 20–50%	→ 34–50% (up to 28% with RO)
Product shelf life	Depends on product DMC and heat treatment(s)	Depends on product DMC and heat treatment(s)	Depends on product DMC and heat treatment(s)

It is essential to take the dry-matter content into account when making the technology selection. Transportation and storage costs decrease with a larger dry-matter content, as the products have lower volume. Larger dry-matter content leads to larger energy consumption at the processing stage, because the processed output per hour reduces and moreover the formation of deposits increases, imposing the need for more frequent cleanings. This is particularly the case for reverse osmosis with around 15 hours runtime between cleanings for 25% dry-matter content, as compared to around 5 hours for 35% dry-matter content. Therefore any attempt to increase the degree of concentration to reduce shipment volumes needs to be balanced with the increased cleaning requirements that impair the efficiency of the production processes. Cleanings lead to high consumption of water and cleaning agents, and cause product waste, which is very costly. Note that only cleanings, not setups, are relevant for this case. Table 2.2 summarizes the key characteristics of the concentration technologies that are important for our model.

Different types of heat treatments are applied after concentration to preserve the product. There is also an option to apply pre-heat treatment before concentration to prolong storage stability. The relevant heat treatments are ultra-high temperature (UHT), extended shelf life (ESL), high-heat treatment (HHT), and pasteurization. Figure 2.4 shows a representation of the technology paths. As a result of interdisciplinary collaboration, different dry-matter contents are selected for each technology path, i.e., 25%, 30%, and 35%. A dry-matter content of 25% is selected to

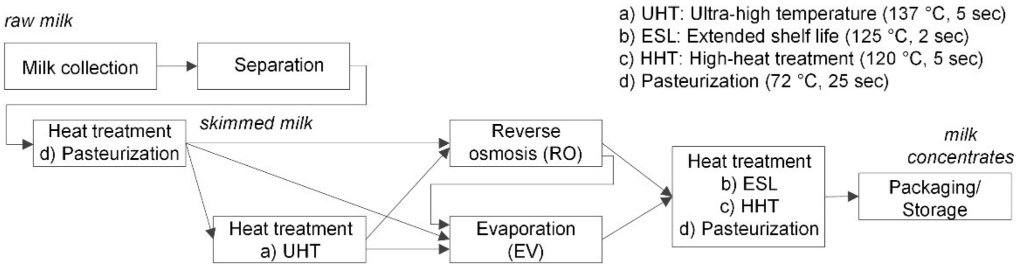

Figure 2.4: Processing technologies for milk concentrates.

Table 2.3: Modeled technology paths (N) and products (P).

Techn. path	Description	Dry-matter content (DMC)		
		25%	30%	35%
N1	RO–HHT	-	P1	-
N2	EV–HHT	-	P2	-
N3	RO–Past.	P3	P4	P5
N4	EV–Past.	P6	P7	P8
N5	RO–EV–Past.	-	-	P9
N6[a]	UHT–RO–ESL	P10	P11	-
N7[a]	UHT–EV–ESL	P12	P13	-
N8	UHT–RO–HHT	-	-	P14
N9	UHT–EV–HHT	-	-	P15
N10	UHT–Combi–HHT	-	-	P16

[a] Transported at ambient temperature.

capitalize on transportation and storage costs, as compared to the minimum degree of concentration of 20% (a volume reduction of 8.9%, see Figure 2.3). Dry-matter contents of 30% and 35% are selected as they can be used in a variety of final products, e.g., in finished meals, filled bakery products, and ice cream blends. Even though higher dry-matter contents are obtainable with concentration, the resulting concentrates cannot undergo the subsequent heat treatment necessary to obtain the required shelf life. Considering the concentration technologies together with the practice-relevant heat treatments leads to ten technology paths, see Table 2.3. However, some technologies have a maximum and/or minimum of dry-matter content such that 16 products result (P1–P16). All products have fixed density depending on their dry-matter content.

The product shelf life varies based on the applied heat treatments and the dry-matter content. The shelf life of pasteurized concentrates increases slightly with an increasing dry-matter content. On the other hand, the shelf life of products treated with UHT as pre-heat treatment and then ESL as post-heat treatment decreases with increasing dry-matter content due to age gelation. Dumpler and Kulozik (2015) show that as dry-matter content increases, heat stability decreases as a function of heating temperature and time. After certain dry-matter content the heat

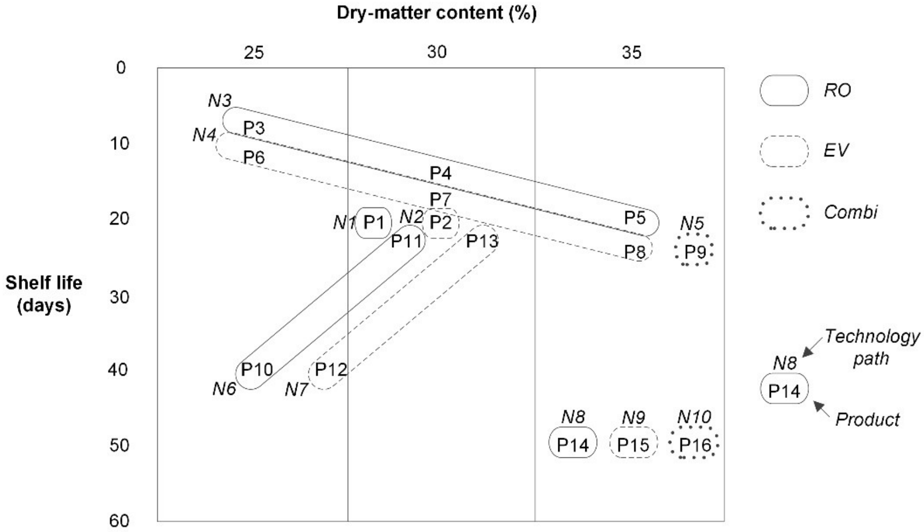

Figure 2.5: Design space for the dairy products and technologies.

treatments can therefore not be applied due to heat instability of the concentrates. The product dry-matter content therefore limits the possible heat treatments. Due to high water content of concentrates there is a need to cool the products at 5 °C during transportation and storage. Only when UHT is applied in combination with ESL, sufficient shelf life is reached for transportation and storage at 20 °C (cf. N6 and N7). Energy consumption of the heat treatment varies also, for instance direct UHT is more energy intensive than pasteurization (Ramírez et al., 2006). The cheapest way of producing a concentrate is to concentrate it with reverse osmosis to 25% dry-matter content and then apply pasteurization.

Product designs of concentrates are both related to product shelf life and dry-matter content. The product specifications, described in Section 2.3.2, are therefore assumed to be the shelf life requirement and the demand composition of dry-matter content. Figure 2.5 shows the design space of the analyzed products.

2.4.3 Industrial setting and parameterization

The case is based on real data from a German dairy company. The planning horizon is selected as five years and one time period in the model represents three months. This planning horizon is considered reasonable, as the dairy company revises their investment decisions every five years. Annual rate at which cash flow is discounted is 10%. The company has one plant that receives raw milk from more than 200 local farms with an average distance of 50 km from the plant. On average per farm supplies around 50,000 liters per month of raw milk. There is seasonality in the supply of raw milk, with the highest supply in spring and the lowest during

Table 2.4: Capacity, runtime, and cleaning time of equipment units at each processing stage.

Processing stage	**Capacity (liters/hour)**	**Runtime between cleanings (hours)**	**Cleaning time (hours)**
(1) Milk collection	80,000 (liters)	23.5	0.5
(2) Separation	25,000	14.0	2.0
(3) Pasteurization (pre-heating)	25,000	14.0	2.0
(4) UHT (pre-heating)	25,000	16.0	1.6
(5) Reverse osmosis (RO)	9,800–12,000[a]	5.0–15.0[a]	2.5
(6) Evaporation (EV)	7,800–26,900[a]	12.0–14.0[a]	1.0
(7) ESL (post-heating)	25,000	2.5–3.6[a]	1.7
(8) HHT (post-heating)	25,000	2.5–3.6[a]	1.7
(9) Pasteurization (post-heating)	25,000	3.6–5.0[a]	2.1
(10) Packaging/Storage (1,000 liters bag-in-box)	3,000	10.0	1.5

[a] Depends on dry-matter content.

autumn. Raw milk is transported with tank trucks and a transportation waste percentage is calculated based on an average waste of truck loads over one year. Costs for raw milk are based on contracts with farms and costs for raw milk procured from spot market are based on historical spot market prices.

The plant will in the future focus its production on skim milk concentrates. Only the portion of the raw milk required for concentrates is accounted for, thereby the by-product cream can be neglected. Concentrates can be sent to secondary (powder) processing yielding a lower profit margin. It is assumed that no equipment is in place at the plant, such that no processing stage is given free usage of present capital. Ten different processing stages must be modeled for the analyzed technology paths (see Table 2.4). Separate stages are modeled for pre-heating and post-heating of same type, because in practice different equipment units are utilized. Capacities, runtime between cleanings, and cleaning times of equipment units were assessed together with the dairy company and equipment manufacturers.

Investment costs were collected together with the dairy company and equipment manufacturers. Maintenance costs are negligible for all stages except for reverse osmosis and evaporation. The reverse osmosis consists of 84 membranes that are exchanged every 1.5 year. For evaporation high pressure cleanings are carried out. Useful lifetime of equipment units is between 6–8 years, in accordance to tax depreciation of dairy equipment. Scrap value of equipment is based on weight of equipment units and scrap value of stainless steel. The modeled resources are electricity, steam, water, and cleaning agents, which are all important cost drivers in the technology selection. Costs for personnel are excluded. Data on resource costs, waste, resource usage during processing, and consumption of resources over cleaning cycle were collected at the dairy

Table 2.5: Scenario structure of industry case.

Shelf life requirement		**Demand composition of dry-matter content (DMC)**		**Demand volume**	
1	50% request ≥ 7 days (1 week) 50% request ≥ 14 days (2 weeks)	I	100% demands ≥ 30% DMC	O-Optimistic	+25% of x
2	50% request ≥ 14 days (2 weeks) 50% request ≥ 21 days (3 weeks)	II	50% demands ≥ 30% DMC 50% demands ≥ 25% DMC	R-Realistic	x = y + 5% in each period
3	50% request ≥ 21 days (3 weeks) 50% request ≥ 28 days (4 weeks)	III	100% demands ≥ 25% DMC	P-Pessimistic	–25% of x

company and with equipment manufacturers. For cleaning-in-place (CIP), 90% re-usage of water and cleaning agents is accounted for.

The potential customers are aggregated into four customer groups; two domestic and two international. The average distance between plants and customers is 500 km and 2,000 km for domestic and international customers, respectively. Prices of concentrates are based on contracts with customers. Data on transportation costs were collected at the dairy, these include resource costs for energy consumption due to cooling.

The uncertainties are the shelf life requirement, demand composition of dry-matter content, and demand volume. Only a minimum level is required for the shelf life (δ_{1ks}^{min}), as customers always accept a longer shelf life product. Dry-matter content is dependent on the specific customer application. Producers of finished meals, for instance, require larger dry-matter content than yoghurt producers. Also, only minimum level is required for the dry-matter content (δ_{2ks}^{min}), because customers can adjust their recipes for larger dry-matter contents. Constraints (2.19) are adjusted such that demand is fulfilled in kilogram dry-matter content (2.A1), in which ρ_p^{prod} is the density of product p and ρ_{ks}^{cust} the density requested by customer k for scenario s (depending on the dry-matter content).

$$\sum_{p \in P} D_{pkts} \cdot \delta_{2p} \cdot \rho_p^{prod} \leq \varphi_{kts} \cdot \delta_{2ks}^{min} \cdot \rho_{ks}^{cust} \quad \forall k \in K, t \in T, s \in S \qquad (2.A1)$$

Scenarios for the demand structure of the dairy products and their probabilities are developed in close collaboration with the dairy company and reflect industry settings, see Table 2.5. The scenarios have equal probabilities. For this type of strategic problem that focuses on selection of novel product designs and processing technologies, this is as much knowledge of the market as the dairy companies have. Distribution of uncertainties are not known for this strategic problem. Scenario sampling can therefore not be applied. The key uncertainty is the acceptance of the new product in the market. Three scenarios are therefore created for the demand volume (i.e., optimistic, realistic, or pessimistic demand volumes) to reflect the general acceptance of concentrates. However, it is assumed that the demand volume uncertainty is not period dependent, but rather follows a specific growth path (5% increase in each period), as more powders will be substituted with concentrates. Optimistic and pessimistic scenarios are constructed as $\pm$25% of the realistic demand volume, reflecting market estimates. In addition, three scenarios for the demand impact of the two most important product specifications are created, i.e., shelf life requirement and dry-matter content. For the shelf life requirement, scenarios are created for different shares between 7, 14, 21, and 28 days minimum shelf life. Thereby, low and high shelf life requirements are captured. Shelf life requirement of less than 7 days is considered unrealistic in practice. Similarly, scenarios are created for different shares between 25% and 30% for the dry-matter content product specification, reflecting different uses of concentrates in final products. Shares are assumed to be the same for domestic and international customers. This results in a total of 27 scenarios (3·3·3).

The model is implemented and solved in IBM ILOG CPLEX Optimization Studio 12.6 on a 2.6 GHz Intel Xeon CPU with 32 GB RAM. The industry case results in a problem size of around 733,000 decision variables and 725,000 constraints, which is solved to optimality in around 5 minutes.

2.5 Analyses of skim milk concentrates

2.5.1 Results of industry case

The results, based on the industrial setting described in Section 2.4.3, show that investing in the new technologies is profitable for the company. Four products that are all concentrated with reverse osmosis are selected; P1, P10, P11, and P14. Figure 2.6 shows the selection together with the number of equipment units. The numerical results show that the technology selection strongly relies on the flexibility to produce different volumes of the resulting set of feasible products. The selected products are selected from the technology paths determined in the first stage (cf. the design space). Two of the selected products (P10, P11) are from the same technology path (N6) and therefore in the second stage the product designs can be adjusted depending on how uncertainties resolve. Also, two of the products (P1, P14) are from technology paths (N1, N8), in which only one processing stage differs.

Table 2.6 shows the share of shipments to customers for all realistic demand volume scenarios. The first three scenarios (1/I/R; 1/II/R; 1/III/R) involve low shelf life requirements. For these scenarios, only P1 that has 20 days shelf life is produced. The share of shipments is shifted to

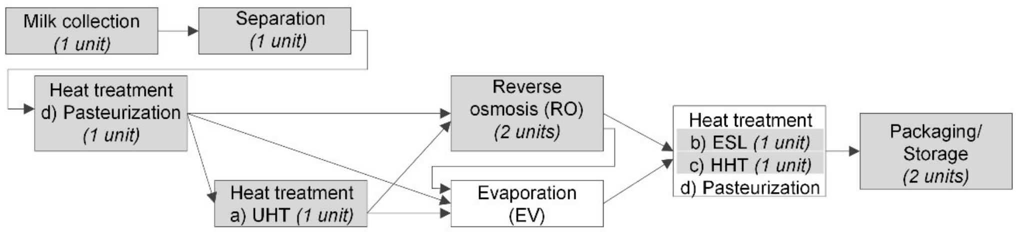

Figure 2.6: Results of industry case highlighting the selected processing technologies.

Table 2.6: Share of shipments to customers for scenarios with realistic demand volumes.

Techn. path	**Product**	**Scenario**[a]								
		(1/I/R)	**(1/II/R)**	**(1/III/R)**	**(2/I/R)**	**(2/II/R)**	**(2/III/R)**	**(3/I/R)**	**(3/II/R)**	**(3/III/R)**
N1	P1 (30% DMC)	100.0%	100.0%	100.0%	54.7%	54.7%	54.7%	-	-	-
N6	P10 (25% DMC)	-	-	-	-	-	30.8%	-	58.0%	68.1%
	P11 (30% DMC)	-	-	-	45.3%	45.3%	14.5%	59.1%	-	28.4%
N8	P14 (35% DMC)	-	-	-	-	-		40.9%	42.0%	3.5%

[a] See Table 2.5: shelf life requirement/demand composition of dry-matter content/demand volume.

other products for higher shelf life requirements. Also, for the product specification related to dry-matter content, the share is shifted to different products as the product specification changes. For example, if all customers request larger than 30% dry-matter content (1/I/R; 2/I/R; 3/I/R) product P10 is not produced.

Figure 2.7 shows the expected costs of the industry case. The raw milk costs constitute the largest portion of around 80% of the total costs, in which around 96% of the raw milk is supplied by farms and 4% is procured from spot market. The importance of minimizing all waste in the supply chain to lessen the required amount of the high value raw milk is apparent. In the dairy industry, the contribution margins are typically low and thus it is of great importance to optimize the other cost items that constitute around 20% of the total costs. The transportation costs constitute a large portion, due to high transportation costs to international customers. The analysis of the resource costs shows that electricity costs constitute the highest percentage and that cleaning agent costs are relatively high, because cleaning of reverse osmosis is expensive. For the different scenarios, on average 13% is sent to powder processing because in scenarios with pessimistic demand volumes the supply is higher than the demand.

A natural product choice from a resource cost perspective, would be product P3 that is concentrated to 25% dry-matter content with reverse osmosis after which pasteurization is applied. This product has the cheapest resource costs per kilogram dry-matter content. However, when making the product and technology selection in a supply chain context, like in our approach, products P1, P10, P11, and P14 are selected. These products have on average around 65.5%

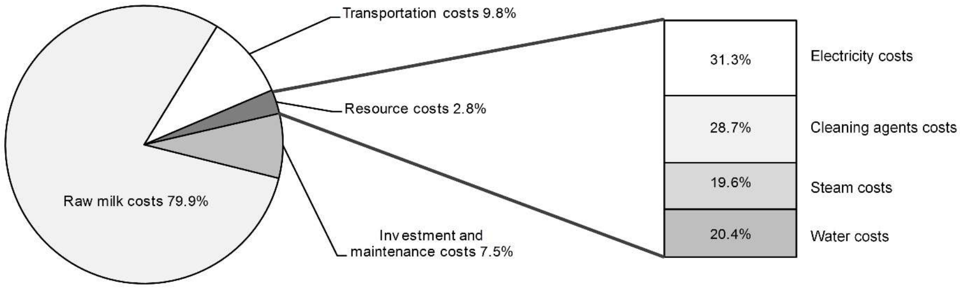

Figure 2.7: Expected costs of industry case.

larger resource costs per kg dry-matter content, as compared to P3. This highlights the importance of making the decisions in a supply chain context accounting for the overall objectives of the supply chain, because otherwise wrong decisions are made.

2.5.2 Impact of demand uncertainties

In this section, we illustrate the impact of the different demand uncertainties by analyzing them separately in three tests. One dimension of uncertainty (see Table 2.5) is removed in each test, whereas the other two uncertainties are still present. The aim of these tests is to gain managerial insights on how the optimal product and technology selection is affected when one of the uncertainties is no longer present.

First, the shelf life uncertainty is removed, assuming that the shelf life requirements of customers are known. The model is run 51 times, i.e., for a known shelf life of 0 to 50 days. Figure 2.8 shows the results in the design space. Additional information as compared to the design space presented in Figure 2.5 is shown on the left part of Figure 2.8. The tests result in four different product selection intervals in which the mix of selected products does not change; 0–9 days, 10–14 days, 15–20 days, and 21–50 days. For a shelf life requirement of up to 9 days, technology path N3 is selected with products P3 and P4. These are pasteurized products, as low shelf life is sufficient. For customers with 10–14 days shelf life requirement, demand is only fulfilled with pasteurized products of 30% dry-matter content (P4). Transportation costs decrease for this selection, but resource costs increase. Product P1, which is concentrated with reverse osmosis and heated with HHT, is selected for 15–20 days shelf life requirement. This product has larger shelf life than the products selected for lower than 15 days. For shelf life requirement larger and equal to 21 days, a pre-heated product (P16) is selected due to its long shelf life. This product is concentrated with combined reverse osmosis and evaporation, because a pure reverse osmosis concentration to 35% dry-matter content is very inefficient due to the short runtime between cleanings.

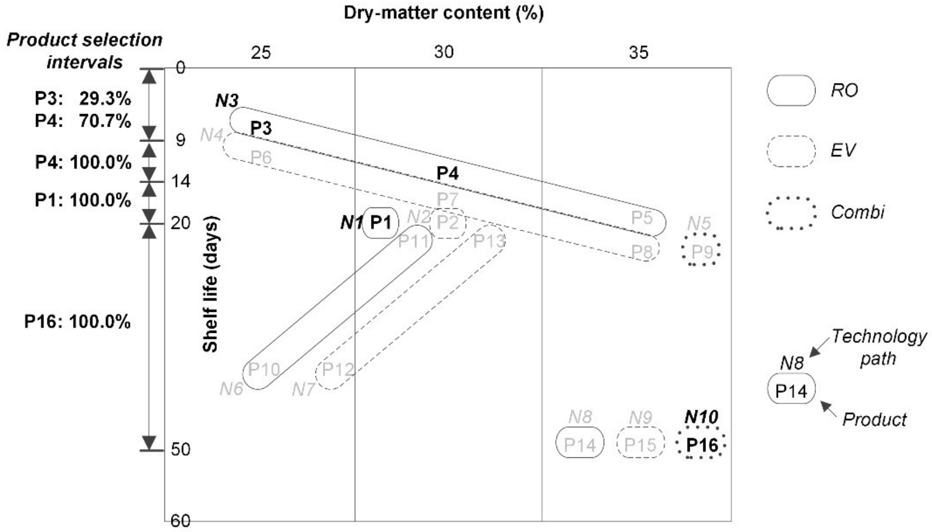

Figure 2.8: Product and technology selection for known shelf life requirements of customers (selected technology paths and products are bolded in the design space, non-selected technology paths and products are shown in light grey).

The structure of the solution in these tests is very different to the solution in Section 2.5.1 in which products P1, P10, P11, and P14 are selected. For low shelf life requirements, pasteurized products (P3, P4) are selected. But, for higher shelf life requirements P1 and P16 are selected, which are not from flexible technology paths.

Next, the requested dry-matter content is investigated. The model is run three times, i.e., for a known dry-matter content requirement of 25%, 30%, and 35%, respectively. Demand is therefore fulfilled with the exact dry-matter content, as opposed to previous tests in which only a minimum level is required for the dry-matter content (cf. constraints 2.A1).

Figure 2.9 shows the results in the design space. Additional information as compared to the design space presented in Figure 2.5 is shown on the lowest part of Figure 2.9. The product selection intervals result from the investigated dry-matter contents; 25%, 30%, and 35%. For a 25% and 30% dry-matter content, pre-heated products (P10, P11) that are concentrated with reverse osmosis are selected. These products are also selected in Section 2.5.1. The structure of the solution is therefore more similar than for the shelf life tests. For a 35% dry-matter content, products P9 and P16 are selected that are concentrated with combined reverse osmosis and evaporation.

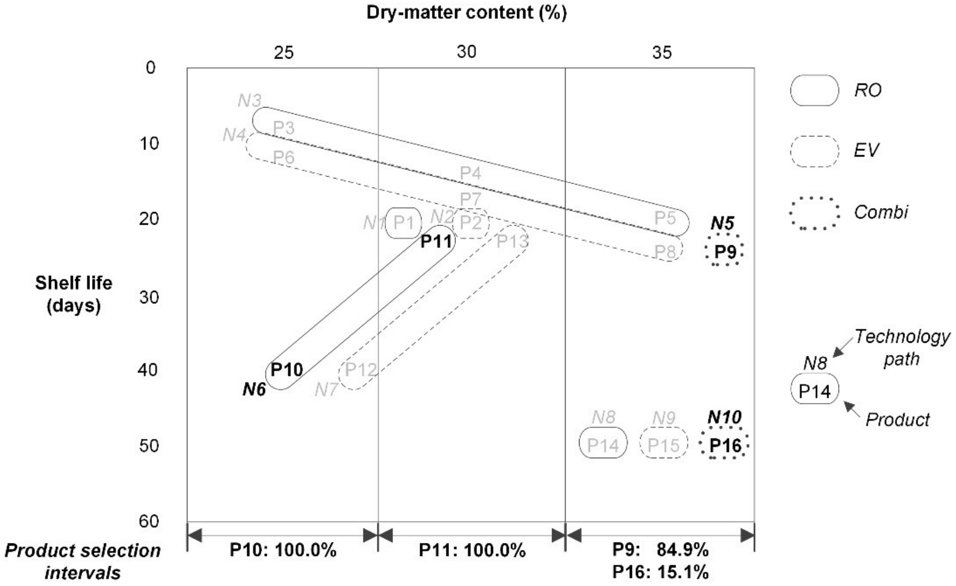

Figure 2.9: Product and technology selection for known customer requirements for dry-matter content (selected technology paths and products are bolded in the design space, non-selected technology paths and products are shown in light grey).

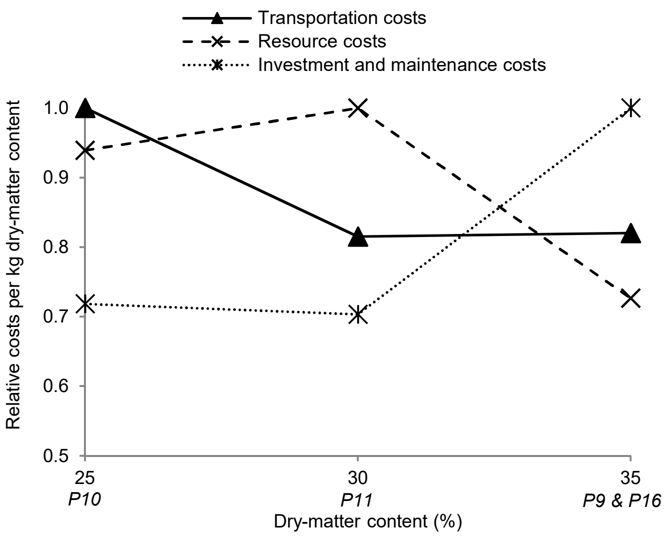

Figure 2.10: Relative costs per kilogram dry-matter content for known customer requirements for dry-matter content.

Figure 2.10 shows the relative costs per kilogram dry-matter content for the three runs. Transportation costs decrease significantly from 25% to 30% dry-matter content, because lower volumes are transported. From 30% to 35% the transportation costs remain constant because product P11 is transported at ambient temperature leveling out the volume reduction. Resource costs increase from 25% to 30% dry-matter content due to higher energy consumption and increased cleaning requirements that impair the efficiency of the processing. However, the resource costs decrease from 30% to 35% dry-matter content because for product P9 no pre-heating is required and pasteurization is applied for post-heating. Investment costs decrease slightly from 25% to

Table 2.7: Product selection for different periodic demand volume increase.

Periodic demand volume increase	**Product**
1%	P1, P10, P11, P14
5%	P1, P10, P11, P14
10%	P1, P2, P15, P16
20%	P3, P4, P6, P7, P8, P9, P16

30%, because one less packaging equipment unit is required. Investment costs increase from 30% to 35%, due to investments in an evaporator and an additional heat treatment equipment.

Finally, the demand volumes are investigated. The model is run three times, i.e., for known optimistic, realistic, and pessimistic demand volumes, respectively. All runs result in the same product selection as in Section 2.5.1. However, the production volumes, procured amounts from spot market, transportation flows, and expected profits differ significantly. Further tests are carried out for the demand volumes by changing the periodic increase. Table 2.7 shows the results for tests with 1%, 5% (results of Section 2.5.1), 10%, and 20% increase. The technology selection is versatile for 1% to 10% increase, with shared equipment. However, for higher demand volumes the processing is more dedicated and it is profitable to further invest in more technology paths. This leads to higher investment costs, but resource costs are reduced.

In summary, it has been shown that the product and technology selection is highly dependent on the uncertain demand characteristics. Reverse osmosis is predominately selected for products with 25% or 30% dry-matter content, but in combination with different heat treatments. For products with 35% dry-matter content reverse osmosis together with evaporation is predominately selected. Managers should strive to obtain accurate information on customer product specifications, especially for the shelf life requirement as the solution structure differs significantly when this product specification is known.

2.5.3 Performance evaluation of stochastic solution

In this section, we compute the expected value of perfect information (EVPI) and the value of stochastic solution (VSS), which are commonly used to evaluate the performance of stochastic approaches. EVPI measures the amount a decision maker would be willing to pay for having perfect information in advance on how the uncertainties will reveal, or formulated negatively, it is the loss of profit due to incomplete information (Birge and Louveaux, 2011). The EVPI is calculated as the difference between the average of the deterministic wait-and-see solutions for each of the scenarios and the here-and-now solution as calculated in Section 2.5.1. For our problem the EVPI amounts to 29.4% of the stochastic objective function value. This large EVPI value highlights that managers should consider putting extra effort in obtaining information about future demand as knowing the demand characteristics in advance leads to much higher profit.

The VSS is defined as the difference between the stochastic here-and-now solution and the expected value solution (Birge and Louveaux, 2011). Two steps are required to calculate VSS. Firstly, the model is solved by substituting all random variables with expected values. Secondly, this solution is utilized to set values to the first-stage variables and the model is solved again. In our case, the expected values are the middle scenarios of each uncertainty, i.e., scenario 2 for the shelf life requirement, scenario II for the dry-matter content, and the realistic scenario for demand volumes (cf. Table 2.5). For our problem, the VSS amounts to even 117.8% of the stochastic objective function value. This large value shows the importance of the uncertainty. In the expected value solution, technologies are selected that cannot fulfill the demand structure of some important scenarios. In summary, it has been shown that the uncertainties have a significant impact on the results. It is therefore advantageous to use the proposed two-stage stochastic modeling approach as compared to a deterministic modeling approach.

Further analyses are carried out to investigate the effect of each of the three demand uncertainties separately. In these experiments, it is assumed that one of the uncertainties is no longer present (value fixed to expected scenario) and new stochastic solutions are computed. Therefore, the EVPI is calculated by assuming there are only two uncertainties (9 scenarios). The results are as follows. If the demand composition of dry-matter content is known, then the EVPI is 27.9% of the stochastic objective function value. If the demand volumes are known, then the EVPI is 21.3% of the stochastic objective function value. Finally, if the shelf life requirements are known, then the EVPI is 0.8% of the stochastic objective function value. Both the EVPI for known demand composition of dry-matter content and the EVPI for known demand volumes are large, showing that even when these uncertainties are eliminated, the loss of profit due to incomplete information is still large. In contrast, a very low EVPI is reached when the shelf life requirement is known. These results demonstrate that this uncertainty has larger impact than the other two uncertainties, and that an accurate information on customer shelf life requirements would be particularly valuable to the dairy company. This also matches the results in Section 2.5.2, in which the solution structure strongly differs for different known shelf life requirements. Also, these solutions are very different from the stochastic solution obtained in Section 2.5.1.

2.6 Conclusions

A modeling approach is developed that covers the nexus between new product introduction, processing technologies, and supply chain, as well as the characteristic uncertainties. As new product introduction frequently requires new processing technologies, these must be evaluated with a holistic assessment, like in our approach. Also, trade-offs among different production and supply chain decisions are addressed in our approach, by capturing the link between the selection of new technologies and products, and the resulting changes in the supply chain, as the whole supply chain is affected through the product and technology innovation.

Uncertain demand characteristics related to new product introduction are captured through two-stage stochastic mixed integer linear programming (MILP) model by mitigating the effects of uncertainties by number of scenarios. The characteristic uncertainties consist of demand volumes and product specifications. In the first stage, decisions on technology selection and number of equipment units at each processing stage are made. Therefore, the set of feasible products is determined. In the second stage, it is determined how the equipment is run to achieve special product designs according to the requested product specifications. Also, decisions on material and resource flows through the supply chain are made. The modeling approach thereby captures the link between technology selection, product designs, and supply chain in a novel way.

Tests for a real-world case at a German dairy company on the introduction of new energy efficient processes for dairy concentrates show the suitability of our approach. Specific product and processing characteristics make the problem at hand complex. As a result of extensive interdisciplinary collaboration, a design space is developed encompassing information on the dairy products and technologies. Several configurations of processing technologies are considered, which moreover can be run in different modes to achieve different product designs. The product-specification uncertainties of the dairy products are related to the shelf life requirements of customers and the demand composition of dry-matter content.

The results show that investing in the new technologies is profitable for the company. For the case, the reverse osmosis concentration technology is selected in combination with different heat treatments. Hereby, flexible processing technologies are selected, which can produce different products in order to react to market uncertainties. Numerical tests provide managerial insights on how the product and technology selection is affected by the uncertainties. They demonstrate that the selection of product designs and processing technologies is highly dependent on the uncertain demand characteristics of the concentrates. We show that shelf life uncertainty is the key driver for the product and technology selection. Knowing the shelf life requirement is therefore very valuable to the dairy company. If customers have low shelf life requirements, pasteurized products concentrated with reverse osmosis are selected, but if customers have high shelf life requirements, pre-heated products concentrated with combined reverse osmosis and evaporation are selected.

The performance of the stochastic modeling approach is also evaluated by computing the expected value of perfect information (EVPI) and the value of stochastic solution (VSS). For the analyzed case, these measures show that it is worthwhile to develop a stochastic modeling approach for the selection of product designs and processing technologies, as compared to a deterministic modeling approach. Managers should bear in mind putting extra effort in obtaining information about future demand, especially with regard to the shelf life requirements, as this leads to significant savings.

In further research, the two-stage stochastic model could be extended by including investments in later periods as the demand evolves. Furthermore, it is of interest to analyze more complex supply chains with, for example, several processing plants in which location of different processing technologies must be determined. Further research could also extend the numerical analyses by investigating other types of products and processes. Interesting would in particular be a comparison of settings, in which product designs are tightly coupled with specific processing technologies against settings, in which product designs are only loosely coupled with specific processing technologies. This would help in providing additional insights on the impact of the flexibility of the processing technologies to produce different product designs. Finally, environmental aspects deserve further consideration, as these also influence the selection of new product designs and processing technologies. Therefore, linking the model to a life cycle assessment and thereby including environmental impacts in decision making, e.g., in a multi-objective optimization framework, could also be the subject of future research.

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Chapter 3. Impact of shelf life on sustainability objectives

This chapter is based on an article published as:

Stefansdottir, B., Depping, V., Grunow, M., Kulozik, U., 2018. Impact of shelf life on the trade-off between economic and environmental objectives: a dairy case. International Journal of Production Economics, 201, 136–148.

Abstract

Food producers introduce more environmental-friendly processes to account for increasing sustainability concerns. However, these processes often go along with a reduction of product shelf life, limiting the delay of sales to future periods with higher prices. We develop a framework to analyze the impact of shelf life on the trade-off between economic and environmental performance of two types of dairy products. Since the differences in shelf life have their key impact at the tactical planning level, we develop an optimization model for this aggregation level. Its objectives reflect profit and relevant environmental indicators. A rolling horizon scheme is used to deal with price uncertainty, using Eurex futures as price predictors. Our framework uses these tactical planning results for strategic decisions on product and process selection. A real-life case study contrasts traditional milk powders against novel milk concentrates. Concentrates require less energy in processing, but have a shorter shelf life. Results show that powders offer a potential profit benefit of up to 34.5%. However, this economic value of shelf life is subject to *a priori* perfect price knowledge. If futures are used as price predictors, the value of shelf life is reduced to only 1.1%. The economic value of shelf life is therefore not a strong argument against the substitution of powders with more environmental-friendly concentrates. We also show that two objectives, profit and eutrophication potential, are sufficient to capture trade-offs in the case. Several product mixes are determined that omit powders and perform well with regard to profit and environment.

3.1 Introduction

Consumer awareness of product sustainability has increased significantly. As a result, manufacturers introduce novel processing technologies, novel combinations of existing technologies often involving less or alternative processing steps, or less intensive, so-called minimal process conditions (Fellows, 2017; Sybesma et al., 2017). In the food sector, there is a quest to replace highly fractionated and processed product with more sustainable products (Van der Goot et al., 2016). Even though environmentally sustainable manufacturing processes are possible, a minimum processing of food products is often required to avoid pre-term spoilage.

The introduction of more environmentally sustainable manufacturing processes often goes along with a reduction of product shelf life. For example, a reduction of the heat treatment intensity results in energy savings in food production, but generally also in a substantial loss of shelf life. The same holds for the substitution of heat treatments with modified atmosphere packaging. The sustainably produced, but more perishable products may require chilled storage and transportation. New products thus need to be assessed carefully along the whole supply chain to determine whether environmental impacts of manufacturing are decreased at the expense of increased perishability and environmental impacts of the downstream chain.

New products with a reduced shelf life may be environmentally sustainable, even when the downstream impacts are taken into account. However, the shelf-life reduction negatively affects the economic performance because it limits the storage duration. Storable, long-shelf-life products are beneficial when price fluctuations occur. For example, if demand volumes or prices increase, long-shelf-life products may be stored for later sale. New sustainable products thus require a comprehensive evaluation of the shelf life's impact on the economic as well as the environmental assessment. The strategic planning of product and process selection must therefore account for short-term decisions on shelf life.

Multi-objective optimization is frequently applied to tackle the trade-offs between economic and environmental objectives (Banasik et al., 2016). Whereas the economic dimension is typically represented in a single objective of either cost minimization or profit maximization, the environmental dimension may require a whole range of environmental indicators. A common tool to assess the performance of products or production processes across different environmental indicators is the Life Cycle Assessment (LCA). The LCA under ISO standards (ISO 14040, 2006; ISO 14044, 2006) is based on the analysis of materials and energy flows at each phase of the life cycle. Thereby, a comprehensive assessment of environmental consequences along the value chain is assured. The use of multi-objective optimization avoids the controversial aggregation of different environmental indicators in a single objective. However, a number of difficulties arises when having many objectives, such as increased computational costs and complications in visualizing the objective space (Deb and Saxena, 2005). The δ-error method can be used to reduce the number of objectives while retaining as much of the problem characteristics as possible.

This study is based on a case from the dairy industry that is well suited to exemplify the impact of shelf-life reduction due to more environmentally sustainable manufacturing processes. The study evaluates a novel and sustainable dairy product in comparison to its more shelf-stable benchmark product. Since drying is one of the most energy intensive processes in the dairy industry, alternative processing variants have been developed in which the drying stage is omitted, which consumes around 50 % of the total energy demand (Ramírez et al., 2006), although only 10 % of the water is removed in this stage. The new product, milk concentrates, has been proposed as a substitute for milk powders in applications in which the latter is reconstituted, e.g., in the production of yoghurts, ice cream, filled bakery products, or finished meals. Milk concentrates can be produced with shelf lives ranging from 9 to 50 days, depending on the selected processing variant. Most milk concentrates require chilled storage. By contrast, milk powders have up to two years shelf life and can be stored under ambient conditions.

Depping et al. (2017) show that switching to milk concentrates is advantageous, even when taking the downstream impacts into account. This analysis only determined environmental impacts and assumed a short and fixed-storage duration. Our study also includes the economic dimension and focuses especially on the impact of shelf life on the environmental and economic assessment. Particularly important is the variability of dairy product prices, which have been fluctuating strongly in the past years including price jumps of up to 43% within one year for skim milk powders traded on the German market (Süddeutsche Butter- und Käse-Börse e.V., 2017).

The paper provides the following contributions:

- We systematically analyze the impact of shelf-life reduction due to sustainable processing on the trade-off between economic and environmental performance for the example of dairy products.
- We develop a framework to allow for a comprehensive sustainability evaluation. Since the differences in shelf life have their key impact at the tactical planning level, we develop an approach that determines the production and storage volumes at this aggregation level. A multi-objective optimization model covers profit and all relevant environmental indicators. We apply the δ-error method to identify trade-offs. Our framework deals with product price uncertainty by updating price information in a rolling horizon scheme. We use the tactical planning results from a rolling horizon application over a historical period to make strategic decisions on product and process selection.

- A real-life case study based on detailed economic and environmental data is used to contrast traditional milk powders against novel milk concentrates that require less energy in processing but have a shorter shelf life. We used historical data on powder prices in the years 2013 up to 2016 and the corresponding prices of futures traded at the Eurex.
- Through objective reduction we show that trade-offs exist between the economic objective and one of the environmental objectives, while other objectives can be reduced without a δ-error.
- We quantify the economic value of the shelf life provided by powders. The results show a potential profit benefit of up to 34.5%. However, this value is subject to *a priori* perfect knowledge of prices. If futures are used as price predictors, the value of shelf life is reduced to only 1.1%. The economic value of the shelf life is therefore not a strong argument against the substitution of powders with more environmental-friendly concentrates.

The remainder of this paper is organized as follows. In Section 3.2, the main related literature is outlined. Section 3.3 introduces the problem definition and the supply chains for milk powders and milk concentrates. In Section 3.4, we present the proposed evaluation framework that supports a selection of products and processes. It includes a multi-objective optimization model, a rolling horizon scheme, and a method for objective reduction. In Section 3.5, the developed methodology is applied to a real-life dairy case study and numerical analyses are carried out. Finally, Section 3.6 summarizes the main conclusions and presents future research opportunities.

3.2 Related literature

In the following, we first review papers that develop planning approaches under economic objectives considering shelf life and demand variability. We also discuss papers that determine the economic value of storage under uncertain prices. Then, we outline studies that have considered products' environmental impacts in combination with their shelf life. Finally, studies that deal with products' environmental and economic benefit in combination with their shelf life are reviewed.

3.2.1 Economic objectives, shelf life, and demand variability

Several studies have accounted for shelf life and demand variability in planning approaches with economic objectives. Stefansdottir and Grunow (2018) study the selection of product designs and processing technologies under demand uncertainties with regard to volumes and product specifications, such as the shelf-life requirement. They show that shelf life is a key driver in the selection of product designs and technologies. Amorim et al. (2013b) review studies on production and distribution planning for perishable products. They identify seven papers that include demand uncertainties. The finding that demand uncertainty is restricted to uncertainty in demand levels is valid across all papers reviewed by Amorim et al. (2013b). In another study, Amorim et al. (2013a) also consider the risk of spoilage and of revenue loss, which results from uncertainties in the decay rates, demand level, and customer purchasing behavior. Pauls-Worm et al. (2014) moreover consider a practical problem in which a food producer faces non-stationary stochastic demand. The existing work on shelf life in planning approaches under economic objectives thus only deals with demand volume uncertainty, while the impact of variable product prices is not discussed. In addition, none of these studies addresses the economic value of shelf life.

3.2.2 Economic value of storage and price variability

A range of analytical papers from the energy sector has analyzed the economic value of storage capacity under uncertain prices. Lai et al. (2011), for instance, develop a heuristic to determine the value of storing liquefied natural gas at a regasification terminal. Their heuristic accounts for seasonal and volatile natural gas prices, shipping models, and inventory control. Arvesen et al. (2013) analyze the option of using different injection and withdrawal rates in natural gas pipelines as a means for short-term gas storage. They value the storage option of this so-called linepack for power plants by applying a Least Squares Monte Carlo algorithm, incorporating both gas price (i.e., input) and electricity price (i.e., output) volatilities. They find that the linepack storage option has significant value for power plants to better exploit the sometimes extreme electricity price fluctuations. While the available analytical papers determine the economic value of storage capacity, the related issue of a limited storage duration (i.e., shelf life) has not been considered so far. The economic value of shelf life under price variability thus has not been tackled. Furthermore, despite the possibility to optimally determine the economic value of storage, a major drawback of analytical approaches is the lacking inclusion of other criteria and thus, for instance, the neglect of economic and environmental trade-offs.

3.2.3 Environmental impacts and shelf life

Several studies consider the impact of novel techniques on products' shelf life and environmental sustainability. Valsasina et al. (2017) describe the future potential of applying one-stage ultrahigh pressure homogenization (encompassing ultrahigh temperature) instead of conventional homogenization followed by ultrahigh heat treatment for the preservation of milk. In their case, the novel technique results in both a higher product shelf life and an improved environmental sustainability. Hoang et al. (2016) and Claussen et al. (2011) compare the environmental impacts of fish cold chains that use traditional chilling or new superchilling technologies. They point to the higher environmental sustainability of superchilled fish along the supply chain, which, in addition, has the advantage of an extended shelf life at the customer stage. Manfredi et al. (2015) assess the environmental impacts of incorporating antimicrobial agents into a packaging film for fresh milk. Although the antimicrobial coating goes along with additional environmental impacts, the authors argue for an overall lower environmental impact due to food waste reduction at the customer stage. This finding is true for the specific case in which an initially low shelf life can be increased significantly (i.e., shelf life increases from two to nine days). The relation between shelf life and environmental sustainability thus depends on the assumption of whether and to what extent food waste is affected. Pardo and Zufía (2012) compare four different technologies for preserving finished meals. They find that the most environmentally sustainable and novel solution, namely modified atmosphere packaging, reduces shelf life by half compared to traditional but less sustainable heat treatment. Novel techniques thus must be assessed carefully to determine whether environmental sustainability is enhanced in line with shelf life or at its expense. Yet, no study explicitly considered the impact of shelf life on environmental sustainability.

The possibility to improve products' environmental sustainability with novel combinations of existing technologies has also been addressed in several studies (e.g., Cespi et al., 2014; Huntzinger and Eatmon, 2009). However, only Depping et al. (2017) so far have considered the effect of these combinations on the products' shelf life. Combinations including less intensive process conditions thereby lead to a reduced shelf life while increasing environmental sustainability. No study has explicitly looked into the challenges that can arise from a trade-off between environmental sustainability and shelf life.

3.2.4 Multiple sustainability objectives and shelf life

Only few studies consider the environmental and economic benefits of products in combination with their shelf life. In multi-objective approaches, shelf life has been included either explicitly as an objective or within the model constraints. Sazvar et al. (2014) develop a bi-objective stochastic mathematical model that accounts for the deterioration process of products and determines both the optimal inventory policy and the type of transportation vehicles. Both economic (i.e., cost) and environmental (i.e., greenhouse gas emission) criteria are considered under uncertain demand volumes. Their generic, bi-objective tactical-operational model is valid for supply chains of perishable products. The analyzed problem settings therefore exhibit some similarities to our paper, but the developed methodologies are different. In the chemical industry, You et al. (2012) determine the optimal network design of a cellulosic ethanol supply chain with a multi-objective optimization model. Besides the minimization of costs and greenhouse gas emissions, a social objective is considered in terms of the maximization of accrued jobs along the supply chain. They account for the shelf life of biomass used for ethanol production. The shelf life, however, is simply modeled as a percentage of deteriorated biomass.

Although challenges associated with highly perishable products are common within the food industry, corresponding papers investigating shelf-life restrictions in multi-objective optimization are scarce. Soysal et al. (2014) design a generic beef network using a bi-objective model with greenhouse gas emissions as an environmental indicator. They consider product perishability by restricting the maximum number of periods that beef can be stored. Furthermore, shelf-life restrictions are accounted for in two multi-objective vehicle routing papers (Bortolini et al., 2016; Govindan et al., 2014). While Govindan et al. (2014) consider the same objectives as Soysal et al. (2014), Bortolini et al. (2016) additionally minimize delivery time as a third objective.

No study to date captures the influence of shelf life on the combined economic and environmental evaluation of products. Based on a real-life case study, we take a first step in assessing the extent to which the choice of food products is determined by perishability. To quantify the effects of shelf-life reduction, we cover product price variability and develop a multi-objective optimization model that includes, besides profit, all relevant environmental indicators.

3.3 Problem definition and dairy supply chain context

The case of substituting milk powders with milk concentrates exemplifies the impact of shelf-life reduction due to sustainable processing. Milk powders are one of the key intermediate products in the dairy sector. They consume large amounts of energy in the drying process. A large proportion of this energy can be saved by producing concentrates instead, using novel processing variants. However, the shelf life of concentrates is significantly lower. We therefore compare the shelf-stable milk powders to novel, shelf-life-reduced milk concentrates. The comparison must capture the impact of price variability. Under fluctuating prices, shelf-stable milk powders allow for the delay of sales until a higher price level is reached. Consequently, higher

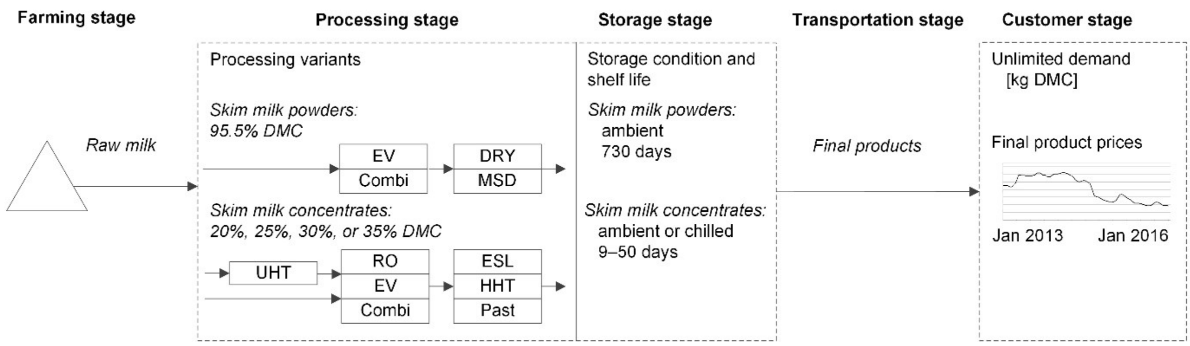

Figure 3.1: Representation of the skim-milk-powder and skim-milk-concentrate supply chain.

profits can be realized; however, this requires information on the upcoming prices. The value of shelf life therefore depends on the accuracy of the price information.

While long shelf life can have an economic benefit in the case of fluctuating prices, environmental impacts increase with longer shelf lives and longer storage durations under chilled conditions. Switching to more environmental-friendly milk concentrates thus impacts the trade-off between the economic and the environmental performance. Moreover, the environmental performance must be assessed through a whole range of environmental indicators.

The following additional problem characteristics have to be captured in the comparison of the two types of dairy products. At the processing stage, a multitude of processing variants results in numerous different powder and concentrate products. These processing variants differ in their processing impacts and product losses. Furthermore, the resulting products differ in storage and transportation impacts. They may require ambient or chilled temperatures. They differ in their degree of concentration that determines the product mass needed to fill customer demand. Therefore, all supply chain stages, from farming to customers, have to be considered. Detailed economic and environmental data for all stages must be elicited.

The supply chain for skim milk powders and concentrates (see Figure 3.1) consists of the following stages: farming, processing, storage, transportation, and customer. The present case considers a dairy plant that has long-term contracts with its supplying dairy farms or a cooperative in which farmers own the plant. Raw milk volumes are therefore delivered to the dairy plant and must be processed into powders or concentrates.

Skim milk powders are typically processed into a dry-matter content (DMC) of around 95.5%. The industrial skim-milk-powder production process comprises a facultative skim milk pre-concentration step involving reverse osmosis (RO), followed by multiple-effect evaporation (EV), and subsequent immediate drying/multi-stage drying (DRY/MSD). Skim milk concentrates, on the other hand, can be produced to different final dry-matter contents. This study considers four concentrate dry-matter contents: 20%, 25%, 30%, and 35%. Processing variants related to obtaining these four degrees of concentration are selected based on previous research (cf. Depping et al., 2017; Stefansdottir and Grunow, 2018). The production process of concentrates consists of an optional pre-heat treatment, a concentration step involving reverse osmosis, evaporation, or a combination of the two (Combi), and, finally, a post-heat treatment. Considered heat treatments include ultra-high temperature (UHT) at 137 °C for 5 seconds, extended shelf life (ESL) at 125 °C for 2 seconds, high-heat treatment (HHT) at 120 °C for 5 seconds, and pasteurization (Past) at 72 °C for 25 seconds.

Powders are stored under ambient conditions. Their shelf life of around two years is limited by caking or other physical changes resulting in decreasing redispersability and flowability in dispensing systems. These effects depend on the processing conditions (e.g., on whether lactose is pre-crystallized) and on the storage conditions (i.e., relative humidity and time). By contrast, most concentrates must be stored under chilled conditions, while ambient storage conditions are only applicable for certain pre-heated concentrates. The perishability of skim milk concentrates is determined mainly by the applied thermal pre-heat and post-heat treatments (Dumpler and Kulozik, 2015; Dumpler and Kulozik, 2016; Dumpler et al., 2017b; Dumpler et al., 2018). In case pre-heat treatment is applied in concentrate production, age-gelation becomes the limiting factor for shelf life. Otherwise, shelf life is restricted by microbial growth. Pasteurized concentrates produced with evaporation have a higher shelf life than those produced with reverse osmosis since the heat treatment via evaporation already leads to a reduced initial bacterial count. Table 3.1 summarizes the different skim-milk powder and skim-milk-concentrate products as well as their storage conditions and shelf lives.

In the downstream chain, powders and concentrates are transported to customers under chilled or ambient conditions. A flexible market with variable demand is considered, as fixed demand can already be subtracted from the total demand volumes. Customers require a certain mass of dry-matter content, which can be fulfilled by either powders or concentrates. Whereas concentrates are directly applied in fluid end products, powders must be reconstituted. Final product prices per kilogram dry-matter content are subject to fluctuations.

Table 3.1: Different skim-milk-powder and skim-milk-concentrate products.

Product (Processing variant–DMC)	Storage condition	Shelf life (days)	Limiting cause for shelf life
Skim milk powders			
EV–DRY–95.5%	ambient	≤ 730	Caking
Combi–DRY–95.5%	ambient	≤ 730	Caking
EV–MSD–95.5%	ambient	≤ 730	Caking
Combi–MSD–95.5%	ambient	≤ 730	Caking
Skim milk concentrates			
RO–Past–20%	chilled	9	Microbial growth – vegetative cells
EV–Past–20%	chilled	9–15	Microbial growth – vegetative cells
RO–Past–25%	chilled	9	Microbial growth – vegetative cells
EV–Past–25%	chilled	9–15	Microbial growth – vegetative cells
UHT–RO–ESL–25%	ambient	40	Age-gelation
UHT–EV–ESL–25%	ambient	40	Age-gelation
RO–Past–30%	chilled	14	Microbial growth – vegetative cells
EV–Past–30%	chilled	14–20	Microbial growth – vegetative cells
RO–HHT–30%	chilled	20	Microbial growth – bacterial spores
EV–HHT–30%	chilled	20	Microbial growth – bacterial spores
UHT–RO–ESL–30%	ambient	22	Age-gelation
UHT–EV–ESL–30%	ambient	22	Age-gelation
RO–Past–35%	chilled	19	Microbial growth – vegetative cells
EV–Past–35%	chilled	19–30	Microbial growth – vegetative cells
Combi–Past–35%	chilled	19–30	Microbial growth – vegetative cells
UHT–RO–HHT–35%	chilled	50	Age-gelation
UHT–EV–HHT–35%	chilled	50	Age-gelation
UHT–Combi–HHT–35%	chilled	50	Age-gelation

3.4 Methodology for a comprehensive sustainability evaluation

3.4.1 Evaluation framework

We develop a framework for evaluating the impact of shelf life on the trade-off between the economic and environmental performance of milk powders and concentrates (see Figure 3.2). The differences in shelf life have their main impact at the tactical planning level. We therefore perform repeated tactical planning and use the results to draw strategic conclusions on product and process selection.

Part of the data relating to the identified processing variants, such as shelf life, is a direct input to the optimization model. The other part forms the basis for calculating economic and environmental parameters required for the objective functions. The environmental parameters are determined with an attributional LCA. An attributional LCA describes the environmental impact of a product system in steady state, therefore providing insight into the average environmental impact of a product over its life cycle at a certain point in time (Hospido et al., 2010). A detailed approach is applied in which inputs and outputs are assessed for each processing step along the supply chain. This allows for a comparison of different processing variants for skim milk powders and concentrates. Economic and environmental parameter values are listed in Section 3.5.1.

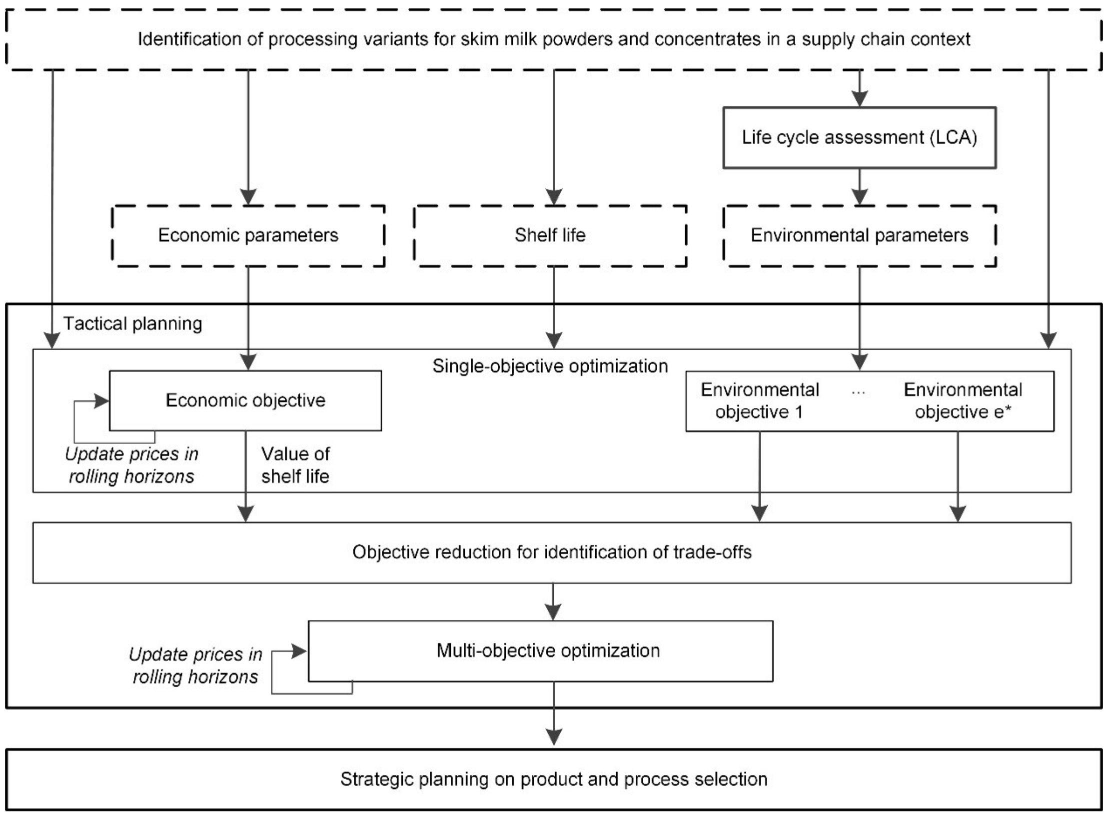

Figure 3.2: Overview of the developed evaluation framework. Standard boxes represent applied methods, dashed boxes represent input/output parameters.

The multi-objective optimization model described in Section 3.4.2 is based on one economic objective and several environmental objectives that are first solved separately (single-objective optimization). To deal with uncertainty in final product prices, a rolling horizon scheme is developed. Model solving with the economic objective is implemented within the rolling horizon scheme. At the beginning of the first period, the model is solved based on price predictions of a selected horizon and only the decisions of the current period are fixed. Then, one period later, the price predictions are updated and the model is solved again. This procedure is repeated within the rolling horizon scheme. Due to the perishability of the products, the age of the stored products must be tracked within the rolling horizon scheme.

After solving each objective of the optimization model separately, objective reduction is carried out to limit the difficulties of dealing with several objective functions. The selected approach for reducing objectives is outlined in Section 3.4.3. Subsequently, the reduced set of objectives is optimized with the multi-objective optimization model and a range of weighted trade-off solutions is determined, among which decision makers can choose according to their preferences. Finally, the results of the repeated tactical planning are used to select products and processes at the strategic planning level.

3.4.2 Multi-objective optimization model

We develop a multi-objective mixed integer linear programming (Mo-MILP) model for the tactical planning of perishable dairy products, accounting both for economic and environmental criteria. The model determines production, storage, and shipment quantities of the different products in each period. The benefit of the storage option, depending on the product's shelf life, is therefore quantified. The following assumptions are made:

- Depreciation costs are excluded, assuming that equipment units are already in place at a tactical planning level. Since capital goods account for less than 1% of the total environmental impacts at the dairy plant, they are excluded from the environmental parameters.
- Product-dependent production costs and impacts include resource consumption (during production and cleaning) and wastewater generation for all processing stages, as well as required packaging materials.
- Storage capacities for different storage conditions (i.e., ambient or chilled) are limited.
- Transportation capacities are sufficient.
- Products must be shipped within their shelf life. Here, shelf life refers to the time that products may be stored at the dairy plant. This excludes the time needed for transportation as well as the minimum remaining shelf life required by customers.

The following notation is introduced for the model:

Indices and index sets

$p \in P$	product
$g \in G$	product type
$p' \in P(g)$	product belonging to product type g
$h \in H$	storage condition
$p'' \in P(h)$	product stored in storage condition h
$t \in T$	time period
$t' \in T$	production period
$e \in E$	environmental indicator

Parameters

ζ_t	contracted supply of raw milk in period t [kg raw milk]
σ^{was1}	waste in raw milk transportation [%]
o_p	raw factor – amount of raw milk required for 1 kg DMC of product p [kg raw milk]
π_p	volume of product p [m^3/kg DMC]
ν_p	shelf life of product p [periods]

β_g	maximum fraction for production of product type *g* per period [%]
θ_h	storage capacity of storage condition *h* [m^3]
ε	transportation distance of final products [km]
σ^{was2}	waste in reconstitution for product *p* [%]
r_t	product price in period *t* [costs/kg DMC]
c_t^{raw}	raw milk costs (including transportation) in period *t* [costs/kg raw milk]
c_p^{prod}	production costs (including packaging material) of product *p* [costs/kg DMC]
c_p^{inv}	inventory costs for product *p* per period [costs/(kg DMC · period)]
c_p^{trans}	transportation costs for product *p* [costs/(kg DMC · km)]
i_e^{raw}	raw milk impact (including transportation) of environmental indicator *e* [impact/kg raw milk]
i_{pe}^{prod}	production impact (including packaging material) of product *p* of environmental indicator *e* [impact/kg DMC]
i_{pe}^{inv}	inventory impact of product *p* per period of environmental indicator *e* [impact/(kg DMC · period)]
i_{pe}^{trans}	transportation impact of product *p* of environmental indicator *e* [impact/(kg DMC · km)]

Decision variables

$X_{pt'}$	quantity of product *p* produced in period *t'* [kg DMC]
$I_{pt't}$	inventory of product *p* produced in period *t'* at the end of period *t* *(t'≤t)* [kg DMC]
$Q_{pt't}$	quantity of product *p* produced in period *t'* and shipped in period *t* *(t'≤t)* [kg DMC]
D_t	demand fulfilled in period *t* [kg DMC]

The multi-objective model is formulated as follows:

$$Max \sum_{t\in T} r_t \cdot D_t - \sum_{t\in T} c_t^{raw} \cdot \zeta_t - \sum_{p\in P}\sum_{t'\in T} c_p^{prod} \cdot X_{pt'} - \sum_{p\in P}\sum_{t'\in T}\sum_{t\in T} c_p^{inv} \cdot I_{pt't} - \sum_{p\in P}\sum_{t'\in T}\sum_{t\in T} c_p^{trans} \cdot \varepsilon \cdot Q_{pt't} \tag{3.1}$$

$$Min \sum_{t\in T} i_e^{raw} \cdot \zeta_t + \sum_{p\in P}\sum_{t'\in T} i_{pe}^{prod} \cdot X_{pt'} + \sum_{p\in P}\sum_{t'\in T}\sum_{t\in T} i_{pe}^{inv} \cdot I_{pt't} + \sum_{p\in P}\sum_{t'\in T}\sum_{t\in T} i_{pe}^{trans} \cdot \varepsilon \cdot Q_{pt't} \quad \forall e \in E \tag{3.2}$$

subject to

$$\zeta_{t'} \cdot (1 - \sigma^{was1}) = \sum_{p \in P} X_{pt'} \cdot o_p \quad \forall t' \in T \tag{3.3}$$

$$I_{pt't} = X_{pt'} - Q_{pt't} \quad \forall p \in P, t' \in T, t \in T: t' = t \tag{3.4}$$

$$I_{pt't} = I_{pt',t-1} - Q_{pt't} \quad \forall p \in P, t' \in T, t = 2, \dots, T: t' < t \tag{3.5}$$

$$\sum_{t' \in T} X_{pt'} \leq \sum_{t' \in T} \sum_{t \in T} Q_{pt't} \quad \forall p \in P \tag{3.6}$$

$$\sum_{p' \in P(g)} X_{p't'} \leq \beta_g \cdot \sum_{p \in P} X_{pt'} \quad \forall g \in G, t' \in T \tag{3.7}$$

$$\sum_{p'' \in P(h)} \sum_{t' \in T} I_{p''t't} \cdot \pi_{p''} \leq \theta_h \quad \forall h \in H, t \in T \tag{3.8}$$

$$\sum_{p \in P} \sum_{t'=t-v_p}^{t} Q_{pt't} \cdot (1 - \sigma^{was2}) = D_t \quad \forall t \in T \tag{3.9}$$

$$X_{pt'} \geq 0 \quad \forall p \in P, t' \in T \tag{3.10}$$

$$I_{pt't} \geq 0 \quad \forall p \in P, t' \in T, t \in T \tag{3.11}$$

$$Q_{pt't} \geq 0 \quad \forall p \in P, t' \in T, t \in T \tag{3.12}$$

$$D_t \geq 0 \quad \forall t \in T \tag{3.13}$$

In the above formulation, the first objective function aims to maximize the profit (3.1). The profit comprises the revenues of sold products and the costs along the supply chain, i.e., raw milk costs, production costs, inventory costs, and transportation costs. The second objective function aims to minimize environmental impacts related to the dairy supply chain (3.2), comprising raw milk impacts, production impacts, inventory impacts, and transportation impacts. The model allows for the consideration of environmental impacts in several environmental impact categories.

Constraints (3.3) guarantee that total supplies of raw milk are sent from the dairy farms to the dairy plant, also accounting for waste in raw milk transportation. Thereafter, the raw milk is processed into different types of final products. Constraints (3.4) and (3.5) represent inventory balances in which the age of the products is tracked. Products in inventory stem either from production in the current period (3.4) or from inventory at the end of the previous period (3.5). Constraints (3.6) ensure that total production quantities of each product are shipped to customers. This restriction is only required for the minimization of environmental impacts, not for profit maximization.

The total production quantities of a specific product type, e.g., powders or concentrates, may be restricted (3.7). Furthermore, storage capacities for different storage conditions must be respected (3.8). Constraints (3.9) ensure that the storage duration of the final products is never longer than the respective shelf life. Products with a long shelf life (like powders) can therefore be stored for more time periods than products with a short shelf life (like concentrates) in order to take advantage of fluctuations in final product prices. Demand fulfillment is also modeled with constraints (3.9), accounting for waste in reconstitution. Finally, constraints (3.10–3.13) are non-negativity constraints.

3.4.3 Objective reduction for identification of trade-offs

Three main methods have been proposed for objective reduction: weighting, including pre-defined weighting schemes like the Eco-Indicator 99, principal component analysis, and the δ-error method. Since weighting omits essential trade-offs between multiple objectives and the principal component analysis lacks to determine the error of combining indicators to principal components, we opt to apply the δ-error method for objective reduction (cf. Brockhoff and Zitzler, 2006). The goal of this method is to identify a subset of objectives so that the error of omitting objectives is at a minimum. The δ-error is thus a measure for the approximation error in objective reduction that quantifies the change in the dominance structure if one solution becomes dominant compared to another. Brockhoff and Zitzler (2006) introduce two different methods for computing the minimum objective subset (MOSS), i.e., the δ-MOSS method, which finds a minimum objective subset for a maximum allowable approximation error and the k-MOSS method, which finds an objective subset of size *k* with a minimum error. In this study, the δ-MOSS method is applied. The δ-error is defined as in Guillén-Gosálbez (2011):

$$(\gamma_{ms'} - \gamma_{ms}) \cdot Y_m \cdot W_{ss'} = \delta_{mss'} \quad \forall m \in M, s \in S, s' \in S \tag{3.A1}$$

The parameter γ_{ms} is the value of the objective *m* for solution s. The decision variable Y_m equals 1 if objective *m* is removed (0 otherwise) and the decision variable $W_{ss'}$ equals 1 if s' dominates s in the reduced space (0 otherwise). The error $\delta_{mss'}$ is then defined as the difference between the value of objective *m* in solutions s' and s. This approach allows for the reduction of objectives, while determining and restricting the error of collapsing indicators. Relevant trade-offs can therefore be identified.

3.5 Analyses of skim milk powders and concentrates

The accessed data on skim milk powders and skim milk concentrates is outlined in the following. Results are presented first for the economic objective, since shelf life can provide an additional value for this objective. Subsequently, economic and environmental objectives are considered jointly and trade-offs arising after objective reduction are analyzed.

3.5.1 Parametrization through LCA, cost analysis, and dairy futures

The model is solved with real-life data from two German dairy companies, one producing powders and concentrates, and one using these intermediates to make final products. We collected economic and environmental data at these companies and at equipment manufacturers at all supply chain stages. This industrial data is complemented with experimental data from food engineering (cf. Dumpler and Kulozik, 2015; Dumpler and Kulozik, 2016; Dumpler et al., 2017a; Dumpler at al., 2017b; Dumpler et al., 2018) and literature data.

The planning horizon is one year with a granularity of weeks, leading to 52 periods t. Altogether 22 products p are assessed (see Table 3.1), which are of two product types g, i.e., powders and concentrates. The products are also subdivided according to their required storage condition h into products that can be stored in an ambient environment and products that require a chilled environment. We conduct an LCA that covers four environmental indicators e: cumulative energy demand (CED), global warming potential (GWP), eutrophication potential (EP), and acidification potential (AP). Indicators are selected for their importance to the dairy products' supply chain (De Vries and De Boer, 2010). To ensure compatibility with the literature-based raw-milk production impacts derived from Guerci et al. (2013), the same environmental impact assessment method and characterization factors are used in the LCA of the downstream chain. The methods specified in EPD (2008) are applied for this purpose. For a more detailed description of the conducted LCA, see Depping et al. (2017). The following parameters result for each supply chain stage.

Farming stage. The dairy plant is supplied by 200 local farms with an average distance of 100 km from the plant. In raw milk delivery, σ^{was1} = 0.04% of raw milk is wasted. The weekly raw milk supply used for variable demand for powder and concentrate production is on average around $\zeta_t = 700{,}000$ kg, which is assumed constant over the year. Raw milk costs (including the delivery costs) are on average over the planning horizon $c_t^{raw} = 0.377$ €/kg, according to

Table 3.2: Economic and environmental data on production, encompassing packaging material.

Product (Processing variant–DMC)	Raw factor[a]	Costs [€/ ton DMC]	CED [MJ/ ton DMC]	GWP [ton CO_2-eq/ ton DMC]	EP [g PO_4^{--}-eq/ ton DMC]	AP [g SO_2-eq/ ton DMC]
Skim milk powders						
EV–DRY–95.5%	7,016	291.81	19,351	1,143.95	2.4495	1.7094
Combi–DRY–95.5%	6,979	224.07	14,617	869.81	1.7477	1.7219
EV–MSD–95.5%	7,000	315.79	21,140	1,278.52	16.9716	3.0247
Combi–MSD–95.5%	6,963	248.21	16,416	1,004.98	16.2714	3.0372
Skim milk concentrates						
RO–Past–20%	6,950	178.75	7,368	414.09	1.4777	1.3558
EV–Past–20%	6,955	226.65	10,749	607.36	1.9984	1.2134
RO–Past–25%	6,949	151.35	6,448	366.41	1.2353	1.2473
EV–Past–25%	6,963	211.65	10,685	610.36	1.8659	1.1521
UHT–RO–ESL–25%	6,957	191.31	9,273	540.43	1.5392	1.6791
UHT–EV–ESL–25%	6,970	251.67	13,515	784.68	2.1703	1.5847
RO–Past–30%	6,946	135.96	5,947	341.77	1.0864	1.2133
EV–Past–30%	6,973	202.77	10,698	615.94	1.7870	1.1317
RO–HHT–30%	6,946	143.04	6,343	366.57	1.1375	1.2645
EV–HHT–30%	6,974	209.85	11,095	640.76	1.8382	1.1829
UHT–RO–ESL–30%	6,953	174.73	8,683	510.46	1.3809	1.6400
UHT–EV–ESL–30%	6,981	241.67	13,444	785.21	2.0825	1.5599
RO–Past–35%	6,959	150.97	6,687	394.09	1.0991	1.5504
EV–Past–35%	6,981	196.28	10,708	619.98	1.7311	1.1274
Combi–Past–35%	6,950	129.91	6,056	351.19	1.0438	1.1880
UHT–RO–HHT–35%	6,967	188.23	9,321	556.57	1.3816	1.9693
UHT–EV–HHT–35%	6,990	233.65	13,351	782.97	2.0144	1.5475
UHT–Combi–HHT–35%	6,958	167.13	8,686	513.48	1.3260	1.6063

[a] Mass of raw milk required to produce 1 ton of dry-matter content.

long-term contracts with the farms. For the raw milk impacts i_e^{raw}, averages of the environmental impact ranges per kilogram energy-corrected milk from Guerci et al. (2013) are used, namely CED–3.4709 MJ, GWP–1.2691 CO_2-eq, EP–0.0032 PO_4^{--}-eq, and AP–0.0169 SO_2-eq.

Processing stage. At the dairy plant, runtimes, cleaning times, resource consumption, wastewater generation, and product losses are assessed for each processing step. In addition, the required packaging material is determined. Table 3.2 summarizes the resulting costs c_p^{prod} and environmental impacts i_{pe}^{prod} as well as the amount of raw milk required, the so-called raw factor o_p to produce one ton dry-matter content of different products. The raw factor comprises necessary volume reduction and product losses in processing. Product shelf lives ν_p are shown in Table 3.1.

Storage and transportation stages. The required storage volume π_p depends on the dry-matter content of the products: 20%–0.0451 m^3/kg DMC, 25%–0.0354 m^3/kg DMC, 30%–0.0289 m^3/kg DMC, 35%–0.0242 m^3/kg DMC, and 95.5%–0.0102 m^3/kg DMC. Unlimited storage capacities θ_h are assumed since there is sufficient ambient storage space at the dairy plant and,

Table 3.3: Economic and environmental data on storage.

	Costs [€/ ton DMC·week]	CED [MJ/ ton DMC·week]	GWP [ton CO_2-eq/ ton DMC·week]	EP [g PO_4^{3-}-eq/ ton DMC·week]	AP [g SO_2-eq/ ton DMC·week]
ambient[a]					
25%	3.2346	-	-	-	-
30%	2.6955	-	-	-	-
95.5%	0.8467	-	-	-	-
chilled[a]					
20%	6.4042	199.93	12.5254	0.0157	0.0482
25%	5.1234	159.94	10.0204	0.0125	0.0385
30%	4.2695	133.29	8.3503	0.0104	0.0321
35%	3.6595	114.25	7.1574	0.0090	0.0275

[a] Dry-matter contents are only considered, if at least one corresponding product exists.

Table 3.4: Economic and environmental data on transportation.

	Costs [€/ ton DMC·km]	CED [MJ/ ton DMC·km]	GWP [ton CO_2-eq/ ton DMC·km]	EP [g PO_4^{3-}-eq/ ton DMC·km]	AP [g SO_2-eq/ ton DMC·km]
ambient[a]					
25%	0.2619	12.84	0.8014	0.0024	0.0005
30%	0.2183	10.70	0.6678	0.0020	0.0005
95.5%	0.0686	3.36	0.2098	0.0006	0.0001
chilled[a]					
20%	0.3921	18.67	1.1732	0.0034	0.0008
25%	0.3137	14.94	0.9385	0.0028	0.0006
30%	0.2614	12.45	0.7821	0.0023	0.0005
35%	0.2241	10.67	0.6704	0.0020	0.0004

[a] Dry-matter contents are only considered, if at least one corresponding product exists.

for chilled storage, there is a natural limit on the stored quantities due to the product's perishability. Table 3.3 shows the inventory costs c_p^{inv} and inventory impacts i_{pe}^{inv} related to storage under both ambient and chilled conditions. Likewise, Table 3.4 shows the transportation costs c_p^{trans} and transportation impacts i_{pe}^{trans} under both ambient and chilled conditions. A typical transportation distance to customers of $\varepsilon = 500$ km is selected. It is assumed that transportation takes 1 day and that customers require a minimum remaining product shelf life of 5 days.

Customer stage. Skim milk powder futures that were traded at the Eurex Frankfurt AG from the years 2013 and 2014 are used as predictors for final product prices r_t and contrasted to the realized prices on the German market. The futures have a horizon of up to 12 months, resulting in price predictions from 2013 up to 2016. Currently, the first skim milk concentrates are on the market and show an identical price per kilogram dry-matter content as powders. Concentrates can be directly applied, while powders must be reconstituted, resulting in an average product loss of $\sigma^{was2} = 4.2\%$ for powders.

The price predictions for the next 52 weeks are updated weekly in the rolling horizon scheme and the model with the economic objective is run over 104 datasets (2 years). It is assumed that futures prices from the first period of each dataset equal the realized prices. All test runs are implemented and solved in IBM ILOG CPLEX Optimization Studio 12.6 on a 2.6 GHz Intel Xeon CPU with 32 GB RAM. Each dataset results in a problem size of around 62,000 decision variables and 32,000 constraints, which is solved to optimality in around 50 seconds. The rolling horizon scheme is solved over 104 datasets in approximately 1.5 hours.

3.5.2 Economic analyses of shelf life

3.5.2.1 Impact of price knowledge on production and storage

The economic performance of *a priori* perfect knowledge of prices is compared with using futures as price predictors. Figure 3.3a shows the actual skim milk powder prices that were realized on the German market in the years 2013 up to 2016. Prices are expressed per ton dry-matter content. While prices were rising or stable in 2013, prices were mostly falling steeply in 2014, reaching only 57% of their initial state at the end of 2014.

The product mix as well as production, inventory, and shipment quantities are determined aiming at profit maximization. Figure 3.3b illustrates the product mix of skim milk powders and concentrates as well as inventory and shipment volumes. The figure summarizes the planning results for the first periods of the rolling horizon approach that are put into operation. Results show that powders are preferred over concentrates if prices are expected to rise, as they can be stored over a longer period of time. The skim milk powder option *Combi–Dry–95.5%* performs best. In the case of stable prices with small variabilities in the near future, the concentrate options *UHT–Combi–HHT–35%* and *Combi–Past–35%* are selected. The concentrate *UHT–Combi–HHT–35%* with a shelf life of 50 days is able to take advantage of near-time price increases, while the less-processed concentrate *Combi–Past–35%* with a shelf life of 19–30 days has a production cost advantage. In a sequence of periods with falling prices, solely the concentrate *Combi–Past–35%* is selected and sold immediately. Together, this shows how shelf life affects the selection of products under fluctuating prices.

Figure 3.4a shows selected skim milk powder future prices. In the following, the first six futures of those are described. In week 12, the futures show a rather stable development of prices. While the futures as of weeks 13 and 14 are slightly increasing with a peak at the end of May 2013, the futures as of weeks 15 and 16 show a slightly faster increase. In week 17, the futures show a slight decrease.

Figure 3.4b shows the product mix of skim milk powders and concentrates when prices are predicted with futures. The same products are selected for price predictions with futures as for *a priori* perfect price knowledge. However, the decisions on storage and shipment volumes are

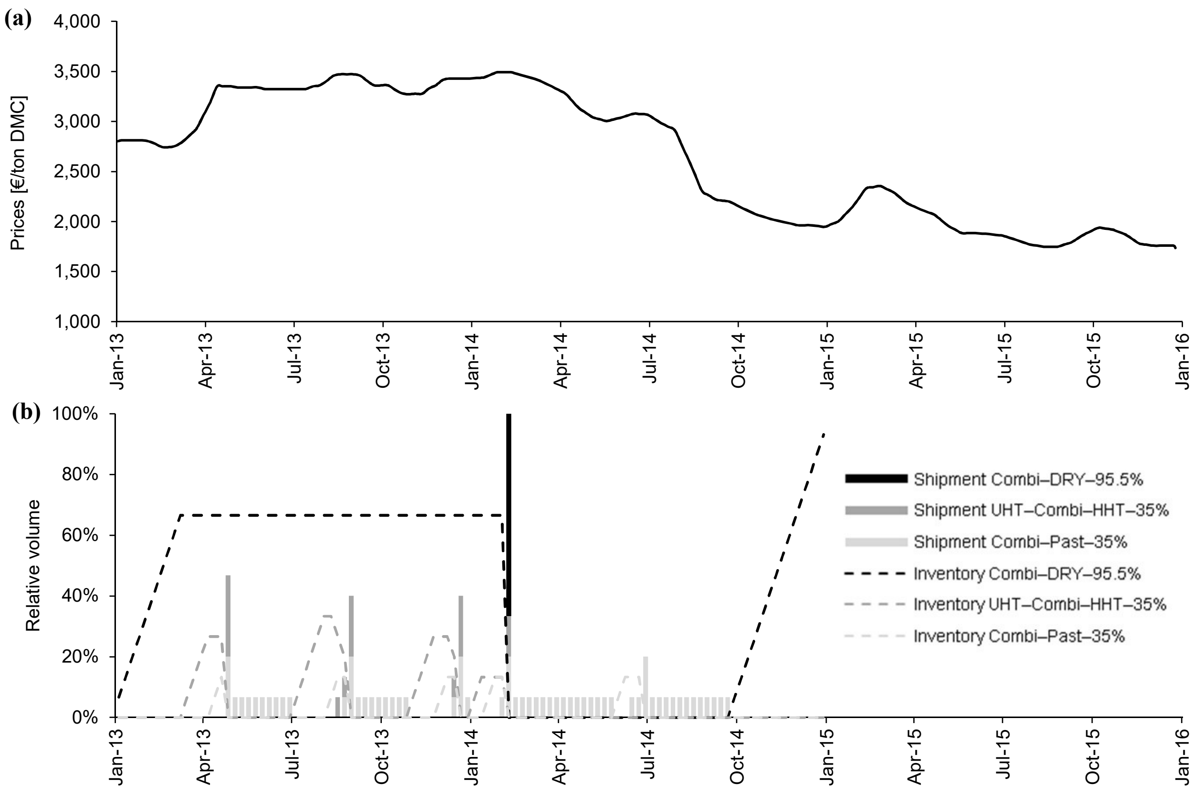

Figure 3.3: (a) Actual German skim milk powder and concentrate prices for years 2013 up to 2016 (Source: Süddeutsche Butter- und Käse-Börse e.V., 2017); (b) Relative shipment and storage volumes resulting from maximization of profit based on *a priori* perfect knowledge of prices for the years 2013 and 2014. Volumes are scaled to maximum shipment volumes reached.

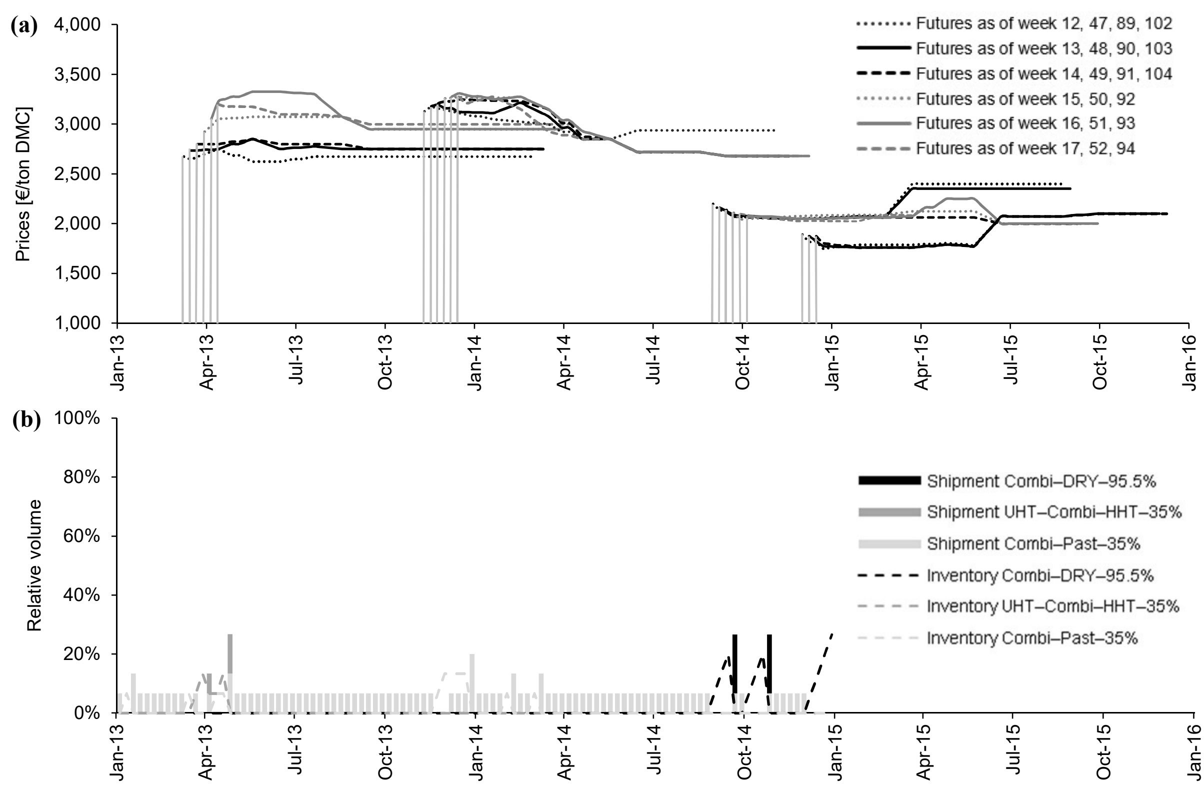

Figure 3.4: (a) Selected skim milk powder future prices for years 2013 up to 2016 (Source: Eurex); (b) Relative shipment and storage volumes resulting from maximization of profit, based on futures as price predictors for years 2013 and 2014. Volumes are scaled to maximum shipment volumes reached based on *a priori* perfect price knowledge.

substantially different. In the case of price predictions with futures, the storage option is not used as much as with *a priori* perfect price knowledge. The lower storage and shipment volumes of powders mainly result from futures not predicting the large price increase in spring 2013 (see futures as of week 12–17). In addition, the recorded price fluctuations differ. The price variance, calculated over the 104 datasets of the rolling horizons, is remarkably higher for the actual prices (variance = 0.46) than the future prices (variance = 0.30). The possibility of using this higher price variability under perfect information therefore leads to an increased short-term storage of the rather shelf-stable concentrate *UHT–Combi–HHT–35%*.

3.5.2.2 Value of shelf life

We analyze the economic value of shelf life provided by powders for both *a priori* perfect price knowledge and price predictions with futures. The aim is to gain managerial insights into whether the long-storage option for powders, which enables the dairy plant to better exploit price variabilities, has a significant economic value. This value of shelf life is lost if producers change from powders to concentrates. In order to determine the value of shelf life, the production of skim milk powders is restricted to an upper limit (β_g) of the production volume in each period, i.e., from 100% to 0% in 25% steps. Figure 3.5 illustrates the resulting relative profits and the product mix for different powder production limits based on *a priori* perfect price knowledge and on price predictions with futures.

The two price scenarios lead to significant differences in profit, as upcoming price fluctuations are only captured to a limited extent by price predictions with futures. For unlimited use of powders ($\beta_{powder} = 1$), the difference is the highest. It amounts to 38.5% of the objective value based on *a priori* perfect price knowledge. This value can be interpreted as the expected value of perfect information (EVPI), i.e., the willingness of a decision maker to pay for perfect information on upcoming prices. Even for product mixes without powders ($\beta_{powder} = 0$), there exists a large profit gap.

For *a priori* perfect price knowledge, the optimal share of powder production amounts to 23.0%. When restricting the upper limit of powder production to zero, production of the 50-days-storable concentrate *UHT–Combi–HHT–35%* increases from 14.4% to 20.2% with the rest being replaced by the less shelf-stable concentrate *Combi–Past–35%*. Profit decreases significantly. Powders have a potential economic value of 34.5%. This shows a potentially large impact of shelf life on the economic performance. In contrast, price predictions based on futures result in an optimal powder share of only 9.6%. When restricting the powder production to zero,

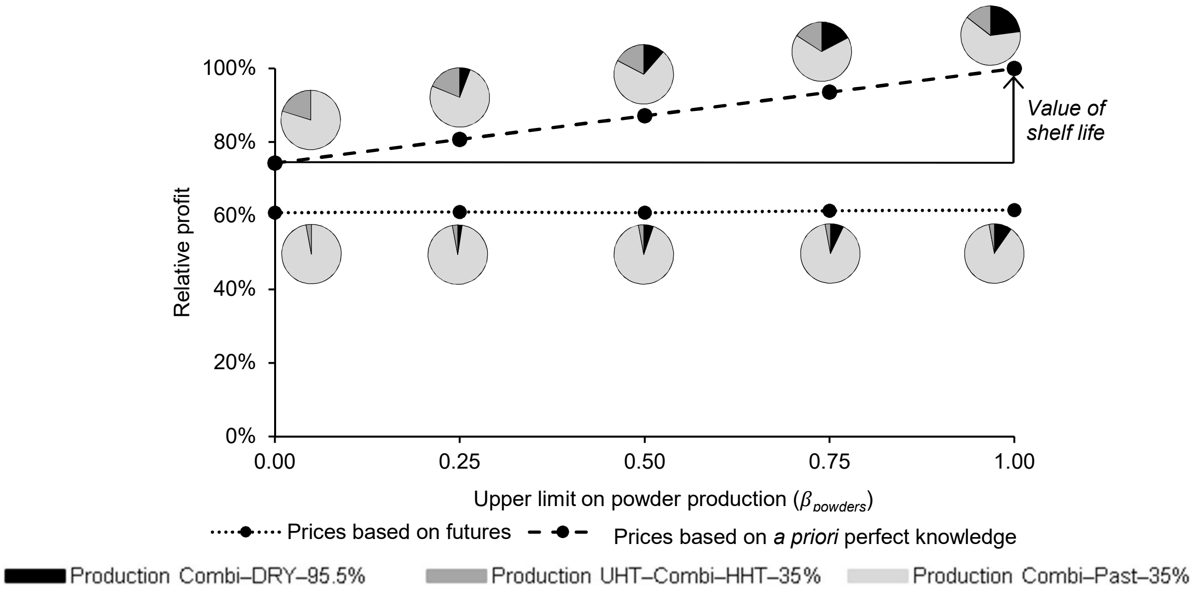

Figure 3.5: Economic value of shelf life. Pie charts indicate share of production volumes over all periods of the planning horizon.

this powder share is replaced exclusively by the production of the less shelf-stable concentrate *Combi-Past–35%.* The economic value of shelf life amounts to merely 1.1%.

We additionally test the effect of not allowing any storage, which is equivalent to using a naïve price forecast. We find that an 8.0% lower profit is realized than with futures as price predictors, implying that predictions with futures are nonetheless valuable.

Overall, our results for this case show that the value of shelf life strongly depends on the forecast accuracy. In the realistic case, in which only limited price information is available, concentrates are selected over powders. If price indicators such as futures are used, the economic value of shelf life is not a strong argument against the substitution of powders with more environmental-friendly concentrates.

3.5.3 Trade-off between economic and environmental objectives

Next, we include the environmental objectives in the analyses. In the following tests, futures are used as price predictors and no upper limit on the production of a specific product type is assumed. After optimizing each objective separately, the δ-error method is applied to identify trade-offs between the different economic and environmental objectives. Figure 3.6 illustrates

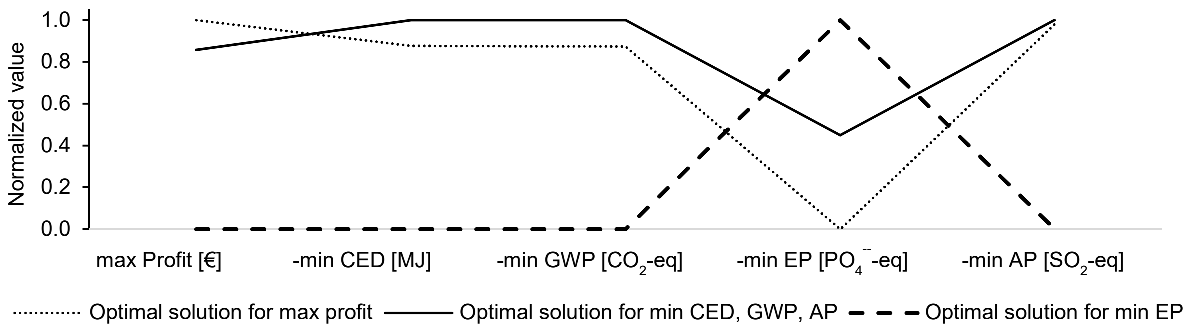

Figure 3.6: Parallel coordinates plot depicting the set of objectives in the horizontal axis and the normalized value of solutions in the vertical axis.

a parallel coordinates plot with the set of objectives on the horizontal axis and the normalized value attained by each solution on the vertical axis. The Pareto solutions are normalized to values between zero and one, based on Marler and Arora (2004). A value of one indicates the best objective value across the Pareto solutions for both maximization and minimization problems. Each line represents a different Pareto solution. The product mix obtained when maximizing profit in Section 3.5.2.1 results in the normalized objective values represented by the dotted line in Figure 3.6. The same Pareto solutions are reached when minimizing cumulative energy demand, global warming potential, and acidification potential (solid line). This solution represents a production of *Combi–Past–35%* in every period with immediate shipments. When minimizing eutrophication potential, *EV–Past–35%* is selected (dashed line). In both cases, the production of concentrates with a low shelf life is optimal. This stems from the use of more environmental-friendly processes (i.e., pasteurization) for low-shelf-life products and from omitting storage, which avoids additional environmental impacts.

To perform objective reduction according to the δ-error method, we analyze redundancies between objectives. There is a redundancy between cumulative energy demand, global warming potential, and acidification potential. Thus, the objective set can be reduced to the subset {profit, CED, EP} without losing any problem characteristics. When also removing cumulative energy demand from the subset, a δ-error of zero results, i.e., the dominance structure is not changed. Hence, a bi-criteria problem with the subset {profit, EP} is obtained.

When optimizing the bi-criteria problem, weighting is selected to determine intermediate solutions between the extreme points generated by single objective optimization. For this purpose, both objectives are normalized. Figure 3.7 illustrates a clear trade-off between profit and eutrophication potential. Here, EP* is defined as the share of eutrophication potential that the dairy plant can influence and thus excludes the fixed eutrophication potential originating from raw milk production. The weight of the profit is ω and the weight of the eutrophication potential is $1-\omega$.

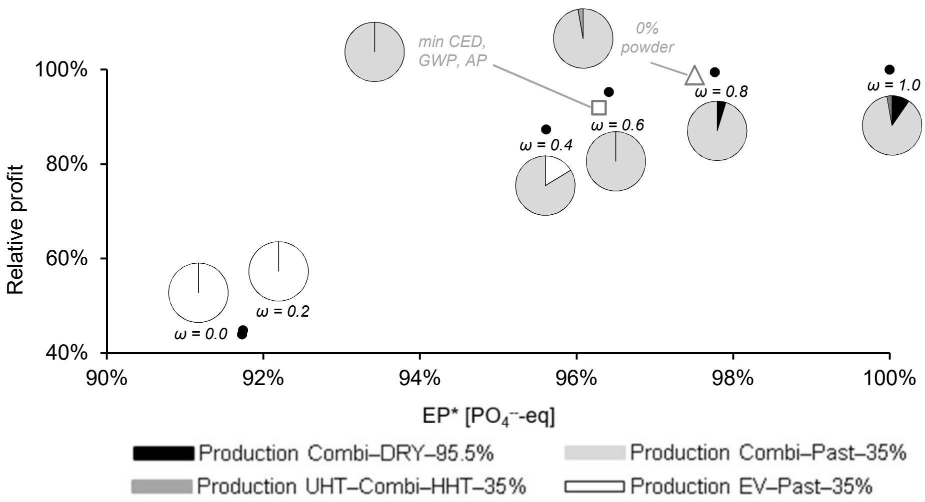

Figure 3.7: Trade-off between profit and eutrophication potential with futures as price predictors. Pie charts indicate shares of production volumes over all periods of the planning horizon.

By decreasing ω from 1 to 0, the initial product mix of *Combi–Past–35%*, *UHT–Combi–HHT–35%*, and *Combi–DRY–95.5%* is altered. At ω = 0.8, *UHT–Combi–HHT–35%* is eliminated and the production of *Combi–DRY–95.5%* is reduced, since both production and storage of longer shelf-life products cause additional eutrophication potential. At ω = 0.6, all powder production is eliminated. Only *Combi–Past–35%* is produced. The profit only decreases by 4.7% compared to the profit for ω = 1. Even if the shelf life of *Combi–Past–35%* is significantly lower, the profit decline is limited. The reason lies in the low value of shelf life. At ω = 0.4, a part of the *Combi–Past–35%* production is substituted by *EV–Past–35%*. Finally, at ω = 0.2 and ω = 0, the entire *Combi–Past–35%* production is substituted by *EV–Past–35%.* Such minimization of the eutrophication potential decreases profits substantially (56.0%) compared to the profit for ω = 1. Thereof, 51.3%-points can be attributed to the shift in the concentration technology from a combined concentration, i.e., reverse osmosis and subsequent evaporation, to exclusively evaporation. This shift is caused mainly by the effect of different energy sources on the indicator eutrophication potential. Reverse osmosis demands more electricity and less natural gas than evaporation. However, electricity provision produced with the German average composition, which contains a large share of electricity produced from lignite, contributes substantially to eutrophication.

Choosing evaporation over combined concentration is specific to the indicator eutrophication potential. Model results for the other environmental indicators favor, in line with the profit objective, concentrates produced with combined concentration. The optimal solution for the indicators cumulative energy demand, global warming potential, and acidification potential (see square in Figure 3.7) is to produce exclusively the pasteurized concentrate *Combi–Past–35%.* This solution differs from the solution for the bi-criteria problem at ω = 0.6 only by omitting short-term storage of the pasteurized concentrate. The profit decrease compared to the profit for $\omega = 1$ amounts to only 8.0%. This represents a dairy plant that switches from powders to concentrates and does not use futures as price predictors, but immediately sells the produced concentrates. In contrast, a dairy that replaces powders by concentrates but still maximizes profits using futures as price predictors, only faces a profit decrease of 1.1% (see triangle in Figure 3.7 and discussion in Section 3.5.2.2).

Overall, the analyses show that only two objectives (i.e., profit and eutrophication potential) are sufficient to capture the trade-offs in the present case. The minimization of the eutrophication potential leads to a significant profit reduction, mostly due to a shift in the concentration technology from a combined concentration to evaporation. Thus, a shift to solutions that minimize eutrophication potential is unrealistic in practice. However, the profit impact of the other environmental objectives is much less pronounced. In our case, environmental-friendly products have lower shelf lives. Yet, the economic value of the shelf life is low. Hence, we are able to determine a range of solutions that perform well with regard to both profit and the environment.

3.6 Conclusions

This study systematically analyzes the impact of shelf life on the trade-off between economic and environmental performance. We present a real-life case study for two types of dairy products that exemplifies the impact of shelf-life reduction due to sustainable processing. Namely, traditional milk powders are contrasted against novel milk concentrates, based on detailed economic and environmental data. Concentrates require less energy in processing, but have a shorter shelf life. Powders and concentrates can be produced in a multitude of processing variants, resulting in numerous different products.

We develop a sustainability evaluation framework. Part of this framework is a multi-objective optimization model covering profit and all relevant environmental indicators. It determines production, storage, and shipment quantities at the tactical planning level, at which the shelf lives of the considered products have their key impact. Our framework deals with product price uncertainty by updating information on prices in a rolling horizon scheme. Furthermore, we apply the δ-error method to identify trade-offs between objectives. The tactical planning results obtained over a historical period are then used to make strategic decisions on product and process selection.

From an economic perspective, the selection of different powders and concentrates is influenced by upcoming price developments. We use historical data on product prices in the years 2013 up to 2016. However, this price information is not known when the tactical planning is done. For comparison, we therefore use the corresponding prices for futures traded at the Eurex that are known at the time of planning and can thus serve as price predictors. For both price scenarios, powders are selected if prices are expected to rise in the future. Novel, more environmental-friendly concentrates that go along with a reduction of product shelf life are selected if prices are predicted to remain stable or fall. The two price scenarios result in large differences in storage and shipment volumes because upcoming price fluctuations are not fully captured by price predictions with Eurex futures.

We also quantify the value of shelf life to gain managerial insights into whether the long-storage option for powders has significant economic value. The numerical results show that, based on *a priori* perfect price knowledge, profit can be increased by as much as 34.5% when including powders in the product mix. However, this value of shelf life generated by powders depends strongly on the forecast accuracy. In the realistic case in which futures are used as price predictors, the advantage of powders is reduced to only 1.1%. Our analysis therefore shows that the economic value of shelf life is not a strong argument against the substitution of long-shelf-life products with more environmental-friendly low-shelf-life products.

Only two objectives (i.e., profit and eutrophication potential) are sufficient to capture the trade-offs in the presented case. The other three environmental objectives (i.e., cumulative energy demand, global warming potential, and acidification potential) are reduced without a δ-error. Results for the two objectives profit and eutrophication potential differ significantly in their optimal product mix and related indicator performance. While the maximization of profit leads to a selection of powders and concentrates produced with combined concentration (i.e., reverse osmosis and subsequent evaporation), the minimization of eutrophication potential leads to a selection of solely low-shelf-life concentrates produced with evaporation. However, profit decreases substantially if evaporation is used instead of combined concentration. A solution resulting from the minimization of eutrophication potential is therefore unrealistic in practice. However, for the minimization of all other environmental objectives, concentrates produced with combined concentration are selected, resulting in a much smaller profit decrease. Hence, we are able to determine a range of solutions that perform well with regard to both economic and most environmental objectives.

In further research, different methodologies could be developed for evaluating the impact of shelf life on economic performance under price uncertainty. Developing an analytical approach would especially be interesting. This work could build on previous analytical research that investigated economic value of storage capacity. Methods for objective reduction also deserve further consideration. A comparison could be carried out between the results achieved with different objective reduction methods. Further research could also extend the numerical analyses to using different price predictions for final product prices.

Finally, further research could also extend the numerical analyses by investigating other types of products. In particular, it would be interesting to analyze products with even lower shelf lives. Here, the differences in shelf life have their main impact at the short-term, operational planning level. The key challenge then relates to finding ways to draw strategic decisions on product selection based on results obtained at this operational planning level.

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Chapter 4. Setups and cleanings in lot sizing and scheduling

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Abstract

Much attention in the lot sizing and scheduling literature has been focused on reducing the number and size of setups. Cleanings, in contrast, remain a key cost driver in large parts of the process industries such as the food and pharmaceutical sectors. Here, quality and safety considerations lead to a diversity of cleaning requirements. A prerequisite for an efficient use of resources is an accurate representation of the constraints imposed by the different setups and cleanings. In this paper, we therefore first develop a general classification scheme for setups and cleanings. Three different classes are identified: batch-, time-, and volume-dependent setups and cleanings. The classes are further differentiated based on their separability, substitutability, reference point, flexibility, product dependency, and batch-size dependency. Secondly, we develop a generic optimization model for lot sizing and scheduling in the typical process-industry setting of flowshops, accurately representing all setup and cleaning classes. Thirdly, we apply the model to the case of cheese production in no-wait flowshops, demonstrating the adaptability of the generic model to industry-specific settings as well as the computational efficiency of the approach. The results show that significant reductions in machine downtime and makespan are achieved. Finally, our numerical tests provide insights into the extent to which a misidentification of cleaning classes may decrease scheduling flexibility and impair solution quality. Our results also show the benefits of considering the heterogeneity in processing times, which can be used to compensate for setup- and cleaning-time differences during successive production stages.

4.1 Introduction

In the design and operation of production systems, a significant effort is normally made to reduce the amount of non-value-adding activities. Recent developments for instance include reducing changeover time by conducting setups simultaneously with production activities (Allahverdi and Soroush, 2008). However, in the process industries, changeovers mainly consist of cleanings. They must be performed while production is stopped. Quality and safety regulations, for instance in the pharmaceutical, chemical, and food sectors, also prevent significant reduction. Cleanings cause long downtimes for machines, waste material, and consume energy, water, and cleaning agents. Together, these are key cost drivers in industries often characterized by high volumes and low profit margins. For lot sizing and scheduling in the process industries, it is therefore fundamental to account for cleanings in addition to setups.

There are many different classes of setups and cleanings that require different approaches in lot sizing and scheduling. Among these are setups and cleanings when switching between two product batches and those when a certain production time or volume has been reached. Furthermore, setup and cleaning classes are often interrelated. Cleanings of different intensities may, for instance, be substitutable. A systematic classification of cleanings and their specific characteristics is however lacking. Such a classification is prerequisite for developing a generic lot sizing and scheduling approach for setups and cleanings. Only a correct representation of the constraints that setups and cleanings impose enables an efficient use of resources. An incorrect formulation leads either to infeasibility or suboptimality. In particular, a formulation that is too rigid reduces problem complexity but also over-constrains the solution space. As a result, the lot sizing and scheduling problem solution cannot exploit the actual flexibility of the manufacturing system. In the application of the modeling approach, the correct identification of the setup and cleaning classes is crucial.

In the process industries, the prevalent type of production systems are flowshops. On an aggregate level, process industry production systems are often modelled as two-machine flowshops. The first machine may for example reflect continuous processing, whereas the second machine may reflect the transfer of the continuous flow into a flow of discrete units. An example of such flowshops are make-and-pack systems, frequently used in the production of consumer goods. The development of a generic lot sizing and scheduling approach covering setups and cleanings in two-machine flowshops can therefore be applied in many process industry settings. Moreover, it can easily be extended to multiple machines by re-utilizing the modelling concepts that link the production stages.

Extensive cleaning requirements typify the food sector. Important aspects for lot sizing and scheduling in this industry include precedence relationships among products, heterogeneous processing times, as well as a variety of setups and cleanings. The example of cheese production exhibits a combination of the characteristics. Cleanings consume a significant share of the of the available production time (typically more than 20%). Several types of cleanings are required, for example, when switching between products and after a certain production time. As the core processes for cheese production can be modelled as a two-machine flowshop with setups and cleanings, this environment is a suitable illustration for the lot sizing and scheduling approach presented in this paper. However, also problem specifics exist, for which a generic modelling approach must be adapted. In cheese production, a no-wait condition applies between the production stages and the usage of forms, into which the cheeses are filled, is an important consideration.

The main contributions of this paper are (i) the development of a classification scheme for setups and cleanings; (ii) the development of an adaptable Mixed Integer Linear Programming (MILP) model for lot sizing and scheduling of flowshops with comprehensive representation of setups and cleanings, including their interrelationships; (iii) the application of the model to a real case at a medium-sized German cheese dairy with additional no-wait condition and capacity restriction on form usage; and (iv) the analysis of the value of the approach depending on the flexibility in scheduling cleanings and the heterogeneity of the processing times.

The remainder of the paper is organized as follows. Section 4.2 presents the developed classification scheme for setups and cleanings. Note that the term "changeovers" is synonymous with "setups and cleanings" in the paper. Section 4.3 outlines the related literature. Section 4.4 presents the developed modeling approach. The application of the model to cheese production is described in Section 4.5, including supplementary modeling that captures industry-specific requirements. Furthermore, the developed approach is solved for a case study at a medium-sized German cheese dairy and numerical analyses are carried out. Finally, Section 4.6 concludes the paper and outlines further research directions.

4.2 Classification scheme for changeovers

We develop a general classification scheme for changeovers. The classification scheme is inspired by classifications presented in several reviews on scheduling with setup operations. Allahverdi et al. (1999, 2008) distinguish setups for batch (family) operations and non-batch (individual jobs) operations, as well as sequence-independent and sequence-dependent setups. Yang (1999) also considers the separability of setup operations. Cheng et al. (2000) include removal activities after production operations, which are typical in discrete manufacturing flowshops. Finally, Floudas and Lin (2004) focus specifically on chemical processes, for which they also consider time- and frequency-dependent setups. To summarize, some differentiating setup

Table 4.1: Classification scheme for changeovers.

Characteristic	Abbreviation	Potential value	Changeover class: Batch (B)	Time (T)	Volume (V)
General					
Separability	{Sep}	•inseparable (insep)	X	X	X
		•separable (sep)	X	X	X
Substitutability	{Sub}	•insubstitutable (insub)	X	X	X
		•within class (wc)	X	X	X
		•across classes (ac)	X	X	X
		•within and across classes (wac)	X	X	X
Reference point	{Ref}	•start/finish of batch (sfb)	X	-	-
		•start of production (sop)	-	X	X
		•last changeover (lc)	-	X	X
		•fixed time point (ftp)	-	X	X
Flexibility	{Flex}	•exact (ex)	X	X	X
		•maximum (max)	X	X	X
		•time window (tw)	X	X	X
Changeover matrix: time/costs					
Product dependency	{Prod}	•product(s) independent (pi)	X	X	X
		•predecessor product dependent (ppd) family (f)/ no family (-f)	X	-	-
		•successor product dependent (spd) family (f)/ no family (-f)	X	-	-
		•product sequence dependent (seqd) family (f)/ no family (-f) natural seq. (ns)/ no natural seq. (-ns) triangular inequality kept (Δ)/ violated (-Δ)	X	-	-
		•predecessor products history (pph)	-	X	X
Batch-size dependency	{Size}	•batch-size(s) independent (bi)	X	X	X
		•predecessor batch-size dependent (pbd)	X	-	-
		•successor batch-size dependent (sbd)	X	-	-
		•pred. and succ. batch-size dependent (psbd)	X	-	-
		•predecessor batch-sizes history (pbh)	-	X	X

characteristics have been considered, but none of these reviews has developed a comprehensive classification scheme for changeovers. Amongst other things, the existing schemes cannot be used to capture the scheduling-relevant characteristics of cleanings. Our scheme is a new and unique way of classifying changeovers. The scheme includes characteristics that have not been captured in other schemes, like substitutability, reference point, flexibility, and batch-size dependency.

Table 4.1 presents the classification scheme developed for changeovers. Each changeover belongs to a certain class or combination of classes (B, T, and/or V), has some general characteristics, as well as characteristics related to the changeover matrix in terms of time and/or costs. The classification scheme characterizes changeovers on single machines. A scheduling problem will often include several machines that can each have multiple changeovers of different classes. This also means that even though a potential scarcity of machine capacities or of changeover resources (e.g., human operators) is an important consideration in scheduling problems (cf.

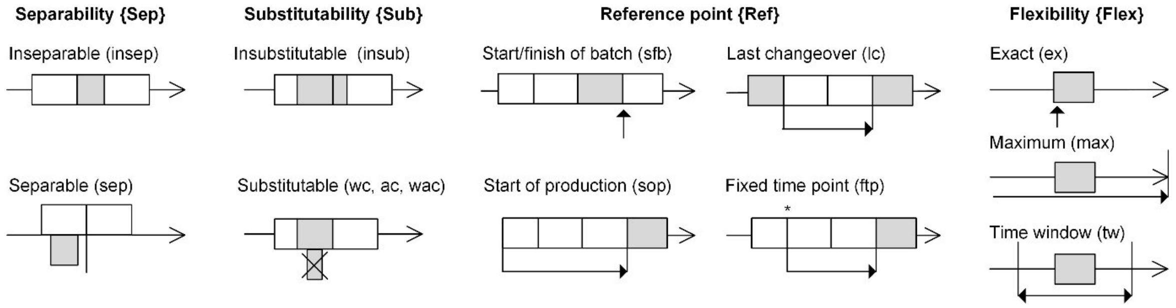

Figure 4.1: Representation of general changeover characteristics.

Tempelmeier and Buschkühl, 2008; Tempelmeier and Copil, 2015), it is not considered in the classification of individual changeovers.

Changeover classes. Three changeover classes are identified in Table 4.1. A batch-dependent changeover (B) may be required when switching between batches. The changeovers can also depend on time or production volume. Time-dependent changeovers (T) are, for example, common in the food industry, in which machines are frequently cleaned at the end of the day to meet hygiene regulations. For volume-dependent changeovers (V), the changeover requirements depend on the produced volume or the frequency of use. These are, for example, often scheduled in the chemical industry after a specific number of batches to prevent buildup of impurities in processing items. Combined time and volume dependency of changeovers is also possible. For example, fouling of pipelines in the process industries could depend on both the time and the volume of product pumped.

General changeover characteristics. Figure 4.1 shows a graphical representation of general changeover characteristics.

Changeovers are classified as inseparable or separable based on their *separability*. Inseparable changeovers require the machine to be idle during the changeover, which is typical for the process industries. Separable changeovers, on the other hand, are prepared offline. These are common in discrete manufacturing. For instance, machine tools are often prepared offline in electronics assembly. However, they also arise in the process industries. An example is cheese production in which cheese forms are cleaned offline. For the just-in-time tool single-minute exchange of die (SMED), inseparable and separable (or internal and external) changeovers are distinguished and as much of the changeover operations as possible are treated as separable while running the machines (Shingo, 1985).

All changeovers are classified based on their *substitutability*. Changeovers may be insubstitutable, i.e., the changeover must take place and may not be substituted by any other changeover. A hierarchical structure may also be imposed on changeovers, leading to potential changeover substitutions. A matrix containing all of the changeovers can represent the changeover hierarchy. Changeovers may be substitutable within a class. For example, a time-dependent changeover that is scheduled every second hour may be substituted with a daily time-dependent changeover. Furthermore, changeovers may be substitutable across classes. For example, in the food industry, a less intensive batch-dependent cleaning may be substituted with an intensive time-dependent cleaning. Finally, changeovers may be substitutable within and across classes, e.g., a time dependent changeover may be substituted with another time-dependent changeover and also with a volume-dependent changeover.

The starting time of a changeover is based on a *reference point*. The starting time for batch-dependent changeovers is always based on the start or finish of a batch. For time- and volume-dependent changeovers on the other hand, the starting time is based on start of production, start of last changeover, or on a fixed time point. The fixed time point is for example the start of planning horizon. The start of production and start of planning horizon are the same for problems with makespan minimization.

All changeovers are also classified based on the *flexibility* of their starting time. Changeovers may require an exact starting time with no flexibility. These are, for example, representative for food production, in which time-dependent cleanings take place at the end of each production day. Changeovers may also be more flexible, i.e., there may be an upper bound on the starting time (maximum) or both upper and lower bounds (time window).

Changeover-matrix characteristics. Figure 4.2 shows a graphical representation of the characteristics related to the structure of the changeover matrix. The changeover-matrix characteristics can both be in terms of time and/or costs. The time and costs required to set up or clean a machine are known as the changeover time and costs, respectively. They do not necessarily have the same changeover-matrix characteristics.

Depending on their *product dependency*, changeovers may be independent of the produced product(s) as is frequently the case for time- and volume-dependent changeovers, but also for batch-dependent changeovers. Batch-dependent changeovers may also depend on the predecessor or successor batch. Family structure is a property of predecessor- and successor-dependent changeovers. Changeovers are minor when switching between products of the same family and major when switching between families. Furthermore, batch-dependent changeovers may be

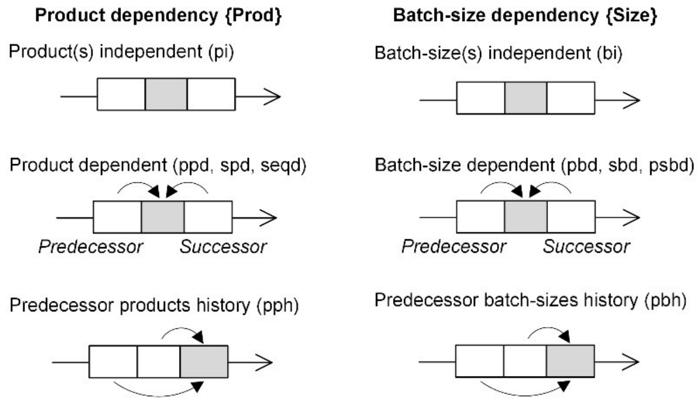

Figure 4.2: Representation of changeover-matrix-related characteristics.

product sequence dependent in which case they depend on both the predecessor and successor batch. Sequence dependency is one of the basic characteristic of the process industries (Kallrath, 2002). Yoghurt production is a good example of a production system with sequence dependency. When switching between products with different colors or flavors, cleaning techniques like cleaning, rinsing, or pushing depend on the preceding and succeeding products (Berlin et al., 2007). For example, an intensive cleaning technique is required when dark colored products precede light colored ones. Sequence-dependent changeovers have three properties. Family structure, the first property, has been described. Natural sequence between products, such as brighter to darker color, natural to stronger taste, or weaker to stronger microbiological contamination, is the second property of sequence dependency. Sorting products based on a natural sequence therefore reduces the required cleaning processes. Block planning, for example, exploits family structures and natural sequences of products for a simplified modeling approach (e.g., Lütke Entrup et al., 2005; Günther et al., 2006). The third property of sequence dependency is triangular inequality. Triangular inequality is retained for most production environments. In this case, the changeover time between any two products is always less than that when a third product is produced between the two. For non-triangular changeovers, an intermediate product (often of lower grade) is produced between certain products to absorb contamination (Menezes et al., 2011). A minimum lot size is usually required for the intermediate product. Production of animal nutrition is a good example in which non-triangular cleanings apply (Clark et al., 2010). Claassen et al. (2016) also show that the optimal production schedule can vary significantly when including non-triangular changeovers. Finally, time- and volume-dependent changeovers may also depend on the history of the products being produced. For example, in meat processing, the knife wear may depend on the product types being produced.

Changeovers may be batch-size(s) independent or dependent depending on their *batch-size dependency*. For batch-size-independent changeovers, changeover duration does not depend on the batch size. For batch-size-dependent changeovers, changeover duration depends on the batch size of the predecessor, successor, predecessor and successor, or the predecessor batch-sizes history. For example for a large successor lot, more packaging material must be prepared leading to a longer setup time.

Classification. All changeovers can be classified according to the classification in Table 4.1, i.e., based on their class (B, T and/or V), their general characteristics (*Sep/Sub/Ref/Flex*), as well as changeover-matrix characteristics with regard to time *t*(*Prod/Size*) and costs *c*(*Prod/Size*). The classification of a changeover then takes the form

Class; (Sep/Sub/Ref/Flex); t(Prod/Size); c(Prod/Size).

Next, we illustrate the classification with two examples from the food industry. In this industry, changeovers often take the form of time-dependent cleanings done on the machines at the end of a production day. Assuming that this cleaning is substitutable across classes, with product- and batch-size-independent changeover matrix defined for times, its classification takes the form *T; (insep/ac/ftp/ex); t(pi/bi); c(-/-)*. The second example concerns a typical changeover from one product to another on a production line. This is often an inseparable and insubstitutable sequence-dependent batch changeover. If we assume a changeover matrix defined for costs, without a family structure or natural sequence, in which triangular inequality is maintained, and which is batch-size independent, then this changeover is classified as *B; (insep/insub/sfb/max); t(-/-); c(seqd(-f;-ns;∆)/bi)*.

4.3 Related literature

The developed classification scheme can be used to facilitate the representation of changeovers when modeling lot sizing and scheduling problems. Our paper focuses on classifying and modeling changeovers with a particular focus on cleanings. Therefore, we have organized our literature review to first cover flowshops, the production environment, in which cleanings are most relevant. Due to their particular relevance for the case, we focus on no-wait flowshops. The second part reviews papers, which cover several changeover classes.

4.3.1 Simultaneous lot sizing and scheduling of flowshops

Lot sizing and scheduling problems have been extensively researched in the academic literature both independently and together. Lot sizing addresses timing and production amounts for satisfying demand over a time horizon (see the review by Buschkühl et al., 2010). Scheduling addresses sequencing of production activities (see the process industry reviews by Kallrath, 2002; Méndez et al., 2006). As a result of sequence-dependent changeover times, different classes of changeovers, due dates, demand fluctuations, and tight capacities, lot sizing and scheduling problems are strongly interrelated and must be made simultaneously.

Two research communities in particular have developed mathematical models for simultaneous lot sizing and scheduling: the Operations Research (OR) community and the Process Systems Engineering (PSE) community (Amorim et al., 2013c). Approaches can be classified by their time representation into discrete- and continuous-time models. For discrete-time representation, all activities are scheduled on a discrete time scale in which the planning horizon is divided into a finite number of time intervals. The discrete-time formulations from the OR community are clustered into small and big bucket formulations, both aimed at minimizing inventory and setup costs (see the review by Copil et al., 2017). For continuous-time representation, all activities are scheduled accurately on a continuous time scale. There are also mixed models, which combine continuous- and discrete-time formulations. The block planning formulation is one of these. The choice of an appropriate time representation is a key issue, which must be addressed with the specific characteristics of the production system in mind.

Flowshop scheduling has received much attention in literature (see e.g., the reviews by Gupta and Stafford, 2006; Hejazi and Saghafian, 2005). However, to the best of our knowledge, lot sizing and scheduling of flowshops with a systematic analyses of changeovers has not been investigated in the literature. No-wait flowshops, which form an important cluster of flowshops, have been studied extensively over the past few decades (see the reviews by Allahverdi, 2016; Hall and Sriskandarajah, 1996). However, only a few studies have addressed simultaneous lot sizing and scheduling of no-wait flowshops. The studies by Sriskandarajah and Wagneur (1999), Lin and Cheng (2001), and Wang and Cheng (2006) develop solution methods for the simultaneous lot sizing (batching) and scheduling of two-machine no-wait flowshops with sequence-independent setup times. Furthermore, Kumar et al. (2000) and Kim and Jeong (2009) develop genetic algorithms for m-machine no-wait flowshops with sequence-independent setups. Also, Hall et al. (2003) develop a dynamic programming algorithm for lot sizing and scheduling of m-machine no-wait flowshops with sequence-dependent setup times. All the analyzed

Table 4.2: Overview of changeovers in the literature on lot sizing and scheduling in the food industry involving several changeover classes.

Publication	Application	Method	Time repr.	Objective	Changeover classification: Class	General characteristics (Sep/Sub/Ref/Flex)	Changeover-matrix characteristics Time(Prod/Size)	Changeover-matrix characteristics Costs(Prod/Size)
Kopanos et al. (2012)	Ice-cream	MILP	Cont.	Min make-span	B; B; T; T;	(insep/insub/sfb/max); (insep/insub/sfb/max); (insep/insub/ftp/ex); (insep/insub/ftp/ex);	t(seqd(-f;ns;Δ)/bi); t(seqd(-f;ns;Δ)/bi); t(pi/bi); t(pi/bi);	c(-/-) c(-/-) c(-/-) c(-/-)
Van Elzakker et al. (2012)	Ice-cream	MILP	Cont.	Min make-span	B; B; T;	(insep/insub/sfb/max); (insep/insub/sfb/max); (insep/insub/sop/tw);	t(seqd(-f;-ns;Δ)/bi); t(seqd(-f;-ns;Δ)/bi); t(pi/bi);	c(-/-) c(-/-) c(-/-)
Doganis and Sarimveis (2007)	Yoghurt	MILP	Mix	Min costs	B; T;	(insep/ac/sfb/max); (insep/ac/ftp/ex);	t(seqd(-f;ns;Δ)/bi); t(pi/bi);	c(seqd(-f;ns;Δ)/bi) c(-/-)
Doganis and Sarimveis (2008)	Yoghurt	MILP	Mix	Min costs	B; T;	(insep/ac/sfb/max); (insep/ac/ftp/ex);	t(seqd(-f;ns;Δ)/bi); t(pi/bi);	c(seqd(-f;ns;Δ)/bi) c(-/-)
Kopanos et al. (2010)	Yoghurt	MILP	Mix	Min costs	B; T; T;	(insep/ac/sfb/max); (insep/ac/ftp/ex); (insep/ac/ftp/ex);	t(seqd(f;ns;Δ)/bi); t(pi/bi); t(pi/bi);	c(seqd(f;ns;Δ)/bi) c(-/-) c(-/-)

Kopanos et al. (2011)	Yoghurt	MILP	Mix	Min costs	B;
					B;
					T;
					T;
						(insep/insub/sfb/max);
						(insep/insub/sfb/max);
						(insep/insub/ftp/ex);
						(insep/insub/ftp/ex);
							t(seqd(f;ns;Δ)/bi);
							t(spd(-f)/bi);
							t(pi/bi);
							t(pi/bi);
								c(seqd(f;ns;Δ)/bi)
								c(-/-)
								c(-/-)
								c(-/-)

Kilic (2011)	Milk	MILP, constr. progr.	Cont.	Min make-span	B; T; T;	(insep/insub/sfb/max); (insep/insub/lc/max); (insep/insub/lc/max);	t(seqd(f;ns;Δ)/bi); t(pi/bi); t(pi/bi);	c(-/-) c(-/-) c(-/-)
Günther et al. (2006)	Scalded sausage	MILP	Mix	Max margin	B; T;	(insep/insub/sfb/max); (insep/insub/ftp/ex);	t(seqd(f;ns;Δ)/bi); t(pi/bi);	c(-/-) c(-/-)

This paper (2017)	Cheese	MILP	Cont.	Min make-span	B;
					T;
					V;
						(insep/insub/sfb/max);
						(insep/*/*/*);
						(insep/*/*/*);
							t(*/*);
							t(pi/bi);
							t(pi/bi);
								c(-/-)
								c(-/-)
								c(-/-)

* Different combinations of characteristics are analyzed.

studies minimize the makespan or maximum lateness, because time is commonly the principal criteria for no-wait flowshops. Furthermore, all of the studies only include one class of changeover and therefore none of the studies systematically addresses different changeovers.

4.3.2 Lot sizing and scheduling involving several changeover classes

In the food industry, scheduling of setups and especially cleanings plays a central role due to extensive hygienic requirements. In the following, we therefore focus on lot sizing and scheduling studies from the food industry in which two or more classes of changeovers are modeled. Table 4.2 presents an overview of the studies based on their application, method, time representation, objective, and changeover classification. Studies of integrated production scheduling and distribution are excluded.

Most of the reviewed papers are from the dairy industry, as there is an increasing interest in investigating changeovers in scheduling approaches from this sector. All papers apply MILP models, and Kilic (2011) also applies constraint programming. Furthermore, two approaches are based on block planning (see the papers by Kilic, 2011; Günther et al., 2006). All of the papers address lot sizing and scheduling; however in Kilic (2011) and Kopanos et al. (2012), it is not carried out simultaneously. Rather, lot sizing is carried out a priori. Either continuous- or mixed-time formulations are applied in the models. The objectives of the models include cost minimization, contribution margin maximization, and makespan minimization.

The changeover classification of the analyzed studies is described next. All of the papers study two changeover classes, i.e., batch- and time-dependent changeovers. Only our paper analyses volume-dependent changeovers. All of the papers focus on inseparable cleanings, because inseparability is common for cleanings. The studies by Doganis and Sarimveis (2007, 2008) and Kopanos et al. (2010, 2011) include substitution across classes. However, only time-dependent changeovers with exact starting times (like daily setup/shutdown) substitute batch-dependent changeovers, assuming that the equipment is clean when production is started on a new day. In our study, we incorporate substitution across classes that depends on the changeover duration. One other study on changeover substitution is found in the literature, see Gellert et al. (2011). They develop a genetic algorithm for scheduling yoghurt production and analyze changeover substitution across batch and time classes. However, this study does not address lot sizing and is therefore excluded from the literature overview.

The batch-dependent changeovers are almost all sequence dependent with diverse changeover-matrix structures. The models that minimize costs include changeover-matrix characteristics related to both time and costs. Many studies analyze cases in which there is a natural sequence, or both natural sequence and family structure, among the products. All studies, except for ours, address only batch-size-independent changeovers. Kopanos et al. (2012) and Van Elzakker et al. (2012) each examine two separate batch-dependent changeovers: at the processing and packaging stages.

Time-dependent changeovers are analyzed in all of the papers. Most studies employ a reference point based on a fixed time point. In Van Elzakker et al. (2012), however, the reference point is based on start of production and in Kilic (2011) it is based on last changeover. Only our study addresses several reference points within the same changeover class, i.e., reference points based on a fixed time point and based on time since last changeover are modeled for time-dependent changeovers. With regard to flexibility, only our paper and the papers by Van Elzakker et al. (2012) and Kilic (2011) study time-dependent changeovers that are scheduled within a specific time window or a maximum upper bound. On the other hand, time-dependent changeovers with exact starting times are analyzed in many papers by reducing the daily production time by the changeovers time (for example, see the papers by Doganis and Sarimveis, 2007, 2008).

Kopanos et al. (2010, 2011) study two separate time-dependent changeovers for a yoghurt packaging line including daily setup and daily shutdown.

There is a clear gap in the literature for a generic modeling approach addressing changeovers based on a systematic classification. As a consequence, none of the previous studies deals with (i) more than two changeover classes, (ii) volume-dependent changeovers, (iii) substitution of changeovers other than an exact time-dependent changeover substituting a batch-dependent changeover, or (iv) batch-size dependency of changeovers. Our study, in contrast, represents all changeover classes and different combinations of their characteristics in a simultaneous lot sizing and scheduling model.

4.4 Lot sizing and scheduling of flowshops

4.4.1 Model overview

We develop a generic MILP model for lot sizing and scheduling of two-machine flowshops. The model provides the core structure for modeling changeovers. When the model is applied in a specific context, it will often be necessary to extend the model such that other aspects than changeovers are included. This can easily be done because of the adaptable and declarative nature of the approach.

Lot sizing and scheduling is conventionally studied using models that trade-off between inventory and setup costs. However, minimizing inventory and setup costs is only suitable if the costs can be identified as out-of-pocket costs for the individual products (Günther, 2014). Furthermore, inventory costs are often low for scheduling problems that typically have short planning horizons, and personnel costs often dominate setup costs. Hence, our objective is to minimize the makespan over a short horizon. Here, we also avoid idle times on machines, which occasion additional cleanings. A sequence-based, continuous-time representation is selected to allow precise scheduling of all activities and due to its flexibility in incorporating different changeovers. Discrete-time formulations are often created in a relatively straightforward manner; however, they are difficult to use in many industrial projects as they often result in large combinatorial problems when selecting sufficiently small intervals.

Deterministic demand volumes of products must be fulfilled. The model determines the number, sequence, size, and starting times of lots as well as the changeovers. The number of potential lots per product is predetermined and may vary for different products. In practice, the number of potential lots per product can, for example, be determined as the maximum number of lots, over which the demand volume will be divided considering the changeover time and other influencing factors. The lots, which are moved through the system without overtaking each other, have heterogeneous processing times, precedence relationships, and due dates. Products are first loaded onto the first machine in lots and then processed there. Afterwards they are loaded onto the next machine.

The model addresses all of the changeover classes in Table 4.1, i.e., those containing batch-, time-, and volume-dependent changeovers. The focus is on the time dimension of the changeover-matrix characteristics, because of the makespan objective. Changeover resources are assumed to be uncapacitated, because the focus is on primary operations. All changeover classes are inseparable, which is common for this type of production environment. Substitution of changeovers on the same machine is incorporated across classes, depending on the changeover duration, meaning that shorter changeovers are substituted with longer ones.

Batch-dependent changeovers, *B; (insep/insub/sfb/max); t(seqd(-f;-ns;Δ)/bi); c(-/-)*, are required on the second machine. This is typical for many process industry problems such as those in which continuous volumes are transferred to discrete and format change is required in the second stage. The reference point for the batch-dependent changeovers is based on the start/finish of last batch and the starting time is within an upper bound (maximum). The model is developed for sequence-dependent changeovers, which is the most complicated case, so other product dependencies can be incorporated. A general changeover-matrix structure in terms of family, natural sequence, and triangular inequality is modeled. The model is developed for batch-size-independent changeovers. Model adjustments for batch-size-dependent changeovers, *B; (insep/insub/sfb/max); t(spd(-f)/sbd); c(-/-)*, are also shown.

We assume that there are time-, *T; (insep/ac/ftp/tw); t(pi/bi); c(-/-)*, and volume-dependent changeovers, *V; (insep/ac/ftp/tw); t(pi/bi); c(-/-)*, on the first machine. The changeovers occur within a specific time window, thereby exact and maximum criteria (upper bound) are also incorporated. An alternative formulation for exact time-dependent changeovers is also shown, *T; (insep/ac/ftp/ex); t(pi/bi); c(-/-)*. The reference point for the time- and volume-dependent changeovers is based on the start of planning horizon (fixed time point). For makespan minimization the start of planning horizon is the same as the start of production. How time-dependent changeovers can be modeled based on the time since last changeover, *T; (insep/ac/lc/max); t(pi/bi); c(-/-)*, is also shown. Figure 4.3 shows the connection between the product speed and changeovers for the two-machine configuration.

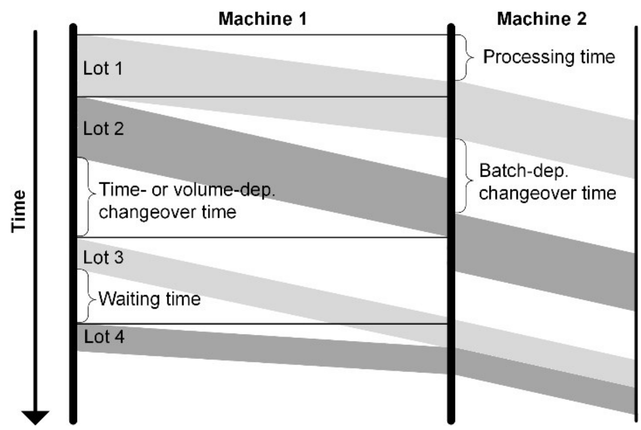

Figure 4.3: Representation of a two-machine flowshop.

4.4.2 Model formulation

The following notation is introduced for the model:

Indices and index sets

$p \in P$	product
$l \in L$	lot
$l \in L(p)$	lot belonging to product *p*
$a \in A$	time-dependent changeover
$b \in B$	volume-dependent changeover

Parameters

α_p	demand for product *p* [units]
β_l	minimum lot size of lot *l* [units]
γ_l	due date of lot *l* [time units]
$\delta_{ll'}$	= 1 if lot *l* must be produced after lot *l'* (0, otherwise)
ε	loading duration of one unit [time units]
ζ_l	processing time of lot *l* on machine 1 [time units]
η	lowest processing time of all lots on machine 1 [time units]
$\theta_{ll'}$	duration of sequence-dependent batch changeover between lot *l* and lot *l'* (*l* precedes *l'*) [time units]
κ	duration of time-dependent changeover [time units]
λ_a^{min}	earliest starting time of time-dependent changeover *a*—lower bound [time units]
λ_a^{max}	latest starting time of time-dependent changeover *a*—upper bound [time units]
μ	minimum number of time-dependent changeovers [changeovers]
ν	changeover interval for time-dependent changeovers [time units]
ξ	duration of volume-dependent changeover [time units]
o_b^{min}	earliest starting of volume-dependent changeover *b*—lower bound [units]
o_b^{max}	latest starting of volume-dependent changeover *b*—upper bound [units]

π	minimum number of volume-dependent changeovers [changeovers]
ρ	changeover interval for volume-dependent changeovers [units]
σ_l	batch-size coefficient
M_1, M_2	sufficiently large positive values

Decision variables

C^{max}	makespan [time units]
X_l	amount produced in lot *l* [units]
$S1_l$	starting time of loading lot *l* on machine 1 [time units]
$C1_l$	completion time of loading lot *l* on machine 1 [time units]
$S2_l$	starting time of loading lot *l* on machine 2 [time units]
$C2_l$	completion time of loading lot *l* on machine 2 [time units]
E_l	duration of batch-dependent changeover before lot *l* [time units]
N_a	starting time of time-dependent changeover *a* [time units]
Q_l	cumulated production amount after finishing lot *l* [units]
$Y_{ll'}$	= 1 if lot *l* processed before lot *l'* (0, otherwise)
K_{la}	= 1 if lot *l* scheduled immediately before time-dependent changeover *a* (0, otherwise)
H_{la}	= 1 if lot *l* scheduled before exact time-dependent changeover *a* (0, otherwise)
O_a	= 1 if time-dependent changeover *a* is scheduled last (0, otherwise)
V_{lb}	= 1 if lot *l* scheduled immediately before volume-dependent changeover *b* (0, otherwise)

The lot sizing and scheduling model is formulated as follows:

Objective function. The objective is to minimize the makespan (4.1).

$$Min\ C^{max} \tag{4.1}$$

subject to

Demand, lot size, makespan, due dates, and precedence relationships. Demand for a product must be fulfilled (4.2). A minimum lot size is introduced with constraints (4.3). If the triangular inequality is violated, then these constraints impose sufficient intermediate product lot sizes to absorb all contamination. This is generally modeled so that a minimum lot size is imposed on all lots and not just on the intermediate lot. Completion time of the last lot on the second machine determines the makespan (4.4). All lots belonging to the same product must be finished before the respective due date of the product (4.5), assuming this is feasible for all problem instances. Due dates are based on customer or downstream processing requirements, reflected for example in instructions from higher planning levels. If due dates are not available for some products, they are set to the end of the planning horizon. Constraints (4.6) model the precedence relationships among products. Alternatively, a large sequence-dependent batch changeover time can be set for these products.

$$\sum_{l \in L(p)} X_l \geq \alpha_p \quad \forall p \in P \tag{4.2}$$

$$X_l \geq \beta_l \quad \forall l \in L \tag{4.3}$$

$$C^{max} \geq C2_l \quad \forall l \in L \tag{4.4}$$

$$C2_l \leq \gamma_p \quad \forall p \in P, l \in L(p) \tag{4.5}$$

$$S1_{l'} \cdot \delta_{ll'} \leq S1_l \quad \forall l, l' \in L \tag{4.6}$$

Timing on machines. Constraints (4.7) define the completion times for loading on machine 1. Note that products are subsequently processed on machine 1 before arriving at machine 2. It is assumed that no changeovers occur before loading the first lot. Constraints (4.8) set the starting times for loading on machine 2. Constraints (4.9) define the completion times on machine 2.

$$C1_l = S1_l + \varepsilon \cdot X_l \quad \forall l \in L \tag{4.7}$$

$$S2_l \geq S1_l + \varepsilon + \zeta_l \quad \forall l \in L \tag{4.8}$$

$$C2_l = S2_l + \varepsilon \cdot X_l \quad \forall l \in L \tag{4.9}$$

Constraints (4.10, 4.11) define the starting times on machine 1, accounting for the waiting times resulting from differences in processing times. If negative values result, constraints (4.15, 4.16) prevent lots from starting earlier than the completion time of the previous lot. Constraints (4.10) apply if lot *l'* is produced after lot *l*, and constraints (4.11) if lot *l* is produced after lot *l'*. The constant M_1 represents the length of the planning horizon in time units. The variable $Y_{ll'}$ is always zero when $l = l'$ (4.12).

$$S1_{l'} \geq C1_l - (\zeta_{l'} - \zeta_l) - M_1 \cdot (1 - Y_{ll'}) \quad \forall l, l' \in L: (l \neq l') \tag{4.10}$$

$$S1_l \geq C1_{l'} - (\zeta_l - \zeta_{l'}) - M_1 \cdot Y_{ll'} \quad \forall l, l' \in L: (l \neq l') \tag{4.11}$$

$$Y_{ll'} = 0 \quad \forall l, l' \in L: (l = l') \tag{4.12}$$

Constraints for all changeover classes are formulated next.

Batch-dependent changeovers. Constraints (4.13, 4.14) define the starting times on machine 2, accounting for the duration of sequence-dependent batch changeovers. The batch-dependent changeovers can be changed to predecessor- or successor-dependent changeovers by changing the parameter $\theta_{ll'}$.

$$S2_{l'} \geq C2_l + \theta_{ll'} - M_1 \cdot (1 - Y_{ll'}) \quad \forall l, l' \in L: (l \neq l') \tag{4.13}$$

$$S2_l \geq C2_{l'} + \theta_{l'l} - M_1 \cdot Y_{ll'} \quad \forall l, l' \in L: (l \neq l') \tag{4.14}$$

The modeling of the batch-dependent changeovers can also be modified to include batch-size dependency. We show this for changeovers dependent on successor product and successor batch size. Predecessor batch-size-dependent changeovers can be modeled analogously. A continuous variable E_l, which defines the duration of changeover before lot *l*, is utilized. In constraints (4.13), the parameter $\theta_{ll'}$ is replaced by $E_{l'}$, and in constraints (4.14) the parameter $\theta_{l'l}$ is replaced by E_l. Furthermore, constraints (4.A1) are added to set value on the new variable. The duration of the changeover depends on the batch size of the lot and a batch-size coefficient (σ_l).

$$X_l \cdot \sigma_l \leq E_l \quad \forall l \in L \tag{4.A1}$$

Time-dependent changeovers. If a time-dependent changeover is scheduled on machine 1 (4.15, 4.16) and it is larger than the processing-time differences in constraints (4.10, 4.11), then the downtime on machine 1 must be larger or equal to the duration of the changeover.

$$S1_{l'} \geq C1_l + \kappa \cdot K_{la} - M_1 \cdot (1 - Y_{ll'}) \quad \forall l, l' \in L: (l \neq l'), a \in A \tag{4.15}$$

$$S1_l \geq C1_{l'} + \kappa \cdot K_{l'a} - M_1 \cdot Y_{ll'} \quad \forall l, l' \in L: (l \neq l'), a \in A \tag{4.16}$$

Constraints (4.17) determine the number of time-dependent changeovers, based on a fixed reference point (since start of planning horizon). Constraints (4.18) set the order of time-dependent changeovers (e.g., if second changeover is scheduled, then first changeover must be scheduled).

$$\sum_{l \in L} \sum_{a \in A} K_{la} \geq \frac{C^{max} - \lambda_1^{max}}{\nu} \tag{4.17}$$

$$\sum_{l \in L} K_{la} \geq \sum_{l \in L} K_{la'} \quad \forall a, a' \in A: (a < a') \tag{4.18}$$

The time-dependent changeovers are flexible, starting within their respective time windows (4.19, 4.20). Also, a value is set on the binary variable that indicates if changeover precedes a specific lot.

$$C1_l \leq \lambda_a^{max} + M_1 \cdot (1 - K_{la}) \quad \forall l \in L, a \in A \tag{4.19}$$

$$C1_l \geq \lambda_a^{min} - M_1 \cdot (1 - K_{la}) \quad \forall l \in L, a \in A \tag{4.20}$$

For time-dependent changeovers with only an upper bound (maximum), only constraints (4.19) are imposed. The upper and lower bounds are equal for exact time-dependent changeovers.

Alternatively, exact time-dependent changeovers can be modeled by substituting constraints (4.15–4.20) with constraints (4.B1, 4.B2).

$$C1_l \leq \lambda_a^{min} + M_1 \cdot (1 - H_{la}) \quad \forall l \in L, a \in A \tag{4.B1}$$

$$S1_l \geq \lambda_a^{min} + \kappa - M_1 \cdot H_{la} \quad \forall l \in L, a \in A \tag{4.B2}$$

In the following, we show an alternative formulation for time-dependent changeovers that are not based on time since start of planning horizon as a reference point, but rather time since last changeover with a maximum upper bound on the starting time (flexibility). Other flexibility characteristics can also be incorporated. Constraints (4.17, 4.19, 4.20) are substituted with constraints (4.C1–4.C7). The changeover frequency is set with constraints (4.C1–4.C3). Only one changeover is the last changeover (4.C4). Constraints (4.C5–4.C7) set the starting times of the changeovers and a value on the binary variable that indicates if changeover precedes a specific lot, similarly as in constraints (4.19, 4.20).

$$N_1 \leq \lambda_1^{max} \tag{4.C1}$$

$$N_{a+1} \leq N_a + \nu \quad \forall a \in A: (a < |A|) \tag{4.C2}$$

$$C^{max} \leq N_a + \nu + M_1 \cdot (1 - O_a) \quad \forall a \in A \tag{4.C3}$$

$$\sum_{a \in A} O_a = 1 \tag{4.C4}$$

$$N_a \leq M_1 \cdot \sum_{l \in L} K_{la} \quad \forall a \in A \tag{4.C5}$$

$$C1_l \leq N_a + M_1 \cdot (1 - K_{la}) \quad \forall l \in L, a \in A \tag{4.C6}$$

$$C1_l \geq N_a - M_1 \cdot (1 - K_{la}) \quad \forall l \in L, a \in A \tag{4.C7}$$

Volume-dependent changeovers. Volume-dependent changeovers are scheduled with constraints (4.21, 4.22), similar to the way time-dependent changeovers are scheduled. Substitution can take place between time and volume-dependent changeovers.

$$S1_{l'} \geq C1_l + \xi \cdot V_{lb} - M_1 \cdot (1 - Y_{ll'}) \quad \forall l, l' \in L: (l \neq l'), b \in B \tag{4.21}$$

$$S1_l \geq C1_{l'} + \xi \cdot V_{l'b} - M_1 \cdot Y_{ll'} \quad \forall l, l' \in L: (l \neq l'), b \in B \tag{4.22}$$

Constraints (4.23) set the number of volume-dependent changeovers, based on a fixed reference point. Formulation similar to that described for the time-dependent changeovers (4.C1–4.C7) can be developed for a reference point depending on volume since last changeover, but adjusted for volumes. Constraints (4.24) set the order of volume-dependent changeovers.

$$\sum_{l \in L} \sum_{b \in B} V_{lb} \geq \sum_{p \in P} \frac{\alpha_p}{\rho} \tag{4.23}$$

$$\sum_{l \in L} V_{lb} \geq \sum_{l \in L} V_{lb'} \quad \forall b, b' \in \mathrm{B}: (b < b') \tag{4.24}$$

The volume-dependent changeovers are flexible, i.e., scheduled within the upper and lower bounds (4.25, 4.26). For volume-dependent changeovers with only an upper bound (maximum), only constraints (4.25) are imposed. Upper and lower bounds are equal for exact volume-dependent changeovers.

$$Q_l \leq o_b^{max} + M_2 \cdot (1 - V_{lb}) \quad \forall l \in L, b \in B \tag{4.25}$$

$$Q_l \geq o_b^{min} - M_2 \cdot (1 - V_{lb}) \quad \forall l \in L, b \in B \tag{4.26}$$

Constraints (4.27, 4.28) set the cumulated production amounts. Constraints (4.29) enforce the cumulated amount of the first lot being greater than or equal to the production amount. Constraints (4.30) restrict the cumulated amount to be less than the total production amount.

$$Q_{l'} \geq Q_l + X_{l'} - M_2 \cdot (1 - Y_{ll'}) \quad \forall l, l' \in L: (l \neq l') \tag{4.27}$$

$$Q_l \geq Q_{l'} + X_l - M_2 \cdot Y_{ll'} \quad \forall l, l' \in L: (l \neq l') \tag{4.28}$$

$$X_l \leq Q_l \quad \forall l \in L \tag{4.29}$$

$$\sum_{l' \in L} X_{l'} \geq Q_l \quad \forall l \in L \tag{4.30}$$

Tightening constraints. Tightening constraints are introduced to reduce computational effort. A lower bound on the makespan similar to that in Kopanos et al. (2012) is introduced. The lower bound is calculated as the minimum processing time plus the net loading times plus a minimum duration of time- and volume-dependent changeovers (4.31). Waiting and sequence-dependent batch changeovers are not included, as they depend on the resulting schedule. Constraints (4.32) break the symmetries of lots of same product assuming that a lower indexed lot is produced first. Constraints (4.33) set the number of lots that immediately precede a changeover to at most one. Likewise, constraints (4.34) set the number of changeovers scheduled immediately after a lot to at most one.

$$C^{max} \geq \eta + \sum_{p \in P} \varepsilon \cdot \alpha_p + \mu \cdot \kappa + \pi \cdot \xi \tag{4.31}$$

$$Y_{ll'} = 1 \quad \forall l, l' \in L(p): (l < l') \tag{4.32}$$

$$\sum_{l \in L} K_{la} \leq 1 \quad \forall a \in A, \qquad \sum_{l \in L} V_{lb} \leq 1 \quad \forall b \in B \tag{4.33}$$

$$\sum_{a \in A} K_{la} \leq 1 \quad \forall l \in L, \qquad \sum_{b \in B} V_{lb} \leq 1 \quad \forall l \in L \tag{4.34}$$

Variable domains. Constraints (4.35, 4.36) define the variable domains of decision variables.

$$C^{max} \geq 0,\ X_l \geq 0,\ S1_l \geq 0,\ C1_l \geq 0,\ S2_l \geq 0,\ C2_l \geq 0,\ E_l \geq 0,\ N_a \geq 0, \\ Q_l \geq 0\ \forall l \in L, a \in A \tag{4.35}$$

$$Y_{ll'} \in \{0,1\},\ K_{la} \in \{0,1\},\ H_{la} \in \{0,1\},\ O_a \in \{0,1\},\ V_{lb} \in \{0,1\} \quad \forall l, l' \in L, \\ a \in A, b \in B \tag{4.36}$$

The developed model comprehensively covers all changeover classes and their various characteristics. On machine 2, batch-dependent changeovers (4.13, 4.14) are scheduled between successive lots. The changeover interactions of time- and volume-dependent changeovers on machine 1 are modeled through substitution across classes. Different changeover classes can therefore be scheduled between successive lots on machine 1, i.e., time- (4.15, 4.16), or volume-dependent changeovers (4.21, 4.22). For insubstitutable time- and volume-dependent changeovers, separate constraints would not be required for each class because the changeover times are added up. Furthermore, for additional changeovers of a certain class, the corresponding sets of constraints, variables and parameters must be duplicated. In the case study below, two time-dependent changeovers are implemented.

4.5 Application to cheese production

We apply the developed model to cheese production. This application is selected, because cleanings play a major role in cheese production for health reasons and due to regulatory standards.

4.5.1 Production process

All cheese types can be roughly categorized into hard, semi-hard, soft, semi-soft, and cream cheeses, depending on moisture content. Each cheese type has its own special production process, ripening process, taste, and texture. The paper focuses on the production of soft and blue cheese (categorized as semi-soft cheese). Figure 4.4 shows the processing steps followed by a short description of each step based on Walstra et al. (2006), Bylund (2003), and information from practice. Note that the term "filling" is used for cheese production as opposed to the term "loading" in the model description.

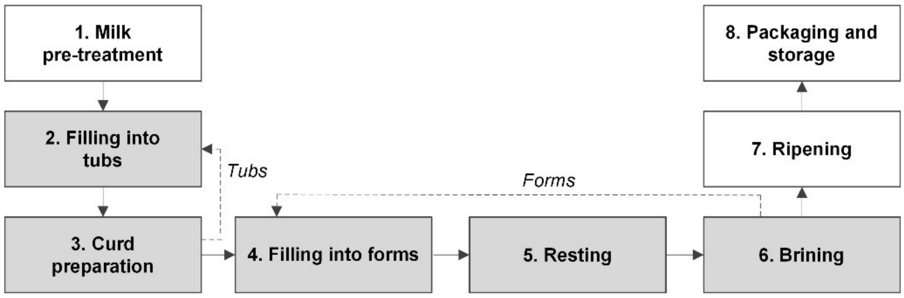

Figure 4.4: Processing steps in soft and blue cheese production (steps 2 through 6 are analyzed in this study).

The raw milk is first standardized to around 3% fat content, pasteurized at approximately 72 °C, and cooled to 32 °C (1). Next, the milk is filled into tubs of uniform size (2). Rennet is then added. The rennet causes the casein in the milk to coagulate, which is a fundamental process in cheese production. The amount depends on the specific cheese type and recipe. Starter culture, or other additives, can also be added. The milk clots after mixing and the clotted milk is then cut to expel the whey from the curd (3). After curd preparation, the curd is filled into forms without waiting (4). The forms give the cheese its size and shape. Next, the cheese rests under special conditions for several hours (5). While resting, the remaining whey is dripped or pressed out to obtain the correct dry-matter content. The cheese is also turned several times. After resting, the cheese is typically salted in a salt bath to increase its shelf life (6). The cheese is subsequently removed from the forms after which it ripens for several days under special conditions (7). Water losses and deterioration of texture should be avoided. After a few days, some cheeses are pierced to enable oxygen to enter so that blue mold can grow. The cheese is ultimately packaged and stored (8).

The main capacity-constrained processes constituting the flowshop are analyzed. Enough tubs are assumed to be available. However the use of different form types, steps 4 to 6, must be tracked as forms are blocked for several hours in a capacitated resting area after being filled and represent a key bottleneck. Addressing processing steps 2 and 3 is also necessary as the product sequence and timing of these steps influences scheduling of the following steps due to a no-wait condition between steps 3 and 4. No-wait conditions often apply in the food industry due to the characteristics of production technologies or of intermediate products. Figure 4.5 shows a representation of machine 1 (coagulator) and machine 2 (filler), which constitute a two-machine no-wait flowshop. A no-wait condition is employed at the interfaces between the machines, whereby lots are immediately loaded onto the next machine. Sequence-dependent batch changeovers result on machine 2 due to exchanging of form types and cleaning of machines.

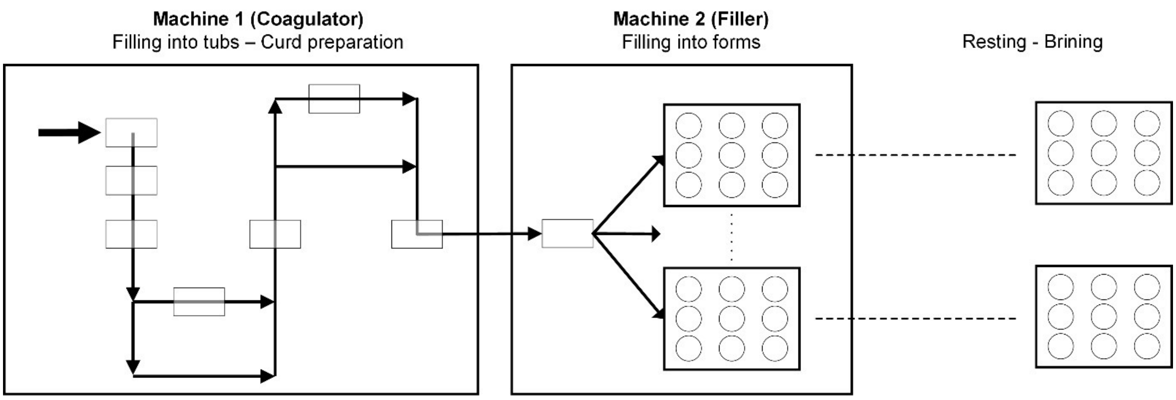

Figure 4.5: Detailed view of the analyzed two-machine no-wait flowshop for cheese production.

Furthermore, time- and/or volume-dependent cleanings must be addressed as cleaning operations are very important in the production of cheeses. Tight coordination of the changeovers across the production stages is required due to the no-wait condition.

Despite increasing interest in lot sizing and scheduling in the dairy industry, the literature focuses mainly on yoghurt production. Cheese production is distinct from yoghurt production, e.g., because products are filled in forms, and heterogeneous clotting and resting times must be accounted for. To the best of our knowledge, only the study by Claassen and Van Beek (1993) examines cheese scheduling. However, this study focuses on packaging without addressing specific cheese production challenges such as cleanings, sequence dependency, and the capacity restrictions of forms.

4.5.2 Modeling no-wait condition and form usage

This section describes the adaptations of the developed approach for modeling the no-wait condition between the machines and for tracking form usage. Discrete time periods are used to track form usage within each time period. That the required number of forms for the whole lot is available when filling starts is assumed, because receiving additional forms after a lot is started is unrealistic from a practical perspective. The notation below is added to the model presented in Section 4.4.

Indices and index sets

$f \in F$ form type

$t \in T$ time period

Parameters

τ length of discrete time period [time units]

υ_l number of forms filled from one tub for lot l [number of forms]

φ_l	resting and brining time of lot l on machine 2, and separable form cleaning time [periods]
χ_{lf}	=1 if lot l requires form type f (0, otherwise)
ψ_f	number of available forms of form type f—capacity [number of forms]
M_3	sufficiently large positive value

Decision variables

G_{lt}	number of filled forms for lot l in period t [number of forms]
R_{lt}	number of released forms for lot l in period t [number of forms]
I_{ft}	inventory of form type f in period t [number of forms]
W_{lt}	= 1 if filling of forms for lot l carried out in period t (0, otherwise)
U_l	consumption period of forms for lot l [period]

No-wait condition. Constraints (4.8) are replaced with constraints (4.37), whereby lots are immediately loaded onto machine 2 after being processed on machine 1. Also, constraints (4.10, 4.11, 4.13, 4.14) are replaced with constraints (4.38, 4.39). The starting times on machine 1 must account for the duration of sequence-dependent batch changeovers and the waiting times resulting from processing-times differences. For example, lot 2 in Figure 4.3 would have to start later on machine 1 due to the no-wait condition.

$$S2_l = S1_l + \varepsilon + \zeta_l \quad \forall l \in L \tag{4.37}$$

$$S1_{l'} \geq C1_l + \left(\theta_{ll'} - (\zeta_{l'} - \zeta_l)\right) - M_1 \cdot (1 - Y_{ll'}) \quad \forall l, l' \in L: (l \neq l') \tag{4.38}$$

$$S1_l \geq C1_{l'} + \left(\theta_{l'l} - (\zeta_l - \zeta_{l'})\right) - M_1 \cdot Y_{ll'} \quad \forall l, l' \in L: (l \neq l') \tag{4.39}$$

Form usage. In the sequel, continuous starting times for filling into forms are transformed into discrete time periods to track form usage. Constraints (4.40) set values on the discrete time periods when forms are consumed. Constraints (4.41) and (4.42) subsequently set the corresponding values for the binary variables that specify if filling of lot l is carried out in discrete time period t. Combined, constraints (4.40–4.42) thereby link the continuous time axis and the discrete time axis through decision variables $S2_l$, U_l, and W_{lt}. Figure 4.6 illustrates the relationship between the time axes with an example. If the starting time for filling forms for lot 1 ($S2_1$) is at 150 time units and the length of the discrete time period is 120 time units, then the discrete time period in which forms are consumed (U_1) is set to 2. Furthermore, the binary variable W_{12} is assigned a value of 1.

$$\frac{S2_l}{\tau} \leq U_l < \frac{S2_l + \tau}{\tau} \quad \forall l \in L \tag{4.40}$$

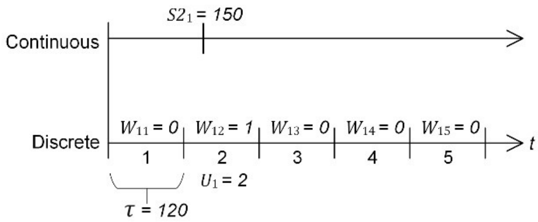

Figure 4.6: Relationship between continuous- and discrete-time axes.

$$U_l = t \cdot W_{lt} \quad \forall l \in L, t \in T \tag{4.41}$$

$$\sum_{t \in T} W_{lt} = 1 \quad \forall l \in L \tag{4.42}$$

At least the whole production lot is filled (4.43). Constraints (4.44) force the value of B_{lt} to zero when J_{lt} is zero. Constraints (4.45) determine the release time of forms by adding the resting time. Forms are not released unless they are first filled (4.46).

$$X_l \cdot v_l = \sum_{t \in T} G_{lt} \quad \forall l \in L \tag{4.43}$$

$$G_{lt} \leq M_3 \cdot W_{lt} \quad \forall l \in L, t \in T \tag{4.44}$$

$$G_{lt} = R_{l,t+\varphi_l} \quad \forall l \in L, t \in T : t \leq T - \varphi_l \tag{4.45}$$

$$R_{lt} = 0 \quad \forall l \in L, t \in T : t \leq \varphi_l \tag{4.46}$$

It is assumed that all forms are available at the beginning of the planning horizon, e.g., due to extensive cleaning at the end of the previous planning horizon. The inventory (number of blocked forms) in the first period equals the number of forms filled in this period (4.47). Constraints (4.48) model the inventory balances of the other periods. The inventory of forms in each period must be less than the number of available forms (4.49).

$$I_{ft} = \sum_{l \in L} G_{lt} \cdot \chi_{lf} \quad \forall f \in F, t \in T : t = 1 \tag{4.47}$$

$$I_{ft} = I_{f,t-1} + \sum_{l \in L} G_{lt} \cdot \chi_{lf} - \sum_{l \in L} R_{lt} \cdot \chi_{lf} \quad \forall f \in F, t \in T : t \geq 2 \tag{4.48}$$

$$I_{ft} \leq \psi_f \quad \forall f \in F, t \in T \tag{4.49}$$

Variable domains. Constraints (4.50, 4.51) define the variable domains of decision variables.

$$G_{lt} \geq 0, \;\; R_{lt} \geq 0, \;\; I_{ft} \geq 0 \quad \forall l \in L, f \in F, t \in T \tag{4.50}$$

$$W_{lt} \in \{0,1\}, \;\; U_l \geq 0 \; and \; integer \quad \forall l \in L, t \in T \tag{4.51}$$

4.5.3 Parametrization

The case study includes the production of 30 different products, in which the weekly demand volumes (α_p) are given. The number of possible lots per product is determined together with the cheese dairy based on the demand volumes. A minimum lot size (β_l) is not required. The objective is to minimize the makespan over a one week planning horizon such that production on weekends is minimized. Total clotting, cutting, and stirring times of products are 80 to 144 minutes (ζ_l). The tubs are all of the same size with filling time (ε) of 104 seconds. There are three different form types and the number of available forms is limited to 1,000 to 4,000 (ψ_f), depending on the type. There are between 5 and 13 forms per tub (υ_l). Resting and brining times of products are 13 to 19 hours (φ_l) including the separable cleaning time of forms. The period length for tracking form usage is set to 2 hours (τ).

The required setups and cleanings are described next. First, there are batch-dependent change-overs on the second machine, *B; (insep/insub/sfb/max); t(seqd(-f;-ns;Δ)/bi); c(-/-)*, in which the sequence-dependent duration ($\theta_{ll'}$) varies depending on whether products require the same form type (either 0 or 15 minutes cleaning) or different form types (15 minutes cleaning plus 15 minutes setup). Also, two time-dependent cleanings classified as *T; (insep/in-sub/ftp/tw); t(pi/bi); c(-/-)* and *T; (insep/insub/ftp/ex); t(pi/bi); c(-/-)* are considered on the first machine. The first one, denoted with superscript (1), is a time-window-based cleaning. It takes 42 minutes ($\kappa^{(1)}$) and is scheduled in the middle of each production day, i.e., between 8 ($\lambda_a^{min(1)}$) and 12 hours ($\lambda_a^{max(1)}$) of production. The cleaning interval is 24 hours ($\nu^{(1)}$). The second time-dependent cleaning, denoted with superscript (2), is an exact cleaning. It takes 4 hours ($\kappa^{(2)}$) and is scheduled at the end of each production day, i.e., after 20 hours ($\lambda_a^{min(2)}$) of production. Substitution within the time-dependent cleaning class will not occur, because clean-ings are scheduled at different times during the day. Also, substitution across classes will not occur, because the classes are scheduled on different machines. The minimum number of clean-ings ($\mu^{(1)}$, $\mu^{(2)}$) is calculated based on demand volumes. Figure 4.7 shows a graphical repre-sentation of the setups/cleanings. In addition, cleanings of forms are carried out with uncapac-itated separable cleanings, and are not shown in the figure.

The precedence relationships among products are described next. Twelve products have due dates early in the production week: Monday to Thursday. This is because these are natural products, which are produced before products with stronger flavors, and because special treat-ment such as pricking or coating is required in further processing, which should not occur on

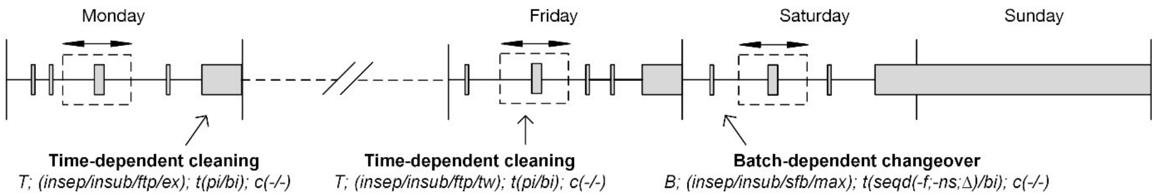

Figure 4.7: Analyzed setups and cleanings for a one week planning horizon.

weekends. Flavored cheeses such as those containing mushrooms or herbs are produced after the natural cheeses ($\delta_{ll'}$). Flavored cheeses need no special treatment during further processing, because the flavors have already been added, and therefore have the end of week as due dates. Strong flavored cheeses are produced after the flavored cheeses. These are six cheeses that must be produced at the end of the production week ($\delta_{ll'}$), because their recipes include garlic or hot peppers. After production of these strong flavored products an extensive cleaning is carried out. Solving the model for all products is computationally hard. We decompose therefore the problem based on the natural sequence of product groups and schedule each group sequentially. The makespan, changeover information, and form usage of previous groups is set as input for the subsequent group. Table 4.3 shows the product groups as well as the form types (χ_{lf}) and due dates (γ_l) of products.

The constraints implemented for the case study are summarized next. Constraints (4.1, 4.2, 4.4, 4.5) are implemented, in which the makespan is defined (as with the dairy) as the completion time on machine 1, which is analogous to the makespan on machine 2 due to the no-wait condition. Constraints (4.6) are not required because groups are solved separately. Batch-dependent changeovers and timing on machines are implemented with no-wait condition (4.7, 4.9, 4.12, 4.37–4.39). Time-window-based cleanings are modeled with constraints (4.15–4.20) and exact cleaning with constraints (4.B1, 4.B2). There are no volume-dependent cleanings. The corresponding tightening constraints (4.31–4.34) and variable domains (4.35, 4.36) are also implemented. Furthermore, tracking form usage is implemented with constraints (4.40–4.51). We apply the model to a case at a medium-sized German cheese dairy. The model is implemented and solved in IBM ILOG CPLEX Optimization Studio 12.6 on a 2.6 GHz Intel Xeon CPU with 32 GB RAM.

Table 4.3: Product groups, form types, and due dates.

Group[a]	Product number	Form type	Due date
1	1	1	Thursday
1	2	1	Thursday
1	3	1	Monday
1	4	1	Monday
1	5	1	Thursday
1	6	2	Thursday
1	7	2	Tuesday
1	8	2	Tuesday
1	9	2	Thursday
1	10	3	Wednesday
1	11	3	Monday
1	12	3	Thursday
2	13	1	-
2	14	1	-
2	15	1	-
2	16	1	-
2	17	2	-
2	18	2	-
2	19	2	-
2	20	2	-
2	21	3	-
2	22	3	-
2	23	3	-
2	24	3	-
3	25	1	-
3	26	1	-
3	27	1	-
3	28	2	-
3	29	3	-
3	30	3	-

[a] Group 1: Natural and blue cheeses.
Group 2: Flavored cheeses.
Group 3: Strong flavored cheeses.

4.5.4 Illustrative results and model performance

Around 3,300 to 3,800 variables and around 3,200 to 6,800 constraints result depending on the product group. Maximum runtime is set to 20 minutes for each group and the optimality gap is reported. The optimality gap is the difference between a theoretical upper bound on the optimal objective value and the achieved objective value. The model is first solved for a particular demand week (week 1) and illustrative results are presented. Group 1 is solved to 2.4% optimality gap, group 2 to 2.1% optimality gap, and group 3 to optimality in a few seconds. The resulting optimality gap is considered acceptable.

The schedule on machine 1 (coagulator) is shown in Figure 4.8. A capacity utilization of 74–84% is achieved depending on the weekday. This is a very high utilization as it also includes the time-dependent cleanings (42 minutes and 4 hours) that are scheduled every day. Waiting times on machine 1 are only 4.5% of the makespan, which is attributable to the smart exploitation of processing-time differences and cleaning coordination. For example, as also illustrated

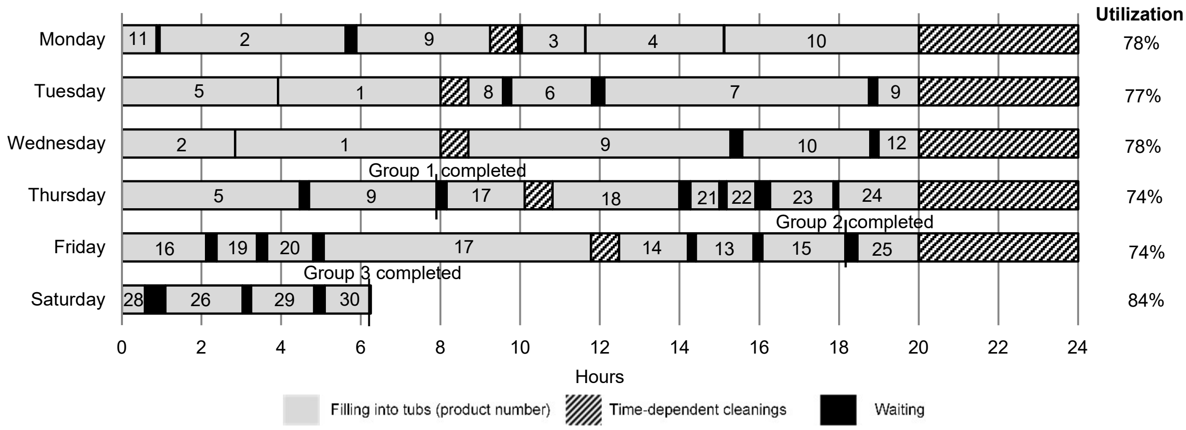

Figure 4.8: Filling schedule on machine 1 (coagulator) for week 1.

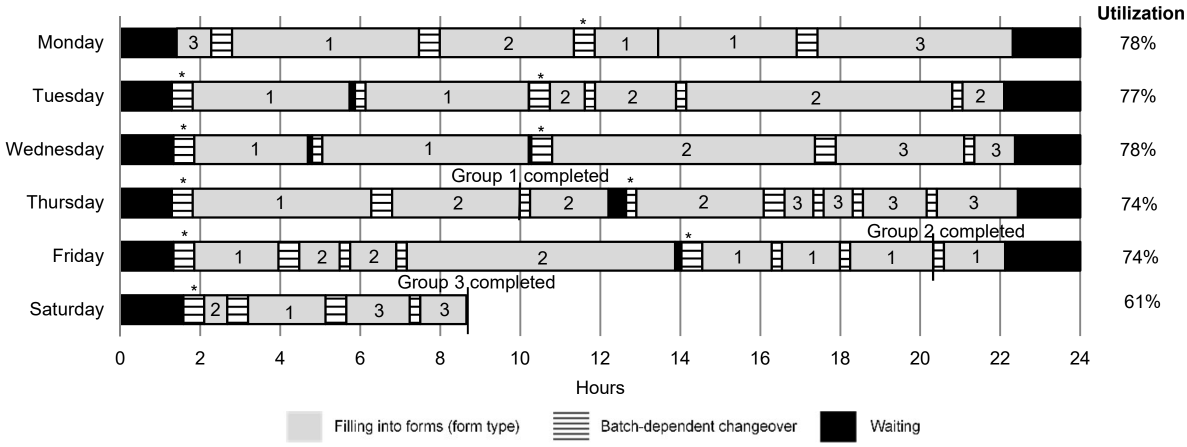

Figure 4.9: Filling schedule on machine 2 (filler) for week 1.

in Figure 4.3, a lot with short processing time is frequently followed by a lot with a longer processing time to minimize waiting. Also, time-dependent cleanings are scheduled when switching from a lot with long processing time to a lot with shorter processing time. The completion times of the product groups are also shown in Figure 4.8, demonstrating the large production volume of group 1. Furthermore, the lot sizing of products is shown. Some products are produced in one lot, while others are in two or more lots due to setup and cleaning requirements as well as restriction on form capacities.

Figure 4.9 illustrates the filling schedule on machine 2 (filler). Several lots with same form type are usually produced subsequently by virtue of longer sequence-dependent batch changeover when switching between form types. Coordination of cleanings is also apparent in the results. Time-dependent cleanings are carried out concurrently with switching to a new form type in nine out of ten cases. In total, 35.8% of the batch-dependent changeover duration is carried out concurrently with time-dependent cleanings (marked with an asterisk in Figure 4.9). Coordination of cleanings, therefore significantly reduces the waiting times of the no-wait flowshop and improves the performance of the model. Figure 4.10 shows the form usage for each form type.

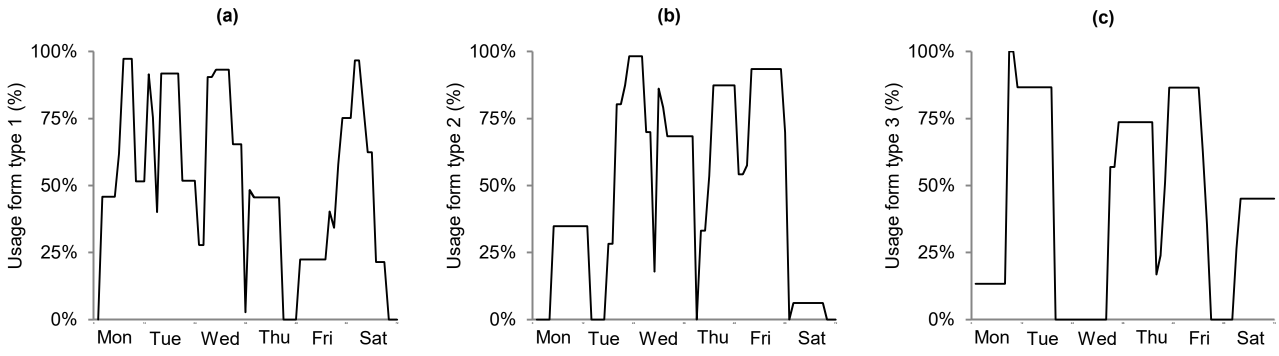

Figure 4.10: Form usage for week 1; (a) form type 1, (b) form type 2, and (c) form type 3.

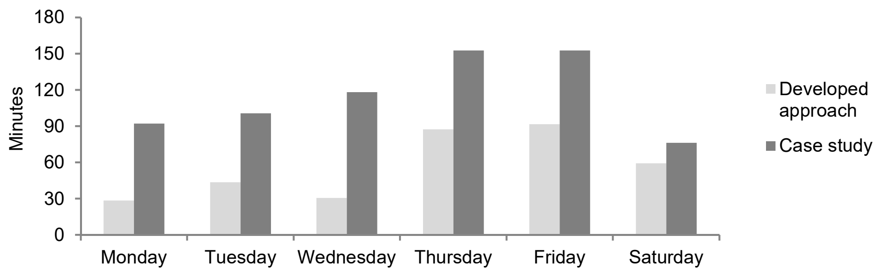

Figure 4.11: Comparison of waiting times on machine 1 for demand week 1.

The same form type is regularly filled until reaching the maximum form capacity after which filling of a new form type is started.

The performance of the developed approach is also compared to current planning at the cheese dairy (case study). The comparison is shown for machine 1, but machine 2 has the same utilization as machine 1 on all days except for Saturdays. Figure 4.11, illustrates the waiting times on machine 1 resulting from the developed approach and the planned schedule for the case study. For this demand week, a 50.9% reduction in waiting times is realized with the developed approach. Since the time-dependent cleanings are scheduled each day, they can only be reduced by finishing before their starting time. On the other hand, the waiting times on machine 1 can be reduced by smart exploitation of processing-time differences and by efficient scheduling of changeovers.

To validate the developed approach further, it is solved for two more demand weeks (weeks 2 and 3) and also compared to the planned schedule for the case study. The results of all weeks are summarized in Table 4.4, which shows the stable performance of the developed approach. On average, a 39.1% reduction in waiting times is achieved. Also, one short time-dependent cleaning is saved in each week leading to a 2.9% reduction in time-dependent cleaning duration. This results in an average of 14.1% reduction in downtimes of machine 1 and a 3.7% makespan improvement. Significant cost reduction is thus realized by utilizing the developed approach,

Table 4.4: Comparison of the developed approach and the planned schedule for the case study.

	Approach	Week 1	Week 2	Week 3
Optimality gap (%) (Group 1; Group 2; Group 3)	Developed approach	2.4; 2.1; 0.0	2.5; 3.0; 0.0	3.5; 1.8; 0.0
	Case study	-	-	-
Makespan on machine 1 (minutes)	Developed approach	7,574.0	7,864.5	7,850.8
	Case study	7,968.3	8,146.2	8,061.0
Downtimes				
Waiting on machine 1 (minutes)	Developed approach	340.0	370.5	450.4
	Case study	692.3	610.2	618.6
Time-dependent cleanings on machine 1 (minutes)	Developed approach	1,410.0	1,410.0	1,410.0
	Case study	1,452.0	1,452.0	1,452.0

because the plant can be closed on average five hours earlier each week and less must be paid in overtime salaries on weekends.

4.5.5 Managerial insights based on sensitivity analyses

Three numerical tests are analyzed in this section. In test 1, the restriction on form capacities is relaxed. The aim is to gain managerial insights on how much the limited form capacities impact the schedule. This may provide insight in the need for investments. In test 2, time-window-based cleanings that are scheduled daily after 8 to 12 hours of production in the original settings must start daily at an exact time point (after 10 hours production). The aim is to analyze the value of providing the organizational flexibilities in scheduling cleanings and of employing a planning approach that is able to exploit it. In test 3, heterogeneous processing times on machine 1 are replaced with homogenous processing times for all products. Here, the aim is to analyze, if management should strive to streamline the product portfolio such that the processing times become similar. The homogeneous processing times are calculated as weighted averages of the heterogeneous processing times (122.9 minutes for week 1, 122.8 minutes for week 2 and 122.2 minutes for week 3). Tests 2 and 3 are conducted with relaxed form capacities and compared to the first test, such that restricted form capacities do not interfere with the results. In all tests, the runtime is set to 20 minutes for each group, as it is in Section 4.5.4. Yet group 3 is always solved to optimality in few seconds. Table 4.5 summarizes the main results.

Comparing the results of test 1 with the original setting in which form capacities are restricted (see Table 4.4) shows an average makespan improvement of 0.8% and waiting time reduction of 15.6%. Figure 4.12 illustrates the form usage of test 1 for week 1. The results show that for relaxed form capacities, more forms are frequently required than the maximum capacity, i.e., above 100% usage. This is the case for all three form types. For example, many lots requiring form type 3 are produced sequentially on Tuesday reaching a usage of 144%. Furthermore, for relaxed form capacities, products are produced in fewer lots with larger lot sizes. The same

Table 4.5: Results of numerical tests.

	Test number[a]	Week 1	Week 2	Week 3
Optimality gap (%) (Group 1; Group 2; Group 3)	1	1.1; 2.1; 0.0	1.3; 2.2; 0.0	1.6; 2.0; 0.0
	2	1.7; 2.3; 0.0	1.7; 2.6; 0.0	2.5; 2.2; 0.0
	3	2.9; 2.7; 0.0	2.1; 2.5; 0.0	2.5; 2.7; 0.0
Makespan on machine 1 (minutes)	1	7,518.2	7,852.5	7,728.3
	2	7,550.5	7,923.8	7,765.0
	3	7,686.4	7,915.2	7,889.2
Downtimes				
Waiting on machine 1 (minutes)	1	284.2	358.5	327.9
	2	316.5	387.8	364.6
	3	452.4	421.2	488.8
Time-dependent cleanings on machine 1 (minutes)	1	1,410.0	1,410.0	1,410.0
	2	1,410.0	1,452.0	1,410.0
	3	1,410.0	1,410.0	1,410.0

[a] Test 1: Relaxed form capacities.
Test 2: Relaxed form capacities and exact scheduling of both time-dependent cleanings.
Test 3: Relaxed form capacities and homogeneous processing times.

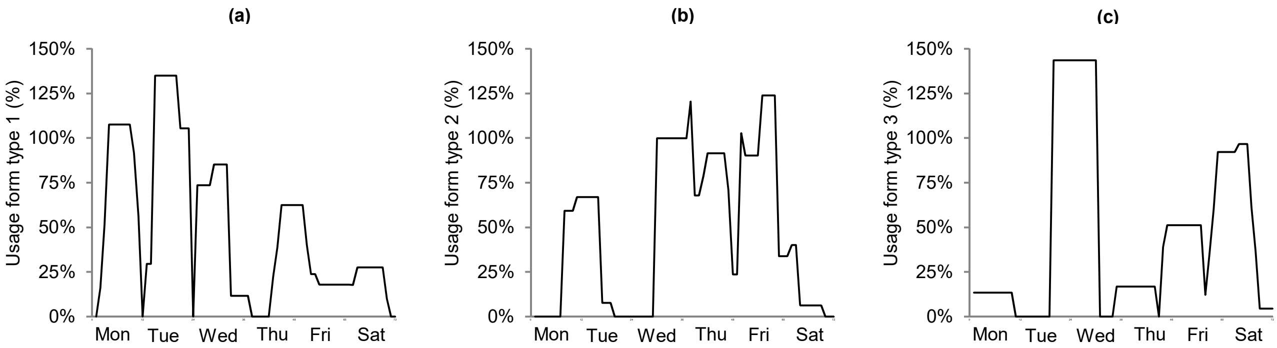

Figure 4.12: Form usage for week 1 with relaxed form capacity restriction; (a) form type 1, (b) form type 2, and (c) form type 3.

pattern is realized for weeks 2 and 3. This shows that limited form capacities greatly impact the schedule. Therefore, the cheese dairy should analyze the possibilities of further investments.

The results of test 2, show that by replacing the time-window-based cleaning with an exact cleaning, an average waiting time increase of 10.2% is realized compared to test 1. Average downtimes increase by 2.7%, because with rigid starting times there is no flexibility when scheduling cleanings. Providing flexibilities in scheduling cleanings is therefore of great value, if the planning method is able to exploit it. The importance of accurately identifying the setup and cleaning classes is also apparent.

The results of test 3 show that homogenous processing times lead to a significant increase in makespan (1.7% on average) compared to heterogeneous processing times. Average waiting times increase by 41.9% and machine downtimes by 7.6%. This substantial increase in waiting times results, because smart exploitation of processing-time differences to schedule setups and cleanings is not possible. Figure 4.13 illustrates this with excerpts from the schedules for week

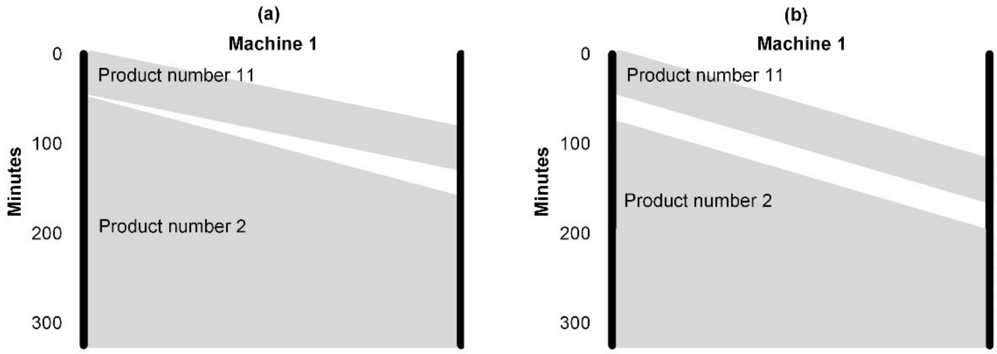

Figure 4.13: Excerpts from schedules for week 1; (a) heterogeneous processing times and (b) homogeneous processing times.

1 for both heterogeneous and homogeneous processing times. During this week, the same products are produced in the first two lots. A form change between these lots is required on machine 2. The figure illustrates how the processing-time difference is exploited in the case of heterogeneous processing times to schedule the form change, which leads to less waiting time on machine 1. To summarize, a portfolio of products with heterogeneous processing times, as compared to homogenous processing times, is advantageous.

4.6 Conclusions

Extensive requirements for setups and cleanings exist in the process industries. These result in prolonged machine downtimes, waste of material, and high resource consumption in terms of energy, water, and cleaning agents. Efficient scheduling of setups and cleanings is therefore fundamental. This paper develops a classification scheme that distinguishes three different classes of setups and cleanings: batch-, time-, and volume-dependent setups and cleanings. Each class is further differentiated based on general characteristics such as separability, substitutability, reference point, and flexibility. In addition, setups and cleanings are characterized according to the determinants of the setup and cleaning time and/or costs, distinguishing product dependency from batch-size dependency.

The developed classification scheme facilitates the representation of setups and cleanings in the modeling of lot sizing and scheduling problems. Setups and cleanings are especially important in the process industries, in which flowshops are the prevalent type of production system. Therefore, a generic lot sizing and scheduling modeling approach for flowshops is developed based on the classification scheme. Besides precedence relationships and heterogeneous processing times, all setup and cleaning classes with various characteristics as well as potential substitution relationships between different setups and cleanings are accurately represented in the model.

The model is applied to a case study at a medium-sized German cheese dairy involving several classes of setups and cleanings. Sequence-dependent batch changeover and two different time-dependent cleanings must be scheduled. The cheese types have heterogeneous processing times and are connected through precedence relationships. A no-wait condition must be employed between the machines, whereby lots are immediately loaded onto the next machine. In the cheese industry, a specific requirement concerns the use of different types of cheese forms. The forms are blocked for several hours after filling and represent a key bottleneck in the production of cheeses. The general model is adapted to account for the associated capacity considerations and the no-wait condition. These adaptations of the general model to the industry-specific requirements can easily be done, because the solution approach is based on a MILP formulation in which algebraic expressions can be altered and added while maintaining computational efficiency.

The numerical results of the case study demonstrate the applicability and the advantages of the developed approach. The cheese dairy realizes significant cost reductions by utilizing the developed approach. An average reduction in machine downtime of 14.1% compared to the outcome of their current manual lot sizing and scheduling process is achieved, which results in a 3.7% makespan improvement. Each week, the cheese dairy can close the plant on average five hours earlier thereby significantly reducing overtime on weekends.

The numerical results show that the model is able to exploit the flexibility of the production system and even benefit from its complexity. However, accurate setup and cleaning class identification is prerequisite. More specifically, not allowing for flexible starting times of cleaning operations may ease planning and execution but over-constrains the solution space. Our results indicate that rigid starting times lead to a 2.7% increase in machine downtimes. Similarly, homogeneous processing times may be easier to handle in manual scheduling. However, the additional complexity that heterogeneity in processing times entails also goes along with the possibility to compensate for setup- and cleaning-time differences in the successive production stages. Our results show that neglecting heterogeneous processing times leads to a 7.6% increase in machine downtimes.

This paper developed a generic lot sizing and scheduling modeling approach for two-machine flowshops, which are common in large parts of the process industries. The model could easily be adapted such that more machines, and their specific setup and cleaning requirements, are included. Further research could also extend the numerical analyses to other industrial applications, because the developed approach provides adaptability to industry-specific features. While the developed models could be solved with sufficiently small optimality gaps using standard solvers, other industries may require the development of more elaborate solution methodologies. Analyzing the computational effort for different combinations of constraints in the developed modeling approach, could also be a subject for future research. Future research could also explore the use of the developed classification scheme in the development of solution approaches for other production environments. An example might be the make-and-pack systems that are frequently found in the food sector and also require different types of cleanings.

In addition to the economic impacts, setups and cleanings also have significant environmental impacts occasioned by material and resource consumption and the corresponding waste and emissions. In the case of the food industry, cleanings for instance contribute substantially to industrial food waste. Even though our approach efficiently utilizes setups and cleanings and thus implicitly reduces related environmental impacts, a more explicit consideration of all relevant environmental impacts may be desirable.

Acknowledgments

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Chapter 5. Summary and future research possibilities

5.1 Summary of findings

In this section, we summarize the conclusions that are drawn in the previous chapters and conclude by revisiting each research question raised in Section 1.4.

RQ1: How can interdependencies between the selection of new product designs and processing technologies including the characteristic uncertainties be addressed?

Chapter 2 focuses on the selection of new product designs and processing technologies in a supply chain context. We propose that a design space should first be derived, in which the interdependencies between products and processing technologies are mapped for different product specifications. This requires interdisciplinary research involving product designers, process engineers, and supply chain experts. As adoption of new products is hard to predict, the selection of product designs and processing technologies is complicated by demand uncertainties. We argue that the key uncertainties for this decision problem are the demand volumes and the product specifications requested by the customers.

We propose a novel decision model relying on two-stage stochastic programming for the planning problem. The model captures the link between the selection of product designs and the selection of processing technologies. Furthermore, the impact on the supply chain is captured. In the first stage of the model, the technologies that determine the set of feasible products are selected. Also, investment decision are made on the number of equipment units at each processing stage. In the second stage of the model, decisions on the types of products to be produced and the production volumes of each type are made. Depending on how uncertainties resolve, the technologies selected in the first stage can therefore be operated differently to obtain the product designs requested by the customers.

We apply the approach to a real-life case on milk concentrates at a German dairy company. This case is well suited to exemplify the interdependencies between the selection of product designs and processing technologies. Specific characteristics of the milk concentrate products and of the dairy processes make the problem at hand complex. As a result of extensive interdisciplinary collaboration with food process engineers, we first derive the design space that encompasses the feasible dairy technologies and the product designs for concentrates. The uncertain characteristics of the concentrate products are the demand volumes and the product specifications related to the shelf life requirements of customers and the demand composition of dry-matter content.

Our analysis shows that it is profitable for the dairy company to invest in the processing technologies for milk concentrates. Hereby, the reverse osmosis concentration technology is selected together with different heat treatments. The numerical tests demonstrate that the technology selection strongly relies on the flexibility of the processing technologies to produce different volumes of the resulting set of feasible products. To react to the uncertainties related to new product introduction, flexible technologies are therefore selected that can process the products into different product designs. The tests also provide managerial insights on how the optimal product and technology selection is affected by the demand uncertainties. Particularly, the effects when one of the uncertainties is no longer present are tested. It is shown that the selection is highly dependent on the demand uncertainties. Here, the uncertainty related to the shelf life requirements of customers has the largest impact and is therefore a key driver for the selection of products and technologies. Managers should therefore strive to obtain accurate demand information on product specifications related to the shelf life requirements of customers.

RQ2: From an integrated economic and environmental perspective, should traditional milk powders be substituted with novel milk concentrates? Is the decision impacted by the value of shelf life?

The case on milk powders and milk concentrates exemplifies the impact of shelf-life reduction due to sustainable processing. In Chapter 3, we develop a sustainability framework for the evaluation of these dairy products and the related dairy processing technologies. The framework includes an optimization model, a rolling horizon scheme, and a method for objective reduction. Since the differences in shelf life have their key impact at the tactical planning level we develop an optimization model at this aggregation level. The results of the tactical level, obtained over a historical period, are then used to draw strategic conclusions on the selection of the dairy products. As substituting traditional milk powders with novel and more environmental-friendly milk concentrates impacts both the economic and the environmental performance, the developed model is a multi-objective optimization model covering profit and all relevant environmental indicators. The model is implemented in a rolling horizon scheme to deal with the fluctuating prices of final products. It is important to capture the price fluctuations in the comparison of these products, as shelf-stable milk powders may be stored until a higher price level is reached, resulting in higher profits.

We apply the developed approach to a real-life case study for a German supply chain, based on detailed economic and environmental data. We first evaluate the substitution of powders with concentrates from an economic perspective. We compare the results obtained using historical data on product prices to the results obtained using Eurex futures as price predictors. It is shown that the product selection is highly influenced by the upcoming price developments. For both price scenarios, powders are favored over concentrates if prices are expected to rise. On the other hand, concentrates are selected in case of stable or falling prices. A product mix of powders and concentrates produced with combined concentration (i.e., reverse osmosis and subsequent evaporation) is selected for both price scenarios. We calculate the economic value of shelf life provided by powders, to evaluate whether the shelf life impacts the substitution decision. We show that powders offer a potential profit benefit of up to 34.5%. However, this economic value of shelf life is subject to *a priori* perfect price knowledge. The value of shelf life strongly depends on the accuracy of the price information, as it is reduced to only 1.1% if in the realistic case in which futures are used as price predictors. The economic value of shelf life is therefore not a strong argument against the substitution of powders by novel concentrates.

We also evaluate the substitution of powders with concentrates from an environmental perspective by including the environmental objectives in the comparison. We show that only two objectives (i.e., profit and eutrophication potential) are sufficient to capture the trade-offs in the case. The minimization of the eutrophication potential results in a selection of concentrates that are concentrated with only evaporation. This results in a large profit reduction, which is unrealistic in practice. However, concentrates produced with combined concentration are selected for the minimization of all other environmental objectives, resulting in a much less pronounced profit impact. We are therefore able to determine a range of solutions that omit powders and perform well with regard to both profit and environment. As a result, we conclude that from an integrated economic and environmental perspective, traditional milk powders should be substituted with novel milk concentrates.

RQ3: How can different setup and cleaning requirements and their interrelationships be systematically addressed in scheduling approaches?

In Chapter 4 we suggest that different setup and cleaning requirements should first be classified, before they can be appropriately represented in scheduling approaches. We develop a novel scheme to support the classification. The scheme distinguishes three different classes: batch-, time-, and volume-dependent setups and cleanings. Also, different characteristics are identified for each setup and cleaning class. Firstly, general characteristics include separability, substitutability, reference point, and flexibility. Hereby, interrelationships between classes are represented through the substitutability characteristic. Secondly, changeover matrix characteristics with regard to time and/or costs include product dependency and batch-size dependency. Next, we develop a simultaneous lot sizing and scheduling model for flowshops, as flowshops are the prevalent type of production system in the process industries such as the food sector. The developed model shows how different setup and cleaning requirements can be systematically addressed in scheduling approaches based on the classification. It includes all setup and cleaning classes with different combinations of their characteristics. Interrelationships between classes are also accurately represented in the model.

We apply the developed classification scheme and modeling approach to a case study on soft and blue cheese production at a German dairy company. The application shows how setup and cleaning requirements as well as their interrelationships can be addressed in a real-life setting with the developed classification scheme and optimization model. The company realizes significant cost reductions by utilizing the developed approach as compared to their current manual lot sizing and scheduling process. Through an efficient scheduling of setups and cleanings, significant reduction in machine downtimes are realized.

We particularly compare flexible and fixed starting times of cleanings. The tests aim at analyzing the value of providing the organizational flexibilities in scheduling cleanings and the value of employing an approach that has the ability to exploit it. The results show that flexible starting times significantly reduce makespan. This demonstrates the importance of accurately identifying the cleaning class and the relevant characteristics through our classification scheme. We also carry out tests that aim at gaining managerial insights into whether the product portfolio should be streamlined, such that the processing times become homogeneous. Even though homogeneous processing times may be easier to handle in scheduling, our results show that neglecting heterogeneous processing times leads to a large increase in machine downtimes. This is because with heterogeneous processing times it is possible to compensate for setup- and cleaning-time differences in the successive production stages.

Overall, this thesis provides insights into the challenging planning of food supply chains. Although the problems studied in this thesis are motivated by problems typically found in the food industry, other industries may also face similar problems. In large parts of the thesis, the developed methodologies are therefore applicable to a wide range of industries. Three different optimization-based approaches are developed at different planning levels, i.e., a two-stage stochastic programming model at the strategic level, a multi-objective optimization model at the tactical level, and a lot sizing and scheduling model at the operational level. The developed approaches are applied to real-life cases from the dairy industry, which are well suited to demonstrate the impact of food-specific product and processing characteristics. The approaches at the strategic and tactical planning levels are applied to a case study on dried dairy products. The approach at the strategic level captures uncertain demand characteristics, like requested product specifications and demand volumes, which are related to the introduction of new products and technologies. The approach at the tactical level also accounts for uncertainty, but with a focus on uncertain final product prices. Here, special attention is given to analyzing the value of shelf life. Finally, the approach at the operational level is applied to a case study on cheese production. Here, special attention is given to analyzing setups and cleanings.

5.2 Future research possibilities

In the previous chapters, suggestions have already been proposed for future research possibilities. In this section, some more general suggestions are outlined.

This thesis investigates the impact of several food-specific product and processing characteristics. However, analyzing the impact of food safety was not within the scope of this thesis. Safety is also an important food-specific characteristic. In the food supply chain, it must be guaranteed that products are processed, handled, and stored in ways that prevent illnesses from the consumption of the products. In recent years, some serious food scandals were realized that resulted in a large financial impact for the food producers and a serious health impact for the consumers. Considering the importance of food safety, there is a great research potential in integrating optimization of appropriate safety measures with the optimization of other supply chain operations from field to fork.

Another food-specific characteristic that has not been analyzed in this thesis is raw material variability. Raw materials are especially important in the food industry, because many different products are usually produced from only a few types of raw materials and the raw material costs typically constitute a large proportion of the total costs of a product. Raw materials are obtained from agricultural and farming industries. Therefore, the quality of the raw materials is often subject to variability. This variability can have a large impact on the planning and scheduling of the production. Accounting for raw material variability in production planning models thus makes an interesting topic for future research.

Future research could also focus on developing further methodologies for evaluating the impact of shelf life on sustainability objectives. Hereby, it would be of interest to capture the decreasing value of products throughout their lifetime, instead of only penalizing for expired products that must be thrown out. Freshness could for example be considered as an additional objective in a multi-objective optimization model. Real-life applications of models that manage the product freshness can contribute to the fight against food waste, which is one of the key challenges in the food industry.

Further research in food supply chains based on real-life case studies is also required. For all three planning approaches developed in this thesis, it would be of interest to apply them also to other real-life case studies. The focus could, for instance, be on different types of food products with shorter shelf life or on production systems with different setup and cleaning requirements. Hereby, detailed data on the food-specific product and processing characteristics must be elicited.

Due to an increasing demand for sustainable products and changing dietary preferences of consumers, new product introductions are common in the food industry. Chapter 2 of this thesis shows that for the selection of new products it is important to capture the interdependencies between the product designs and the processing technologies. However, in previous research on product and technology selection it is always assumed that the product is given. This area therefore deserves further attention, for example through the development of different types of decision models. Furthermore, future research should focus on capturing stochasticity in the developed food supply chain approaches. Uncertainties are inherently associated with food supply chains, for example with regard to the supply of raw materials, the processing parameters, and the demand specifications of the products.

In future years, the manufacturing sector will continue to transform due to an increasing digitization in economy and society. Through modern technologies, data sets are growing rapidly in both size and complexity. To stay competitive, food companies must improve their data management and take advantage of big data. Therefore, supply chain experts must continue to find ways to analyze and integrate available data in planning tools to support data-driven decisions.

Industry 4.0, or the fourth industrial revolution, refers to a development in the manufacturing sector in which production technologies are combined with state-of-the-art communication and information technologies. These technologies include, for example, cyber-physical systems, cloud computing, cognitive computing, and big data analytics. In Industry 4.0, production and logistics processes will be intelligently and digitally connected, providing real-time information on the whole supply chain. This will result in improved efficiency and flexibility. The food industry is highly innovative with frequent introduction of new technologies. It is therefore likely that food companies will eagerly embrace the innovations related to Industry 4.0. The food industry can profit from Industry 4.0 in many ways, e.g., in tracking and tracing products, in monitoring and optimizing resource consumption and environmental impacts, and in intelligent temperature control of sensitive processing tasks. Also, Industry 4.0 can support setup, cleaning, and maintenance activities through increasingly autonomous machines that manage their own requirements. Industry 4.0 therefore results in many interesting research topics for food supply chain planners.

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Appendix A – Abbreviations

AP	Acidification potential
CED	Cumulative energy demand
CIP	Cleaning-in-place
Combi	Reverse osmosis and subsequent evaporation
DMC	Dry-matter content
DRY	Spray drying
EP	Eutrophication potential
ESL	Extended shelf life
EV	Evaporation
EVPI	Expected value of perfect information
GWP	Global warming potential
HHT	High-heat treatment
ISO	International Organization for Standardization
LCA	Life cycle assessment
MI(N)LP	Mixed integer (non) linear programming
Mo-MI(N)LP	Multi-objective mixed integer (non) linear programming
MOSS	Minimum objective subset
MSD	Multi-stage drying
OR	Operations research
Past	Pasteurization
PSE	Process systems engineering
RO	Reverse osmosis
SMED	Single minute exchange of die
UHT	Ultra-high temperature
VSS	Value of stochastic solution

Appendix B – Notation

Notation for Chapter 2

Indices and index sets

$i \in I$	producer
$j \in J$	processing plant
$k \in K$	customer
$u \in U$	resource
$n \in N$	technology path
$m \in M$	processing stage
$p \in P$	product
$p \in tech(n)$	product belonging to technology path *n* as determined in design space
$m' \in suc_p(m)$	stage that is immediate successor of stage *m* for product *p*
$o \in O$	product specification
$t \in T$	time period
$s \in S$	scenario

Parameters

γ_s	probability of scenario *s*
ϕ	discount rate
ζ_{it}	supply of producer *i* in period *t*
ε_{ij}^{dist1}	distance between producer *i* and plant *j*
ε_{jk}^{dist}	distance between plant *j* and customer *k*
σ_{ij}^{was1}	waste fraction of raw material transported from producer *i* to plant *j*
σ_{mp}^{was2}	waste fraction at stage *m* for product *p*
μ_{mp}	fraction of unconverted product at stage *m* for product *p*
α_{um}^{proc}	usage rate of resource *u* during processing at stage *m* (e.g., kW, liters/hour)
α_{um}^{set}	consumption of resource *u* over setup/cleaning cycle at stage *m* (e.g., kWh, liters)
η_m	useful lifetime of equipment unit at stage *m* (in time periods)
κ_{mj}	number of equipment units in place at stage *m* in plant *j*
θ_{mp}	capacity per equipment unit at stage *m* for incoming flow of product *p* (e.g., liters/hour)
τ	number of time units in a time period (e.g., number of hours)
λ_{mp}	runtime at stage *m* for product *p*
ξ_m	setup/cleaning time at stage *m*
δ_{op}	value for product specification *o* of product *p*

δ_{oks}^{min} minimum value for product specification *o* requested by customer *k* for scenario *s*

δ_{oks}^{max} maximum value for product specification *o* requested by customer *k* for scenario *s*

φ_{kts} demand volumes for customer *k* in period *t* for scenario *s*

ρ_p^{prod} density of product *p*

ρ_{ks}^{cust} density requested by customer *k* for scenario *s* (depending on dry-matter content)

B_1, B_2 sufficiently large positive values

r_{pkt}^{cust} price of product *p* sold to customer *k* in period *t*

r_{pt}^{sec} price of product *p* sold to secondary market in period *t*

r_{mt}^{sep} price of separated stream from stage *m* in period *t*

c_{it}^{raw1} costs of raw material supplied from producer *i* in period *t*

c_t^{raw2} costs of raw material supplied from spot market in period *t*

c^{trans1} unit transportation costs of raw material

c_p^{tran} unit transportation costs of product *p*

c_u^{res} unit costs of resource *u*

c_n^{in1} investment costs of technology path *n*

c_m^{in2} investment costs per equipment unit at stage *m*

c_{mt}^{main} maintenance costs of equipment unit at stage *m* in period *t*

v_m scrap value of equipment unit at stage *m*

Decision variables

G_{nj} =1 if technology path *n* is selected in plant *j* (0, otherwise)

H_{mj} number of invested equipment units at stage *m* in plant *j*

R^{HN} first stage revenues

C^{HN} first stage costs

E_{pjs} =1 if product *p* is selected in plant *j* for scenario *s* (0, otherwise)

F_{ijts} flow quantity of raw material from producer *i* to plant *j* in period *t* for scenario *s*

L_{jts} amount of raw material procured from spot market for plant *j* in period *t* for scenario *s*

Z_{mpjts}^{in} flow into stage *m* of process stream for product *p* in plant *j* in period *t* for scenario *s*

Z_{mpjts}^{out} flow out of stage *m* of process stream for product *p* in plant *j* in period *t* for scenario *s*

Z_{mpjts}^{sep} flow out of stage *m* of separated stream from product *p* in plant *j* in period *t* for scenario *s*

Z^{res}_{umpjts}	flow of resource *u* into stage *m* for processing product *p* in plant *j* in period *t* for scenario *s*
X_{pjts}	production quantity of product *p* in plant *j* in period *t* for scenario *s*
W_{pjts}	quantity of product *p* sold to secondary market in plant *j* in period *t* for scenario *s*
Q_{pjkts}	flow quantity of product *p* from plant *j* to customer *k* in period *t* for scenario *s*
D_{pkts}	total shipment of product *p* to customer *k* in period *t* for scenario *s*
R^{WS}_{s}	second stage revenues for scenario *s*
C^{WS}_{s}	second stage costs for scenario *s*

Notation for Chapter 3

Indices and index sets

$p \in P$	product
$g \in G$	product type
$p' \in P(g)$	product belonging to product type *g*
$h \in H$	storage condition
$p'' \in P(h)$	product stored in storage condition *h*
$t \in T$	time period
$t' \in T$	production period
$e \in E$	environmental indicator
$m \in M$	objective
$s \in S$	solution

Parameters

ζ_t	contracted supply of raw milk in period *t* [kg raw milk]
σ^{was1}	waste in raw milk transportation [%]
o_p	raw factor – amount of raw milk required for 1 kg DMC of product *p* [kg raw milk]
π_p	volume of product *p* [m^3/kg DMC]
ν_p	shelf life of product *p* [periods]
β_g	maximum fraction for production of product type *g* per period [%]
θ_h	storage capacity of storage condition *h* [m^3]
ε	transportation distance of final products [km]
σ^{was1}	waste in reconstitution for product *p* [%]
r_t	product price in period *t* [costs/kg DMC]
c^{raw}_t	raw milk costs (including transportation) in period *t* [costs/kg raw milk]
c^{prod}_p	production costs (including packaging material) of product *p* [costs/kg DMC]
c^{inv}_p	inventory costs for product *p* per period [costs/(kg DMC · period)]
c^{trans}_p	transportation costs for product *p* [costs/(kg DMC · km)]

i_e^{raw}	raw milk impact (including transportation) of environmental indicator e [impact/kg raw milk]
i_{pe}^{prod}	production impact (including packaging material) of product p of environmental indicator e [impact/kg DMC]
i_{pe}^{inv}	inventory impact of product p per period of environmental indicator e [impact/(kg DMC · period)]
i_{pe}^{trans}	transportation impact of product p of environmental indicator e [impact/(kg DMC · km)]
γ_{sm}	value of objective m for solution s
ω	weight of profit objective [%]

Decision variables

$X_{pt'}$	quantity of product p produced in period t' [kg DMC]
$I_{pt't}$	inventory of product p produced in period t' at the end of period t $(t' \leq t)$ [kg DMC]
$Q_{pt't}$	quantity of product p produced in period t' and shipped in period t $(t' \leq t)$ [kg DMC]
D_t	demand fulfilled in period t [kg DMC]
$\delta_{ss'm}$	difference between the value of objective m in solutions s' and s
Y_m	=1 if objective m is removed (0, otherwise)
$W_{ss'}$	=1 if s' dominates s in the reduced space (0, otherwise)

Notation for Chapter 4

Indices and index sets

$p \in P$	product
$l \in L$	lot
$l \in L(p)$	lot belonging to product p
$a \in A$	time-dependent changeover
$b \in B$	volume-dependent changeover
$f \in F$	form type
$t \in T$	time period

Parameters

α_p	demand for product p [units]
β_l	minimum lot size of lot l [units]
γ_l	due date of lot l [time units]
$\delta_{ll'}$	= 1 if lot l must be produced after lot l' (0, otherwise)
ε	loading duration of one unit [time units]
ζ_l	processing time of lot l on machine 1 [time units]
η	lowest processing time of all lots on machine 1 [time units]

$\theta_{ll'}$	duration of sequence-dependent batch changeover between lot *l* and lot *l'* (*l* precedes *l'*) [time units]
κ	duration of time-dependent changeover [time units]
λ_a^{min}	earliest starting time of time-dependent changeover *a*—lower bound [time units]
λ_a^{max}	latest starting time of time-dependent changeover *a*—upper bound [time units]
μ	minimum number of time-dependent changeovers [changeovers]
ν	changeover interval for time-dependent changeovers [time units]
ξ	duration of volume-dependent changeover [time units]
o_b^{min}	earliest starting of volume-dependent changeover *b*—lower bound [units]
o_b^{max}	latest starting of volume-dependent changeover *b*—upper bound [units]
π	minimum number of volume-dependent changeovers [changeovers]
ρ	changeover interval for volume-dependent changeovers [units]
σ_l	batch-size coefficient
τ	length of discrete time period [time units]
υ_l	number of forms filled from one tub for lot *l* [number of forms]
φ_l	resting and brining time of lot *l* on machine 2, and separable form cleaning time [periods]
χ_{lf}	=1 if lot *l* requires form type *f* (0, otherwise)
ψ_f	number of available forms of form type *f* —capacity [number of forms]
M_1, M_2, M_3	sufficiently large positive values

Decision variables

C^{max}	makespan [time units]
X_l	amount produced in lot *l* [units]
$S1_l$	starting time of loading lot *l* on machine 1 [time units]
$C1_l$	completion time of loading lot *l* on machine 1 [time units]
$S2_l$	starting time of loading lot *l* on machine 2 [time units]
$C2_l$	completion time of loading lot *l* on machine 2 [time units]
E_l	duration of batch-dependent changeover before lot *l* [time units]
N_a	starting time of time-dependent changeover *a* [time units]
Q_l	cumulated production amount after finishing lot *l* [units]
$Y_{ll'}$	= 1 if lot *l* processed before lot *l'* (0, otherwise)
K_{la}	= 1 if lot *l* scheduled immediately before time-dependent changeover *a* (0, otherwise)
H_{la}	= 1 if lot *l* scheduled before exact time-dependent changeover *a* (0, otherwise)
O_a	= 1 if time-dependent changeover *a* is scheduled last (0, otherwise)
V_{lb}	= 1 if lot *l* scheduled immediately before volume-dependent changeover *b* (0, otherwise)
G_{lt}	number of filled forms for lot *l* in period *t* [number of forms]
R_{lt}	number of released forms for lot *l* in period *t* [number of forms]

I_{ft}	inventory of form type *f* in period *t* [number of forms]
J_{lt}	= 1 if filling of forms for lot *l* carried out in period *t* (0, otherwise)
U_l	consumption period of forms for lot *l* [period]