Optimization-based decision support systems for planning problems in processing industries

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This research was conducted under the auspices of Wageningen School of Social Sciences (WASS)

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Thesis

submitted in fulfillment of the requirements for the degree of doctor
at Wageningen University
by the authority of Rector Magnificus
Prof. Dr M.J. Kropff,
in the presence of the
Thesis Committee appointed by the Academic Board
to be defended in public
on Monday 8 December 2014
at 11 a.m. in the Aula.

G.D.H. Claassen
Optimization-based decision support systems for planning problems in processing industries
172 pages.

PhD thesis, Wageningen University, Wageningen, NL (2014)
With references, and summaries in English and Dutch

ISBN 978-94-6257-208-9

Preface

More than a quarter of a century ago I discovered my appreciation for the theory and application of mathematical models and techniques for decision support in practice. Barely two years after my MSc-graduation I wrote a letter of application for an assistant professorship at the department of mathematics. Hardly difficult to remind, after all, I just wrote one successful letter in my entire life. Let's see what that single letter spawned and might bring into play ☺.

At the time of my application for employment I just finished my first contribution in a collaborative approach to bridge the gap between theory and the scientific challenge of its applicability in real life. We worked on a planning and scheduling problem. This problem resulted in, and was deliberately chosen as, the first case study for this thesis in Chapter 2. The study intends to demonstrate the anticipating value of case-based research for daily practice. Meanwhile it is clear that the main architecture of currently available (commercial) Advanced Planning Systems (APS) provide in what has been proposed in (many) earlier case studies. The downside of that remarkable observation is that, in spite of the tremendous progress that has been made in all these years, the real problem in Chapter 2 has neither been solved (generically) in literature, nor in this thesis (Chapter 3). But we should ask whether this is really bad. At least there is hope for the applicability and relevance of case-based research outside a given application area (e.g. the chapters 4 and 5).

A thesis like this calls for a day to finalise something that – according to present-days standards – should have been finished many years earlier. The question remains: "Should I regret my unrestrained search for professional satisfaction far beyond the social significance of a PhD-degree?" Definitely not! Partly unconsciously following personal motives, never satisfied with what has been reached, horribly abasing my own results and incessantly pushing the bar to almost unreachable limits; it is simply me! Let me give my readership some basic sense for the preceding character sketch. Once, somebody in the academic community stated – I quote – : "*You cannot be a good teacher if you are not a good researcher*". Well, without that elementary formal degree in research, I must be a horrible teacher. So, think as a good researcher and define the next "*research question*" (of course to be answered after the 8th of December 2014): "How to prove that the opposite holds?" Any future PhD-candidate who launches the proposition "*You cannot be a good researcher if you are not a good teacher*" may provoke an interesting debate.

In all those years of employment, my search for understanding, insight and overview was, and still is, indispensable. As the years passed, teaching became one of my prime activities. It provided significantly in my ceaseless quest for professional satisfaction. From my point of view, students are the best potential ambassadors for any applied (research) field in practice. So, I constantly ask myself: "How to get large audiences of students daily in my lecture rooms, inspiring them to study the subjects such that the added value of our profession will become a second nature for every generation we deliver for a professional career?". Meanwhile, I'm convinced that the related mission of any university cannot be projected on, or captured by commonly accepted tape measures.

I should emphasize that teachers and/or researchers have had teachers too, in the broadest sense of the word. Many people contributed to my professional satisfaction in one way or another. I would like to thank them all. Some of them need to be mentioned in particular.

In the first place, I express my sincere gratitude to Jack van der Vorst. Not just as a patient promotor but also as our valued head of the department. It's amazing how you manage to guide a complete corridor of different personalities with all their strengths and weaknesses through rapidly changing environments. Our interpretation and perception on research and education may not always be the same but you constantly showed to be a great listener and extremely fast thinker. Always radiating patience, confidence, and continuous support. Your ability to take the necessary distance and keep the big picture in mind is indispensable to structure my activities. I always left your room with new energy (particularly at difficult times) and valuable notes for the next moves. I have to admit, sometimes I was crashed by the idea that I went in "for a blue sweater" but in the end, implicitly, bought a "vacuum cleaner". A great gift for any manager ☺.

I'm also much obliged to Theo Hendriks, my former colleague and mentor who patiently taught me, for instance, how to use the most simple and powerful tools in educational settings. I remember one of my first educational experiences. At that time we had two groups of students, all following the same course in dynamic programming. After two weeks Theo visited my room in the mathematics building and asked with that well-known expression of sympathy around his eyes: "How do you do?" I knew enough. Apparently, the major part of my initial audience filled the window sills of his classroom. In spite of that devastating experience, you always showed confidence and contributed to my everlasting learning curve, i.e. to find a proper balance between mathematical correctness and its applicability in real life. You simply knew, I would never give up. Hence, you mined my skills and enthusiasm ceaselessly. Two chapters of this thesis are based on research you initiated. Over the years I learned to accept that the outcome, e.g. this thesis, will never be *Theo-proof*. The disillusionment might start already in the first paragraph of each chapter ☺.

Joke and Eligius, I owe you my great debt of gratitude for all continuous support, the contributions and involvement that allowed me to finish this piece of work! Your completely different personal styles and skills floated the vessel successfully at times there was something wrong with the engine. Eligius, I suggest we wait for the moment that our mutual opinion regarding "*research questions*", is widely approved ☺. Joke, in spite of our preference for deterministic behaviour, several of your colleagues (including myself) experienced the impact of stochastic, "superior forces". I will make a splendid picture for our audience and provide for your ultimate relief as a paranymph: only the two of us know which question of the opposition will be yours to answer during my defense ☺.

I should mention the continuous and mostly invisible support of all my colleagues who never showed any hesitation in assisting or taking over parts of my work and give substance to my responsibilities. Teaching activities, in the broad sense of the word, seem to expand exponentially at our university. Yes indeed, a problem of luxury. However, it is usually done at the expense of measured indicators. Dear Joke, Argyris, Karin, Aleksander, Willem and Mehmet thanks for your dedication and involvement in my activities.

Last and certainly not least, I want to thank all my current and former LDI-colleagues, the members of the TIFN project team and all other (former) colleagues within and outside our university for the close collaboration and their contributions to my daily professional satisfaction!

The major part of this thesis had to be done outside regular working hours. Finally the mess on my desk at home can be stored. It will certainly feel as a great relief, not just for me. Within this context it seems almost impossible to find the right words for the most important person in my life. In some way I am convinced she does not want to be mentioned at all. It is reassuring that she does not need my words to communicate, we simply look, feel and know…

Liefste Kim en Li-An, de aandachtige lezer mag ook iets van jullie leren! Wij allen begrijpen nu waarom uitgevers gruwelen van het woord "kaft". Dat wordt een "omslag" genoemd; wat een mooi woord!

G.D.H. (Frits) Claassen   Valburg, November 1, 2014

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Chapter 1

General introduction

A study of decision making for “stochastic, multi-objective fractional programming with conditional terms, subject to a non-linear, fuzzy set of constraints in integer variables*“ (title arbitrarily chosen) may be of little value, unless the usefulness of such a study is demonstrated* (Schaible and Ibaraki 1983).

1.1 Introduction

Nowadays manufacturing strategy is an important part of corporate strategy, particularly in food processing industry (FPI). Due to global competition, the diversity of products increased considerably in this branch of industry which forced manufacturers to participate in an on-going trend towards increased variety (i.e. ingredients and flavours, customised packaging, prints and/or labels) and new products. In this environment, efficient production planning and scheduling is of vital importance and has become one of the most challenging problems for decision support in practice. To keep up with global competition and deal with developments in today’s society, management teams of enterprises have to take all kinds of interrelated decisions on different levels and timeslots within the organization. As a consequence, the need for computerized support has increased substantially.

The tremendous progress in hard- and software of the past decades was an important gateway for developing computerized systems that are able to support decision-making on different levels within enterprises. The history of such systems started in the late 1960s, and in 1971 the concept of Decision Support Systems (DSS) emerged (Gorry and Morton 1971). Meanwhile, the field of DSS has evolved into a broad variety of directions. DSS is not a homogenous field and over its history a number of distinct subfields have emerged (Arnott and Pervan 2008). There are a number of fundamentally different approaches to DSS and each has had a period of popularity in both research and practice (Arnott and Pervan 2005). Due to its interdisciplinary context, a unique framework for categorizing the different types of DSS does not exist. However, based on the dominant architectural components providing the functionality of decision-making, Power and Sharda (2007) identified five categories of DSS, i.e. model-driven, communication-driven, data-driven, document-driven and knowledge-driven DSS.

According to Power and Sharda (2007), model-driven DSS emphasize access to and manipulation of a quantitative model (e.g. accounting and financial models, representation models, and/or optimization models). Hence, quantitative models are the dominant component in the architecture that provides the functionality for the DSS. Communication-driven DSS derive their functionality from communications and information technologies that are used in the system to support shared-decision-making (e.g. computer-based bulletin boards or group decision support systems). The functionality of data-driven DSS results from access to and manipulation of large databases of structured data (e.g. management report systems, data warehousing and analysis systems or business intelligence systems). Document-driven DSS integrate a variety of computer storage facilities and processing technologies in which a search engine is a primary tool to provide sophisticated document retrieval and analysis to support decision-makers. Finally, knowledge-driven DSS suggest or recommend actions based upon knowledge that has been stored using Artificial Intelligence or statistical tools like case-based reasoning, rules, frames and Bayesian networks. The knowledge component, usually based on specialised problem-solving expertise, provides the primary functionality for knowledge-based DSS.

This thesis will explore DSS developments for current-days practice including its added value for industrial practice in the future. We focus on the category of model-driven DSS. In addition, the term model-driven DSS is further refined to modelling and solving (production) planning problems.

Production planning is considered here as the planning of the acquisition of raw materials, the planning of production activities required to transform raw materials into intermediate and final products, and the coordination of production scheduling with physical distribution of finished products to clients in order to meet customer demand in the most efficient or economical way possible. In industrial environments, the problems to be addressed in this field call for (interrelated) decisions with respect to the required kind of raw materials, the types of production quantities to be manufactured, the lot-sizes (or batch-sizes) of the different products to be processed and - last but not least - the time at which the raw materials and production orders must be available.

Due to a high complexity in production structure and layout, process industries show a distinctive role among the various industries, particularly with respect to production planning and scheduling (Entrup 2005). Processing industries are characterized by specific production operations like blending, milling, refining, heating and/or cooling which in turn change and/or define the final properties of (intermediate) products (Kallrath 2002; Günther and van Beek 2003). Usually, specific processes can only be performed efficiently using large installations, which tend to be very expensive (Fransoo and Rutten 1994). Moreover, margins are often relatively low in capital-intensive process industries (e.g. pulp and paper production). Process industries often obtain their raw materials from mining or agricultural industries. These materials have natural variations in quality which often lead to variations in recipes and prices of (alternative) ingredients (Fransoo and Rutten 1994).

Processing can take place in batches or by continuous flows and quite often shared or multi-purpose equipment is used to produce a wide variety of products (Kallrath 2002; Günther and van Beek 2003). As a consequence, sequence-dependent changeover costs and/or times are often incurred (Soman, Van Donk et al. 2004a; Stadtler 2005; Stadtler and Kilger 2008). For instance, for the sake of pureness and safety regulations exhaustive cleaning operations may be prescribed in food processing industry (Günther and van Beek 2003; Soman, Van Donk et al. 2004a). Both, between different types of process industries as within a specific branch, product structures may be completely different, i.e. converging (e.g. paper production industry) or diverging (e.g. dairy industry). The complexity of lot-sizing and scheduling in food processing industry may also be determined by an inevitable decline in quality of products or limited shelf lives, finite intermediate storage facilities, the use of product specific storage devices, no-wait production for certain types of products, and complex packaging facilities (Günther and van Beek 2003; Soman, Van Donk et al. 2004a). Compared to, for instance, discrete parts manufacturing, the specific characteristics of processing industry complicate planning problems considerably which give rise to focus in this thesis on model-driven (i.e. optimization-based) decision support in the domain of processing industry.

As the field of decision support concerns the process of choosing the most attractive alternative, the underlying process of decision-making needs to be analysed to a certain extent in Section 1.2. Section 1.3 will discuss the current state of the art for industrial practice and provides the basis for a basic perception on the question “Which decision-making processes in processing industry need to be supported and how?” Section 1.4 will present the overall research objective including its translation into a number of research questions to be addressed in the next chapters. An outline of the thesis is presented in Section 1.5.

1.2 Concepts and relevance of model-based DSS

This section offers a brief overview of the main developments in DSS including its basic principles. The origin and main concepts of DSS are described (Section 1.2.1) followed by its general architecture (Section 1.2.2). After more than four decades of research in DSS, Section 1.2.3 briefly summarizes the current state of affairs with respect to its professional relevance. The described perception of DSS will be the starting point for one of the research premises for this thesis.

1.2.1 Concepts and origin of DSS

Decision problems arise in many varieties. Some problems are simple while others are extremely complex. Problems can be deterministic and/or contain stochastic elements. Simon (1960) described decision problems as existing on a continuum from programmed (routine, repetitive, well structured, and easy to solve) to non-programmed (new, ill-structured, and difficult to solve). A programmable task can be captured in clear rules, substituting the judgement of the decision-maker. For example, setting up a bill of materials for material requirement planning is a programmable task. For these kinds of programmable tasks, the decision-maker can be replaced by a computer program. However, ambiguity, creativity, and ingenuity may also be involved in decision-making. In these situations, human decision-makers cannot be simply replaced by computers. According to Simon’s taxonomy of decision types, the process of decision-making includes four phases, i.e. *intelligence*, *design*, *choice* and *review*. The phase of intelligence comprises the search for problems i.e. which problems need a decision. The design phase involves the development of alternatives i.e. finding possible courses of action. The third phase consists of the selection of available courses of action. Finally, past choices are evaluated in the review phase.

Anthony (1965) introduced one of the most generally accepted categories of management activities or frameworks for planning problems which consists of three decision levels i.e. *strategic, tactical and operational* control level. Anthony defines strategic planning problems as “*the process of deciding on the objectives of the organization, on changes in these objectives, on the resources used to attain these objectives, and on the policies that are to govern the acquisition, use and deposition of these resources”.* Strategic decisions are extremely important because they are, to a great extent, responsible for maintaining the competitive capabilities of a firm. Strategic decisions determine the rate of growth, and eventually define the success or failure of an enterprise. An essential characteristic of strategic decisions is that they have long-lasting effects, thus forcing long planning horizons in their analysis (Hax and Candea 1984). Once strategic decisions have been made, the next problem to be resolved is the effective allocation of resources on tactical planning level, also called management control. Anthony defines tactical decisions as "*the process by which managers assure that resources are obtained and used effectively and efficiently in the accomplishment of the organization's objective".* Tactical decisions usually involve the consideration of a medium-range time horizon, divided into several periods, and require significant aggregation of the relevant managerial information. Typical tactical planning decisions are purchasing of raw materials, utilization of regular and overtime workforce, allocation of aggregate capacity resources to product families, maintenance planning, and order acceptance strategy. After an aggregate allocation of resources, it is necessary to deal with day-to-day (operational) decisions in a small-range time horizon. Anthony defines operational decision-making as "*the process of assuring that specific tasks are carried out effectively and efficiently on a day to day basis"*. Typical decisions at this level are the assignment of customer orders to individual machines, the scheduling of orders or vehicle routing problems. For an overview of the major elements of Anthony's management activities, the interested reader is referred to Hax and Candea (1984). Anthony's framework and Simon's description of decision problems are considered as the cornerstones of Decision Support Systems (DSS).

The term and concept of DSS was introduced and defined by Gorry and Morton (1971) who integrated Anthony's categories of management activities and Simon's taxonomy of decision types. The authors defined DSS as "*Computer systems that support decision-making for problems that are at least at some stage semi-structured or unstructured*". Computer systems could be developed to deal with the structured part of a problem, but the judgement of a decision-maker is needed on the unstructured part, hence constituting a human-machine problem-solving system. The concept of DSS aimed to assist and make ill-structured, non-programmable tasks more tractable. Models and computers proved to be very valuable for many (programmable) decision problems. However, they can easily demonstrate their weakness too for decision-making in daily practice; particularly with respect to model-based DSS. In the late 1980's it became clear that the added value and applicability of (mathematical) models and computers in daily practice, needed a general architecture which will be discussed in the next section.

1.2.2 Classical architecture of DSS

Model-driven or optimization-based decision support is usually associated with the field of Operations Research (OR). One of the main characteristics of OR (also called Management Science) is the attempt to quantify aspects of decision problems with abstract (mathematical) models. A model of a decision problem is always an abstract description of reality. No model can capture all characteristics of an unstructured decision problem, and is by default a simplification of reality (Ackoff 1977; Claassen and

Hendriks 2007). In order to handle models and use them for generating solutions, assumptions are necessary. Moreover, it is often hard or even impossible to quantify certain aspects of a decision problem. Sometimes, these aspects are either disregarded (Ackoff 1977) or artificially embedded into models as a compromise to the applied technique (Claassen and Hendriks 2007). One (recognized) way to cope with the limits of mathematical models and computers for daily practice is a profound architecture for model-based DSS.

The most basic and classical architecture of a DSS was given by Sprague Jr (1980). According to this scheme the software system of model-based DSS comprises three components, i.e. the *Model Base Management System* (MBMS) or model-base, the *Data Base Management System* (DBMS) or database and the user interface which Sprague called the *Dialog Generation Management System* (DGMS). The components are briefly discussed here.

For many OR scientists, the model base is the actual core of the system. It contains abstract models and algorithms for generating high-quality plans to be used for further analyses. Building models requires profound insight in the problem. Therefore, the focus on the problem itself leads to better insight into the decision situation and part of the problem may already be solved. The exercise of building models often reveals relationships that are scarcely apparent to decision-makers. As a result, there is an increase in insight and understanding of the object being modelled. On the other hand, the gained insight and understanding of the underlying problem is often a prerequisite to solve the generated problems in practice. Solving real-life problems by OR models generally implies that the focus must be towards taking advantage of important problem characteristics, i.e. to recognize them and to exploit special structures for solving the generated problems efficiently. In addition, the motivation to solve real-life problems may also provide new theoretical insight including the basis for new approaches in new contexts that have an added value of their own, even outside the original application area. The main principles for designing models and solution techniques are defined by Little (1970) in his seminal paper “The concept of decision calculus”. The author presents a set of guidelines along six issues (i.e. simplicity, robustness, ease of control, adaptability, completeness and ease of communication) to bridge the gap between mathematical theory and the scientific challenge of its applicability in real-life enterprises.

The database can be seen as the facts of a decision situation. It contains all data necessary to create problem instances for models in the model base (e.g. the type, dimension or quality of raw materials, semi-finished products and end products, inventory levels and demand figures of the products, machinery specification, work force, available capacities and lay-out. Databases fulfil a crucial role in a DSS as they are the key to separate the data from models (Carlsson and Turban 2002). A strict separation of data and models can be considered as the gateway for the applicability of model-based DSS in real-life practice.

The software, managing the interface between the user and the system, is called the user interface. The user-friendliness of this component is of extreme importance for the acceptance of the DSS. The user interface carries all communication between the end-user and the system in practice. Even if a DSS offers a wide range of functional routines and delivers incredibly good solutions, it will hardly be accepted when the underlying routines are hard to use or do not look like what the end-users expect.

Historically, OR-scientists consider the development of models and algorithms as the dominant component of optimization-based DSS (Power and Sharda 2007). However, the contributions and continuous development of other design issues like databases, effective user interfaces and particularly tools to analyse the generated solutions, may be even more important for the applicability of model-based DSS. Kallrath (2004) confirmed the importance of the latter issue and described it as the final stage in decision processes, which includes the delivery and analysis of the generated solutions in a usable form to non-technical end-users.

1.2.3 Professional relevance of DSS

Carlsson and Turban (2002) mentioned in a special issue about the future of decision support systems that the term DSS was seen less and less frequently, both in trade journals and in vendor web sites. The paper mentioned the conception that DSS matured to a point of losing its identity and may even disappear as a stand-alone field. The authors stated the opposite and claimed that the developments of DSS will actually thrive into the next decade because most of the challenges of DSS are still valid. Moreover, the so-called second generation of Enterprise Systems recognized the need for supporting not only transaction processes, but also analytical processing (Carlsson and Turban 2002).

After four decades of DSS research, Arnott and Pervan (2008) reported on a long-term project that critically analysed the academic field of DSS and showed that the gap between research and practice, still exists. The authors analysed almost 1100 articles published in fourteen major journals and showed that almost half of the analysed research was regarded as having low or no practical relevance while only ten per cent of the research was regarded as having a (very) high relevance. The authors argue that the practical contribution of DSS research faces a crisis of relevance due to a long-term issue, i.e. the tension between academic rigor and professional relevance.

Framinan and Ruiz (2010) confirmed the gap between theory and practice in their review on the development of customised and realistic manufacturing scheduling systems. The authors stated that a vast amount of literature is available for manufacturing and scheduling models including solution techniques. However, very little has been written on how to bring these models and procedures into practice. The evidenced trend regarding a lack of relevance and applicability of model-based DSS was an important premise for this thesis:

Research premise P1: Professional relevance and applicability
A professionally oriented academic area like DSS needs a reasonable balance between development of theory and real-life applications since research and practice inform each other (Arnott and Pervan 2008).

Since the field of DSS aims to be an application-oriented discipline, a logical step is to focus in the next section on its elaboration in practice, i.e. in processing industry.

1.3 Decision support for industrial practice

Although Arnott and Pervan (2008) found a moderate to low impact for DSS in practice, the basic concepts of model-based DSS did find their application in a subset of commercial software suites called Advanced Planning Systems (APS) (Günther and van Beek 2003; Stadtler 2005; Pochet and Wolsey 2006; Stadtler, Fleischmann et al. 2012). APS can be regarded as the latest offspring in the development of Enterprise Systems (ES) like Material Requirement Planning (MRP) and its successors. APS particularly aim to give substance to the lack of decision support in (prior) enterprise systems (Entrup 2005). The next sections aim to describe the basic architecture of APS including its relation with the field of DSS. The main architecture of APS constitutes the basis for *i*) positioning the core of this study by defining additional research premises and a further demarcation of the types of problems to focus on in the next chapters, *ii*) exposing the needs for additional decision support in daily practice, particularly with respect to processing industry.

1.3.1 Origin of advanced planning systems

In the 1960's manufacturing strategies were mainly focused on inventory control (Umble, Haft et al. 2003). In those days, companies could afford to keep lots of ''just-in-case'' inventory on hand to satisfy customer demand and stay competitive. In the late 1960's it became increasingly clear that companies could no longer afford the luxury of maintaining large quantities of inventory. The conventional thrust of product-focused manufacturing strategies based on high-volume production, cost minimization and assuming stable economic conditions came to an end (Jacobs and Weston 2007). At that time, and simultaneously with the emergence of DSS, software vendors recognized the high potentials of available data and developed software, i.e. Enterprise Systems (ES), to standardize and control production planning problems (Jacobs and Weston 2007). In those early days, the wave of real-world DSS applications was still in its infancy. Nevertheless, the introduction of Material Requirement Planning (MRP) was a major step forwards (Pochet and Wolsey 2006).

The name Material Requirement Planning (MRP) was coined in the late 1960s through a joint effort between J.I. Case, a manufacturer of tractors and other construction machinery, and IBM which resulted in one of the earliest software applications for planning and scheduling materials for complex manufactured products

(Jacobs and Weston 2007). Pochet and Wolsey (2006) state that the first serious efforts to formulate mixed integer programming (MIP) models for planning problems of the type that MRP systems are designed to tackle, date from the 1960s and 1970s. However, at that time, MIP systems were only able to solve "toy" instances and efforts to solve these problems mainly concentrated on simple and rapid heuristics. Powerful (personal) computers with internal data storage facilities became available and the era for computerized planning and control systems started. However, despite of the fact that generic optimization-based Material Requirement Planning models were available for at least discrete parts manufacturing systems, MRP and its successors were first, and foremost transaction and information-oriented systems, necessary but not sufficient for efficient planning and decision support at factory level or for planning problems of complete enterprises (Pochet and Wolsey 2006).

The interested reader is referred to Pochet and Wolsey (2006) for a basic insight in mathematical formulations of classical production planning models considered in Enterprise Resource Planning (ERP) or MRP systems. This includes the drawbacks and limitations of these systems due to the applied decomposition approach on product level in order to solve these models. Pochet and Wolsey (2006) stated that the observed limitations all relate to the MRP decomposition approach and planning process, and not to the MRP model itself. Nevertheless, the concept of MRP systems can be considered as the basic vein that would become the key for all subsequent developments on the software market with respect to enterprise systems for industrial practice (Pochet and Wolsey 2006). The authors stated that superior results can be obtained for production planning problems if today's transaction-oriented systems are changed into planning systems for coordination and optimization.

Nowadays, large companies face the challenge of increasing competition, expanding markets, and rising customer expectations. Software industry provides software suites consisting of a number of interrelated modules each intended for specific planning tasks (Umble, Haft et al. 2003). These so-called Advanced Planning Systems (APS) share one major characteristic, namely extending transaction- and information-oriented systems by optimization-based tools for decision support. APS incorporate models and solution approaches attributed to Operations Research (Stadtler 2005; Stadtler and Kilger 2008). The introduction of APS intended to shift the objective of production planning for industrial practice from generating plans to solutions that are subject to constraints and company-specific optimization criteria (Entrup 2005). APS are either add-ons or direct integral components of enterprise resource planning (ERP) systems, which create the support mechanism for planning and decision-making at the strategic, tactical, and operational planning level (Møller 2005; Jonsson, Kjellsdotter et al. 2007). Advanced Planning Systems particularly aim to support decision-making. They do not intend to substitute MRP systems or their successors but can be regarded as a top layer for these systems in order to support planners in making decisions on different levels in organizations (Entrup 2005; Jonsson, Kjellsdotter et al. 2007; Stadtler and Kilger 2008). Due to the added functionality of optimization-based decision support, industrial practice started to demand for APS. The historical development and market penetration of computerized planning systems is depicted in Figure 1.1 (Entrup 2005).

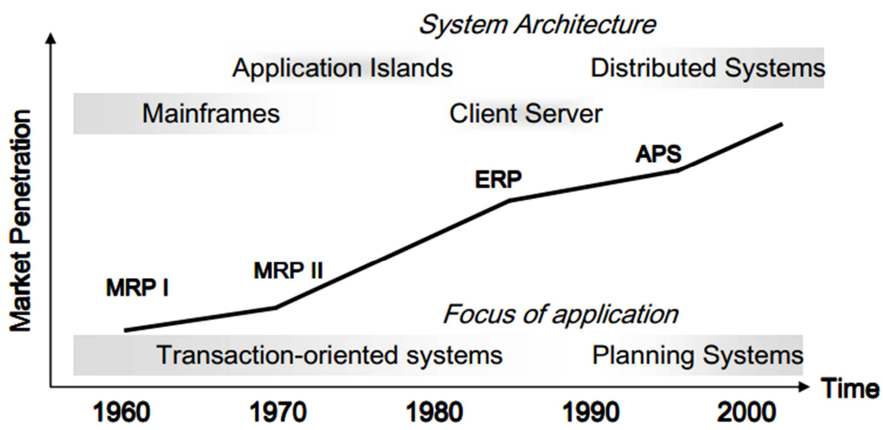


Figure 1.1 Historical development of planning systems (Entrup 2005)

1.3.2 Main architecture of APS systems

It is well known that the strength of transactional systems like enterprise resource planning (ERP) is not in the area of planning (Stadtler 2005). APS are developed to fill this gap. The three main characteristics of an APS are *integral planning* (i.e. coordination of the planning processes of an entire supply chain), a *hierarchical planning approach* (i.e. the decomposition into planning modules, and their vertical and horizontal coordination) and *true optimization* (Pochet and Wolsey 2006; Stadtler and Kilger 2008). The MRP concept in nearly all ERP systems is a planning system restricted to the procurement and production area. It does not optimize and in most cases even not consider an objective function (Stadtler and Kilger 2008).

Rohde, Meyr et al. (2000) introduced the main structure or architecture of planning processes in APS which is known as the *Supply Chain Planning Matrix* (SCPM). Different variants of the SCPM exist but they all share the same basic principle, i.e. to support the main planning tasks related to material flows in organizations along two dimensions: the supply chain process and the planning horizon. The main focus from a supply chain point of view is to support decision-making at different stages or phases in the material flow, i.e. from procurement, production, distribution to sales (horizontal-axis), within the framework of Anthony’s levels of aggregation (vertical-axis) ranging from strategic (long-term) to operational (short-term) planning (Anthony 1965). Figure 1.2 depicts a variant of the SCPM. The interested reader is referred to literature for an extensive description of the SCPM (Stadtler and Kilger 2008; Stadtler, Fleischmann et al. 2012). APS systems typically consist of different software modules, each of them covering a certain range of planning tasks in the SCPM.

Due to the earlier mentioned complexity of the production structure in process industries, the impact of specific production operations on (intermediate) products, and the need for an efficient use of expensive installations, this thesis will mainly focus on medium- to short-term decision support at production phase, including its horizontal integration with decision problems on procurement and distribution phase.

Monolithic models for all planning tasks in the SCPM will neither be solvable nor accepted by various managers of specific tasks (Stadtler, Fleischmann et al. 2012). Monolithic models will also require large amounts of up-to-date data, and revising data will result in frequent replanning.

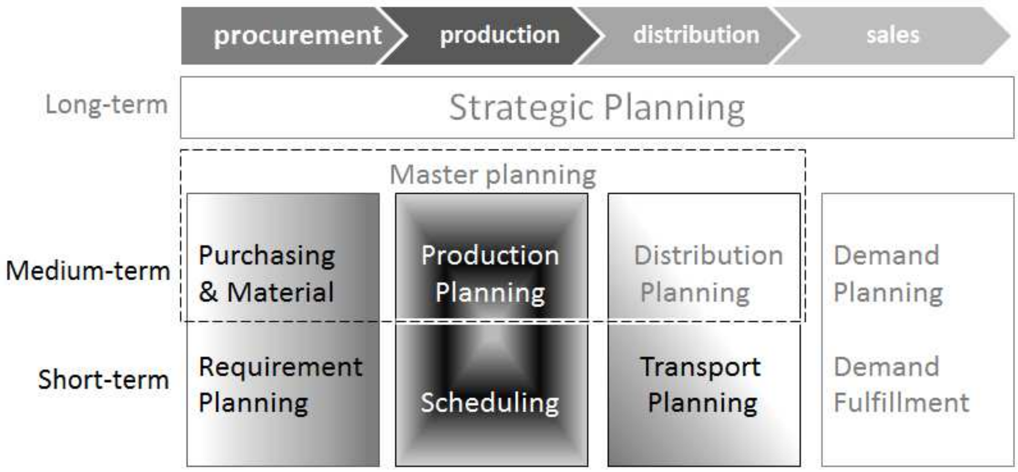


Figure 1.2 Supply Chain Planning Matrix; based on Rohde (2004). The dark shaded parts refer to the focus of the research in this thesis.

Moreover, bottom-line managers will be reluctant to input their local knowledge into an abstract model at the top of an organization's hierarchy (Stadtler, Fleischmann et al. 2012). Consequently, different models are proposed for individual building blocks and/or between (adjacent) blocks in the SCPM. According to Stadtler and Kilger (2008) it is not possible and not recommended to perform optimization on detailed data. In order to reduce the complexity and the need for detailed data, the principles of *aggregation, decomposition* and *reformulation* are important starting points for model development in hierarchical planning approaches like APS.

Aggregation is particularly important on higher planning levels. Wijngaard (1982) stated that aggregation can be achieved along four dimensions: aggregation over time, i.e. the length of periods in the time horizon, aggregation over product types, aggregation over capacities or resources and aggregation over product stages. Aggregation is crucial on medium-term planning level because it reduces the size of models (i.e. computational complexity). Moreover, detailed data (e.g. demand) may not be available over the complete planning interval. However, aggregation is done at the expense of accuracy which may imply that decision-makers in practice poorly support the generated solutions (Stadtler, Fleischmann et al. 2012). The latter gives rise to the next research premise.

Research premise P2: Aggregation
Models for decision support should be based on adequate aggregation levels, carried by decision-makers at crucial decision levels in practice.

Besides aggregation, the principle of *decomposition* is often applied in order to reduce the computational complexity of solving (monolithic) models and the need for detailed data. Decomposition may refer to the scope of the problem, the developed model and/or the applied solution techniques. The SCPM in Figure 1.2 can be regarded as an example of decomposition as it divides an “overall problem” for supply chains into sub problems for each planning or decision unit in the SCPM (Stadtler, Fleischmann et al. 2012). A disadvantage of decomposition approaches in hierarchical planning systems is that separate mathematical models are used for every level. The major drawback of decomposition in hierarchical systems is the risk of a weak linkage between different models. Because of the separate models, some mechanism is needed for obtaining solutions which are consistent across planning levels.

Reformulation is often needed for improving the (initial) formulation of a specific problem. Many companies try to develop planning systems able to optimize productivity. The first step is often to develop new planning models. The resulting large-size mixed integer programming problems are typically much harder to solve to (near) optimality than linear models. Nevertheless, it is often possible to (re)formulate these models such that the solution time is drastically reduced. Unfortunately, some of these reformulation techniques are not generic and depend on specific structures in the problem/model. The identification of special structures in planning problems is important during model construction, especially for the use of reformulation techniques (Pochet and Wolsey 2006). Kallrath (2002) confirmed that many problems in process industries lead to complex MI(N)LP models. Moreover, solution efficiency strongly depends on the individual problem and model formulation. However, for both problem types, MILP and MINLP, it is recommended that the full mathematical structure of a problem is exploited, appropriate reformulations of models are made and/or specific valid inequalities or cuts are used (Kallrath 2000). Pochet and Wolsey (2006) confirmed that the identification of special structures in production planning problems is important during model construction, especially for the use of reformulation techniques.

The computational complexity of (monolithic) planning approaches force model developers to apply principles of aggregation and decomposition. However, their disadvantages should be considered at model construction. Taking advantage of specific (domain-oriented) problem characteristics, identifying and exploiting special (mathematical) structures, and applying favourable reformulation approaches may be even more important to solve problems faster and to generate solutions that are actually carried by decision-makers in practice. The latter gives rise to the next premise for this research:

Research premise P3 : Decomposition and reformulation
Decision support in practice requires decomposition and/or reformulation. These principles may refer to the scope of the problem, the developed model and/or the applied solution techniques. Characteristics of the problem domain including the requirements of specific industries should be taken into account and exploited in order to find effective decomposition schemes and/or reformulation approaches.

The next section will focus on two major aspects at production planning stage: the aggregation level in time (i.e. segmentation of the planning horizon) on different planning levels and the (related) decomposition of planning and scheduling at production level, which are both of particular relevance for processing industry.

1.3.3 Vertical integration of production planning and scheduling

While master planning in Figure 1.2 particularly coordinates material flows between locations, production planning and detailed scheduling is usually run on single locations (Stadtler 2005). On short-term planning level, the aggregated master production plan should be disaggregated to derive detailed plans for different plants and production units. The aim of production planning and scheduling modules in APS should be to generate detailed production schedules for the shop floor over a relatively short interval of time (Stadtler and Kilger 2008). On medium-term planning level, the time horizon is usually divided into (big) time-buckets of variable length. However, sequence-dependent set-up costs and times on flow lines in processing industry cannot be represented properly by big bucket models (Stadtler and Kilger 2008). Due to for instance sequence-dependent set-up times, big-bucket-oriented production plans on a medium-term planning level may lead to infeasible solutions after disaggregation on a lower planning level. Reversely, the generated schedules on the shop floor often fail to realise production targets because changeover losses are not correctly accounted for on a higher planning level. As a consequence, the planning process has to be redone (with or without over-time) and/or frequent rescheduling takes place in daily practice (Kreipl and Pinedo 2004). One option on the higher planning level may be to reserve a certain portion of available capacity for set-up times. However, the portion may be either too large or too small (Stadtler and Kilger 2008).

The time horizon for production planning usually covers a period between weeks and months with time buckets of days or weeks while a typical horizon for production scheduling covers a period between hours and days (Entrup 2005). In order to reduce the complexity of decision problems at production phase, Stadtler, Fleischmann et al. (2012) propose to separate (i.e. decompose) the planning tasks into at least two levels: production planning first and sequencing and scheduling second. In general practice, lot-sizing and scheduling problems are usually solved separately in successive hierarchical phases (Claassen and Beek van 1993; Drexl and Kimms 1997; Kreipl and Pinedo 2004; Soman, Van Donk et al. 2004a; Soman, van Donk et al. 2007; Framinan and Ruiz 2010; Stadtler, Fleischmann et al. 2012). First optimal lot sizes for given product families are determined and afterwards production schedules of customer orders are generated. Stadtler and Kilger (2008) suggested to take the industrial sector as a starting point to determine the planning interval including its segmentation. The authors also stated that the production type at the shop floor should determine whether production planning and scheduling are executed by a single planning level or by a, less elegant, two-level planning hierarchy. Stadtler (2005) stated that if the loading of resources and lot-size decisions are strongly affected by the sequence of jobs, which often applies to the process industry, both production planning and scheduling should be performed simultaneously.

Although most of the lot sizing literature is focused on discrete manufacturing, there exists an increasing interest for other areas like processing industries (Günther and van Beek 2003; Quadt and Kuhn 2008; Clark, Almada-Lobo et al. 2011). Nowadays there is also a general consensus regarding a closer integration of planning and scheduling (Meyr 2000; Jans and Degraeve 2008; Clark, Almada-Lobo et al. 2011). However, today's APS systems do not provide modules for simultaneous lot-sizing and scheduling (Stadtler, Fleischmann et al. 2012). This lack of integration is of particular relevance for processing industry. The utilization of flow lines in this branch of industry is usually high and different products (lot-sizes) have to compete for scarce available capacity. Solving models for the two types of problems simultaneously, usually takes a large computational burden.

The complexity of (mixed) integer programming models to describe these kinds of problems can easily exceed today's hardware and algorithmic capabilities (Kallrath 2002). Although the computational complexity may increase, Soman, Van Donk et al. (2004a) stated that the majority of research contributions do not address specific characteristics of food processing industry in production phase, e.g. high capacity utilisation, sequence-dependent set-ups and limited shelf life due to product decay. The latter gives rise to the next research premise:

Research premise P4: Vertical integration in production phase
Due to specific characteristics of processing industry, decision support in the production phase should include simultaneous planning and scheduling in which sequence-dependent set-ups and product decay are considered.

Although the borders between the different building blocks of the SCPM may be less strict than depicted in Figure 1.2 (e.g. between production planning and scheduling), Stadtler (2005) stated that the general aim of APS is to achieve a better fit between modules, planning tasks and decision-making. The next section will focus on the importance of a close (horizontal) integration and coordination between building blocks of the SCPM.

1.3.4 Horizontal integration of planning tasks

APS hierarchically decompose all planning tasks in a supply chain into partial planning problems and solve them within single modules (Entrup 2005). A strong coordination (i.e. the configuration of data flows and the division of planning tasks to modules) of APS modules is a prerequisite to achieve consistent plans for the different planning phases and for each entity of the supply chain (Stadtler and Kilger 2008). The authors defined the incremental update and major changes on master data in ERP systems as the key for integration between APS and (transactional-oriented) ERP systems. Although different APS modules can interact directly by sending messages, exchanging data and information between different decision phases, coordination and integration is often restricted to the exchange of data flows between different modules and/or the related IT infrastructure (Stadtler and Kilger 2008). Literature on integrated modelling approaches for separated planning issues in the SCPM, is relatively sparse (Kanyalkar and Adil 2005). Studies, in which issues of integration are considered, mostly refer to simultaneously considering production and distribution planning (Kanyalkar and Adil 2005). Recently, Mula, Peidro et al. (2010) presented a review of mathematical programming models for supply chain production and transport planning. The authors found 44 studies within a time frame of 25 years that focussed on tactical and/or operational decision levels and their possible combination with aspects of a strategic nature. Kanyalkar and Adil (2005) developed a single model for consumer goods industry integrating aggregated and detailed production planning with a detailed distribution plan. In a follow-up study, the authors focussed on the missing link with procurement (Kanyalkar and Adil 2007). Although planning issues between production and distribution have been the concern of research, integrated modelling approaches between other building blocks of the SCPM retrieved remarkably little attention.

Sourcing of (various) raw materials needs planning both on medium-term and short-term planning level, particularly in processing industry. On a medium-term planning level, decisions regarding which, how much, and when various raw materials must be purchased and delivered at processing sites, are of major importance for production environments that are characterized by *i*) (semi-) batch type production processes (e.g. the choice of various raw materials to be processed in different batches on shared or multi-purpose equipment), *ii*) decline in quality of raw materials (e.g. raw milk in dairy industry), and *iii*) limited capacity of (special) storage facilities, both on supply and processing level. For instance, if perishable raw materials are produced at a constant level in a push-oriented supply chain (e.g. raw milk) and processing of different end products is planned on shared resources at a limited number of discrete moments in a planning horizon, sourcing and production planning decisions are interrelated and complicated. In those situations, the collection schedules at supply phase are not restricted to solving vehicle routing problems. On a short-term level, the routing problem for collecting perishable raw materials (e.g. in dairy industry) is more complicated than solving a classical vehicle routing problem (VRP) with a typical planning period of a single day (Chao, Golden et al. 1995). If raw materials at supply level are collected at various frequencies, the collection problem can be classified as a periodic vehicle routing problem (PVRP). The PVRP extends the classical VRP from a single day to a time horizon of *T* days in which each supplier must be visited at least once but some of them may or must be visited several times during the *T*-days period (Chao, Golden et al. 1995; Cordeau, Gendreau et al. 1997). However, this class of problems either concerns the construction of pickup routes or delivery routes, not both. For an integrated approach between procurement and production, both pickup and delivery conditions should be considered simultaneously.

Another special feature in processing industry refers to specific processing operations like blending, refining or heating (Günther and van Beek 2003). These operations may have a variable impact on multi-component streams entering a processing unit which in turn defines the final composition of the combined mass flow. If flows of raw materials with different chemical or physical properties are treated by processing units at variable technical settings, the impact of processing operations refers both to the final properties of end products and (simultaneously) to the required types of raw materials. This two-sided impact requires a close integration and coordination between procurement and production.

Research premise P5: Horizontal coordination and integration
There is a need for integrated approaches in processing industry particularly on the tangent plane between procurement and production.

1.4 Research motivations, objective and questions

Many resources emphasise the need for developing specific (integrated) decision models for each production segment and planning step in APS (Günther and van Beek 2003; Entrup 2005; Stadtler and Kilger 2008; Stadtler, Fleischmann et al. 2012). According to Entrup (2005), it is crucial to examine the requirements of specific industries and develop industry-specific solutions. Given the need for specific (integrated) decision support in process industries, the general research objective (RO) of this study is:

To support medium- to short-term planning problems by optimization-based models and solution techniques such that:

- *i)* *The applicability and added value of (prototype) systems is recognized and carried by decision-makers in practice*
- ii) *The proposed approaches contribute to knowledge, understanding and insights from a model-building and -solving point of view.*

A number of planning issues are studied to give substance to the research objective. The translation of the general objective into concrete research questions (RQ's) is based on the research premises *P1* to *P5* in the Sections 1.2 and 1.3.

Due to the complexity of decision problems on production level in process industries, both the first and second RQ focus on the relation and integration between planning and scheduling.

In companies where APS are implemented, planning and scheduling decisions are often transferred from the shop floor to the new APS. As a result, there can be a disagreement between the system and the shop floor which may lead to problematic use of APS in practice (Wiers 2009). The reserved use of APS in daily practice corresponds with the findings of earlier studies (Kreipl and Dickersbach 2008; Ivert and Jonsson 2011; Ivert 2012). As the field of decision support systems was initiated and aims to be an application-oriented discipline and APS particularly intend to support decision-making in practice, the first research question (RQ) is:

RQ1
How to apply aggregation, decomposition and reformulation in model-based DSS at planning and scheduling level such that the aspect of decision support is recognized and appreciated by decision-makers in practice, and which level of aggregation is needed to integrate production planning (i.e. lot-sizing) and scheduling problems in a single model?

Literature shows that the boundaries between planning (i.e. lot-sizing) and scheduling are fading, but further integration still constitutes a challenging research track (Jans and Degraeve 2008; Quadt and Kuhn 2008). Both reviews showed that there is an on-going research trend directed towards incorporating real-world issues and specificities of simultaneous lot-sizing and scheduling. For instance, the problem of contamination is a key aspect in animal food production. An ingredient needed for one type of animal can be lethal for another (Wiers 2009). These kinds of typical characteristics in food processing industry make it necessary to relax all assumptions with respect to changeover matrices, particularly with respect to the so-called triangular set-up conditions. Moreover, lot sizing and scheduling models in food processing industry should include issues of deterioration due to perishability of inventory. In a recent special issue on lot-sizing and scheduling Clark, Almada-Lobo et al. (2011) confirmed and emphasized the need for more realistic and practical variants of models for simultaneous lot-sizing and scheduling. Features like non-triangular set-ups, perishability, and delivery time windows were explicitly labelled by the authors as open research opportunities. Therefore, the next research question refers to both a vertical integration of production planning and scheduling at production level, and a closer coordination between production and physical distribution level in the SCPM:

RQ2
How to integrate production planning (i.e. lot-sizing) and scheduling problems in a single model, such that common assumptions regarding the triangular set-up conditions are relaxed and issues of product decay and limited shelf lives are taken into account?

Both production and distribution planning of (end) products are part of the APS framework. However, coordination and integration issues should not be restricted to these two phases in material flows. Comparable planning problems of integration may manifest at procurement phase with a reverse impact on planning problems in the production phase. In their literature review, Kanyalkar and Adil (2007) explicitly concluded that issues of integration between distribution at procurement level with production, are rarely addressed. The critical issue is to implement systems that integrate organizational decision-making vertically (among strategic, tactical, and operational levels) and horizontally (among many functional fields at the same level) to coordinate and manage conflicts among the various subunits of the organization (Eom and Lee 1990). The next research question focuses on the observed need and missing link between both phases procurement and production (horizontally) and the time horizon (vertically) in the APS framework (see Figure 1.2). Special emphasis is directed to integrated decision support across organizational borders. If the “strongest” partner is in charge of a supply chain and dictates decision-making in the production phase, the planning and distribution problem at the supply phase becomes even more complicated and challenging for a “weaker” partner in the same supply chain. Therefore, the third research question is:

RQ3
How to model and solve an integrated planning problem between procurement and production, both on a medium-term and short-term planning level, in an inter-organizational supply chain?

A special feature in processing industry with major impact on computational efficiency, refers to specific processing operations like blending, refining or heating (Günther and van Beek 2003). These operations may have a variable impact on multi-component streams entering a processing unit which in turn define the final composition of the combined mass flow. An almost classical example in OR is the non-linear “pooling or fuel mixture” problem in refinery and other branches of process industry (Amos, Ronnqvist et al. 1997). If these types of production planning problems are treated in the context of mathematical optimization, they may lead to MINLP problems which are often hard to solve (Kallrath 2002). Other (non-linear) problems may occur if flows of raw materials with different chemical or physical properties are treated by processing units at different technical settings which in turn determine the final properties of end products. Production according to customer specifications requires interrelated decision-making with respect to procurement of raw materials, assignment of available raw materials to different end products including the technical setting of processing units. Depending on changing production targets of final products, optimization-based decision support may provide a way for selecting the right raw materials (on the market), to be processed at various technical settings in available production units, and assign them to end products that meet customer specifications.

RQ4
How to support decision-makers in practice if crucial properties of end products simultaneously depend on (endogenous) types of raw materials with different chemical or physical properties and (endogenous) technical settings of processing units?

1.5 Research method and outline of the thesis

The extensive analysis of DSS by (Arnott and Pervan 2008) showed that the gap between research and practice of DSS is widening, which is confirmed by (Framinan and Ruiz 2010) in their study on the development of customised and realistic manufacturing scheduling systems.

In a recent review, particularly devoted to mathematical programming models for supply chain production and transport planning, Mula, Peidro et al. (2010) mentioned a striking finding that more proposed models were validated by numerical examples than by case studies applied to real supply chains. Arnott and Pervan (2008) proposed a strategy for improving the relevance of DSS research by increasing the number of case studies which automatically increases the commitment of all parties involved. A field that is removed from practice needs case study work to ensure that the questions it is addressing are both relevant and important (Arnott and Pervan 2008). The authors stated that researchers need to select problems with a consideration for professional relevance and interest, in addition to considering the recommendations of previous academic research. According to Arnott and Pervan (2008), case studies are the research papers with the highest proportional relevance scores and can illuminate areas of contemporary practice in ways that experimental studies or surveys cannot. The review of Mula, Peidro et al. (2010) affirms that applying planning models to real case studies needs more attention. We take this statement as a starting point for the case-based approach in (most of) the following chapters. All studies concern modelling and solving (production) planning problems in process industries by optimization-based decision support.

We introduced five research premises *P1* to *P5*. Premise *P1* refers to the first part of the research objective (RO) in Section 1.4, while all other premises are related to the second part of the RO, i.e. model-building and/or -solving. The relation between the defined premises and research questions is given in Table 1.1. Each research question RQ(n) refers to the Chapter (n+1).

Table 1.1 Relation between research questions and premises

Premise		*RQ1*	*RQ2*	*RQ3*	*RQ4*
P1	*Professional relevance and applicability*	✓	(✓)	✓	✓
P2	*Aggregation*	✓		✓	
P3	*Decomposition and/or reformulation*	✓	✓	✓	✓
P4	*Vertical integration*	✓	✓		
P5	*Horizontal integration*		✓	✓	✓

Chapter 2 is based on a pilot DSS in dairy industry. The study aims to demonstrate the validity and contribution of case-based DSS research in the past to the current framework of APS. The study focuses on a medium-term planning problem (i.e. lot-sizing) and short-term scheduling problem. Chapter 3 focuses on complete integration of production planning (i.e. lot-sizing) and scheduling in a single model. The emphasis is to incorporate specific issues for food processing industry (i.e. non-triangular set-ups, product decay and delivery time windows) into the model and to demonstrate its impact on generated solutions. The case-study in Chapter 4 deals with integrated decision support combining procurement and production in an inter-organizational supply chain. The goal of the study is to demonstrate the importance of a distribution level for decision-making between procurement and production in the SCPM. Chapter 5 studies the impact of technical settings of production units on raw material flows in processing industry. Moreover, the study demonstrates the impact of continuously changing decision environments in practice for a real-life DSS, both from a modelling and solving point of view. Chapter 6 presents a general discussion, an overview of findings and points out some directions for further research.

Chapter 2

Planning and scheduling in food processing industry

The big problem with management science models is that managers practically never use them (Little 1970)

This chapter is based on:

Claassen, G.D.H., and Beek, P. van, (1993)
Planning and Scheduling Packaging Lines in Food-Industry
European Journal of Operational Research
Vol. 70 (2), pp. 150 – 158.

Claassen, G.D.H. and Hendrix, E.M.T., (2014)
On Modelling Approaches for Planning and Scheduling in Food Processing Industry
In: ICCSA 2014, Part II, Lecture Notes in Computer Science 8580
Eds: B. Murgante et al.
Springer, pp. 47 – 59

Abstract

This chapter consists of two parts. Part I concerns the development and implementation of a pilot Decision Support System for the bottleneck packaging facilities of a large dairy company. The planning and scheduling problem has been decomposed into two levels: a tactical and operational control level. On the tactical level a feasible (daily) production schedule of the orderbook is determined. A Mixed Integer Linear Programming model is the basis for making this schedule. On the operational control level two sequencing sub problems are solved. For the solution of these sub problems well-known heuristics have been used.

As the case study is based on an earlier study, Part II consists of a literature research on modelling developments for simultaneous lot-sizing and scheduling. We consider developments in lot-sizing and scheduling, particularly relevant for problem settings arising in food processing industry. Food processing industry (FPI) reveals several specific characteristics which make integrated production planning and scheduling a challenge. First of all, set-ups are usually sequence-dependent and may include the so-called non-triangular set-up conditions. Secondly, planning problems in FPI have to deal with product decay due to deterioration of inventory. We give an overview of lot-sizing and scheduling models, and assess their suitability for addressing sequence-dependent set-ups, non-triangular set-ups and product decay. We show that a trend exists towards so-called big bucket models. However, the advantage of these approaches may become a major obstacle in addressing the identified characteristics in FPI.

Part I

Planning and Scheduling Packaging Lines

2.1 Introduction

This first part deals with an approach to solve a planning and scheduling problem for the bottleneck packaging facilities of the cheese production division of a large dairy company. This approach is mainly concerned with the development and evaluation of a pilot Decision Support System (DSS) in order to generate and to display 'high-quality' schedules with a reasonable efficiency. The pilot DSS should combine the power of human judgement and experience on the one hand with the accuracy and speed of the computer on the other hand. Special attention should be paid to the development and implementation of a user interface.

Figure 2.1 illustrates the goods flow of the cheese product division. The divergent product structure can be partitioned as follows: during the first stage the company produces about 300 different kinds of cheese-varieties. Next, the cheese has to be stored in a large warehouse for the purpose of ripening. The duration of this so called maturation period determines the taste of the final product. Consequently the number of cheese varieties triples in this stage of the goods flow. Finally the cheese will be transported to the packaging department. In this stage several treatments or operations have to be performed in order to cope with the specific demand for packaging requirements of each individual customer. As a result the total number of final products increases dramatically to 2500. If we take the time horizon of the various stages Figure 2.1 into account, then it will be obvious that the packaging department is the bottleneck facility of the cheese product division.

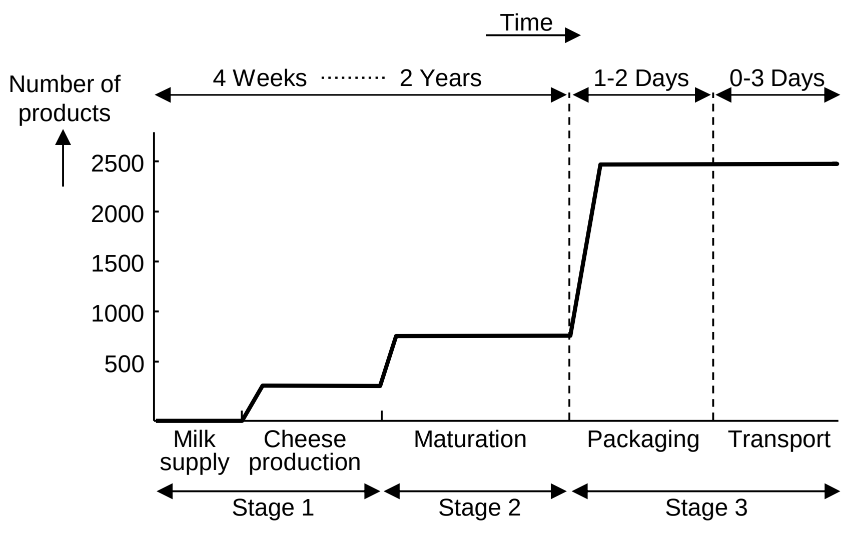


Figure 2.1 Overview of the product increase in time

In order to handle a throughput of five million pounds of cheese weekly, the packaging department is equipped with ten packaging lines. Actually, in this case, a packaging line consists of *m* machines arranged in series. Generally a job requires *m* operations, each operation being performed on a different machine. As the machines of a packaging line are physically connected, the processing time of each job depends on the bottleneck operation to be performed. The flow of work is unidirectional: each job has to pass each machine in a prescribed order. Moreover, it is not possible to interrupt an operation on a machine before completion of the corresponding job (nonpreemptive scheduling). In general a job can only be processed on one packaging line that is specific for that job. However, there are also some jobs that can be processed on more, not necessarily identical lines. All the products are strictly made to order and in general no inventory of final products is carried (on open shop). According to Hax and Candea (1984) the problem can be considered as a generalisation of an open nonpreemptive, *n*-job *m*-machine flow shop problem. The job arrival process can be classified as a deterministic dynamic shop with a time horizon of two weeks. This means that the new jobs are periodically released to the shop floor and the processing times of the intermittently arriving jobs are more or less known.

Several planners of the packaging department are in charge of drawing up a working schedule for the next few days. This planning process is executed manually and principles of developing a schedule are strictly based on experience. Moreover, the transfer and reuse of the specialized expertise to other (often non expert) planner seldom takes place. It can be a nasty task to obtain a feasible schedule and the procedure does not lead to an optimal solution in general. Once the generation of a schedule has been completed, it turns out to be extremely difficult to handle rush orders by changing this schedule.

The management team of the cheese product division had gained the insight that the manual planning and scheduling procedure was inadequate for future planning. An increasing flexibility of the packaging department should get higher priority in order to meet due dates, reduce lead times, optimize utilisation of resources and reduce minimize changeover costs.

2.2 Problem analysis

The ultimate goal of the management team was twofold. At first the aim was to support planners concerned with the planning and scheduling of the packaging lines by drawing up an effective and efficient working schedule of the order book. Furthermore, the system should also support the order entry process. If the sales manager possesses a thorough overview of the working schedule of the packaging department, the order acceptance department will be able to anticipate more adequately on the remaining capacity.

The scheduling problem introduced before turns out to be disappointingly difficult to solve (Hax and Candea 1984). Garey, Johnson et al. (1976) proved that the nonpreemptive scheduling flow shop problem belongs to the class of NP-hard problems. In order to reduce the complexity of the stated problem, several researches proposed a decomposition of this kind of problems into a number of control levels. Anthony (1965) classifies decisions into three categories: decisions on strategic planning level, tactical planning level and operational control level. Strategic planning is mainly concerned with long-term decision-making, related to investment decisions, product development etc. The emphasis of tactical planning is effective and efficient use of all resources. Having allocated all resources, it is necessary to deal with day-to-day operational decisions. This is called operational control. Van Wassenhove and Vanderhenst (1983) also discuss a hierarchical framework for the development and implementation of a (similar) planning problem for a set of production facilities of a large chemical firm. Our research is only focussed on both the tactical and the operational control level.

2.2.1 The tactical planning level

On the tactical planning level a feasible (daily) ‘master packaging schedule’ of the orderbook has to be determined. This notion will be explained in the sequel. The time horizon is subdivided into ten working days (two weeks). The emphasis is on the fulfilment of the due dates of the individual jobs. Early handling of orders is possible but restricted to a small extent (due to the ongoing maturation of the new cheese). Furthermore, it is also desirable (for reasons of capacity utilization) to minimize the total changeover time on the packaging lines. For this purpose, the packaging department created clusters of similar jobs. The jobs belonging to one specific cluster consist of several similar operations and the changeover costs related to the jobs within one cluster are negligible. However, for different clusters the jobs require different operations. For that reason switching over from one cluster to another on a specific packaging line implies a substantial changeover time. We distinguish about fifty different clusters; forty of them can be processed on only one, not necessarily the same, packaging line. The remaining clusters can be processed on several, mostly not identical, lines working in parallel. Changeover time reduction is achieved by scheduling the jobs daily to production lots consisting of one or more clusters, taking into account the availability and due dates of the individual jobs. Moreover, clustering the jobs into large clusters complies with the endeavour to minimize the remnants of the fixed lots in the storage yard.

Most of the jobs can only be processed on one specific packaging line. However, there are also jobs that can be processed on alternative, not necessarily identical, lines with different processing times. In order to optimize the capacity utilization, the elapsed time between the arrival and completion of the jobs on the shop floor (the mean flow time) has to be minimized.

In general a crew of workers on the shop floor can operate only one specific packaging line. The department can make use of a so-called special shift. This shift can only be scheduled in the night and has the skills to process any cluster on any packaging line. The special shift is not considered as overtime; it just fills up a shortage of capacity in a flexible manner. Moreover it is possible to increase the available capacity by overtime of the regular labour. An important goal is to minimize the hours of overtime and special shift.

2.2.2 Modelling

In this section we describe a Mixed Integer Linear Programming (MILP) model for the tactical planning level. This model turns out to show a great similarity with the 'capacitated facility location model'. For that reason we briefly review the latter model before dealing with the tactical planning model.

Capacitated facility location model

The Capacitated Facility Location Model (CFLM) deals with the problem how to locate a number of facilities (with finite capacity) which have to service a given set of customers, at minimum cost. Mathematically, this problem can be formulated as a MILP model in which the index *i* refers to *I* potential locations where facilities can be established and the index *j* to *J* customers. Let us now formulate the CFLM, specified by the following parameters:

F_i ~ The fixed costs associated with a facility at location *i*.
$C_{i,j}$ ~ The transportation costs of supplying the demand of customer *j* from facility *i*.
S_i ~ The capacity of facility *i* (units per year).
D_j ~ The demand of customer *j* (units per year).

Furthermore, define the following decision variables:

$X_{i,j}$ = The fraction of the total demand D_j of customer *j* that is supplied from facility *i*

$$Y_i = \begin{cases} 1 & \text{if facility } i \text{ is opened,} \\ 0 & \text{if facility } i \text{ is closed.} \end{cases}$$

Now the capacitated facility location model can be formulated:

$$\min\left\{\sum_{i=1}^{I} F_i Y_i + \sum_{i=1}^{I}\sum_{j=1}^{J} C_{i,j} X_{i,j}\right\} \tag{1}$$

Subject to

$$\sum_{i=1}^{I} X_{i,j} = 1 \qquad \forall\, j, \tag{2}$$

$$\sum_{j=1}^{J} D_j X_{i,j} \le S_i Y_i \qquad \forall\, i, \tag{3}$$

$$X_{i,j} \geq 0 \qquad \forall\, i, j, \tag{4}$$

$$Y_i \in \{0, 1\} \qquad \forall\, i. \tag{5}$$

Equations (2) ensure that the demand of every customer is satisfied. The equations (3) are the capacity constraints, a facility at location i cannot handle more than S_i units a year. Moreover, these constraints imply that no customer can be supplied from a not existing facility at location i (Y_i =0). The conditions in (4) and (5) complete the set of constraints.

If there is no restriction on the capacity of the facilities (S_i is a very large number), the solution of the LP relaxation represented by (1)-(4) supplemented with the restriction

$$0 \leq Y_i \leq 1, \qquad \forall i \tag{6}$$

is mostly integer in the Y_i's. We call this LP model the LP relaxation of problem (1)-(5). Erlenkotter (1978) developed for this so-called uncapacitated facility location problem an efficient solution procedure.

The capacitated facility location problem, however, is much harder to solve. Substantial research has been focussed on this particular problem class. One approach is directed to the definition of Variable Upper Bound (VUB) constraints. Adding the (redundant) inequalities

$$X_{i,j} \leq Y_i \qquad \forall i, j \tag{7}$$

will enrich the model formulation (1)-(5) in such a way that the LP relaxation of this problem, (1)-(4) together with (6) and (7), tends to generate integer Y_i's (Schrage 1975). In order to see that (7) is valid, note that Y_i are binary variables. If Y_i = 1, (7) is implied by $\sum_{i=1}^{I} X_{i,j} \leq 1$ see (2). If Y_i = 0, (3) implies that $X_{i,j}$ = 0 and in that case (7) is also true. According to Vanroy (1986), these VUB constraints yield a much tighter LP relaxation than the formulation without (7). The author reported several studies in which the inclusion of the inequalities (7) gave very tight lower bounds and sparse search trees. Cornuejols, Sridharan et al. (1991) described a comparison of several approaches which are mainly based on heuristics and Lagrangean relaxation.

The tactical planning model

As described before, our main goal on the tactical planning level is to determine the clusters and to assign clusters to each time period of the planning horizon in such a way that the due dates of the individual jobs are met and total changeover time is minimized. These kinds of production scheduling problems are closely related to the above-mentioned 'capacitated facility location problem'. In both cases the decision variables can be subdivided into two classes: the (binary) location variables (Y_i) and the (continuous) allocation variables ($X_{i,j}$).

However, in or case the managerial decisions require the consideration of more goals: optimizing (*i*) the capacity utilization, (*ii*) the hours of special shift and (*iii*) the hours of overtime. Moreover, these goals are incommensurable with each other. For this purpose we approached the problem partly as a goal programming model. The hours of overtime as well as those of special shift are modelled as deviational variables which are a part of both the capacity constraints (slack) and the objective function. By means of several penalty and weighing coefficients in the objective function, we are able to include all the decision criteria into the model and to assign weights to them.

Mathematically the problem can be formulated as a MILP model, in which the index j refers to the individual jobs of the orderbook (j = 1, 2,…, J), l to the packaging lines (l =1, 2,…, L) and i to the potential clusters I (i = 1, 2,…., I). The index t denotes the specific day within the planninghorizon T (t = 1, 2,…, T). Now we define the following coefficients:

$PST_{j,t}$ ~ A penalty coefficient for the starting time t of each job j.
$PPT_{j,l}$ ~ A penalty coefficient for the processing time of each job j on packaging line l.
$PFD_{l,t}$ ~ A penalty coefficient for the forecasted demand on day t at each packaging line l.
$WSC_{i,t}$ ~ A set-up cost coefficient for scheduling a cluster i on day t.
$WSS_{l,t}$ ~ A cost coefficient for hours of special shift scheduled on packaging line l on day t.
$WOT_{l,t}$ ~ A cost coefficient for hours of overtime scheduled on packaging line l on day t.
$PT_{j,l}$ ~ The processing time on job j on packaging line l.
$RM_{l,t}$ ~ The total hours of regular labour available on packaging line l on day t.
RZS_{t} ~ The total hours of special shift labour available on day t.
RZO_{l} ~ The total hours of overtime labour available on packaging line l.
JOB_{I} ~ The set of jobs (collected at the start of the planning horizon) belonging to cluster i.

Let the following variables be defined:

$X_{j,l,t}$ = The fraction of job j to be processed on packaging line l on day t.

$$Y_{i,t} = \begin{cases} 1 & \text{if cluster } i \text{ will be scheduled on day } t, \\ 0 & \text{otherwise.} \end{cases}$$

$ZS_{l,t}$ = The planned hours of special shift on packaging line l on day t.
$ZO_{l,t}$ = The planned hours of overtime on packaging line l on day t.

Now, the tactical planning model can be stated as follows:

$$\mathrm{Min}\left\{\sum_{j=1}^{J}\sum_{l=1}^{L}\sum_{t=1}^{T}\left(\mathrm{PST}_{j,t}+\mathrm{PPT}_{j,l}+\mathrm{PFD}_{l,t}\right)X_{j,l,t}+\sum_{i=1}^{I}\sum_{t=1}^{T}\mathrm{WSC}_{i,t}Y_{i,t}+\sum_{l=1}^{L}\sum_{t=1}^{T}\mathrm{WSS}_{l,t}\,\mathrm{ZS}_{l,t}\right.$$
$$\left.+\sum_{l=1}^{L}\sum_{t=1}^{T}\mathrm{WOT}_{l,t}\,\mathrm{ZO}_{l,t}\right\} \qquad (8)$$

$$\sum_{l=1}^{L}\sum_{t=1}^{T}X_{j,l,t}=1 \qquad \forall\, j, \qquad (9)$$

$$\sum_{j=1}^{J}\mathrm{PT}_{j,l}X_{j,l,t}-\mathrm{ZS}_{l,t}-\mathrm{ZO}_{l,t}\le \mathrm{RM}_{l,t} \qquad \forall\, l,t, \qquad (10)$$

$$\sum_{l=1}^{L}\mathrm{ZS}_{l,t}\le \mathrm{RZS}_{t} \qquad \forall\, t, \qquad (11)$$

$$\sum_{t=1}^{\frac{1}{2}T-1}\mathrm{ZO}_{l,t}\le \mathrm{RZO}_{l} \qquad \forall\, l,$$

$$\sum_{t=\frac{1}{2}T}^{T}\mathrm{ZO}_{l,t}\le \mathrm{RZO}_{l} \qquad \forall\, l, \qquad (12)$$

$$\mathrm{ZO}_{l,t}+\mathrm{ZS}_{l,t}\le \mathrm{RM}_{l,t} \qquad \forall\, l,t, \qquad (13)$$

$$\sum_{l=1}^{L}X_{j,l,t}-Y_{i,t}\le 0 \qquad \forall\, i,t,\quad \forall\, j\in \mathrm{JOB}_i,\ \mathrm{JOB}_i\subset \mathrm{JOB}:=\{1,2,\dots,J\} \qquad (14)$$

$$Y_{i,t}\in\{0,1\} \qquad \forall\, i,t, \qquad (15)$$

$$X_{j,l,t}\ge 0 \qquad \forall\, j,l,t, \qquad (16)$$

$$\mathrm{ZS}_{l,t},\mathrm{ZO}_{l,t}\ge 0 \qquad \forall\, l,t. \qquad (17)$$

Equation (9) ensures that all the jobs are processed within the planning horizon *T*. The capacity constraints are formulated in (10): A nine-hour working day can be augmented by the available special shift ($ZS_{l,t}$) or by overtime of the regular labour ($ZO_{l,t}$). The constraints (11) put a daily maximum on the total amount of special shift labour, while the constraints in (12) restrict the total manhours of overtime to a weekly limit. In addition, the combined manhours of overtime and special shift labour is restricted to a certain extent, represented by (13). The constraints in (14) imply that a job *j* can only be processed on day *t* if cluster *i*, to which job *j* belongs, will be scheduled on that particular day. Moreover, these VUB constraints enrich the model formulation in a way already discussed. Constraints (15)–(17) complete the set of restrictions.

One important goal is to meet the due dates of the individual jobs. Early handling of orders is possible but, regarding the maturation period of the cheese, restricted to a small extent. So each job has to be scheduled somewhere on the time horizon between its availability date and its due date. Within the specified period the emphasis is to match the completion time of the jobs with the day preceding their due dates. For this purpose the square of the deviation between the due date of each job and the planned arrival time plus one is minimized. The corresponding penalty coefficient for the starting time t of each job j ($\mathrm{PST}_{j,t}$) has been defined as:

$$\mathrm{PST}_{j,t} = c_1\{\mathrm{DD}_j - (t+1)\}^2 \quad \text{for} \quad \mathrm{AV}_j \le t \le \mathrm{DD}_j$$

in which

c_1 ~ A weighing coefficient.
DD_j ~ The due date of job j.
AV_j ~ The availability date of job j.

A quadratic function has been preferred to a linear one because it reduces the number of jobs which will be divided over more than one day within the planning horizon (see Figure 2.2).

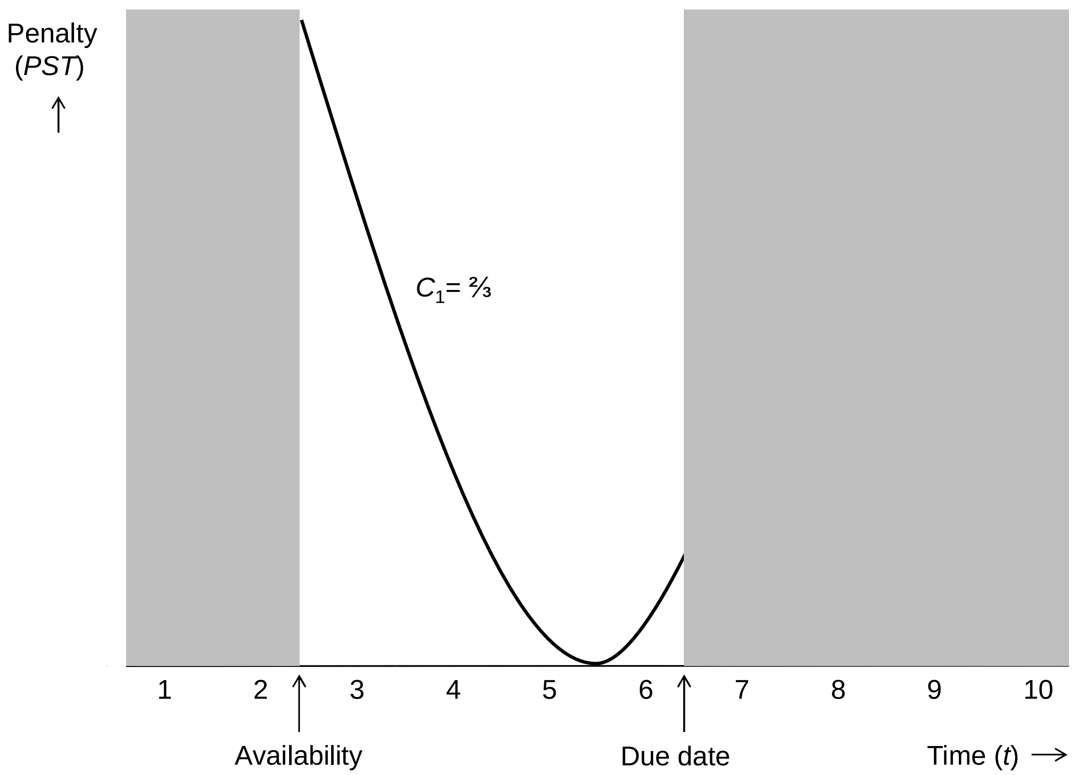


Figure 2.2. Penalty coefficients dependent on the starting time t of each job j

So most of the allocation variables $X_{j,l,t}$ will get a binary value. As a result the LP relaxation of the problem tends to give solutions which are integer in the $Y_{i,t}$ (see (14)).

As stated before, 30% of the jobs can be processed on alternative, not necessarily identical, packaging lines with different processing times. In order to optimize capacity utilization, the elapsed time between the arrival and completion of the jobs on the shop floor (the mean flow time) has to be minimized. For this purpose the objective function contains a penalty coefficient ($PPT_{j,l}$), which has been defined as,

$$\mathrm{PPT}_{j,l} = c_2 \frac{\mathrm{SI}_j}{\mathrm{PS}_l}$$

in which

c_2	~	A weighing coefficient.
SI_j	~	The size of job *j*.
PS_l	~	The processing speed of packaging line *l*.

In practice a scheduler has a restricted knowledge of the amount of intermittently arriving jobs. However, he/she tries to create a smooth working schedule. In order to anticipate in an adequate way the future demand, a packaging plan should not only be based on the jobs in the orderbook. If a reliable estimation of the future demand is taken into account, the system will be forced to smooth peak production which is mostly related to some specific days within the planning horizon. In relation to this aspect we assume that a rolling horizon of two weeks is adequate to anticipate on a short-term trend in orderbooking. A forecast of the future demand is based on the order process of the last two weeks and the inventory level in the storage yard. It is incorporated into the model by a penalty coefficient (see Figure 2.3).

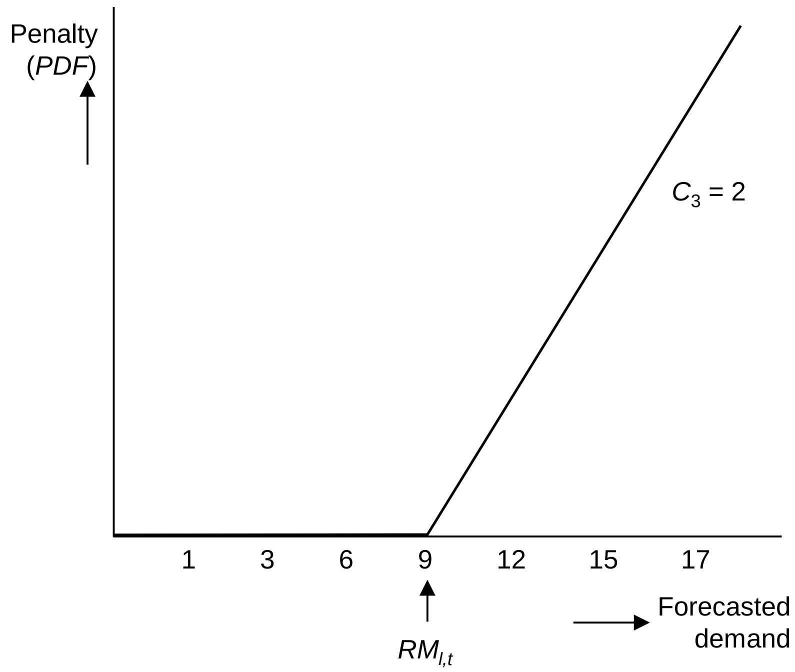


Figure 2.3. Penalty coefficients dependent on the forecasted demand on line l at day t

The coefficient $PFD_{l,t}$ has been defined as,

$$PFD_{l,t} = c_3 \max\{0, FD_{l,t} - RM_{l,t}\}$$

in which

c_3 = A weighing coefficient.

$FD_{l,t}$ = The forecasted demand on day *t,* on packaging line *l*.

$RM_{l,t}$ = The total hours of regular labour available on packaging line *l,* on day *t*.

Operational control

The tactical planning is concerned with the grouping of jobs into clusters and to assign these clusters to a particular packaging line within a feasible timetable. In this way the complexity of the problem can be reduced substantially. The remaining problem on operational level can be partitioned into two sub problems. In both cases the problem is a sequencing problem; however the measures of performance are different. At first the sequence in which the clusters should be processed on each packaging line has to be determined. This problem, with sequence-dependent set-up times, can be considered as the well-known ‘asymmetric traveling salesman problem for whose solution a satisfactory heuristic approach has been chosen based on a savings algorithm.

Subsequently, the sequence in which the individual jobs within each cluster are processed has to be determined. This sequence depends on several (logical) rules. The related planning criteria in descending order of importance are:

- The orders within a cluster are grouped to production code and article number. Together, these distinguishing marks make up an indication about the cheese variety, ordered by the customers. As the various cheese varieties are stored in fixed batches in a warehouse, a grouping into varieties within each cluster prevents unnecessarily large remnants in the warehouse.
- By clustering the jobs to customer name, a large inventory level on the shipping department can be avoided.

As the invoicing process cannot start previous to the completion of the packaging process, the invoice department is served most by a processing sequence of the jobs in the last (two) cluster to an increasing extent. This working method prevents excessive activities on the invoice department at the end of the day.

2.3 Results

The development of the (pilot) interactive planning system was started in the spring of 1989. From the beginning it was obvious that a regular and intensive dialogue with the planners of the company would be of crucial importance. In this way we gained both a thorough insight into the planning process and substantial support from the planning department. After about one year a first release of the pilot DSS was implemented on a VAX-8600 main-frame computer. Some characteristics of the problem on the tactical planning level are given in Table 2.1. Here, case 1 refers to a stand-alone packaging line while the figures concerning a number of three parallel lines are summarized by the second case.

Table 2.1 Some characteristics of the MIP problem matrix

	Case 1	Case 2
Rows	1104	2324
Columns	539	1309
Density (%)	0.3	0.3
Binary variables	380	190

Several test runs showed that the selected decomposition and solution techniques could solve the problem in a satisfactory way. In order to test the model it had to be implemented and evaluated in a real-world environment. Within this context special attention had to be given to the development of a user-friendly Man-Machine Interface (MMI). The development of a pilot interactive planning system including a direct interface to the local mainframe (IBM AS/400), on behalf of the daily data collection, has been completed by the end of 1990. It has been implemented on a powerful personal computer (IBM PS/2). The software package XPRESS-MP (DOS extended) was used to handle the tactical planning level. The system uses two modules: the model builder and the optimizer. The input consists of the relevant data files and a model file. The model builder (or matrix generator) interprets the symbolic specification statements of the model file and generates a problem matrix. This matrix file can be read by the optimizer which performs the optimization part. Moreover, it produces a readable (ASCII) representation of the solution, which in turn constitutes the input for the modules of the operational control level and the man-machine interface.

For about two months the planning model has been run several times a day. In spite of the intensive communication with the planners of the packaging department, they showed substantial detachment in the beginning. This was mainly caused by the competitive aspect of the system, the initial teething trouble as well as unacquaintance with computers of the target group. However, after a couple of weeks the planners appreciated the potential value of the system by its true merits. On the one side they realized that every computer system has its own deficiencies. Only the human way of reasoning and his/her experience can compensate for these deficiencies. On the other hand, the DSS made it possible to generate schedules at any time and within a reasonable amount of time (about two minutes for each collection of similar packaging lines). The favourable performance of the MIP model can mainly be contributed to the VUB constraints (14).

Without the DSS, a planner needs a few hours in order to finish the daily planning and scheduling problem at the agreed time. Occasionally he has to start the scheduling process even before all the jobs for the next day have been blocked. This working method implies that the remaining jobs, partly with a due date of only one day ahead in the planning horizon, will never fit optimally into the schedule. Moreover, coping with rush orders is an extremely difficult and frustrating task. With the help of the DSS the planner can postpone the start of his scheduling task at least until all the orders with a due date of the next day have been booked. The system has also shown to be very powerful in generating alternatives or revised plans when unforeseen disturbances occur; for example a breakdown of a packaging line or a sudden change in demand (rush orders).

During the period of testing the planners were delighted with the speed in which some time-consuming clerical actions and data processing were completed. Because a planner always possesses more information than the system, we created the possibility to review the generated schedules critically. In this connection the gain of time during the total scheduling process is of great value. With the help of a menu-driven man-machine interface the planner is able to modify the computed schedules in such a way that the solution will be tuned to the actual and future situation on the packaging department. In most cases the generated schedules have proven to be a good starting point for the planners and they are on the average of better quality than those drawn up by hand in the present situation. An additional advantage of the various utilities of the MMI is the possibility to employ human judgement and experience optimally, in order to improve the generated schedule.

The (daily) graphical presentation of the complete orderbook and the proposed final working schedule to the sales manager at the order entry level has proven to be very valuable. It enables the order acceptance department to make use of the remaining capacity optimally. As a result the interactive planning system made for a better and smoother working schedule for the packaging department.

2.4 Conclusions Part I

We described the development and implementation of a pilot Decision Support System for the bottleneck packaging facilities of a large dairy company. Its major benefits was the generation of packaging line schedules in a more efficient and effective way. The quality of the final schedule turned out to be on the average of higher quality than the solutions found by hand. The efficiency enables the decision-maker to ‘optimize’ his/her own performance with respect to his/her planning mission.

The conceptual approach to the problem appears to be appropriate. The quadratic penalty coefficient $PST_{j,t}$ in the objective function of the MIP model prevents an excessive split up of the jobs within the feasible part of the planning horizon. Therefore, most of the allocation variables ($X_{j,l,t}$) will get a binary value automatically. Fortunately only a limited part of the potential jobs possess a processing time which exceeds the daily capacity. If the priority of the set-up cost coefficient $WSC_{i,t}$ is high, a large number of jobs ($X_{j,l,t}$) will be allocated to each planned cluster ($Y_{i,t}$). As a result the LP solution tends to give answers which are integer in the $Y_{i,t}$'s (see (14)).

The desired or 'optimal' working schedule turned out to be strongly dependent on all kinds of unpredictable situations at the packaging department. Consequently an appropriate and mutual adjustment of the penalty functions and weighing coefficients in the objective function is very hard. Even restricted access to the relevant coefficients via the interactive MMI was not always satisfactory. Hence the system should not be considered as an optimizer but rather as a tool for generating high-quality schedules to be used for further analyses. In this connection the various utilities of the user-friendly and fully interactive MMI are essential.

Initially we planned to extend the heuristic approach on the operational control level by a 2- or 3-OPT improvement algorithm. However, experiments showed that this additional effort was hardly relevant.

Acknowledgements

This research has been supported by the Dutch Ministry of Economic Affairs. The authors wish to express their thanks to the dairy company FRIESLAND FRICO DOMO B.A. for the fruitful and constructive discussions. They commemorate Drs. Irene Goris (member of the software house CAPGEMINI PANDATA) who was involved in the development of the Decision Support System. She died early in 1992 due to a road accident. The authors dedicate this publication to her.

Part II
Modelling approaches for planning and scheduling

2.5 Introduction

Adequate and efficient production planning and scheduling is one of the most challenging problems for present-days enterprises. Especially scheduling and sizing of production lots, is an area of increasing research attention within the wider field of production planning and scheduling (Clark, Almada-Lobo et al. 2011). Although lot-sizing problems have been studied extensively, most of the literature is focused on discrete manufacturing. Moreover, there is an on-going research trend directed towards incorporating real-world issues and specificities of simultaneous lot-sizing and scheduling (Jans and Degraeve 2008; Quadt and Kuhn 2008).

Lot-sizing and scheduling in Food Processing Industry (FPI) is usually more complex than in other continuous and discrete processing environments. This is primarily due to issues like inevitable decline in quality of products, related quality requirements and safety regulations of products, market-driven standards regarding shelf life and variability of demand and prices. Secondly, the diversity of products in FPI increased considerably in the past decades and global competition on the food market has forced manufacturers to participate in an on-going trend towards increased variety (i.e. ingredients and flavors, customized packaging, prints and/or labels) of (new) products. Soman, Van Donk et al. (2004a) state that the majority of research contributions do not address specific characteristics of food processing, e.g. high capacity utilization, sequence-dependent set-ups and limited shelf life due to product decay.

Production lines in FPI usually operate under tight capacity constraints. As products take the same route, a production line may be planned as a single resource. Changeovers between products that share the same line in a food processing environment often imply that both changeover costs and times depend on the production sequence of individual items. In order to avoid unnecessary changeovers and improve efficient use of available production capacity, customer demand has to be pooled in production orders (lots). When sequence-dependent set-up times are predominant, available capacity for production depends on both the sequence and the size of the lots. In such a situation, lot-sizing and scheduling should be applied simultaneously (Meyr 2000).

In general practice, lot-sizing and scheduling problems are solved separately in successive hierarchical phases (Claassen and Beek 1993; Drexl and Kimms 1997; Kreipl and Pinedo 2004; Soman, Van Donk et al. 2004a; Soman, van Donk et al. 2007).

First optimal lot-sizes for given product families are determined and afterwards production schedules of customer orders are generated. The generated schedules on the shop floor often fail to realize production targets because changeover losses are not correctly accounted for on a higher planning level. As a consequence, the planning process has to be redone (with or without over-time) and/or frequent rescheduling takes place in daily practice (Kreipl and Pinedo 2004). Currently, there exists a general consensus regarding a closer integration of lot-sizing and scheduling decisions (Meyr 2000; Gupta and Magnusson 2005; Almada-Lobo, Oliveira et al. 2008; Jans and Degraeve 2008; Clark, Almada-Lobo et al. 2011; Menezes, Clark et al. 2011).

Although the survey of Drexl and Kimms (1997) already focused on the integration of lot-sizing and scheduling, Jans and Degraeve (2008) conclude after another decade in their review that the boundaries between lot-sizing and scheduling are fading, but further integration still constitutes a challenging research track. The latter may explain why even in present-days Advanced Planning and Scheduling (APS) systems, the planning and scheduling modules are seen as unusable, or unable to handle the complexity of the underlying capacitated planning problems (Pochet and Wolsey 2006).

Planning (i.e. lot-sizing) models differ from scheduling models in a number of ways. Kreipl and Pinedo (2004) give an extensive overview of practical issues for planning and scheduling processes. In a recent special issue on lot-sizing and scheduling, Clark, Almada-Lobo et al. (2011) confirm the need for more realistic and practical variants of models for simultaneous lot-sizing and scheduling. Features such as (i) non-triangular set-ups, (ii) perishability, and (iii) delivery time windows are labelled by the authors as hot topics and open research opportunities. We focus on two interrelated problem characteristics that argue the need for simultaneous planning and scheduling, particularly in FPI:

(i) *Sequence-dependent set-ups and non-triangular set-ups.*
With respect to sequence-dependent set-up costs and times under tight capacity constraints there is a complicating issue, referred to as the triangular set-up conditions (Gupta and Magnusson 2005; Almada-Lobo, Oliveira et al. 2008; Clark, Almada-Lobo et al. 2011), that holds for FPI too (Menezes, Clark et al. 2011). Due to processing conditions of different product variants (e.g. several heating and/or cooling levels) and other product specific requirements (e.g. flavors, addition of specific additives and/or the danger of contamination between subsequent production runs), the common assumption regarding the triangular set-up conditions often does not hold in FPI. If these conditions don not hold, it implies that changeover costs and times between two subsequent products *i* and *j* may become substantially less by processing another product *k* between *i* and *j*. Consequently, applying models that assume triangular set-up conditions may generate non-consistent solutions from a scheduling point of view.

(ii) *Product decay.*
The quality or value of perishable food products usually deteriorates rapidly after production. Product decay may be delayed by conditioned storage, but quality depends

on product age, and restricted shelf lives are inevitable. Considering product decay in lot-sizing enforces smaller production quantities for perishable products. Consequently, individual products are produced i.e. scheduled at higher frequency. This increases the difficulty of sequencing.

The literature overview intends to contribute to the recognized need for more realistic variants of models for simultaneous lot-sizing and scheduling under tight capacity constraints (Almada-Lobo, Klabjan et al. 2007; Almada-Lobo, Oliveira et al. 2008; Jans and Degraeve 2008; Clark, Almada-Lobo et al. 2011; Menezes, Clark et al. 2011). We give an overview of model developments for simultaneous lot-sizing and scheduling directive for a problem with the following characteristics: a multi-item, single machine lot-sizing and scheduling problem for FPI with sequence-dependent set-up costs and times and product decay. The set-up state of the machine should be preserved over period boundaries including idle time (i.e. set-up carry-overs) and any additional assumption with respect to the changeover matrices should be relaxed (e.g. the triangular set-up conditions).

We assess the proposed models for addressing sequence-dependent set-ups (including non-triangular set-ups) and product decay. The objective here is to focus on modelling developments in time that are directive for the identified problem characteristics, and to expose their shortcomings and disadvantages. For a general overview of lot-sizing problems we refer to several reviews of the past (Kuik, Salomon et al. 1994; Drexl and Kimms 1997; Karimi, Ghomi et al. 2003) and two more recent overviews (Jans and Degraeve 2008; Quadt and Kuhn 2008).

The overview in this paper shows that a trend exists of preferred modelling approaches. However, these approaches may *i*) disrupt a crucial balance between total set-up costs and inventory-holdings costs and *ii*) hamper a further integration between production and distribution planning. We state that crucial aspects for integrated planning and scheduling may unfoundedly disappear from sight. One of the most important features of models for lot-sizing and scheduling is the segmentation of the planning horizon. From a modelling point of view it is convenient to distinguish two general classes of models (Eppen and Martin 1987), i.e. small bucket (SB) and big (or large) bucket (BB) modelling approaches. In SB models, the planning horizon is divided into a finite number of small time periods such that in each period either at most two products can be produced, or there will be no production at all. Conversely, in BB approaches the planning horizon is divided into longer periods, usually of the same length. In each period, multiple products may be produced. As a consequence, SB models have been applied mostly over short time planning horizons and BB models are usually associated with medium-term planning horizons.

Sections 2.6 and 2.7 provide an overview of model developments for SB and BB approaches respectively. Section 2.8 describes the state of affairs regarding issues of product decay for lot-sizing and scheduling. A summary can be found in Section 2.9 to analyse the literature overview. Section 2.10 concludes.

2.6 Small bucket approaches

Crucial for small bucket modelling approaches is that at most one set-up may occur in a period. In this class of models, the so-called 'all-or-nothing' assumption usually holds. In most models only one item may be produced in a time interval and, if so, production uses (in most cases) full capacity. In SB models, lot-sizes include the production of the same product for one or several consecutive periods. Alternatively, if a set-up is performed and when it comes to non-zero set-up times, both set-ups and production runs comprise a number of time intervals. A lot includes the production of a single product for one or several consecutive periods. Next, we discuss development in time of SB-approaches.

2.6.1 DLSP: Discrete Lot-sizing and Scheduling Problem

The Discrete Lot-sizing and Scheduling Problem (DLSP) is a typical example within the class of small bucket approaches. The basic DLSP includes (sequence-independent) set-up costs and set-up carry-over but at zero set-up times (Fleischmann 1990). Inclusion of set-up carry-over implies that set-up states of a machine are carried over between period boundaries. Porkka, Vepsalainen et al. (2003) compare models with and without set-up carry-overs. The authors show that substantial savings (regarding costs and production time) can be derived from fundamentally different production plans enforced by carry-overs. Comparable results are found by Sox and Gao (1999). However, in the basic DLSP, set-up states are not preserved over idle time. Sequence-dependent set-up costs and times are neither considered in the DLSP. Many extensions of the (basic) DLSP have been described in literature. We refer to Drexl and Kimms (1997) and Salomon, Kroon et al. (1991) for a broader view on variants of the DLSP.

2.6.2 Extensions of the DLSP

Fleischmann (1994) analyses the multi-item single machine DLSP with sequence-dependent set-up costs. An artificial product (i=0) is introduced to represent idleness of the machine. Salomon, Solomon et al. (1997) continue this work and reformulate the DLSP to capture the characteristic of sequence-dependent times (DLSPSD). However, the triangular set-up conditions are assumed to hold. Machine idleness is represented by an artificial product. Jordan and Drexl (1998) present a comparable model in which idleness is indicated by an artificial product too. It should be mentioned that for models in which idleness is represented by an artificial product (i=0), the changeover matrix must comply with strict conditions to cope with sequence-dependent set-up times. In all other cases the set-up state of the machine is not correctly carried over across the boundaries of idleness.

Wolsey (1997) extended the work of Constantino (1996) for problems with sequence-independent set-ups to formulations with sequence-dependent set-up times and costs. In this paper, the presented model will be referred to as (GSB), i.e. the general small bucket model. In the (GSB), idleness is not represented by an artificial product (i=0). However, the triangular set-up conditions should hold.

2.6.3 CSLP: Continuous Set-up Lot-sizing Problem

An early paper in which sequence-dependent costs are modelled is due to Karmarkar and Schrage (1985). Their model is called the Continuous Set-up Lot-sizing Problem (CSLP). The CSLP is closely related to the DLSP. Main difference is that the CSLP allows production of quantities less than the available production capacity in a time period. Still, at most one product can be produced in each time interval.

2.6.4 PLSP: Proportional Lot-sizing and Scheduling Problem

The fundamental assumptions of the DLSP and the CSLP stimulated Drexl and Haase (1995) to study a new type of model, the Proportional Lot-sizing and Scheduling Problem (PLSP). The PLSP is based on a widening of the common "all-or-nothing" production principle in SB models. The PLSP assumes that at most one set-up may occur within a period. Hence, at most two products can be produced in a period. Main difference between the PLSP and the DLSP is the possibility to compute continuous lot-sizes and to preserve the set-up state over idle time. However, set-up costs and times of (extended) PLSP formulations are considered to be sequence-independent (Suerie 2006).

2.7 Big bucket approaches

In contrast to small bucket models, the planning horizon of a big bucket (BB) model is usually divided into longer periods, mostly of equal length. Time intervals in a BB model may represent a time slot of one week (or more) in the real world (Drexl and Kimms 1997). In each period, multiple products can be manufactured. Relaxing the "all-or-nothing" production principle of (most) SB models implies that a BB model includes the possibility to determine continuous lot-sizes.

2.7.1 CLSP: Capacitated Lot-Sizing Problem

The Capacitated Lot-Sizing Problem (CLSP) is a typical example of a big bucket model. It is closely related to the (small bucket) DLSP; decision variables, parameters and objective function are the same for both problems (Drexl and Kimms 1997). However, sequence-dependent set-up costs and times, or more in general scheduling decisions, are not integrated into the CLSP. As a consequence, set-up carry-overs between period boundaries are not included either. Suerie and Stadtler (2003) use the simple plant location problem to obtain a tight and new model formulation for set-up carry-overs in the CLSP with sequence-independent set-up costs and times.

2.7.2 GCLP: Generalized Capacitated Lot-sizing Problem

Sox and Gao (1999) introduce the Generalized Capacitated Lot-sizing Problem (GCLP). The GCLP uses less binary variables for including set-up carry-overs in the CLSP with sequence-independent set-up costs and no set-up times. Sequence-independent set-up times can be included; probably at the expense of additional computational effort. The authors also apply the network reformulation approach as proposed by Eppen and Martin (1987) and compare the behavior of a set of models. The results demonstrate that incorporating set-up carry-over has a significant effect on both costs and lot-sizes.

In all aforementioned BB approaches, the emphasis is directed towards combining characteristics of a big bucket model like the CLSP (i.e. allow production of more products per period without set-up carry-overs) with a small bucket model like the DLSP (production of only one product per period with set-up carry-overs) in a single framework. Still, sequence-dependent set-up costs and times are not considered in the BB models above.

2.7.3 GLSP: General Lot-sizing and Scheduling Problem

Fleischmann and Meyr (1997) proposed a combination of CLSP and DLSP, i.e. the General Lot-sizing and Scheduling Problem (GLSP). The GLSP is a big bucket model in which the planning horizon is divided into T macro-periods. To obtain the production sequence of the items, each macro-period is subdivided into a subset of micro-periods of variable length. The GSLP assumes all-or-nothing production for micro-periods. The number of micro-periods within each macro-period must be fixed in advance in the MIP model. As a consequence, a lot (i.e. a sequence of micro-periods assigned to the same item) may contain idle micro-periods. Sequence-dependent costs are considered, but set-up times are disregarded in the (basic) GLSP. In order to cope with cases in which the triangular set-up conditions of the cost matrix do not hold, the authors introduce minimum lot-sizes. Meyr (2000) extended the GLSP with sequence-dependent set-up times. Again, minimum lot-sizes are used to avoid a wrong evaluation of set-up costs (and set-up time, respectively) if the set-up matrices do not satisfy the triangular set-up conditions. It should be mentioned that the introduction of minimum lot-sizes may have an impact on economical lot-sizes.

Transchel, Minner et al. (2011) present a tailored hybrid mixed-binary model based on the GLSP for a practical problem from process industry and show that minimum production quantities affect the MIP performance for real world test instances. Ferreira, Morabito et al. (2009) present a GLSP-based model too that integrates production lot-sizing and scheduling decisions for a Brazilian soft drink plant.

Block planning approaches can be considered as a practical variant of the GLSP in which macro- (i.e. blocks) and micro periods are distinguished. An important assumption in block planning approaches is a predefined production sequence of (variable) batch-sizes (Entrup, Gunther et al. 2005; Bilgen and Günther 2010; Baumann and Trautmann 2012). In other words, there is a unique period-block assignment and each product occurs at the same given position (micro-period) in each block. As a consequence, within the planning horizon of T periods, each product $i = 1..N$ is scheduled T times. The number of production lots in the schedule equals $N*T$. We refer to Gunther, Grunow et al. (2006) for a complete description of block planning.

2.7.4 Extensions of the CLSP

A study to extend the CLSP was initiated by Gopalakrishnan, Miller et al. (1995). The authors developed a modelling framework for the (single machine) CLSP with set-up carry-overs. Set-up times and costs were assumed to be constant across all products and time periods. This assumption was relaxed in a modified framework that included product-dependent and sequence-independent set-up costs and times (Gopalakrishnan 2000).

Haase (1996) takes the CLSP as a starting point but extends the model with sequence-dependent set-up costs. Moreover, the set-up state of the machine can be preserved over idle times. The model formulation does not consider (sequence-dependent) set-up times and it is assumed that the triangular set-up conditions for set-up costs hold. Haase and Kimms (2000) consider both sequence-dependent set-up costs and times. It is assumed that set-up times satisfy the triangular set-up conditions. The authors formulate the problem by considering only efficient (predefined) production sequences. Efficient sequences are found by solving a travelling salesman problem.

Gupta and Magnusson (2005) extend the framework of Gopalakrishnan (2000) by including sequence-dependent set-up times and set-up costs. From a scheduling point of view, the CLSP with sequence-dependent set-up times is closely related to the travelling salesman problem (TSP). In every period a connected tour (or sequence) between multiple products has to be determined. The distance matrix in the TSP corresponds to the matrix of set-up costs in the (extended) CLSP. Almada-Lobo, Oliveira et al. (2008) show that the model formulation as proposed by Gupta and Magnusson (2005) does not eliminate disconnected sub tours. As a consequence, it may generate infeasible solutions. Almada-Lobo, Klabjan et al. (2007) present two correct model formulations for the identified problem characteristics, provided that the triangular set-up conditions with respect to the set-up matrices (costs and times), hold. In order to avoid disconnected sub tours, the authors add a polynomial set of sub tour elimination constraints. Menezes, Clark et al. (2011) present an extension of the CLSP which handles non-triangular set-up costs and times while enforcing minimum lot-sizes.

Next, we will focus on papers that discuss lot-sizing and scheduling of perishable products.

2.8 Product decay

Although a vast body of literature exists on inventory management for perishable products, surprisingly little has been done to include product decay in traditional lot-sizing and scheduling models. One of the first contributions in this area is provided by Soman, van Donk et al. (2004b). The authors focus on shelf-life considerations in the economic lot scheduling problem (ELSP). Models of this class usually assume constant demand, do not account for sequence-dependent set-up times and aim to generate production cycles for several products on a single resource. Entrup, Gunther et al. (2005) propose three MILP models that integrate shelf-life issues into production planning and scheduling for an industrial case study of yoghurt production. The authors apply a block planning approach (see Section 3.3) in which a block covers all products based on the same recipe. Shelf-life aspects are taken into account by considering a shelf-life-dependent pricing component that may also include inventory-holding costs. Chen, Hsueh et al. (2009) and Kopanos, Puigjaner et al. (2012) argue the need to develop models for better coordination between production scheduling and vehicle routing for perishable food products. Lee and Yoon (2010) consider a coordinated production-and-delivery scheduling problem that incorporates different inventory-holding costs between production and delivery stages. The results may only apply to specific situations but the study can be regarded as a first attempt to allow different (stage-dependent) inventory-holding costs. Chen, Hsueh et al. (2009) conclude that papers discussing production scheduling and/or distribution of perishable goods are relatively rare. Amorim, Antunes et al. (2011) state that papers discussing simultaneous lot-sizing and scheduling for perishable goods are even rarer. These authors deal with simultaneous lot-sizing and scheduling of perishable products using a multi-objective framework. The main idea is to separate economic production tangible costs from intangible value of having fresher products in two conflicting objectives.

2.9 Literature overview

Table 2.2 summarizes the literature research and gives an overview of key publications that are directive for the problem formulation in the next chapter. The basic problem can be characterized as a multi-item, single machine lot-sizing and scheduling problem with sequence-dependent set-up costs and times. The set-up state of the machine should be preserved over period boundaries (including idle time) and any additional assumption with respect to the changeover matrix (e.g. the triangular set-up conditions) is excluded.

Note that Table 2.2 only refers to the presented model formulations and not to the proposed solution approaches. The (GSB) is a SB formulation for the specified problem without product decay, provided that the triangular set-up conditions hold. If these conditions do not hold, set-up state changes will occur without production changes. Literature shows that there is a clear tendency to propose BB models for short time horizons too. Moreover, both the survey of Quadt and Kuhn (2008) and the results in Table 2.2 reveal an interesting trend in which BB approaches are preferred to SB models.

Table 2.2 Overview of key publications *

Year	Author	Basic	extension of /or Model name	SB	BB	Set-up carry-over	Sequence-dependent costs	Sequence-dependent times	Non-triangular set-ups
		DLSP		✓		–	–	–	–
1985	Kamarkar & Schrage		CSLP	✓		–	✓	–	–
1994	Fleishmann		DLSP	✓		–	✓	–	–
1995	Drexl & Haase		PLSP	✓		✓	–	–	–
1997	Salomon et al.		DLSP	✓		–	✓	–	–
1997	Wolsey		GSB	✓		✓	✓	✓	–
		CLSP			✓	–	–	–	–
1996	Haase		CLSP		✓	✓	✓	–	–
1997	Fleishmann & Meyr		GLSP	✓	✓	✓	✓	–	–
1999	Sox & Gao		GCLP		✓	✓	–	–	–
2000	Gopalakrishnan et al.		CLSP		✓	✓	–	–	–
2000	Meyr		GLSP	✓	✓	✓	✓	✓	–
2003	Suerie & Stadtler		CLSPL		✓	✓	–	–	–
2005	Gupta & Magnusson		CLSP		✓	✓	✓	–	–
2007	Almada-Lobo et.al.		CLSP		✓	✓	✓	✓	–
2011	Menezes et al.		CLSP		✓	✓	✓	✓	✓

* A minus sign in Table 2.2 means that the issue is either not considered in the model formulation or not adequately modelled.

2.10 Conclusions Part II

Purpose the second part of this chapter was to study how literature deals with practical variants of models for simultaneous lot-sizing and scheduling models. We considered developments in lot-sizing and scheduling particularly relevant for problem settings arising in food processing industry (FPI) and focus on *i*) sequence-dependent set-ups (including non-triangular set-ups), *ii*) product decay of inventory due to perishability, and (*iii*) a desired tuning of modules for production planning with physical distribution planning (i.e. delivery time windows).

Although Big Bucket (BB) models are usually associated with medium-term planning horizons, literature reveals an interesting trend in which these models are proposed for short-term planning horizons too. From a computational point of view, models with large time intervals (i.e. a week) are preferred over Small Bucket (SB) approaches. However, we argue that segmentation of the planning horizon is a key issue for simultaneous lot-sizing and scheduling. The observed preference for segmentation in BB approaches implies that the following crucial aspects may disappear from sight:

- *Main principle of optimality for lot-sizing models.*
  The general accepted principle of optimality for lot-sizing models is based on the best compromise between total production costs on the one hand and total inventory-holding costs on the other hand. Inventory costs in lot-sizing models are calculated from inventory levels at the end of each period. As time intervals in BB models represent long periods (e.g. a week) multiple batches can be produced in a single period. As a consequence, inventory costs for batches manufactured at the start of periods are assumed to be equal to inventory costs of batches produced at the end of the same period. As a result, total inventory-holding costs are underestimated and the crucial principle of optimality for lot-sizing problems may be disrupted. Segmentation of the planning horizon is the key in modelling this balance correctly. SB models offer the framework to calculate these costs more adequately.

- *Decline of product quality and limited shelf lives.*
  In FPI, product decay is primarily associated with the "age" of products. Incorporating perishability issues like product decay requires defining the moments of production for manufactured products, unambiguously. Segmentation of the planning horizon is the key to capture the age of manufactured products.

- *Delivery time windows for physical distribution*
  Obviously, a close coordination of production scheduling and delivery planning will become an important issue (Chen, Hsueh et al. 2009; Clark, Almada-Lobo et al. 2011). Products in FPI usually include highly perishable items that must be delivered within allowable time frames. In order to contribute to improved logistical performance, production planning and scheduling modules for FPI should have, at least to a certain extent, the flexibility to take issues for physical distribution into consideration. In contrast to BB models, SB approaches offer the timeframe to attune short-term physical distribution planning to production planning and scheduling, e.g. by assigning demand to specific time slots in a 24-hours production environment.

- *Scheduling lots*
  A major advantage of small time intervals may be a better control of the sequence of lots. Using large time intervals implies that sequencing the lots within each period may become complex. Moreover, planned maintenance for production facilities can be scheduled much easier and accurately by applying SB models. In each period of a BB model, a sequencing problem (i.e. travelling salesman problem) has to be solved. Incorporating this feature may become complex, especially in case the triangular set-up conditions do not hold.

In spite of a larger number of time periods in the planning horizon, the strengths of SB approaches will be used in the next chapter to develop models that (*i*) can handle sequence-dependent set-ups (including non-triangular set-ups), (*ii*) addresses product decay by using age-dependent holding costs. Such models offer (*iii*) a starting point to integrate solutions of a production planning with delivery time windows for physical distribution of products to customers.

Chapter 3

Vertical integration of lot-sizing and scheduling in food processing industry

The optimal solution of a model is not an optimal solution of a problem unless the model is a perfect representation of the problem (Ackoff 1977).

This chapter is based on:

Claassen, G.D.H., Gerdessen, J.C., Hendrix, E.M.T., and van der Vorst, J.G.A.J.,

On production planning and scheduling in food processing industry: modelling non-triangular set-ups and product decay

Under review

Abstract

Based on the conclusions in the preceding chapter we consider a complete vertical integration of lot-sizing and scheduling problems which is particularly relevant for food processing industry (FPI). Problem settings in FPI require to take specific characteristics into account. First of all, set-ups are usually sequence-dependent and may include the so-called non-triangular set-up conditions. These conditions make it necessary to relax all assumptions with respect to the changeover matrices (both with respect to costs and times). Secondly, lot sizing and scheduling models in FPI must take product decay into consideration. We present an MILP model that handles these characteristics. We study its behaviour and complexity and show that optimal production schedules become significantly different when non-triangular set-ups and product decay are taken into account. Numerical results are provided for small size instances and a time-based decomposition heuristic is applied to solve larger problem instances.

3.1 Introduction

Adequate and efficient production planning and scheduling is one of the most challenging problems for present-days enterprises. Lot-sizing and scheduling in Food Processing Industry (FPI) is usually more complex than in other continuous and discrete processing environments. First of all, planners have to deal with decline in quality of products, related quality requirements and safety regulations of products, market-driven standards regarding shelf life, and variability of demand and prices. Secondly, the diversity of products in FPI increased considerably in the past decades and global competition on the food market has forced manufacturers to participate in an on-going trend towards increased variety (e.g. ingredients and flavours, customised packaging, prints and/or labels) of (new) products. Soman, Van Donk et al. (2004a) state that the majority of research contributions do not address specific characteristics of food processing, e.g. high capacity utilisation, sequence-dependent set-ups and limited shelf life due to product decay.

In general practice, lot-sizing and scheduling problems are solved separately in successive hierarchical phases (Claassen and Vanbeek 1993; Drexl and Kimms 1997; Kreipl and Pinedo 2004; Soman, Van Donk et al. 2004a; Soman, van Donk et al. 2007). First optimal lot-sizes for given product families are determined and afterwards production schedules are generated. The generated schedules on the shop floor often fail to realise production targets, because changeover losses are not correctly accounted for on a higher planning level. As a consequence, the planning process has to be redone (with or without over-time) and/or frequent rescheduling takes place in daily practice (Kreipl and Pinedo 2004). Currently, there exists a general consensus regarding a closer integration of lot-sizing and scheduling decisions, see Meyr (2000), Gupta and Magnusson (2005), Jans and Degraeve (2008), Almada-Lobo, Oliveira et al. (2008), Clark, Almada-Lobo et al. (2011), and Menezes, Clark et al. (2011).

Planning (i.e. lot-sizing) models differ from scheduling models in a number of ways. Kreipl and Pinedo (2004) give an extensive overview of practical issues for planning and scheduling processes. In a special issue on lot-sizing and scheduling, (Clark, Almada-Lobo et al. 2011) confirm the need for more realistic and practical variants of models for simultaneous lot-sizing and scheduling. Features such as (*i*) non-triangular set-ups, (*ii*) perishability, and (*iii*) delivery time windows are labelled by the authors as hot topics and open research opportunities. The research question of this paper is how to include the first two characteristics in models for simultaneous lot-sizing and scheduling.

(*i*) *Sequence-dependent set-ups and non-triangular set-ups*. There is a complicating issue with respect to sequence-dependent set-up costs and times, commonly referred to as the assumption of the triangular set-up. Menezes, Clark et al. (2011) confirm that non-triangular set-ups may occur in FPI. Due to processing conditions of different product variants (e.g. several heating and/or cooling levels) and other product specific requirements (e.g. flavours, addition of specific additives, the danger of contamination between subsequent production runs), changeover costs and times between two subsequent products *i* and *j* may become substantially less by processing another product *k* between *i* and *j*. As a consequence, applying models that assume triangular set-up conditions may generate non-consistent solutions from a scheduling point of view.

(ii) *Product decay*. In many FPI cases, the quality or value of perishable food products deteriorates rapidly after production. Considering product decay in lot-sizing enforces smaller production quantities. Consequently, individual products are produced at higher frequency. This increases the difficulty of sequencing.

This paper investigates implementing the characteristics into models for simultaneous lot-sizing and scheduling under tight capacity constraints. We present an MILP model that includes the identified characteristics. Moreover, the approach offers a natural starting point for integrating delivery time windows in lot-sizing and scheduling models as mentioned by Clark, Almada-Lobo et al. (2011). Small scale examples demonstrate that optimal production schedules become significantly different when including non-triangular set-ups and product decay. Two model formulations are presented and compared with a known approach from literature.

The remainder of the paper is organised as follows. Section 3.2 embeds the model in existing approaches from literature. Section 3.3 presents two MILP models for the problem under consideration. Section 3.4 provides small scale numerical examples to demonstrate the impact of non-triangular set-ups and product decay. Moreover, the complexity of the model is studied. Section 3.5 provides numerical results for medium size instances, including a comparison with a straightforward MP-based heuristic. Concluding remarks and suggestions for further research are given in Section 3.6.

3.2 Embedding in the literature

Models for lot-sizing and scheduling can be classified according to the segmentation of the planning horizon. From a modelling point of view, it is convenient to distinguish two general classes of models (Eppen and Martin 1987), i.e. small bucket (SB) and big (or large) bucket (BB) modelling approaches. In SB models, the planning horizon is divided into a finite number of small time periods such that in each period either at most two products can be produced, or there will be no production at all. Conversely, in BB approaches the planning horizon is divided into longer periods, usually of equal length. In each period, multiple products may be produced. As a consequence, SB models are usually associated with short-term planning horizons and BB models with medium-term planning horizons.

3.2.1 Small bucket approaches

A typical example of SB approaches is the Discrete Lot-sizing and Scheduling Problem (DLSP). The basic DLSP includes (sequence-independent) set-up costs and set-up carry-over at zero set-up time (Fleischmann 1990). Inclusion of set-up carry-over implies that set-up states of a machine are carried over between period boundaries. Porkka, Vepsalainen et al. (2003) compare models with and without set-up carry-overs. They show that substantial savings in costs and production time can be achieved by fundamentally different production plans enforced by carry-overs. Comparable results are found by (Sox and Gao 1999). However, in the basic DLSP, set-up states are not preserved over idle time. Sequence-dependent set-up costs and times are neither considered in the DLSP. Many extensions of the (basic) DLSP have been described in literature (Salomon, Kroon et al. 1991; Drexl and Kimms 1997).

Fleischmann (1994) analyses the multi-item single machine DLSP with sequence-dependent set-up costs. An artificial product is introduced to represent idleness of the machine. Salomon, Solomon et al. (1997) continue the latter study and reformulate a DLSP that captures sequence-dependent set-up times (DLSPSD). The triangular set-up conditions are assumed to hold. However, machine idleness is represented by an artificial product. Jordan and Drexl (1998) present a comparable model in which idleness is indicated by an artificial product too. It should be mentioned that if idleness is represented by an artificial product, the changeover matrix must fulfil very strict conditions to cope with sequence-dependent set-up times. Otherwise the set-up state of the machine is not correctly carried over across the boundaries of idleness.

Wolsey (1997) extended the work of Constantino (1996) for problems with sequence-independent set-ups to formulations with sequence-dependent set-up times and costs. Idleness is not represented by an artificial product. However, the triangular set-up conditions are assumed to hold. We will refer to Wolsey’s model as the general small bucket model (GSB).

3.2.2 Big bucket approaches

In contrast to small bucket models, the planning horizon of a big bucket (BB) model is usually divided into longer periods of equal length. Time intervals in a BB model may represent a time slot of one week (or more) in practice (Drexl and Kimms 1997). In each period, multiple products can be manufactured. Releasing the “all-or-nothing” production principle of (most) SB models implies that a BB model includes the possibility to determine continuous lot-sizes.

The Capacitated Lot-Sizing Problem (CLSP) is a typical example of a big bucket model. It is closely related to the (small bucket) DLSP. Decision variables, parameters and objective function are comparable in both problems (Drexl and Kimms 1997). However, the

CLSP does not include sequence-dependent set-up costs and times. As a consequence, set-up carry-over between period boundaries is not included either. Suerie and Stadtler (2003) use the simple plant location problem to obtain a tight new model formulation for set-up carry-over in the CLSP with sequence-independent set-up costs and times.

Sox and Gao (1999) introduce the Generalized Capacitated Lot-sizing Problem (GCLP). The GCLP uses less binary variables for including set-up carry-over in the CLSP with sequence-independent set-up costs and no set-up times. Sequence-independent set-up times may be included; probably at the expense of additional computational effort. The authors also apply the network reformulation approach as proposed by Eppen and Martin (1987) and compare the behaviour of a set of models. The results demonstrate that incorporating set-up carry-over has a significant effect on both costs and lot-sizes.

We observe a tendency in simultaneous lot-sizing and scheduling to incorporate characteristics of small bucket models into big bucket models. For confirmation we refer to proposed variants of the CLSP (Gopalakrishnan, Miller et al. 1995; Gopalakrishnan 2000; Haase and Kimms 2000; Gupta and Magnusson 2005; Almada-Lobo, Klabjan et al. 2007; Almada-Lobo, Oliveira et al. 2008; Menezes, Clark et al. 2011), variants of hybrid BB and SB models like the General Lot-sizing and Scheduling Problem (Fleischmann and Meyr 1997; Meyr 2000; Ferreira, Morabito et al. 2009; Transchel, Minner et al. 2011), and variants of block planning approaches, originally introduced by Gunther, Grunow et al. (2006). The literature review on extensions of capacitated lot-sizing by Quadt and Kuhn (2008) confirm the trend in which BB approaches are preferred to SB models.

3.2.3 Product decay

Although a vast body of literature exists on inventory management for perishable products, surprisingly little has been done to include product decay in traditional lot-sizing and scheduling models. One of the first contributions in this area is provided by Soman, van Donk et al. (2004b). The paper studies shelf life considerations in the economic lot scheduling problem (ELSP). Models of this class usually assume constant demand, do not account for sequence-dependent set-up times and aim to generate production cycles for several products on a single resource. Entrup, Gunther et al. (2005) propose three MILP models that integrate shelf-life issues into production planning and scheduling for an industrial case study of yoghurt production. The models use a block planning approach in which a block covers all products based on the same recipe. Shelf-life aspects are taken into account by considering a shelf-life-dependent pricing component that may also include inventory-holding costs. Lee and Yoon (2010) consider a coordinated production-and-delivery scheduling problem that incorporates different inventory-holding costs between production and delivery stages. The results may be only applicable to limited situations but the study can be regarded as a first attempt to allow different (stage-dependent) inventory-holding costs. Chen, Hsueh et al. (2009) conclude that papers discussing production scheduling and/or distribution of perishable goods are relatively rare. Amorim, Antunes et al. (2011) state that papers discussing simultaneous lot-sizing and scheduling for perishable goods are very rare.

3.3 Model formulation

This section presents two SB models and demonstrates the impact of (i) relaxing the triangular set-up conditions and (ii) taking product decay into account. Section 3.3.1 describes the problem which is then modelled in Section 3.3.2 as a lot-sizing and scheduling problem with non-triangular set-ups. In Section 3.3.3 we extend the model such that it addresses product decay of inventory by including an age-dependent component in the inventory-holdings costs.

3.3.1 Outline of the lot-sizing and scheduling problem

The complete problem under study is characterized as follows:

- Consider N products to be scheduled over a finite planning horizon of T periods. Consider a small bucket problem i.e. in each time period at most one item can be produced at full capacity, or there is no production at all.
- A lot or batch of item *i* is defined as an uninterrupted sequence of periods in which production takes place for item *i*.
- Manufacturing items requires a common equipment or resource with limited capacity. Without loss of generality, machine capacity is normalised to 1 unit per period.
- Demand is assumed to be varying and deterministic and expressed in the number of required production periods.
- Demand must be satisfied (without backlogging) either by production in the same period or from stock. In the latter case, an inventory carrying cost is incurred.
- It is assumed that the Wagner-Whitin cost condition holds, i.e. given the set-ups, it always pays to produce as late as possible. This condition is also referred to as the absence of speculative motives for early production.
- Unit production costs are assumed to be constant over periods and are therefore ignored.
- A changeover between items incurs a loss of production capacity (non-zero set-up times) and associated set-up and changeover costs. Both are sequence-dependent.
- Set-up costs are assumed to be proportional to changeover times.
- The triangular set-up conditions refer to the changeover matrix A (with respect to set-up times), the changeover matrix S (with respect to set-up costs), or both:

$$a_{ij} \le a_{ik} + a_{kj} \quad \text{and/or} \quad s_{ij} \le s_{ik} + s_{kj} \quad \text{for all items } i, j, k \tag{1}$$

- If changeover and idleness occur in subsequent time intervals, we follow common practice and assume that periods of idleness are preceded by changeover time.
- In contrast to the DLSP, the set-up state of the machine should be preserved over idle time. This assumption is made in many lot-sizing and scheduling models (Drexl and Kimms 1997). Generally speaking, it is also valid in FPI.
- Starting inventory levels for product i are assumed to be zero, i.e. $I_{i,0} = 0$ for all i.

The objective is to determine the production sequence and lot-sizes that minimise the sum of set-up and inventory carrying costs over the complete planning horizon.

3.3.2 Notation and model formulation

The following notation is used to formulate the problem:

Parameters

N	number of items or products i.e. $i, j = 1...N$
T	number of time intervals (i.e. periods) in the planning horizon; $t = 1...T$
$h_{i,t}$	unit storage costs of item i at the end of period t
S_t	fixed set-up costs in period t
$d_{i,t}$	demand for item i in period t (expressed in units of required capacity)
$a_{i,j}$	changeover time between products i and j in units of lost capacity

Variables

$I_{i,t}$ inventory level of item i at the end of period t

$$Y_{i,t} = \begin{cases} 1 & \text{if product } i \text{ is produced in period } t \\ 0 & \text{otherwise} \end{cases}$$

$$V_{j,t} = \begin{cases} 1 & \text{if the machine is changing over to product } j \text{ in period } t \\ 0 & \text{otherwise} \end{cases}$$

$$W_{j,t} = \begin{cases} 1 & \text{if the machine is idle in period } t \text{ and the next item to produce is product } j \\ 0 & \text{otherwise} \end{cases}$$

Now, the problem can be formulated as follows:

$$\text{Min} \left\{ \sum_j \sum_t S_t V_{j,t} + \sum_i \sum_t h_i I_{i,t} \right\} \tag{2}$$

s.t.

$$I_{i,t-1} + Y_{i,t} - d_{i,t} = I_{i,t} \qquad \forall\ i,t \tag{3}$$

$$\sum_i Y_{i,t} + \sum_j V_{j,t} + \sum_j W_{j,t} = 1 \qquad \forall\ t \qquad (4)$$

$$Y_{i,t} - \sum_{k:k\neq i\neq j} \sum_{s=t+1}^{t+\tau-1} Y_{k,s} + Y_{j,t+\tau} \leq 1 \qquad \forall\ (i,j) \in A := \{(i,j) \mid a_{i,j} > 0\} \qquad (5)$$

$$t = 1,\dots,T-\tau\ ,\ \tau = 1,\dots,a_{i,j}$$

$$V_{j,(t-a_{i,j}+\tau)} \geq Y_{i,(t-a_{i,j}-1)} + Y_{j,t} + W_{j,t} - \sum_{k:k\neq i\neq j} \sum_{l=t-a_{ij}}^{t-1} Y_{k,l} - 1 \qquad \forall\ (i,j) \in A := \{(i,j) \mid a_{i,j} > 0\} \qquad (6)$$

$$t = (a_{i,j}+2),\dots,T\ ,\ \tau = 0,\dots,(a_{i,j}-1)$$

$$\sum_j W_{j,t} + \sum_j V_{j,t+1} \leq 1 \qquad \forall\, t = 1,\dots,T-1 \qquad (7)$$

$$W_{i,t} + \sum_{j\neq i} Y_{j,t+1} + \sum_{j\neq i} W_{j,t+1} \leq 1 \qquad \forall\ i,\ t = 1,\dots,T-1 \qquad (8)$$

$$Y_{i,t}, V_{j,t} \in \{0,1\} \qquad \forall\ i,j,t \qquad (9)$$

$$I_{i,t}, W_{j,t} \geq 0 \qquad \forall\ i,j,t \qquad (10)$$

Objective function (2) minimises the sum of changeover and inventory-holding costs. Constraints (3) represent the inventory balance equations and assures demand $d_{i,t}$ for item i in period t is fulfilled without backlogging. Equations (4), together with (9) and (10), guarantee that in each time interval the machine is either producing item i at full capacity $\left(\sum_i Y_{i,t} = 1\right)$, changing over $\left(\sum_j V_{j,t} = 1\right)$, or idle $\left(\sum_j W_{j,t} = 1\right)$ before manufacturing the next batch of an item. Constraints (5) assures that between two subsequent production batches i and j, sufficient time ($a_{i,j}$) is reserved for changeover. For positive change over time ($a_{i,j}$>0), inequalities (6) enforce the set-up variables to be non-zero between two subsequent batches i and j; if item j is produced in period t $(Y_{j,t} = 1)$ or the machine is idle in period t $(W_{j,t} = 1)$ before manufacturing item j in period t' (t'>t), set-up variables $V_{j,(t-a_{i,j}+\tau)}$ should get a value of one for $\tau = 0,\dots,(a_{i,j}-1)$. The term $\sum_{k:k\neq i\neq j} \sum_{l=t-a_{ij}}^{t-1} Y_{k,l}$ in (6) represents the production of another item than i and j within time interval $\lfloor t-a_{i,j}\ , t-1 \rfloor$. Constraints (7) assure that periods of idleness are scheduled after a changeover. The inequalities (8) prevent that idleness in period t before manufacturing item i is followed by the production (or preliminary idleness) of another item *j*. Finally, constraints (9) and (10) define the integrality and non-negativity requirements.

3.3.3 Modelling product decay

When a traditional objective function like (2) is used for perishable items, traditional linear holding costs in lot-sizing models may disrupt a crucial balance between changeover costs on the one hand and inventory-holding costs on the other hand. Product decay has an impact on the remaining shelf life of products. This aspect is included by an age-dependent component in the inventory-holding costs (Entrup, Gunther et al. 2005).

Product decay of inventory can be incorporated in a SB type model like (2)-(10) in the following way. Let additional parameter $pr_i \geq 1$ represent the perishability rate of item *i*. Next, we redefine the inventory variables $I_{i,t}$ by $I_{i,t,q} \geq 0$ (for all *i, t, q* in which $q \leq t$) as the inventory level of item *i* at the end of period *t,* produced in period *q*. Now, objective function (2) is replaced by (2b) in which (t - q) represents product age:

$$\text{Min } \left\{ \sum_j \sum_t S_t V_{j,t} + \sum_i \sum_t \sum_{q=1}^{t} h_i \, pr_i^{(t-q)} I_{i,t,q} \right\} \tag{2b}$$

Note that if the perishability rate is $pr_i = 1$ for all items *i*, then objectives (2) and (2b) are equal. Replacing (3) by (3a)-(3e) describes the age dynamics of the inventory levels:

$$I_{i,t,q} = Y_{i,t} - d_{i,t} \qquad \forall\ i, t = 1, q = 1 \tag{3a}$$

$$I_{i,t,q} \geq I_{i,t-1,q} - d_{i,t} \qquad \forall\ i, t = 2...T, q = 1 \tag{3b}$$

$$I_{i,t,q} = \sum_{\tau=1}^{t} \left(Y_{i,\tau} - d_{i,\tau}\right) - I_{i,t,q-1} \qquad \forall\ i, t = 2, q = 2 \tag{3c}$$

$$I_{i,t,q} \geq \sum_{\tau=1}^{q} I_{i,t-1,\tau} - d_{i,\tau} - \sum_{\tau=1}^{q-1} I_{i,t,\tau} \qquad \forall\ i, t = 3...T, q = 2...t-1 \tag{3d}$$

$$I_{i,t,q} = \sum_{\tau=1}^{t} \left(Y_{i,\tau} - d_{i,\tau}\right) - \sum_{\tau=1}^{t-1} I_{i,t,\tau} \qquad \forall\ i, t = 3...T, q = t \tag{3e}$$

3.4 Numerical illustrations and benchmark

This section illustrates the impact of (i) (relaxing) the triangular set-up conditions and (ii) incorporating product decay of inventory on optimal production schedules. We use small numerical examples to compare the behaviour and characteristics of the model with the general small bucket model GSB from literature (Wolsey 1997). Model formulation

(2)-(10) is referred to as SB1, and formulation (2b), (3a)-(3e), (4)-(10) is referred to as SB2. We first consider a tailored problem for N=3 and T=10.

3.4.1 Impact of (non-)triangular set-up and product decay

The impact of (relaxing) the triangular set-up conditions and modelling product decay by age-dependent holding costs is demonstrated by three illustrative problem instances.

Example 1. Triangular set-ups, no product decay

Consider inventory-holding costs of $(h_i) = (30, 25, 23)$. The (nonzero) values of demand $d_{i,t}$ and changeover times $a_{i,j}$ (expressed in required periods of capacity) given by:

Table 3.1 Demand

$i \setminus t$	1	2	3	4	5	6	7	8	9	10
1						1			1	
2										1
3					1					2

Table 3.2 Changeover matrix A_1

$i \setminus j$	1	2	3
1	0	1	2
2	1	0	2
3	2	1	0

Let the set-up costs $S_t = 100$ for all t and the processing time be unitary for all items i. Note that the triangular set-up conditions (1) hold for matrix A_1. However, the matrix is asymmetric. Table 3.3 shows the optimal production schedule for this instance.

Table 3.3 Optimal solution Example 1
Total costs 767

t	State	$\sum_j S_t V_{j,t}$	$\sum_i h_i I_{i,t}$
1	3		23
2	3		46
3	3		69
4	Setup	100	69
5	Setup	100	46
6	1		46
7	Idle		46
8	1		76
9	Setup	100	46
10	2		
Costs:		300	467

Table 3.4 Optimal solution Example 2
Total costs 775

t	State	$\sum_j S_t V_{j,t}$	$\sum_i h_i I_{i,t}$
1	1		30
2	1		60
3	Setup	100	60
4	Setup	100	60
5	3		60
6	Idle		30
7	3		53
8	3		76
9	Setup	100	46
10	2		
Costs:		300	475

Model formulations GSB, SB1, and SB2 with $pr_i = 1$ all obtain the same solution in Table 3.3 with total costs of 767 units. The set-up state of the machine is preserved over idle time in period 7.

Example 2. Non-triangular set-up, no product decay.

Increasing the changeover time $a_{3,1}$ between item 3 and 1 to $a_{3,1} > 2$ results into changeover matrix $A_2 = \begin{pmatrix} 0 & 1 & 2 \\ 1 & 0 & 2 \\ 3 & 1 & 0 \end{pmatrix}$ for which one of the triangular set-up conditions (1) does not hold, as $a_{3,1} > a_{3,2} + a_{2,1}$. The optimal production schedule obtained by model SB1 and SB2 with $pr_i = 1$ is presented in Table 3.4. Obviously, the optimal production schedules in the Tables 3.3 and 3.4 are substantially different.

Model formulation GSB generates again the production schedule of Table 3.3. Clearly, this solution is infeasible: a changeover from item i =3 (in period 3) to item j =1 (in period 6) requires 3 time intervals. Apparently, using model formulation GSB for cases in which the triangular set-up conditions (1) do not hold, implies that set-up state changes will occur (a changeover from item i =3 to item j =2 in period 4 and from item i =2 to item j =1 in period 5) without a production change, i.e. no associated production for item 2.

Example 3 Non-triangular set-up and product decay.

We include product decay of inventory by using age-dependent holding costs: a perishability rate $pr_i = 1.12$ is used for all items and applied to model SB2. All other data from Example 2 remain unchanged, including changeover matrix A_2.

Model SB2 yields a completely different production schedule as presented in Table 3.5. Apparently, a small change in the balance between inventory holding- and changeover costs has a major impact on the generated production schedules, see Tables 3.4 and 3.5.

Table 3.5 Optimal Solution Example 3 by model SB2

Total costs 916.38

t	State	$\sum_j S_t V_{j,t}$	$\sum_i \sum_q h_i\, pr_i^{t-q}\; I_{i,t,q}$
1	3		23.00
2	Setup	100	25.76
3	2		53.85
4	Setup	100	60.31
5	1		61.36
6	1		65.12
7	Setup	100	72.94
8	Setup	100	81.69
9	3		72.35
10	3		
Costs:		400	516.38

3.4.2 Complexity discussion

The time required to solve a MIP by a branch-and-bound approach depends heavily on the way in which problems are formulated (Pochet and Wolsey 2006). We conduct a model benchmark for the problem size of the formulations GSB, SB1 and SB2. Table 3.6 provides a general overview. The general problem size is expressed in a common notation, i.e. the dominating term of the number of constraints and variables. Table 3.6 shows that adding the functionality to cope with non-triangular set-ups for simultaneous lot-sizing and scheduling requires more constraints, see column "Constraints" for the rows GSB and SB1. On the other hand, formulation SB1 requires substantially less (binary) variables than model GSB. Nevertheless, the models GSB, SB1, and SB2 are all potentially very large formulations. The impact of the time horizon on problem sizes for an SB-approach becomes most obvious for model SB2 (adding product decay).

Table 3.6 Complexity of the models

Model	Constraints	Variables
GSB	$O[N^2T]$	$O[N^2T]$
SB1	$O[\lambda(A)\,N^2T]$ [1)]	$O[NT]$
SB2	$O[NT^2]$	$O[NT^2]$

[1)] $\lambda(A) > 1$ depends on the values of the elements in changeover matrix A

Complexity considerations for (variants of) the DLSP are published in Salomon, Kroon et al. (1991) and Brueggemann and Jahnke (2000). If set-up times are ignored, it is rather easy to test whether a feasible solution exists by comparing cumulative demands (expressed in required capacity) with cumulative capacity. However, if set-up times are considered, even the feasibility problem is NP-complete (Trigeiro, Thomas et al. 1989; Salomon, Kroon et al. 1991). The latter indicates the need to develop effective and efficient approximation techniques to generate good feasible solutions for larger problem dimensions. Nevertheless, the availability of a correct model formulation offers the possibility to measure the quality of heuristically generated solutions for small to medium sized examples.

3.4.3 Heuristic approach

In a small bucket model like SB2, the number of time periods (t = 1…T) have a significant impact on the problem dimensions and the complexity of the problem. Therefore, it is obvious to focus on time-based decomposition approaches. The concept of the relax-and-fix (R&F) heuristic (Dillenberger, Escudero et al. 1994; Stadtler 2003) is a typical example of a time-oriented decomposition approach. The R&F belongs to the class of mathematical programming-based heuristics that use a mathematical programming (MP) procedure to generate solutions. Heuristics of this class have the advantage that modules of many commercial solvers can be used, possibly with some (minor) customisation. Moreover, the R&F heuristic provides guidance for the assessment of the quality of generated solutions by generating both a lower and an upper bound on the optimal objective function value. We briefly describe a variant of the R&F approach. Numerical results are given in Section 3.5.

Outline Relax-and-Fix

The relax-and-fix algorithm solves sequentially P different mixed integer programming problems, denoted by MIP^p with $1 \leq p \leq P$. The set of integer variables Q is partitioned into P disjoint subsets Q^1... Q^P. For model SB2, Q^1 consists of all production and idle variables $\underline{Y}$ and $\underline{W}$ associated with the time periods $t := \{1, ..., t_1\}$, Q^2 contains all binary variables associated with the periods $t := \{t_1 + 1, ..., t_2\}$ up to Q^P consisting of all binary variables associated with the periods $t := \{t_{p-1} + 1, ..., T\}$. In all iterations the variables of a single subset are defined as integers while all other variables in Q are either relaxed (i.e. defined as continuous variables) or fixed to the (binary) values found in earlier iterations. We apply a backward procedure, i.e. in the first iteration the subproblem MIP^P is solved in which the integrality restrictions are imposed on the variables in the subset Q^P. In other words, production and idle decisions are only made within the window $t = t_{P-1} + 1, ..., T$ .In the next iteration, the integer variables in the subset Q^P are fixed at their optimal values as found in iteration P. Next, problem MIP^{P-1} is solved to find integer values for the subset of binary variables in Q^{P-1} and so on. In each problem MIP^p, the production and idle variables are fixed at their optimal values in earlier iterations. We do not apply a common forward procedure in the R&F algorithm. As demand matrices for small bucket models are usually sparse (i.e. many if not most entries of the matrix are zero), finding a feasible solution at the end of the R&F algorithm strongly depends on the solution procedure (i.e. forward or backward). In a forward procedure, production is postponed in early iterations. If capacities are tight, the concept of fixing the production and idle variables at their optimal values from previous iterations, will easily lead to infeasible solutions in case a forward procedure is applied. It should be mentioned that (only) problem MIP^p in the first iteration of the R&F algorithm is a relaxation of the original problem. This automatically implies that the objective value of problem MIP^p in the first iteration of the R&F procedure provides a valid lower bound on the optimal objective function value.

3.5 Numerical analysis

We investigate the computational behaviour of model SB2 and the potential value of a backward Relax-and-Fix solution procedure. We compare the objective values reached and the required computing time to run the solution procedures. All problems were solved using Xpress-Mosel on a personal computer with an Intel Core i3 CPU, 2.13 GHz, RAM 4GB. The results are given in Table 3.7.

Table 3.7 Computational results

	Optimal solutions		Relax-and-Fix		
N / T	Objv	CPU	Objv_RF	GAP	CPU_RF
3/20	3475.7	2	3475.7	0.0%	1
3/30	5453.2	4	5453.2	0.0%	2
3/40	6805.6	17	6805.6	0.0%	6
3/50	8245.7	132	8245.7	0.0%	14
3/60	10341.2	12371	10341.2	0.0%	74
3/90	–	–	15686.1	–	102
3/120	–	–	19852.7	–	115
4/20	3948.7	1	Infeasible		
4/30	6114.9	5	6287.3	2.8%	5
4/40	8554.5	75	8554.5	0.0%	194
4/50	11373.5	268	11373.5	0.0%	33
4/60	14095.2	2380	14095.2	0.0%	453
4/90	–	–	20518.0	–	84
4/120	–	–	27595.2	–	407
5/20	3781.8	2	Infeasible		
5/30	5996.5	51	6219.7	3.7%	15
5/40	9569.3	1821	10492.8	9.7%	284
5/50	12780.5	3405	13152.7	2.9%	51
5/60	14479.5	21299	14888.0	2.8%	112
5/90	–	–	26143.3	–	193
5/120	–	–	36985.8	–	486
6/30	8322.8	970	8322.8	0.0%	41
6/40	10197.0	6565	10228.6	0.3%	135
6/50	13478.0	209716	13478.0	0.0%	631
6/60	–	–	17848.2	–	1387
6/90	–	–	30353.3	–	770
6/120	–	–	39951.2	–	610

Test cases were generated from small to moderate size. Both the number of items N and the number of time periods T are varied according to $N = 3,4,5,6$ and $T = 30,40,50,60,90,120$. The perishability rate is set at $pr = 1.1$ and set-up-costs $S_t = 500$ for all t in all cases. The inventory-holding costs differ between items i but remain unaltered between cases.

Demand is expressed in discrete units of production capacity and may occur at any timeslot in the planning horizon. Demand on a timeslot may be larger than a single unit of production capacity. The changeover matrix is asymmetric, sequence-dependent and such that the triangular set-up conditions (1) do not hold. All changeover times $a_{i,j} > 0$ for $i \neq j$.

Table 3.7 shows the results for a set of instances solved by model SB2. The first column indicates the problem size, i.e. the number of items N and the planning horizon T. Columns 2 and 3 refer to the objective function value of the optimal solution (Objv) and the time needed to find the solution (CPU). The results in column 3 confirm that finding optimal solutions requires high computation times for medium size instances. The search procedure for optimal solutions was interrupted after eight hours of CPU time, provided that for each value of $N = 3,4,5,6$ at least three test cases were solved to optimality. An interrupted solution procedure is indicated by entry '−' in Table 3.7. The columns 4 to 6 refer to solutions found by the Relax-and-Fix (R&F) heuristic, i.e. the objective function value found in the final iteration (Objv_RF), the relative deviation between the optimal objective value and the objective value of the R&F solution (GAP), and the computation time needed to find the R&F solution (CPU_RF). For all instances in Table 3.7, the R&F heuristic performed remarkably well: for 10 out of 18 cases the optimal solution was found, and time savings were substantial.

3.6 Concluding remarks

This paper studies how to include realistic features of food processing industry (FPI) in models for simultaneous lot-sizing and scheduling, in particular (i) sequence-dependent set-ups (including non-triangular set-ups), and (ii) product decay of inventory due to perishability.

Although big bucket (BB) models are usually associated with medium-term planning horizons, various extensions of these models are proposed for short-term planning horizons too. From a computational point of view it is explainable to prefer models with large time intervals over small bucket (SB) approaches. However, we state that segmentation of the planning horizon is a key issue for simultaneous lot-sizing and scheduling, particularly in food processing industry. Using large time periods implies that some basic principles for lot-sizing and scheduling (unfoundedly) disappear from sight. We give two reasons to underpin the latter statement.

Firstly, if the objective for simultaneous lot-sizing and scheduling should include the best compromise between total set-up costs and total inventory holding costs, a time-oriented aggregation (e.g. in BB models and its variants) may easily disrupt the general principle of optimality for lot-sizing (Pochet and Wolsey 2006). If time intervals represent long periods (e.g. a week or more) multiple batches can be produced in each period. Consequently, inventory costs for batches manufactured at the start of lengthy periods are assumed to be equal to inventory costs of lot sizes produced at the end of the same period. As a result, total inventory costs in (2) or (2b) are underestimated, the main principle of optimality for lot-sizing may become disrupted, and production schedules will change accordingly. Secondly, product decay in food processing industry is primarily associated with the "age" of products. Incorporating issues of perishability like product decay requires capturing the precise moments of production for manufactured products.

We developed an SB model that (*i*) can handle sequence-dependent set-ups (including non-triangular set-ups), (*ii*) addresses product decay by incorporating age-dependent holding costs. Small-scale examples are used to demonstrate the impact of non-triangular set-ups and product decay on the generated solutions. The models show how a small change in the balance between inventory holding- and changeover costs may generate significantly different solutions, especially when the triangular set-up conditions do not hold.

As expected, the computational effort for the SB model is substantial. We performed exploratory research with a straightforward implementation of a Relax-and-Fix heuristic. Numerical tests show that the quality of R&F solutions is promising at manageable computational effort. Additional research is needed to find more enhanced variants of the R&F and an effective (algorithmic) segmentation of the time horizon, e.g. by exploiting the sparse demand matrix in a SB approach. Smoothing the heuristic solution by creating some overlap between successive iterations may be an option for further research (Pochet and Wolsey 2006). We refer to Escudero and Salmeron (2005) and (Federgruen, Meissner et al. 2007) for an overview of various strategies in an R&F framework.

Another interesting question for further research is to improve computational performance by adding valid inequalities (VI's) a priori to the initial formulation. Preliminary research revealed that adding the inequalities $Y_{j,t} + W_{j,t} \leq Y_{j,t-1} + W_{j,t-1} + V_{j,t-1} \quad \forall j,t$ tightened the linear relaxation and provided substantially better heuristic solutions in an R&F framework. The inequalities are based on feasibility conditions within any production scheme and are added before calling the MP-solver. The proposed model offers a unique possibility to measure the quality and performance of any (heuristic) approach.

Chapter 4

Integrated planning between procurement and production

Simplicity always beats complex optimization (Little 2004)

This chapter is based on:

Claassen, G.D.H., and Hendriks, Th.H.B., (2007)
An application of Special Ordered Sets to a periodic milk collection problem
European Journal of Operational Research
Vol. 180 (2), pp. 754 – 769.

Claassen, G.D.H., and Hendriks, Th.H.B., (2007)
Modelling techniques for (non)linear and integer programming
In: Decision Science, Theory and applications, Ch. 9
Eds: G.D.H. Claassen et al.
Wageningen Academic Publishers, pp. 185 – 226

Abstract

This chapter focusses on the need for integrated decision support between procurement and production in the Supply Chain Planning Matrix (SCPM), particularly important across organizational borders. We take different cooperative organizations in dairy industry as a starting point and focus on the impact of (dominant) batch type production processes on push-oriented sourcing of perishable raw materials. Various raw milks are processed in different batches on shared resources. Capacities of special storage facilities are limited on supply, distribution, and processing level. The study intends to develop and test a pilot DSS in practice, particularly helpful for non-dominant partners in a food supply chain. We present an OR-based approach to support milk collection in a special branch of dairy industry. The annual growth of the sector and the continuous imbalance between milk supply and demand, has urged the sector to look for a different approach to their daily milk collection problem. Specific details of the problem environment (i.e. the continuous production on supply level and the delivery conditions on demand level) gave rise to choose for a short- to medium-term planning approach. The proposed decision support system has to be considered as an efficient tool for generating stable milk collection plans which in turn serves as an effective starting point for the vehicle routing problem. From a computational point of view it turned out that the application of Special Ordered Sets type 1 (SOS1) was very useful. Although it appears from literature that the computational advantage of SOS1 is restricted to supplementary model conditions, this study shows that these conditions are not necessarily needed.

4.1 Introduction

The introduction of the so-called milk quotation system for cow's milk in 1984, implied a strong stimulus for the annual growth of milk goats for professional use in the Netherlands. The continuous growth since 1984 was intensified by the favourable profit for the production of goat's milk on a biological and professional scale. Nowadays, Dutch goatherds for professional use produce about 40 million litres of milk yearly. The main part is used for domestic cheese production but export of fresh milk to Belgium, Germany and the UK is also quite common. The remainder of the supply is sold at an unattractive price level for food (milk powder) of young animals and dairy concentrates.

The annual growth of the sector and the increasing imbalance between the continuous production of milk on supply level and the delivery conditions of dairy factories has urged the sector to look for a different approach to their milk collection problem. Milk collection in this sector is usually not set up by processing industry or by (local) transportation companies. Individual farmers are mostly united in cooperative associations. All costs and profits are shared with the members of the association. The (yearly) negotiations with processing industry about the expected amounts of milk to deliver, the delivery days, the selling prices, the contracts with local transportation companies and the (daily) construction of milk collection schedules are all covered by the cooperative association. This study has been done for one of the largest cooperative associations in goatherd industry in the Netherlands. The main questions were:

1. How to support the vehicle schedulers of the cooperative association in their daily job to build milk collection schedules such that the (financial) interests of the farmers are served as well as possible. It is significant to realize that collecting milk effectively from the supplier farms and deliver the milk to the different parties on demand level is not restricted to solving vehicle routing problems. Common dairy factories call for large amounts of raw material and their demand for goat's milk is scheduled to arrive at a very limited number of fixed days. As a consequence, the milk collection schedules should balance milk supply and demand such that the raw material can be sold at the best possible price level.

2. How to support other decision-makers of the cooperative association in their (yearly) negotiations with processing industry, (third party) transportation companies and suppliers.

Although a lot of literature, e.g. (Toth and Vigo 2002; Ghiani, Guerriero et al. 2003; Gayialis and Tatsiopoulos 2004), has been dedicated to (the application of) vehicle routing problems and even on milk collection problems in common dairy industry (Basnet, Foulds et al. 1996; Gerdessen 1996; Butler, Williams et al. 1997), the collection problem for goat's milk is characterised by rather specific details. The routing aspect could be classified as a

Periodic Vehicle Routing Problem (PVRP). The PVRP is an important generalization of the classical Vehicle Routing Problem (VRP). The VRP consists of constructing delivery routes for a fleet of vehicles at minimum costs. The capacity of each vehicle is fixed and may not be exceeded. Moreover, each vehicle must return to its departure site. Customers have a known demand that must be fully satisfied. Each customer is visited exactly once by a single vehicle (Cordeau, Gendreau et al. 1997). There may be constraints that limit the distance travelled by each vehicle (Chao, Golden et al. 1995; Cordeau, Gendreau et al. 1997). Typically, the planning period is a single day. The VRP is a hard combinatorial problem that received a great deal of attention in literature. Usually the problem is tackled by means of heuristics (Cordeau, Gendreau et al. 1997).

The PVRP generalizes the classical VRP by extending the planning period from a single day to T days (Chao, Golden et al. 1995). Over this planning horizon the clients are not to be served on a daily bases, but are characterized in terms of some sort of periodicity of the demand. Each customer *i* on demand level specifies a service frequency by a set of allowable combinations of visit days (Cordeau, Gendreau et al. 1997). Each customer must be visited at least once but some of them require several visits during the T-days period. Now the problem consists of simultaneously selecting a visit combination for each customer and establishing vehicle routes for each day of the planning horizon according to the VRP rules as outlined above. An integer programming formulation of the PVRP can be found in (Gaudioso and Paletta 1992). The periodicity of demand implies that it is not possible to solve the problem on a daily bases and subsequently replicate the solution over time. Chao, Golden et al. (1995) classifies the PVRP as a multi-level combinatorial optimization problem. At the first level it is necessary to assign an allowable visit combination to each customer. At the second level a classical VRP (i.e. assigning vehicles to routes) for each day of the planning period should be solved. At the third level, a classical Travelling Salesman Problem (TSP) should be solved. As the TSP has been shown to be NP-hard, the PVRP is at least as difficult (Chao, Golden et al. 1995). Within this context it is hardly surprising that most papers on the PVRP reported in literature present heuristic methods. See for example (Gaudioso and Paletta 1992; Chao, Golden et al. 1995; Cordeau, Gendreau et al. 1997).

A review of solution approaches for the PVRP can be found in Chao, Golden et al. (1995). Practical applications of the PVRP are for example in grocery distribution (Golden and Wasil 1987) but in Chao, Golden et al. (1995) more areas of application can be found. Many efforts in the literature have been established to extend the basic PVRP model to incorporate additional constraints or different objectives. However, at our knowledge the PVRP assumes either pickup or delivery operations, not both. In other words: it either concerns the construction of pickup routes for raw material(s) from several suppliers to a single manufacturer or the construction of delivery routes from a single supplier (for example a warehouse) to several customers. Typically in a PVRP, suppliers or customers are characterized by some kind of periodicity of visiting days over a *T*-day planning horizon and their geographically dispersed locations. The collection problem also concerns the construction of routes over a T-day period but in this case both the suppliers and the customers specify a set of allowable combinations of visit days. Although customers specify a service frequency, it is not necessary to satisfy the periodic demand completely for every customer. Moreover, customers may be visited by more than one vehicle from different routes. Finally, the problem is even more complicated by keeping qualities of the raw material. In contrast to the common PVRP, emphasis is not at first towards routing costs or fleet size but towards fitting and balancing milk supply and demand by assigning allowable visit combination simultaneously to farmers and customers. The goal of this research is twofold.

First we discuss how an OR-based approach, the related optimization techniques, structured data queries and additional analysis tools can support a specific milk collection problem such that several, mostly conflicting, goals of the relevant players (i.e. farmers, processing industry and transporters) are taken into consideration. Analogous to the PVRP, the most critical decision is to assign allowable visit combination to farmers and customers, once this is done the daily routing of vehicles is relatively straightforward. For assigning allowable and stable visit combinations we propose a mixed integer linear programming model that is solved by applying the concept of Special Ordered Sets type 1 (SOS1), introduced by Beale and Tomlin (1970). Although Williams (1990) stated that there is a great computational advantage to be gained in the SOS-formulation, the questions "why, when and how to apply Special Ordered Sets of type 1", have not got much attention in literature yet.

The second goal of this study is to contribute to the insights of an effective use of special ordered sets of type 1. From a theoretical point of view we prove that there is no advantage in branching on sets of variables by using the SOS1 concept or branching on individual (integer) variables in a commonly applied branch-and-bound procedure. We show that the efficiency of the SOS1 formulation strongly depends on the ordering of the variables within each set.

The remainder of this chapter is organized as follows. In the next section, we describe the problem environment in more detail and focus on the main differences between milk collection problems for cow's - and goat's milk. In Section 4.3 we present a model formulation that turns out to be quite hard to solve for real sized problems. In Section 4.4 we focus on an efficient use of the SOS1-formulation and the related computational performance. In the last section we finalize by a general discussion and some concluding remarks.

4.2 Problem description

Although the yearly supply of goat's milk is of minor importance for the Dutch dairy industry, the market for the related end products is growing annually. The exclusive end products, mainly cheese, are processed by a limited number of dairy factories. Actually, just a few factories are processing goat's milk and their production capacity is mainly based on processing large quantities of common cow's milk. As a consequence, set-ups for processing goat's milk on demand level are usually restricted to one or at most two days weekly for every factory. However, in view of meeting all predefined quality standards, the freshness or "age" of the milk at arrival time, is of major importance. This implies that the raw material has to be collected before the "age" of the (oldest) milk exceeds three days. This time restriction is fixed and independent of the final destination of the raw material, inside or outside the Netherlands. So on the one hand, dairy factories call for large amounts of raw material and their demand is only scheduled to arrive at some fixed days. On the other hand, looking at supply level, the number of goat's for professional use are small compared to common dairy farms, the average milk production yields on individual farms are substantially less and goat's farms are geographically spread over the country. So, from a transportation point of view the complexity of the collection problem for goat's milk is quite different from collecting cow's milk. Especially if we take into account that (cooled) storage of milk at supply level is restricted to at most three days and the dairy factories only take delivery of goat's milk at a small number of fixed days. This in turn enhances the problem that the transported amount of milk between the supply- and demand level is often out of balance with the capacity of modern transportation vehicles.

These conflicting interests, together with the annual growth of the sector, urged for a different approach of the daily milk collection problem in the goatherd sector. It raised the question to develop an interactive planning tool in order to support the milk collection problem and attune the imbalance between milk supplies on the one hand and the individual demand levels of dairy factories on the other hand. The system should have a major focus on constructing stable, short- to medium-term milk collection and delivery plans rather than solving the daily VRP (i.e. assigning vehicles to routes) and subsequently, the Travelling Salesman Problem TSP for each vehicle.

4.3 Model formulation

Part of the system is based on a mixed integer linear programming model. This model takes a (rolling) planning horizon of two weeks into account. Milk supply and demand is exactly known for two weeks in advance. Individual farms are clustered to larger entities. This grouping is primary based on the geographical location of the farms and the available quantity of milk within a cluster. The main idea is that within each cluster the entire milk production will be collected at days, i.e. collection rhythms, still to be determined within the planning horizon (see Table 4.1).

Table 4.1: some feasible milk collection rhythms; to be repeated every two weeks

	← Week 1 →							← Week 2 →						
Rhythm	Mo1	Tu1	We1	Th1	Fr1	Sa1	Su1	Mo2	Tu2	We2	Th2	Fr2	Sa2	Su2
1	✓		✓		✓			✓		✓		✓		
2	✓		✓		✓			✓		✓			✓	
3		✓		✓		✓		✓		✓			✓	
:														
r	✓			✓	✓			✓		✓		✓		
:														
R	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	

The available amount of milk after one, two or three days should match with the different carrying capacities of (several) transportation vehicles. A surplus of milk at supply level can be sold at an unattractive price level to a selected number of surplus companies. Now the question is not only which cluster should be visited but also when to visit the farms in a cluster such that the allowed visit days and delivered quantities on demand level are satisfied as well as possible. In order to meet the most important quality standards of the collected milk, the period of time between two consecutive visits within a cluster should not exceed three days. In fact this quality constraint means that the potential number of milk collection schemes or rhythms, for a two weeks planning horizon, is finite and limited (see Table 4.1). Collecting milk at Sundays is not allowed. After the milk collection rhythms are chosen they will be repeated every two weeks. The introduction of these so-called milk collection rhythms reduced the complexity of the problem considerably. After all, the problem is now which milk collection rhythm should be assigned to each cluster such that the individual visit days demand levels are served as well as possible. This problem can be formulated as a mixed integer linear programming model. Suppose we define:

Indices

$c = 1 .. C$ ~ the different clusters at supply level

$b = 1 .. B$ ~ the different buyers or factories at demand level

$r = 1 .. R$ ~ the available milk collection rhythms

$t = 1 .. T$ ~ the relevant days of the planning horizon

Data

$S_{c,r,t}$ ~ the milk supply in cluster *c* on day *t* according to milk collection rhythm r

$D_{b,t}$ ~ the demand of milk for buyer b on day *t*

P_b^+ ~ penalty for every unit of milk delivered more than the actual demand of buyer *b*

P_b^- ~ penalty for every unit of milk delivered less than the actual demand of buyer *b*

Variables

$x_{c,r,b,t}$ ~ delivered amount of milk from cluster c, at rhythm r for buyer b on day t

$xd_{b,t}^+$, $xd_{b,t}^-$ ~ surplus or shortage of milk at demand level (buyer *b*) on day *t*

$Y_{c,r}$ ~ binary variable in order to assign milk collection rhythms to clusters

Model formulation

$$\text{Min}\left\{\sum_b \sum_t (P_b^+ \cdot xd_{b,t}^+ + P_b^- \cdot xd_{b,t}^-)\right\} \qquad (1)$$

$$\sum_r y_{c,r} = 1 \qquad \forall c \qquad (2)$$

$$\sum_b x_{c,r,b,t} \leq S_{c,r,t} \cdot y_{c,r} \qquad \forall c,r,t \qquad (3)$$

$$\sum_c \sum_r x_{c,r,b,t} - xd_{b,t}^+ + xd_{b,t}^- = D_{b,t} \qquad \forall b,t \qquad (4)$$

$$y_{c,r} \in \{0,1\} \qquad \forall c,r \qquad (5)$$

$$x_{c,r,b,t} ,\ xd_{b,t}^+ , xd_{b,t}^- \geq 0 \qquad \forall c,r,b,t \qquad (6)$$

The objective function (1) minimizes the total weighted sum of deviations on demand level. Especially the penalty coefficients $P_b^+ \ \forall b$ (surplus) are important in order to weight any amount of milk delivered at an unattractive price level to (i) the subset of surplus companies or to (ii) buyers that accept deliveries above their contractual maximum amounts. The constraints in (2) ensure that exactly one milk collection rhythm will be assigned to every cluster of farmers. The equations in (3) are classical logical conditions between the continuous variables at the left-hand side and the binary variables at the right-hand side. They imply that no milk can be transported from a cluster on a day to any buyer if it is not in accordance with the chosen milk collection rhythm. Moreover, the equations in (3) ensure that the total amount of milk to be transported from a cluster to the buyers may not exceed the available quantity on supply level. The equations in (4), together with the objective function, ensure that demand levels of all buyers are (more or less) satisfied. The deviation between the delivered amount of milk and the actual demand level is expressed by the auxiliary variables $xd_{b,t}^+$ (surplus) and $xd_{b,t}^-$ (shortage).

4.4 Solving the model

Despite of the limited number of both the predefined milk supply clusters *C* and the milk collection rhythms *R*, the problem turned out to be disappointingly hard to solve. In most cases practice defined ten to twelve different milk supply clusters. An (arbitrary) upper bound of ten cpu-minutes for solving a problem is already reached at six potential milk collection rhythms.

Instead of defining $C * R$ different binary variables and subsequently branch on individual variables in a branch-and-bound (B&B) tree, the integrality constraints (5) can be relaxed and it is possible to apply the concept of special ordered sets type1 (SOS1), introduced by Beale and Tomlin (1970). An SOS1 is defined as a set of variables within which at most one variable may be non-zero. In this case we defined for each milk supply cluster *c,* an SOS1 set $S1_c$ of continuous variables such as:

$S1_c := \{Y_{c,1}, Y_{c,2}, \ldots, Y_{c,R}\}$ together with the conditions at most one of the variables within this set can be non-zero $\quad \forall c \quad$ (5.1)

Note that it is not necessary to treat the variables $Y_{c,r}$ in (5) as binary variables since the $S1_c$-conditions in (5.1) together with the constraints in (2) ensure that within each $S1_c$-set exactly one continuous variable will get a final value of one. As an alternative to define the variables $Y_{c,r}$ as 0–1 integers $\forall c, r$ in (5), it is convenient to consider each $S1_c$ -set as a discrete entity or generalisation of a 0–1 variable.

Conditions (5.1) can be dealt with algorithmically through the method of integer programming (Williams 1993). Treating each set as an entity makes it possible to branch in a branch-and-bound (B&B) algorithm on entities rather than on individual variables. The non-zero variable in each feasible $S1_c$ -set of (5.1) will lie either to the left, or to the right, of any marker placed between two consecutive variables within a set. So:

either $\{Y_{c,1}, Y_{c,2}, \ldots, Y_{c,j}\}$ are all zero

or $\{Y_{c,j+1}, Y_{c,j+2}, \ldots, Y_{c,R}\}$ are all zero

These two possibilities correspond to a branch in a solution tree as demonstrated in Figure 4.1 in which $P_{c,k}$ is defined as a subproblem *P* for a $S1_c$ -set in node *k* of the search-tree (Williams 1993).

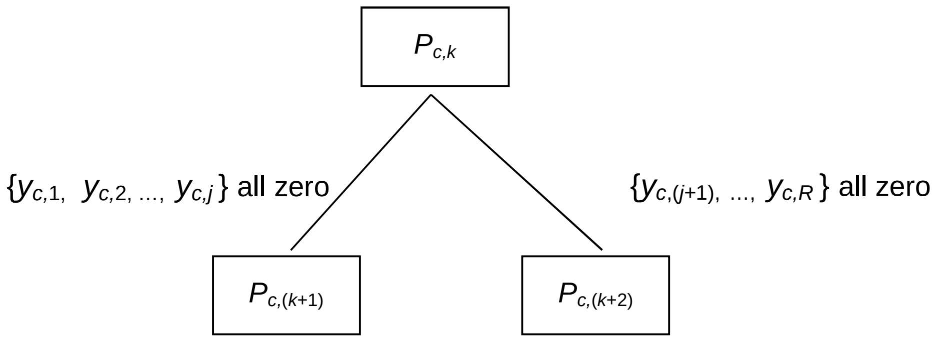


Figure 4.1: The branching procedure in a SOS1 search-tree (Williams 1993)

For any node in the search tree, for example, problem $P_{c,(k+1)}$, one of the following situations holds:

- problem $P_{c,(k+1)}$ is infeasible which implies that the search-tree stops below node $P_{c,(k+1)}$.
- problem $P_{c,(k+1)}$ is feasible. Now, two possibilities are left:
  - the subset $\{y_{c,(j+1)},\ldots,y_{c,R}\}$ is feasible, i.e. at most one of the variables in the set is non-zero. If the objective function value w for problem $P_{c,(k+1)}$ is better than the best bound w_b so far, the value for w_b is updated ($w_b := w$). The search tree stops below node $P_{c,(k+1)}$.
  - the subset $\{y_{c,(j+1)},\ldots,y_{c,R}\}$ is infeasible i.e. at least two variables in this subset are non-zero. If the objective function value w for problem $P_{c,(k+1)}$ is worse or equal to the bound w_b found so far, the search tree stops below node $P_{c,(k+1)}$. If the value of the objective function w for problem $P_{c,(k+1)}$ is better than the best bound w_b, the branching procedure is to be continued on the subset $\{y_{c,(j+1)},\ldots,y_{c,R}\}$. Note that in any node below problem $P_{c,(k+1)}$, at least the variables $\{y_{c,1},\ldots,y_{c,j}\}$ are all zero.

In Appendix 4.1 of this chapter we prove by means of complete induction that the upper bound $\overline{B}$ for the number of branches B, in case of C different S1-sets (milk supply clusters) and R different milk collection rhythms, is defined by:

$$\overline{B} = \sum_{c=1}^{C} R^{c-1}(2R - 2) \tag{7}$$

Increasing the number of clusters C will have a larger impact (exponentially) on the potential size of the search-tree than the number of milk collection rhythms R. Using complete induction (see Appendix 4.1) we can also proof that the potential number of branches $\overline{B}$ for a common B&B approach, i.e. branching on individual binary variables $Y_{c,r}$

for problem (1) to (6), is also equal to (7). However, from literature it appears that there is a great advantage to be gained in the SOS-formulation, provided that the variables within the sets have a so-called natural ordering (Williams 1990).

As the upper bound $\overline{B}$ of an SOS-based search tree is equal to a 'conventional' branch-and-bound tree (B&B-tree), any computational advantage of the SOS-formulation must be based on finding strong and/or early bounds in the search-tree. For that purpose (Williams 1990) adds that the variables should have a natural ordering within the sets. Unfortunately, in our case the variables (i.e. the milk collection rhythms) within the sets can hardly be ordered in a natural way. In the following, we primary focus on the concept of finding early bounds in a SOS1-based search-tree. Next we will present an alternative procedure for ordering the variables within the sets in case there exists no natural ordering.

If more than one variable in (5.1) takes a non-zero value, the S1-set is infeasible. In order to measure this infeasibility analogous to the fractionality of an integer variable, the variables in each set of (5.1) have to be associated with a monotonic, increasing or decreasing, set of numbers ($a_1, a_2, \ldots, a_R$) known as the reference row (Beale and Tomlin 1970; Williams 1990). In the formulation of some applications this set of numbers arises from a constraint. In case these constraints are not present, the index numbers can be used in order to associate each variable with its place in the ordering, so $a_1 = 1$, $a_2 = 2$, …, $a_R = R$. Now, the fractionality of an infeasible $S1_c$-set in any node of the B&B-tree, can be calculated as follows (Williams 1993):

$$\sum_{r=1}^{R} a_r \tilde{y}_{c,r} \Big/ \sum_{r=1}^{R} \tilde{y}_{c,r} \qquad \forall c \qquad (8)$$

In which $\tilde{y}_{c,r}$ denotes the solution value of the variables in the current node of the B&B-tree. Since the numbers a_r are monotonic, there will be some a_r such that

$$a_r \leq \sum_{r=1}^{R} a_r \tilde{y}_{c,r} \Big/ \sum_{r=1}^{R} \tilde{y}_{c,r} < a_{r+1} \qquad \forall c$$

(9)

indicating that the "centre of gravity" of the set has come out between the index r and $r+1$ (Williams 1993). If the set is infeasible the branching marker will be placed between the variables $Y_{c,r}$ and $Y_{c,r+1}$.

Now the problem is how to order the (continuous) variables $Y_{c,r}$ within every $S1_c$-set such that the branch and bound (B&B) procedure can be executed more efficiently than in case of branching on the individual (binary) variables $Y_{c,r}$ in problem (1) to (6).

Obviously, finding strong bounds in an early stage of the B&B procedure will have a significant effect on the efficiency of a B&B algorithm. However, a general strategy for strong bounds may be hard to find. Nevertheless, we could try to set up the branching-tree in such a way that the chances for fathoming large(r) parts of the search-tree in an early stage of the B&B algorithm are increasing. Within this context we will focus on a sorting procedure for the individual variables within the $S1_c$-sets. According to (9) the position of the branching marker in an infeasible $S1_c$ -set depends both on the values for a_1, a_2 ,…, a_R in the reference row and on the position of the non-zero variables within the set. Within this study the reference row itself remains unaltered, so $a_1 = 1$, $a_2 = 2$,…, $a_R = R$. If the actual position of the decision variables $Y_{c,r}$ within a set is such that the corresponding non-zero variables $\tilde{y}_{c,r}$ of an infeasible $S1_c$ -set will be located on the left-hand (or right-hand) side within a set, the position of the branching marker will be placed in the same area. As a result, the subsets corresponding to each of the branches in Figure 4.1 will be unequal in size. This in turn means that the potential depth of the branch related to the largest subset will be less than the depth of the opposite branch. So, it is likely to expect that the chances for finding an early solution (i.e. bound) will be larger in a node beneath the branch on the largest subset. After all, according to the constraints in (2), every $S1_c$ -set has to be feasible in the end. Note that for all potential milk collection rhythms a feasible solution for problem (1) to (6) can be found.

Next, we focus on an ordering procedure for the decision variables $Y_{c,r}$ within the $S1_c$ -sets such that the value of the corresponding non-zero variables $\tilde{y}_{c,r}$ of an infeasible set will be located on the left-hand (or right-hand) side within the set. Within this ordering context it is convenient to define some measure of performance for each milk collection rhythm r on supply level. Suppose we define a parameter $DS_{c,r}$ for every decision variable $Y_{c,r}$ within an infeasible $S1_c$-set. The value of these parameters should be regarded as an heuristic fit for applying milk collection rhythm r in cluster c (supply level) to all needs on demand level. The value for $DS_{c,r}$ is defined as:

$$DS_{c,r} = \sum_{t=1}^{T} \left| \left(\sum_{b=1}^{B} D_{b,t} - S_{c,r,t} \cdot \tilde{y}_{c,r} \right) \right| \quad \forall r \text{ in all infeasible } S1_c \text{ - sets}. \qquad (10)$$

Now, the actual position from $r=1$ to R of the variables $Y_{c,r}$ within an infeasible $S1_c$-set is based on an increasing (or decreasing) value for $DS_{c,r}$. So, in case of an increasing ordering for $DS_{c,r}$, the corresponding (non-zero) variables $Y_{c,r}$ in the linear programming relaxation (LP-relaxation) will be placed on the left-hand side in the set and vice versa (right side) for a decreasing ordering. These ordering strategies will be called S1_LEFT and S1_RIGHT respectively. The strategy in which the corresponding (non-zero) variables $Y_{c,r}$ of the lowest values for $DS_{c,r}$ are placed in the middle of the S1-sets, is called S1_MID.

Suppose for a cluster $c=i$ the solution values $\tilde{y}_{i,r}$ of the LP-relaxation for $r=1,..,6$ are: $\left\{\tilde{y}_{i,1}=0\ ,\tilde{y}_{i,2}=0.4\ ,\tilde{y}_{i,3}=0\ ,\tilde{y}_{i,4}=0\ ,\tilde{y}_{i,5}=0.6\ ,\tilde{y}_{i,6}=0\right\}$ then the ordering of the variables $Y_{i,r}$ for each strategy within the $S1_i$-set is given in Table 4.2. The arrows below the sets denote the position of the branching marker which values are calculated by (9). The branching marker defines the two subsets in the SOS1 branching procedure (see Figure 4.1).

Table 4.2 Fictitious example of the ordering strategies within the $S1_c$-set

$DS_{i,r}$ *for* $r=1,..6$	$DS_{i,1}=10\ ,DS_{i,2}=6\ ,DS_{i,3}=9\ ,DS_{i,4}=8\ ,DS_{i,5}=4\ ,DS_{i,6}=8$
Ref. row	$\{1,\quad 2,\quad 3,\quad 4,\quad 5,\quad 6\}$
S1_LEFT	$\{y_{i,5}\}\ \underset{1.4}{\uparrow}\ \{y_{i,2},y_{i,4},y_{i,6},y_{i,3},y_{i,1}\}$
S1_MID	$\{y_{i,1},y_{i,6},y_{i,2}\}\ \underset{3.6}{\uparrow}\ \{y_{i,5},y_{i,4},y_{i,3}\}$
S1_RIGHT	$\{y_{i,1},y_{i,3},y_{i,4},y_{i,6},y_{i,2}\}\ \underset{5.6}{\uparrow}\ \{y_{i,5}\}$

The experiments related to the impact of the number of milk collection rhythms on the computational effort, are summarised in Figure 4.2. Every marked point in Figure 4.2 represents the average result for three different cases in which individual farms were grouped into ten different clusters. This grouping remained unaltered between the cases. The curves represent four different strategies. One of the curves (BIN) is based on a common B&B approach, i.e. branching on individual binary variables $Y_{c,r}$ for problem (1) to (6). All other curves are related to the application of different SOS1 branching strategies as discussed before and demonstrated in Table 4.2.

As expected, Figure 4.2 shows that the computational effectiveness of the S1_LEFT and S1_RIGHT strategy are comparable. From a computational point of view these strategies are much better than branching on individual binary variables in a common B&B approach (the BIN-curve) or the S1_MID strategy. The difference in effectiveness of the S1_LEFT or S1_RIGHT strategy on the one hand and the BIN or S1_MID strategy on the other hand becomes more evident in case the number of milk collection rhythms increases.

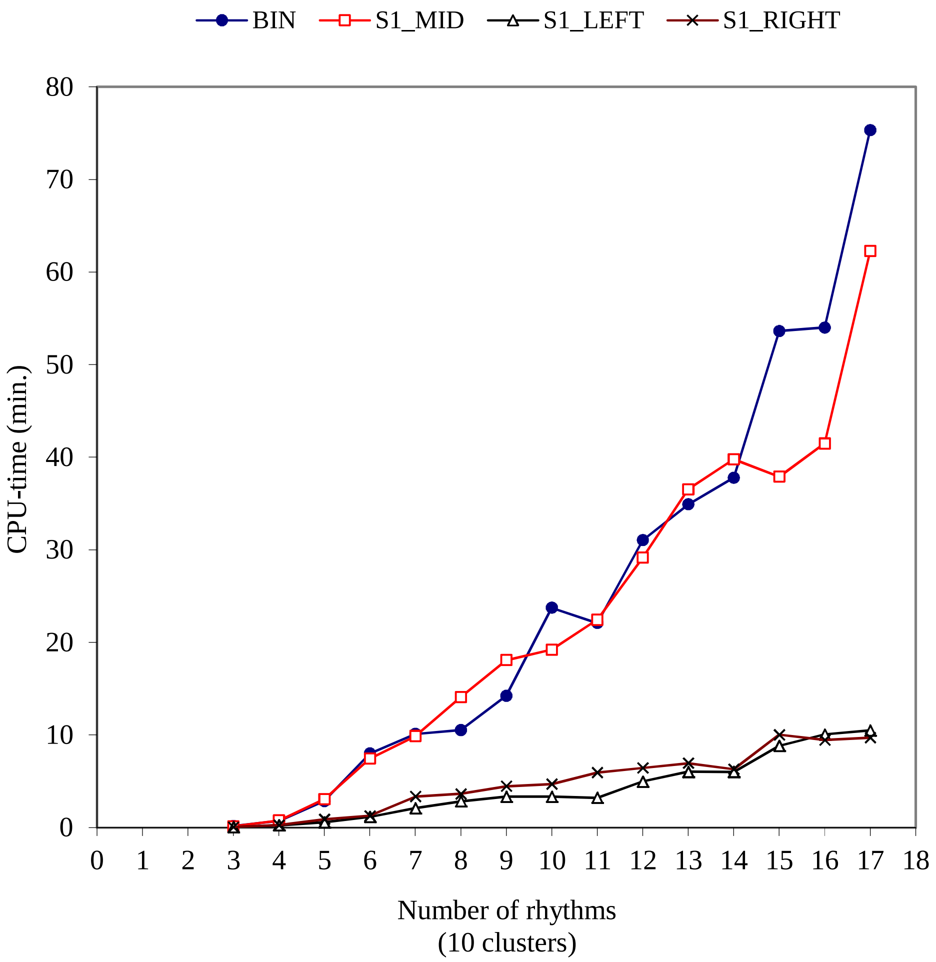


Figure 4.2 The impact of the number of collection rhythms on the calculation time

The impact of the number of clusters on the computational effort is demonstrated in Figure 4.3. The observations in Figure 4.3 are all based on a single case in which we defined seventeen different milk collection rhythms for an increasing number of clusters on the horizontal axis. Although there is still a difference in effectiveness between the BIN (or S1_MID) and the S1_LEFT (or S1_RIGHT) strategy, the computational advantage of the latter strategies is less beneficially for an increasing number of clusters. This observation becomes obvious if we take into account that only the number of milk supply clusters *C* will affect the number of global entities (i.e. the $S1_c$-sets) in an SOS1-based B&B algorithm. The number of milk collection rhythms *R*, mainly affect the size of each global entity or $S1_c$-set. Moreover, in equation (7) we already showed that increasing the number of clusters *C* will have a larger impact (exponentially) on the potential size of the search-tree than a comparable increase of *R* (i.e. the number of milk collection rhythms).

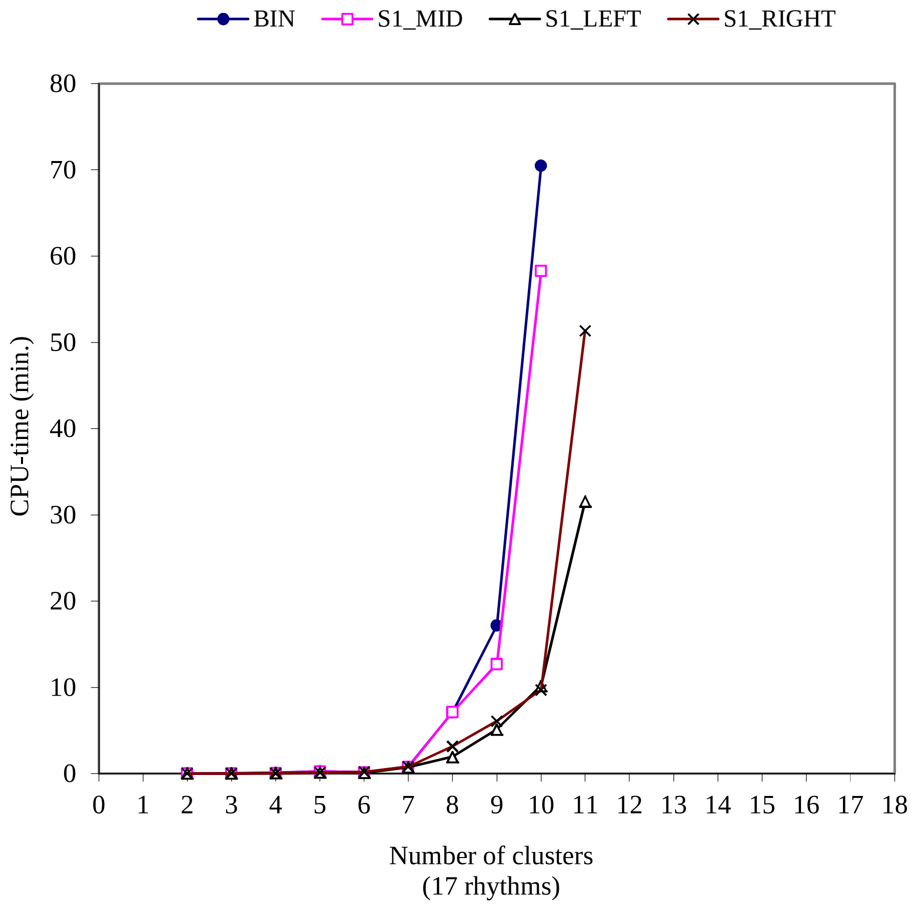


Figure 4.3 The impact of the number of clusters on the calculation time

As mentioned before, the S1_LEFT (or S1_RIGHT) strategy aims to affect the position of the branching marker in an $S1_c$-set such that the two branching subsets in Figure 4.1 will be split efficiently into two subsets of unequal size. The main idea is to find early solutions (i.e. bounds) in nodes beneath the largest subset. We already found a theoretical upper bound $\bar{B}$ for the number of branches *B* in case there are *C* different $S1_c$-sets and *R* different milk collection rhythms. This upper bound $\bar{B}$ has been calculated for a case in which we defined 10 milk supply clusters *C* and an increasing number of (different) milk collection rhythms from *R*= 3 to *R*=17 in the second column of Table 4.3. The columns 3 to 6 in Table 4.3 represent the explored number of nodes at the end of the B&B algorithm for each strategy. In the columns 7 to 10 the explored number of nodes are expressed as a percentage of the upper bound $\bar{B}$ in the second column. The results of column 9 (S1_LEFT) and 10 (S1_RIGHT) show that the latter strategies are more effective than the S1_MID strategy in case the S1-setsize increases.

Table 4.3 efficiency B&B search procedure per strategy for C = 10 and increasing R

		Total nodes explored				Total nodes explored as a percentage of $\bar{B}$			
R	$\bar{B}$	BIN	S1_ MID	S1_ LEFT	S1_ RIGHT	BIN	S1_ MID	S1_ LEFT	S1_ RIGHT
3	1.18E+05	1040	1291	1382	1408	0.8806395	1.0931784	1.1702344	1.1922504
4	2.10E+06	4062	10611	2616	3234	0.1936914	0.5059724	0.1247407	0.1542093
5	1.95E+07	13615	18668	4726	4761	0.0697088	0.0955802	0.0241971	0.0243763
6	1.21E+08	17285	41628	7142	4345	0.0142931	0.0344226	0.0059058	0.0035929
7	5.65E+08	18316	43478	8457	8245	0.0032421	0.0076959	0.0014969	0.0014594
8	2.15E+09	20559	45287	8084	6077	0.0009574	0.0021088	0.0003764	0.0002830
9	6.97E+09	20272	53201	10415	8124	0.0002907	0.0007629	0.0001493	0.0001165
10	2.00E+10	25404	47496	8924	1182	0.0001270	0.0002375	0.0000446	0.0000059
11	5.19E+10	26962	36206	7418	7086	0.0000520	0.0000698	0.0000143	0.0000137
12	1.24E+11	22602	52491	9520	7938	0.0000183	0.0000424	0.0000077	0.0000064
13	2.76E+11	18924	41598	8845	7288	0.0000069	0.0000151	0.0000032	0.0000026
14	5.79E+11	23071	48194	7456	7452	0.0000040	0.0000083	0.0000013	0.0000013
15	1.15E+12	27477	40730	9077	9753	0.0000024	0.0000035	0.0000008	0.0000008
16	2.20E+12	30301	39470	10030	7734	0.0000014	0.0000018	0.0000005	0.0000004
17	4.03E+12	24299	57393	8852	6682	0.0000006	0.0000014	0.0000002	0.0000002

4.5 Discussion and concluding remarks

The main purpose of this study was to find effective ways in supporting several decision-makers on different decision levels in a cooperative association. Management of the cooperative association realized that, due to the annual growth, the increasing imbalance between the continuous production on supply level and the fixed delivery conditions on demand level, could not be solved solely by detailed scheduling of routes and tours on a daily basis. The current, low-level oriented, approach of the milk collection problem was hardly viable in the future. It was expected that a first draft of a PC-based system was necessary in order to show the potential benefits of a different approach and the related improvement of individual and organizational performance. The system should have a major focus on short- to medium-term planning rather than building detailed routes and tours on a daily basis. One of the goals was to build a pilot system for generating stable milk collection plans. From a computational point of view the optimisation module should be able to generate plans within a reasonable amount of time.

4.5.1 The pilot decision support system

The pilot system was divided into four major components: a user interface, database, simulation-, and an optimisation module. The menu-driven user interface and the database and simulation module were all developed in Microsoft Access. The optimisation part, i.e. the model in Section 4.3, has been specified and solved by the advanced modelling and solving language Xpress-Mosel. The modelling component also provides for a set of procedures and functions that enable a connection to the database by an Open Data Base Connectivity (ODBC). All necessary data for the input of the model can be retrieved directly from the data source. Reversely, the output of the optimisation- or simulation routine can be written directly into the database by the ODBC interface.

Achieving the mission of a DSS, i.e. to help end-users in making better decisions, implies that such a system does not replace the decision-maker. Only the end-users have the skills and specialized knowledge to review the quality of the generated plans. The DSS aims to assist decision-makers and should not be considered as an optimiser but rather as a tool for generating and storing high-quality plans to be used for further analyses. Within this context the facilities of a user-friendly and interactive man-machine interface are essential.

The user interface has been divided into an input and planning i.e. analysing part. A basic start-up screen offers access to each part. Any other screen of the user interface includes a link to return to the start-up form. The start-up screen also offers an option to start a run of the optimisation routine and assign (required) vehicle capacities to routes (VRP) directly, or to use stored solutions from the past to simulate and compare options for the VRP.

The input forms enable the modification of fields in existing records in the underlying database or the addition of new records. The system distinguishes different forms for suppliers, transportation companies, buyers on demand level, the defined milk collection clusters and the potential milk collection rhythms. All input forms are provided with navigation buttons and record selectors, enabling the movement between records in the database. The supplier form contains text boxes for a unique identification number, address data, the (default) assigned milk collection cluster, the daily milk production and available (cooled) storage capacity at supply level. Apart from standard fields for an identification number and address data, the input form on demand level contains fields for specifying a daily minimum and maximum amount to deliver, maximum age of the delivered milk (default three days) and a check box indicating whether the buyer accepts milk on days without demand (the so-called surplus companies). A push button gives access to a linked subform in which the daily demand levels are specified. As demand levels are usually based on contracts of either a weekly or a two weekly repetitive pattern, the planning horizon is set on a default period of two weeks. A third input form contains adjustable fields for the available transportation companies, i.e. a list box of (daily) available transportation vehicles for each company and the related loading capacities. The last input forms contain a list box for all defined clusters, an overview of all suppliers in a cluster and a subform, comparable with Table 4.1, for the set of defined milk collection rhythms.

Any generated solution, either obtained by recovering a stored plan of a former run or running the optimisation routine with (changed) data from the input part, enables access to the planning and analysing part. This part of the system is roughly divided into output forms on supply and demand level. The basic screen on supply level contains a drop-down box in which the defined milk collection clusters are listed including the option for an overview that takes all clusters together. Selecting one of the listed options will expand the contents of all relevant fields and subforms in the output screen. The screen is subdivided into two identical parts for each week of the planning horizon containing orderly information with regard to the (daily) offered quantities of the cluster(s) and the planned amounts of milk to deliver from each cluster to the intended buyers in case the proposed milk collection rhythm would be followed. In a subscreen the user can ask for a (daily) overview of available transportation vehicles and the (remaining) loading capacity of each vehicle. The allocation of vehicle capacities to milk collection clusters has to be done by the end-user. We suppose that only the end-users have the skills and specialized knowledge to recognize patterns in the location of suppliers, (third party) transportation companies and buyers on demand level. Nevertheless, the system can be very helpful. It constantly updates the values of several indicators like the remaining loading capacities of the vehicles and the average distances between the (different) departure points, the centre of a milk collection cluster, and the different points of destination. The lay-out of the output screen on demand level is comparable with the form(s) on supply level. A drop-down box enables the selection of individual buyers including the option for a general overview that takes all buyers together. The output form contains orderly information with respect to the (daily) demand levels and the planned amounts to deliver to the buyer(s) in case the proposed milk collection rhythm would be followed.

In the output screens on supply and demand level several (conflicting) measurements of performance are calculated and presented in the reports. Changing the data, for example moving farms from one cluster to another, or changing the milk collection rhythm for a cluster in the generated plan, is possible. However, the consequences of any modification in the data or the proposed plan will affect the measures of performance too. In this way the pilot system combines the power of the human judgement and experience on the one hand with the calculation speed, accuracy and storage facilities of computer systems on the other hand.

4.5.2 Conclusions

From the start it was clear that the emphasis of the system should be to support decision-making on different levels within the cooperative association. Vehicle schedulers as well as managers of the cooperative association were looking for ways that helped them to make better decisions. The visualization of (modified) plans and the possibility to store plans over the year enables the decision-maker to 'optimize' his / her performance with respect to his or her mission.

In a way the problem can be viewed as an instance of the periodic vehicle routing problem (PVRP) with the following characteristics: it concerns pickup and delivery operations simultaneously. Consequently there is a stronger focus on balancing supply and demand as opposed to the routing of vehicles. Referring to the multi-level classification of the PVRP by Chao, Golden et al. (1995), the short- to medium-term planning model turns out to be a successful approach for the first level of the PVRP in which it is necessary to assign allowable visit combinations to suppliers as well as customers, such that the continuous production on supply level will be balanced with periodic demand. The generated plans also serve as a starting point for the next level of the PVRP. This level consists of solving several vehicle routing problems (VRP; i.e. the construction of routes and the assignment of vehicles to routes) for each day of the planning period. Although the system does not generate detailed solutions for the vehicle schedulers, the plans offer a solid and stable starting point for the daily VRP. The idea of assigning feasible milk collection rhythms to clusters of suppliers was adopted in an early stage by the vehicle schedulers. Once supplier farms are (geographically) grouped into clusters and the complete milk production within a cluster is assigned to a single rhythm with fixed collection days (see Table 4.1), the daily routing problem has been simplified substantially. The overview of available transportation vehicles ordered by the (remaining) loading capacities or the average distances between the departure point of vehicles, the centre of a milk collection cluster, and the intended points of destination, turns out to be very useful. Nevertheless, if the cooperative association ultimately decides to set up a final software development project, management should reconsider the functional characteristics of the system again. Extending the current pilot system by an additional module that enables the construction of starting solutions for the daily VRP, might be helpful for vehicle schedulers too. However, the construction of this type of system in a real world environment tends to be a time-consuming and expensive software development project. Third party software developers have to be contracted for the development of custom-made software.

Especially the stored plans and their information regarding the delivered amounts of milk (sold at unattractive price levels) to so-called surplus companies or the shortages of deliveries to regular buyers (at attractive price levels), can be very helpful in order to attune the future imbalance between milk supply and the individual demand levels of dairy factories. A profound analysis of these data will be very beneficial for the outcome of the yearly negotiations on demand level with respect to the expected amounts of milk to deliver and the desired delivery days weekly. Moreover, the analysis of stored plans can be quite helpful for the negotiations with third party transportation companies regarding the (daily) required vehicle capacities in different seasons of the year.

From a computational point of view it turned out that the application of Special Ordered Sets was useful. The numerical experiments confirm that the efficiency of the SOS-formulation strongly depends on the ordering of the variables within the sets. However, we also showed that the computational advantage of the SOS-formulation is not restricted to cases in which the variables within the sets have a natural ordering. A reordering procedure of the variables, based on their solution values of the LP-relaxation of problem (1) to (6), turned out to be very effective. However, it is too premature to conclude that a natural ordering of the variables within S1-sets is superfluous for an efficient use of SOS1-formulations. In this study it turns out that the values of the numbers in the reference row are of minor importance for the computational efficiency of the SOS-formulation. As a result, the relevance of a reference row defined by the model developer personally might be omitted in the future for mathematical programming software. Further research in this area (i.e. numerical results of other cases) has to be done.

Appendix 4.1

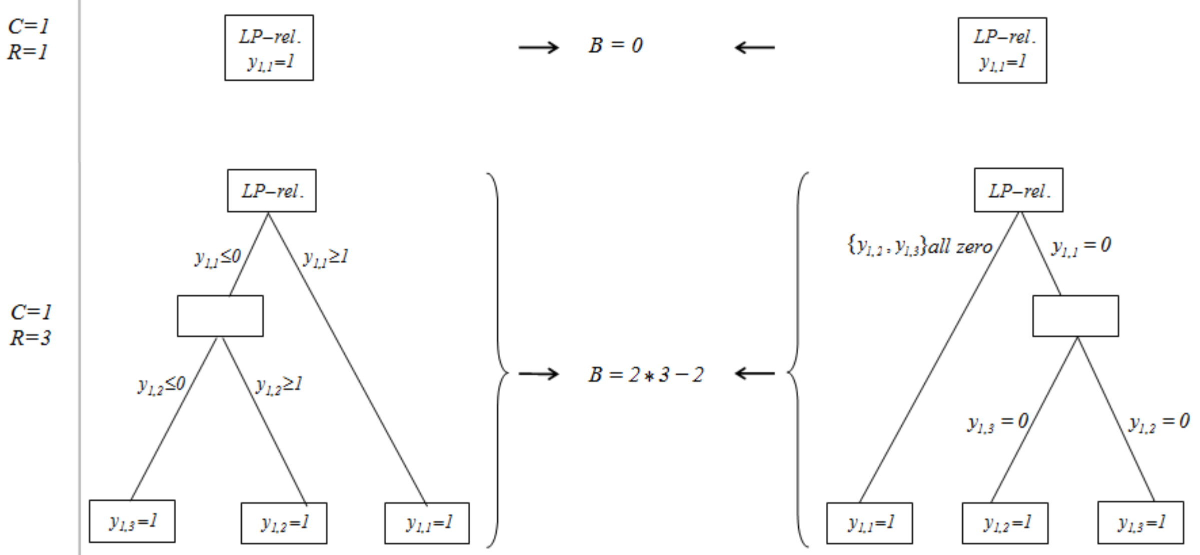
We will proof that the upper bound for the number of branches B in an SOS-based branch-and-bound search tree is defined by:

$$B = \sum_{c=1}^{C} R^{c-1}(2R - 2) \qquad (7)$$

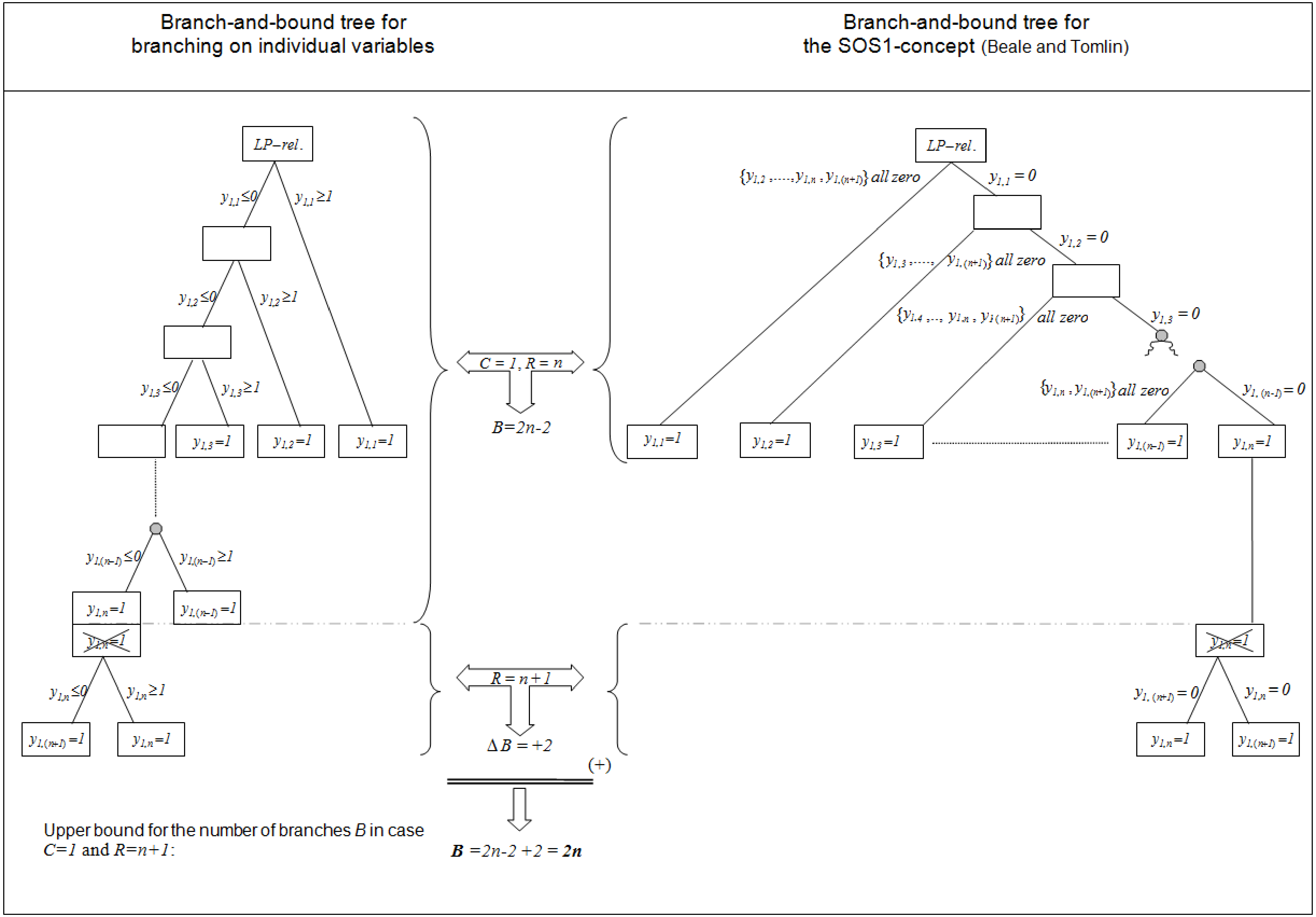
in which C denotes the number of milk supply clusters (S1-sets) and R denotes the number of different milk collection rhythms. We also proof that the potential number of branches B in a common branch-and-bound approach, i.e. branching on individual binary variables $Y_{c,r}$ in problem (1) to (6), equals (7) too.

A) First we focus on the impact of R (the number of milk collection rhythms) on the number of branches B and prove that $B = (2R - 2)$ in case we define only one milk supply cluster (C=1)

	Classical B&B tree	*B ~ # branches*	*SOS1 B&B tree*
	$\sum_{r=1}^{R} y_{c,r} = 1 \quad \forall c$ $y_{c,r} \in \{0,1\} \quad \forall c,r$	$B = (2R - 2) \quad (1)$	$S1_c := \{y_{1,1}, y_{1,2}, \ldots, y_{1,R}\} \quad \forall c$ $\sum_{r=1}^{R} y_{c,r} = 1 \quad \forall c$ $y_{c,r} \geq 0 \quad \forall c,r$



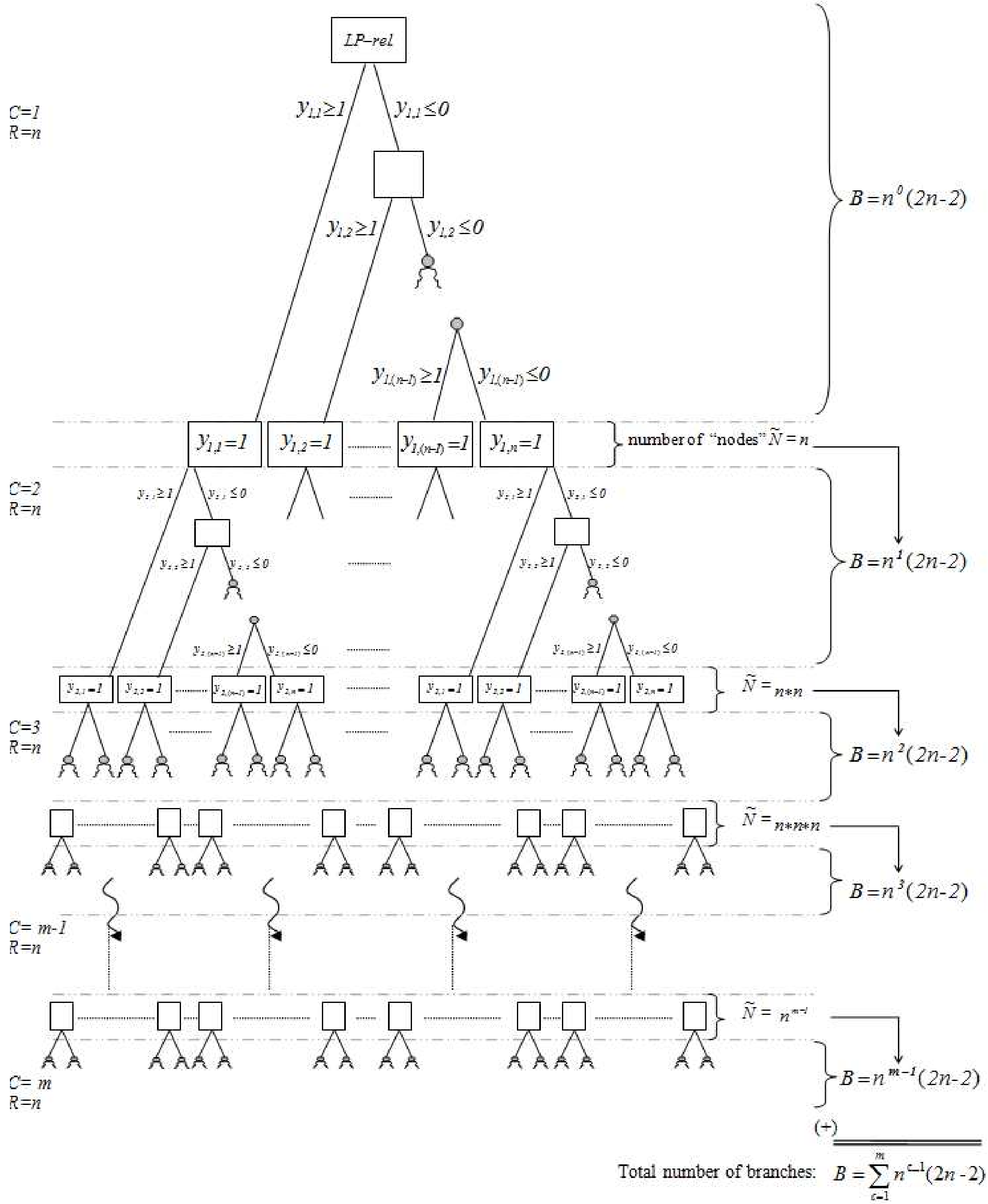
$C=1$ $R=n$	Suppose relation (1) is correct for both methods. The potential number of branches B in case $R=n$ is equal to $B = (2n\text{-}2)$ Using the assumption that $B=(2n\text{-}2)$ for $C=1$ and $R=n$, we have to prove that relation (1) holds for $C=1$ and $R=n+1$ too.
$C=1$ $R=n+1$	For $R=n+1$ the potential number of branches B for both principles should be equal to $\boldsymbol{B} = (2\,(n+1) - 2)$ **=** $\boldsymbol{2n}$.



Branch-and-bound tree for
branching on individual variables
Branch-and-bound tree for
the SOS1-concept (Beale and Tomlin)
LP–rel.
y1,1≤0
y1,1≥1
y1,2≤0
y1,2≥1
y1,3≤0
y1,3≥1
y1,3=1
y1,2=1
y1,1=1
y1,(n–1)≤0
y1,(n–1)≥1
y1,n=1
y1,(n–1)=1
y1,n≤0
y1,n≥1
y1,(n+1)=1
y1,n=1
C = 1, R = n
B=2n-2
R = n+1
ΔB = +2
(+)
B =2n-2 +2 = 2n
Upper bound for the number of branches B in case
C=1 and R=n+1:
LP–rel.
{y1,2 ,….,y1,n , y1,(n+1)} all zero
y1,1 = 0
y1,2 = 0
{y1,3 ,…., y1,(n+1)} all zero
{y1,4 ,…, y1,n , y1,(n+1)} all zero
y1,3 = 0
{y1,n , y1,(n+1)} all zero
y1,(n-1) = 0
y1,1=1
y1,2=1
y1,3=1
y1,(n–1)=1
y1,n=1
y1,(n+1) = 0
y1,n = 0
y1,n=1
y1,(n+1)=1

By means of complete induction we proved that the relation between the potential number of branches B and the available number of milk collection rhythms R is equal to $B=2R-2$ for both branching principles in case we define only one cluster $C=1$.

B) Next we prove that the potential number of branches is defined by $B=\sum_{c=1}^{C} R^{c-1}(2R-2)$ for an arbitrary number of clusters $c=1 \ldots C$. Note: exactly one rhythm must be chosen in each cluster.



Chapter 5

Mixed Integer (0-1) fractional programming in Paper Production Industry

Fractional programming gave itself a somewhat questionable reputation in the Operations Research community by divorcing itself too much from the applications (Schaible and Ibaraki 1983)

This chapter is based on:

Claassen, G. D. H., (2014)
Mixed Integer (0-1) Fractional Programming for Decision Support in Paper Production Industry
Omega, the International Journal of Management Science
Vol. 43, pp. 21 – 29.

Claassen, G. D. H., and Hendriks, Th. H. B., (2007)
Modelling techniques for (non)linear and integer programming
In: Decision Science, Theory and applications, Ch. 9
Eds: Claassen et al.,
Wageningen Academic Publishers, pp. 185 – 226

Abstract

This chapter presents an efficient and effective method for solving a special class of mixed integer fractional programming (FP) problems. We take a classical reformulation approach for continuous FP as a starting point and extend it for solving a more general class of mixed integer (0-1) fractional programming problems. To stress the practical relevance of the research we focus on a real-life application in paper production industry. The constantly advancing physical knowledge of large scale pulp- and paper production did have a substantial impact on an existing DSS in which mixed integer (0-1) fractional programming is introduced. We show that the motivation to solve a real-life fractional programming problem can provide the basis for a new approach in a new context that has an added value of its own, even outside the given application area. We describe the main characteristics of the DSS, the necessity to develop a non-iterative solution procedure and demonstrate the efficiency of the proposed approach from practical data sets.

5.1 Introduction

Amply before the era of decision support systems, Little (1970) launched “The concept of decision calculus” starting with a provoking phrase: “The big problem with management science models is that managers practically never use them”. The author presents a set of guidelines to bridge the increasing gap between (mathematical) theory and the scientific challenge of its applicability in real-life enterprises. At the time of appearance the impact of developed theory in practice and the wave of real-world applications (e.g. in decision support systems) was still in its infancy. After more than three decades, Little (2004) reflected back on his original paper: ”The good news is that more managers than ever are using models. The bad news is that many managers do not even realize they are using models! (But we should ask whether this is really bad)”. In other words: today, (decision support) models are used! However not by managers themselves, but by management scientists and management assistants acting as intermediates to frontline managers.

We illustrate the significance of Little’s concept for a novel application of fractional programming in practice and describe the latest developments of an OR-based DSS for a continuously changing decision environment in pulp- and paper production industry. Pressed by changed circumstances, management teams of global enterprises continuously aim to exploit innovation due to advanced physical knowledge of large scale pulp- and paper production. Investments in flexible tools for global decision support on different decision levels within the enterprise (e.g. marketing-, production-, R&D etc.) are of utmost importance to remain competitive. Once the system demonstrated its added value and validity to management scientists, it gained the trust of end-users and was preferred to be adapted to new decision environments. We show that the motivation to solve a practical problem in a real-world environment forces researchers to find new and efficient approaches. In this paper we focus in particular on the impact of progressive physical insight on an existing optimization module in the DSS. An efficient, non-iterative solution procedure was needed to solve mixed integer (0-1) fractional programming problems in a real-world situation.

Fractional programming (FP) may be an illustrative field in mathematical programming demonstrating the separation between theoretical developments and its applicability in practice. According to Schaible and Ibaraki (1983), research in FP divorced itself too much from real applications and the majority of FP models analysed in literature were still waiting for their actual implementation in real-world situations. Meanwhile, several surveys have been published on FP (Schaible 1995; Stancu-Minasian 1999; Stancu-Minasian 2006). The extensive survey of Schaible (1995) was published in 1995 and contains almost twelve-hundred entries. The latest bibliography (Stancu-Minasian 2006) covers the period 1997 – 2005 with almost 500 entries. Although the interest for applications of FP has increased since the nineties, the bibliography shows that between 1997 and 2005 less than 10% of the papers are application oriented (including potential applications and case studies). Hardly 7% of all covered papers (including theoretical studies) in Stancu-Minasian (2006) are devoted to integer FP. Schaible and Shi (2004) also stated that integer FP is a somewhat neglected field that deserves more attention. The problem we describe belongs both to the class of real-life applications and the class of mixed integer fractional programming problems. To the best of our knowledge, there exists no simple and non-iterative solution technique for solving mixed integer (0-1) linear fractional programming problems.

The paper is organized as follows. In the next section we characterize the pulp and paper industry and give an overview of the progress in OR-based decision support for this branch of industry. Section 5.3 describes the actual mixed integer (0-1) fractional programming problem and gives a basic outline of the model formulation which is necessary to understand the impact of progressive (physical) insight on both the existing model formulation and the necessity to find an efficient solution procedure for solving this new problem (Section 5.4). The added value of the FP model, including the efficiency of the proposed solution technique, will be tested from several practical data sets (Section 5.5). Discussion and conclusions follow in the Sections 5.6 and 5.7.

5.2 Background

Pulp and paper industry is an extremely large business characterised by low margins and high capital costs. Large mills can cost hundreds of millions of US$ to construct. As a consequence, only a few companies are active on this huge and global market. The company and sponsor of the research is a leading producer of coated fine paper in North America, Europe and South Africa. The fine paper division (e.g. copy papers, writing papers etc.) is a business with manufacturing assets in eight countries on three continents and customers in over 100 countries. Their production capacity is about 6 million tons of fine paper per annum, produced in 14 different mills in North America (3), Europe (8) and Africa (3). In 2011 the total sales of the company reached 6.01 billion US$; the operating profit was 404 million US$.

As margins are low in this capital-intensive branch of industry, a continuous search for efficient production and decision support is of utmost importance. Faced with rising raw material and energy costs, pulp and paper producers have to optimise the performance of their processes to remain competitive. Reducing costs, e.g. for raw materials, is an important way to increase or at least maintain the annual operating profit.

Several OR-based applications have been described in literature, tailored for pulp and paper industry. We refer to (Johnston 1980; D'Amours, Rönnqvist et al. 2008) for an overview of OR applications in pulp and paper industry. The papers provide a good insight in the progress that has been made in recent decades regarding the application of OR models and -techniques in this branch of industry. Nowadays, decision support for planning and management in pulp and paper industry includes the complete supply chain from strategic-, tactical- to operational control level.

Typical studies on a strategic level concern investment studies or models for optimization of the supply chain i.e. determining the facility location, optimally allocate suppliers to mills, products to paper machines i.e. mills and machines to markets (Berends and Romme 2001; Philpott and Everett 2001(a); Philpott, Everett et al. 2001(b); Everett, Philpott et al. 2002) strategic design of distribution networks (Gunnarsson, Rönnqvist et al. 2006; Pati, Vrat et al. 2008) and/or studies on the conflict between economic optimization and environmental efficiency (Hua, Bian et al. 2007; Pati, Vrat et al. 2008).

On a tactical level decision-making refers to planning problems in different links of the supply chain. Carlsson and Rönnqvist (2007) focused on the wood procurement stage of the supply chain. Medium-term (i.e three months) production planning schedules for pulp mills are developed in (Bredström, Lundgren et al. 2004). The case study (Bouchriha, Ouhimmou et al. 2007) discusses a specific production planning (i.e. lot sizing) problem for a single paper machine of a fine paper mill. Different (synchronized) models for production, transportation and inventory planning problems in the fine paper industry are studied in (Martel, Rizk et al. 2005). Chauhan, Martel et al. (2008) deals with tactical demand fulfilment of sheeted paper in the fine paper industry. The authors propose an integer programming model to find the stock keeping units of parent rolls in order to minimize expected inventory holding and trim loss costs.

Typical decision problems on an operational control level refer to short-term production- and distribution planning problems in single (Alemayehu and Arora 2002) or multiple successive stages of paper manufacturing for multiple paper machines and distribution centres (Murthy, Akkiraju et al. 1999; Rizk, Martel et al. 2006).

Although literature provides a good insight in the progress that has been made in OR-based decision support for pulp and paper industry, none of the studies focuses on the impact of raw material composition and its technical treatments on the final properties of paper grades. To the best of our knowledge there exists no other DSS to support this practical problem adequately.

In the next section we describe the impact of raw material composition and its technical treatments on the final properties of paper grades and present an outline of the model formulation. Section 5.3 aims to set the boundaries of the decision environment which is needed to understand the core of the research in Section 5.4.

5.3 Problem description and model formulation

Trees provide the primary raw material for paper production. Wood is comprised of cellulose fibres which are bound together by the natural “glue”, called lignin. In the first step of paper production the cellulose fibres are separated from one another into a mass of individual fibres called pulp. This is done in a pulp mill by using either chemical or mechanical processes. Using chemical pulp for paper production is more expensive than mechanical pulp or recovered paper. However, as the cellulose fibres of mechanical pulps are more or less “damaged”, the resulting paper has lower strength characteristics. The chosen pulping process will also affect other properties of the final paper.

Wood fibres can be divided into hardwood (i.e. deciduous trees) and softwood (i.e. pine trees) fibres. Softwood fibres are longer and coarser than fine hardwood fibres. Usually softwood pulp is used to provide the required strength when producing light-weight publication papers. Fine papers (e.g. copy papers, writing papers etc.) are mainly produced from hardwood pulp, which is reinforced by a minor amount of stronger and more expensive softwood pulp. Pulp may be fed directly to a paper machine in an “integrated mill” or dried and pressed into bales to be used as a raw material by paper mills elsewhere.

It is convenient to decompose the process of paper production into three major steps: pulp production, stock preparation and paper production. We focus in particular on the decision problems in the stock preparation process. Stock preparation is a critical part in paper production. It consists of combining and preparing the raw material into a mixture of several bleached softwood , hardwood and mechanical pulps. Part of stock preparation is the refining process of bleached pulps. This operation is a crucial step to provide the surface properties for printing grades according to customer specifications. At the refiners, the pulp composition passes a system of rotating and stationary blades. Depending on the beating intensity, fibres are more or less shortened and damaged to give the final mix, more correctly termed the “furnish”, the exact properties required for a particular type of paper. After the stock preparation, the furnish is suitable to create a uniform web of paper on a paper machine.

Given the technical characteristics of a mill (machine size, type of production equipment and automation level) there are many variables that determine the final quality of the paper grade. Throughout the past decades the R&D department quantified the paper quality by introducing several, partly physically, measurable characteristics. These so-called properties can be divided into several groups, i.e. subsets of properties that are indicative for the dehydration of the pulp, strength of the paper, optical properties of a paper grade, fibre dimensions, total costs etc. All property values depend on the mixture of raw materials: i.e. chemical softwood, hardwood and mechanical pulps. Moreover, a substantial number of property values depend on the beating intensity of the refiners. Other characteristics are so-called beating independent properties.

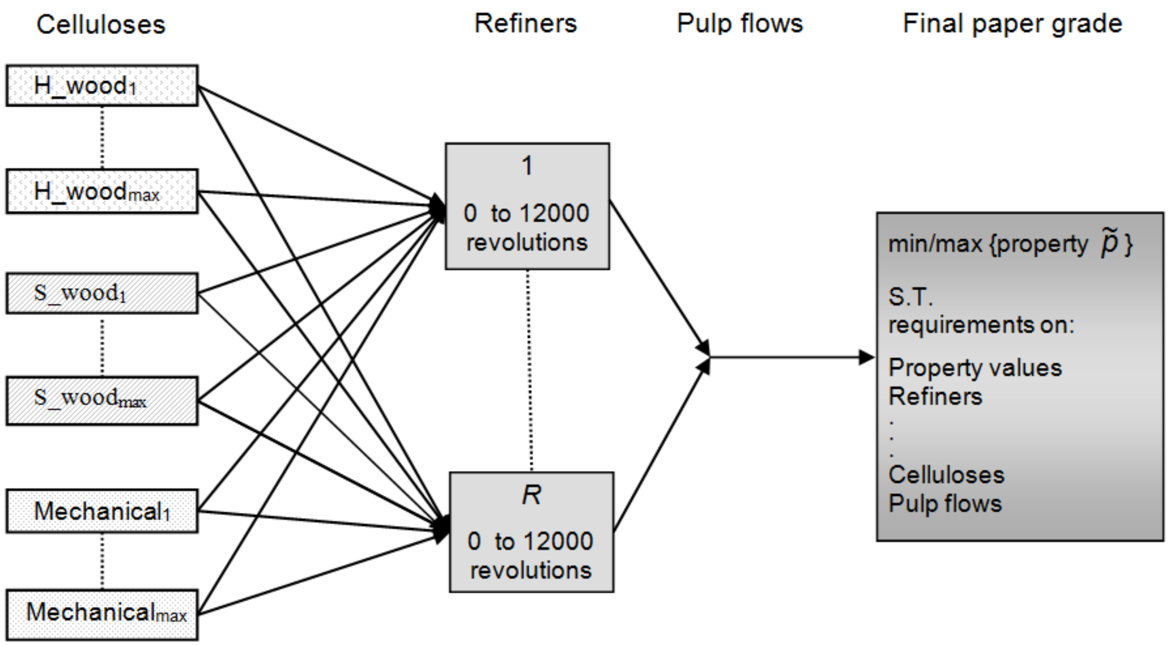
Several interrelated decisions must be made to produce paper that meets all requirements. An outline of the stock preparation problem is given in Figure 5.1. Key decisions to be made are:

1) The raw material composition, i.e. which mixture of chemical softwood and hardwood pulps and mechanical pulps to choose.

2) The choice of the available refiners, their beating intensity including the assignment of combinations of celluloses to individual refiners. The sequence of treatment of different celluloses in the refiners is not important.

3) The contribution (i.e. mass fractions) of the individual pulp flows from the refiners to the final furnish for paper production.

Figure 5.1 Stock preparation process



A major issue from practice is that a common principle of an overriding objective is too restrictive for modern decision support in globally operating enterprises. Management assistants in paper production industry usually focus on a variety of properties $prop := \{1, 2, .., P\}$ of the paper grades (e.g. total costs, tear index, dewatering rate, bursting strength, opacity etc.). Depending on the case to study, tools are needed to calculate the best upper and/or lower bounds for individual property values. Decision support systems should foster "out of the box thinking" and make decision-makers aware of the impact of personal trade-offs with respect to requirements of individual properties on other properties. For example total costs of a paper grade is an important property in the set $prop := \{1, 2, .., P\}$ to minimize. However, optimizing any other property after an acceptable upper bound has been set on the total costs, may deliver insight as well, and consequently contribute more to the decision-making process.

Based on progressive physical knowledge, laboratory tests show that the predicted values for a subset of properties (i.e. all properties related to the compactness of final paper grades), can be improved if these property values are calculated as a function of the total number of fibres in the furnish. It appears that the combination of this progressive physical knowledge with abandoning the common principle of an overriding objective (e.g. total costs), has a significant impact on the optimization routine in the DSS. To illustrate the latter, it is convenient to decompose the complete set of properties $prop := \{1, 2, .., P\}$ into two disjoint subsets p_{mass} and p_{vol}. So, $prop = p_{mass} \cup p_{vol}$. We define:

Indices

$c = 1,\ldots,C$ ~ the different types of celluloses

$p = 1,\ldots,P$ ~ the different properties

$b = 0,\ldots,B$ ~ the beating intensity of a refining line

$r = 1,\ldots,R$ ~ the available refiners

Variables

$x_{c,\,r,\,b}$ ~ mass fraction of cellulose *c* in the total mixture, refined in line *r,* at beating level *b*

$y_{r,\,b}$ ~ $\begin{cases} 1 \text{ if refiner } r \text{ operates at beating intensity level } b \\ 0 \text{ else} \end{cases}$

Property values for the subset p_{mass} (e.g. total costs, opacity, dewatering rate, brightness etc.) are calculated by using mass fractions, i.e. $x_{c,r,b}$. Properties in the subset p_{vol} are related to the compactness of the final paper grade (e.g. bursting strength, tear index, coarseness, breaking length etc.). In the past, all property values for p_{mass} and p_{vol} were calculated by using mass fractions. However, progressive physical knowledge learned that property values in the subset p_{vol} should be calculated by a non-linear function $g(x_{c,r,b})$. The function $g(x_{c,r,b})$ is defined as the volume fraction of cellulose *c* in the total mixture, refined in line *r,* at beating level *b.* Using volume fractions instead of mass fractions may change the contribution of individual celluloses to the total number of fibres in the furnish. The final values for all properties in a paper grade are given by (1) and (2):

$$f_p = \sum_c \sum_r \sum_b PV_{c,p,b} \cdot x_{c,r,b} \qquad \forall p \in p_{mass} \tag{1}$$

$$f_p = \sum_c \sum_r \sum_b PV_{c,p,b} \cdot g(x_{c,r,b}) \qquad \forall p \in p_{vol} \tag{2}$$

in which $PV_{c,p,b}$ is defined as the property value of property *p* for cellulose *c,* at beating level *b*. The relation between volume fractions and mass fractions is given in (3).

$$g(x_{c,r,b}) = \frac{V_c \cdot x_{c,r,b}}{\sum_{c=1}^{C} V_c \cdot x_{c,r,b}} \tag{3}$$

in which V_c denotes the number of fibres per gram of cellulose c. The value for the parameter V_c strongly depends on the type of cellulose. After a few additional data definitions, an outline of the core problem can be formulated.

Data

L_p	~	Lower bound for property value *p*
U_p	~	Upper bound for property value *p*
Cap_r	~	Capacity of refiner *r* expressed in a percentage of the total flow

$$\underset{x_{cbr};y_{rb}}{Max} \left\{ f_{\tilde{p}} \right\} \qquad \text{for some } \tilde{p} \in prop \tag{4}$$

s.t.

$$\sum_c \sum_r \sum_b x_{c,r,b} = 1 \tag{5}$$

$$\sum_b y_{r,b} = 1 \qquad \forall\, r \tag{6}$$

$$f_p \geq L_p \qquad \forall\, p \neq \tilde{p} \tag{7a}$$

$$f_p \leq U_p \qquad \forall\, p \neq \tilde{p} \tag{7b}$$

$$\sum_c x_{c,r,b} \leq Cap_r \cdot y_{r,b} \qquad \forall\, r, b \tag{8}$$

$$x_{c,r,b} \geq 0 \qquad \forall\, c, r, b \tag{9}$$

$$y_{r,b} \in \{0,1\} \qquad \forall\, r, b \tag{10}$$

The objective function (4) optimizes the desired property value $f_{\tilde{p}}$ of the final paper grade. In case of a minimization problem, $f_{\tilde{p}}$ is multiplied by minus one. Equation (5) ensures that the sum of the fractions of all celluloses in a mixture equals one. As all variables $y_{r,b}$ are defined to be binary (10), constraints (6) require that each refiner will run at only one beating level. Constraints (7a) and (7b) put lower- and upper bounds on the property values in the final pulp. The capacity constraints of the refiners are formulated in (8). Moreover, constraints (8) state that the total throughput of raw materials in each refiner at a certain beating level *b* can be positive only if the value of the corresponding binary variable $y_{r,b}$ equals one. The conditions (9) and (10) complete the set of restrictions.

Replacing Eq (1) by (2) in (7a) and (7b) $\forall p \neq \tilde{p} \in p_{vol}$ will hardly affect the structure and complexity of the problem. The original model (4) – (10) remains linear after multiplying both the left- and right-hand sides of (7a) and (7b) by the denominator in (3). However, for objective function (4) two cases need to be distinguished. The optimizing property function $f_{\tilde{p}}$ may refer to a mass-fraction-dependent property $\tilde{p} \in p_{mass}$ (e.g. $\tilde{p}$ may express total costs, see (4a) below) or to a volume-fraction-dependent property $\tilde{p} \in p_{vol}$ (e.g. $\tilde{p}$ may express the Burst index, see (4b) below).

$$Max \left\{ -\left(\sum_c \sum_r \sum_b RCost_c \cdot x_{c,r,b} + \sum_r \sum_b ECost_{r,b} \cdot y_{r,b} \right) \right\} \tag{4a}$$

in which $RCost_c$ and $ECost_{r,b}$ denote the raw material costs of cellulose *c* and the total energy costs of refiner line *r,* at beating level *b*, respectively.

$$Max \left\{ \sum_c \sum_r \sum_b Burst_{c,b} \cdot g\left(x_{c,r,b}\right) \right\} \tag{4b}$$

in which $Burst_{c,b}$ denotes the contribution of cellulose *c* to the Burst-index at beating level *b*.

If the objective function (4) refers to $\tilde{p} \in p_{mass}$, the problem is a straightforward mixed integer linear programming problem, e.g. (4a)–(10). However, if (4) refers to $\tilde{p} \in p_{vol}$, then Eq. (3) implies that the objective function becomes a ratio of two linear functions. Such models, e.g. (4b)–(10), belong to the class of Linear Fractional Programming or Hyperbolic Programming problems (Bajalinov 2003; Bazaraa, Sherali et al. 2006). Models for which the objective function (4) refers to mass-fraction-dependent properties $\tilde{p} \in p_{mass}$, or volume-fraction-dependent properties $\tilde{p} \in p_{vol}$, will be referred to as (MFM) or (VFM) models, respectively. Generally, a continuous linear fractional programming model (LFP) can be formulated as:

$$\max_{\underline{x}} \left\{ \frac{\underline{c}'\underline{x} + c_0}{\underline{d}'\underline{x} + d_0} \right\}$$
$$s.t. \qquad \qquad \text{(LFP)}$$
$$\underline{x} \in S$$

The solution space or set $S := \{\underline{x} \mid A\underline{x} \leq \underline{b};\ \underline{x} \geq \underline{0}\ \}$ is assumed to be compact, i.e. convex, non-empty and bounded. Note the difference between a basic (LFP) problem and model (VFM), i.e. a subset of decision variables in (VFM) are defined as binary variables in (10).

In the next section we follow the reformulation approach introduced in Charnes and Cooper (1962) for the transformation of a continuous fractional programming problem (LFP) into an equivalent linear programming model (LP). Next, we extend this approach for solving mixed integer (0-1) fractional programming problems arising from any (VFM).

5.4 Solving mixed integer (0-1) fractional problems

Fractional programming (FP) can be considered as a separate entity within the field of non-linear programming. Apart from some isolated papers, a systematic study in this area started in the early seventies. Meanwhile a rich collection of papers has been devoted to this field of non-linear programming. For an overview we refer to some extensive review papers (Schaible and Ibaraki 1983; Schaible 1995; Stancu-Minasian 1999; Stancu-Minasian 2006).

The study of fractional programs with a single ratio dominated literature for a long time. Dinkelbach (1967) introduced a very popular and general parametric approach that can be applied to all types of (non)-linear, (integer) fractional problems. Generally, for integer fractional programming problems parametric approaches are used (Barros 1998). However, parametric approaches like Dinkelbach (1967), and its variants, require an iterative evaluation of a parametric function. From a practical point of view, these approaches were not preferred for a single ratio linear fractional problem. The focus was directed towards taking advantage of important properties of the (VFM), i.e. a single ratio problem and to exploit special structures for solving the mixed (0-1) integer problem by a fast, non-iterative, solution procedure. Such an approach is proposed in Robillard (1971) for a special class of (0-1) fractional programs with a single term in the objective function. The algorithm takes advantage of an assumed special structure of the feasible set. However, the required structure of the constraints is too restrictive for problem (VFM). Moreover, the approach needs a special purpose branch-and-bound algorithm.

The relationship between problem (LFP) and linear programming is also exploited in Granot and Granot (1977). The authors develop cutting planes which can be systematically generated if some variable of the original problem (LFP) is not integer. However, the approach needs a special purpose cutting plane algorithm.

Alemayehu and Arora (2002) described an alternative approach in which a mixed (0,1) linear fractional problem is reformulated into a bi-level FP problem. The concept is demonstrated on a small scale example. Bi-level programming involves two optimization problems where the constraint region of the first level problem is implicitly determined by another optimization problem (Calvete and Galé 2004). However, the reformulation in Alemayehu and Arora (2002) needs an iterative/nested solution approach too. To avoid these obstacles we start from a classical reformulation approach for solving continuous fractional programming models like problem (LFP) and extend it for mixed integer (0-1) fractional problems.

A single ratio of linear functions is neither convex nor concave. However, any local maximum of problem (LFP) is global (Bazaraa, Sherali et al. 2006). Likewise, a local minimum is also a global minimum over the set *S*. Moreover, if the solution space is compact, then the objective function has both a minimum and a maximum at an extreme point of the feasible area (Bazaraa, Sherali et al. 2006). As the optimal solution for a (mixed) integer linear FP problem is a vertex of the convex hull for the set of feasible discrete solutions, it gives rise to apply a solution procedure that moves from one extreme point to an adjacent and use a branch-and-bound technique to eliminate non-discrete solutions.

In 1962 Charnes and Cooper introduced their classical paper in which a continuous model (LFP) is transformed into an equivalent linear programming model (LP). The model (LP) needs exactly one additional variable and only one additional constraint. With reference to the general problem (LFP), the reformulation approach is based on the definition of a vector $\underline{w}$ and a scalar *t* of decision variables:

$$\underline{w} = \frac{\underline{x}}{\underline{d}'\underline{x} + d_0} \tag{11}$$

$$t = \frac{1}{\underline{d}'\underline{x} + d_0} \tag{12}$$

From (11) and (12) it follows that:

$$\underline{w} = t \cdot \underline{x} \tag{13}$$

The basic idea is to reformulate model (LFP) by means of (11) and (12) such that a linear programming model arises in terms of the variables $\underline{w}$ and *t*. If this new model can be solved for all relevant values of *t*, the solution of any fractional problem derived from

(LFP) can be found by (13). Next, the reformulation method will be illustrated for cases in which the denominator in the objective function of (LFP) is positive over the entire set S. So, $\underline{d}'\underline{x} + d_0 > 0$ for all $\underline{x} \in S$.

The objective function of the model (LFP) can be rewritten as follows:

$$\max_{\underline{x}} \left\{ \frac{\underline{c}'\underline{x} + c_0}{\underline{d}'\underline{x} + d_0} \right\} = \max_{\underline{x}} \left\{ \underline{c}' \cdot \frac{\underline{x}}{\underline{d}'\underline{x} + d_0} + c_0 \cdot \frac{1}{\underline{d}'\underline{x} + d_0} \right\}$$

Using definition (11) and (12) this can be reformulated as:

$$\max_{\underline{w},t} \left\{ \underline{c}'\underline{w} + c_0\, t \right\} \tag{14}$$

Using (13), i.e. $\underline{x} = \dfrac{\underline{w}}{t}$, the constraints $A\underline{x} \le \underline{b}$ of the set S can be written as:

$A\underline{x} \;\le\; \underline{b} \;\Rightarrow\; A \cdot \underline{w}/t \;\le\; \underline{b} \;\Rightarrow\; A\underline{w} \;\le\; \underline{b}\,t$. So,

$$A\underline{w} - \underline{b}\,t \le \underline{0} \tag{15}$$

Definition (12) of the (new) variable t in (14) and (15) needs to be added:

$t = \dfrac{1}{\underline{d}'\underline{x} + d_0} \;\Rightarrow\; t\,(\underline{d}'\underline{x} + d_0) = 1 \;\Rightarrow\; \underline{d}'t\,\underline{x} + t\,d_0 = 1$. Using $\underline{w} = t \cdot \underline{x}$:

$$\underline{d}'\underline{w} + t\,d_0 = 1 \tag{16}$$

Note, we assume $\underline{d}'\underline{x} + d_0 > 0$. So, $t > 0$.

Reformulating the non-negative constraints $\underline{x} \ge \underline{0}$ of the set S in terms of the variables $\underline{w}$ and t using $\underline{w} = t \cdot \underline{x}$ and $t > 0$ gives:

$\underline{x} \;\ge\; \underline{0} \;\Rightarrow\; \underline{w}/t \;\ge\; \underline{0}$, $t > 0$. So,

$$\underline{w} \ge \underline{0},\; t > 0 \tag{17a}$$

If we suppose $t \ge 0$, then the following linear programming model is equivalent to the original fractional model (LFP), provided that $\underline{d}'\underline{x} + d_0 > 0$.

$$\max_{\underline{w},t} \left\{ \underline{c}'\underline{w} + c_0 t \right\} \tag{14}$$

s.t.

$$A\underline{w} - \underline{b}\,t \le \underline{0} \tag{15}$$

$$\underline{d}'\underline{w} + t\,d_0 = 1 \tag{16}$$

$$\underline{w} \ge \underline{0},\; t \ge 0 \tag{17b}$$

Note that $t \geq 0$ in (17b) is just for the form's sake of linear programming. If $\underline{d}'\underline{x} + d_0 > 0$, $\underline{x} \in S$, S is compact and $t > 0$ (see 12), then the optimal value $t = t^* > 0$ for model (14) – (16) including (17a) will also satisfy model (14) – (16) including (17b).

In summary, any finite maximum of the fractional programming problem (LFP) can be found by solving the LP model in Table 5.1.

Table 5.1 General structure of the transformed model (LP) for continuous model (LFP)

(LFP)	(LP)
$\max\limits_{\underline{x}} \left\{ \dfrac{\underline{c}'\underline{x} + c_0}{\underline{d}'\underline{x} + d_0} \right\}$	$\max\limits_{\underline{w},t} \left\{ \underline{c}'\underline{w} + c_0 t \right\}$
$A\underline{x} \leq \underline{b}$	$A\underline{w} - \underline{b}\,t \leq \underline{0}$
$\underline{x} \geq \underline{0}$	$\underline{d}'\underline{w} + t\,d_0 = 1$
	$\underline{w} \geq \underline{0}$, $t > 0$

After solving model (LP), the solution $\underline{x}$ of any fractional problem derived from (LP) can be found by (13). The denominator $\underline{d}'\underline{x} + d_0$ of problem (LFP), should be either strictly positive (or strictly negative) for all possible values of $\underline{d}$ and d_0. If not, then there exists a solution for the non-negative variables $\underline{x}$ for which the denominator $\underline{d}'\underline{x} + d_0 = 0$. In such cases the (transformed) problem (LP) in Table 5.1 is obviously not defined. According to physicists of the R&D department, both the data $PV_{c,p,b}$ (i.e. the property values) and V_c (the number of fibres per gram of cellulose) comply to the assumption that these values are always positive.

Applying the reformulation approach of Table 5.1 to a mixed integer FP model, e.g. model (VFM), implies that the integrality constraints (10) must be relaxed. As a consequence, solutions of model (LP) are mostly infeasible for the original mixed integer fractional problem (VFM). A method must be found to fulfil the binary conditions (10) of the original problem.

The vector $\underline{w}$ of continuous variables in Table 5.1 can be partitioned into $\underline{w} = \begin{pmatrix} \underline{w}^x \\ \overline{\underline{w}^y} \end{pmatrix}$ where the vector $\underline{w}^x$ refers to the continuous variables $x_{c,r,b}$ in (9) and $\underline{w}^y$ to the binary variables $y_{r,b}$ in (10) of problem (VFM). According to (13), the vector $\underline{w}^y$ in model (LP) is defined by $\underline{w}^y = t \cdot \underline{y}$. If $t > 0$ (Table 5.1) and $\underline{y}$ must be binary according to (10), then branching on individual variables in $\underline{w}^y$ and *t*, is not applicable for problem (LP) because the solution ratios $\left(\underline{w}^y / t\right)$ must be binary. It should be mentioned that the variable *t* will always be positive (i.e. basic) in an optimal vertex of problem (LP). If the denominator $\underline{d}'\underline{x} + d_0 \neq 0$, $\underline{x} \in S$ and *S* is a compact set, then according to (12) the optimal value for $t = t^* > 0$.

Now, suppose we decompose the vector $\underline{w}^y$ of continuous variables in model (LP) into *r=1…R* disjoint subsets. For each refiner *r,* we distinguish a subset $W^y_{r,b} := \{w^y_{r,0}, \ldots, w^y_{r,B}\}$. Indices $b = 0, \ldots B$ refer to the beating level. Note that all variables $w^y_{r,b} \ \forall r,b$ are continuous in problem (*LP*). If the optimal value for $t = t^* > 0$, $\sum_b y_{r,b} = 1 \ \forall r$ in (6) and $y_{r,b} \in \{0,1\} \ \forall r,b$ in (10), then at most one of the variables in each subset $W^y_{r,b}$ for *r=1…R* can be non-zero. Now it is convenient to treat these disjoint subsets $W^y_{r,b} \ \forall r$ as discrete entities or generalisations of a 0–1 variable and apply the SOS1 branching concept, originally introduced in (Beale and Tomlin 1970) and extensively discussed in the previous chapter. In problem (LP) we define the sets $W^y_{r,b}$ of continuous variables:

$W^y_{r,b} := \{w^y_{r,0}, \ldots, w^y_{r,B}\} \ \forall r$ together with the conditions that at most one of the variables $\{w^y_{r,0}, \ldots, w^y_{r,B}\}$ can be non-zero $\forall r$. (14)

If we can prove that the optimal value $t = t^* > 0$ equals the non-zero value in each subset $W^y_{r,b} \ \forall r$ in (14), then we may solve problem (VFM) by adding (14) to problem (LP) of Table 5.1. Problem (LP) including (14) will be referred to as problem (VFM^{LP}).

Lemma

Assume that for problem (VFM), $(\underline{x}, \underline{y})' \in S$, *S* is a compact set and the assumption with respect to the denominator $\underline{d}'\underline{x} + d_0 \neq 0$ holds, then the optimal value $t = t^* > 0$ for problem (VFM^{LP}) equals the non-zero values in the subsets $W^y_{r,b} \ \forall r$.

Proof

Applying the reformulation approach as summarized in Table 5.1 to problem (VFM), implies that the constraints in (6) are transformed into $\sum_b w^y_{r,b} - t = 0 \quad \forall r$. If at most one of the variables $\{w^{y}_{r,0}\ , \ldots ,\ w^{y}_{r,B}\}\ \forall r$ can be non-zero according to (14), then the optimal value for $t = t^*$ equals the non-zero values, i.e. $\sum_b w^{y}_{r,b}$, in each subset $W^{y}_{r,b}\ \ \forall r$.

The conditions (14) can be dealt with algorithmically through the method of integer programming (see Chapter 4). Treating each set as an entity instead of a collection of variables makes it possible to apply a different branching scheme. We refer to Chapter 4 for a complete description of the concept. The single, non-zero variable in each feasible $W^{y}_{r,b}$ -set of (14) will lie either to the left, or to the right, of any marker placed between two consecutive variables within a set:

either $\quad \{w^{y}_{r,0}\ , \ldots ,\ w^{y}_{r,j}\}\quad$ or $\quad \{w^{y}_{r,j+1}\ , \ldots ,\ w^{y}_{r,B}\}\quad$ are all zero

In summary: instead of defining $R \cdot B$ different binary variables $y_{r,b}$ in the original model (VFM), the integrality constraints (10) can be relaxed. The reformulation approach of Table 5.1 can be applied and (14) must be added to model (LP). The conditions in (14) can be handled algorithmically. The optimal solution for $\underline{w}^*$ and t^* will automatically satisfy the conditions (10) of the original problem after the substitution $\underline{x} = \underline{x}^* = \dfrac{\underline{w}^*}{t^*}$.

5.5 Numerical results

We used several data sets from practice and compared the solutions of the former mass fraction based model (MFM), with the solutions derived from the volume fraction based model (VFM^{LP}). In all cases some property $\tilde{p} \in p_{vol}$ was optimized. Characteristics of the cases are summarized in Table 5.2.

The first column specifies the type of case (i.e. case number, minimization / maximization problem, optimized property and beating-dependent BD or beating-independent BI property). The second, third and fourth columns refer to the available number of celluloses, the relevant number of properties and refiner numbers, respectively. The revolution interval for each refiner is indicated in column five. The columns six and seven indicate the lower- and upper bounds on the flow constraints (i.e. the fractions of the contributions to the final furnish). All cases are based on step sizes of 50 units in the revolution interval of column five. The problem size, i.e. the numbers of constraints (m), variables (n) and binary variables (Nr_bin) of the MFM are given in the last three columns of Table 5.2, respectively.

Table 5.2. Case characteristics

Case_nr / min (max) / Prop_nr / BD (BI)	Nr_cel	Nr_prop	Ref_nr	Revolution interval	LB-flow	UB-flow	m	n	Nr_bin
0 / min / 7 / BD							7733	8194	482
	16	21	29	0 – 12000		0.7			
			30	0 – 12000		0.7			
1 / min / 7 / BD							9050	9571	563
	16	23	27	2000 – 6000		1.0			
			29	0 – 12000		0.7			
			30	0 – 12000		0.7			
2 / min / 11 / BD							1239	1453	242
	5	9	25	0 – 6000	0.1	1.0			
			26	0 – 6000	0.2	1.0			
3 / max / 12 / BD							1651	2010	402
	4	29	25	0 – 10000		1.0			
			26	0 – 10000		1.0			
4 / max / 53 / BI							9074	9571	563
	18	23	27	2000 – 6000		1.0			
			29	0 – 12000		0.7			
			30	0 – 12000		0.7			

The solutions for all cases of Table 5.2 are given in Table 5.3. The abbreviations used in the second column (Model) of Table 5.3 refer to the type of model used (i.e. mass- or volume fraction based model). The columns 3 to 8 refer to the optimal objective value (Obj-value), the time needed to solve the problem (cpu), refiner number (r), chosen beating level (b) in the revolution interval, the selected cellulose number (c) and the fraction of cellulose c in the total mixture ($x_{c,r,b}$). All values in the column ($x_{c,r,b}$) are expressed in, or converted to, mass fractions. The last column (Furnish) shows the share (i.e. percentage) of each refiner flow to the total furnish. Table 5.3 shows that cpu-times for the volume fraction based model (VFM^{LP}) are less for all cases. Except for the third case (3/max/12/BD), the chosen beating levels are substantially different for the MFM and VFM. The latter statement holds in particular if we take the refiner flows (see Furnish) into consideration too.

Table 5.3. Optimal solutions using two models

Case	Model	Obj-value	cpu	*r*	*b*	*c*	$x_{c,r,b}$	Furnish
0 / min / 7 / BD	MFM	352.50	58.1	29	6100	36	0.65	
						76	0.05	0.70
				30	3500	33	0.27	
						36	0.03	0.30
	VFM	56.74	9.2	29	7200	31	0.15	
						36	0.47	0.62
				30	2600	52	0.09	
						53	0.06	
						68	0.23	0.38
1 / min / 7 / BD	MFM	355.80	1008.9	27	3000	33	0.20	
						44	0.05	0.25
				29	6650	31	0.15	
						36	0.44	
						39	0.04	
						44	0.05	0.68
				30	850	36	0.03	
						39	0.04	0.07
	VFM	56.24	13.6	27	3000	33	0.04	
						44	0.05	0.09
				29	1000	31	0.02	
						36	0.09	
						39	0.05	
						44	0.05	0.21
				30	6200	31	0.60	
						36	0.06	
						39	0.04	0.70
2 / min / 11 / BD	MFM	91.46	6.8	25	6000	29	0.38	0.38
				26	6000	54	0.62	0.62
	VFM	11.54	3.9	25	3000	29	0.70	0.70
				26	6000	52	0.30	0.30
3 / max / 12 / BD	MFM	1.61	7.8	25	0	61	0.43	0.43
				26	3000	31	0.45	
						53	0.12	0.57
	VFM	0.17	1.9	25	0	31	0.12	
						61	0.11	0.23
				26	3000	31	0.72	
						53	0.05	0.77

Continued on the next page

Case	Model	Obj-value	cpu	r	b	c	$x_{c,r,b}$	Furnish
4 / max / 53 / BI	MFM	7.29	38.2	27	5150	31	0.04	
						36	0.44	
						43	0.24	
						44	0.05	0.77
				29	1950	31	0.06	
						39	0.04	
						44	0.05	0.15
				30	7250	39	0.04	
						43	0.04	0.08
	VFM	0.93	9.0	27	3050	31	0.24	
						33	0.04	
						36	0.07	
						44	0.05	0.40
				29	2200	36	0.13	
						39	0.04	
						44	0.05	0.22
				30	7300	31	0.34	
						39	0.04	0.38

Further analysis and observations of the results in Table 5.3 are summarized in Table 5.4. The second column in Table 5.4 refers to the difference in the optimal beating level of the refiners between the two models, MFM and VFM. The degree of difference is expressed in four qualitative expressions, i.e. “strong” (represented by ++ ; more than 1000 units), “substantial” (represented by + ; between 500 and 1000 units), “moderate” (represented by ± ; between 0 and 500 units), and “none” (represented by −).

The fractions in the third column of Table 5.4 (Furnish) show the differences between the compositions of the mixtures using the two models. The latter is expressed by two subcolumns: the “common” fractions in MFM and VFM, i.e. the total fraction of celluloses selected by both models independent of the refiner choice and beating level: $\sum_c \min\left\{\sum_r\sum_b x_{c,r,b}^{MFM}, \sum_r\sum_b x_{c,r,b}^{VFM}\right\}$, and the total fraction of completely different celluloses (“other”) in the furnish of the VFM.

For example, in the case “3/max/12/BD” the fraction in the column “common” equals 0.11 + 0.45 + 0.05 = 0.61 for c=61, c=31 and c=53 respectively (see Table 5.3). The fraction of the furnish denoted by “other” in Table 5.4 equals zero because both models select identical celluloses. For the case “0/min/7/BD” in Table 5.4 the column “common” fraction equals 0.47 for c=36. The total fraction of “other” celluloses for the VFM in Table 5.4

equals 0.15 + 0.09 + 0.06 + 0.23 = 0.53 for c=31, c=52, c=53 and c=68 respectively (see Table 5.3).

Table 5.4 shows that in all instances at least (100-61=) 39% of the furnish (sub column “common” for 3/max/12/BD) is different for both models.

The last two columns in Table 5.4 show the results of the reverse solutions (i.e. the optimal furnish for the VFM fixed in the MFM and vice versa). Except for one case, all reverse solutions are infeasible in the alternative model (i.e. objective value “-- “). The optimal objective values of the MFM and VFM are given between brackets in column four and five respectively.

Table 5.4. Analysis of the solutions using two different models

	Difference in beating levels per refiner_nr					Furnish		Reverse solution			
								VFM in MFM		MFM in VFM	
	25	26	27	29	30	common	other	status	objv.	status	objv.
0 /min / 7 / BD				++	+	0.47	0.53	Inf.	-- (352.5)	Inf.	-- (56.74)
1 /min / 7 / BD			−	++	++	0.52	0	Inf.	-- (355.80)	Inf.	-- (56.24)
2 /min / 11 / BD	++	−				0.38	0.30	Feas.	156.56 (91.46)	Inf.	-- (11.54)
3 /max / 12 / BD	−	−				0.61	0	Inf.	-- (1.61)	Inf.	-- (0.17)
4 /max / 53 / BI			++	±	±	0.48	0.04	Inf.	-- (7.29)	Inf.	-- (0.93)

5.6 Discussion

Although we focussed in particular on the reformulation and solution approach of an OR-model inside a DSS, it should be mentioned that the core of the system consists of three main building blocks: a user interface, a simulation- and an optimization routine.

The first release of the DSS was handed over in 1990. At that time the development and use of Windows applications on personal computers was just evolving. From the beginning it was clear that the user interface is the lubricant between decision-makers on the one the hand and the underlying database for data storage, the simulation and optimization routines on the other hand. Between 1990 and 2005 the user interface hardly changed and desired major changes were postponed. Finally a clear picture and blueprint emerged for new features and improved ease of control. Unlike the previous release, the final development of the user interface was outsourced to a software company. The latter secured the inevitable maintenance for continuous use of the DSS in daily practice.

The simulation module provides a fast and systematic tool to support understanding and insight regarding the impact of (technical) settings on all properties of a paper grade. Based on recipes that were stored in the past, the simulation module enables end-users to study the impact of changes in a recipe (i.e. the contribution of different combinations of raw materials and additives in the pulp flows) and/or to study (altered) settings of the technical equipment (i.e. number of refiners, beating intensity and pulp flows) on the final property values. Various indicators are immediately calculated and visualised. In this way decision-makers become aware of their trade-offs between various targets. The simulation module makes clear how difficult it is to find a (feasible) solution that meets all requirements. On the other hand, upper and lower limits on property values or settings of the technical equipment are rarely treated as hard constraints in practice. Depending on the case to study, upper and lower bounds are mainly seen as aspiration levels rather than hard limits.

The optimization module fosters “out of the box thinking”. It provides a powerful tool to find feasible solutions and the best (surprising) recipes for any available set of raw materials. Moreover, it provides an innovative way of decision support for purchasing (new) pulps on the market, for assigning available pulps to different paper grades and for attuning available stock levels of raw materials to changing production targets for different paper grades. The results of the optimization routine are mainly used to obtain alternative recipes for different paper grades. Usually, these recipes are adapted to daily practice in the simulation module. Tests by practical experience showed that the tendencies predicted by the system fit very well with the final properties of the paper grades on a paper machine.

In the past twenty years the DSS has become a valuable, regularly used resource which played a significant role in all kind of projects. Nowadays, the DSS supports significantly more mills and, depending on the plant, revolution intervals [*LL*, … , *UL*] can vary by choosing different values for the lower limit *LL*, the step size *s* and upper limit *UL* of the refiners, i.e. [*LL*, *LL*+*s*, *LL*+2*s*, …, *UL*-*s*, *UL*]. Although the decision to apply an iterative approach of stepwise refinement for revolution intervals (i.e. increasing *LL*, decreasing *s* and decreasing *UL*) in successive runs was initiated from a computational point of view (i.e. to reduce the number of binary variables in model (4)-(10)), it turns out that especially this approach is of unexpected and remarkable importance for practice. The approach fosters understanding and enables end-users to study the impact of different combinations of raw materials at different technical settings in successive runs on property values.

As another iterative procedure for purely technical reasons was not preferred, the focus to solve the mixed integer (0-1) fractional programming problem was directed to a non-iterative approach that takes advantage of the problem characteristics and exploits the special structure between the original non-linear mixed integer model and a linear reformulation. The proposed solution procedure in Section 4 neither needs an iterative procedure nor a special purpose algorithm. From a computational point of view the approach turns out to be very effective. The calculation time for optimizing volume-fraction-dependent properties is on average even faster than optimizing mass-fraction-dependent properties. The experimental results show that the distinction between $\tilde{p} \in p_{mass}$ and $\tilde{p} \in p_{vol}$ improved the added value of the optimization routine in the DSS because the generated solutions meet the true physical requirements in case $\tilde{p} \in p_{vol}$ without any loss of computational efficiency.

Determination of the decision-maker's preferences between different property values of a final paper grade is currently achieved by interaction between the decision-maker and the system. Objectives (i.e. targets values) for properties $p \neq \tilde{p}$ are translated into lower and upper tolerance limits L_p and U_p in (7a) and (7b). In each run a single, not necessarily the same, property function $f_{\tilde{p}}$ is optimized in (4) while (re)setting lower and upper tolerance limits on other properties. However, tolerance limits in (7a) and (7b) are vague or imprecise in practice. These values are merely considered as aspiration levels and rarely treated as hard values. Moreover, frequently several valid combinations of aspirations levels exist. Additional research is needed to find approaches that reach a higher overall aspiration level in the initial stage of the iterative solution process. If imprecise aspiration levels are introduced to different valid combinations of property values, the problem turns into a fuzzy, multi-choice, multi-objective, mixed integer (0-1) FP problem. This problem cannot be solved by applying conventional linear goal programming techniques (Chang 2007). The author proposed approaches that provide a way to solve multi-choice aspiration levels in a linear programming context. Chakraborty and Chandra (2005) approached a blending problem with imprecise specifications as a multi-criteria decision-making problem and applied fuzzy set theory while Ahlatcioglu and Tiryaki (2007) introduced interactive fuzzy programming approaches to obtain an overall satisfactory balance for linear FP problems. The studies (Chakraborty and Chandra 2005; Ahlatcioglu and Tiryaki 2007; Chang 2007) may be a starting point for new approaches that reach a higher overall aspiration level in a mixed integer (0-1) FP context.

5.7 Conclusions

We focused on the impact and relation between progressive physical insights and desired new functionalities from management on an OR-module in paper production industry. The choice of management to upgrade the system for future decision support in new decision environments may be indicative for the added value and validity of the system in practice.

The experimental results show that the generated solutions are effective and more accurate than formerly used mass fraction based solutions as they meet the true physical requirements. The described extension of the classical reformulation approach by Charnes and Cooper (1962) for a more general class of mixed integer (0-1) FP problems is, to the best of our knowledge, a novel contribution in (0-1) fractional programming. Moreover, it neither requires an iterative evaluation of a function in commonly applied parametric approaches for fractional programming problems, nor a special purpose algorithm. The branching concept of Beale and Tomlin (1970) may even be available in modern, state-of-the-art, mathematical programming packages. This broader availability contributes to the adaptability of the system in practice. Inevitable application-oriented maintenance in the future will hardly be disturbed by locally developed (special purpose) solution techniques.

Without any value judgement on the (theoretical) value and progress in the field of (mixed integer) FP, we showed that the motivation to solve a real-life mixed integer FP problem can provide the basis for a new approach in a new context that has an added value of its own, even outside the given application area. Any mixed integer 0/1 linear FP problem that contains common constraints like (6) (i.e. out of a set of decisions, at most one decision variable may be positive) can be solved by the proposed combination of methods.

Future research and improvements will focus on two main issues, i.e. to contribute to an on-going trend in paper production industry to use alternatives and additives for predominant expensive wood fibres as raw materials and secondly to optimize various conflicting MFM and/or VFM properties simultaneously.

Acknowledgement

The author gratefully acknowledges the valuable comments and suggestions on earlier versions of the paper by all anonymous reviewers, including the associate editor who processed the article and lifted the review process to a stimulating and constructive experience. Thanks to all involved employees of the R&D department in pulp and paper industry for the fruitful discussions we had in all these years of collaboration.

Chapter 6

General discussion

Operations Research (OR) is preoccupied with efficiency, not effectiveness. Effectiveness is evaluated efficiency. In other words efficiency is concerned with doing things right; effectiveness with doing the right thing (Ackoff 2001).

6.1 Introduction

Literature shows that research in the field of Decision Support Systems (DSS) enjoyed its strongest growth in the first two decades after its inception in 1971. Since its peak in 1994 there is a consistent decline of annual DSS publications (Eom, Lee et al. 1998; Arnott and Pervan 2005; Eom and Kim 2006; Arnott and Pervan 2008). Barely four decades after its birth, Carlsson and Turban (2002) and Arnott and Pervan (2008) evidenced a trend in which the term DSS matured to a point of losing its identity and might disappear as a stand-alone field. Arnott and Pervan (2008) stated that the practical contribution of the broad field of DSS research, which includes model-driven DSS, faces a crisis of relevance due to a long-term issue, i.e. the tension between academic rigor and professional relevance. The reviews of Framinan and Ruiz (2010) and Mula, Peidro et al. (2010) confirmed the identified gap between theory and the use of (mathematical programming) models in practice. Arnott and Pervan (2008) defined, among others, professional relevance (i.e. the disconnection of DSS research from practice), case study research (currently under represented), low industry support, and the presence of DSS in ‘A’ journals other than the journal ‘Decision Support Systems’ as key issues for the field to focus on in the future.

As the field of decision support systems aims to be an application-oriented discipline, the strategy of what is referred to as “*application-driven theory*” (Cooper and McAlister 1999; Cooper 2005) is taken as the preferred approach for this thesis. “Application-driven” refers to a bottom-up approach which means that the relevance of the research should both be initiated and obtained from concrete problems in real-life environments. The intended successful use of the proposed approaches should, where possible, be represented by tests of adequacy. Simultaneously, the contribution to “theory” aims to be a recognizable part of the research effort. This implies that obtained understanding and insights from problems in practice can be generalized to and provide the basis for new approaches. The following two-sided research objective was defined to reflect this goal.

To support medium- to short-term planning problems by optimization-based models and solution techniques such that:

- *i)* *The applicability and added value of (prototype) systems is recognized and carried by decision-makers in practice*
- *ii)* *The proposed approaches contribute to knowledge, understanding and insights from a model building and solving point of view.*

In Chapter 1 we described the focus of the research which, resulted in five recurring research premises. This sharable set of premises constitutes the connecting link between the general objective and its translation into four research questions (RQ’s), which are all addressed in the preceding chapters. Table 6.1 shows the relation between the research premises and their contribution to the different chapters. We merely show the key elements of the research premises in Table 6.1 and refer to Chapter 1 for their complete description.

Each chapter refers to at least two premises for different planning issues in the supply chain planning matrix (SCPM) of Figure 1.2. Besides the first overarching premise, i.e, *professional relevance and applicability*, all other premises refer to model building and/or solving in optimization-based DSS. To make the research premises visible, their key elements will be printed in italics in the next sections.

Table 6.1 Relation between research premises (P_m) and chapters (Ch_n)

Premise		Ch_2	Ch_3	Ch_4	Ch_5
P_1	*Professional relevance and applicability*	✓	(✓)	✓	✓
P_2	*Aggregation*	✓		✓	
P_3	*Decomposition and/or reformulation*	✓	✓	✓	✓
P_4	*Vertical integration*	✓	✓		
P_5	*Horizontal integration*		✓	✓	✓

The first goal of this final chapter is to reflect on the RQ's and to summarize the bare findings of each chapter in Section 6.2. In Section 6.3 we aim to take some distance from the RQ's. The main goals of Section 6.3 are *i*) to position the main findings in the current context of research and literature which is for instance particularly relevant for the studies in Chapter 2 and 4, and *ii)* to take the research premises as a guideline for an integrated discussion of the findings. Both Sections 6.2 and 6.3 provide the basis for the last goal of this chapter, i.e. to summarize the main conclusions and to define some directions for future research (Section 6.4).

6.2 Reflection on research questions and main findings

In Chapter 1 we formulated four research questions (RQ's). This section describes how the RQ's are addressed in the preceding chapters and what we learned from the studies. The related main findings in each chapter will be summarized in bullet points in each subsection. Findings will be grouped into three main categories: *i*) model-building, *ii*) model-solving, and *iii*) professional relevance and applicability.

6.2.1 Research question 1

Chapter 2 addresses RQ1: *"How to apply aggregation, decomposition and reformulation in model-based DSS at planning and scheduling level such that the aspect of decision support is recognized and appreciated by decision-makers in practice, and which level* *of aggregation is needed to integrate production planning (i.e. lot-sizing) and scheduling problems in a single model?*

The chapter consists of two parts. Part I refers to a case study for production planning and detailed scheduling problems at a bottleneck production facility in food processing industry. Part II refers to a literature research for integrated production planning (i.e. lot-sizing) and scheduling.

The aim of the case study was to develop, implement and test a pilot DSS, able to deliver solutions recognized and carried by decision-makers in practice. The latter aim implies that a straight-forward *aggregation* on time, product type, resources or product stage (Wijngaard 1982) was not preferred. The key to develop a solvable approach for regular use was to identify and take advantage of specific problem characteristics. Experience from practice offered a way to cluster the numerous jobs of the order book into a restricted number of families of jobs. Each cluster of jobs shared a set of comparable operations with comparable machine setups. Whenever a production line is prepared to produce an item in a family, all other items in the same cluster can be produced with negligible changes in setups. In order to reduce the complexity of the problem, planning tasks were separated i.e. *decomposed* into two hierarchical levels: (i) production planning over a short- to medium-term rolling horizon, and (ii) sequencing of jobs at a daily level second. However, *decomposition* was still insufficient to solve the daily problems within an acceptable time frame. Clustering while retaining information at order level could be exploited in a *reformulation* approach by the inclusion of (combined) generalized- and variable upper bound constraints which gave very tight lower bounds and sparse search trees.

Decision-making at this production level implies the consideration of several, mostly incommensurable, objectives. The suggested solution, i.e. to assign penalties and/or weights to different criteria in a single objective function, was effective to combine different goals in this case study. For the acceptance of the generated production plans, it was of particular importance to generate recognizable and valued production sequences for the shop floor. At this lowest (i.e. short-term) level, several logical sequencing rules from practice were considered and programmed, all ranked in a given order of importance.

The main benefit of the approach is the constant and initial quality of the generated plans including the time needed to generate these schedules. Hence, decision-makers could *i)* postpone their planning tasks, *ii)* conveniently cope with rush orders or planned maintenance and *iii)* easily generate alternatives or revised plans when unforeseen disturbances occur. Moreover, the graphical presentation and overview of the planned working schedule enabled order acceptance to make use of remaining capacity.

Basic understanding on how the production schedules are calculated turned out to be an important issue for acceptance and usability of the generated plans. Decision-makers usually have more information at their disposal than is modelled in a DSS. Not all observations in practice can be captured in a (simplified) model particularly in a barely stable decision environment. Therefore decision-makers need the opportunity to modify automatically generated plans manually and use human judgement and experience such that the solution is tuned to the actual situation. Hence, the DSS should not be considered as an optimizer but rather as a tool for generating high-quality plans to be used for further analysis. Within this context the various utilities of a user-friendly, graphical, and fully interactive user interface, was of major importance.

To summarize the findings of the case study in Part I of Chapter 2:

Model-building (RQ1, Part I)

- The separation of planning and scheduling implies that some (unknown) capacity must be reserved at planning level in order to compensate capacity losses due to changeovers at sequencing level.
- *Decomposition* without *aggregation* was insufficient to solve the generated problems within an acceptable time frame. A combined approach based on *i*) taking advantage of specific problem characteristics (i.e. a case-based clustering procedure instead of *aggregation*) and *ii*) the identification of special model structures (i.e. a *reformulation* which offered the inclusion of combined generalized- and variable upper bound constraints) resulted in very tight lower bounds and sparse search trees.

Professional relevance and applicability (RQ1, Part I)

- The research clearly demonstrates the anticipating value of earlier case-based DSS research, funded and tested by industrial practice. Meanwhile, the applied principle of *decomposition* at production level became a commonly accepted starting point in the framework of APS in Figure 1.2 (Stadtler and Kilger 2008; Stadtler, Fleischmann et al. 2012).
- A user-friendly, graphical, and fully interactive user interface is of major importance for both the development and adoption of automated systems in practice.
- Personalized and customized modules are particularly important on lower decision levels

The proposed approach in Chapter 2 may reduce the computational burden and provide adequate decision support in specific cases, but it is hardly a generic solution for the intended *vertical integration* between lot-sizing and scheduling. Stadtler and Kilger (2008) stated for instance, if products (lot-sizes) have to compete for scarce resources (e.g. flow lines with sequence dependent setup costs and times), a separation into two planning levels is inadequate. Due to specific characteristics in FPI, e.g. non-triangular setups and product decay, the need for simultaneous lot-sizing and scheduling may be even more relevant for this branch of industry.

As the case study in Chapter 2 was based on an earlier study, a literature research on modelling developments for simultaneous lot-sizing and scheduling was carried out too. The research was restricted to contributions that are directive for the identified problem characteristics, i.e. setup carry-overs, sequence dependent setup costs and times, relaxation of the triangular setup conditions and product decay.

According to literature, two main classes of models can be distinguished, i.e. Small Bucket (SB) and Big Bucket (BB) models. In SB models, the planning horizon is divided into a finite number of small time periods. Conversely, in BB approaches the planning horizon is divided into longer periods, usually of equal length, and in each period multiple products may be produced. As a consequence, SB models are usually associated with short-term planning horizons and BB models with medium term planning horizons. We noticed a tendency in literature in which special Big Bucket (BB) models are proposed for short-term time horizons too; particularly within the (broad) context of sequence dependent changeovers and triangular setup conditions. Despite of the *aggregation* in time, these BB models, including intermediate variants like the General Lot-sizing and Scheduling Problem (GLSP) or block planning approaches, consider both the size and the production sequence of lots within these larger time-intervals.

To summarize the findings of the literature research in Part II of Chapter 2:

Model-building (RQ1, Part II)

- There exists a noticeable trend in simultaneous lot-sizing and scheduling in which Big Bucket (BB) approaches or hybrid variants are preferred to Small Bucket (SB) models.
- Non-triangular setups are hardly considered, particularly not in SB models.
- A substantial number of proposed SB models introduce an artificial product to represent idleness of resources. For these models the changeover matrices must comply with very strict, usually unrealistic, conditions to cope with sequence-dependent changeover times and non-triangular setups. If these conditions are not met, the setup state of the production facility is not correctly carried over across the boundaries of idleness.
- Block planning approaches can be regarded as a practical variant of the General Lot-sizing and Scheduling Problem (GLSP). However, in the concept of block planning the production sequence of (variable) batch sizes is pre-defined (Lütke-Entrup, Günther et al. 2005; Günther, Grunow et al. 2006; Bilgen and Günther 2010; Baumann and Trautmann 2012). These approaches may be difficult to apply if the triangular setup conditions do not hold.
- Surprisingly little research has been devoted to include issues of product decay in traditional lot-sizing and scheduling models.
- In contrast to BB models, SB approaches offer the timeframe to attune short-term physical distribution planning to production planning and scheduling, e.g. by assigning demand to specific time slots in a 24-hours production environment.

- Although the separation between production planning (i.e. lot-sizing) and scheduling in successive hierarchical phases is commonly accepted, e.g. in APS software, these planning steps are closely linked areas which should (ideally) be considered simultaneously.

The findings of the literature review laid the foundation for additional research on a complete *vertical integration* of planning and scheduling tasks. The goal was to develop a single model for both planning tasks simultaneously, to study its behaviour, the complexity, and to investigate the impact of non-triangular setups and product decay on optimal production schedules.

6.2.2 Research question 2

Chapter 3 addresses RQ2: *"How to integrate production planning (i.e. lot-sizing) and scheduling problems in a single model, such that common assumptions regarding the triangular setup conditions are relaxed and issues of product decay and limited shelf lives are taken into account?"*

Although BB approaches may have a computational advantage, Chapter 3 argues that segmentation of the planning horizon (i.e. *aggregation* over time) is a key issue for simultaneous lot-sizing and scheduling in food processing industry. Defining large time intervals in BB approaches implies that the general principle of optimality for lot-sizing may unfoundedly disappear from sight. Moreover, product decay is primarily associated with the "age" of manufactured products and consequently relates to the segmentation of the time-horizon. Therefore, two consistent SB models are developed to demonstrate the impact of non-triangular setups and product decay on the generated solutions. Small-scale examples are used to demonstrate the impact of minor changes in the balance between inventory-holding and changeover costs.

The developed models are potentially very large formulations. Basic complexity analysis for the developed models shows that particularly the segmentation of the time horizon in SB approaches has a substantial impact on problem sizes. Solving the developed models for large (i.e. real-size) problem instances, requires effective and efficient approximations techniques. Exploratory research was conducted based on a Relax-and-Fix (R&F) heuristic in which the principle of *decomposition* was applied to the solution procedure. Numerical results of small- to medium-sized problem instances are presented.

To summarize the main findings of the study in Chapter 3:

Model-building (RQ2)

- If the objective for simultaneous lot-sizing and scheduling should include the best compromise between total setup costs and total inventory-holding costs, a time-oriented *aggregation* (like in BB models and its variants) easily disrupts the general principle of optimality for lot-sizing. As a result, total inventory-holding costs are underestimated and lot-sizes become too large.

- Product decay in food processing industry is primarily associated with the "age" of manufactured products, which argues the need to capture the precise moments of production. If multiple batches are planned in larger time intervals, it implies that all lot-sizes in each period share the same moment of production. As a consequence, the age of manufactured products on stock is underestimated.
- Product decay has an impact on the remaining shelf life of products. This aspect was included by an age-dependent component in the inventory-holding costs. Numerical results show how a small change in the balance between inventory - and changeover costs may generate significantly different solutions, especially when the triangular setup conditions do not hold.

Model-solving (RQ2)

- The developed models are potentially very large formulations. Computation times grow very fast, both with the number of products *N* and (particularly) with the number of periods *T* in the planning horizon.
- Although R&F algorithms in (mixed) integer programming literature are commonly presented as forward procedures, a backward R&F procedure is favourable for simultaneous lot-sizing and scheduling. Demand matrices for SB models are usually sparse (i.e. many, if not most entries of the matrix are zero). Numerical tests confirm that in a forward procedure, production will be postponed in early iterations. If capacities are tight, the concept of fixing production and idle time at their optimal values from previous iterations will easily lead to infeasible solutions in a forward solution procedure.
- The quality of the R&F solutions is promising at manageable computational effort. However, solving real-size problem instances may not be possible yet. Nevertheless, the availability of a correct MP model for the given problem description offers at least the possibility to measure the quality of small- to medium-sized problems solved by any (other) heuristic.

Professional relevance and applicability (RQ2)

- Although the boundaries between planning (i.e. lot-sizing) and scheduling are fading in literature, there is a need for more practical cases of simultaneous lot-sizing and scheduling, particularly in food processing industries.

6.2.3 Research question 3

Chapter 4 addresses RQ3: *"How to model and solve an integrated planning problem between procurement and production, both on a midterm and short-term planning level, in an inter-organizational supply chain?*

Both production and distribution planning of (end) products are part of the APS framework and issues of integration between both phases have been the concern of research. However, surprisingly little research has been devoted to issues of *horizontal integration* between procurement and production. The lack of both a midterm distribution and a short-term transportation module between procurement and production in the APS framework of Figure 1.2 may be an illustrative observation within this context. Comparable problems of coordination may manifest between procurement and production particularly in push-oriented supply chains. The case study in Chapter 4 focused on *horizontal coordination and integration* between the phases procurement and production for a milk collection problem in practice, which is of particular importance in inter-organizational supply chains. The aim was to develop a pilot DSS that lifted decision support for a "weaker" partner in a food supply chain (i.e. a stakeholder who is not in charge of planning process) to a higher level, and to illustrate the importance of *horizontal coordination and integration* between the phases procurement and production in an APS framework.

Initially, the case was presented by the stakeholder as a complex, daily vehicle routing problem. Problem analysis revealed that the problem can be classified as an extension of the Periodic Vehicle Routing Problem (PVRP). However, the basic PVRP in literature assumes either pickup or delivery operations, not both simultaneously like the case study in Chapter 4.

In order to solve the PVRP in a practical setting, the complete problem was *decomposed* into more tractable subproblems on different levels, i.e. to separate the daily routing problem from a new medium-term planning problem. On the higher planning level, numerous supplier farms were *aggregated* such that total supply within a cluster met (multiple) vehicle loading capacities. Based on limited storage capacities at supplier level and additional requirements for the freshness of raw milk, feasible collection frequencies (rhythms) for aggregated supply were introduced (see Table 4.1). The geographical location of supplier farms was the starting point for *aggregation* on supply level. A model was developed to generate stable collection schedules. The continuous supply of relatively small amounts from many suppliers had to be balanced with strict delivery conditions at processing level (i.e. large amounts of raw milk scheduled to arrive at processing facilities on a limited number of fixed days in the planning horizon). The aim of the model was to assign a single collection rhythm to each cluster such that the total, weighted deviation (i.e. surplus and shortage) of desired processing levels at fixed days in the planning horizon was minimized.

The computational complexity of the problem could be reduced by taking advantage of specific, application-based properties and to exploit them in a specific branch-and-bound scheme. The improved computational efficiency of the branching concept made it possible to solve the generated problems exactly for real-size problem instances.

The applied *aggregation* on the higher planning level turned out to be very beneficial for the required disaggregation at the lower planning level, i.e. the daily vehicle routing problem. Once supplier farms were geographically grouped into clusters and the aggregated supply within a cluster was assigned to a single collection rhythm with fixed collection days, the (initial) daily routing problem was considerably easier to solve for vehicle schedulers.

Besides the added value on the mid- and short-term level, the planning model turned out to be a very helpful strategic tool for the cooperative association at supply level (i.e. the "weaker" partner). When periodic delivery conditions are set by stronger partners in an inter-organizational network (in this case stakeholders at processing level) the generated plans can be used effectively by a weaker partner (e.g. for their regular negotiations with both processing and transportation companies).

The visualization of (modified) plans including the possibility to store plans over the year enabled decision-makers to 'optimize' their performance with respect to his or her planning tasks. Within this context, the various facilities of a user-friendly and interactive man-machine interface were essential. The user interface was divided into an input, planning, simulation and analysing part. Changing the data, e.g. moving supplier farms to other clusters or changing the milk collection rhythm for a cluster was possible. However, the impact of any modification of the data in the simulation module was immediately visualized by several (conflicting) indicators in the output screens, both on supply and demand level.

To summarize the findings of the study in Chapter 4:

Model-building (RQ3)

- The case study demonstrated that an additional planning phase (i.e. distribution) between procurement and production contributes considerably to *horizontal integration* in the SCPM, particularly in a push-oriented, inter-organizational food supply chain.
- The main problem to solve was a special variant of the Periodic Vehicle Routing Problem (PVRP) which concerns pickup and delivery operations, simultaneously. The focus for this variant of the PVRP in practice should be on *decomposition* of the problem into more tractable sub problems on different hierarchical levels.
- Although *aggregation* on higher planning levels is often associated with an (undesired) loss of information, the applied *aggregation* at medium-term planning level was very beneficial for the (inevitable) *disaggregation* at the lower planning levels.

Model-solving (RQ3)

- Although literature on the tactical PVRP focuses primarily on heuristic methods (Mourgaya and Vanderbeck 2007; Francis, Smilowitz et al. 2008; Baldacci, Mingozzi et al. 2011), we showed that real-sized problems can be solved using exact methods at the highest level in the PVRP. Francis, Smilowitz et al. (2008) confirmed the latter finding in their book on vehicle routing problems and refer to the study in Chapter 4 as an example for the applicability of exact methods.

- We focused on the algorithmic side for the given case. Compared to a conventional branch-and-bound scheme for integer programming, we showed that there is no advantage in the SOS1-branching scheme itself. The potential sizes of search trees for branching on single variables or sets of variables are equal. Consequently, any potential benefit of the SOS1-concept is due to the efficiency of the search procedure.
- We showed that the efficiency of the SOS1-concept primarily depends on a (re-)ordering procedure of the variables within the sets rather than on the weights associated with each variable in the set.
- Numerical tests confirm that substantial computational advantages can be gained by applying an SOS1-based solution procedure, provided that a (re-)ordering of the variables within the sets is considered.
- The case study showed that an efficient use of the SOS1-based solution procedure is not necessarily restricted to problems with supplementary model conditions. We showed that a natural ordering of the variables within the sets (Williams 1990; ILOG 2009), is not necessary to make their use worthwhile and/or applicable in a broader context. In addition to the latter statement, we also refer to the reflection on RQ4 in the next Section 6.2.4.

Professional relevance and applicability (RQ3)

- The case study demonstrated that the adoption and added value of DSS in practice can be increased by including both a simulation module and scenario management tools.
- The necessity of a (separate) reference row or weights associated to the variables might be omitted in future implementations of the SOS1-based branching scheme.

6.2.4 Research question 4

Chapter 5 addresses RQ4: *"How to support decision-makers in practice if crucial properties of end products simultaneously depend on (endogenous) types of raw materials with different chemical or physical properties and (endogenous) technical settings of processing units?"*

The study refers to a specific characteristic of process industries where technical settings of processing units have a variable (physical) impact on material flows which in turn determine the final properties of end products. If the related planning problems are treated in the context of mathematical optimization, they may lead to (mixed integer) non-linear problems, which are often hard to solve.

Pressed by changed circumstances and constantly advancing physical knowledge of large scale pulp and paper production, the goal was to revise and upgrade an existing, locally used DSS, to a tailored and flexible tool within the enterprise. The cornerstones simplicity, ease of control, adaptability and completeness from Little's seminal paper were taken as a guideline for developing models and techniques that are actually used in practice (Little 1970; Little 2004).

One of the main concerns from practice was that the principle of a single overriding objective is too restrictive for future decision support and had to be abandoned. Management scientists of corporations usually focus on a variety of objectives. The study revealed that the aimed extension towards multi-objective decision support, together with new physical insight for calculating properties of end products due to process operations, had a significant impact on the optimization module. From a practical point of view, the method to solve the non-linear programming problem should neither be based on an iterative solution procedure nor a locally developed special purpose algorithm.

The proposed solution procedure takes advantage of the problem characteristics and gives rise *i*) to apply and extend a classical *reformulation* approach for continuous linear fractional programming (FP) problems to a more general class of mixed integer (0-1) FP problems and *ii*) to exploit the special structure between the original non-linear mixed integer model and the continuous, linear *reformulation* by applying the concept of Special Ordered Sets type 1 (SOS1).

Although Chapter 5 focuses in particular on the *reformulation* and solution approach, the DSS consists of four main building blocks, i.e. the user interface, a scenario manager, a simulation- and optimization routine. The user interface is the lubricant between decision-makers on the one hand and the underlying database for data storage, scenario manager tools, simulation and optimization routines on the other hand. Between 1991 and 2005 the user interface had hardly changed and desired (major) changes were postponed. Finally a clear picture and blueprint emerged for new features and improved ease of control and ease of communication. Unlike earlier releases, the final development of the user interface was outsourced to a software company. The latter secures the inevitable maintenance (i.e. adaptability) for continuous use of the DSS in daily practice.

Scenario manager tools were developed to store, structure and analyse multiple solution scenarios such that it benefits the understanding of underlying patterns. The simulation module provides a fast and systematic tool to support understanding and insight regarding the impact of (technical) settings on all properties of a paper grade. Based on stored recipes in the past (e.g. by the scenario manager), the simulation module enables end-users to study the impact of changes in a recipe (i.e. the contribution of different combinations of raw materials and additives in adjustable fractions in the pulp flows) and/or to study the (altered) settings of the technical equipment (i.e. number of refiners, beating intensity and pulp flows) on the final property values. From the perception of the end-user, the simulation module also makes clear how difficult it is to find a (feasible) solution that meets all requirements.

The optimization module provides a powerful tool to find feasible solutions and the best (unexpected) recipes for any available set of raw materials. Moreover, it provides an innovative way of decision support for purchasing (new) pulps on the market, for assigning available pulps to different paper grades, and for attuning available stock levels of raw materials to (changing) production targets for different paper grades. The results of the optimization routine are mainly used to obtain alternative recipes for different paper grades. Usually, these recipes are stored as base scenarios and adapted to daily practice in the simulation module.

To summarize the findings of the study in Chapter 5:

Model-solving (RQ4)

- The applied combination of methods neither requires a commonly applied iterative evaluation of a parametric function for (non-linear) fractional programming (FP) problems, nor a special purpose algorithm.
- The applied concept was easy to implement in a DSS and may even be available in modern, state-of-the-art, mathematical programming packages.
- Numerical results show that the proposed approach can be applied to problems with real-life dimensions. In this particular case even without a loss of computational efficiency.
- We proved that the concept of Special Ordered Sets type 1 (SOS1) can extend a classical *reformulation* approach for continuous FP problems to a specific class of mixed integer (0-1) FP problems.

Professional relevance and applicability (RQ4)

- From a decision-maker point of view, the simulation module exceeds the added value of the optimization module. It enables end-users to study and explain the impact of minor (technical) changes. Practical use of the system in real-life shows that simulation contributes significantly to basic understanding and insights of the underlying problem.
- The optimization module mainly fosters “out-of-the-box thinking”. Minor changes in (technical) settings may result in completely different solutions which are less easy to grasp and accept in practice.
- The study showed once again the importance of solid scenario management tools for the adoption and regular use of the DSS in real-life.
- The study showed that a broader availability of the SOS1 branching concept in modern mathematical programming packages contributes to the adaptability of systems in practice. Inevitable application-oriented maintenance in the future will be hardly disturbed by locally developed special purpose solution techniques.

The next Section 6.3 provides a wider discussion of findings along the main objective of the research including the defined research premises in Chapter 1. The main goal of Section 6.3 is to position the bare findings of Section 6.2 in the current context of insights, to take some distance and place them in a slightly broader perspective. Based on our experiences and gained insights in developing model-based DSS we finally revisit current developments in decision support for industrial practice, i.e. Advanced Planning Systems (APS) as described in Section 1.2 of Chapter 1.

6.3 Discussion of findings

Given the need for computerized decision support, the objective of this study was *i*) to contribute to the applicability of DSS in process industries using model-based approaches and *ii*) to acquire additional optimization-based insights and contribute to new approaches, both from a modelling and solving point of view. Carlsson and Turban (2002) stated that the term decision support systems may be seen less and less frequently but its basic concepts, aims, and added value for practice are still valid.

In Section 1.4 of Chapter 1 we motivated why a case-based approach was taken as a starting point for this thesis. The general goal of this section is to contribute to the question "How to shape model-based DSS studies such that they actually persuade decision-makers for using normative approaches for decision support in practice and simultaneously contribute to existing knowledge, understanding and insights from a theoretical point of view?". An answer to this question may be to combine the strong elements of normative models with (descriptive) observations in practice, i.e. to tune normative models both to specific situations and to the needs of decision-makers in practice. The studies in Chapter 2, 4 and (particularly) 5 are illustrative examples within this context. Starting point in each case was not to focus solely on the most obvious component in a model-based DSS but to develop blueprints of usable systems in practice.

A set of five research premises was introduced in Chapter 1, providing the basis for a recurring link between the general objective and its translation into research questions. In Section 6.1 we separated the overarching research premise P1 "*professional relevance and applicability*" from the other premises P2 – P5, all referring to "model building and/or solving". The separation of premises into these two headings will be the starting point for the following discussion. Analogous to the preceding section, references to research premises are printed in italics.

6.3.1 Model building and solving

Although automated decision support can be very valuable for (programmable) decision problems, it can easily demonstrate its weakness too in complex decision-making, particularly with respect to model-driven DSS. The core of that weakness may originate from OR scientists who are primarily concerned with developing and solving (normative) models, i.e. to identify the best decision to take and to describe how decision-makers ought to make decisions. According to Ackoff (2001), management scientists are preoccupied with “doing things right”, but simultaneously may neglect to design models of what the decision-making process is really about or what decision-makers actually do, i.e. “doing the right thing”. The study in Chapter 5 on a class of fractional programming problems may be an illustrative example within this context. Problem classes are often preferred to be narrowed down by scientists to one specific problem that suits personal research interests best rather than trying to model and solve the real problem in the environment in which it is embedded. According to Williams (2013) it is surprising that comparatively little attention has been paid in literature to the problem of formulating and building mathematical programming models and deciding when (normative) models are *applicable*. According to our view, an application-oriented field like model-based DSS needs to apply OR knowledge and experience such that systems are developed in which decision-making based on preferred and/or historical lines of thoughts in practice are predisposed by adopting combined normative and descriptive approaches with recognized, favoured added value and outcome. Our aim is to contribute to this major issue. We take the premises *P2 – P5* as guidelines and project them to modelling and solving the described problems in the previous chapters.

Aggregation (P2), *decomposition* and *reformulation (P3)* are commonly applied to reduce primarily the computational complexity and secondly the need for detailed data. *Aggregation* usually includes a loss of information and may be done at the expense of accuracy. The principles of *decomposition* and (a priori) *reformulation* are much broader and a clear distinction between them is less delineated. Generally, *decomposition* schemes are based on breaking up the original problem into smaller, more tractable subproblems and may refer to the scope of the initial problem, the proposed model(s), and/or the applied solution technique(s). Liberti (2009) defined a *reformulation* of a mathematical program as a formulation which shares some properties with, but is in some sense better than, the original program. *Reformulations* are widespread in mathematical programming and important with respect to the choice and efficiency of solution algorithms (Liberti 2009). The aim of this section is not to contribute to a fundamental discussion regarding clear definitions and/or general statements on when to use *aggregation*, *decomposition* and/or *reformulation* but to demonstrate where and how (a combined use of) these principles contributed to the studies in the preceding chapters.

Towards complete vertical integration at production level

A major drawback of *aggregation* is that it is done at the expense of exactness (Stadtler, Fleischmann et al. 2012). Aggregated solutions may be difficult or even impossible to disaggregate into feasible, detailed plans on lower decision levels. Consequently, the generated solutions may be less recognized and appreciated by decision-makers, even after a cumbersome (ex post) disaggregation procedure. However, the unavoidable computational complexity of non-aggregated planning and scheduling models may neither be an option, even after applying a *decomposition* approach by separating planning tasks from scheduling (see Figure 1.2 in Chapter 1). Clear examples within this context refer to the studies in Chapter 2 and 3.

The average number of (expected) orders in the order book for the case study in Chapter 2 was too large to solve the problem within an acceptable time frame. At model construction level a clustering could be exploited in a *reformulation* approach which takes advantage of a favourable model structure. Instead of defining continuous production variables expressed in absolute amounts, production variables were defined as a fraction of demand at order level. The latter definition and the related inclusion of both generalized upper bounds (GUB) and variable upper bound (VUB) constraints was crucial to make the difference between a “weak” and a “strong” model formulation. The VUB constraints enriched the model formulation in Chapter 2 and induced tight LP relaxations which tend to give answers that are integer in the binary variables. Several studies, mostly devoted to the facility location problem, confirmed that the inclusion of variable upper bounds can give tight lower bounds and sparse search trees (Schrage 1978; Christofides and Beasley 1983; Vanroy 1986). The applied combination of *decomposition*, clustering while retaining detailed information at order level, and *reformulation* was crucial to solve the problems in Chapter 2 within a few minutes on a PC.

Unfortunately, the applied combination of clustering and *reformulation* is not generically applicable because *i)* the number of jobs in the order book should be substantially larger than the number of defined clusters, *ii)* processing times of the majority of jobs in the order book should be considerably smaller than daily production capacity, and *iii*) only a minority of jobs in the order book may have processing times that exceed daily capacity. A quadratic penalty function for the starting time of each job within its feasible time frame (see Figure 2.2) was (in this specific case) sufficient to prevent an excessive split of jobs over more than a single production day. However, the overall conclusion with respect to the case study in Chapter 2 is that the applicability of the approach highly depends on taking advantage of specific, case-based characteristics. Moreover, the main drawback of a hierarchical *decomposition* approach at production stage in Figure 1.2, remains an issue. This issue may be of minor importance if changeovers are not sequence dependent (Roosma and Claassen 1996). However, if capacity losses in planning and scheduling problems are caused by sequence dependent changeover matrices, whether or not including the triangular setup conditions, the hierarchical *decomposition* approach easily results in infeasible or suboptimal solutions (Kreipl and Pinedo 2004; Shah and Ierapetritou 2012).

Complete vertical integration at production level

Although undesired losses of production capacity due to sequence dependent setup-times could be reduced in the case study of Chapter 2 by penalising the number of clusters in the time horizon, an unknown portion of daily capacity had to be reserved for changeovers. Both Stadtler and Kilger (2008) and Stadtler, Fleischmann et al. (2012) in their books suggested a comparable approach. However, reserved capacity at the higher decision level is either under- or overestimated and may become a serious problem, particularly in case the triangular setup conditions do not hold.

An obvious way to address such problems is to release the general principle of *decomposition* in Figure 2.1 and to accomplish a complete *vertical integration* (P4) between planning and scheduling at production stage. The main issue for model-building and -solving is that integrated models are much more complicated to develop and usually much harder to solve (Kallrath 2002).

As has been shown in Chapter 3 and confirmed in literature (Salomon, Solomon et al. 1997; Méndez, Cerdá et al. 2006; Pochet and Wolsey 2006; Stadtler and Kilger 2008), computational effort increases very fast, particularly with the number of time periods in the planning horizon. This well-known issue turns out to be an incentive for the construction of integrated models which are based on *aggregation* in time, i.e. a segmentation of the planning horizon into large time intervals. Due to a significantly smaller number of time periods, the related big bucket (BB) models and their practical variants have a major computational advantage (Méndez, Cerdá et al. 2006; Baumann and Trautmann 2012). As a result, there exists a trend in simultaneous lot-sizing and scheduling that moves away from small bucket (SB) to big bucket (BB) models or intermediate variants. In Chapter 2 and 3 we argue that applying *aggregation* over time in model-building at production level is ineffective for both a complete *vertical integration* (P4) at production level and the need for *horizontal coordination and integration* (P5) between the phases production and physical distribution in the SCPM of Figure 1.2. Modelling approaches that take a continuous time axis as a starting point, i.e. consider no time buckets at all, may end up in the most appropriate models but these approaches will usually result in the largest computational effort (Méndez, Cerdá et al. 2006; Stadtler and Kilger 2008). Compared to BB models, an SB approach takes the closest approximation for a continuous representation of time.

If *aggregation* and *decomposition* are not eligible at model construction level, other approaches must be found to address planning (i.e. lot-sizing) and scheduling problems simultaneously, e.g. *reformulation* or a *decomposition* approach applied to solution techniques. In their book on production planning and mixed integer programming, Pochet and Wolsey (2006) stated that only a very few *reformulations* exist concerning those models. The authors stated that the most commonly applied optimization approach in solving such problems is to integrate existing approaches for single-item problems, using a *decomposition* technique. We conducted exploratory research on a *decomposition*-based solution technique. The applied heuristic considers a *decomposition* of variable definitions in the time horizon, but it can be changed easily into a decomposition approach on product and/or constraints level. The main advantage of an R&F procedure is its broad applicability in mathematical programming. Dedicated, special purpose algorithms may perform better, but these algorithms usually have to be redesigned or even abandoned in case certain (minor) features change (Hax and Candea 1984; Günther and van Beek 2003).

The need for horizontal coordination and integration

In Chapter 3 we argued that an SB approach at production level has the flexibility to take issues of *horizontal coordination* between production planning and physical distribution into consideration. In Chapter 4 we addressed the problem of *horizontal coordination and integration* between procurement and production. Fleischmann and Meyr (2003) stated that the bill of materials (BOM) in consumer goods industries is generally rather flat, which makes procurement usually unproblematic. According to the authors, mostly only a few raw materials with a low value are sourced from a handful of suppliers in consumer goods industry. As a consequence, supplier lead times are relatively short and reliable. We argue in Chapter 4 that, despite of a flat BOM with reliable supplier lead times, issues of coordination and (*horizontal*) integration should not be restricted to material flows between the stages production and distribution in push-oriented supply chains. Even if perishable raw materials are produced at a constant level, they are usually processed in (semi-) batch type production processes, mostly on shared or multi-purpose equipment.

As shown in Chapter 4, integrated (midterm) distribution and (short-term) transportation planning between procurement and production level becomes even more complicated if procurement and processing of raw materials is carried out by different companies. Stadtler (2005) stated that issues facing an inter-organizational supply chain are mainly addressed in research areas associated with the integration of individual organizations. The author concluded that advanced planning across company borders is still in its infancy. Akkermans, Bogerd et al. (2003) mentioned that it becomes increasingly apparent that supply chains, rather than individual organizations, compete. Consequently, there is an increasing demand for collaborative architectures in decision support software (Akkermans, Bogerd et al. 2003). Stadtler (2005) confirmed that hierarchical coordination is possible and prevailing in intra-organizational supply chains, but the real challenge arises in inter-organizational supply chain where hierarchical coordination is no longer possible. The author stated that the centralistic view of hierarchical planning underlying today's commercial planning systems like APS, may even be a questionable assumption. It might be suitable in intra-organizational supply chains but not across organizational borders (Stadtler 2005). The case study in Chapter 4 confirms the latter view. The interests of partners in the chain were clearly contradictory. As a consequence, the weaker partner focuses on his own planning domain, is reluctant to share data, and constantly tries to strengthen his position. In addition, the case study demonstrated the added value of an additional (distribution) phase between procurement and production in a push-oriented, inter-organizational food chain (see Figure 1.2).

Model-building for horizontal coordination and integration

From an OR point of view, the problem in the proposed distribution phase of Chapter 4 can be classified as a periodic vehicle routing problem (PVRP). We refer to Golden, Raghavan et al. (2008) for an overview of papers including the most important advances of (new) variants in the vehicle routing domain. The extension of the PVRP in Chapter 4 concerns the link between the stages procurement and production in the APS framework by considering both pickup and delivering conditions in the PVRP.

Recently, Baldacci, Mingozzi et al. (2011) confirmed that over the past 30 years, PVRP literature focused primarily on heuristic methods and no exact methods have been proposed so far. The authors stated that the PVRP contains many variants and special cases in terms of objectives or sets of additional constraints, strongly specific to the application area. The Tactical Planning Vehicle Routing Problem (TPVRP) is most closely related to the study in Chapter 4. In its general form, the TPVRP is a strategic model because, in practice, the routes of a solution for a T-day planning period remain unchanged for several months. Only a very few publications can be found in optimization literature on solving the TPVRP (Mourgaya and Vanderbeck 2007; Baldacci, Mingozzi et al. 2011).

A *decomposition* approach was applied to reduce the complexity of the PVRP. Literature confirmed that the PVRP is a multi-level optimization problem (Chao, Golden et al. 1995; Mourgaya and Vanderbeck 2007). Commonly, three levels are defined. Firstly, allowable visit combinations should be assigned to each “customer”. In the second level vehicles are assigned to routes, i.e. a classical vehicle routing problem (VRP). Thirdly, the classical Travelling Salesman Problem (TSP) remains to be solved at daily decision level. Mourgaya and Vanderbeck (2007) applied a comparable approach as described in Chapter 4 by ignoring the third problem level of the PVRP too. The authors confirmed that problem-specific criteria are usually more important in the eyes of the practitioners than solving the classical third level for the PVRP in literature. The authors stated that the emphasis for PVRP problems in practice should be primarily directed on the first level such that the remaining VRP and TSP problems at the levels two and three are easier to solve.

In contrast to the studies in Chapter 2 and 3, the case study in Chapter 4 showed that a loss of information due to *aggregation* can also be very helpful at lower decision levels. Once the *aggregated* supply is assigned to a single collection scheme with fixed collection days, both the VRP and the TSP are considerably easier to solve. Total supply within each cluster is known in advance and can be assigned to available vehicle capacities. Moreover, after *disaggregation* at the lowest decision level, all suppliers within each cluster share the same collection days which makes the TSP problems considerably easier to solve.

Wider applicability of special ordered sets type 1

From a computational point of view, the first level planning model in Chapter 4 was disappointingly hard to solve by standard solution techniques. Mourgaya and Vanderbeck (2007) confirmed that comparable problems with wide time windows are much harder to solve than problems with very tight time windows. The authors applied a heuristic to solve specific balancing problems at the highest decision level for the PVRP. We focused on the algorithmic side.

Problem specific properties were exploited and incorporated in a non-standard way i.e. an adapted application of Special Ordered Sets type 1 (SOS1) to solve the generated problems exactly. Literature stated that there is a great advantage to be gained in the SOS1 formulation, provided that the variables within the sets have a natural ordering (Williams 1990; Ashford and Daniel 1992). Documentation of modern mathematical programming software states that if there is no ordered relationship among the variables (such that weights cannot be specified or would not be meaningful), other formulations should be used instead of a special ordered sets (ILOG 2009). The background, understanding, and added value of “a natural ordering” remains undiscussed and seems to be based purely on computational experiments (Beale and Tomlin 1970; Williams 1990; Ashford and Daniel 1992; Williams 1993). The aim in Chapter 4 was to understand the potential benefits of the SOS1-concept and, if possible, to find a way that makes their use worthwhile in a broader context. In Chapter 4 we showed that an effective use of the SOS1 solution procedure is not necessarily restricted to problems with supplementary model conditions, i.e. a natural ordering of the variables within the sets.

The applicability of SOS 1 is very common in mathematical programming. As a matter of fact, treating SOS1 restrictions algorithmically, can be applied to all proposed models in the chapters 2, 3, 4 and 5. A notable extension for their use refers to a subset of models in Chapter 5. The gained insight in Chapter 4 was the basis for an efficient use of SOS1 in a *reformulation* approach for a specific class of mixed integer non-linear problems in Chapter 5.

Abandoning the principle of an overriding monetary objective (e.g. total costs), implied that the some problems in Chapter 5 changed into a special class of mixed integer, (0-1) fractional programming problems. Several extensive reviews showed that fractional programming (FP) is an illustrative field in mathematical programming demonstrating the separation between theoretical developments and its applicability in practice (Schaible and Ibaraki 1983; Stancu-Minasian 1999; Schaible and Shi 2004; Stancu-Minasian 2006). From a practical point of view, the focus was directed towards taking advantage of specific problem characteristics and to exploit the structure between two continuous linear models for solving the original mixed integer (0-1) FP problem. As indicated in Chapter 5 we firstly applied a *reformulation* approach to the continuous relaxation of the original, mixed integer non-linear problem. Next, we proved that the SOS1 concept can extend Charnes’ and Cooper’s *reformulation* approach for continuous FP problems to a specific class of mixed integer (0-1) FP problems. We showed that the combination of concepts can solve problems in practice without a loss of computational efficiency.

Although the case in Chapter 5 refers to an industry-specific problem, the study demonstrates that the motivation to solve real-life problems can provide the basis for a new approach that has an added value of its own, even outside the given application area. Other mixed integer (0-1) fractional programming problems containing common (convexity) constraints like (6) in Chapter 5 can be solved by the proposed combination of methods. The solution procedure neither requires an iterative evaluation of a function in commonly applied parametric approaches, nor a special purpose algorithm. The SOS1 branching concept may even be available in modern, state-of-the-art, mathematical programming packages, which contributes to the adaptability of the approach in daily practice. Inevitable application-oriented maintenance in the future will hardly be disturbed by locally developed (special purpose) solution techniques.

6.3.2 Professional relevance and applicability of DSS in practice

From an *applicability* point of view it is paradoxical that Arnott and Pervan (2008) evidenced a trend in which the *professional relevance* and contribution of DSS research is facing a crisis of relevance while on the other hand Entrup (2005) found an opposing interest from practice for commercial, OR-based Advanced Planning Systems (APS). Industrial practice started to demand for APS particularly due to the added functionality of optimization-based decision support (Rudberg and Thulin 2009; Ivert and Jonsson 2010).

The dominant aspect of building models and solving them in optimization-based DSS has been addressed in the previous Section 6.3.1. In this section we pay attention to other aspects, i.e. effective user interfaces and additional modules and tools to analyse the generated solutions beyond the classical sensitivity analysis. Based on the findings in the case studies of Chapter 2, 4 and 5 we believe these aspects are still underestimated or simply viewed as obvious. The importance of these modules for improving the *applicability* and adoption of model-based approaches makes it necessary to pay some attention to these design issues. Following the findings in Chapter 2, 4 and 5, we describe our experiences regarding *i*) user interfaces, and *ii*) simulation and scenario management tools.

User interface

Models may be the dominant component in a model-driven DSS, but the final stage of a modelling process is the analysis, which includes the delivery of solutions in a usable form and to enhance the ability to analyse and understand the problem (Kallrath 2004). In the end, decision-making must be executed by end-users who have the final insight in the problem, know the real constraints and have the ultimate feeling regarding the feasibility of generated plans.

The case studies in Chapter 2, 4 and (particularly) 5 showed that tailored user interfaces are crucial for the *applicability* and adoption of DSS in practice. Within this context it should be mentioned that the case study in Chapter 2 was developed at the time that DSS applications on a PC were just evolving. The developed graphical user interface (GUI) was state of the art at that time and showed the importance of a tailored GUI. The user interfaces for the case studies in Chapter 4 and 5 were built using widely available and more general development tools. The developed user interfaces demonstrated how significant a tailored user interface including a period of testing in practice is for *i*) the communication between system and non-technical specialists, *ii*) integrating new technology into decision-maker's (daily) tasks, *iii*) the elicitation of specific domain knowledge needed to identify and exploit special structures during model construction and/or to take advantage of specific characteristics to solve problems faster and *iv*) the adoption of an automated system in practice. Our experience in the case studies was that using widely available general-purpose development software simplifies the development time of effective user interfaces. However, personalization remains an area that must be addressed.

Nowadays, tools for developing user interfaces are widely available and the continuous growth of visualization tools will benefit the process of solution delivery in model-driven DSS applications. Power and Sharda (2007) confirmed that the goal of making these systems accessible to non-technical specialists implies that the design and capabilities of the user interface are important to the success of the system. According to Kallrath (2004), standard interface-design factors mean that users can quickly adopt new DSS with less training and more confidence. However, while standards are advantageous from a developing point of view, both Kallrath (2004) and Power and Sharda (2007) confirmed that personalization of user interfaces is important and should be addressed by developers and researchers. A high-quality user interface will not guarantee the success of a DSS. However, a poor user interface may be a missed opportunity to test the added value including the *applicability* of the proposed system in real life. It may even be a serious threat for the survival of a DSS. Framinan and Ruiz (2010) even highlighted in their literature review on manufacturing scheduling systems the need to shift the research pattern and increase the investigation on areas such as user interfaces, data management, and other tools and methods for a better design and implementation of manufacturing systems.

In all of the preceding case studies, end-users were actively involved in the development of the (G)UI. Test phases in practice were crucial to spot functional convenience of the complete system for end-users. The effort devoted to personalize the (G)UI and test the DSS for a certain period was of striking importance to make ill-structured domain knowledge more tractable and to exploit semi-structured knowledge and understanding from practice in the process of developing models and solution techniques. Based on our experiences, building blueprints of DSS (i.e. the user interface including all underlying components) in a laboratory environment and restrict feedback from practice to a confrontation of the generated results, is barely sufficient to convince daily practice for the added value of a DSS and to mirror its intended *professional relevance and applicability*. From all case studies we learned that the ultimate way to reduce the tension between descriptive decision-making and the adoption of normative approaches in practice, is to associate blueprints of model-based DSS with a serious period of testing, i.e. shadowing, in a real-life environment. The choice of management to upgrade and revise an existing, customized DSS in Chapter 5 for future decision support in new decision environments may be indicative for the validity, added value and adoption of the developed DSS with all its components in practice.

Simulation and scenario management

Although several types and a variety of overlapping terms are used to identify simulation, we define simulation as an approach for imitating the behaviour of an actual or anticipated physical system (Power and Sharda 2007). The authors give an overview of simulation modules in model-driven DSS either as a dominant or an additional component in DSS and typify simulation as a descriptive tool that can be used for both prediction and exploration of the behaviour of a specific system. Jacobs and Weston (2007) confirmed that simulation will be an increasingly important element of integrated and extended enterprise planning systems. Kallrath (2004) stated the importance of scenario management and typify scenario management tools as a trend to store and analyse multiple solution scenarios such that it benefits the understanding of underlying patterns. Particularly the studies in Chapter 4 and 5 showed that the classical architecture of model-based DSS as described in Chapter 1 (Sprague Jr 1980), should be extended by embedding additional descriptive models, e.g. a simulation module, and profound scenario manager tools.

From a decision support perspective, the main difference between the system in Chapter 2 and those described in the chapters 4 and 5 are the added functionality of simulation and scenario management. Both in Chapter 4 and Chapter 5 simulation is used as an additional descriptive component embedded in the DSS. Simulation modules turned out to be powerful tools *i*) to assist decision-makers in calculating alternative plans and to anticipate on the impact of changes in practice, *ii*) to study the consequences and support the awareness of those changes on threshold values for different indicators, and finally *iii*) to support the assessment of specific actions. Tools for scenario management, i.e. to store, visualize, systematically keeping track of generated solutions, and particularly to combine and analyse different scenarios (e.g. on input settings and generated solutions) were mainly experienced in practice as indispensable tools to support the insight and understanding of the underlying problem. The results of the optimization routine and stored plans of the past by the scenario manager were mostly used as a point of reference to study the impact of any change and/or to obtain alternative (favoured) plans.

The case studies in Chapter 2, 4 and 5 showed that a model-based DSS should not be considered as an optimizer but rather as a tool to ‘optimize’ the insights and performance of decision-makers. The main added value of an optimization module is its ability to foster out-of-the-box thinking and lift decision-making in practice to a higher level. Particularly its integration with simulation and scenario manager is important for real use in practice. Changing “optimal” solutions is necessary in practice. However, simultaneously quantifying the impact of those changes on different (conflicting) indicators is even more important to lift decision-making to a higher level and, in the end, convince decision-makers to adopt systems in practice.

6.3.3 Advanced Planning Systems

Meanwhile the basic concepts of model-based DSS did find their application in commercial software suites, called Advanced Planning Systems (APS). The historical development and market penetration of these systems in Figure 1.1 (see Chapter 1) shows a clear interest from industrial practice for automated decision support. Although APS are viewed in general as an extension of transactional-oriented ERP systems, APS modules originate from many in-house developed DSS that aid planners at various levels in the decision hierarchy (Rudberg and Thulin 2009; Ivert and Jonsson 2010). Starting point for APS modules is to introduce a standardized way of performing planning tasks, i.e. to find an effective architecture for modules that are on the one hand easy to use and maintain, and on the other hand deliver realistic planning results for contemporary practice. Nowadays, modern APS provide generic modules to convert planning tasks into abstract mathematical models (Stadtler, Fleischmann et al. 2012). For the translation of these models into software modules, Stadtler and Kilger (2008) advocate and expect in their book on APS that vendors will provide a similar mathematical modelling language (MPL) for all modules.

The introduction of MPL's for the PC market, as for instance used in the case study of Chapter 2, was indeed a major step forward to simplify the construction of optimization models and allowed for a crucial separation between data and models. However, as indicated in the previous sections, solving real-life problems often requires that problem-specific characteristics are exploited either with respect to modelling and/or solving the related models. Compared to tailored systems like the blueprints in Chapter 2 and 4 and the custom-made DSS in Chapter 5, a potential drawback of standardized and generic (APS) modules may be that problems in practice differ between companies and it might be hard to create generic modules that fit many companies or specific markets, even within the unified framework of today's APS.

A striking observation we experienced in developing model-based DSS is a trend that moves away from generic and easy-to-use modelling languages (MPL) to new generations of mathematical programming suites in which generic MPL's are combined with classical programming languages. This move towards open modular architectures for optimization software was, particularly in the study of Chapter 5, experienced as one of the most convenient developments in MPL-technology. It combines the strengths of two concepts, i.e. a mathematical modelling and a classical programming language, into a single environment. As opposed to a (traditional) modelling language and a (classical) programming language there exists no difference between a modelling statement (e.g. expression of a constraint) and a procedure that actually solves a problem (Ciriani, Colombani et al. 2002; Ciriani, Colombani et al. 2003; Colombani, Daniel et al. 2004). Yunes, Aron et al. (2010) defined the need for more flexibility and efficient model-solver integration as a central trend in the optimization community.

The reached synergy between a generic MPL and a classical programming language enables developers to interlace, for instance, specific data handling, modelling statements, built-in or external solving procedures, predefined or new user-written subroutines in a single environment, all according to the required needs for embedding model-based decision support in real-life environments. For instance, the required interpolation and extrapolation routines for calculating property values in Chapter 5 were conveniently realized by *i*) defining simple and fast executable SQL-commands to retrieve the basic data from any database and *ii*) programming the necessary routines in the same environment. From a developer's point of view, the move (backwards) to programming languages was experienced as extremely convenient and great advantages would have been possible if these architectures had been available at the time that the systems as described in Chapter 2 and 4, were developed.

Based on our experiences, these new architectures provide the required extension of functionality for developers but simultaneously may decrease their general use by a wider audience of less-specialized experts. Extensive support from highly trained modellers remains necessary, which may result in great (consultancy) dependence and spending much time in the development and maintenance of those systems.

6.4 Main conclusions and future research

The first study in this thesis on optimization-based decision support appeared at the time that research in DSS prospered and since its peak in 1994 the exposure of the research field has been in consistent decline. The (name of the field) field may face a crisis of relevance but the question remains: "Is the former added value of an application-oriented research field like optimization-based DSS less important nowadays?"

We believe the opposite holds. Developments in optimization-based DSS will continue, regardless of what name(s) the field is going to appear. Complex and integrated decision-making is for instance still done semi- or completely manually in contemporary (food) processing industry. Many sources in the preceding chapters emphasized the need for developing (integrated) decision models for each planning step in the supply chain planning matrix of Figure 1.2. The current generation of enterprise systems responded to this need and extended information-oriented enterprise systems by offering optimization-based tools as a top layer on transaction-oriented (ERP) systems in so-called Advanced Planning Systems (see Figure 1.1)

This final section aims to look back briefly on the essentials, i.e. to draw some main conclusions, and to look forward on what remains, i.e. to define some directions for future research. We continue to make a distinction between model-building and -solving on the one hand and professional relevance and applicability on the other hand.

Model-building and -solving

As stated earlier, an important issue or tension in an applied research field is the extent to which the academic field leads or follows industrial practice. Based on the studies in the chapters 2 and 3 and the current state of affairs in enterprise systems, we conclude on the one hand that today's APS apply the same (hierarchical) planning approach as in the first case study of this thesis, i.e. by separating planning tasks from scheduling. APS systems do not provide modules for simultaneous planning and scheduling (Stadtler, Fleischmann et al. 2012). On the other hand, many sources from literature argue that both decisions should be made simultaneously, especially in processing industries.

Despite the progress that has been reached to eliminate the main drawback of hierarchical production planning approaches, many of the developed models and methods in literature for simultaneous planning and scheduling are not intended to be generically applicable and/or solvable for problems of realistic sizes. We believe that more industry-specific solutions are needed which try to incorporate specificities of different production environments into models. Starting from our experiences in modelling and solving problems, the key to develop solvable approaches in practice may be *i*) to use knowledge and experience from practice and take advantage of specific characteristics in different problem domains during model-construction, i.e. to find tighter models and stronger (problem-specific) valid inequalities, and/or *ii*) to identify and exploit special problem structures for solving the related models using existing -, novel - , and combined solution techniques.

We conclude that most of the lot-sizing literature addresses (extensions of) problems for discrete manufacturing environments. Although recent reviews on lot-sizing confirm the need for more practical variants of models addressing typical characteristics in processing industries (Jans and Degraeve 2008; Quadt and Kuhn 2008; Clark, Almada-Lobo et al. 2011), we believe it deserves serious consideration to relax the existing focus on optimality for lot-sizing, particularly on lower decision levels. In many production planning models the quality of a plan is historically evaluated by the value of a single objective function in which possibly several terms or criteria (if recognized) are expressed in a monetary unit. In practice, decision-makers on lower decision levels are foremost interested in the generated plans. The quality of these plans is usually not measured in value of the objective function. An extreme orientation towards optimal solutions may carry the risk of ignoring the human nature of multi-objective decision-making. We believe that in many practical situations decision-makers are not infinitely sensitive to changes in the objective value, particularly when the differences become small. Instead, (s)he may intend to include other criteria. To give an example, maximizing the freshness of delivered products may be on the one hand hard to express (efficiently) in a monetary unit, but on the other hand it has to be done at the expense of total production costs, e.g. by splitting lot-sizes.

The chapters 1 and 4 indicate that surprisingly little research has been devoted to issues of coordination and integration between the building blocks “procurement” and “production” in the supply chain planning matrix (SCPM) of Figure 1.2. We do not share the view that a very limited number of required raw materials in processing industries, with relatively low value and reliable lead times, would make procurement unproblematic for this branch of industries. The study in Chapter 4 clearly shows that sourcing needs more attention in processing industries, particularly in push-oriented, inter-organizational supply chains. Based on the findings in Chapter 4, we conclude that the valorisation of raw materials needs additional planning in order to fit the quantities of raw materials at supply level to strict delivery conditions at processing level. Within this context, the study in Chapter 4 should not been considered as an isolated example. Comparable considerations hold for the application area in Chapter 5.

Although the planning model in Chapter 4 enables different partners in a supply chain to sell and/or to source raw materials at more attractive price levels, the proposed approach limits to balancing quantities of material flows between successive links in a supply chain. We believe that the valorisation of raw materials could be improved even more if the composition of raw materials is considered in planning too. From a collection point of view, milk is for instance still viewed as being "just white" but the suitability of different types of milk for various processing operations and the quality of the related final products is strongly affected by changes in supply and the composition of raw milk (Banaszewska, Cruijssen et al. 2013). Taking the composition of raw materials for collection problems in food industry into consideration may imply that further research on the class of Periodic Vehicle Routing Problems (PVRP) should focus on a close integration between the Tactical Planning Vehicle Routing Problem (TPVRP) and the related Vehicle Routing problem (VRP) problems.

It should be mentioned that the interrelated impact of processing operations including the composition of materials flows on the properties and quality of final products is even more obvious in the application area of Chapter 5. The latter enhances the need for additional research on a closer integration and coordination between procurement and production.

In Chapter 4 we focused on an alternative algorithmic implementation of Special Ordered Sets type 1 (SOS1). In Chapter 5 we proved that the SOS1 concept can extend a classical *reformulation* approach for continuous fractional programming (FP) problems, to a more general class of mixed integer (0-1) FP problems. Based on our findings we conclude, in contrast to literature, that a natural ordering of the variables within the sets is not necessary to make their use worthwhile. We believe that the necessity of a separate (user defined) reference row or weights associated to the variables in the sets may be omitted for an effective use of the SOS1 branching scheme. In Chapter 4 we applied a problem specific procedure for (re-)ordering the variables within the sets which resulted in substantial computational advantages. Re-ordering the variables within the sets, solely on their continuous value in each node of the search tree might be a promising option to generalize the concept to an effective and broader use in mathematical programming software. This requires, however, further research and extensive computational tests.

Professional relevance and applicability of optimization-based DSS

Attention in OR literature was, and to a certain extent still is, focused on developing models and algorithms and its use is supposed to be a distinctive step in the decision-making process. However, the final stage in decision processes includes the delivery and analysis of the generated solutions in a usable form. We believe that an important contribution in bridging the gap between theory and practice is to recognize and combine the strong elements of normative models in optimization-based decision support (i.e. what practice ought to do) with descriptive decision-making (i.e. what practice actually does), such that systems arise that provide in what practice should and can do.

Within the context of complex decision-making we foremost conclude that optimization mainly fosters out-of-the-box thinking. The integration of (normative) optimization with (descriptive) simulation and scenario management in a single environment provides a valuable combination of tools for successive questioning, to clarify available options and to obtain a greater understanding of what is possible in practice. In addition, customization and personalization should be addressed for the adoption of DSS in practice.

Finding the right balance between generic models and solution techniques in APS on the one hand and tailored DSS for specific (problems in) industries on the other hand, may be a major challenge for the future, particularly for decision support on lower hierarchical levels. Within the latter context it is remarkable that despite of the industrial interest for APS, almost no systematic research has been conducted regarding adoption, implementation, usage and/or failures of APS in practice (Lin, Hwang et al. 2007; Wiers 2009; Ivert and Jonsson 2010; Ivert 2012). We believe it is crucial to examine the requirements of industries and develop either industry-specific solutions (Entrup 2005), and/or open architectures that allow for industry-specific approaches.

More real-life case studies will contribute to get insights and understanding of the strong and weak aspects of APS systems including the needs from industrial practice. In their book on APS, Stadtler, Fleischmann et al. (2012) confirmed this view by their statement "*New findings in research and good business practices should find their way into future developments of APS*".

Summary

Samenvatting

References

Summary

Nowadays, efficient planning of material flows within and between supply chains is of vital importance and has become one of the most challenging problems for decision support in practice. The tremendous progress in hard- and software of the past decades was an important gateway for developing computerized systems that are able to support decision making on different levels within enterprises. The history of such systems started in 1971 when the concept of Decision Support Systems (DSS) emerged. Over the years, the field of DSS has evolved into a broad variety of directions. The described research in this thesis limits to the category of model-driven or optimization-based DSS.

Simultaneously with the emergence of DSS, software vendors recognized the high potentials of available data and developed Enterprise Systems to standardize planning problems. Meanwhile, information oriented systems like MRP and its successors are extended by the basic concepts of optimization based decision support. These systems are called Advanced Planning Systems (APS). The main focus of APS is to support decision making at different stages or phases in the material flow, i.e. from procurement, production, distribution to sales (horizontal-axis), on different hierarchical aggregation levels (vertical-axis) ranging from strategic (long-term) to operational (short-term) planning. This framework of building blocks decomposes planning tasks hierarchically into partial planning problems. This basic architecture of the planning processes in APS is known as the *Supply Chain Planning Matrix* (SCPM).

Compared to, for instance, discrete parts manufacturing, planning tasks are much more complicated in processing industries due to a natural variation in the composition of raw materials, the impact of processing operations on properties of material flows, sequence dependent change-over times, the inevitable decline in quality of product flows and relatively low margins. These specific characteristics gave rise to focus on optimization-based decision support in the domain of processing industries. The problems to be addressed in this field call for (inter-related) decisions with respect to the required raw materials, the production quantities to be manufactured, the efficient use of available resources, and the times at which raw materials must be available.

Although different APS modules can interact directly, coordination and integration is often restricted to the exchange of data flows between different modules. Given the need for specific integrated decision support, the research presented in this thesis focusses particularly on medium to short term decision support at production stage in processing industry, including the vertical and horizontal integration and coordination with adjacent building blocks in the SCPM.

Extensive reviews from literature show that the gap between research and practice of DSS is widening. As the field of DSS was initiated as an application oriented discipline, the strategy of what is referred to as “*application-driven theory*” was taken as the preferred approach for this thesis. “Application-driven” refers to a bottom-up approach which means that the relevance of the research should both be initiated and

obtained from practice. The intended successful use of the proposed approaches should, where possible, be represented by tests of adequacy. Simultaneously, the contribution to "theory" aims to be a recognizable part of the research effort, i.e. obtained understanding and insights from problems in practice should provide the basis for new approaches. Based on the preceding considerations we defined the following general research objective:

General research objective

To support medium- to short term planning problems by optimization-based models and solution techniques such that:

i) *The applicability and added value of (prototype) systems is recognized and carried by decision makers in practice*
ii) *The proposed approaches contribute to knowledge, understanding and insights from a model building and – solving point of view.*

In order to link the general objective with the different studies in the thesis, we defined five, recurring research premises, i.e. *Professional relevance and applicability* (P1)*, Aggregation* (P2)*, Decomposition and reformulation* (P3)*, Vertical integration at production level* (P4)*, and Horizontal coordination and integration* (P5)*.*

The overarching premise P1 refers to the first part of the research objective. All other premises refer to the second part of the research objective, i.e. *model building and/or – solving*. Several planning issues are studied to give substance to the research objective and each study is connected to at least two research premises.

Study 1**: **Planning and scheduling in food processing industry

The main question in Chapter 2 was:" *How to apply aggregation, decomposition and reformulation in model-based DSS at planning and scheduling level such that the aspect of decision support is recognized and appreciated by decision makers in practice, and which level of aggregation is needed to integrate production planning (i.e. lot-sizing) and scheduling problems in a single model?*

The study consists of two parts. The first part of the study refers to a case study for the bottleneck packaging facilities of a large dairy company. The goal was to develop, implement and test a pilot DSS which was able to deliver solutions recognized and carried by decision makers at lower decision levels. The latter aim implied that a straight-forward *aggregation* on time, product type, resources or product stage, was not preferred. The key to develop an approach for regular use was to identify and take advantage of specific problem characteristics. Clustering of numerous jobs, while retaining information at order level, could be exploited in a *reformulation* approach. The inclusion of (combined) generalized- and variable upper bound constraints gave very tight lower bounds and sparse search trees.

An extensive test phase in daily practice showed that the main benefit of the DSS was the initial quality of the generated plans including the time needed to generate these schedules. Hence, decision makers could *i)* postpone their planning tasks, *ii)* conveniently cope with rush orders or planned maintenance and *iii)* easily generate alternatives or revised plans when unforeseen disturbances occur. Moreover, the graphical presentation and overview of the (future) working schedule enabled order acceptance to make use of remaining capacity.

The study also showed that planning problems in practice cannot be captured exhaustively by a (simplified) model. Decision makers need the opportunity to modify automatically generated plans manually and use human judgement and experience such that the solution is tuned to the actual situation. Hence, the DSS should not be considered as an optimizer but rather as a tool for generating high quality plans to be used for further analysis. Within this context the various options of a user-friendly, graphical, and fully interactive user interface, were of major importance.

Although the case study clearly demonstrates the validity of earlier case based DSS research for current days APS, the proposed approach is hardly a generic solution for a complete *vertical integration* between lot-sizing and scheduling. If lot-size decisions are strongly affected by the sequence of jobs, production planning and scheduling should be performed simultaneously.

As the described case refers to an earlier study and today's APS do not provide modules for integrated lot-sizing and scheduling, the second part of the study gives an overview of developments in literature regarding lot-sizing and scheduling models and assess their suitability for addressing sequence-dependent setups, non-triangular setups and product decay. The review shows a tendency in which so-called Big Bucket (BB) models are currently proposed for short term time horizons too. However, we argue that segmentation of the planning horizon is a key issue for simultaneous lot-sizing and scheduling. The advantage of BB models may become a major obstacle for *i*) the effectiveness of simultaneous lot-sizing and scheduling, and *ii*) addressing specific characteristics in food processing industry.

Study 2: Vertical integration of lot-sizing and scheduling in food processing industry

Chapter 3 focused on a complete integration of lot-sizing and scheduling decisions in a single model. The main question was:" *How to integrate production planning (i.e. lot-sizing) and scheduling problems in a single model, such that common assumptions regarding the triangular setup conditions are relaxed and issues of product decay and limited shelf lives are taken into account?"*

The literature research in Chapter 2 revealed that the computational advantage of time oriented *aggregation* in BB models may become a major obstacle in addressing the identified characteristics in FPI. In addition, product decay is primarily associated with the "age" of products and consequently relates to the segmentation of the time-horizon. Therefore, two SB models are developed to demonstrate the impact of non-triangular setups and product decay on the generated solutions. Small scale examples were used to demonstrate how a small change in the balance between inventory - and changeover costs may generate significantly different solutions, especially when the triangular setup conditions do not hold.

The developed models are potentially very large formulations and, as expected, hard to solve. Exploratory research was conducted with a Relax-and-Fix (R&F) heuristic. The heuristic is based on a *decomposition* of the time horizon. Numerical results of small to medium sized problem instances are promising. However, solving real-size problem instances is not possible yet.

Study 3: Integrated planning between procurement and production

The case study in Chapter 4 focussed on the need for *horizontal coordination and integration* between the phases procurement and production, which is of particular importance in inter-organizational supply chains. The main question was:" *How to model and solve an integrated planning problem between procurement and production, both on a mid-term and short-term planning level, in an inter-organizational supply chain?* The research question was projected on an illustrative milk collection problem in practice.

The aim was to develop a pilot DSS that lifted decision support for a "weaker" partner in a food supply chain to a higher level, and to illustrate the importance of *horizontal integration* between the phases procurement and production in an APS framework.

Problem analysis revealed that the problem can be classified as an extension of the Periodic Vehicle Routing Problem (PVRP). The problem was *decomposed* into more tractable sub problems on different hierarchical levels, i.e. the daily (vehicle) routing problem was separated from a medium-term planning problem. On the higher planning level, numerous suppliers were *aggregated* such that total supply within a cluster met (multiple) vehicle loading capacities. The continuous supply of relatively small amounts from many suppliers had to be balanced with strict delivery conditions at processing level. A model was developed to assign a single (stable) collection rhythm to each cluster such that the total, weighted deviation of desired processing levels on various days in the planning horizon was minimized.

The applied *aggregation* on the higher planning level turned out to be very beneficial for the required disaggregation at the lower planning level. Once supplier farms were geographically grouped into clusters and the aggregated supply within a cluster was assigned to a single collection rhythm with fixed collection days, the (initial) daily routing problem was considerably easier to solve for vehicle schedulers.

The computational complexity of the problem was reduced by exploiting application-based properties algorithmically in a specific branch-and-bound scheme, i.e.

a customized approach of Special Ordered Sets type 1 (SOS1) This approach made it possible to solve the generated problems exactly for real-size problem instances.

The various facilities of a user-friendly and interactive man-machine interface (i.e. an input, planning, simulation and analysing module) turned out to be essential. Decision makers could easily change the data, and the generated plans, in a separate simulation module. However, the impact of any modification was immediately visualised by several (conflicting) indicators in the output screens, both on supply and demand level.

***Study 4**: Mixed Integer (0-1) Fractional Programming in Paper Production Industry*

The study in Chapter 5 focussed on the impact of technical settings of production units on material flows. The main question was:" *How to support decision-makers in practice if crucial properties of end products simultaneously depend on (endogenous) types of raw materials with different chemical or physical properties and (endogenous) technical settings of processing units?*

The goal of the study was to revise and upgrade an existing, locally used DSS, to a tailored and flexible tool for decision support within the enterprise. The study revealed that the aimed extension towards multi-objective decision support, together with new physical insight for calculating properties of end products due to process operations, had a substantial impact on the optimization module.

The proposed solution procedure takes advantage of the problem characteristics and gives rise *i*) to apply and extend a classical *reformulation* approach for continuous linear fractional programming (FP) problems to a more general class of mixed integer (binary) FP problems and *ii*) to exploit the special structure between the original non-linear mixed integer model and the continuous, linear *reformulation* by applying the concept of Special Ordered Sets type 1 (SOS1).

Although Chapter 5 focusses in particular on the *reformulation* and solution approach, the DSS consists of four main building blocks, i.e. the user interface, a scenario manager, a simulation- and optimization routine. The optimization module provides a powerful tool to find feasible solutions and the best (unexpected) recipes for any available set of raw materials. Moreover, it provides an innovative way of decision support for purchasing (new) pulps on the market, for assigning available pulps to different paper grades, and for attuning available stock levels of raw materials to (changing) production targets for different paper grades. The results of the optimization routine are mainly used to obtain alternative recipes for different paper grades. Usually, these recipes are stored as base scenarios and adapted to daily practice in the simulation module.

Main conclusions and future research

Based on the studies in the Chapters 2 and 3 we conclude that no generically applicable models and/or solution approaches exist for simultaneous planning and scheduling in processing industries. More industry-specific solutions are needed incorporating specificities of different production environments into those models. The key to develop solvable approaches for contemporary practice may be *i*) to use knowledge and experience from practice and take advantage of specific characteristics in different problem domains during model construction, and/or *ii*) to identify and exploit special problem structures for solving the related models.

We conclude that surprisingly little research has been devoted to issues of coordination and integration between “procurement” and “production”. The studies in the chapters 4 and 5 confirm that sourcing of (raw) materials flows needs more attention in processing industries, particularly in push-oriented, inter-organizational networks. The valorisation of raw materials can be improved even more if the composition of raw materials is considered too in future planning problems at production level.

In the second part of this thesis we focused on extensions for the applicability of Special Ordered Sets type 1 (SOS1), both from an algorithmic (Chapter 4) and modelling (Chapter 5) point of view. We conclude that the concept of SOS1 can extend a classical *reformulation* approach for continuous fractional programming (FP) problems, to a specific class of mixed integer (0-1) FP problems. Moreover, we conclude that a natural ordering of the variables within the sets is not necessary to make their use worthwhile. A separate (user defined) reference row or weights associated to the variables in the sets might be omitted for an efficient use of SOS1 in commercially available mathematical programming packages. However, this requires further research and extensive computational tests.

Samenvatting

Het efficiënt plannen van goederenstromen binnen en tussen logistieke netwerken is uitgegroeid tot een van de grootste uitdagingen voor beslissingsondersteuning in de dagelijkse praktijk. De enorme vooruitgang in hard- en software van de laatste decennia heeft de ontwikkeling van software modules voor beslissingsondersteuning op verschillende niveaus binnen ondernemingen in een stroomversnelling gebracht. De oorsprong van dergelijke systemen dateert uit 1971 toen het concept van "*Decision Support Systems*" (DSS), ofwel beslissingsondersteunende systemen, werd geïntroduceerd. Sindsdien heeft het onderzoeksveld van DSS zich in tal van richtingen ontwikkeld. Het onderzoek in deze dissertatie beperkt zich tot de categorie van modelgestuurde, of op de optimalisering gebaseerde, systemen.

Gelijktijdig met het ontstaan van DSS onderkenden softwareverkopers de mogelijkheden die de beschikbare gegevens boden en ontwikkelden bedrijfssystemen om planningproblemen te standaardiseren. Intussen werden informatie-georiënteerde systemen als MRP en de daaraan gerelateerde opvolgers uitgebreid met de basisbeginselen van beslissingsondersteuning gebaseerd op optimaliseringsmodellen. Deze systemen worden "*Advanced Planning Systems*" (APS) genoemd. APS richten zich met name op de toepassing van wiskundige technieken uit de besliskunde voor het modelleren en kwantitatief ondersteunen van besluitvormingsprocessen in bedrijven. Hiertoe werd een raamwerk van bouwstenen gedefinieerd waarin twee dimensies worden onderscheiden. Op de horizontale as worden verschillende fasen in de goederenstroom onderscheiden, d.w.z. van inkoop, productie, distributie tot verkoop. Op de verticale as worden verschillende hiërarchische beslissingsniveaus onderscheiden, variërend van strategische (lange termijn) tot operationele (korte termijn) besluitvorming. Dit raamwerk van bouwstenen verdeelt planningstaken in deelproblemen en staat ook wel bekend als de "*Supply Chain Planning Matrix*" (SCPM), ofwel de goederenstroom-planningsmatrix.

Planningstaken zijn in de procesindustrie veelal gecompliceerder dan in, bijvoorbeeld, de stukgoedindustrie. Het verschil in complexiteit wordt onder andere veroorzaakt door de natuurlijke variatie in de samenstelling van grondstoffen, het effect van (chemische) bewerkingen op de eigenschappen van (half)producten, volgorde-afhankelijke omsteltijden, de onvermijdelijke kwaliteitsachteruitgang van materiaal-stromen en de relatief lage marges op eindproducten. Planningsproblemen in dit veld vragen om (onderling samenhangende) beslissingen met betrekking tot de benodigde (hoeveelheden) van verschillende grondstoffen, de te produceren hoeveelheden, het efficiënt gebruik van beschikbare hulpbronnen, alsmede de tijdstippen waarop grondstoffen beschikbaar moeten zijn.

Ofschoon interactie tussen verschillende APS modules mogelijk is, blijven coördinatie en integratie veelal beperkt tot het uitwisselen van data. Gezien de behoefte aan geïntegreerde beslissingsondersteuning richt het onderzoek in dit proefschrift zich vooral op de ondersteuning van middellange- tot kortetermijnbeslissingen in de productiefase voor de procesindustrie, inclusief de verticale en horizontale integratie met aangrenzende bouwstenen in de SCPM.

Uitgebreide literatuuroverzichten laten zien dat de kloof tussen het onderzoek en de praktijk van DSS steeds breder wordt. Juist omdat onderzoek naar DSS een toepassingsgerichte discipline beoogt te zijn, werd Cooper's concept van "Applications driven theory", ofwel toepassingsgedreven theorievorming, als uitgangspunt gehanteerd voor dit proefschrift. "Toepassingsgedreven" verwijst naar een bottom-up benadering, hetgeen betekent dat de relevantie van het onderzoek wordt ontleend aan en getoetst in concrete praktijksituaties. Tegelijkertijd beoogt de bijdrage aan de "theorie" van de besliskunde een herkenbaar deel van de onderzoeksinspanning te zijn. Begrip van en inzicht in praktijkproblemen moeten de basis vormen voor nieuwe benaderingen. Gebaseerd op de voorgaande overweging is de volgende onderzoeksdoelstelling gedefinieerd:

Algemeen onderzoeksdoel

Het ondersteunen van middellange- tot kortetermijnplanningsproblemen met modellen en oplossingstechnieken die zijn gebaseerd op de OR (Operations Research), zodanig dat:

- *i) De toepasbaarheid en toegevoegde waarde van (prototype) systemen wordt herkend en gedragen door beslissers in de praktijk,*
- *ii) De voorgestelde benaderingen bijdragen aan kennis, begrip en inzicht in het bouwen van modellen en het oplossen van de gegenereerde problemen.*

Om het breed gedefinieerde onderzoeksdoel met de beschreven studies in dit proefschrift te verbinden, zijn een vijftal uitgangspunten gedefinieerd, te weten: *professionele relevantie en toepasbaarheid* (P1), *aggregatie* (P2), *decompositie* en *herformulering* (P3), *verticale integratie* op productieniveau (P4) en *horizontale coördinatie en integratie* (P5).

Het overkoepelend uitgangspunt P1 refereert aan het eerste deel van het onderzoeksdoel. Alle andere uitgangspunten hebben betrekking op het tweede deel van de onderzoeksdoelstelling. Verschillende planningsproblemen uit de SCPM zijn bestudeerd, waarbij elk onderzoek met tenminste twee van de gedefinieerde uitgangspunten is geassocieerd.

Studie 1: Planning en roostering in de voedingsmiddelenindustrie

De hoofdvraag in hoofdstuk 2 was: "Hoe kunnen *aggregatie*, *decompositie* en *herformulering* worden toegepast op plannings- en roosteringsproblemen, zodanig dat de toegevoegde waarde van modelgebaseerde beslissingsondersteuning in de praktijk wordt herkend en gedragen, en welk *aggregatieniveau* is nodig om productieplanning (d.w.z. seriegrootteplanning) en roostering in één enkel model te integreren?"

De studie omvat twee delen. Het eerste deel verwijst naar een casus uit de praktijk voor de planning en roostering van verpakkingsfaciliteiten op de productieafdeling van een grote zuivelfabrikant. Het doel was een blauwdruk DSS te ontwikkelen, te implementeren en te testen waarmee de praktijk in staat zou zijn om oplossingen te genereren die door beslissers op lagere beslissingsniveaus werden herkend en gedragen. Deze laatste doelstelling impliceerde dat rechttoe rechtaan *aggregatie* naar tijd, producttype, beschikbare productiefaciliteiten en/of productiestadium niet de voorkeur had. Het antwoord voor het ontwikkelen van een werkbare aanpak voor regelmatig gebruik was om casus gebonden probleemkarakteristieken te identificeren en tijdens de modelvorming uit te buiten. Het gericht clusteren van grote aantallen orders, zonder dat daarbij informatie op orderniveau verloren ging, kon worden benut in een *herformuleringsaanpak* waardoor een combinatie van zogenaamde “Generalized- and Variable Upper Bound constraints” (GUB, VUB) in de modelvormingsfase bereikbaar werd. De aanpak leidde tot zeer strakke ondergrenzen in een gangbare, impliciete aftelmethode en ijle zoekbomen.

Een uitgebreide testfase in de praktijk liet zien dat de constante kwaliteit van de gegenereerde oplossingen gecombineerd met de vereiste rekentijd die nodig was om de startoplossingen te genereren, het grootste voordeel van het DSS waren. Beslissers konden daardoor *i*) hun planningstaken uitstellen, *ii*) gemakkelijker omgaan met spoedorders of gepland onderhoud, en *iii*) eenvoudig alternatieven genereren dan wel de opgestelde plannen herzien wanneer zich onvoorziene verstoringen voordeden. Bovendien stelde de grafische weergave en het overzicht van het (toekomstige) werkplan de afdeling orderacceptatie in staat om restcapaciteit beter te benutten.

Het onderzoek toonde ook aan dat planningsproblemen uit de praktijk niet volledig in een (vereenvoudigd) model beschreven kunnen worden. Beslissers hebben behoefte aan mogelijkheden om automatisch gegenereerde planningen aan te passen ten einde menselijk inzicht en ervaring aan te wenden voor afstemming op de feitelijke situatie. Het DSS moet derhalve niet worden beschouwd als een optimalisatie gereedschap in de meest letterlijke zin van het woord, maar veeleer als hulpmiddel om kwalitatief hoogwaardige (start)oplossingen te genereren voor aanvullende analyse. De verschillende hulpmiddelen in een gebruikersvriendelijk, grafisch en volledig interactief gebruikersinterface waren daarbij van groot belang.

Ofschoon het belang van eerder casus-gebaseerd DSS-onderzoek voor huidige APS systemen overduidelijk wordt aantoond in de eerste twee hoofdstukken, is de voorgestelde aanpak in hoofdstuk 2 nauwelijks een algemene oplossing voor de beoogde verticale integratie tussen seriegrootte- en roosteringsproblemen. Als beslissingen over seriegroottes sterk worden beïnvloed door de productievolgorde van de geplande series is integratie van productieplanning en roostering noodzakelijk.

Aangezien de beschreven casus in hoofdstuk 2 betrekking heeft op een eerdere studie en de huidige APS niet in modules voorzien voor geïntegreerde seriegrootte-bepaling en roostering, richt het tweede deel van de studie in hoofdstuk 2 zich op een literatuuronderzoek naar modelontwikkelingen voor simultane seriegroottebepaling en roostering. Voorts beoogt de studie de geschiktheid van modellen te evalueren ten aanzien van volgorde afhankelijke omstellingen, omstelmatrices waarvoor de driehoeks-voorwaarden niet gelden, en de bederfelijkheid van geproduceerde producten. Het onderzoek toont een tendens aan waarin middellangetermijn modellen, zogenaamde "Big Bucket models" (BB), ook worden voorgesteld voor problemen met een kortetermijn planningshorizon. Wij betogen echter dat de segmentatie van de planningshorizon (i.e. het *aggregatieniveau* in de tijdshorizon) cruciaal is voor simultane seriegroottebepaling en roostering. Het voordeel van BB modellen kan een groot obstakel vormen voor *i*) de effectiviteit van simultane seriegrootteplanning en roostering, en *ii*) het aanpakken van specifieke probleem karakteristieken uit de voedingsmiddelenindustrie.

Studie 2: Verticale integratie van seriegrootteproblemen en roostering in de voedingsmiddelenindustrie.

Hoofdstuk 3 is gericht op volledige integratie van seriegrootteproblemen en roostering in één enkel model. De hoofdvraag was: *"Hoe kunnen productieplanning (d.w.z. planning van seriegroottes) en roostering in één enkel model worden opgenomen, zodanig dat de gebruikelijke aannames over de driehoeksongelijkheden worden losgelaten en de bederfelijkheid en beperkte houdbaarheid van producten modelmatig worden mee-genomen?"*

Het literatuuroverzicht in hoofdstuk 2 bracht aan het licht dat het rekentechnische voordeel van tijdsgeoriënteerde *aggregatie* in BB modellen een groot struikelblok kan vormen voor het aanpakken van de vermelde probleemkarakteristieken in de voedingsmiddelenindustrie. Bederfelijkheid is primair geassocieerd met de "leeftijd" van producten, en is bijgevolg gerelateerd aan de segmentatie van de tijdshorizon. Derhalve zijn twee SB modellen ontwikkeld. Deze modellen laten zien welk effect zowel bederfelijkheid als het loslaten van de driehoeksvoorwaarden[1] hebben op de gegenereerde oplossingen. Aan de hand van illustratieve voorbeelden wordt duidelijk hoe kleine veranderingen in de balans tussen voorraad- en omstelkosten tot wezenlijk verschillende oplossingen kunnen leiden. Dit laatste geldt vooral als de driehoeks-ongelijkheden niet gelden.

De ontwikkelde modellen kunnen in een praktische context tot zeer grote problemen leiden, en zijn – zoals verwacht – uiterst moeilijk oplosbaar. Een verkennend onderzoek werd verricht met een Relax-and-Fix (R&F) heuristiek. De heuristiek is gebaseerd op een *decompositie* van de tijdshorizon. De numerieke resultaten van kleine tot middelgrote problemen zijn bemoedigend. Het is echter nog niet mogelijk om problemen van realistische probleemomvang op te lossen.

[1] De driehoeksvoorwaarden beschrijven de aanname dat de totale omstelkosten en -tijden tussen twee achtereenvolgende productieseries voor verschillende producten niet toe-nemen door een derde product tussen betreffende productiehoeveelheden te produceren.

Studie 3: Geïntegreerde planning tussen verwerving en verwerking.

De casus in hoofdstuk 4 richt zich op de noodzaak tot *horizontale coördinatie en integratie* tussen de verwerving en verwerking van de grondstoffen tot eindproducten. Deze integratie is van bijzonder belang voor situaties waarin de interactie tussen verschillende productieketens centraal staat. De hoofdvraag was: *"Hoe kan de integratie van een planningsprobleem voor de verwerving en verwerking van grondstoffen in een logistieke keten die uit meerdere partijen (i.e. coöperaties) bestaat, zowel op het niveau van korte- als middellangetermijn worden gemodelleerd en opgelost?* De casus betrof een melkophaalprobleem.

Het doel was wederom een blauwdruk DSS te ontwikkelen dat beslissingsondersteuning voor een "zwakkere" ketenpartner naar een hoger niveau kon tillen. Voorts beoogt de studie te illustreren hoe belangrijk *horizontale integratie* tussen de fasen verwerving en verwerking in een APS raamwerk is.

De probleemanalyse toonde aan dat het probleem kan worden geclassificeerd als een uitbreiding van het zogenaamde "Periodic Vehicle Routing Problem" (PVRP). Via *decompositie* naar hiërarchische niveaus ontstonden beter oplosbare deelproblemen. Het dagelijks routeringsvraagstuk werd daarmee gescheiden van een middellangetermijn planningsprobleem. Op het hoogste planningsniveau werden de talrijke leveranciers *geaggregeerd* tot clusters zodanig dat het totale aanbod van melk binnen een cluster de maximale transportcapaciteit van (meerdere) vrachtwagens benaderde. De continue productie van relatief kleine hoeveelheden melk door vele leveranciers moest in balans worden gebracht met strikte aflevercondities op verwerkingsniveau. Een model werd ontwikkeld voor het toewijzen van één enkel (stabiel) ophaalschema aan elk cluster, zodanig dat de totale gewogen afwijking van de gewenste hoeveelheden op diverse verwerkingslocaties op verschillende dagen in de planningshorizon zo laag mogelijk was.

De toegepaste *aggregatie* op het hogere planningsniveau bleek van grote waarde te zijn voor de uiteindelijke disaggregatie op het laagste planningsniveau. Nadat alle toeleverende bedrijven geografisch waren geclusterd en het *geaggregeerde* aanbod van melk aan één schema (per cluster) met vaste ophaaldagen was gekoppeld werd het dagelijkse routeringsvraagstuk aanzienlijk eenvoudiger op te lossen voor de planners.

De rekentechnische complexiteit van het probleem kon worden gereduceerd door specifieke eigenschappen van de casus algoritmisch te gebruiken voor de ontwikkeling van een (specifiek) branch-and-bound schema. Hierdoor werd het mogelijk om problemen van realistische omvang exact op te lossen.

De verschillende functionaliteiten die via een gebruikersvriendelijk en interactief gebruikersinterface werden aangereikt (i.e. een invoer-, plannings-, simulatie- en analysemodule) bleken essentieel te zijn. In de simulatiemodule konden eindgebruikers bijvoorbeeld eenvoudig zowel de data als de gegenereerde planningen veranderen. Via de uitvoerschermen werd het effect van zulke veranderingen direct zichtbaar gemaakt via diverse (veelal conflicterende) indicatoren.

Studie 4: Gemengd geheeltallige (binaire) fractionele programmering in de papierindustrie.

Het onderzoek in hoofdstuk 5 concentreert zich op het effect van machine-instellingen op goederenstromen. De hoofdvraag was: *"Hoe kunnen beslissers in de praktijk worden ondersteund als cruciale eigenschappen van eindproducten gelijktijdig afhangen van (te bepalen) typen grondstoffen met verschillende chemische en fysische eigenschappen en van (te bepalen) instellingen van procesbewerkingseenheden in een productie-proces?"*

Het doel van het onderzoek was om een bestaand, lokaal gebruikt DSS door te ontwikkelen tot een flexibel instrument voor beslissingsondersteuning binnen de onderneming. Het onderzoek bracht aan het licht dat de beoogde flexibiliteit in doelstellingsfuncties voor de mathematische programmering, gecombineerd met nieuwe fysische inzichten voor het berekenen van eindproducteigenschappen na procesbewerkingen, een aanzienlijk effect had op de optimaliseringsmodule.

De voorgestelde methode om deze categorie van niet-lineaire probleem op te lossen maakt gebruik van probleemkarakteristieken en leidt ertoe dat een klassieke *herformulerings*aanpak voor de continue lineaire fractionele programmering (FP) – na uitbreiding – ook kan worden toegepast op een meer algemene klasse van gemengd-geheeltallige (binaire) FP-problemen. De speciale samenhang tussen het oorspronkelijke, niet-lineaire, gemengd-geheeltallige model en de continue, lineaire *herformulering* werd benut door gebruik te maken van Special Ordered Sets type 1 (SOS1).

Ofschoon hoofdstuk 5 zich met name richt op de *herformulering*s- en oplossingsaanpak bestaat het DSS uit vier bouwstenen, namelijk het gebruikers-interface, een scenario manager, een simulatie- en een optimaliseringsmodule. De optimalisatiemodule voorziet in een krachtig hulpmiddel voor het zoeken naar toegelaten oplossingen en de beste (onverwachte) recepturen voor elke beschikbare verzameling van grondstoffen. Bovendien biedt de module op innovatieve wijze ondersteuning bij de besluitvorming over de aankoop van (nieuwe) pulpsoorten, voor het toewijzen van beschikbare pulpsoorten aan diverse papiersoorten, en voor het afstemmen van beschikbare grondstofvoorraden op (veranderende) productiedoelen. De resultaten van de optimalisatieroutine worden vooral gebruikt om alternatieve recepturen te genereren. Gewoonlijk worden deze recepturen als basis-scenario's bewaard en in de simulatiemodule afgestemd op de dagelijkse praktijk.

Voornaamste conclusies en toekomstig onderzoek

Op basis van het onderzoek in de hoofdstukken 2 en 3 concluderen we dat geen algemeen toepasbare modellen en/of oplossingstechnieken bestaan voor simultaan plannen en roosteren in de procesindustrie. Meer industrie-specifieke oplossingen zijn nodig die de specifieke kenmerken van verschillende productieomgevingen in die modellen opnemen. De sleutel tot het ontwerp van effectieve oplossingen voor de hedendaagse praktijk zou kunnen zijn *i*) het gebruik van praktijkkennis en -ervaring en het benutten van domeinspecifieke probleemeigenschappen tijdens het bouwen van het model, en/of *ii*) het identificeren en benutten van speciale probleemstructuren.

We concluderen dat opvallend weinig onderzoek is gewijd aan de coördinatie en integratie tussen de verwerving en verwerking van grondstoffen. De studies in hoofdstuk 4 en 5 bevestigen dat planningsproblemen met betrekking tot het verwerven van grondstoffen in de procesindustrie meer aandacht verdienen, met name in “push”-georiënteerde logistieke netwerken waarbij de interactie tussen verschillende productieketens van belang is. De verwaarding van grondstoffen kan nog verder worden verbeterd indien bij productieplanningsproblemen ook de samenstelling van de grondstoffen in beschouwing wordt genomen.

In het tweede deel van dit proefschrift richtten we ons op begrip en inzicht in, alsmede de uitbreiding van, de toepasbaarheid van Special Ordered Sets type 1 (SOS1), zowel vanuit algoritmisch (hoofdstuk 4) als vanuit modelmatig oogpunt (hoofdstuk 5). We concluderen dat met SOS1 een klassieke *herformuleringsaanpak* voor continue fractionele programmeringsproblemen kan worden uitgebreid tot een klasse van gemengd-geheeltallige (binaire) FP-problemen. Bovendien concluderen we dat het gebruik van SOS1 ook zonder een natuurlijke ordening van de variabelen binnen de sets rekentechnisch interessant is. Voor een efficiënt gebruik van SOS1 in commerciële software voor de mathematische programmering zou de door de gebuiker te definiëren referentierij kunnen vervallen. Dit laatste vereist echter nader onderzoek en uitgebreide rekentests.

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