DOKUZ EYLÜL UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

PLANNING AND SCHEDULING IN SUPPLY CHAIN ENVIRONMENT WITHIN PROCESS INDUSTRY

by
Çağrı SEL

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İZMİR

PLANNING AND SCHEDULING IN SUPPLY CHAIN ENVIRONMENT WITHIN PROCESS INDUSTRY

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Ph.D. THESIS EXAMINATION RESULT FORM

We have read the thesis entitled **"PLANNING AND SCHEDULING IN SUPPLY CHAIN ENVIRONMENT WITHIN PROCESS INDUSTRY"** completed by **Çağrı SEL** under supervision of **Assoc. Prof. Dr. Bilge BİLGEN** and we certify that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Doctor of Philosophy.

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PLANNING AND SCHEDULING IN SUPPLY CHAIN ENVIRONMENT WITHIN PROCESS INDUSTRY

ABSTRACT

Process manufacturing is common in the food, beverage, chemical, pharmaceutical and consumer packaged goods industries. There is a continuous stream of input materials and output products. The structural characteristics of the process industry are sequence dependent setup times, high changeover costs, numerous flavored and colored product types with the complicated changeover rules, limited shelf life restricting the storage duration and delivery conditions for each perishable raw material, intermediate and final product. In this environment, efficient planning and scheduling of the supply chain is of vital importance and has become one of the most challenging problems in practice.

This dissertation concerns planning and scheduling problems in the process industry. The main goal is to develop mathematical formulations of the supply chain problems. In this thesis, the characteristics of the process industry are analyzed. The major trends and research opportunities are explored from the existing literature. The existing models in the literature do not address many realistic aspects of the planning and scheduling problems in the process industry. Starting from this point of view, a production and distribution problem is studied in the soft drink industry. A mixed-integer linear programming model is introduced and, due to the high complexity in production and distribution structure, a hybrid solution methodology is developed to solve the realistic problems.

The operational scheduling represents the realization of tactical planning decisions in operational level. Having created a plan for defining the production tasks has to be sequenced ensures that the planning activities are indeed applicable. The integration of planning and scheduling can be an effective way to make more applicable decisions. Accordingly, a production and distribution problem is studied in the dairy industry. A mixed-integer linear programming formulation is introduced to integrate tactical planning and operational scheduling decisions and, a heuristic approach is proposed to decompose the different time buckets of the decisions.

In real life, intermediates are more perishable than final products. The final products can survive for long shelf life periods, but the lifetimes of the intermediates are only restricted with several hours. The perishability should not be only included in inventory level or shelf life of final products, it should also be realized that the perishability limits the intermediate storage and affects run-lengths of production. A scheduling problem is studied in the make-and-pack production process. A stochastic mixed-integer linear programming model is introduced to schedule the production. A simulation of the production process is introduced to evaluate the proposed production schedule in terms of the production waste, mostly caused by the variability in lifetime of intermediates.

In summary, the industry specific characteristics, incorporation of the decision levels providing interrelated feedbacks to each other and perishability issues are recent challenges confronted by the process industry. These challenges require specific models to support decision making in supply chain. In response, this thesis develops mathematical models and optimization approaches applicable to different processes industries and can easily be modified for process specific operating conditions.

Keywords: Supply chain management, process industry, planning, scheduling, mixed-integer linear programming, stochastic programming, constraint programming, simulation

PROSES ENDÜSTRİSİ KAPSAMINDA TEDARİK ZİNCİRİNDE PLANLAMA VE ÇİZELGELEME

ÖZ

Proses tipi üretim, gıda, içecek, kimya ve tüketici ürünleri endüstrilerinde yaygın olarak karşımıza çıkmaktadır. Girdi malzemelerinin ve çıkan ürünlerin sürekli akışı söz konusudur. Proses endüstrisinin yapısal karakteristiği, sıra bağımlı hazırlık sürelerine, yüksek kalıp değiştirme maliyetlerine, karmaşık kalıp değiştirme kurallarına, değişik tatlarda ve renklerde ürün tiplerine, hammadde, yarımamül ve nihai ürün bazında stokta bulundurma sürelerini ve teslim şartlarını etkileyen kısıtlı raf ömrüne sahip olmasıdır. Bu ortamda, etkin tedarik zincirinin etkin planlanması ve çizelgelenmesi hayati öneme sahiptir ve uygulamada zor problemlerden biri haline gelmiştir.

Bu tez proses endüstrisinde planlama ve çizelgeleme problemleri ile ilgilenmektedir. Ana hedef tedarik zinciri problemlerinin matematiksel formülasyonlarının geliştirilmesidir. Tezde, proses endüstrisinin karakteristikleri araştırılmıştır. Eğilimler ve araştırma fırsatları mevcut literatürden faydalanılarak ortaya çıkarılmıştır. Literatürde yer alan modeller proses endüstrisindeki gerçekçi yönlerden birçoğunu göz ardı etmektedir. Bu bakış açısından yola çıkarak, alkolsüz içecek endüstrisinde bir üretim ve dağıtım planlama problemi çalışılmıştır. Bir karışık tamsayılı programlama modeli geliştirilmiş. Üretim ve dağıtım yapısındaki karmaşıklık sebebiyle gerçekçi problemleri çözmek için bir melez çözüm yöntemi önerilmiştir.

Operasyonel çizelgeleme taktiksel planlama kararlarının gerçekleşmesini temsil etmektedir. Çizelgelenmesi gereken üretim görevlerinin belirlenmesi için bir planın ortaya konulması alsında planlama kararlarının uygulanabilirliğini göstermektedir. Bu doğrultuda, süt ve süt ürünleri endüstrisinde bir üretim dağıtım problemi çalışılmıştır. Taktiksel planlama ve operasyonel çizelgeleme kararlarını bir araya getiren bir karma tamsayılı programlama modeli ve bu kararları farklı zaman aralıklarına ayıran bir sezgisel yöntem geliştirilmiştir.

Gerçek hayatta, yarımamüller nihai ürünlerden daha kolay bozulabilmektedir. Nihai ürünler daha uzun raf ömrü süresince sağlam kalabilmektedirler, fakat yarımamüllerin ömürleri yalnızca birkaç saat ile sınırlıdır. Bozulabilirlik yalnızca envanter seviyesinde değil aynı zamanda üretim süresini ve yarımamüllerin stokta bulundurma süresini kısıtlaması açısından da ele alınmalıdır. Yap-paketle üretim sürecinde bir çizelgeleme problemi çalışılmıştır. Üretimin çizelgelenmesi için bir stokastik karma tamsayılı programlama modeli geliştirilmiştir. Önerilen çizelgenin çoğunlukla yarımamüllerin ömürlerindeki değişkenlikten kaynaklanan üretim israfı açısından değerlendirilmesi için bir benzetim modeli geliştirilmiştir.

Özetle, endüstriye has bu karakteristikler, birbirleri ile ilişkili geri-besleme sağlayan karar seviyelerinin birleştirilmesi ve bozulabilirlik konuları proses endüstrisinde karşılaşılan yeni zorluklardır. Bu zorluklar tedarik zincirindeki kararları desteklemesi açısından özel modeller gerektirmektedir. Bunun üzerinde, bu tez farklı proses endüstrilerinde de uygulanabilir matematiksel modeller ve eniyileme yöntemleri geliştirmektedir ve sürece özgü farklı operasyon şartları için kolayca düzenlenebilmektedir.

Anahtar kelimeler: Tedarik zinciri yönetimi, proses endüstrisi, planlama, çizelgeleme, karma tamsayılı doğrusal programlama, stokastik programlama, kısıt programlama, benzetim

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CHAPTER ONE
INTRODUCTION

1.1 Introduction to the Field of Research

In the production environment, there are two distinct types of manufacturing systems. These are discrete and continuous manufacturing systems. The discrete manufacturing systems involve a certain number of product batches. In continuous production, there is a continuous stream of input materials and output products. The continuous manufacturing industries have typically products such as foods, drugs, petroleum, and chemicals. Other, the discrete manufacturing industry is quite diverse and includes automotive industry, appliances industry (Kreipl and Pinedo, 2004). Planning and scheduling in continuous manufacturing often deal with the issues differing from discrete manufacturing by means of product and process characteristics.

Product characteristics: The continuous manufacturing systems are well-known as process industries. In the process industry, multiple intermediate products are produced by a few production recipes and then converted into great types of different finished goods. To avoid contamination of the products, the product dependent cleaning, sterilizing, re-tuning issues arise in processing units. Perishability issues of intermediate and final products restrict their production run-lengths, storage durations and delivery conditions.

Process characteristics: The continuous manufacturing basically involves two fundamental production stages. The first is a make-stage including such operations as processing, milling or mixing. Taking in raw milk, mixing with the required ingredients (e.g., culture, fruit) to produce yoghurt or ice-cream and, transportation using pipes or vessels is the dairy production operations can be evaluated in the make-stage. The second is a pack-stage consisting of finishing, converting or packaging operations. Filling into cups and packaging with parallel packaging lines can be evaluated in the pack-stage.

Planning and scheduling of continuous manufacturing systems should encompass these characteristics together and, requires specific models to support decision making in process industries (Kallrath 2002, 2005). The dairy and the soft-drink are process industry examples and, offer a real-life make-and-pack production problems. Whereas many research has been carried out to investigate the planning and scheduling problems in the literature, there is still need on research taking into account the mentioned unique characteristics of the process industries (see Chapter2).

1.2 Research Objectives

The overall objective of this research is to obtain insights planning and scheduling decisions by developing decision support models and solution approaches that can address the inherent characteristics of process industry. The research will focus on four main research objectives and studies:

Research objective 1: *Searching the major research opportunities and trends on production planning and scheduling problems encountered in the process industry?*

A literature review is introduced to provide a critical review on quantitative supply chain models within the dairy industry. A number of problem variants are investigated in terms of solution approaches, problem and model characteristics, decision levels. Through the analysis of the literature review, a framework is developed for the existing literature to reveal problem characteristics, major trends, explore research opportunities and give several directions for future research

Research objective 2: *Developing a solution approach which can be used as decision aids under consideration of uncertain machine failures in the production allocation and distribution planning problem.*

A production and distribution planning problem is studied in the soft drink industry. The problem involves the allocation of production volumes among the different production lines in the manufacturing plants, and the delivery of products to the distribution centers (DCs). A mixed-integer linear programming (MILP) model is developed for the problem. We present a hybrid solution methodology combining simulation and MIP based fix-and-optimize (F&O) heuristic to solve the considered problem. First, MIP based fix-and-relax (F&R), F&O heuristics are proposed. The solution quality and performance of the proposed heuristics are analyzed with the randomly generated demand figures for the three granularity categories and various capacity load scenarios. Computational performances of these heuristic procedures are compared with the standard MIP results. The computational experiments carried out on a large set of instances have shown that the F&O heuristic algorithm provides good quality solutions in a reasonable amount of time. Second, simulation model is introduced to represent the problem with stochastic machine failures. Hybrid methodology combining the MIP based F&O heuristic and simulation model is implemented. The optimization model uses an F&O heuristic to determine the production and delivered quantity. Subsequently the simulation model is applied to capture the uncertainty in the production rate. Numerical studies from the data which have a tight production capacity and high demand granularity demonstrate that the developed hybrid approach is capable of solving real sized instance within a reasonable amount of time and demonstrate the applicability of the proposed approach.

Research objective 3: *Integrating tactical planning and operational scheduling decisions in dairy industry and challenging with bottleneck incubation process in set type yoghurt production.*

An integrated planning and scheduling problem is studied for the set type yoghurt production in dairy industry. A MILP formulation is introduced to integrate tactical and operational decisions and a heuristic approach is proposed to decompose time buckets of the decisions. The decomposition heuristic improves computational efficiency by solving big bucket planning and small bucket scheduling problems. Further, MILP and constraint programming (CP) methodologies are combined with the algorithm to show their complementary strengths. Numerical studies using illustrative data with high demand granularity (i.e., a large number of small-sized customer orders) demonstrate that the proposed decomposition heuristic has consistent results minimizing the total cost (i.e., on average 8.75% gap with the best lower bound value found by MILP) and, the developed hybrid approach is capable of solving real sized instances within a reasonable amount of time (i.e., on average 92% faster than MILP in CPU time).

Research objective 4: *Dealing with perishability issues and uncertainty of quality decay in the make-and-pack production process.*

In food processing, the diversity of products to make and pack restricts productivity due to contamination issues. Moreover, rapid quality decay of intermediates forces organizations to carefully schedule their production. A scheduling problem is studied in the make-and-pack production and, a stochastic MILP model is proposed. The aim of the problem is to find an optimal schedule with minimum makespan (total time needed to finish the daily production) taking into account uncertainty in quality decay. A yoghurt production case is presented to illustrate the typical structure of a two-stage semi-continuous make-and-pack production process. Accordingly, a simulation of the production process is introduced to evaluate the proposed production schedule in terms of product waste. The scenario analysis shows that the proposed schedule results in 62.3% decrease of product waste with only 4.3% increase of makespan.

1.3 Outline of the Thesis

The rest of the dissertation is divided into five chapters. According to the three research questions, the second chapter aims at answering the first research question with a literature review and concludes research directions. To deal with the outstanding research opportunities, the third chapter provide a mathematical model and a solution approach on the production and distribution planning problem, the fourth chapter provide a mathematical model and a solution approach on the integration of planning and scheduling decisions, the fifth chapter introduce a research accounting for perishability issues and uncertainty of quality decay as major trends in the field.

Figure 1.1 summarizes the research framework followed in this PhD thesis. It shows that the studied supply chain problems deal with production and/or distribution activities and planning and scheduling decisions. The literature review in Chapter 2 identifies the problem characteristics and analysis presents the available quantitative models, points out modelling challenges and research opportunities of supply chain problems in process industry. The subsequent chapters (Chapter 3, 4 and 5) focus on developing decision support models defined by research opportunities.

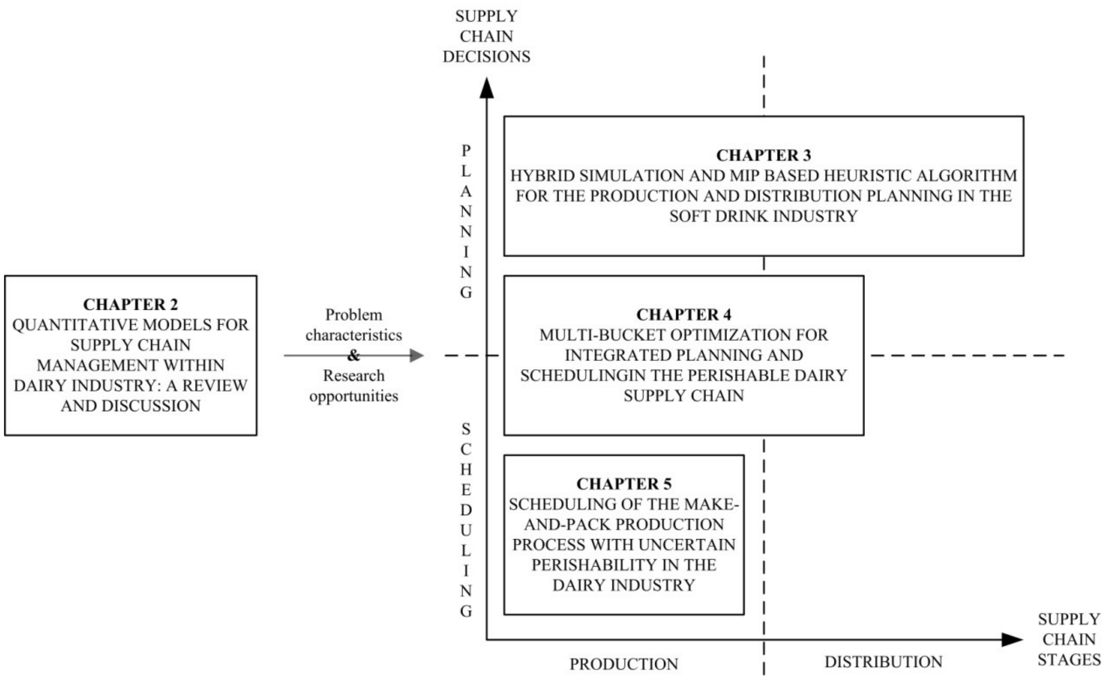

Figure 1.1 Research framework

In the last chapter (i.e., Chapter 6) the conclusions from the conducted studies and general discussion of the results are presented. In addition, limitations of the conducted studies and recommendations on further research are provided.

1.4 Included Publications

This thesis is a collection of four research that all aim at the improvement of planning and scheduling in supply chain environment within process industry. The papers are either published, accepted for publication, or under review for journal publication. The chapters contain the following papers.

Chapter 2: Sel, Ç., and Bilgen, B. (2014). Quantitative models for supply chain management within dairy industry: a review and discussion. European Journal of Industrial Engineering, In press.

Chapter 3: Sel, Ç., and Bilgen, B. (2014). Hybrid simulation and MIP based heuristic algorithm for the production and distribution planning in the soft drink industry. Journal of Manufacturing Systems, 33 (3), 385-399.

Chapter 4: Sel, Ç., Bilgen, B., Bloemhof-Ruwaard, J. M., & van der Vorst, J. G. A. J. (2015). Multi-bucket Optimization for Integrated Planning and Scheduling in the Perishable Dairy Supply Chain. Computers & Chemical Engineering, 77, 59-73.

Chapter 5: Sel, Ç., Bilgen, B., and J. M. Bloemhof-Ruwaard. (2015). Scheduling of the Make-and-Pack Production Process with Uncertain Perishability in the Dairy Industry. (Submitted to an International Journal)

CHAPTER TWO
QUANTITATIVE MODELS FOR SUPPLY CHAIN MANAGEMENT WITHIN DAIRY INDUSTRY: A REVIEW AND DISCUSSION

2.1 Introduction

Supply chain management (SCM) has become one of the most important strategies for achieving competitive advantage in different industries. During the last three decades, SCM is a common approach with wide range of applications to take an integrated look at closely related procurement, production, storage and distribution processes. Nowadays, more effective planning and control of these processes in supply chains begin to be directed towards food SCM.

The most important fresh food segments are dairy products. Dairy industry is a significant component of many economies, and is a major industry in the most developed and developing economies of the world. Dairy product is the collective name for products milk, cream, yoghurt, kefir, buttermilk, butter, cheese, ice-cream, condensed milk and milk powder. In the literature, these products and manufacturing processes are explained in detail from the primary production of the milk to the following phases by Bylund (1995). The individual products are made through a complex, multi-step process. A typical production process consists of a number of stages such as, receiving materials, mixing and blending according to recipe, processing and packaging. Out of a limited number of raw materials (e.g., raw milk) still a moderate number of intermediate products (e.g., full-fat milk, diet milk, aroma milk) are produced within the processing step. High product complexity typically occurs at the packaging level due to different tastes and customer individual packaging forms (Lütke Entrup, 2005).

The dairy industry is characterized by unique features that differentiate it from the other industries. The specific characteristics of dairy industry are summarized such as high number of products and variants, divergent product structure, complicated setup operations with sequence dependent times having different changeover rules, capital intensive processing equipment, shared resources, identical machines, hygienic factors, multi-stage production process, necessity for lot traceability due to quality and environmental issues, special needs for handling, transportation and storage technologies, and shelf life restriction for raw materials, intermediate products, and final products which has directly influence on wastage, inventory levels and out of stock rates and product preference of the customer (Nakhla, 1995; Lütke Entrup, 2005; Amorim et al., 2011).

Due to the mentioned factors, production planners face a complex task in which a number of constraints have to be met. Deciding which and how much white mass to produce in each tank given the available connections to the filling and packaging lines is a challenging task. The synchronization of production stages is difficult due to the difference between processing and packaging rates and the limitations on intermediate storage. Furthermore, the technical constraints such as cleaning and traceability requirements interfere with the timing and assignment decisions. To these production challenges must be added those for high demand variability. Moreover, in the dairy industry, the challenges associated with demand variability are compounded by the short shelf life of the finished products and relatively long production lead times. These all together make the planning and scheduling of the processing system a challenging task (Kilic, 2011). Besides, transportation is a significant component of total cost for a company where the movement of raw materials or products is required. Major components of the transportation costs include the labor cost of the drivers, the cost of fuel, and the cost of the vehicles. These costs are especially important where perishable products are being transported and specialized handling is required (Butler et al., 2005). It is important nowadays that dairy products must be delivered within allowable delivery times or time-windows.

In this research, based on the characteristics, we review the most relevant and recent literature on the supply chain problems within the dairy industry. The aim is to provide a detailed literature review of previous research on quantitative models addressing a variety of problem types and solution approaches to be subject of production planning, distribution planning and scheduling problems. The research presents a literature review consisting of past reviews and surveys besides the current research articles. Due to the diversity of available publications, the search has to be directed by setting appropriate limits. As for the methodology, we review the peer-reviewed articles published in the English language, proceeding papers, PhD dissertations commonly cited in the literature. Furthermore, we review past reviews and review articles to obtain some related research in addition to corresponding literature.

In this review, we confine ourselves to the production planning and scheduling, distribution planning, and vehicle routing problems (VRPs) within dairy SCM. Inventory models with deteriorating or perishable products have also received considerable attention in the literature. For a complete review on perishable inventory models, the reader is referred to Nahmias (1982), Raafat (1991), Goyal and Giri (2001), Karaesmen et al. (2011) Bakker et al. (2012). Inventory management is a topic beyond the scope of this review.

Since dairy industry is an important part of the food sector, interested readers are referred to following review articles on food, and the agricultural supply chain: Ahumada and Villalobos (2009) reviewing models for the agricultural food business; Akkerman et al. (2010) addressing research done in the field of food distribution where different characteristics are identified as key issues such as quality, safety and sustainability; Tarantilis and Kiranoudis, (2005) and Grunow and Van der Vorst (2010) providing an editorial perspective on food production and SCM; Pahl et al. (2007) focusing on deterioration constraints of production planning, lot sizing and inventory; Amorim et al. (2013c) reviewing the production-distribution planning problems tackling with perishability explicitly; Soysal et al. (2012) reviewing the quantitative models for sustainable food logistics management; Shukla and Jharkharia (2013) providing a state of the art on agri-fresh product SCM.

Dairy industry that is a sub-segment of the food industry shares similar fundamental properties. However, there are several differentiating characteristics: the production is semi- continuous/continuous make-and-pack process operating with shared resources and parallel packaging machines; the setup operations are more complicated with sequence dependent time; there are different changeover rules for not only the products but also the product groups; more critical hygienic factors should be taken into account; a variety of intermediate and final products is produced by a single raw material (e.g., milk). Moreover, dairy shows the highest criticality with regard to very restricted and limited shelf life reflecting not only physical state but also representing whether it is in a saleable condition or not. The main objective of this research is to review existing operations research literature on SCM problems in the dairy industry and to identify the areas where further research is needed. The fundamental motivation for this review comes from the practical significance of the supply chain planning problems in the dairy industry. In the last decade, the literature is replete with publications related to the applications of operations research methodologies to SCM problems within the dairy industry. However, a unified body of literature that deals SCM problems in the dairy industry does not exist yet. To the best of our knowledge, there is no previous literature review particularly focusing on SCM problems in the dairy industry. The main contribution of this review is to fill the perceived gap by providing a comprehensive overview of the current literature on the applications of SCM in the dairy industry.

We have scrutinized the previous reviews, in order to determine the classification criteria. To our knowledge, although there is no review offering assessments especially on dairy supply chain problems, the literature on the food SCM includes many surveys. Various classification schemes are available to categorize the SCM research. Ahumada and Villalobos (2009) classify the reviewed perishable and non-perishable agricultural foods into modelling approaches under the consideration of different planning levels. Akkerman et al. (2010) concentrate on the food distribution by focusing on quality, safety and sustainability. Pahl et al. (2007) present a categorization on perishability, deterioration and classify the articles in terms of material flow along the supply network. Amorim et al. (2013c) categorize production and distribution planning problems by gathering the lot sizing, scheduling, vehicle routing articles into one group. Of all the previously published review literature, the classification scheme used by Amorim et al. (2013c) is the closest one to what we present.

Figure 2.1 presents the factors used to dissect and organize this review. The classification scheme followed presents problem areas along with the solution methodology developed. From the perspective of the problem scope, we divide the research into three main problem types such as production planning and scheduling, vehicle routing and distribution planning, integrated production and distribution planning. In a second level of the classification, we make a further categorization using the particularities of the solution approaches used. The reviewed research is classified by problem types based on solution approaches. The papers are listed as summary tables in the every subsection of the review with the fundamental subdivisions such as perishability, product types, supply chain processes, fictitious data or case study, product stages, solution approach, decision levels, objective function, shelf life, capacity and time constraints, labor and working time restrictions, production overtimes, setups. The supply chain planning matrix developed by Meyr et al. (2002) classifies the planning tasks into two dimensions planning horizon and supply chain processes. The framework presented by Meyr et al. (2002), as seen in Figure 2.2, is used to display the supply chain processes focused on. These processes are highlighted in the figure.

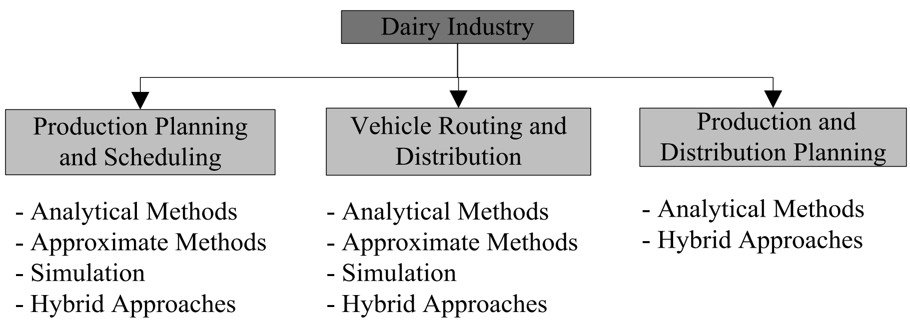

Figure 2.1 Classification scheme

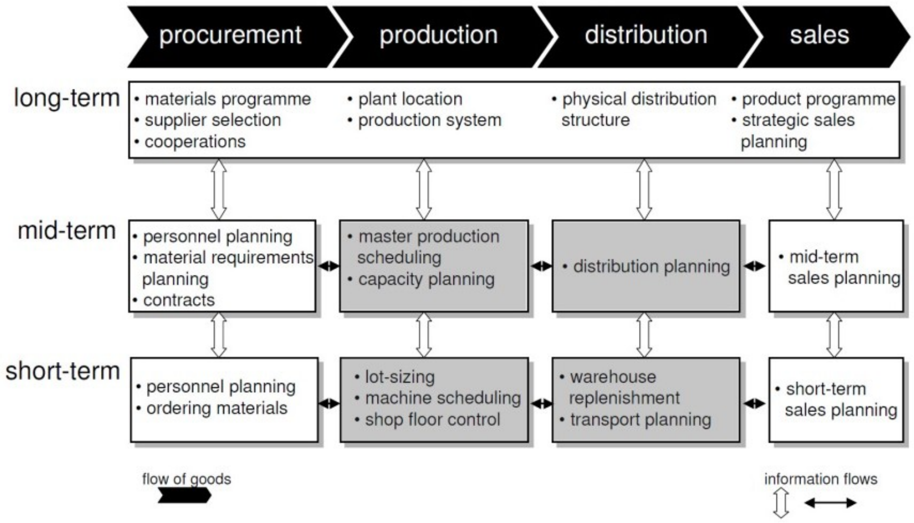

Figure 2.2 Supply chain planning matrix (Meyr et al., 2002)

The remainder of this chapter is organized as follows. In section 2, literature review on quantitative models in the dairy industry is presented with the subsections corresponding with the variety of problem types and solution approaches. In section 3, the chapter ends with conclusions, and possible directions for the future research.

2.2 Quantitative Models in Dairy Industry

In this section, we review quantitative models in the supply chain literature within the dairy industry. The three subsections corresponding to the various problems types arising from the dairy industry are presented with respect to the solution approaches. The covered problem types are: production planning and scheduling; vehicle routing and distribution planning; integrated production and distribution planning problems. The reviewed works are ordered chronologically. They have been classified according to the solution approach proposed.

2.2.1 Production Planning and Scheduling

Production planning and scheduling is crucial for achieving competitive advantage in different industries (Grunder et al., 2013; Hsu et al., 2009). As well, the dairy industry contains various complex optimization problems. Several production planning problems arise from the different processing stages. The individual products are made through a complex, multi-step process. Extra care must be taken to ensure high standards of sanitizations, control of allergens, batch traceability, and product freshness. Due to divergence of the product structure, pressure on product freshness, respecting lot sizing policies, demand variability, synchronizing material consumption among the production stages, the task of planners becomes more complex in the dairy industry. The production environment has several industry-specific characteristics involving traceability requirements, limited production resources, time-dependent and sequence-dependent cleaning of production units. The characteristics together lead to challenging of scheduling problems which require efficient and flexible modelling approaches (Kilic, 2011). In the remainder of this section, we classify the production planning and scheduling research in the dairy industry based on the solution methodologies used. These classifications are analytical methods, approximate methods, simulation and hybrid approaches.

2.2.1.1 Analytical Methods

Pioneering research is done by Sullivan and Secrets (1985), Rutten (1993), and Jakeman (1994) in the field of production planning within the dairy industry. Sullivan and Secrets (1985) design a small optimization based decision support system (DSS) for production planning and inventory forecasting of dairy industry and they implement it to a real world application. The designed milk flow analysis program is prepared as an interactive and user-friendly primal linear programming (LP) model. Rutten (1993) considers the operational level planning problem in a process industry producing milk replacer. The considered problem is handled with a hierarchical approach decomposing the large problem into two sub-problems, which can be solved using an LP approach. The objective is to minimize the total costs of raw materials. They develop a DSS operating in an acceptable solution time. Jakeman (1994) discusses a knowledge based production management system using modelling techniques, handling industry specific issues of food production and providing expert information to assist operators and production management to make decisions in complex production operating environments. The proposed system is applied to practical applications of ice cream and yoghurt production. A case study is presented on yoghurt production process by taking into account various important specific restrictions. The knowledge based production management system yields interesting results in improving efficiency and understanding plant operations. This is the first fundamental research considering the incubation process incorporated into the filling and packaging.

Until recently, the use of optimization based techniques for the production planning problem in the dairy industry has received little attention in the operations research literature. Lütke Entrup et al. (2004) and Lütke Entrup et al. (2005b) consider shelf life issues for integrated production planning and scheduling problem in an industrial case of stirred type of yoghurt within the dairy industry. The focus is particularly on the filling and packaging stages of the production process. The MILP models are based on the principle of block planning and combination of a discrete and a continuous time representation. The objective function is maximization of the contribution margin considering revenues and variable costs. Both of the papers take into account a shelf life dependent pricing component, sequence independent setups and cleaning time. While Lütke Entrup et al. (2005b) consider the planning periods based on the production day, Lütke Entrup et al. (2004) present a position based planning model. As an extension of the both research, Lütke Entrup et al. (2005a) develop several block programming MILP models for the same industrial case of yoghurt production. These are standard models with day bounds, setup conservation allowing the overnight production and position based splitting the planning horizon up into consecutive enumerated positions. The models aim at the maximization of the contribution margin taking into account shelf life integrated price component. However, the MILP models focus on flavoring and packaging stages. Thus, operations involving the processing and storage of products are neglected. The improvement of the position based model, integration of the fermentation process into the planning procedure and incorporation of uncertainty are presented as the future directions of the research.

Bongers and Bakker (2006) introduce a multi-stage scheduling model derived from a medium size ice cream manufacturer. The model handles a simplified process consisting of only one pasteurization and packaging process. The solutions of the model are achieved using commercial scheduling software. Later, Subbiah and Engell (2009) and Subbiah and Engell (2010) study on the same case which is considered by Bongers and Bakker (2006). While Subbiah and Engell (2009) demonstrate an application of the timed automata (TA) based approach to the problem of scheduling batch processes with resources subject to sequence dependent changeovers, Subbiah and Engell (2010) describe the application of the TA based approach to model and solve batch scheduling problems, which are subject to sequence dependent changeovers and limited discrete resources with the objective of makespan minimization.

Doganis and Sarimveis (2007) propose an MILP model for production scheduling in yoghurt industry. The model considers the sequencing limitations, sequence dependent changeover times and costs in addition to standard constraints encountered in the production scheduling such as material balances, inventory limitations, machinery capacity, labor shifts and manpower restrictions. The objective of the proposed MILP model is only minimization of all major sources of variable costs such as setup, inventory and labor costs. However the model is limited to the single production line. Doganis and Sarimveis (2008) extend their previous research by presenting a customized MILP model to optimize yoghurt packaging lines consisting of multiple parallel machines where actions have to be synchronized across all machines due to common feeding line. The proposed model decides the produced quantities of each product at each machine, the starting and finishing time for the production of each item in each machine, the total machine utilizations including changeover times, the inventory levels at the end of the day with the given data of the demand during the scheduling horizon. The model incorporates sequence dependent setup costs and times, the cleaning task at the end of the day, multiple intermediate due dates, job mixing and splitting, product specific machine speed, and minimum lot sizes. The performance of the proposed model is illustrated through its application to the yoghurt production plant of a leading dairy product manufacturing company. Doganis and Sarimveis (2009) address a new MILP model that combines the advantages of the models presented by Doganis and Sarimveis (2007) and

Doganis and Sarimveis (2008). They integrate the production constraints, management directives with the proposed model. The shelf life restriction is not only considered in the constraints to keep stable the remaining shelf life on the production process, but also in the objective function in which there is a penalization to control the freshness on delivery. The number and sizes of lots are not limited and the total production time is limited by the available machine time. The objective of the MILP model is a minimization function involving setup, storage, machine utilization, overtime labor costs and a term for marketability loss.

Environmental considerations are taken into account by a number of researchers in the dairy industry. Stefanis et al. (1997) consider environmental conditions in the optimal design and scheduling of batch/semi-continuous processes and present examples from the cheese production process. They use life cycle analysis based methodology within general multi-objective formulation consisting of process economics and environmental impact. The process of interest is investigated to evaluate environmental impact with a set of metrics such as air, water pollution, global warming. Vaklieva-Bancheva and Kirilova (2010) focus on both the environmental consideration and the choice of the production recipes for the products within the scheduling framework. They propose a mathematical formulation to solve the multi-objective optimization problems for a special class of schedules. These papers contribute to the literature in terms of the consideration of environmental issues as well as design and scheduling within the dairy industry.

Wang et al. (2010) take into consider the determination of buffer capacity in dairy filling and packaging lines. They use the transient analysis method to analyze the performance of the filling and packing system using Bernoulli two-machine model. They also perform sensitivity analysis on larger buffer capacity, higher filling station throughput, and initial inventory buildup. The performance parameters of the system are production rate, work in process during transients, necessary extra time of filling station, operating, blockage and starvation times of filling and packaging stations.

Jang and Klein (2011) consider business-to-customer and business-to-business aspects of an agricultural supply chain model motivated by the needs of a local dairy farm. They present an optimization model using mathematical modelling techniques. They study on the strategic planning issue by forming cooperative agreements, deciding the size of cooperative, and defining the production quantities. The research differentiates from the literature by dealing with business-to-customer and business-to-business aspects on strategic level decisions of dairy industry.

Guan and Philpott (2011) develop a multi-stage stochastic programming model taking into account uncertainty and a linear price–demand curve to solve the production planning problem in the dairy industry. In addition, they analyze sales policy by a multi-stage stochastic quadratic model using a decomposition algorithm. This is the only work that takes into account uncertainty and dynamic policies in dairy SCM.

Kopanos et al. (2009, 2010a) study on the lot sizing and scheduling problem in a multi-product yoghurt production line of a real life plant. A mixed discrete/continuous time MILP model is proposed. The problem under question is mainly focused on the packaging stage, whereas timing and capacity constraints are imposed with respect to the pasteurization, homogenization and fermentation stage. Sequence dependent setup times and costs are explicitly taken into account and optimized by the proposed framework. However, the scheduling problem they consider only involves the packaging stage. Kopanos et al. (2011a), present a MILP framework for the resource constrained production planning problem in a semi-continuous food process, similar to the dairy industry. Quantitative as well as qualitative optimization goals are included in the proposed model. Renewable resource limitations are appropriately taken into account. All of the above mentioned works are related to the single stage production systems in the dairy industry. Kopanos et al. (2011b) present a novel MILP formulation and solution strategy to address the challenging production scheduling problems in the multi-product, multi-stage dairy industry. The main features of the proposed approach rely on the integrated production stages, and the inclusion of strong valid integer cuts favoring shorter computational times. In a paper by Kopanos et al. (2012b), the MILP model developed by Kopanos et al. (2011b) is further enhanced by introducing new sets of tightening constraints in order to improve computational efficiency in industrial size scheduling problems in food industry. Both of the papers consider production scheduling problem in a real world multi-stage food processing industry with the limited shelf life of intermediate mixes in the aging stage.

Amorim et al. (2013a, 2014) investigate the production planning problem with a different point of view from the existent literature. While Amorim et al. (2013a) assess the suitability of financial risk measures for mitigating crucial risks in the production planning of perishable goods, Amorim et al. (2014) consider the influence of customer purchasing behavior on the production planning of perishable goods. The paper presented by Amorim et al. (2013a) goes beyond the literature considering risk management within dairy supply chain. They explore the tradeoff between expected profits and risk under perishable nature of goods by developing risk-averse production planning model. The model is developed as a stochastic programming model. In this model, they asses the sustainability of financial risk measures and consider uncertainty in the demand level, decay rates and customer purchasing behavior. They present deterministic and stochastic mathematical models accounting consumer purchasing behavior. The impact of customer purchasing behavior is investigated by the influence of the age dependent demand, and the effect of faithfully representing product quality risk in the model. Investigation of demand uncertainty under risk management perspective is highlighted as a promising area. Apart from these, Amorim et al. (2013b) focus on lot sizing and scheduling decisions of the production process consisting of multi-product and multi-parallel lines with complex setup structure. They analyze the performance of existent and well identified formulations in the literature for small bucket and big bucket capacitated lot sizing and scheduling problems.

Recently, Kilic et al. (2013) and Banaszewska et al. (2013) take into account blending and intermediate production stages besides the final production stage. Kilic et al. (2013) consider a capacitated intermediate product selection and blending problem which is a two-stage production system. They focus on a baker industry example but the model is applicable with small modifications to the dairy industry. They introduce a MILP model and give scenario based analysis. Banaszewska et al. (2013) present a comprehensive dairy valorization model for mid-term allocation of raw milk to final products and production planning. They present a MILP model that allocates raw milk to the most profitable dairy products by taking into account recipes, composition variations, dairy production interdependencies, seasonality, demand, supply, capacities, and transportation flows. They also analyze the effect of seasonality for milk valorization.

2.2.1.2 Approximate Methods

Nakhla (1995) expresses the increasing need for flexibility due to rising logistical demands as the result of the change in the market conditions for food processing companies. The problem arises from a yoghurt production process being a specific dairy product industry. A rule-based scheduling approach is introduced for packaging lines.

Vaklieva et al. (2005) consider a multi-objective optimization problem analyzing the trade-off between plant profit and environmental impacts in curds manufacturing process of a dairy industry. They use a genetic algorithm (GA) technique as a solution approach to find the conditions leading to the best compromise between both objectives taking into account the effect of the amount and composition of processed milk, processing unit's assignment and number of processed batches. The paper presents a salient research contribution by considering the amount and composition of processed milk and inherent losses in addition to production constraints.

Marinelli et al. (2007) present a real capacitated lot sizing and scheduling problem with parallel machines and shared buffers in a packaging company producing yoghurt. The discrete mathematical planning model aims at minimizing the setup, storage and processing costs. As a solution methodology, they propose a two-stage heuristic based on the decomposition of the problem into lot sizing on tanks and scheduling on lines. In order to obtain the lower bounds, the proposed model formulation is relaxed in five ways, while the upper bound value is calculated with the two-stage optimization heuristic consisting of a nested local search framework. In the computational efforts, the data is generated with the two different scenarios for the dedicated and general purpose lines. The proposed two-stage heuristic is very effective and produces near optimal solutions within very short computational times. However, it is assumed that the production rate is fixed by a single bottleneck stage, setup time, and setup cost are sequence independent.

Banerjee et al. (2008) consider the planning and scheduling of milk food processing process. They propose a hybrid meta-heuristic approach based on a multi-objective Bee Colony algorithm combined with the constructive rough set heuristics. They also present a case study on process scheduling of a milk production centre.

Gellert et al. (2011) consider an integrated sequencing and scheduling problem of filling lines in the dairy industry. The fundamental focus is to sequencing and scheduling of dairy industry production process under consideration of cleaning and sterilizing issues. They introduce an application of the general sequencing and scheduling framework. They utilize a GA for the sequencing by incorporating a problem specific algorithm for the fixed sequence scheduling. They also propose the sub-optimal greedy and optimal shortest path algorithms. The aim is to find a production plan consisting of a processing order or sequence, and a feasible schedule, which minimizes the makespan. This research differentiates itself from the literature in the sense that it focuses on the scheduling under consideration of cleaning and sterilizing issues.

In a recent study, Van Elzakker et al. (2012) present a new MILP scheduling model and algorithm for the scheduling in the fast moving consumer goods industry. A problem specific formulation is used since the efficiency of the model is crucial to be able to address larger cases. They focus on the ice cream production process of parallel mixing and parallel packing lines. The objective is the minimization of the makespan. An algorithm is proposed to tackle with the periodic cleaning characteristic of the production process. The proposed model is evaluated based on the ice cream scheduling case study presented by Bongers and Bakker (2006).

2.2.1.3 Simulation

Kuriyan et al. (1987) present a preliminary research using simulation to solve the scheduling problem in the dairy industry. In this research, production schedules are generated by using efficient sub-optimal algorithms and the performance of the algorithms are evaluated by using simulation package. The use of a simulation approach is a research direction which has a gap on the production planning and scheduling application area in the dairy industry.

2.2.1.4 Hybrid Approaches

Claassen and Van Beek (1993) develop and implement a pilot DSS to solve a planning and scheduling problem for the packaging line which is the most bottleneck process of the cheese production of a large dairy company. They handle the problem for both tactical and operational control levels. On the operational control level, the sequence of packaging lines is identified with the sequence dependent setup times by an asymmetric travelling salesman heuristic solution approach and the sequence of jobs is determined by logical rules. On the tactical level, an MILP model is introduced to determine the feasible and daily master production schedule.

The research papers stated below contribute to the literature using a seminal solution approach to incorporate environmental considerations in the scheduling problems. Berlin et al. (2007) present a method to calculate the sequence of yoghurt products to minimize milk waste of yoghurt production. The goal of the research is to find a practical method to calculate a sequence of a great number of cultured products. Furthermore, they design a method which describes an interdisciplinary approach incorporating a heuristic sequencing approach fundamentally based on the production rules, constraints with the life cycle assessment methodology. They take into account the environmental impact and economic aspects simultaneously, by combining environmental systems analysis and production scheduling. As an extension of previous research, Berlin and Sonesson (2008) present an application of the proposed method to minimize the waste caused by a sequence for a given set of products and to calculate the environmental impact of a waste in the dairy industry. The environmental impact of the proposed sequences is calculated with a detailed scheduling model and life cycle assestment method.

Adonyi et al. (2009) consider the short-term flow shop scheduling problem in the dairy industry. They propose two distinct approaches aiming at makespan minimization. First, they introduce an s-graph representation and apply the branch and bound technique. Second, they introduce integer programming (IP) formulation and apply the basic GA as a solution technique.

Amorim et al. (2011) present multi-objective MIP models using block planning approach to solve a lot sizing and scheduling problems considering perishability issues on packaging process of yoghurt production having a fixed shelf life. The setup considerations are handled as sequence dependent for the major setups and sequence independent for the minor setups. The model is analyzed for two distinct scenarios depending on make-to-order and hybrid make-to-order/make-to-stock production systems. The proposed MILP model is hybridized with a non-dominated sorting GA. It differs from the literature by introducing a multi-objective MIP model to solve lot sizing and scheduling problems.

2.2.1.5 Research Directions

To summarize the reviewed literature on production planning and scheduling within the dairy industry, the preliminary research on production planning and scheduling problem presents analytical methods applications and DSSs (Sullivan and Secrets, 1985; Rutten, 1993; Jakeman, 1994). Scheduling problems are initiative research areas (Bongers and Bakker, 2006; Subbiah and Engell, 2009, 2010). They extensively presented as the mathematical modelling applications (Doganis and

Sarimveis, 2007, 2008, 2009; Kopanos et al., 2011a, 2011c, 2012a; Van Elzakker et al., 2012). As well, the integrated production planning and scheduling problems are taken into account with the mathematical modelling applications (Kopanos et al. 2009, 2010a, 2011b; Lütke Entrup et al., 2004; Lütke Entrup et al., 2005a, 2005b). A systematic methodology is used to incorporate environmental considerations in the optimal scheduling and design of batch processes (Stefanis et al., 1997; Vaklieva-Bancheva and Kirilova, 2010). Buffer capacity determination with transient analyses, strategic planning with optimization models and production planning with stochastic programming are other miscellaneous applications (Guan and Philpott, 2011; Jang and Klein, 2011; Wang et al., 2010). The contribution by Guan and Philpott (2011) is the first example that considers stochastic parameters within dairy SCM. Recently, Amorim et al. (2013a, 2014) present research directions considering stochastic parameters by means of two distinct perspectives (e.g., consumer purchasing behavior and risk management).

Although, the perishability and shelf life issues, capacity and time constraints, working time and overtime restrictions, changeover considerations are not explicitly taken into account by pioneering research papers, these problem characteristics have gained attention in recent research. Perishability, consideration of shelf life, sequence dependent setup time, and environmental aspects appear to be the most promising aspects that support the realistic representations.

Approximate methods such as heuristic and metaheuristic methods support the solution efforts by requiring less running times. Whereas research papers using these methods are capable of representing the specific characteristics of dairy industry, capacity and time constraints with working time and overtime restrictions, sequence dependent setup and cleaning times and perishability and shelf life issues are rarely taken into account (Banerjee et al., 2008; Gellert et al., 2011; Marinelli et al., 2007; Nakhla, 1995; Vaklieva et al., 2005).

Kuriyan et al., (1987) is the only paper that applies simulation methodology for the production scheduling in the dairy industry. Simulation applications allow production scheduling to be modeled more realistically.

Some of the preliminary research papers combine heuristics, and exact optimization methods by a DSS (Claassen and Van Beek, 1993). The environmental issues within the production planning are considered with the optimization heuristics for travelling salesman problem and life cycle assessment methodology (Berlin et al., 2007; Berlin and Sonesson, 2008). Integrated production planning and scheduling problem is commonly taken into account by mathematical modelling integrated with heuristic and metaheuristic methods (Adonyi et al., 2009; Amorim et al., 2011). Research papers using hybrid approaches rarely consider some of the specific characteristics of dairy industry. These characteristics are stressed in a recent article by Amorim et al. (2011) within the hybrid approach.

Table 2.1 summarizes the reviewed literature of production planning and scheduling within the dairy industry. The papers are listed in the order presented in the review. For each research, the table illustrates the different characteristics in a systematic manner.

2.2.2 Vehicle Routing and Distribution Planning

The dairy industry is an important part of the food sector, and the attention has been shifted towards faster replenishment and improved logistical performance in addition to the production costs in this industry. The dairy industry is a large-scale industry due to numerous farms, collection centers, manufacturing facilities, DCs and markets. The dairy products are sensitive to environmental conditions and can be affected by rapid changes of environmental conditions. Logistic activities are especially important where dairy products are being transported and specialized handling is required. Furthermore, they show continuous quality changes throughout the supply chain, all the way until final consumption. Hence, in the dairy industry, quality, health, and safety require central consideration and more effort for the routing and distribution planning (Akkerman et al., 2010).

Several authors have previously addressed VRPs arising in the dairy industry. In the remainder of this section, we classify the vehicle routing and distribution research in the dairy industry based on the solution methodologies used. These classifications are analytical methods, approximate methods, simulation, and hybrid approaches.

2.2.2.1 Analytical Methods

Milk collection issues and DSS development are challenging logistics problems that have long been of interest to researchers using analytical methods (Butler et al., 1997; Butler et al., 2005; Claassen and Hendriks, 2007). Butler et al. (1997) consider a symmetric travelling salesman problem applied to milk collection problem in the dairy industry. A number of possible IP formulations are presented and valid cutting plane inequalities are combined with branch and bound method to identify optimal integer solutions. Wide variety of DSS applications appears in the literature. Butler et al. (2005) introduce a DSS based on previous technique to plan milk collection operations and to schedule the routes. They also discuss automatic data capture devices and database management systems to provide effective management. Both of the papers contribute to the literature by providing optimization techniques and introducing efficient DSS for milk collection in the dairy supply chain. Claassen and Hendriks (2007) develop a MILP model to solve a milk collection problem. They propose a DSS generating milk collection plans associated with daily milk collection routes combined with the midterm planned milk demand.

The paper presented by Nicholson et al. (2011) focus on the effects of localization on supply chain costs which are complex to analyze in multi-product, multi-process dairy supply chain. They develop an optimization model to minimize total supply chain costs, including assembly, processing, interplant transportation and final product distribution. The research contributes to the literature by presenting a strategic level transshipment model.

Table 2.1 Summary of production planning and scheduling research

Reviewed Literature	Perish-ability	Product Types	Supply Chain Processes	Fictitious Data / Case Study	Product Stages	Production Stages	Solution Approach	Decision Levels	Objective	Shelf Life	Capacity and Time Constraints	Labor, Working Time, Overtimes	Setups
Analytical Methods													
Sullivan and Secrest (1985)	-	D	PRD	CS	RM-FP	O	LP & DSS	O	S	-	C	-	-
Rutten (1993)	-	D	PRD	CS	RM-IP-FP	O-P	LP & DSS	O	S	-	C	O	-
Jakeman (1994)	-	I-Y	PRD	CS	IP-FP	I-P	OT	O	S	-	-	-	-
Bongers and Bakker (2006)	P	I	PRD	CS	FP	O-P	OT	O	S	SL	CT	-	
Subbiah and Engell (2009)	P	I	PRD	CS	FP	O-P	OT	O	S	SL	CT	-	SD
Subbiah and Engell (2010)	P	I	PRD	CS	FP	O-P	OT	O	S	SL	CT	-	SD
Kopanos et al. (2011a)	P	I	PRD	CS	FP	O-P[MP]	MILP	O	S	SL[IC]	CT	-	P-SD
Kopanos et al. (2011c)	P	I	PRD	CS	FP	O-P[MP]	MILP	O	S	SL[IC]	CT	-	P-SD
Kopanos et al. (2012b)	P	I	PRD	CS	FP	O-P[MP]	MILP	O	S	SL[IC]	CT	-	P-SD
Van Elzakker et al. (2012)	P	I	PRD-STR	CS	IP-FP	O-P[MP]	MILP	O	S	-	CT	-	P-SD
Lütke Entrup et al. (2004)	P	Y[ST]	PRD	CS	FP	F-P[MP]	MILP	O	S	SL[IO]	CT	O	SI
Lütke Entrup et al. (200b)	P	Y[ST]	PRD	CS	FP	F-P[MP]	MILP	O	S	SL[IO]	CT	O	SI
Lütke Entrup et al. (2005a)	P	Y[ST]	PRD	CS	FP	F-P[MP]	MILP	O	S	SL[IO]	CT	O	SI
Doganis and Sarimveis (2007)	-	Y	PRD-STR	CS	FP	P[SP]	MILP	O	S	-	T	-	SD
Doganis and Sarimveis (2008)	-	Y	PRD-STR	CS	FP	P[MP]	MILP	O	S	-	T	-	SD
Doganis and Sarimveis (2009)	P	Y	PRD-STR	CS	FP	P[MP]	MILP	O	S	SL[IO]	T	-	SD
Kopanos et al. (2010)	-	Y	PRD-STR	CS	FP	F-P[MP]	MILP	O	S	-	CT	-	G-SD
Kopanos et al. (2009)	-	Y	PRD-STR	CS	FP	F-P[MP]	MILP	O	S	-	CT	-	G-SD
Kopanos et al. (2011b)	-	Y[SE&ST]	PRD	CS	FP	P[MP]	MILP	O	S	-	CT	-	G-SD & P-SI
Wang, Hu and Li (2010)	-	D	PRD	CS	IP-FP	P	OT	O	M	-	-	-	-
Guan and Philpott (2011)	P	D	PRD-STR-DST	CS	FP	O	SP	O	S	-	C	-	-
Stefanis et al. (1997)	-	C	PRD	CS	RM-IP-FP	O	LCA	O	M	-	CT	-	-
Vaklieva-Bancheva and Kirilova (2010)	-	C	PRD	CS	RM-FP	O	OT	O	M	-	T	-	-
Jang and Klein (2011)	-	D	PRD	CS	FP	-	OT	S	S	-	-	-	-
Amorim et al. (2013a)	P	O-D-Y	PRD-STR	CS	FP	P[MP]	SP	O-T	S	SL[IC]	CT	-	SI
Amorim et al. (2014)	P	O-D-Y	PRD-STR	CS	FP	P[MP]	SP	O-T	S	SL[IC]	CT	-	G-SI & P-SI
Amorim et al. (2013b)	-	O-D-Y	PRD-STR	HY	FP	P[MP]	MILP	O	S	-	CT	-	G-SD & P-SI
Kilic et al. (2013)	-	O-D	PRD-STR	CS	IP-FP	O	MILP	O	S	-	CT	-	SI
Banaszewska et al. (2013)	-	D	PRD	CS	RM-FP	O	MILP	O	S	-	C	-	-
Approximate Methods													
Nakhla (1995)	-	D-Y	PRD	HY	FP	P	HE	O	S	-	-	-	-
Vaklaiva et al. (2005)	-	C	PRD	CS	RM-IP-FP	O	GA	O-T	M	-	-	-	-
Banerjee et al. (2008)	P	D	PRD	CS	FP	O	HE	O	M	-	T	-	-
Marinelli et al. (2007)	-	Y	PRD-STR	CS	FP	P[MP]	MILP-HE	O	S	-	C	-	SI
Gellert et al. (2011)	-	D	PRD	HY	FP	P[SP]	MH	O	S	-	C	-	P-SD
Simulation													
Kuriyan et al. (1987)	-	D-Y	PRD	CS	IP-FP	O-P	SM & HE	O	S	-	-	-	-
Hybrid Approaches													
Claassen and Van Beek (1993)	-	C	PRD	CS	FP	P[MP]	HD[MILP-HE]& DSS	O-T	S	-	-	L-O	SD
Adonyi et al. (2009)	-	D-C	PRD	CS	FP	O	HD[IP-HE] & OT	O	S	-	-	-	-
Amorim et al. (2011)	P	Y	PRD	CS	FP	P[MP]	HD[MILP-MH]	O	M	SL[IO]	T	-	G-SD & P-SI
Berlin et al. (2007)	-	Y	PRD	CS	FP	P	HD[LCA-HE]	O-S	S	-	-	-	-
Berlin and Sonesson (2008)	-	D-Y	PRD	CS	FP	P	HD[LCA-HE]	O-S	S	-	-	-	-

*** Perishability**; P-*Perishability* ***Product Types**; C-Cheese, D-Dairy and Milk, I-Ice cream, Y-Yoghurt [SE-Set or ST-Stirred], O-Others ***Supply Chain Processes;** PRC-Procurement, PRD-Production, STR-Storage, DST-Distribution ***Fictitious Data or Case Study;** HY-Hypothetical Application, CS-Case Study ***Product Stages;** RM-Raw Materials, IP-Intermediate Products, FP-Final Products ***Production Stages;** F-Fermentation, I-Incubation, P-Filling and Packaging [SP-Single Packaging Line or MP-Multiple and/or Parallel Packaging Line], O-Other Production Processes ***Solution Approach;** DSS-Decision Support System, MIP-Mixed-Integer Programming, MILP-Mixed-Integer Linear Programming, MINLP-Mixed-Integer Non-Linear Programming, LP-Linear Programming, IP-Integer Programming, NLP-Nonlinear Programming, SP-Stochastic Programming, HE-Heuristic, MH-Metaheuristic, FZ-Fuzzy, HD- Hybrid Approaches, HI-Hierarchical Solution Approaches, SM-Simulation, AN-Analytical Methods, LCA-Life Cycle Analysis, TA-Timed Automata, GA-Genetic Algorithm, OT-Other ***Objective;** S-Single Objective, M-Multi Objective ***Shelf Life;** SL-Shelf Life [IO-In objective function or IC-In constraints] ***Capacity and Time Constraints;** C-Capacity, T- Time, CT-Capacity & Time*Labor, Working Time & Overtimes; L-Labor, W-Working Time, O-Overtime ***Setups;** G-Product Group (Family) Setups, P-Product Setups, SD-Sequence-Dependent, SI-Sequence-Independent

2.2.2.2 Approximate Methods

The limitations of mathematical techniques have forced the use of heuristics in finding feasible solutions for large-scale VRP problems in the dairy industry. Chung and Norback (1991) present the VRP of foods including dairy and frozen goods. They introduce a heuristic approach consisting of clustering, insertion procedures for the allocation of drivers and vehicles. Sankaran and Ubgade (1994) consider a routing problem in the dairy industry. They introduce an operational level DSS by using a novel heuristic approach for the minimization of the transportation cost. Adenso-Diaz et al. (1998) consider the dairy routing problem as a version of the travelling salesman problem with the time windows. They propose a hierarchical approach and a local search heuristic as the solution methodologies. They also design and implement a DSS to organize the delivery network for a dairy industry.

As pioneering research in the literature, Tarantilis and Kiranoudis (2001, 2007) analyze the distribution of fresh milk. They formulated the problem as a heterogeneous fixed fleet VRP. Tarantilis and Kiranoudis (2001) developed a threshold-accepting based algorithm for a heterogeneous fixed-fleet VRP applied to a fresh milk industry with the goal of minimizing the total transportation time. Tarantilis and Kiranoudis (2007) propose a metaheuristic methodology for solving a practical variant of the well-known VRP. Using a two-phase construction heuristic, the proposed metaheuristic approach enhances its flexibility to easily adopt various operational constraints. Via this approach, two real-life distribution problems faced by a dairy and a construction company are tackled and formulated as a VRP. Both of the papers have salient contributions to the literature as the pioneering vehicle routing applications in the dairy industry.

In the literature, GA is used as a common alternative solution approach (Lin and Chen, 2003; Xu et al., 2011). Lin and Chen (2003) present a dynamic allocation problem with uncertain supply for the perishable commodity supply chain to develop an analytical model and an optimal control mechanism for the allocation of orders. The objective of the problem is to maximize the total net profit, which involves total sales, costs, and penalties, of the perishable commodity supply chain subject to the dynamic variations in supply capabilities and demand uncertainties. The model determines the optimal orders placed to suppliers, and the amount of perishable commodities allocated to retailers. A two-stage extended GA is developed to control the dynamic orders and allocation quantities of suppliers and retailers. Simulation experiments are conducted to evaluate the performance of GA under various sizes of problem domains and different status of supply uncertainties. The perishability and uncertainty considerations within a dynamic assignment problem are the main contributions to the dairy industry literature. Xu et al. (2011) develop a multi-objective programming model with random fuzzy coefficients for solving the logistics distribution centre location problem. Chance-constrained programming is used to represent the uncertainty in the model. The spanning tree-based GA is proposed to solve the problem.

Lahrichi et al. (2012), Dayarian et al. (2015a, 2015b) present real life applications of milk collection and distribution in the dairy industry. Although the problems addressed similar characteristics, they handle the problem with different perspectives and propose different solution approaches. Lahrichi et al. (2012) consider dairy transportation problem taking into account supply, demand and transportation details. The problem has different characteristics such as delivery destination at the end of the routes, different capacities for the vehicles, different number of vehicles at each depot, multiple depots and periods at the same time. They introduce a mathematical model, and propose a heuristic solution approach which is a generalized version of tabu search algorithm. Dayarian et al. (2015a) present a deterministic multi-attribute VRP. They introduce a branch and price methodology adapted to the special structure of the problem. Main contributions are introduction of VRP problem within an extra level of difficulty associated with the assignment of routes to plants, development of branch and price algorithm including structural exploration that improve the computational efficiency, and presentation of extensive analysis to illustrate algorithm efficiency and investigate the characteristics of the problem. Dayarian et al. (2015b) consider multi-period VRP. They introduce dynamic programming based label correcting algorithm. The problem is a VRP problem in which suppliers of producers vary on a seasonal basis and inspired from a dairy industry. The solution is based on branch and price algorithm, strong branching rule to find integer solutions.

More recently, Li and Wang (2013) consider a VRP for dairy cold chain with random demands and time window. They introduce a mathematical model with chance constrained programming and penalty function. A scanning insert algorithm is proposed to solve the model. While the scanning stage classifies the customers accordance with capacity of the vehicle and time window restrictions, insertion stage adjust the vehicle route to find the final optimal distribution.

2.2.2.3 Simulation

There are very few research papers addressing VRP by using simulation approach in the literature. The available literature focuses fundamentally on milk distribution issues (Manzini et al., 2005; Quinlan et al., 2012). Manzini et al. (2005) provide a supply chain optimization model for the milk distribution by presenting an industrial case. They introduce a simulation model to handle shipping and distribution process. They study on two important strategic aspects as make-to-order and make-to-stock production policy by simulation. Quinlan et al. (2012) consider milk transport problem under different seasonality assumptions. They propose a simulation model to estimate milk transport costs and carbon emissions from milk transport associated with alternative milk supply patterns.

2.2.2.4 Hybrid Approaches

Most of the early works on hybrid approaches has used DSS and heuristic algorithms. Basnet et al. (1996, 1997 and 1999) introduce a DSS for milk tanker routing as a particular version VRP within New Zealand dairy industry. Basnet et al. (1996) give a general description of the milk collection scenario, DSS and graphical interfaces. While Basnet et al. (1997) introduce a typical allocation problem and heuristic solution approaches, Basnet et al. (1999) present an exact algorithm incorporating a MILP problem with additional nonlinear constraints.

Most of the papers on hybrid applications have been devoted the use of MIP and simulation applications with the heuristic approaches. Foulds and Wilson (1997) have proposed two heuristics algorithms for an allocation problem arising in the New Zealand dairy industry. The research differs from the literature by considering the problem as a variant of generalized allocation problem. It is a pioneering research presenting hybrid approach combining MILP model and heuristics to tackle with milk collection and transportation problem in the dairy industry. Dooley et al. (2005) consider a milk transport simulation model to estimate transport costs by taking into account milk segregation. It is also used to evaluate alternative transport management strategies in the dairy industry. They use GA as a solution mechanism to search for the least cost solution for the collection of milk from farms. Another application is provided by Bottani and Rizzi (2006). They introduce a solution methodology based on a fuzzy multi-attribute decision making approach for selection and ranking problem of the most suitable third party logistic service provider. The proposed fuzzy TOPSIS methodology is tested by a real case application of a firm operating in the dairy industry. The research differentiates form the literature with a quantitative methodology based on a structured framework for the selection of the most appropriate third party logistic service provider.

2.2.2.5 Research Directions

To summarize the reviewed literature on vehicle routing and distribution within the dairy industry, due to complexity on modelling and solution of problems representing dairy industry characteristics, there is limited research using analytical methods. Most of the research papers focus on procurement stage. The models are represented as a variant of travelling salesman problem, DSS using analytical methods, transshipment models for dairy supply chains (Butler et al., 1997, 2005; Claassen and Hendriks, 2007; Nicholson et al., 2011).

In the literature, analytical methods are commonly supported by heuristic and metaheuristic methods. In the preliminary research of approximate methods, the research papers present vehicle routing and DSS development examples (Chung and Norback, 1991; Sankaran and Ubgade, 1994; Adenso-Diaz et al., 1998). Most of the VRPs in the dairy industry are solved using metaheuristic solution approaches (Tarantilis and Kiranoudis, 2001, 2007). The dynamic allocation problem and the distribution centre location problem with fuzzy application are other research areas in the approximate methods literature (Lin and Chen, 2003; Xu et al., 2011). The development of efficient solution approaches to tackle the special structure of the milk collection and distribution problems are recent issues in the literature (Lahrichi et al., 2012; Dayarian et al., 2015a, 2015b).

There are limited simulation applications on milk distribution problems (Manzini et al., 2005; Quinlan et al., 2012). The simulation applications are still the promising research direction in the literature.

Most of the papers study on mathematical models integrated with the heuristic approaches (Basnet et al., 1996, 1997, 1999; Foulds and Wilson, 1997). In addition, the milk transportation problems have been solved using metaheuristic algorithms (Dooley et al., 2005). There also exist hybrid approximate methods dealing with multi-criteria decision making problems (Bottani and Rizzi, 2006). The hybrid methodologies need to be considered recently in the literature, because of their more flexible frameworks. Table 2.2 summarizes the reviewed literature of vehicle routing and distribution within the dairy industry. The papers are listed in the order presented in the review. For each research, the table illustrates the different characteristics in a systematic manner.

Table 2.2 Summary of vehicle routing and distribution research

Reviewed Literature	Perish-ability	Product Types	Supply Chain Processes	Fictitious Data / Case Study	Product Stages	Production Stages	Solution Approach	Decision Levels	Objective	Shelf Life	Capacity and Time Constraints	Labor, Working Time, Overtimes	Setups
Analytical Methods													
Butler et al. (1997)	-	D	PRC	CS	RM	-	IP & DSS	O	S	-	-	-	-
Butler et al. (2005)	-	D	PRC	CS	RM	-	OT & DSS	O	S	-	CT	-	-
Claassen and Hendriks (2007)	-	D	PRC	HY	RM	-	MILP & DSS	O	S	-	-	-	-
Nicholson et al. (2011)	-	D	DST	CS	IP-FP	-	OT	S	S	-	-	-	-
Li and Wang (2013)	-	D	DST	HY	FP	-	MILP	O	S	-	CT	-	-
Approximate Methods													
Chung and Norback (1991)	-	D	DST	CS	FP	-	HE	O	S	-	-	O	-
Sankaran and Ubgade (1994)	-	D	DST	CS	RM	-	HE & DSS	O	S	-	CT	-	-
Adenso-Diaz et al. (1998)	-	D	DST	CS	FP	-	HE	O	S	-	-	-	-
Tarantilis and Kiranoudis (2001)	P	D	DST	CS	FP	-	MH	O	S	-	-	-	-
Tarantilis and Kiranoudis (2007)	P	D	DST	CS	FP	-	MH	O	S	-	-	-	-
Lin and Chen (2003)	P	D	STR-DST	HY	FP	-	LP-MH-SM	T	S	-	-	-	-
Xu, Yao and Zhao (2011)	-	I	DST	CS	FP	-	MILP-FZ-MH	T	M	-	C	-	-
Lahrichi et al. (2012)	-	D	PRC-DST	CS	RM		MILP-MH	O-S	S	-	CT	-	-
Dayarian et al. (2015a)	-	D	PRC-DST	CS	RM	-	MILP-HE	T-S	S	-	CT	-	-
Dayarian et al. (2015b)	-	D	PRC-DST	CS	RM	-	MILP-HE	T	S	-	CT	-	-
Simulation													
Manzini et al. (2005)	P	D-C-Y	DST	CS	RM-FP	-	SM	O-T-S	S	SL[IC]	-	-	-
Quinlan et al. (2012)	-	D	DST	CS	RM	-	SM	O	S	-	CT	-	-
Hybrid Approaches													
Basnet et al. (1996)	-	D	DST	CS	FP	-	HD[OT-HE- IP] & DSS	O-S	S	-	C	-	-
Basnet et al. (1997)	-	D	DST	CS	FP	-		O-S	S	-	C	-	-
Basnet et al. (1999)	-	D	DST	CS	FP	-		O-S	S	-	C	-	-
Foulds and Wilson (1997)	-	D	PRC	CS	RM	-	HD[MILP-HE]	O	S	-	-	-	-
Dooley et al. (2005)	-	D	PRC-STR	HY	RM	-	HD[GA-SM]	O	S	-	C	-	-
Bottani and Rizzi (2006)	-	D	DST	CS	FP	-	HD[FZ-OT]	S	S	-	-	-	-

*** Perishability**; P-*Perishability* ***Product Types**; C-Cheese, D-Dairy and Milk, I-Ice cream, Y-Yoghurt [SE-Set or ST-Stirred], O-Others ***Supply Chain Processes;** PRC-Procurement, PRD-Production, STR-Storage, DST-Distribution ***Fictitious Data or Case Study;** HY-Hypothetical Application, CS-Case Study***Product Stages;** RM-Raw Materials, IP-Intermediate Products, FP-Final Products ***Production Stages;** F-Fermentation, I-Incubation, P-Filling and Packaging [SP-Single Packaging Line or MP-Multiple and/or Parallel Packaging Line], O-Other Production Processes ***Solution Approach;** DSS-Decision Support System, MIP-Mixed-Integer Programming, MILP-Mixed-Integer Linear Programming, MINLP-Mixed-Integer Non-Linear Programming, LP-Linear Programming, IP-Integer Programming, NLP-Nonlinear Programming, SP-Stochastic Programming, HE-Heuristic, MH-Metaheuristic, FZ-Fuzzy, HD- Hybrid Approaches, HI-Hierarchical Solution Approaches, SM-Simulation, AN-Analytical Methods, LCA-Life Cycle Analysis, TA-Timed Automata, GA-Genetic Algorithm, OT-Other ***Objective;** S-Single Objective, M-Multi Objective ***Shelf Life;** SL-Shelf Life [IO-In objective function or IC-In constraints] ***Capacity and Time Constraints;** C-Capacity, T- Time, CT-Capacity & Time*Labor, Working Time & Overtimes; L-Labor, W-Working Time, O-Overtime ***Setups;** G-Product Group (Family) Setups, P-Product Setups, SD-Sequence-Dependent, SI-Sequence-Independent

2.2.3 Production and Distribution Planning

In the dairy industry market demand is no longer confined to local or regional supply. The strong competition in dairy food market, product variety and short shelf lives force the companies to a closer coordination of production and distribution activities for more flexible utilization of resources and faster response to demands while reducing production costs, and increasing throughput. Especially, there are tight shelf life restrictions for dairy products, and customer prefers the product that has maximum available shelf life. To avoid excessive inventories and to allow a quick response to customer enquiries are important aspects that require more attention. Therefore, an efficient integration of production and distribution plans into a unified framework is critical to achieve competitive advantage. In the remainder of this section, we classify the production and distribution research in dairy industry based on solution methodologies used. These classifications are analytical methods, approximate methods and hybrid approaches.

2.2.3.1 Analytical Methods

Most of the seminal publications reported in the literature address the integrated production and distribution planning problem from a strategic and tactical point of view (Mellalieu and Hall, 1983; Benseman, 1986; Pooley,1994). Mellalieu and Hall (1983) present a long term planning model focusing on processing and transportation operations of dairy industry. They introduce a network formulation with the objective function which maximizes net revenue based on product prices, variable process and transport costs, subject to factory capacity, product demand and raw material supply constraints. Benseman (1986) develops a MILP model for medium-term production planning problem. A milk collection and distribution process is considered in addition to milk production and allocation to maximize the profit by taking into account transportation costs and the variable production costs. Pooley (1994) considers production and distribution facility network planning problem in dairy processor company. A tactical level MILP model is proposed to minimize total supply chain cost consisting of fixed and variable costs corresponding to production and distribution activities.

MIP has been widely used to formulate production and distribution planning problem in the dairy industry. Wouda et al. (2002) present an MILP model to optimize a supply chain network. The focus of the research is to evaluate the regionalization, product and process specialization strategies with the real life industrial scenarios. The objective is to find optimal number of plants, their locations and allocation to the product portfolio in order to minimize the total production cost and the transportation cost. Subbaiah et al. (2009) present a supply chain model mainly focusing on production and distribution activities in the dairy industry. The model consists of four echelons as raw milk suppliers, plant, warehouse and customers and incorporates the purchase plan of raw milk, production plan of product mix and final product transportation. They propose a LP model with a single objective function handling various supply chain costs. The objective function is to minimize the total supply chain cost consisting of material, production and transportation costs. The research contributes to the literature by presenting a real world application of the coordinated supply chain planning model. The model developed by Kopanos et al. (2012a) appears as the most comprehensive model in dairy industry. They present a novel MILP framework based on a hybrid discrete/continuous time representation for the simultaneous detailed production and distribution planning problem of multi-site, multi-product, semi-continuous food processing industry. The novelty of the proposed mathematical formulation is the integration of the different modelling approaches and consideration of the detailed production and distribution operations.

Recently, Van Elzakker et al. (2013, 2014) present a tactical production-distribution planning problem of fast moving consumer goods and develop a MILP model which is also applicable to dairy industry. While, one of the main challenges is the size of the problem considered by Van Elzakker et al. (2014), Van Elzakker et al. (2013) account additionally shelf life restrictions and waste. Van Elzakker et al. (2014) propose a decomposition algorithm to be capable of solving real sized case. In the decomposition, sub-models containing single stock keeping unit are optimized sequentially while a penalty cost is introduced for violating capacity. The penalty cost is increased after each optimization until it becomes high to obtain a feasible solution. Van Elzakker et al. (2013) present computationally efficient methods to accurately track the shelf life (e.g., direct, indirect and hybrid). In the direct method, age of each product is tracked. While the direct method can guaranty the optimal, it is computationally inefficient. In the indirect method, products are forced to leave inventory at the end of shelf life. Indirect method cannot guaranty the optimal but it reaches close results to optimal. Hybrid method combines the advantages of these two approaches. Product age is handled directly in the first stage while considering the shelf life indirectly in the second stage. It provides near optimal solutions with respectively efficient computational times. In addition, Yu and Nagurney (2013) develop a network-based food supply chain model under oligopolistic competition and perishability, with a focus on fresh produce. They introduce a network based model which is highly relevant to dairy products. Their study differs from the literature with several aspects such as capturing the deterioration of fresh food for entire supply chain, exponential time decay, oligopolistic competition with product deterioration, disposal of spoiled foods with associated cost and assessment of alternative technologies.

2.2.3.2 Hybrid Approaches

Hybrid approaches usually considers a combination of optimization and simulation models. As a preliminary research, Sonesson and Berlin (2003)present scenario based analysis on the environmental impact of milk supply chain. The scenarios are handled with simulation experiments and the analysis is mainly based on life cycle assessment methodology. The objective of the study is to assess the potential environmental impact of various supply chains for dairy products as well as to test and develop the material flow approach to analyze the sustainability of food supply systems. Li et al. (2008) introduce a simulation and optimization based DSS to cope with the complexity and uncertainties. The production activities are handled in order to meet the market demand and minimize the difference between supply and demand. In addition, the supply and collection of raw milk from farmers is implemented as a VRP. The main contribution of the research is to incorporate the production and distribution planning by using optimization with simulation model to deal with uncertainty. Amorim et al. (2012) present multi-objective MIP models using block planning approach to solve an integrated production and distribution planning problem integrating the economic aspects and freshness at an operational level. The models are formulated for two distinct cases with a fixed and a loose shelf life of rapidly deteriorating goods. While the first objective is concerned with minimizing the total costs over the supply chain covering transportation, production, setup and spoilage costs, the second one maximizes mean remaining shelf life of products at the DCs over the planning horizon. They propose a simple hybrid genetic heuristic to solve the problem where the shelf life is loose. Amorim et al. (2012) is the pioneering research that addresses the integrated production and distribution planning of perishable dairy products in a multi-objective framework.

Recently, Bilgen and Çelebi (2013) consider an integrated production scheduling and distribution planning problem in yoghurt production. They present a hybrid method combining MILP and simulation approaches. The model obtains optimal production and delivery plan and hybrid approach is introduced to explore the dynamic behavior of the real world system. Operation times are considered as a dynamic factor and adjusted using optimization and simulation in an iterative manner. While in the most of the previous studies the problem parameters are accepted as deterministic, they handle the stochastic failures on operation times to obtain more realistic solutions. Jouzdani et al. (2013) present a dynamic facility location problem for transportation of raw milk and dairy products and under consideration of traffic congestion and demand uncertainty. They consider possible changes in transportation network, facility investment cost, and monetary value of time changes in production process. Fuzzy linear programming and mixed-integer non-linear programming (MINLP) are used as solution approaches.

2.2.3.3 Research Directions

To summarize the reviewed literature on production and distribution planning research, Mellalieu and Hall (1983), Benseman (1986) and Pooley (1994) are the pioneering research papers that consider the strategic, tactical network models, respectively. In the last decade, the research papers present integrated production and distribution models considering tactical level decisions by using fundamentally LP and MILP methodologies (Kopanos et al., 2012a; Subbaiah et al., 2009; Wouda et al., 2002). The perishability and deterioration issues have been recently taken into account in MILP models in tactical decision level. These models are more realistic models which are capable of representing the specific dairy industry characteristics (Van Elzakker et al., 2013, 2014; Yu and Nagurney, 2013).

Besides, there are hybrid approaches taking into account the environmental issues using simulation and life cycle assessment methodologies (Li et al., 2008; Sonesson and Berlin, 2003). Recently, hybrid approaches have begun used in yoghurt production process to get advantage of mathematical programming and metaheuristic approaches and to tackle with perishability issues (Amorim et al., 2012). Since there are few papers in the literature, the simulation and approximate methods based applications are still promising areas (Bilgen and Çelebi, 2013). Apart from these, Jouzdani et al. (2013) present an MINLP example using approximate methods. Table 2.3 summarizes the reviewed literature of production and distribution within the dairy industry. The papers are listed in the order presented in the review. For each research, the table illustrates the different characteristics in a systematic manner. Table 2.4 illustrates the reviewed literature by presenting number of papers with the classification scheme used in the review.

Table 2.3 Summary of production and distribution planning research

Reviewed Literature	Perish-ability	Product Types	Supply Chain Processes	Fictitious Data / Case Study	Product Stages	Production Stages	Solution Approach	Decision Levels	Objective	Shelf Life	Capacity and Time Constraints	Labor, Working Time, Overtimes	Setups
Analytical Methods													
Mellalieu and Hall (1983)	-	D	PRD-DST	CS	RM-FP	O	OT	O	S	-	CT	-	-
Benseman (1986)	-	D	PRC-PRD-DST	CS	FP	O	MILP	O	S	-	C	-	-
Subbaiah et al. (2009)	-	D	PRC-PRD-STR-DST	CS	RM-IP-FP	O	LP	T	S	-	-	-	-
Kopanos et al. (2012a)	-	Y	PRD-STR-DST	CS	FP	P[MP]	MILP	O-T	S	-	CT	-	G-SD & P-SI
Pooley (1994)	-	D	PRD-DST	CS	FP	O	MILP	T	S	-	C	-	-
Wouda et al. (2002)	-	D	PRC-PRD-DST	CS	RM-FP	P	MILP	T	S	-	-	-	SI
Van Elzakker et al. (2014)	-	OT	PRC-PRD-DST	HY	RM-IP-FP	O-P	MILP	T	S	-	-	-	G-SD & P-SD
Van Elzakker et al. (2013)	P	OT	PRC-PRD-DST	HY	RM-IP-FP	O-P	MILP	T	S	SL[IC]	CT	-	G-SI & P-SI
Yu and Nagurney (2013)	P	OT	PRD-DST	CS	FP	O	OT	T	S	-	-	-	-
Hybrid Approaches													
Sonesson and Berlin (2003)	-	D	PRD-DST	CS	RM-FP	O	HD[SM-LCA]	O-S	S	-	-	-	-
Li, Zhang and Jiang (2008)	-	D	PRC-PRD-DST	CS	RM-FP	P	HD[SM-HE-OT] & DSS	O	M	-	CT	-	-
Amorim et al. (2012)	P	D-Y	PRD-DST	HY	FP	P[MP]	HD[MILP-MINLP &GA]	O-T	M	SL[IO-IC]	CT	-	G-SD & P-SI
Bilgen and Çelebi (2013)	P	Y	PRD-DST	CS	FP	P[MP]	HD[MILP-SM]	O	S	SL[IO-IC]	CT	O	P-SD
Jouzdani et al. (2013)	-	D	PRC-PRD-DST	CS	RM-FP	o	HD[FZ & MINLP]	T-S	S	-	CT		

*** Perishability**; P-*Perishability* ***Product Types**; C-Cheese, D-Dairy and Milk, I-Ice cream, Y-Yoghurt [SE-Set or ST-Stirred], O-Others ***Supply Chain Processes;** PRC-Procurement, PRD-Production, STR-Storage, DST-Distribution ***Fictitious Data or Case Study;** HY-Hypothetical Application, CS-Case Study ***Product Stages;** RM-Raw Materials, IP-Intermediate Products, FP-Final Products ***Production Stages;** F-Fermentation, I-Incubation, P-Filling and Packaging [SP-Single Packaging Line or MP-Multiple and/or Parallel Packaging Line], O-Other Production Processes ***Solution Approach;** DSS-Decision Support System, MIP-Mixed-Integer Programming, MILP-Mixed-Integer Linear Programming, MINLP-Mixed-Integer Non-Linear Programming, LP-Linear Programming, IP-Integer Programming, NLP-Nonlinear Programming, SP-Stochastic Programming, HE-Heuristic, MH-Metaheuristic, FZ-Fuzzy, HD- Hybrid Approaches, HI-Hierarchical Solution Approaches, SM-Simulation, AN-Analytical Methods, LCA-Life Cycle Analysis, TA-Timed Automata, GA-Genetic Algorithm, OT-Other ***Objective;** S-Single Objective, M-Multi Objective ***Shelf Life;** SL-Shelf Life [IO-In objective function or IC-In constraints] ***Capacity and Time Constraints;** C-Capacity, T- Time, CT-Capacity & Time*Labor, Working Time & Overtimes; L-Labor, W-Working Time, O-Overtime ***Setups;** G-Product Group (Family) Setups, P-Product Setups, SD-Sequence-Dependent, SI-Sequence-Independent

Table 2.4 Number of papers

Solution Approaches **Problem Types**	Analytical Methods	Approximate Methods	Simulation	Hybrid Approaches	***Total***
Production Planning and Scheduling	30	5	1	5	***41***
Vehicle Routing and Distribution	5	10	2	6	***23***
Production and Distribution Planning	9	-	-	5	***14***
Total	***44***	***15***	***3***	***16***	***78***

2.3 Conclusions and Future Research Directions

In this chapter, we have reviewed quantitative operations research literature on dairy SCM to reveal major trends, to explore research opportunities. Moreover, we have identified the characteristics that a model should have to address adequately dairy SCM planning needs. The reviewed research is classified by problem types based on the solution approaches.

As can be easily seen from the various tables throughout the review, the most widely used solution approaches are analytical methods and they are extensively accepted tools in the dairy industry for well-defined problems. In addition, most of the research addresses case studies and real-life problems in the literature. Due to the nature of the dairy industry problems, the models and methods should meet the requirements of practical applications which consist of complex scenarios. Although analytical approaches have advantages on providing mathematical frameworks to represent specific characteristics of problems and to get optimal solutions, they may be not powerful enough to handle real sized problems with regard to the computational efforts. Another inadequacy of some analytical approaches is that it is not easy to model uncertainty mathematically by analytical methods. Alternatively, simulation approaches are capable of introducing more flexible and handling real cases in the dairy industry. However, complex simulation models could require large amount of installation and running time. Approximate methods have been proven useful in many cases since they overcome the computing time limitation. Approximate methods provide less computational efforts, however optimum cannot be guaranteed. They are especially convenient to analyze real cases. On the other hand, hybrid methods integrate the best capabilities of the solution approaches for the effective decision making.

For each of the problem types examined in this review, some generalized results can be concluded in terms of the quantitative methods. Production planning and scheduling issues are extensively solved by analytical methodologies. Most of the formulations in this field are in the form of MILP models with several assumptions. Much research is still needed on application of approximate methods, simulation, and hybrid approaches. The areas of vehicle routing and distribution issues, integrated production and distribution problems in the dairy industry have also received much attention. The most widely used solution approach in application of VRP is the metaheuristics. A number of applications on integrated production and distribution planning are formulated as MILP models. It is an evidence gap that there is no research using approximate based methods and simulation approach to tackle with integrated production and distribution planning problem within the dairy industry. Traditional production scheduling focuses on the determination of schedules for production such that some performance measures are optimized without considering the distribution planning. Very few works have been devoted to investigate the coordination of production scheduling and delivery planning for dairy products. Therefore, the coordination of production scheduling and distribution planning becomes an important issue in the dairy industry and needs further studies. The literature integrating uncertainty in dairy SCM is still scarce. In particular, very few papers address stochastic parameters combined with other aspects. Another aspect that requires more attention is the integration of postponement strategies within dairy SCM problems. Future research directions are stated with respect to different perspectives.

2.3.1 Multi-Stage Production Planning Perspective

The vast majority of the papers in dairy production planning process focus on the packaging process. The structure of the production process is considerably simplified. However, the integrated modelling and simultaneous optimization of all stages (e.g., fermentation/incubation and packaging) needs to be considered. The integrated models should be introduced to get advantages of simultaneously optimization of production, fermentation, incubation, filling and packaging processes. Another finding that can be drawn from the reviewed research is that there is abundant literature on supply chain planning of dairy products at operational decision level. Another aspect requiring more attention is the integration and/or the hierarchical structure of the tactical and operational planning levels in the dairy SCM context.

2.3.2 Sustainability Perspective

Until recently, the models very often fail to incorporate especially perishability and shelf life issues. Perishability issues are extensively taken into account in terms of final products within the literature. The consideration of perishability constraints on raw materials and/or intermediate products is a promising area. Incorporation of perishability and batch dispersion, traceability, food safety considerations are promising research directions. Other promising research areas are to take into account waste minimization and the environmental considerations within the optimization models in the dairy industry.

2.3.3 Integrated Production-Distribution Planning and Scheduling Perspective

Another aspect that requires more attention is the full integration of production, distribution planning and scheduling activities within dairy SCM. The dairy industry characteristics should be taken into account more intensively by the integrated production, distribution planning and scheduling models.

2.3.4 Single, Multi-objective Perspective

The consideration of multi-objective functions within the models requires more attention. The most of the reviewed literature consider the problems which have only single objective mainly expressed as a cost or cost related function. However, in real applications, there exist multiple conflicting objectives. Therefore, the multi-objective treatments need to be considered to represent the conflicting objectives corresponding to joint procurement, production and inventory planning decisions.

2.3.5 Uncertainty Perspective

In real life applications, consideration of stochastic parameters is more common owing to uncertain environment. Hence, stochastic parameters such as demand, waste, production delays, machine failures, and process times should be included into the problem. Scenario based analysis can support the decision making process effectively. The risk assessment is a promising research area for the more realistic scenarios. Robust designs and optimization approaches can be added as promising research directions to tackle with the unexpected events that severely impact performance.

The further research also should be directed towards the incorporation of uncertainty in the mathematical framework. Stochastic programming, which models optimization problems that involve uncertainty, and multi-parametric programming techniques, where some of the parameters vary between specified lower and upper bounds, may be important application areas within the dairy SCM. To the best of our knowledge, there is no research handling stochastic parameters by using stochastic or multi-parametric programming techniques with perishability consideration within the dairy industry.

Simulation approach is a suitable solution technique to study the impact of stochastic environment. To the best of our knowledge, there are very few studies combining the mathematical programming approach with simulation within the perishable dairy SCM.

Some of the researchers have attempted to solve dairy industry problems by the well-known traditional static and deterministic models. Nevertheless, optimizing the dynamic systems comprising continuous changes has been a difficult task for the researchers. In this concept, though the analytical methods can provide optimal results, they cannot effectively handle dynamic and stochastic situations separately. Instead of these methods, approximate methods, simulation and hybrid methodologies may be more convenient and development of real time optimization tools can be promising research direction to address the dynamic and stochastic nature of the dairy supply chain problems.

2.3.6 Alternative Solution Techniques Perspective

Recently, CP receives considerable attention as a common alternative method to mathematical programming technique for solving optimization problems by offering a more flexible modelling framework. To the best of our knowledge there is no research that uses CP on production, distribution planning and scheduling within the dairy industry SCM. The application of the CP may provide an important contribution to the corresponding literature.

The MIP techniques are extensively used in production-distribution planning and scheduling problems of perishable products. However, there are respectively few studies using heuristics, meta-heuristics or hybrid solution methodologies. These methodologies emerge as promising solution alternatives especially on computational efforts and future research needs to introduce detailed procedures to use advantages of these alternative solution mechanisms.

The complexity of the MIP models increases significantly with the number of products, length of planning horizons, number of demand points. Efficient decompositions schemes and hierarchical methodologies can be introduced to tackle with the complexity of the problems. In addition, to improve the computational efficiency of the MIP models for solving large scale problems, MIP based decomposition heuristics, especially such as F&O, F&R, rolling horizon approaches, can be suggested for large sized instances.

2.3.7 Postponement and Decoupling Point Theory Perspective

Postponement and decoupling point theory practices are fairly low in the dairy industry in contradiction to other industries. Hence, the application of postponement and decoupling point theory under consideration of the special characteristics in the dairy industry is one of the promising future research directions.

Production-distribution problems are mostly considered by analytical methods to model the deterministic problems. The problem complexity of the problems is inherently high because of the considered constraints restricting the problem structure (e.g., shelf life, capacity and time constraints, setups). Approximate methods are quite appropriate achieving close optimum solutions in reasonable solution times for industrial cases rather than the exact solution approaches. Reviewed literature commonly presents the problems using industrial case studies and most of them neglect the uncertainty issues confronted in most of the real cases. For example, the machine failures can be stated as an uncertain parameter affecting the cost driven objectives in consequence of restricting the production capacity. Simulation can be used as a technique to study the impact of the uncertainty environment.

In the next chapter, alternative solution techniques and uncertainty perspectives of the literature review is discussed. A production-distribution planning problem is considered and a MILP model is presented. MILP based heuristics are introduced to solve the problem with reasonable computational efforts. Operation times are considered as an uncertain parameter and represented by probability distributions of machine failures and repair a simulation model of the production process. Accordingly, a simulation optimization methodology is introduced to solve the problem.

CHAPTER THREE
HYBRID SIMULATION AND MIP BASED HEURISTIC ALGORITHM FOR THE PRODUCTION AND DISTRIBUTION PLANNING IN THE SOFT DRINK INDUSTRY

3.1 Introduction

In recent years, the achievement of effective supply chain operations to avoid excessive inventories and operation costs depends on closer coordination of production and distribution activities. MIP is a popular optimization approach in the literature to model this coordination. Due to the extensive and complex nature of organization, MIP techniques may not have acceptable solution times for a wide range of real case applications. To overcome this obstacle of MIP technique for larger problem size, the MIP based heuristics emerge as promising solution methodologies.

Our research is motivated by the production-distribution planning problem encountered by a soft-drink company, which has to decide routinely the quantity produced and, the best way of delivering a set of orders to its customers over a multi-day planning horizon. The problem is formulated as an MILP model. In this research, operation times in the MILP model are considered as the dynamic factor and adjusted by the results from independently developed simulation model. Hybrid MIP based heuristic and simulation model are aimed at combining the strength of MIP based heuristic and the simulation model and reducing the impact of limiting characteristics of these models. Iterative use of MIP based heuristic and simulation methodologies exploit the benefit of obtaining optimal solutions, while revealing the impact of operation time uncertainty on system performance.

The main contributions of this research are (i) implementation of the MIP based rolling horizon heuristics to the production allocation and distribution planning problem, (ii) propose a hybrid approach that combines simulation and MILP based

F&O heuristic in an iterative process in order to gain the advantages of MILP based heuristics and simulation to minimize the overall cost for the considered problem.

The remainder of this chapter is organized as follows. The relevant literature is reviewed in Section 2.In section 3, the key characteristics of the problem are outlined, and the MILP model is described in detail. The solution approaches are described in Section 4.Numerical results are presented in Section 5.Conclusions and directions for further work are discussed in Section 6.

3.2 Literature Review

The efficient coordination of production and distribution systems becomes a challenging problem as companies move towards higher collaborative and competitive environments. In the literature, integrated production and distribution planning problem has been subject of many studies during the last decade. Interested readers are referred to Bilgen (2010), Kanda and Deshmukh (2008), Mula et al. (2010), Farahani et al. (2014), De Matta and Miller (2004) for a complete review of production and distribution models in supply chain environments. In the last decade, several models which address the supply chain coordination issues at different decision levels are developed (e.g., Lei et al., 2006; Ekşioğlu et al, 2007; Tsiakis & Papageorgiou, 2008; Rizk et al, 2008; Bilgen and Günther, 2010; Ahumada and Villalobos, 2011; Bashiri et al., 2012).

In this section we review the most relevant and recent literature on MIP based heuristic applications and application of hybrid analytic and simulation modeling approach to the production and distribution planning problem.

3.2.1 Literature on MIP Based Heuristics

In terms of the solution procedures, the common MIP based heuristics, which are widely used in the literature, are F&R and F&O. The applications of these MIP based heuristics fundamentally focus on the production planning, lot-sizing and scheduling problems.

F&R Heuristic: F&R approach is originally described as a time decomposition heuristic by Dillenberger et al. (1994). There are various extensive F&R studies concerning the lot sizing and scheduling applications in the literature (e.g., Dillenberger et al., 1994; Stadtler, 2003; Kelly and Mann, 2004; Absi and Kedad-Sidhoum, 2007; De Araujo et al., 2007; Federgruen et al., 2007; Beraldi et al., 2008; Pochet and Warichet, 2008; De Araujo et al., 2008; Akartunalı and Miller, 2009; Ferreira et al., 2009, Mohammadi et al., 2010). Stadtler (2003) considers a dynamic multi-item multi-level lot-sizing problem. He solves the problem on a rolling basis by adding later periods and removing the earlier ones. Kelly and Mann (2004) present a methodology using F&R decomposition heuristic with a constraint dropping strategy on a lot sizing problem. Absi and Kedad-Sidhoum (2007) propose new MIP-based heuristics to address a multi-item capacitated lot sizing problem with setup times that arises in real world production planning context. De Araujo et al. (2007) develop an F&R procedure to solve lot sizing and scheduling model that considers backorders and sequence dependent setup costs and times for group changeovers. Federgruen et al. (2007) present a so called progressive interval heuristic for the capacitated lot sizing problem with joint setup cost. Beraldi et al. (2008) present a new rolling horizon and F&R heuristics for the single machine and identical parallel machine capacitated lot sizing problem with sequence dependent setup costs. Pochet and Warichet (2008) present a continuous time MILP formulation for the cyclic scheduling. De Araujo et al. (2008) consider lot sizing and scheduling problem in a manufacturing plant for animal feed compounds. F&R approach is developed to solve the problem. Akartunali and Miller (2009) present a heuristic framework that can generate high quality feasible solutions quickly for various kinds of lot sizing problems. Ferreira et al. (2009) introduce a MIP model that integrates the production lot sizing and scheduling decisions of beverage plants with sequence dependent setup times and costs. A relaxation algorithm and various F&R strategies that explore the model structure are proposed and used to solve real instances of the problem. Mohammadi et al. (2010) consider the multi-product multi-level capacitated lot sizing problem with sequence dependent setups. Four variants of F&R heuristics are developed. F&R heuristic is the most widely applied in production planning, in particular lot sizing and scheduling problems. In addition to F&R heuristic applications on lot sizing and scheduling problem, there are few papers that use F&R heuristic on supply chain planning problems. Ouhimmou et al. (2008) present a mathematical model for furniture supply chain planning problem. They develop a heuristic using a time decomposition approach. Alonso-Ayuso et al. (2006) and Alonso-Ayuso et al. (2009) consider a multi-period single-sourcing supply chain problem under uncertainty. Uggen et al. (2013) have applied F&R time decomposition heuristics to solve the maritime inventory routing problem, and this is a new approach for this problem class. Table 3.1 summarizes the relevant literature in a systematic manner to clarify the application areas of the F&R heuristic algorithm.

F&O Heuristic: Pochet and Wolsey (2006) describe an improvement heuristic similar to the F&R heuristic, which they called "exchange" heuristic. The same approach is used in Sahling et al. (2009) and Helber and Sahling (2010) for the multi-level capacitated lot sizing problem, where the authors called it the F&O heuristic (James and Almada-Lobo, 2011). James and Almada-Lobo (2011) integrate F&O in a stochastic local search algorithm to improve the initial solution obtained with the F&R heuristic, delivering solutions within a small deviation from theoretical lower bounds to solve the capacitated lot sizing problem with sequence dependent setup times and costs in single and multi-machine settings.

The F&O heuristic is introduced by Sahling et al. (2009), Helber and Sahling (2010) for solving the dynamic multi-level capacitated lot sizing problem with setup carry over. Their algorithm solves a series of MIPs in an iterative F&O approach. Helber and Sahling (2010) present an optimization based solution approach for the dynamic multi-level capacitated lot sizing problem with positive lead times. Lang and Shen (2011) consider a capacitated single-level dynamic lot-sizing problem with sequence-dependent setup costs and times that includes product substitution options. They develop a MIP formulation of the problem and introduce MIP-based F&R and

F&O heuristics. More recently, Helber et al. (2013) present a stochastic version of the single-level, multi-product dynamic lot-sizing problem subject to a capacity constraint. They use an adapted version of the flexible F&O heuristic proposed by Helber and Sahling (2010).

The last few years have seen increasing interest and efforts in the integration of MIP based heuristics and the other metaheuristics. Gören et al. (2012) introduce a novel hybrid approach by combining genetic algorithms and an F&O heuristic to solve the capacitated lot sizing problem with setup carryover.

Seeanner et al. (2013) present an improvement heuristic based on the principles of the variable neighborhood decomposition search and F&O to solve multi-level lot sizing and scheduling problems. Toledo et al. (2013) propose a multi-population based metaheuristic using F&O heuristic and mathematical programming techniques to solve the multi-level capacitated lot sizing problem with backlogging. Stadler and Sahling (2013) present a new model formulation for lot-sizing and scheduling of multi-stage flow lines which works without a fixed lead-time offset. They present a solution approach based on F&R and F&O. Ghaderi and Jabalameli (2013) formulate the multi-period health care facility location problem as a budget-constrained model. A greedy heuristic and an F&O heuristic based on simulated annealing and exact methods are proposed to solve the model. Guimarães et al. (2013) present a novel mathematical model and a mathematical programming based approach to deliver superior quality solutions for the single machine capacitated lot sizing problem with sequence-dependent setup times and costs. They propose a solution approach, based on a large bucket sequence related model, integrates column generation in F&R and F&O schemes. Xiao et al. (2013) examines capacitated lot sizing problem with sequence-dependent setup times, time windows, machine eligibility and preference constraints. Two MIP-based F&O algorithms are proposed.

Table 3.1 F&R applications

	Prod. plan.	Lot-sizing	Sch.	Inven. plan.	SCM	Information
Absi and Kedad- Sidhoum (2007)	✓	✓				A multi-item capacitated lot-sizing problem with setup times that arises in real-world production planning contexts.
Akartunali and Miller (2009)	✓					A heuristic framework that can generate high quality feasible solutions quickly for various kinds of lot-sizing problems.
Alonso-Ayuso et al. (2006)					✓	Multi-period single-sourcing SCM problem under uncertainty
Alonso-Ayuso et al. (2009)					✓	Multi-period single-sourcing SCM problem under uncertainty
Beraldi et al. (2008)	✓	✓	✓			New rolling-horizon and F&R heuristics for the identical parallel machine lot sizing and scheduling problem with sequence-dependent set-up costs.
De Araujo et al. (2007)		✓	✓			Present a MIP model taking into account sequence-dependent setup costs and times
De Araujo et al. (2008)		✓	✓			Present lot sizing and scheduling in a manufacturing plant for animal feed compounds
Dillenberger et al. (1994)	✓	✓				F&R application to MIP on production planning and lot sizing problem
Federgruen et al. (2007)		✓		✓		Main objective of the paper is to find a lot sizing strategy that satisfies the demands for all items over the entire horizon without backlogging
Ferreira et al. (2009)		✓	✓			A MIP model that integrates production lot sizing and scheduling decisions of beverage plants with sequence-dependent setup costs and times
Kelly and Mann (2004)		✓				An F&R decomposition heuristic strategy is used with a constraint dropping strategy on a lot sizing problem.
Mohammadi et al. (2010)		✓	✓			The multi-product multi-level capacitated lot sizing problem with sequence-dependent setups.
Ouhimmou et al. (2008)					✓	A mathematical model for tactical planning of the supply chain structure
Pochet and Warichet (2008)			✓			A continuous time MILP formulation for the cyclic scheduling of a mixed plant
Stadtler (2003)		✓				A dynamic multi-item multi-level lot sizing problem

Table 3.2 summarizes the relevant literature in a systematic manner to clarify the application areas of the F&O algorithm and displays that production planning, inventory planning and SCM are promising areas for the future research. Most of the literature has been focused on the lot sizing and scheduling problem.

3.2.2 Hybrid Simulation based Optimization Approaches

Mathematical approaches require too many simplifications to model realistic supply chain planning problems. Real world situations are characterized by a high degree of uncertainty. Inclusion of uncertainties often makes pure mathematical modeling intractable. Discrete event simulation is emerging as a decision support tool for the food industry due to powerful and realistic modeling and analysis characteristics (Yoo et al, 2010). On the other hand hybrid approaches proposed in the literature offer the advantages of simulation based methodologies together with the optimization capabilities of mathematical programming models for the effective decision making.

Table 3.2 F&O applications

Authors & Date	Application Area	Information
Sahling et al. (2009)	Production planning and Lot Sizing	A new algorithm so-called F&O approach for the dynamic multi-level capacitated lot sizing problem with setup carryovers.
Helber and Sahling (2010)	Production planning and Lot Sizing	An optimization-based solution approach for the dynamic multi-level capacitated lot sizing problem with positive lead times.
James and Almada-Lobo (2011)	Capacitated Lot Sizing and Scheduling problem	F&O is integrated in a stochastic local search algorithm to improve the initial solution obtained with the F&R heuristic.
Lang and Shan (2011)	Production planning, Lot Sizing and Scheduling	A capacitated single-level dynamic lot-sizing problem with sequence-dependent setup costs and times that includes product substitution options. Solution procedures are MIP, F&R and F&O heuristics.
Helber et al. (2013)	Dynamic lot sizing problem	Stochastic single level multi product dynamic lot sizing problem
Gören et al. (2012)	Production planning and Lot Sizing	A hybrid F&O application using genetic algorithm to solve the capacitated lot sizing problem with setup carryover.
Seeanner et al. (2013)	Lot sizing and scheduling problem	Hybrid variable neighborhood decomposition search and F&O Heuristic to solve multi-level lot sizing and scheduling
Toledo et al. (2013)	Multi-level Capacitated lot sizing problem	Multi population based metaheuristic using F&O to solve lot sizing problem with backlogging
Stadler and Shaling (2013)	Lot sizing and scheduling	F&R and F&O are used to solve the multi-stage flow line lot sizing and scheduling problem
Ghaderi and Jabalameli (2013)	Healthcare facility location problem	A greedy heuristic, F&O and simulated annealing are proposed to solve the problem
Guimarães et al. (2013)	Capacitated lot sizing and scheduling	Column generation algorithm is integrated with F&R and F&O heuristic.
Xiao et al. (2013)	Capacitated lot sizing and scheduling	Two MIP based F&O algorithm is proposed capacitated lot sizing problem with sequence-dependent setup times, time windows, machine eligibility and preference constraints.

Major drawback in most past research on supply chain planning problems is the assumption that the critical parameter such as the operation time is deterministic, whereas the uncertainty can be observed, such as machine breakdowns, late deliveries. Therefore it is necessary to handle the uncertainty. Discrete event simulation allows production scheduling to be modeled more realistically.

Shanthikumar and Sargent (1983) discuss comparative advantages and disadvantages of analytic versus simulation models giving a unifying definition for hybrid simulation, analytic approaches and modeling. Several researchers have developed iterative solution approaches for various types of problems that integrate optimization and simulation approaches. Byrne and Bakir (1999) study a hybrid algorithm combining mathematical programming and simulation models of a manufacturing system for the multi-period, multi-product production planning problem. Kim and Kim (2001) propose an iterative approach for finding the capacity-feasible production plan, applying the hybrid framework by Byrne and Bakir (1999). An extended formulation of linear programming (LP) model is proposed to consider the workload profile of the production quantity and the actual amount of the capacity to be allocated to the requirements for each machine. Lee and Kim (2002) develop an integrated multi-period, multi-product, multi-shop production and distribution model. They also take into consideration various kinds of uncertain factors so that the integrated supply chain system can reflect the dynamic characteristics of the real system. Operation time in the analytic model is considered as a dynamic factor. They propose a hybrid approach that combines both the analytic and the simulation model. In another paper, Lee et al. (2002) study the same model. While the operation time is a stochastic factor in their previous work (Lee and Kim, 2002), machine capacity and distribution capacity are considered as stochastic factors. Hsieh (2002) reviews hybrid approaches and their applications and proposes a new hybrid modeling class, and illustrates a cost function for selecting analytic or simulation modeling approaches through a problem solving process. Gnoni et al. (2003) consider the production planning problem of a multi-site manufacturing system subject to capacity constraints in case of an uncertain, multi-product and multi-period demand. A hybrid model, resulting from the integration of a MILP model and a simulation model, is developed to solve a lot sizing and scheduling problem. Byrne and Hossain (2005) describe an extended LP model for the hybrid approach proposed by Byrne and Bakir (1999) incorporating JIT concepts.

Recently, Almeder et al. (2009) present a new approach that combines the advantages of complex simulation models and abstract optimization models. They include simulation and optimization in an iterative process in order to gain the advantages of optimization (exact solution) and simulation (nonlinearities, complex structure, stochasticity). Safaei et al. (2010) propose a hybrid mathematical-simulation model to solve the multi-product, multi-period, multi-site production-distribution planning problem. Acar et al. (2010) develop a decision support framework for a global specialty chemical manufacturer that operates under demand, supply, and transportation lead-time uncertainties. Their modeling approach combines optimization and simulation methodologies to obtain optimal supply chain plans via mathematical modeling, while incorporating uncertainties in the execution of these plans via simulation. In a recent paper, Nikolopoulou and Ierapetritou (2010) propose a hybrid simulation and optimization approach for the integrated planning and scheduling problem. The simulation based optimization strategy uses an agent based system to model the supply chain network. In another paper, Sahay and Ierapetritou (2013) study on the same model. Compared to their work, they present a multi-objective model by taking the environmental impact of the supply chain as an additional objective for decision making. They propose a more flexible approach in which optimization is only used as a target setting. More recently, Bilgen and Çelebi (2013) propose an efficient hybrid solution methodology based on a MILP formulation and a simulation approach to address production scheduling and distribution planning problem in the dairy industry. The discussion of previous literature establishes the need for a hybrid approach that efficiently recognizes uncertainty. This research proposes a hybrid approach for the production allocation and distribution planning problem within the soft drink industry.

3.3 Problem Definition

This research is motivated by the production-distribution problem encountered by a soft-drink company, which has to decide routinely the best way of delivering a set of orders to its customers over the multi-day planning horizon. In this research, the model developed by Bilgen (2010) is extended to include backordering. When customer demand exceeds product held in inventory, unmet demand is backordered and delivered to customers as soon as it becomes available in stock. It is generally not economical to install production equipment at each plant for the entire portfolio of products due to the high investment costs. For this reason, dedicated lines for the production of a specific range of products are established at each plant. Each individual plant has two production lines. No plant can produce the whole product range but just a part of the product range. Each production line at each individual plant can be viewed as a single stage process capable of producing several product groups. Setup costs are incurred at each plant whenever a production line changes production to a different product group. Each plant has an attached DC which serves as a buffer for the local production, and storage for products, which cannot be produced at the corresponding plant. Each DC is able to deliver the whole range of products. The products which cannot be produced in the corresponding plant must be delivered to a DC from another plant or another DC. Delivery takes place by means of homogenous vehicles with limited capacity.

In our model, the most common transportation modes, namely less than truckload (LTL), and full truckload (FTL) are used. The distribution of goods from the plants to the DCs occurs in one of two ways (1) on a straight-and-back basis, i.e., there is only one DC on a given delivery vehicle’s path, which is the case if the customer requirements constitute a FTL, or (2) in a route involving multiple DCs on the route have individual requirements for LTL. For LTL multiple customers are served in a single route. In this case, transportation costs only depend on the transportation distance, not on the specific load. Figure 3.1 illustrates the considered production–distribution system.

The problem is to assign products to the production lines, and to determine the routes to be travelled to coordinate the production and transportation routing operations so that the customer demand, capacity constraints, production, and inventory constraints are all satisfied, while the resulting cost (i. e. the sum of the production, inventory, set up, and transportation costs) over a given planning horizon is minimized.

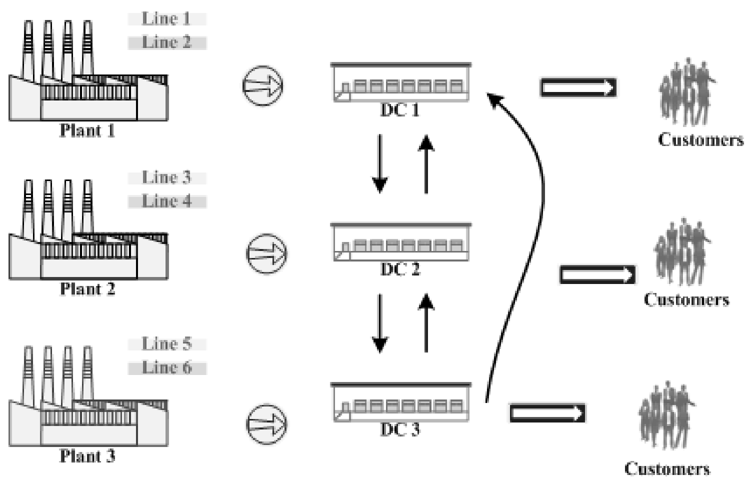

Figure 3.1 Supply chain network

The following considerations further define and delimit the problem:

- The supply network consists of several plants which deliver the final products to various DCs.
- Each plant comprises several not necessarily identical production lines. Each line produces a given range of products. Multiple assignments of products to the production lines are allowed.
- Each product inventory balances at DCs is updated on a daily basis according to the production output from the various lines at the plants, the inbound and outbound transportation quantities, backorder quantity and the given external demand. Backorder is allowed in every period except the last one.
- All vehicles used in LTL transportation are assumed to be identical.
- No specific handling capacities and costs at DCs are considered.
- Transportation activities are carried out within a single day. Nevertheless,

lead times for long-distance transportation can be modeled simply by offsetting the time index of the respective decision variables.

- Each vehicle can only travel according to the predefined route with fixed operational cost. It is assumed that a vehicle can pick up products from a plant in a travel.

The objective of the MIP model is to determine (i) production quantities which are produced on each production line, (ii) setup operations for each product and the corresponding product groups, (iii) number of vehicles which are used for transportation operations, (iv) inventory, and backordered quantity level of each time period. The external demands of each product and period at DCs are given and have to be satisfied. Whenever a product is produced during a time period, a setup operation of the product and the corresponding product group is required which results in setup cost. The capacity of the production lines cannot be extended and limits the production quantities. Also, each transportation vehicle is allowed to discharge cargo at most two DCs.

For convenience and readability, the parameters and notations of the MIP model are described in the nomenclature at the end of the chapter.

Objective Function

$$min \sum_{i \in I} \sum_{l \in L} \sum_{t \in T} C_{il}^{\Pr od} x_{ilt} + \sum_{i \in I} \sum_{l \in L} \sum_{t \in T} C_{il}^{SMin} z_{ilt} + \sum_{j \in J} \sum_{l \in L} \sum_{t \in T} C_{jl}^{SMaj} u_{jlt} + \sum_{r} \sum_{t} C_{r}^{LTL} n_{rt}$$
$$\sum_{i} \sum_{w} \sum_{t} C_{iw}^{Inven} I_{iwt} + \sum_{i} \sum_{w} \sum_{t} C_{iw}^{Bord} b_{iwt} \tag{3.1}$$

Subject to

$$\sum_{i} a_{il} x_{ilt} + \sum_{i} ts_{il} z_{ilt} + \sum_{j} TS_{jl} u_{jlt} \le PCap_{l} \qquad \forall l, t \tag{3.2}$$

$$x_{ilt} \le M.z_{ilt} \qquad \forall i, l, t \tag{3.3}$$

$$\sum_{i \in J_i} z_{ilt} \le M.u_{jlt} \qquad \forall j, l, t \tag{3.4}$$

$$\sum_{r} \sum_{w} y_{irwt} + \sum_{w} q_{ipwt} = \sum_{l} x_{ilt} \qquad \forall p, i, t \tag{3.5}$$

$$\sum_i \sum_w y_{irwt}\alpha_i \le Vn_{rt} \qquad \forall r,t \qquad (3.6)$$

$$I_{iwt-1} + \sum_r y_{irwt} + \sum_p q_{ipwt} - d_{iwt} - I_{iwt} + b_{iwt} - b_{iwt-1} = 0 \quad \forall i,w,t \text{ with } I_{iw0} = given \qquad (3.7)$$

x_{ilt} , y_{irwt} , q_{ipwt} , $I_{iwt} \ge 0$, $b_{iwt} \ge 0$, $n_{rt} \ge 0$, and integer,

$$z_{ilt}\ ,\ u_{jlt} \in \{0,1\} \qquad \forall i,j,l,p,w,r,t \qquad (3.8)$$

The first term in objective function (3.1) defines the production costs and the second and the third terms represent the minor and major setup costs for products, and product groups, respectively. Finally, the last three terms represent the transportation cost of the system, inventory and backorder costs. Constraints (3.2) are the time capacity constraints. Capacity is the upper bound on the total time that can be consumed to produce products. It specifies that the time used for processing (manufacturing) on a line cannot exceed the capacity of that line in time period t. Constraints (3.3) enforce the production quantity i on line l to zero, if no corresponding setup operation is performed (i. e. $z_{ilt} = 0$). Constraints (3.4) ensure that product i belong to product group j can only be set, if the line is setup for the product group j. In the constraints (3.5), total output quantities achieved from producing product i at the production lines in plant p must be equal to the FTL shipping quantities on the routes starting from plant p and including DC w plus the LTL shipping quantities to the DCs which are supplied from plant p. That is, it ensures the availability of the product i at plant p in time period t. In the constraints (3.6), the total quantity of products (converted into unit loads) to be transported to the various DCs w included in LTL route r determines the number of vehicles n_{rt} required for that route in time period t. Note that variable n_{rt} is defined as an integer number of identical vehicles each having a transportation capacity of V unit loads. The daily demands of products must be satisfied. Constraints (3.7) ensure the inventory flow balance at DCs, and require each DC to have enough supply (from either inventory and/or the quantity arrived in that period) to meet the demand and the backordered quantity. That is, the inventory of product i at DC w at the end of time period t is determined by the ending inventory of the previous time period, the quantities received, the quantity backordered and the external demand to be satisfied on the respective time period. Finally, constraints (3.8) are integrity and non-negativity constraints.

3.4 Solution Approaches

3.4.1 MIP Based Heuristics

In our research, the proposed MIP based rolling horizon methods are F&R and F&O heuristics. These heuristics operate basically with the similar procedure which processes to solve the problem in a systematic manner by fixing the binary variables in the certain time periods. The setup variables are progressively fixed at their optimal values. The distinctive points of the processing procedures are in the relaxing and optimizing phases. F&R heuristic allows the corresponding binary variables to get continuous values within the 0 and 1 range. But, F&O heuristic seeks only discrete values for these binary variables in the same range. In addition, F&O heuristic needs to be a given feasible initial solution and the corresponding objective function value to start the algorithm. The use of the appropriate initial solution and objective value provides explicit advantages to get more favorable feasible solutions to the F&O heuristic.

F&R Heuristic: F&R heuristic is introduced to provide good solutions in deterministic environments by Dillenberger et al. (1994). It is an approach to find feasible solutions for larger instances of complex problems. The basic idea of the method is to divide the planning horizon into a number of finite time intervals and to solve the sub-problems in iterations corresponding to the time intervals Uggen et al. (2013).

The structure of the F&R algorithm with time decomposition is outlined in Figure 3.2. The algorithm can be explained basically in three steps. In the first step, the time interval is equal to 1.The first sub-problem is solved with the binary variables in the initial time interval, while the remaining binary variables for other time intervals are relaxed to get continuous values. In the second step, time interval is increased step by step by controlling the stopping criterion. The integer variables from the previous intervals are fixed to the solution values obtained from the previous iteration. Simultaneously, integrality constraints are reintroduced for the integer variables, while all other variables are kept non-fixed and continuous. After solving the new sub-problem, the iteration is completed. The iteration is then repeated until all intervals except last one are completed. If the stopping criterion is satisfied with the feasible solutions for all n-1 intervals, the algorithm is directed through the third step. In this last step, after solving the binary variables of the last interval by fixing other previous solutions, a complete solution is found for the original problem.

F&O Heuristic: The fundamental idea of the F&O heuristic is to solve the problem in a systematic manner by setting most of the binary variables to the fixed values at each of the iterations (Sahling et al, 2009; Helber and Sahling, 2010). This procedure reduces the number of non-fixed binary variables which are optimized in the problem and leads to very reasonable solution time. Then, the problem is solved to get the temporary solution which is utilized in the next iterations. Hence, there is a new problem with a different subset of fixed binary variables and the rest of the binary variables are optimized (Helber and Sahling, 2010).

The basic structure of the F&O algorithm with time decomposition is outlined in Figure 3.3.The F&O heuristics start with an initial solution which yields an initial objective. Firstly, the algorithm starts with the adjustment of the Best Solution as Initial Solution and Objective $^{(Old)}$ as Initial Objective. Objective $^{(Old)}$ indicates the objective value calculated using the last valid and best solution. Best Solution shows the binary variable values of the best solution ever achieved from the algorithm. Initial objective value is calculated to adjust the first value of the Objective $^{(Old)}$. The performance of the algorithm depends on the initial solution.

Many heuristics are available in the literature to construct an initial solution. However, since the aim is not spend too much computation time for any construction heuristic, four simple initial solutions are investigated for the test instance with low granularity level, and 90% capacity load.

The test results are obtained for four different initial cases (i) in which all binary variables are fixed to 0, (ii) in which all binary variables are fixed to 1, (ii) in which the binary variable assignments are made randomly, (iv) in which the initial solution is generated based on the F&R heuristic. The results are summarized in Table 3.3. As an initial solution, we start similarly to Helber and Sahling (2010) with a pattern, i.e., all binary setup variables are fixed to 1, since it results in the best solution. After initial adjustments, the algorithm checks the stopping criteria, which decide either continue or finish the processing. The stopping criteria consist of two distinct controls, Iteration Limit and Feasible Solution. The first control limits the number of iteration to the maximum allowed iteration number. And, the second checks whether the feasible solution is achieved for all time intervals. In any case, algorithm tries to complete the Iteration Limit. When the maximum iteration limit is reached, the F&O algorithm stops and represents the feasible solution. But, if Iteration Limit is exceeded and there is no feasible solution, algorithm represents "No solution". For the experimental studies, it is enough to run the algorithm for a single iteration to get feasible and relatively close objective values to the optimal in a small computational time.

Table 3.3 Initial solutions with test case- 90% capacity load and low demand granularity level

	Initial Solution	**Objective Function (€)**	**Time (h:m:s:ms)**
UFO Heuristic	Initial 0	370145890.62	00:00:15:75
	Initial 1	307650973.31	00:00:17:70
	Initial RND	350883593.08	00:00:16:97
	Initial UFR	370145890. 62	00:00:55:20
ZFO Heuristic	Initial 0	445348753.94	00:00:14:83
	Initial 1	294133498.81	00:00:17:70
	Initial RND	445348753.94	00:00:16:97
	Initial ZFR	445348753.94	00:01:05:90

After controlling the stopping criteria, the F&O procedure divides the time period into certain intervals and generates the sub-problems. There are three steps in F&O procedure to operate with the generated sub-problems; Step1: Optimize–Fix, Step 2: Fix–Optimize–Fix, Step 3: Fix–Optimize. These steps are quite similar procedures to each other with small differences. In Step1, the lower and upper bounds of the corresponding binary variable are released as 0 – 1 to optimize the first interval and the following intervals are fixed to the Best Solution. Hence, the temporary solution is calculated by solving the model with these predefined binary variable values. Then, there is a comparison to evaluate the solution. Each temporary solution yields an Objective $^{(New)}$ and the temporary solution is only accepted as a new solution if it yields the Objective $^{(New)}$ value lower than Objective $^{(Old)}$. After the comparison, if the temporary solution is accepted, Temporary Solution is assigned to Best Solution variable and Objective $^{(New)}$ value is assigned to Objective $^{(Old)}$. Then, algorithm continues with Step2.

In Step2, the lower and upper bounds of the corresponding binary variable are released as 0 – 1 to optimize the intermediate intervals and the other remaining intervals are fixed to the Best Solution. Hence, the temporary solution is calculated by solving the model with these predefined binary variable values. If the temporary solution is accepted, Temporary Solution is assigned to Best Solution variable and Objective $^{(New)}$ value is assigned to Objective $^{(Old)}$.

Step3 is the final procedure releasing the lower and upper bounds of the corresponding binary variable as 0 – 1 to optimize the last interval and fixing the remainder intervals to the Best Solution. If the temporary solution is accepted, Temporary Solution is assigned to Best Solution variable and Objective $^{(New)}$ value is assigned to Objective $^{(Old)}$ with the temporary solution control procedure. Then, iteration counter is updated.

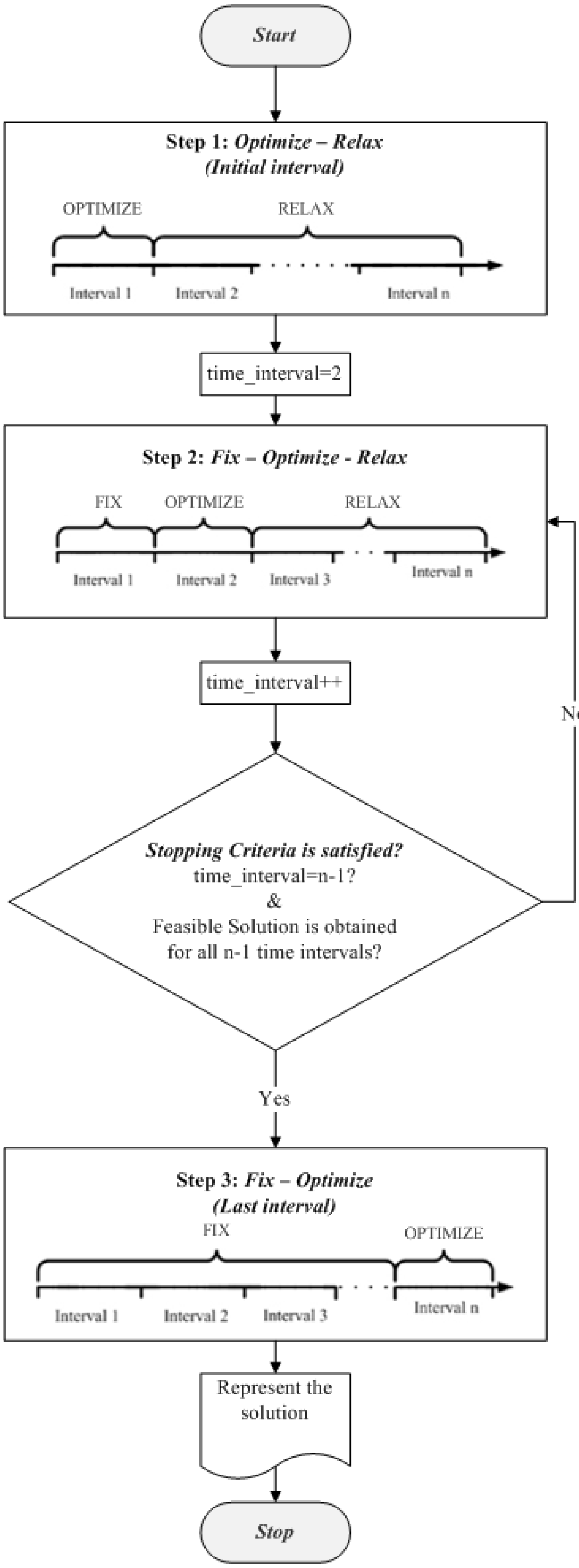

Figure 3.2 Fix & Relax algorithm

3.4.2 Simulation

Optimization models have been proved useful, but they require too many simplifications to model realistic supply chain problems. Real world situations are characterized by a high degree of uncertainty. Inclusion of uncertainties often makes pure mathematical modeling intractable. Simulation models include nonlinearities, complex structure and uncertainty which are main features of the real systems. In this research, simulation modeling and analysis is introduced to include the stochastic factor to the solution as unexpected delays and changes on operation time causing from queuing and machine failure. All machines in the line have the same processing rates, and all the machines are subject to breakdown. The simulation model is established to represent MILP model and it enhances the predefined problem by queuing and machine failures. The conceptual model of the system is shown in Figure 3.4.

In this model, the simulation model starts with the creation of semi-products which have different Product_IDs and Product_Groups. The production quantity and machine allocation data is received from the MILP results. The simulation model always starts with the first product considering the queue ranking criterion. While the first product is operating on the line to produce desired quantity, the model controls the conditions of other lines and products, and then starts the production of the second and the following products. When the plan given according to MILP results for the corresponding day is completed, the model starts the production of the next day. In real systems, the theoretical capacities for machines cannot be used completely because of the failures. During the program, the failures become active. Thus, we can measure the operation time on each production line for the production schedule given by the MILP model.

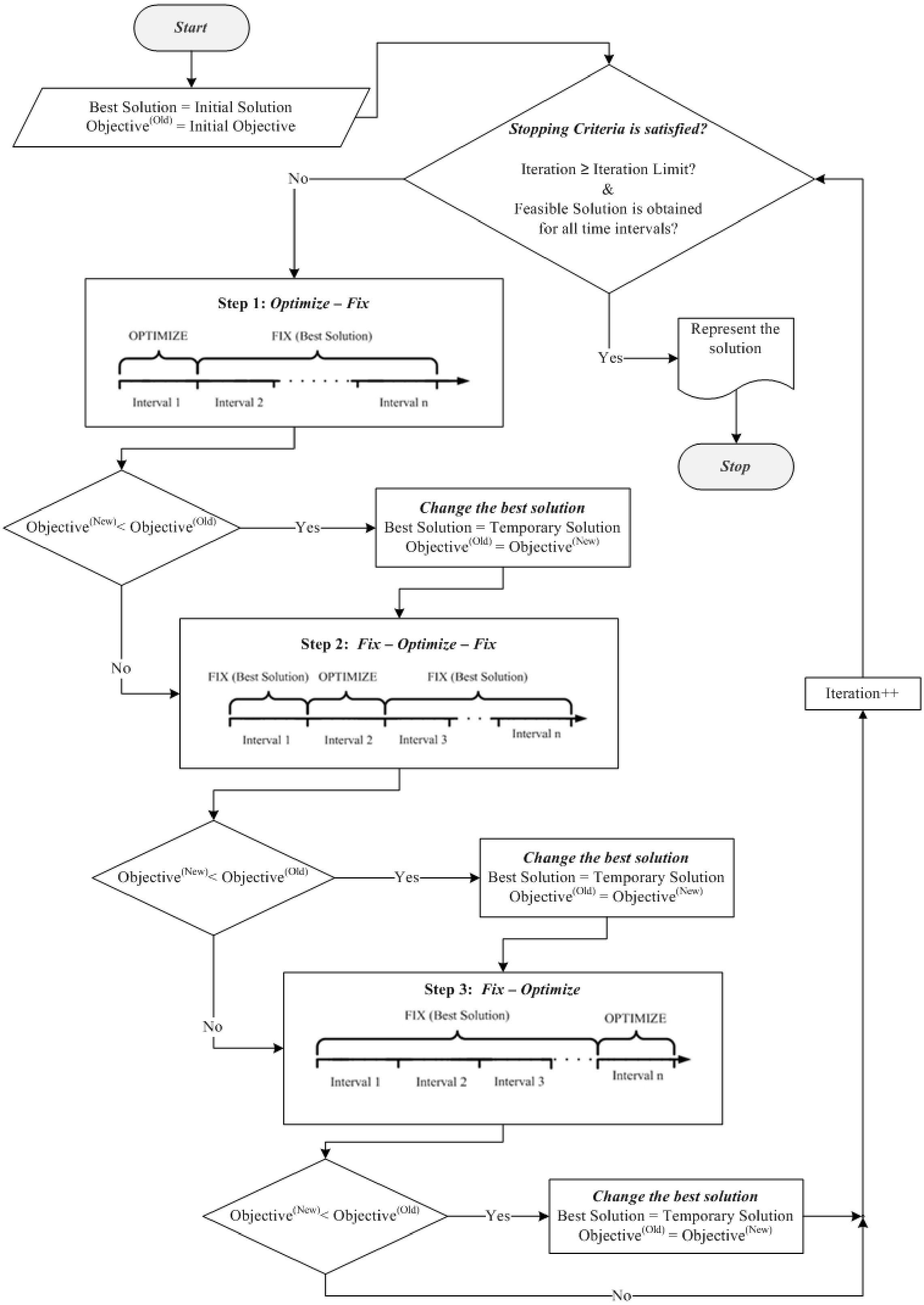

Figure 3.3 Fix & Optimize algorithm

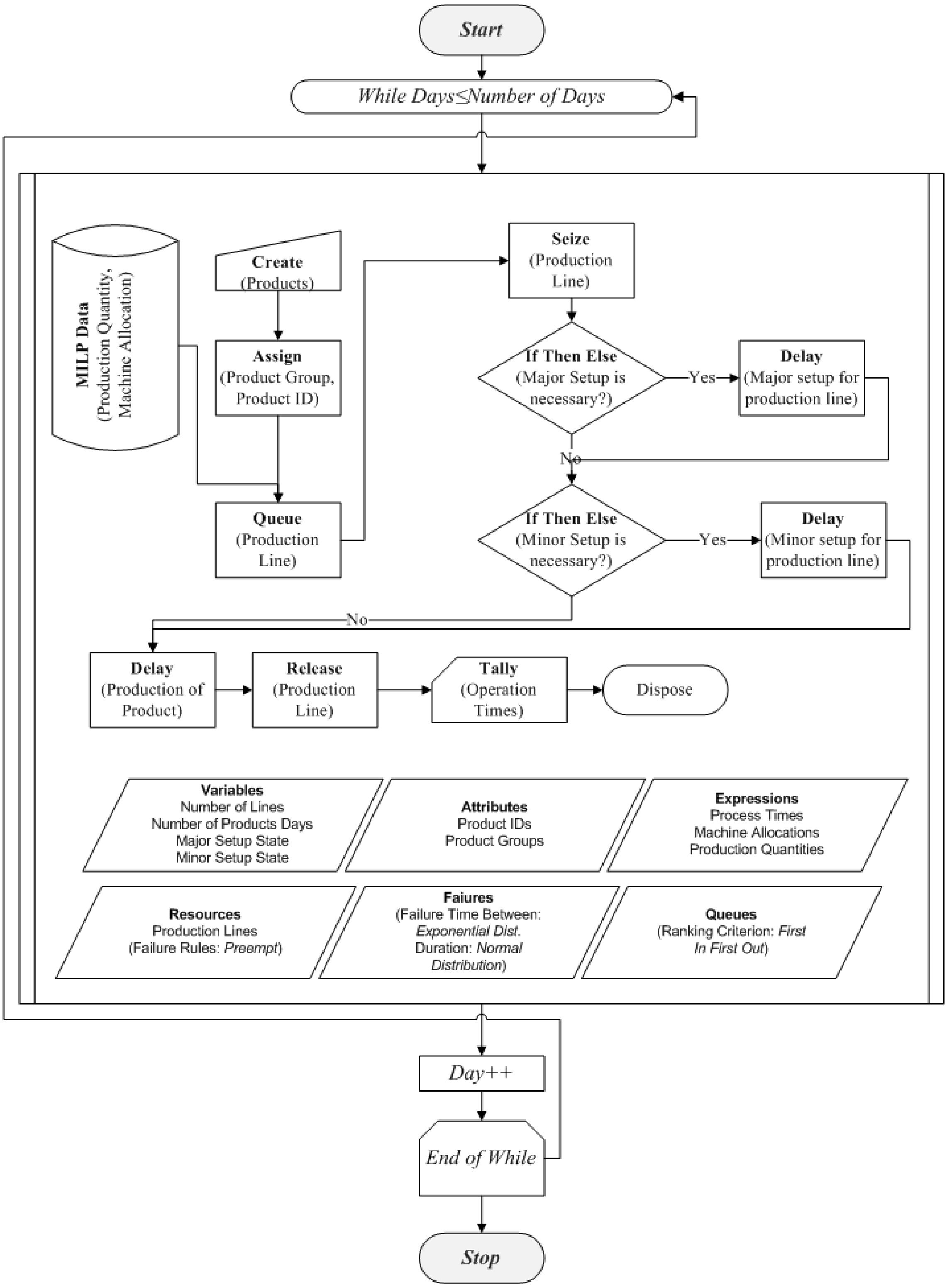

Figure 3.4 The conceptual model

3.4.3 Hybrid Approach

The hybrid approach combining simulation and MILP optimization merges independent analytic and simulation model of the production system to make use of their solution procedures together for problem solving. The goal of the hybrid approach is to achieve near optimal, more realistic production-distribution plans. The connection of two corresponding models is shown in Figure 3.5.

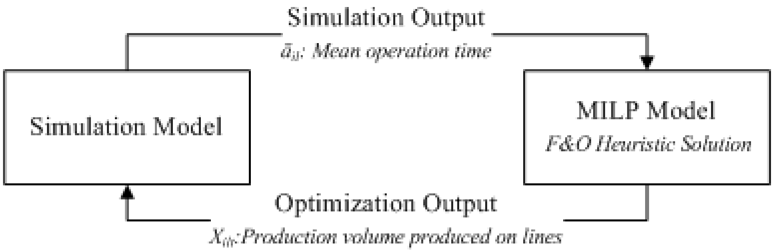

Figure 3.5 Connection of the simulation and optimization models

In this research, a hybrid solution approach is developed by applying MIP based F&O heuristic solution approach and simulation approach. The algorithm of hybrid approach basically consists of two consecutive procedures. First, F&O heuristic solution of the mathematical model gives the near optimal solution that minimizes the costs for set up, production, inventory, and distribution without considering the stochastic factors (i. e. unexpected delays as queuing and machine failures. Second, simulation approach adjusts the capacities of the production lines by updating operation times under consideration of uncertainty. The corresponding algorithm is explained in details with the following steps and illustrated in Figure 3.6 (Safaei et al., 2010).

Step 1. Solve the MILP model using F&O heuristic algorithm to generate the initial production-distribution plan.

Step 2. Run the simulation model based on the current production-distribution plan with ten independent replications.

Step 3. Calculate average operation times by means of ten replications.

Step 4. If the difference rate between preceding operation times (POT) and current operation times (COT) is not within the rate of 0. 025, then go to Step 5.Otherwise go to Step 6.

Step 5. Solve the MILP model with COT using F&O heuristic algorithm to update production-distribution plan.

Step 6. Solve the MILP model using F&O heuristic and present near optimal production-distribution plan.

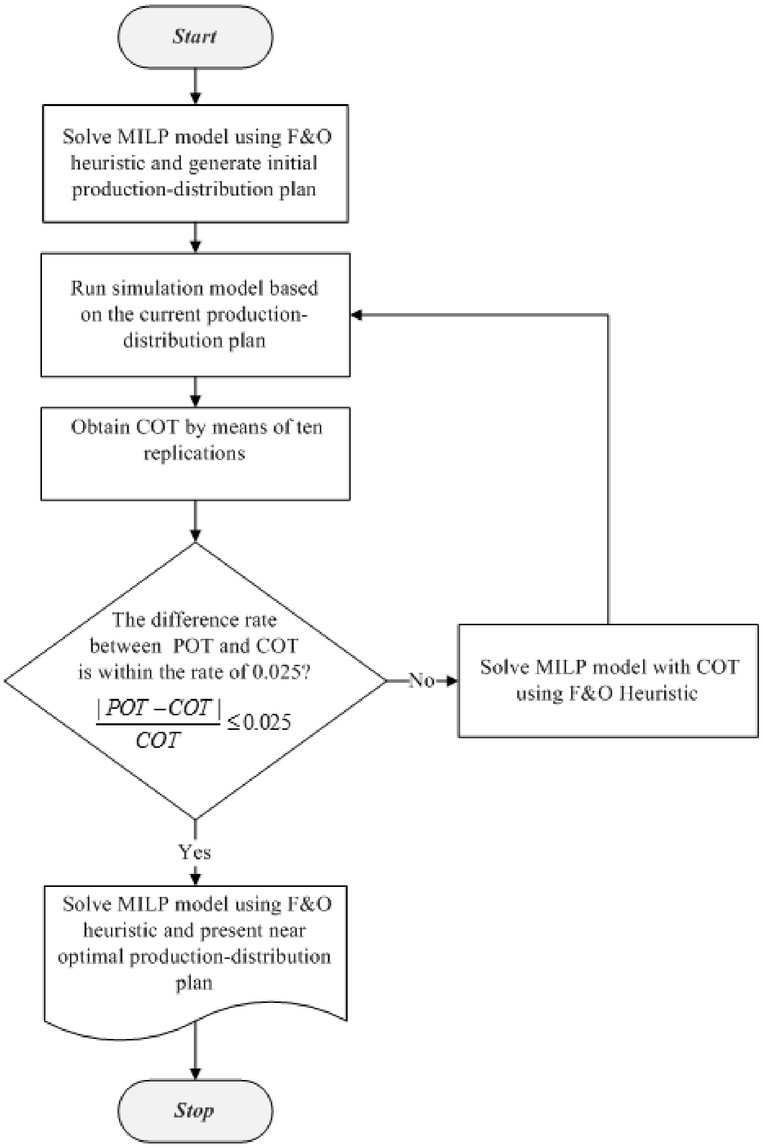

Figure 3.6 The hybrid simulation-optimization procedure

3.5 Case Study

To demonstrate the validity and practicality of the proposed heuristics and hybrid methodology, an industrial case inspired from a soft-drink industry is presented. The case study is presented to demonstrate the efficiency of the proposed method to highlight the characteristics of the proposed model. The supply chain network involves three plants, six production lines and three DCs located in different customer zones. There are two different types of product groups, and 19 different product types.

Other relevant data are summarized as follows.

- The planning horizon consists of 4 weeks with daily periods.
- The manufacturing plants operate 16 hours per day and 5 days per week.
- The processing speed of the six production lines is given as 8000 (line 1), 6000 (line 2), 7000 (line 3), 7000 (line 4), 8000 (line 5), 6000 (line 6) liters per hour as independent from the specific beverage produced on the line. The corresponding line-specific processing costs per day are defined as 8, 12, 10, 10, 8 and 12 € for the individual lines.
- A major setup time is considered as 1 hour for setting up a specific production line and product group, while a minor setup time of 18 minutes is required for setting a product on a production line. The minor setup time is the same for all production lines and products. Setup costs including material losses amount to 150 € per major and 30 € per minor setup.
- For transportation, trucks with 26 tons loading capacity to be hired from an external logistics service provider are considered.

The MILP formulations and MIP based F&O, and F&R heuristic algorithms are implemented and solved using IBM ILOG CPLEX 12.1.The simulation model is implemented in Arena version 10. 0. They are solved on a Dual CPU notebook with 4GB RAM and 2.16 GHz.

3.5.1 Numerical Results of MIP Based Heuristics

In the numerical examples, a short-term planning horizon of four weeks is considered, and seasonal demand variations are not essential. However, depending on the time of the year, the average workload may be higher or lower. These conditions are reflected by five scenarios which assume an average workload of 50, 60, 70, 80 and 90% of the available total capacity, respectively. Moreover, since demand in the fast moving consumer goods industry is driven by customer orders of various sizes, granularity of demand elements is considered as a key factor. In order to reflect these issues, three distinct demand data are examined to represent the demand granularity: high, medium, and low. These different degrees of demand granularity are reflected by scenarios with the randomly generated demand figures. For instance, while high demand granularity indicates a large number of small-sized customer orders, low demand granularity implies comparatively small number of large-sized orders for the same aggregate demand volume. The proposed test bed is designed to cover a large set of combinations regarding the capacity loads, and demand granularity levels, from relatively easy instances to very challenging ones. In order to evaluate the solution quality of the proposed algorithms, three different variants of MIP based heuristics are introduced and compared with the optimum.

These are: (i) Method ZFO-F&O algorithm applied on z_{ilt} binary variable, indicating setup operations for each product. (ii) Method UFO-F&O algorithm applied on u_{jlt} binary variable, indicating setup operation for each of product group. (iii) Method UFR-F&R algorithm applied on u_{jlt} binary variable, indicating setup operation for each of product group.

Table 3.4 shows the main results of the computational test. The computation time and MIP gaps are obtained by MILP, F&R and F&O solutions for the five scenarios of 50, 60, 70, 80 and 90% capacity load, and for the three different levels of demand granularity, respectively. The gap values are calculated to reveal the differences between the heuristic solution value and optimal solution value. Optimal solutions and the required computational times to get these optimal solutions are presented in the MILP column. 300 numerical experiments are carried out in order to evaluate the proposed MILP model and MIP based F&R and F&O algorithms. Each experiment is repeated five times with the randomly generated demand data. Runtime limit of the MILP model is adjusted as 600 seconds. While optimal results are obtained for some of 50, 60 and 70% capacity loads, lower bound values are determined for the other large scaled and complex instances within the considered time limit.

Note from Table 3.4 that capacity loads and granularity levels affect both the gap values and the solution time. Our numerical results reveal that MIP gap decreases and computational time increases considerably when customer orders get smaller size (i. e. low to high granularity level). In particular, the computational complexity considerably increases in the high demand granularity scenario, since comparatively large number of production lots have to be established. In terms of the capacity loads, the increasing capacity load expresses the problem on manufacturing with more tightly used resources and represents the more realistic problem. It complicates the problem and computational efforts systematically and rises up both of the MIP gap and computational time, simultaneously.

When the performances of the F&R and F&O algorithms are analyzed using the subtotal values, it is concluded that the F&O outperforms with respect to both the MIP gap values and the computational time with a considerable difference. In this concept, ZFO can be determined as the favorable. F&O Heuristic algorithm with ZFO variant has an average 6.39-% MIP gap value, and noticeably shorter computational time than the standard MILP solution. It is an expected result that the start with an appropriate initial solution provides explicit advantages to F&O heuristic. Hence, the proposed F&O heuristic has a more reasonable computational performance in comparison with F&R. The gap values of F&R alternatives are too big and alternative algorithms may be implemented that overcome this limitation for the further research.

Table 3.4 Experimental results

Capacity Util. (%)	Gran. Level	UFR			UFO			ZFO			MILP (time limit=600)		
		Result (€)	**Comp. Time (h:m:s:ms)**	**Gap (%)**	**Result (€)**	**Comp. Time (h:m:s:ms)**	**Gap (%)**	**Result (€)**	**Comp. Time (h:m:s:ms)**	**Gap (%)**	**Result (€)**	**Comp. Time (h:m:s:ms)**	
50	Low	190,715,072.99	00:00:14:95	12.92	174,632,736.49	00:00:15:70	1.83	172,278,472.12	00:00:12:74	0. 65	171,163,895.74	00:00:21:63	*
50	Med.	210,482,749.74	00:00:20:83	25.66	170,275,606.26	00:00:21:38	0. 97	168,993,545.96	00:00:14:75	0. 27	168,553,859.30	00:02:47:60	*
50	High	150,815,375.65	00:00:21:65	6.99	141,266,784.24	00:00:28:55	0. 91	140,415,563.71	00:00:16:70	0. 25	140,068,640. 99	00:03:35:40	*
50 AVG		*184,004,399.46*	*00:00:18:92*	*15.19*	*162,058,375.66*	*00:00:21:65*	*1.24*	*160,562,527.26*	*00:00:14:73*	*0. 39*	*159,928,798.68*	*00:01:47:77*	
60	Low	540,170,050. 52	00:00:14:41	67.93	338,433,376.74	00:00:10:33	7.75	319,328,678.53	00:00:09:42	0. 35	318,255,541.91	00:00:11:75	*
60	Med.	313,307,041.65	00:00:22:56	29.97	242,406,425.81	00:00:18:50	0. 47	241,921,265.74	00:00:15:40	0. 27	241,282,435.91	00:04:75:68	*
60	High	282,081,791.32	00:00:40:61	49.61	205,869,202.42	00:00:32:68	7.27	193,807,424.90	00:00:22:86	1.57	190,600,306.47	00:10:01:45	
60 AVG		*378,519,627.83*	*00:00:25:64*	*49.17*	*262,236,334.99*	*00:00:20:50*	*5.16*	*251,685,789.72*	*00:00:15:67*	*0. 73*	*250,046,094.76*	*00:04:42:74*	
70	Low	335,236,334.41	00:00:12:60	48.62	360,385,539.44	00:00:13:56	63.25	229,927,951.57	00:00:10:69	0. 56	228,678,071.69	00:00:19:47	*
70	Med.	320,893,374.03	00:00:33:82	40. 09	261,804,181.29	00:00:20:76	14.79	257,344,768.24	00:00:18:33	11.41	232,367,883.60	00:10:01:55	
70	High	392,798,546.69	00:00:33:84	70. 14	278,232,873.32	00:00:29:26	22.13	229,185,418.42	00:00:20:62	0. 83	227,492,538.44	00:10:01:56	
70 AVG		*349,642,751.71*	*00:00:19:75*	*52.95*	*300,140,864.69*	*00:00:20:75*	*33.39*	*238,819,379.41*	*00:00:16:55*	*4.26*	*229,512,831.24*	*00:06:20:64*	
80	Low	440,435,573.91	00:00:16:46	36.62	388,295,466.34	00:00:10:63	13.55	423,589,301.14	00:00:10:91	26.21	343,138,070. 97	00:10:01:46	
80	Med.	555,013,133.20	00:00:29:57	63.75	421,733,109.97	00:00:25:57	21.05	371,814,399.07	00:00:21:89	6.97	352,105,487.47	00:10:01:82	
80	High	434,665,274.03	00:00:38:80	70. 77	343,002,993.49	00:00:30:75	36.75	272,987,090. 36	00:00:24:82	10. 95	248,222,933.55	00:10:01:50	
80 AVG		*476,704,660. 38*	*00:00:27:83*	*57.05*	*384,343,856.60*	*00:00:21:87*	*23.78*	*356,130,263.52*	*00:00:18:98*	*14.71*	*314,488,830. 66*	*00:10:01:59*	
90	Low	1,195,419,386.21	00:00:19:82	166.87	927,513,127.97	00:00:11:73	97.2	496,125,533.95	00:00:13:51	10. 71	446,602,618.96	00:10:01:64	
90	Med.	736,140,181.09	00:00:28:78	102.7	646,720,298.90	00:00:17:75	84.71	411,659,665.87	00:00:20:44	12.66	362,209,142.12	00:10:01:81	
90	High	470,005,118.81	00:00:39:51	53.23	417,264,826.28	00:00:30:56	35.24	347,943,264.48	00:00:23:69	12.13	311,620,332.99	00:10:01:77	
90 AVG		*800,521,562.04*	*00:00:28:93*	*107.6*	*663,832,751.05*	*00:00:19:79*	*72.38*	*418,576,154.77*	*00:00:18:77*	*11.84*	*373,477,364.69*	*00:10:01:74*	
Overall AVG		***437,878,600. 28***	***00:00:25:69***	***56.39***	***354,522,436.60***	***00:00:20:62***	***27.19***	***285,154,822.94***	***00:00:16:68***	***6.39***	***265,490,784.01***	***00:06:16:66***	

* Optimum results

Figures 3.7 displays and summarizes the MIP gap and the computation time for the instances, which have different granularity levels and capacity loads. The analyses on gap indicate that the F&O algorithm gets solutions with low MIP gap values in comparison with F&R algorithm. High demand granularity, which has a large number of small-sized customer orders, and low demand granularity, which has a comparatively small number of large-sized orders do not make the F&O algorithm more difficult to reach good solutions. The results show that the ZFO is the most promising procedure which has the best gap values.

The computational time for the cases which has low demand granularity and lower capacity level requires less computational effort. Hence, the span between the CPU times for high granularity level instances is quite large. In addition, both of heuristic procedures outperform the standard MIP solution procedure in terms of the computation time. As it can be observed form Figure 3.7, the ZFO procedure may be chosen as a favorable structure for the F&O heuristic.

3.5.2 Numerical Results of Hybrid Approach

In the numerical analysis of hybrid approach, the proposed simulation model and ZFO algorithm is hybridized and a numerical example with %90 capacity load and high granularity level is chosen as the most challenging test instance. The hybrid method starts with the MIP-based F&O heuristic which provides near optimal production and distribution plan by minimizing the total cost. Then, the simulation model that reflects the dynamic situations as queuing, machine failure and repair times is applied to obtain the results of the real system behavior. The failures come out during production exponentially with the mean value of 100 minutes and repair operations actualize with normal distribution which has the mean value of 30 minutes and standard deviation of 30 minutes. In order to obtain mean operations times, ten independent replications are applied in the simulation model. The independence of the replications is accomplished by different random numbers using for each replication. The results of the initial condition for operation times and mean of results gathered from simulation replications are listed in Table 3.5 and illustrated in Figure 3.8. Operation times are fluctuating. However the width of fluctuation decreases as iteration is increased. It can be seen from the Table 3.5 of results that dramatic changes have occurred in operation times immediately after the initial iteration.

Table 3.5 Simulation results for each iteration

Operation Times (Hour/Unit)	**Initial Solution**	**1.iteration**	**2.iteration**	**3.iteration**	**4.iteration**	**5.iteration**
Line 1	0. 000125	0. 000169	0. 000162	0. 000166	0. 000167	0. 000166
Line 2	0. 000167	0. 000218	0. 000221	0. 000228	0. 000219	0. 000224
Line 3	0. 000143	0. 000184	0. 000185	0. 000187	0. 000195	0. 000193
Line 4	0. 000143	0. 000191	0. 000188	0. 000189	0. 000190	0. 000186
Line 5	0. 000143	0. 000159	0. 000165	0. 000164	0. 000167	0. 000165
Line 6	0. 000167	0. 000224	0. 000221	0. 000219	0. 000217	0. 000223
Solution Time		*0. 08 min*	*0. 07 min*	*0. 07 min*	*0. 08 min*	*0. 07 min*

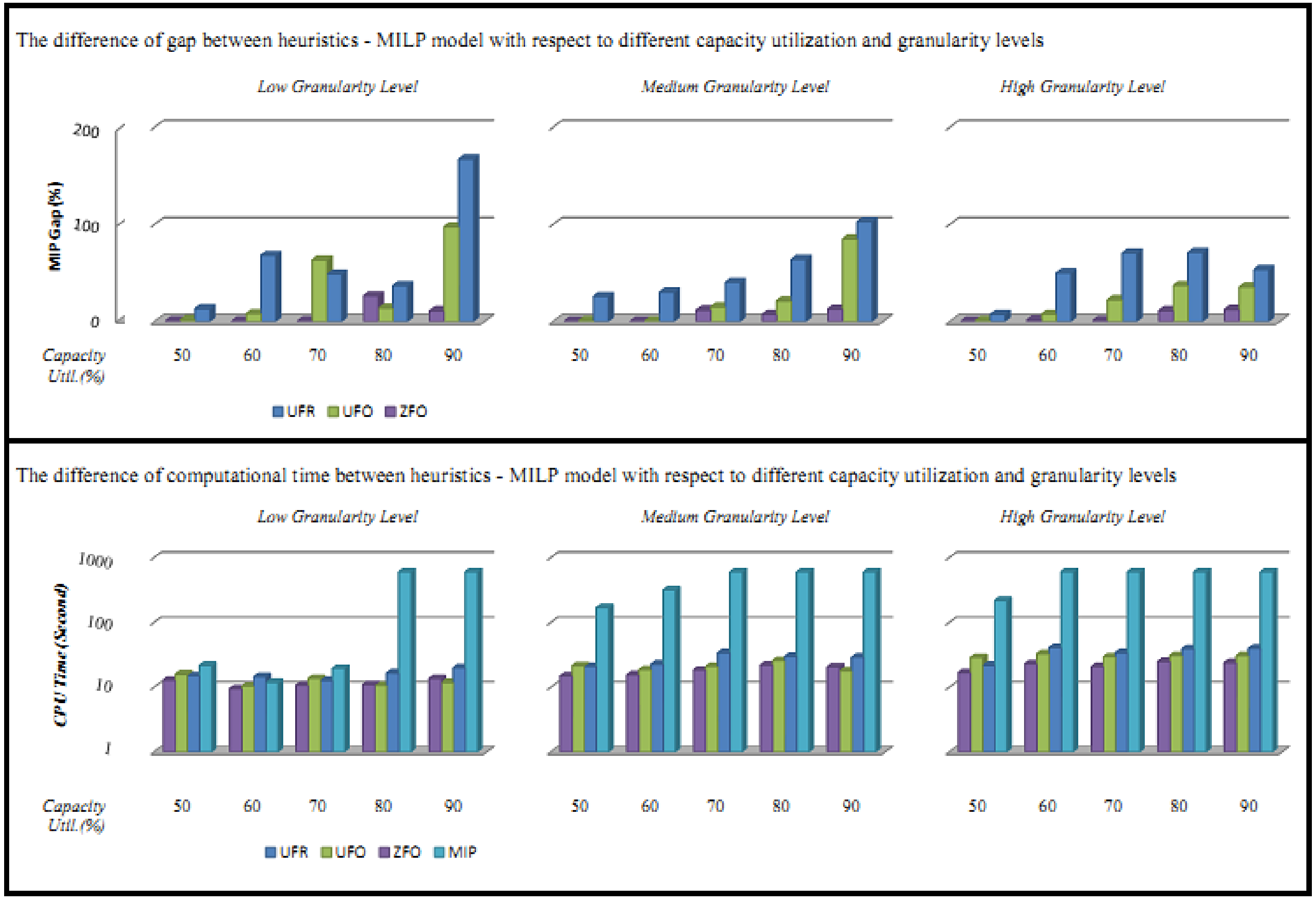

Figure 3.7.The computational comparison

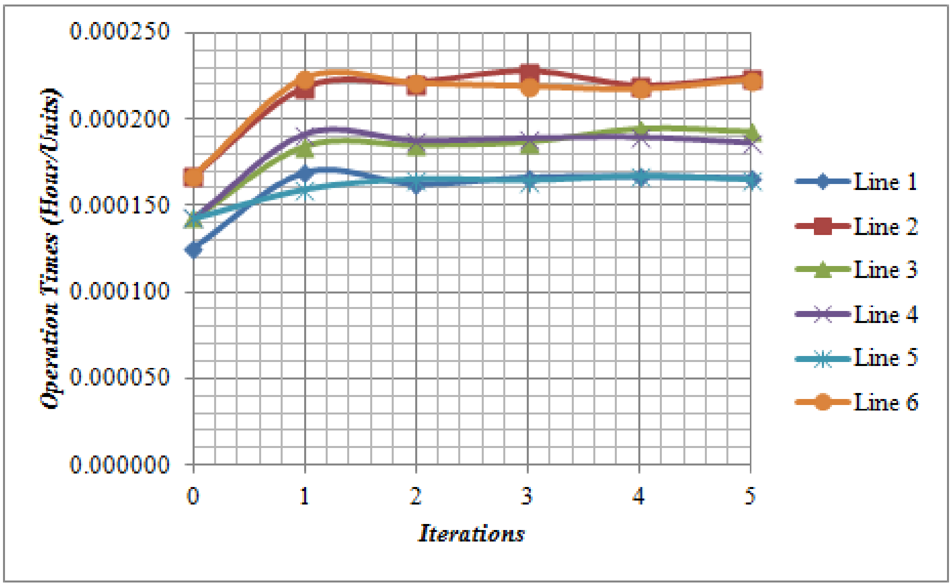

Figure 3.8 Simulation results for each of the iterations

The solution identified by the initial iteration of hybrid procedure results in increased operation time. The changes in operation time have also resulted in substantial increase in total system costs over the original analytic optimum. This solution incurs high costs, due the capacity disruption. Despite of increasing in objective value, the last iteration gives us a more realistic and practical solution for the problem. The objective values of MILP model are tabulated in Table 3.6 and illustrated in Figure 3.9.

Table 3.6 MILP results for each iteration

Total Cost (€)	**Initial Solution**	**Iterations**				
		1.	**2.**	**3.**	**4.**	**5.**
Objective	321,214,990	373,463,399	370,592,741	378,058,418	372,119,302	371,596,141
S.Time (m:s:ms)	00:25:36	00:34:78	00:29:47	00:30:60	00:34:19	00:32:68

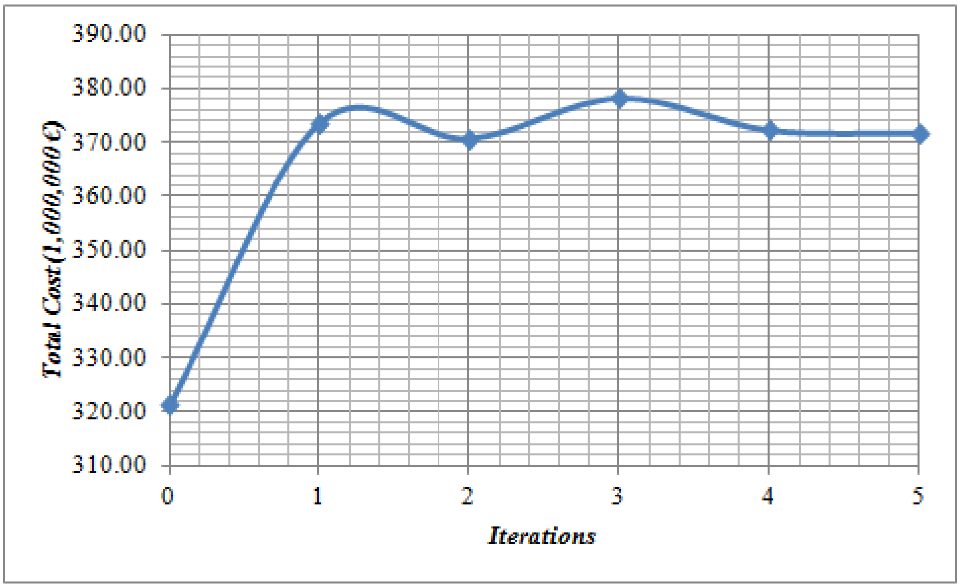

Figure 3.9 MILP results for each of the iterations

As can be seen in Table 3.7 hybrid approach is stopped in five iterations with the control of critical rate indicating the consistency between iterations. The critical rate values and threshold controls are presented in Table 3.7 and illustrated in Figure 3.10.

Table 3.7 Computation of critical rate for each iteration

	Critical Rate 1	Critical Rate 2	Critical Rate 3	Critical Rate 4	Critical Rate 5
Line 1	**0. 261011**	**0. 042099**	0. 024930	0. 003194	0. 006631
Line 2	**0. 234296**	0. 012303	**0. 029591**	**0. 038883**	0. 022609
Line 3	**0. 224862**	0. 003421	0. 009365	**0. 040068**	0. 008810
Line 4	**0. 252483**	0. 019995	0. 007234	0. 003166	0. 017721
Line 5	**0. 101571**	**0. 035451**	0. 005076	0. 015195	0. 012449
Line 6	**0. 254298**	0. 014113	0. 007681	0. 007741	0. 024886

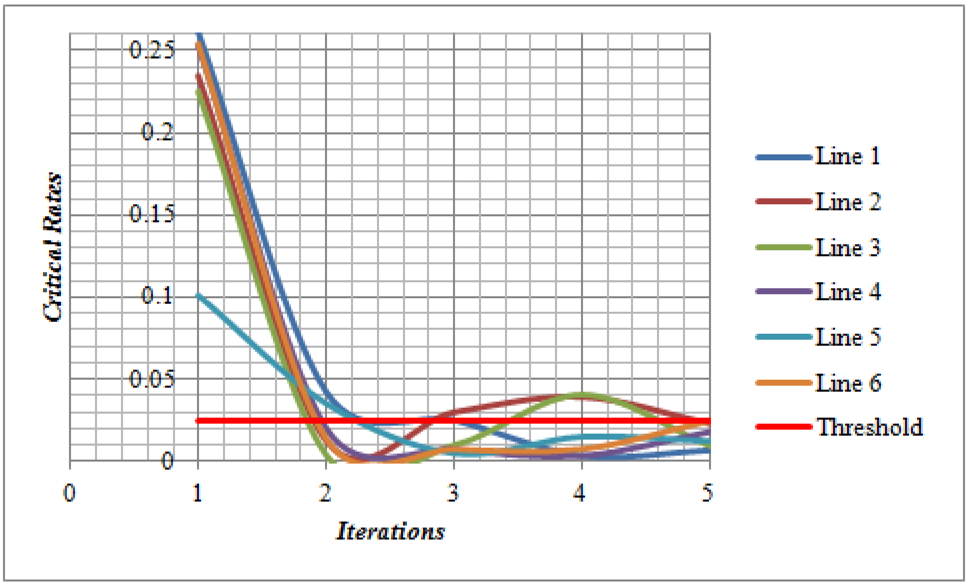

Figure 3.10 Critical rates for each of the iteration

The numerical results of hybrid approach demonstrate summarily that the overall cost increases in comparison with the initial solution. However, the results obtained by considering stochastic factors reflect the real system features.

3.6 Conclusion

In this research, production allocation and distribution planning problem arises in the soft drink industry is considered. Analytical methods have advantages on providing mathematical frameworks to model problems by representing specific characteristics and to get optimal solutions. Due to the complex natures of the supply chains, solution of the complicated models requires large amount computational times and heuristic methods are appropriate solution techniques for solving the complex optimization problems. Three different variants of MIP based heuristics are proposed.

For the computational performance tests, randomly generated demand figures for the three granularity categories and different capacity loads are examined to compare the standard MIP procedure and MIP based heuristic approaches. We have found that F&O heuristic with ZFO variant yields the best solution.

Operation time is inserted as a stochastic parameter for the realistic solution. It is adjusted according to the simulation model results. For determining operation time, probability density of machine failures and repair times are considered in the simulation model.

Hybrid method integrate the best capabilities of MILP model and simulation model, which lead to more realistic planning environments for the considered supply chain planning problem. The hybrid methodology merges the advantages of these two distinct modeling techniques to introduce the production and distribution planning model which has more acceptable results in practice.

Further research should address improving the computational efficiency of the proposed heuristics and making use of the advantageous of alternative heuristic techniques. Developing similar hybrid approach to deal with the other distinctive stochastic characteristics of different supply chain network problems may be promising further research directions.

The scheduling represents the realization of the tactical planning decisions in operational level. Having created a plan for defining the production tasks has to be sequenced to ensure that the planning activities are indeed applicable. Therefore, the integration of planning and scheduling or even incorporation as processes providing interrelated feedbacks to each other can be an effective way to make more applicable production plans. Planning and scheduling of process industry includes operational decisions on allocation of the productions to packaging lines, sequencing the multi-stage production and corresponding setups. Although soft-drink production does not include explicit perishability issues by means of final product which has a shelf-life period varying between months and years, most of other industrial examples should be planned and scheduled under shelf life and perishability constraints. Dairy industry includes highly perishable products and offers real life planning and scheduling problems.

In the next chapter, multi-stage-production planning, integrated production planning and scheduling perspectives of the literature review is discussed. An integrated planning and scheduling problem is considered in yoghurt production process and a MILP model is presented. The product perishability is considered as loss function in a cost-driven objective and shelf life constraints are taken into account. Working time and overtime are planned and bottleneck production operations are scheduled by the time and capacity constraints. Due to the high complexity of integrating planning and scheduling decisions in a single mathematical model, a decomposition approach is introduced and MILP/CP methodologies are combined to show their complementary strengths.

Nomenclature

For the mathematical description of the models the following notation is introduced;

Sets:

I Set of products (i=1,2,…,I)

J Set of product groups (j=1,2,…,J)

L Set of production lines (l=1,2…,L)

W Set of DCs (w=1,2,…,W)

T Set of time periods

R Set of routes

Parameters:

$PCap_l$ capacity of production line l

d_{iwt} external demand of product i at DC w, in period t

a_{il} time consumed to produce product i on line l

α_i factor for converting quantities of product i into unit loads, e.g., pallets

V loading capacity of a vehicle

ts_{il} minor setup- time of product i on line l

TS_{jl} major setup time of product group j on line l

C_{il}^{prod} processing cost of product i on production line l

C_{il}^{SMin} minor setup cost of product i on production line l

C_{jl}^{SMaj} major setup cost of product group j on production line l

C_{iw}^{Inven} inventory holding cost of product i at DC w in time period t

C_r^{LTL} transportation cost per vehicle on route r

C_{iw}^{Bord} backorder cost of product i at DC w

M extremely big number

Decision Variables:

x_{ilt} production volume for product i produced on production line l in time period t

y_{irwt} quantity of product i delivered to DC w via route r in time period t

q_{ipwt} quantity of product i shipped from plant p to DC w in time period t

I_{iwt} inventory level of product i at DC w at the end of time period t

b_{iwt} backorder quantity

n_{rt} the number of vehicle used on route r in time period t. (identical vehicles are used)

z_{ilt} 1, if product i is setup on line l in period t

0, otherwise

u_{jlt} 1, if product group j is setup on line l in period t

0, otherwise

CHAPTER FOUR
MULTI-BUCKET OPTIMIZATION FOR INTEGRATED PLANNING AND SCHEDULINGIN THE PERISHABLE DAIRY SUPPLY CHAIN

4.1 Introduction

The yoghurt production is a semi-continuous process and subject to individual characteristics. Yoghurt is a notably perishable product within the category of dairy industry (Lütke Entrup, 2005). The perishability highly restricts its storage duration and delivery conditions. It has a wide variety of retail cup sizes or labels, contents and special ingredients with numerous flavored and colored types. When it comes to producing large numbers of products from a few initial product recipes, product dependent cleaning, sterilizing, re-tuning issues of pipes and mixing units arise to avoid contamination (Montagna et al., 1998). Especially, long sequence-dependent setup times and high costs are considerable at the filling and packaging stages of the yogurt production and, they cause a noticeable reduction of available production times and increase the costs. Hence, planning and scheduling of the yoghurt production require specific models to support decision making.

MILP models provide mathematical frameworks to represent specific characteristics of problems and to get optimal solutions. The MILP is an extensively accepted tool in the dairy industry for well-defined problems (*e.g.,* Banaszewska et al., 2013; Kopanos et al., 2011a, 2012b). Bilgen and Çelebi (2013) present a MILP model addressing the production scheduling and distribution planning problem in a yoghurt production line of multi-product dairy plants. They consider the yoghurt production with perishability and sequence-dependency issues by focusing on the packaging stage operating with parallel units sharing common resources. Sel and Bilgen (2014a) state that integrated multi-echelon, multi-period planning and scheduling models accounting for multi-stage semi-continuous yoghurt production particularities are found to be of practical use in the field. Accordingly, the contribution of this research is aligned with the gap pointed out by Sel and Bilgen

(2014a) presenting a literature review and discussion on quantitative models for SCM within dairy industry.

In this research, we consider a production and distribution problem for a two-stage semi-continuous set type yoghurt production which is also comparable to other dairy production processes (*e.g.,* cheese, butter and ice cream). The production side fundamentally corresponds to packaging and fermentation/incubation operations. The distribution side considers the storage of products and the delivery to DCs. The scope of the considered problem is illustrated in Figure 4.1. For the problem, we introduce a multi-echelon, multi-period integrated MILP model with shelf life consideration. The model is extended by considering timing and capacity constraints with respect to the incubation operation of set type yoghurt. The scheduling constraints corresponding to both packaging and incubation operations are reformulated efficiently inspired by the generic MILP model of parallel machine scheduling with sequence dependent setup times, which is studied by Guinet (1993) as a vehicle routing formulation.

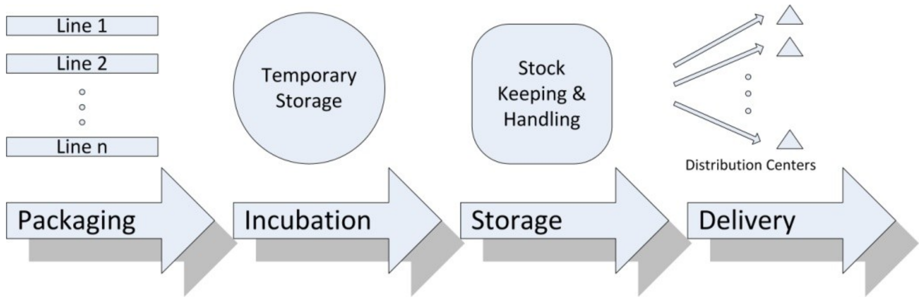

Figure 4.1 Scope of the yoghurt production problem

MILP software may be not powerful enough to handle the computational effort of integrated models of real sized problems. A production schedule typically comprises 500-1500 operations and complex technological constraints such as parallel processing units, sequence-dependent changeovers (Baumann and Trautmann, 2014). The inadequacy of MILP is the usage of various big M constraints and an enormous number of binary variables for making scheduling decisions. In this case, decomposition heuristic which divides the model into different planning and scheduling time buckets can reduce the complexity caused by the scheduling decisions.

CP has been developed as a useful modelling and solution paradigm overcoming the computational limitations for many scheduling cases such as staff, train, assembly line, batch plant and flexible manufacturing system scheduling (Novas and Henning, 2014). The CP models provide more convenient analyses for real cases by requiring less computational efforts. However, they search values of decision variables in a certain domain and the optimum cannot be guaranteed for planning problems which have large domains of continuous variables concerning to the production and distribution decisions (Sel and Bilgen, 2014a).

Since the integrated planning and scheduling problem contains aspects that are individually difficult for each approach, a relevant contribution would be the development of an effective hybrid approach (Steger-Jensen et al., 2011). The hybrid MILP/CP decomposition strategies integrating the best capabilities of the MILP and the CP models iteratively, are used as a common way to overcome the computational limitations of scheduling problems (*e.g.,* Erdirik-Dogan and Grossmann, 2006; Harjunkoski and Grossmann, 2002; Roe et al., 2005). Jain and Grossmann (2001) present a generic hybrid MILP/CP approach for optimization problems. The approach focuses on only operational scheduling. Grossmann (2004) present the integration planning and scheduling at the supply chain level as a future challenge. They define the major difficulty of the integration on ensuring consistency, feasibility and optimality across models that are applied over large changes in time scales varying as months, weeks, days, down to hours. To overcome this challenge, we propose a decomposition heuristic which divides the integrated planning and scheduling model into big bucket planning, and small bucket scheduling sub-models. The iterative decomposition heuristic links the different time horizons. In each of the iterations, the heuristic limits tactical production planning and distribution decisions (*e.g.,* stock keeping, demand satisfaction) with an actual production capacity determined by a simulated annealing based optimization heuristic. Further, MILP and CP methodologies are combined with the proposed algorithm to show their complementary strengths.

In this concept, the research aims at making a twofold contribution to the planning and scheduling literature in the dairy industry. The first is to introduce an integrated MILP model for the planning and scheduling problem considering particular characteristics of set type yoghurt production. The second is to deal with the problem complexity through the development of a computational efficient decomposition heuristic and MILP/CP hybrid approaches.

The rest of the chapter is organized as follows. A detailed description of the production system under consideration is described in Section 2.The relevant literature is reviewed in Section 3.The mathematical formulation of the integrated planning and scheduling model is described in Section 4.The proposed solution approach is described in Section 5. An illustrative case study is discussed with the results in Section 6. Finally, the main conclusions are given in Section 7.

4.2 Description of the Yoghurt Production Process

In this research, we address an integrated planning and scheduling problem in a yoghurt production process. The yoghurt production process starts with the collection of milk and continues with pasteurization, standardization, homogenization, culture addition, fermentation/incubation, packaging and cold storage, distribution operations.

Fresh milk can be collected from dairy farms to the production plant with churn collection (*i.e.,* uncooled milk in churns with churn-collecting lorries) or bulk collection (*i.e.,* cooled milk in insulated tankers with cooled containers). The pasteurization of milk is a special type of heat treatment which is used to get rid of pathogenic organisms in milk. It must be applied as quickly as possible after the milk has arrived at the dairy plant. After pasteurization, standardization and homogenization takes place in order to enhance the quality of the yoghurt product.

Standardization involves adjustment of the fat or dry solids contents of milk and, homogenization is basically disruption of fat globules into much smaller ones. Then, starter cultures are added to incubate the mix. For fermentation, the cultured milk must be held at the optimum temperature for certain duration in tanks and cooled quickly to stop the fermentation process. Filling and packaging operations are performed in parallel packaging machines. The packed yoghurt is placed in cooling storage containers and usually delivered to DCs by third-part logistics companies. Interested readers are referred to Bylund (1995) for details on yoghurt production.
The yoghurt is subdivided into different groups based on chemical composition (*e.g.,* plain, flavored, vitamin addition), fat content (fat, or skimmed yoghurt), cup sizes or its texture (*e.g.,* set or stirred). The cup size is determined in the packaging operation, the chemical composition and the fat rate is arranged with standardization operation.

Stirred yoghurt is a common type which is generally mixed with different ingredients such as fruit, flavor and nuts. In the stirred yoghurt production, warm cultured milk mixture is fermented, cooled and stirred before packaging for a creamy texture. Set yoghurt is a particular type of yoghurt especially preferred because of its thick texture. The set type is fermented and cooled in retail cups without any further stirring operation. The incubation operation which comes after the packaging operation, blocks the production process with specialized incubation rooms which have tight capacity restrictions. The incubation is operated with heating and chilling units in which the set type yoghurt is put with specific temperature conditions and predefined duration.

4.3 Related Literature and Positioning

In this section, we review the most relevant and recent literature considering planning and scheduling problems in yoghurt production. We provide distinguished publications which are selected due to the novelty of the proposed model formulation. Reviewed research is investigated in terms of several subdivisions defining problem characteristics and extensively accepted solution methodologies. For more detailed information, interested readers are referred to the review and discussion article on quantitative models for SCM within the dairy industry by Sel and Bilgen (2014a).

4.3.1 Problem Characteristics

We make a further categorization to clarify the significance of the research in terms of the problem characteristics such as decision levels, supply chain processes, product type, production process, perishability, working time and changeovers.

4.3.1.1 Decision Levels

The decisions take place at operational and tactical level. The difference between the two levels lies in their decision time horizon. The time scales range from short term to medium term, respectively. The operational level fundamentally refers to scheduling decisions and most of the research deals with this level (*e.g.,* Lütke Entrup et al., 2005a; Marinelli et al., 2007; Doganis and Sarimveis, 2007). The tactical level concerns further planning decisions. Integration of operational and tactical level decisions leads to better solutions (Maravelias and Sung, 2009). Only a few authors address integration challenges (Kopanos et al., 2012a; Amorim et al., 2012, 2013a, 2014; Bilgen and Çelebi, 2013).

4.3.1.2 Supply Chain Processes

The supply chain consists of complementary production, storage and distribution processes which require an adequate coordination and collaboration (Sel and Bilgen, 2014b). Lütke Entrup et al. (2005a) focus only on the production. The inventory decisions are considered by the inventory available at the beginning of the planning period. The initial inventory may be used to satisfy a demand if shelf life requirements are respected. Production and storage are mostly integrated components (e.g., Marinelli et al., 2007; Doganis and Sarimveis, 2007; Kopanos et al., 2009). Amorim et al. (2012), Kopanos et al. (2012a) and Bilgen and Çelebi (2013) differ from those in the remaining literature optimizing production, storage and distribution processes simultaneously.

4.3.1.3 Product Type

There are two yoghurt product types (i.e., set and stirred yoghurt). Whereas stirred yoghurt is commonly considered in the literature (Lütke Entrup et al., 2005a; Kopanos et al., 2009; Bilgen and Çelebi, 2013). Kopanos et al. (2011b, 2012a) present the only research on set yoghurt. The rest of the reviewed research does not define the type of yoghurt, nor consider the process order of set yoghurt and sequencing of the additional incubation operation explicitly (e.g., Marinelli et al., 2007; Doganis and Sarimveis, 2007; Amorim et al., 2011, 2013c).

4.3.1.4 Production Processes

The fundamental yoghurt production comprises of fermentation, filling/packaging and incubation operations. The packaging process can consist of a single unit or multiple parallel units. Doganis and Sarimveis (2007) is the only research presenting a methodology for optimal scheduling of a single packaging line which is later extended to parallel units (Doganis and Sarimveis, 2008, 2009). Other research deals with independently packaging process with multiple or parallel units using hybrid solution approaches (e.g., Marinelli et al., 2007; Amorim et al., 2011; Bilgen and Çelebi, 2013), the fermentation process is considered for stirred type yoghurt production with time and capacity constraints (e.g., Lütke Entrup et al., 2005a; Kopanos et al., 2009).

4.3.1.5 Perishability

The recent reviews covering various supply chain planning problems highlight the importance of perishability consideration (Akkerman et al., 2010; Amorim et al., 2013c; Karaesmen et al., 2011). The dairy production is relatively complex due to its highly perishability nature and limited shelf life (Lütke Entrup, 2005). In order to account for the perishability, the formulation of the production planning and scheduling problems has to keep track of the age of inventories and/or products (Amorim et al., 2013a, 2014). The shelf life can be considered as a loss or benefit function accounting for the economic value of freshness products in objective functions (Amorim et al., 2011, 2012). In addition, Doganis and Sarimveis (2009), Lütke Entrup et al. (2005a), Bilgen and Çelebi (2013) consider the shelf life both to keep track of the age of inventories and to take into account the economic value of freshness.

4.3.1.6 Working Time

The production activities are performed daily in a maximum allowed time. The maximum allowed time, consisting of regular time and overtime components. Further, working time planning supports valuable information to make cleaning programs which are essential for the dairy industry. Lütke Entrup et al. (2005a) and, Bilgen and Çelebi (2013) are the only research considering regular time and overtime issues.

4.3.1.7 Changeovers

The changeover operations can be taken into account as sequence independent and sequence dependent. Some of the research handles changeover operations as sequence independent by assuming negligible differences or that the different products have almost similar setup durations (*e.g.,* Marinelli et al., 2007; Amorim et al., 2013a, 2014). This assumption simplifies the analysis; however it affects the solution quality of applications which require explicit setup treatment (Allahverdi et al., 1999, 2008). Sequence dependent changeovers are much closer to the reality of dairy supply chains (*e.g.,* Bongers and Bakker, 2006; Subbiah and Engell, 2009, 2010; Van Elzakker et al., 2014). Hence, the vast body of literature take into account sequence dependency (*e.g.,* Lütke Entrup et al., 2005a; Doganis and Sarimveis, 2007; Kopanos et al., 2009).

In the literature, most of the research ignores the interrelation of tactical planning and operational scheduling decisions. However, operational scheduling receives tactical planning as its input. The integration of the planning and scheduling decisions provides coordination between production, storage and distribution processes. Hence, the integration constitutes a research direction at supply chain level. Perishability issues, sequence dependency and working time planning are other components which can help for the decision making process of the set yoghurt production. In brief, there is a need for a research on the set type yoghurt production (i) considering production, storage and distribution decisions in an integrated way, (ii) focusing on not only the packaging, but also the incubation stage of set type yoghurt production process, (iii) addressing the perishability and shelf life restrictions, (iii) taking into account planning working time and (iv) sequence dependency of changeovers.

4.3.2 Modelling Methods and Solution Approaches

The modelling methods vary from MILP and CP to stochastic programming and simulation. MILP is commonly used to define planning and scheduling problems of dairy industry in a mathematical framework (*e.g.,* Lütke Entrup et al., 2005a; Marinelli et al., 2007; Doganis and Sarimveis, 2007). Stochastic programming and simulation are used to account for stochastic properties of the yoghurt production problem (*e.g.,* Amorim et al., 2013a, 2014; Bilgen and Çelebi, 2013). CP is accepted as an effective approach in solving scheduling problems (Maravelias and Grossmann, 2004b; Harjunkoski and Grossmann, 2002).

In addition to the modelling methods using exact methods, the solution approaches found in the literature are hybrid approaches and evolutionary strategies. Marinelli et al. (2007) develop a two stage optimization heuristic using a local search strategy. The heuristic is based on the decomposition of the integrated problem in lot sizing and scheduling sub-problems. Amorim et al. (2011) introduce a bi-objective model on maximization of the freshness and minimization of production related costs. They propose a hybrid multi-objective genetic algorithm to evaluate these two conflicting objectives. Bilgen and Çelebi (2013) propose an iterative hybrid optimization-simulation procedure to explore operation times as the dynamic factor of the scheduling problem in yoghurt production.

For the planning and scheduling problems, MILP and CP can be used for decomposition heuristics to solve the problem more efficiently (Kilic, 2011). The CP applications (*e.g.,* Castro et al., 2006; Novas and Henning, 2010; Zeballos et al., 2011) and the hybrid MILP/CP approaches (*e.g.,* Harjunkoski et al., 2000; Jain and Grossmann, 2001; Maravelias and Grossmann, 2004a) have been formulated for batch plant scheduling problems. As the yoghurt production is a semi-continuous production in a discrete time period, CP and hybrid MILP/CP approaches can be adopted for the yoghurt production problems.

The summary of the literature review is presented in Table 4.1. Table 4.1 shows the characteristics of the considered problem, and confirms the lack of an integrated MILP model, decomposition and MILP/CP hybrid approaches.

Table 4.1 Literature summary – characteristics of the planning and scheduling of yoghurt production problem

Reviewed Literature	Problem characteristics														
	Decision Levels		Supply Chain Processes			Product Type		Production Processes			Perishability		Working Time		Setups
	Operational	Tactical	Production	Storage	Distribution	Set	Stirred	Fermentation	Packaging	Incubation	Objective	Constraints	Regular	Overtime	Sequence dependent
Lütke Entrup et al. (2005a)	✓		✓				✓	✓	✓		✓	✓	✓	✓	✓
Marinelli et al. (2007)	✓		✓	✓					✓						
Doganis and Sarimveis (2007)	✓		✓	✓					✓				✓	✓	✓
Doganis and Sarimveis (2008)	✓		✓	✓					✓				✓	✓	✓
Doganis and Sarimveis (2009)	✓		✓	✓					✓		✓	✓	✓	✓	✓
Kopanos et al. (2009)	✓		✓	✓			✓	✓	✓						✓
Kopanos et al. (2011b)	✓		✓	✓		✓	✓	✓	✓						✓
Kopanos et al. (2012a)	✓	✓	✓	✓	✓	✓	✓	✓	✓						✓
Amorim et al. (2011)	✓		✓	✓					✓		✓				✓
Amorim et al. (2012)	✓	✓	✓	✓	✓				✓		✓				✓
Amorim et al. (2013a)	✓	✓	✓	✓					✓			✓			
Amorim et al. (2014)	✓	✓	✓	✓					✓			✓			
Amorim et al. (2013b)	✓		✓	✓					✓						✓
Bilgen and Çelebi (2013)	✓	✓	✓	✓	✓		✓		✓		✓	✓	✓	✓	✓
This research	✓	✓	✓	✓	✓		✓		✓	✓	✓	✓	✓	✓	✓

– defined otherwise undefined

Table 4.1 Literature summary (continued) – modelling and solution approaches for the planning and scheduling of yoghurt production problem

Reviewed literature	Modelling approaches					Solution approaches
	MILP	MINP	SM	SP	CP	
Lütke Entrup et al. (2005)	✓					
Marinelli et al. (2007)	✓					Two stage decomposition heuristic
Doganis and Sarimveis (2007)	✓					
Doganis and Sarimveis (2008)	✓					
Doganis and Sarimveis (2009)	✓					
Kopanos et al. (2009)	✓					
Kopanos et al. (2011b)	✓					
Kopanos et al. (2012a)	✓					
Amorim et al. (2011)	✓					Hybrid multi-objective genetic algorithm
Amorim et al. (2012)	✓	✓				
Amorim et al. (2013a)				✓		
Amorim et al. (2014)	✓			✓		
Amorim et al. (2013b)	✓					
Bilgen and Çelebi (2013)	✓		✓			Iterative hybrid optimization-simulation procedure
This research	✓				✓	**Decomposition heuristic and MIL/CP hybrid approach**

✓ – defined otherwise undefined, MILP – Mixed-Integer Linear Programming, MINP – Mixed-Integer Non-linear Programming, SM – Simulation, SP – Stochastic Programming, CP – Constraint Programming

4.4 Mathematical Formulation

The problem statement and the integrated planning and scheduling MILP model are given as follows. The corresponding parameters and decision variables are listed in the nomenclature at the end of the chapter.

4.4.1 Problem Statement

This problem is motivated by a production-distribution problem encountered by a dairy company and, originally introduced and studied by Bilgen and Çelebi (2013). The problem consists of tactical planning and operational scheduling decisions. The production, storage and distribution operations are considered in the tactical planning decisions. The product type is set type yoghurt, the packaging and incubation operations are considered in the scheduling decisions. Because of the perishability issues, the planning and scheduling decisions take the age of inventories into consideration. Work time planning with regular time and overtime components, and sequence dependent setup times are considered in the problem.

The problem that is investigated in this research has the following structure;

1. The supply network consists of a single plant which delivers the final products to various DCs.
2. The demand for each product in each day is collected from the DCs respectively. The demands have certain due dates and backlogging is not allowed. Unmet demand cannot be transferred to the next periods. The unmet demand is discarded at costs.
3. The planning and scheduling is performed in a short-term horizon. For each product, inventory balances are updated on a daily basis according to the production output from the plant. There is a certain inventory capacity for final products and they are stored in pallets. Storage costs depend on product types. Transportation to DCs is operated by third party logistics using cold chain trucks.

4. The plant comprises several identical packaging lines. Each packaging line is able to produce all products and has different operation cost. A product cannot be processed on more than one line simultaneously and a line cannot process more than one job at a time. The production precedence, pre-emption, cancellation, batch splitting and mixing are not allowed. There are no recycle streams. Lines are always available. The production is limited with minimum and maximum lot-sizes.
5. Processing times are independent of the schedule. Variable production costs of the products that can be produced at any of the identical packaging lines differ from each other. Therefore, the variable production costs are computed for each product.
6. Sequence dependent setups are required because of hygiene and contamination rules. Cleaning operations (*i.e.,* automatic washing and sterilization of the product tank and the filling valves) are processed for every packaging operation with regard to changeover rules and, can also be planned weekly on idle times of the production. The cleaning time is a part of setup times. The changeover time and cost are involved for possible transitions between products.
7. The process leads each production directly to the incubation process after the packaging. The incubation unit has a limited capacity and it can only serve to one lot simultaneously to avoid contamination between products. Incubation duration and corresponding costs depend on each product.
8. Finished products are checked in the final control process. The quality analyses require a certain control time. It is not allowed that the products are delivered before they complete the required time for the quality control process.
9. The freshness is a significant part in competition. Freshness can be measured with shelf life which is a small duration (*i.e.,* varying between 7 and 21 days for homogenized and cooled products under refrigerated keeping conditions) that the products can be used by final consumers. The minimum shelf life required by the customers is defined as a critical rate which is a fraction of

maximum shelf life. The decrease of shelf life is considered by a loss function.

10. The available working hours for the lines are defined according to working days. An overtime production is allowed in every working day under environment of heavy demand.

The key decisions for each planning and scheduling period are; (i) the produced quantity of each product on each line (ii) distribution quantity of each product transported to each DC and corresponding unmet demand, (iii) inventory level of each product, (iv) finishing time of each product on each line, production time of each product and overtime (v) maximum completion times of each product and each line, (vi) number of incubation operation required for each product and incubation sequence of the products (vii) production assignments of each product and changeover assignment between products on each line.

4.4.2 Integrated Planning and Scheduling MILP model

Objective function:

$$\begin{aligned}
\min Z = {} & \sum_{ijld} x_{ijld}.Lost_j.\left[\frac{(d-i)}{(1-CrRate_j).ShelfLife_j}\right] + \sum_{ijld} x_{ijld}.VarCost_j + \sum_{ij} inv_{ij}.StrgCost_j \\
& + \sum_{ijkl} binsetup_{ijkl}.SetupCost_{jk} + \sum_{i} overtime_i.OverTCost + \sum_{il} CmaxLine_{il}.LineCost_l \\
& + \sum_{ij} CmaxProduct_{ij}.PwCost_j + \sum_{ij} IncNb_{ij}.IncCost + \sum_{jda} y_{jda}.TransCost_a \\
& + \sum_{jda} UnmD_{jda}.UnmDCost_j
\end{aligned} \tag{4.1}$$

In Equation (4.1), the linear objective function aims at minimizing total cost. The total cost corresponds to cost of the loss of product value caused by deterioration and, production, inventory, changeover, waste, overtime, packaging and incubation operations, transportation and unmet demand costs. The loss of product value caused by deterioration is calculated using a shelf life dependent loss function which is adopted from Lütke Entrup et al. (2005a). The shelf life dependent loss increases linearly for the customer with every additional day of shelf life. For instance suppose that product j has a total shelf life of 15 days (*i. e.,* $ShelfLife_j = 15$), the customers require 66% of shelf life as a minimum residual shelf life (*i. e.,* $CrRate_j = 0.66$). If the production starts on day 2 (*i. e.,* $i = 2$) and the product is delivered to the DC on day 2 (*i. e.,* $d = 2$) then the loss of the value is minimum (*i. e.,*0). However, if the product is delivered to the DC on day 4 (*i. e.,* $d = 4$) then the loss become slightly higher (*i. e.,* $0.40 \cdot Lost_j$). When it comes to delivery on day 6 (*i. e.,* $d = 6$), the loss increases to $0.80 \cdot Lost_j$.

Constraints:

Shelf life;

$$x_{ijld} = 0 \qquad \forall i,j,l,d \; : i > d \; : QContTime > (d - i) > \left(1 - CrRate_j\right).ShelfLife_j \tag{4.2}$$

Equation (4.2) guarantees that the demand of demand day d cannot be produced after the demand day. Also, difference between production day and demand day should be enough to perform the quality control operation and should meet the maximum shelf life of product j. The shelf life and the quality control time are defined as a precondition for the achievement of the desired sensory qualities (Lütke Entrup et al. 2005a).

Demand satisfaction;

$$\sum_a y_{jda} \le \sum_{il} x_{ijld} \qquad \forall j,d \tag{4.3}$$

$$Demand_{jda} \le y_{jda} + UnmD_{jda} \qquad \forall j,d,a \tag{4.4}$$

Equation (4.3) provides that the total quantity of product j transferred to DCs for demand of day d is less than or equal to the total quantity of product j produced on line l on day i. Equation (4.4) computes the quantity of unmet demand. Backorder is not allowed. The demand of DC a for product j on demand day d is less than or equal to the sum of the quantity of product j transported to DC a for demand of day d and the unmet demand DC a for product j on demand day d .

Inventory balance;

$$inv_{ij} \leq \sum_{dl} x_{ijld} - \sum_{a} y_{jia} \qquad \forall i,j : i = 1 \qquad (4.5)$$

$$inv_{ij} \leq inv_{(i-1)j} + \sum_{dl} x_{ijld} - \sum_{a} y_{jia} \qquad \forall i,j : i > 1 \qquad (4.6)$$

$$\sum_{j} inv_{ij} . \gamma_j \leq StCapacity \qquad \forall i \qquad (4.7)$$

Equation (4.5) shows the inventory level only for the first day. The inventory of product j at the end of first day is less than or equal to difference between the quantity of product j produced on line l during the first day and the delivered quantity of product j produced on line l to the DCs. Equation (4.6) refers to the inventory level of product j at the end of day i . The inventory level is computed by adding the production quantity of product j on line l on day i to difference between the inventory of the previous day and the delivered quantity of product j produced on line l to the DCs. Equation (4.7) converts the inventory of product j on day i into unit storage (*e.g.,* pallets) by multiplying with the corresponding factor γ_j and limits the stored inventory level.

Sequencing of parallel packaging machines;

$$PT_{ij} \geq \sum\nolimits_{ld} x_{ijld} \Big/ MchSpeed_j \qquad \forall i,j \qquad (4.8)$$

$$\sum_{j \in P^{S0}, l : j \neq k} binsetup_{ijkl} \leq 1 \qquad \forall i,k \qquad (4.9)$$

$$\sum_{j \in P^{S0} : j \neq t} binsetup_{ijtl} - \sum_{k \in P^{S0} : k \neq t} binsetup_{itkl} = 0 \qquad \forall i,t,l \qquad (4.10)$$

$$\sum_{k \in P^{S0}} binsetup_{i0kl} \leq 1 \qquad \forall i,l \qquad (4.11)$$

$$FT_{ikl} \geq FT_{ijl} + SetupTime_{jk} + PT_{ik} + \left(binsetup_{ijkl} - 1\right).M \qquad \forall i, j \in P^{S0}, k, l \qquad (4.12)$$

$$FT_{ijl} \leq \sum_{k \in P^{S0}: j \neq k} binsetup_{ikjl}.M \qquad \forall i,j,l \qquad (4.13)$$

$$FT_{ijl} \leq CmaxLine_{il} \qquad \forall i,j,l \qquad (4.14)$$

Equation (4.8) shows that processing time of a product depends on the production quantity and the machine speed for the product. Equation (4.9) ensures that each product is processed maximum once. Equation (4.10) specifies that each product must have a predecessor and a successor. Equation (4.11) ensures that each machine has at most one first product (*i.e.,* one product sequence). Equation (4.12) calculates the product completion times which depend on processing time, sequence dependent setup time and the order of products assigned to the machine. It also prevents a product to be the predecessor and the successor of the same product. Equation (4.13) enforces the finishing time j on line l on day i to zero, if no corresponding production operation is performed. Equation (4.14) defines the maximum completion time of day i corresponding with line l.

Sequencing of incubation operation

$$\sum_{t \in P^{S0}: j \neq t} IncSequence_{itj} = \sum_{k \in P^{S0}, l: j \neq k} binsetup_{ikjl} \qquad \forall i,j \qquad (4.15)$$

$$\sum_{j \in P^{S0}: j \neq k} IncSequence_{ijk} \leq 1 \qquad \forall i,k \qquad (4.16)$$

$$\sum_{j \in P^{S0}: j \neq t} IncSequence_{ijt} - \sum_{k \in P^{S0}: k \neq t} IncSequence_{itk} = 0 \qquad \forall i,t \qquad (4.17)$$

$$\sum_{k \in P^{S0}} IncSequence_{i0k} \leq 1 \qquad \forall i \qquad (4.18)$$

$$IncNb_{ij} \geq \sum_{ld} x_{ijld}.\gamma_j \, / \, IncCapacity \qquad \forall i,j \qquad (4.19)$$

$$CmaxProduct_{ik} \geq CmaxProduct_{ij} + IncTime_k.IncNb_{ik} + \left(IncSequence_{ikj} - 1\right).M \qquad \forall i, j \in P^{S0}, k \qquad (4.20)$$

$$CmaxProduct_{ij} \geq \sum_{l} FT_{ijl} + IncTime_j.IncNb_{ij} \qquad \forall i, j \in P^{S0}, k \qquad (4.21)$$

$$\sum_{l} FT_{ikl} \geq CmaxProduct_{ij} + \left(IncSequence_{ikj} - 1\right).M \qquad \forall i, j \in P^{S0}, k \qquad (4.22)$$

Equation (4.15) inserts the product j into the incubation sequence if product j is produced on line l on day i . Equation (4.16) ensures that each product is processed once and only once. Equation (4.17) specifies that each product must have a predecessor and successor. Equation (4.18) provides that the incubation sequence has at most one first product, (*i.e.,* one product sequence). Equation (4.19) calculates the number of products lots regarding to maximum capacity of incubation room. Equation (4.20) and Equation (4.21) are balance equations for the incubation process. Completion time of production on day i must be greater than or equal to end of prior packaging and incubation operations, respectively. Equation (4.22) presents the timing between packaging and incubation operations. It provides that the packaging operations are finalized just before incubation operation. The finishing time of the product k on line l on day i must be greater than the maximum completion time of the previous product j .

Working time;

$$RTime_i + overtime_i \leq MaxTime_i \qquad \forall i \qquad (4.23)$$

$$CmaxProduct_{ij} - RTime_i \leq overtime_i . M \qquad \forall i, j \qquad (4.24)$$

$$CmaxProduct_{ij} \leq overtime_i + RTime_i \qquad \forall i, j \qquad (4.25)$$

Equation (4.23) limits the total working time with the maximum available time on day i . Equation (4.24) limits the maximum completion time on day i with the regular working time if the overtime is not necessary (*i. e.,* $overtime_i = 0$). Equation (4.25) shows that the maximum completion time on day i is limited with maximum working time consisting of regular hours and required overtime.

Lot-sizing;

$$\sum_{dl} x_{ijld} \leq MaxLot_j \ . \sum_{k \in P^{S0}: j \neq k} binsetup_{ikjl} \qquad \forall i, j \qquad (4.26)$$

$$\sum_{dl} x_{ijld} \geq MinLot_j \ . \sum_{k \in P^{S0}: j \neq k} binsetup_{ikjl} \qquad \forall i, j \qquad (4.27)$$

Equation (4.26) and Equation (4.27) defines minimum and maximum production lot-sizes by the value of the binary variable as equal to 1 if and only if product j is produced on line l on day i for demand of day d .

Integrality and non-negativity;

$$\begin{aligned}&x_{ijld}, y_{jda}, inv_{ij}, PT_{ij}, FT_{ij \in P^{S0} l}, overtime_i, \\ &UnmD_{jda}, CmaxLine_{il}, CmaxProduct_{ij \in P^{S0}}, Z, \qquad \forall i, j, l, d, a\end{aligned} \tag{4.28}$$

$$\begin{aligned}&IncNb_{ij} \geq 0 \, and \, integer \\ &IncSequence_{ijk}, binsetup_{ijkl} \in \{0,1\} \qquad \forall i, j \in P^{S0}, k \in P^{S0}, l\end{aligned} \tag{4.29}$$

Finally, Equation (4.28), and Equation (4.29) are integrality and non-negativity constraints which define the domain of the decision variables.

4.5 Multi-bucket Optimization Models

The integration includes a big bucket planning and a small bucket scheduling grid. The basic idea of the proposed solution strategy is to handle these different time horizons by dividing the entire model into two distinct sub-models. The ability to generate qualified solutions of each planning and scheduling problem and strong linkage constraints are crucial. In our approach, the planning sub-model acts as a master process calling the scheduling sub-models for every scheduling decision and a search procedure improves the current solution using capacity linkage.

4.5.1 Big Bucket Planning Sub-model

A MILP sub-model addresses the planning sub-problem. The big bucket planning sub-model, the planning part of the integrated model is simplified to obtain production targets with a solution which is likely to be sub-optimal. Then, the scheduling sub-model is fed with an input of planning decisions. The planning sub-model is formulated as follows and the corresponding parameters and decision variables are listed in the nomenclature at the end of the chapter.

Objective function:

The same monetary objective function Z in Equation (4.1), which aims at minimization of total costs, is used to be comparable with the integrated model.

Constraints:

Equation (4.2) of shelf life constraints, Equations (4.3), (4.4) of demand satisfaction constraints, Equations (4.5), (4.6) and (4.7) of the inventory balance constraints, Equation (4.8) calculating process time of production, Equation (4.19) calculating the number of incubation operations, Equation (4.25) deciding on overtime are used in the planning sub-model.

Lot-sizing;

$$\sum_{dl} x_{ijld} \leq MaxLot_j \ .bin_{ijl} \qquad \forall i,j,l \qquad (4.30)$$

$$\sum_{dl} x_{ijld} \geq MinLot_j \ .bin_{ijl} \qquad \forall i,j,l \qquad (4.31)$$

Equation (4.30) and Equation (4.31) define minimum and maximum production lot-sizes with the value of the binary variable corresponding with production decision. The lot-sizing restrictions are adopted from Equation (4.26) and Equation (4.27). Since the planning sub-model considers planning issues and takes the scheduling information from the scheduling sub-model, it is enough to decide only on allocation of the products to the packaging lines and to the production days instead of determination of production precedence. Therefore, bin_{ijl} is modified from $binsetup_{ijkl}$ to shorten the redundant indices.

Linkage Constraints;

$$\sum_{djl} x_{ijld} \leq Capacity_i \qquad \forall i \qquad (4.32)$$

Equation (4.32) is a linkage constraint which is used in the hybrid method to represent the relation of planning MILP and scheduling sub-models. The equation limits the capacity produced quantity for each day by taking the capacity values from the heuristic as a parameter.

Integrality and non-negativity;

$$x_{ijld}, y_{jad}, inv_{ij}, PT_{ijl}, overtime_i,\ UnmD_{jda}, Z, \qquad \forall i,j,l,d,a \qquad (4.33)$$
$$IncNb_{ij} \geq 0\, and\ integer, bin_{ijl} \in \{0,1\}$$

Equation (4.33) provides the integrality and non-negativity constraints and defines the domain of the binary decision variables.

4.5.2 Small Bucket Scheduling Sub-models

The small bucket scheduling problem is to assign each packaging operation to the parallel lines, to order the packaging and the following incubations operations such that makespan is minimized. For the small bucket scheduling sub-problem, useful modelling methods are selected to achieve the computational efficiency. Two alternative sub-models which are the MILP and CP formulation are introduced for the scheduling sub-problem.

4.5.2.1 The MILP Sub-model

The scheduling MILP sub-model is formulated as follows and the corresponding parameters and decision variables are listed in the nomenclature at the end of the chapter. The objective is to minimize the completion time of the production and the constraints are adopted from the scheduling constraints of the integrated MILP model by removing the redundant i day indices, since the scheduling corresponds to small bucket time horizon.

Objective function:

$$min\, Cmax \qquad (4.34)$$

Equation (4.34) illustrates the objective function of the scheduling MILP model aiming at minimization of makespan.

Constraints:

Sequencing of parallel packaging machines;

$$\sum_{j \in P^{S0}, l: j \neq k} binsetup_{jkl} \leq 1 \qquad \forall k \qquad (4.35)$$

$$\sum_{j \in P^{S0}: j \neq t} binsetup_{jtl} - \sum_{k \in P^{S0}: k \neq t} binsetup_{tkl} = 0 \qquad \forall t, l \qquad (4.36)$$

$$\sum_{k \in P^{S0}} binsetup_{0kl} \leq 1 \qquad \forall l \qquad (4.37)$$

$$FT_{kl} \geq FT_{jl} + SetupTime_{jk} + PT_k + \left(binsetup_{jkl} - 1\right).M \qquad \forall j \in P^{S0}, k, l \qquad (4.38)$$

$$FT_{jl} \leq \sum_{k \in P^{S0}: j \neq k} binsetup_{kjl}.M \qquad \forall j, l \qquad (4.39)$$

$$FT_{jl} \leq CmaxLine_l \qquad \forall j, l \qquad (4.40)$$

Equation (4.35) ensures that each product is processed maximum once. Equation (4.36) specifies that each product must have a predecessor and successor. Equation (4.37) ensures that each machine has at most one first product (*i.e.,* one product sequence). Equation (4.38) calculates the product completion times which depend on processing time, sequence dependent setup time and the order of products assigned to the machine. It also prevents a product to be the predecessor and the successor of the same product. Equation (4.39) enforces the finishing time j on line l to zero, if no corresponding production operation is performed. Equation (4.40) defines the maximum completion time of line l .

Sequencing of incubation operation;

$$\sum_{t \in P^{S0}: j \neq t} IncSequence_{tj} = \sum_{k \in P^{S0}, l: j \neq k} binsetup_{kjl} \qquad \forall j \qquad (4.41)$$

$$\sum_{j \in P^{S0}: j \neq k} IncSequence_{jk} \leq 1 \qquad \forall k \qquad (4.42)$$

$$\sum_{j \in P^{S0}: j \neq t} IncSequence_{jt} - \sum_{k \in P^{S0}: k \neq t} IncSequence_{tk} = 0 \qquad \forall t \qquad (4.43)$$

$$\sum_{k \in P^{S0}} IncSequence_{0k} \leq 1 \tag{4.44}$$

$$IncNb_j \geq \sum_{ld} x_{jld}.\gamma_j \,/\, IncCapacity \qquad \forall j \tag{4.45}$$

$$CmaxProduct_k \geq CmaxProduct_j + IncTime_k.IncNb_k + \left(IncSequence_{kj} - 1\right).M \qquad \forall j \in P^{S0}, k \tag{4.46}$$

$$CmaxProduct_j \geq \sum_l FT_{jl} + IncTime_j.IncNb_j \qquad \forall j \in P^{S0}, k \tag{4.47}$$

$$\sum_l FT_{kl} \geq CmaxProduct_j + \left(IncSequence_{kj} - 1\right).M \qquad \forall j \in P^{S0}, k \tag{4.48}$$

Equation (4.41) inserts the product j into the incubation sequence if product j is produced on line l. Equation (4.42) ensures that each product is processed once and only once. Equation (4.43) specifies that each product must have a predecessor and successor. Equation (4.44) provides that the incubation sequence has at most one first product, (*i.e.,* one product sequence). Equation (4.45) calculates the number of products lots regarding to maximum capacity of incubation room. Equation (4.46) and Equation (4.47) are balance equations for the incubation process. Completion time of product j must be greater than or equal to end of prior packaging and incubation operations, respectively. Equation (4.48) presents the timing between packaging and incubation operations. It provides that the packaging operations are finalized just before incubation operation. The finishing time of *product* k on line l must be greater than the maximum completion time of the previous product j.

4.5.2.2 The CP Sub-model

The CP methodology is chosen as useful modelling technique overcoming the computational limitations for the scheduling problem. Activities are fundamental building blocks of any scheduling problem modeled by CP. The activities represent an interval of time during which an operation is performed. The positions of the intervals are determined by the sequence variables of the scheduling model. Each of the intervals is characterized by a start time, an end time and duration between these times. Additionally, the intervals can be considered as optional by using alternative constraints. This feature provides to handle the intervals by parallel resources. In the proposed model mainly two activities are presented; Production activities (*i. e.,* $Task_j$, $OptTask_{jl}$ with size of $Duration_j$) and Incubation activities (*i. e.,* Inc_j with size of $IncDuration_j$). The sequence of these activities is decided with a sequence variable $Schedule_l$. The scheduling CP sub-model is formulated as follows and the corresponding parameters and decision variables are listed in the nomenclature at the end of the chapter.

Objective function:

Minimize

$$max(endOf(Inc_j) : j \in J^S) \tag{4.49}$$

Equation (4.49) illustrates the objective function of the scheduling CP model aiming at minimization of makespan. $endOf$ is an expression used to access the end time of the given interval. The maximum of the incubation intervals corresponding to job j represent the makespan value of the schedule.

Constraints:

Alternative formation;

$$alternative(Task_j, OptTask_{jl}) \qquad \forall j \tag{4.50}$$

Equation (4.50) provides an alternative constraint between each of $Task_j$ intervals and a set of $OptTask_{jl}$ intervals. This constraint specifies that if the $Task_j$ interval is presented in the solution, then exactly one interval variable of the $OptTask_{jl}$ set exists in the solution. $Task_j$ starts and ends together with this chosen $OptTask_{jl}$ interval.

Overlap prevention;

$$noOverlap(Schedule_l, Setup) \qquad \forall l \tag{4.51}$$

Equation (4.51) presents a *noOverlap* constraint on the interval sequence variable $Schedule_l$ states that the sequence defines a chain of non-overlapping intervals, where any interval in the chain is constrained to end before the start of the next interval in the chain. The sequence dependent setups are modeled as a triple Setup set that specifies a minimal distance between pairs of jobs. It states that if a job is scheduled after another job in the sequence, a sequence dependent setup time must separate the end of the first interval from the start of the following second interval.

Precedence;

$$startAtEnd(Inc_j, Task_j) \qquad \forall j \qquad (4.52)$$

$$endBeforeTask(Inc_{(j-1)}, Inc_j) \qquad \forall j : j > 1 \qquad (4.53)$$

Equation (4.52) and Equation (4.53) are precedence constraints which ensure relative positions of intervals in the solution. Equation (52) is a *startAtEnd* constraint stating that the start of Inc_j interval variable equals the end of a $Task_j$ interval variable. Equation (4.53) is a *endBeforeStart* constraint stating that the end of a preceding interval variable is less than or equal to the start of following Inc_j interval variable.

Presence;

$$presenceOf(Task_j) = 0 \qquad \forall j : Duration_j = 0 \qquad (4.54)$$

$$presenceOf(Task_j) = 1 \qquad \forall j : Duration_j \neq 0 \qquad (4.55)$$

Equation (4.54) and Equation (4.55) are precedence constraints ensure that the tasks which have duration values must be scheduled. Otherwise, the tasks are not included to the proposed schedule.

4.5.3 Decomposition Heuristic

The algorithm includes a decomposition function and a search procedure. In the decomposition function, the planning sub-model is solved with given capacity limitations and the planning decisions are given to the scheduling sub-model. Then, the scheduling sub-model is solved to schedule planned productions for each day. The scheduling decisions are given to the planning sub-model to calculate the total cost of the proposed production plan and schedule. Note that, the planning sub-model is operated for the first iteration by giving an initial capacity. The initial solution should be large enough to satisfy the demand to start from a broad range of solution space. Hence, the initial capacity is chosen as sum of the demand data (*i. e,* $\sum_{jda} Demand_{jda}$).

Once a feasible solution has been reached, the heuristic enters a search procedure that aims to improve the current solution. The decomposition function is embedded in the search procedure to evaluate the other suitable capacity limitations by a simulated annealing algorithm. In the search procedure, the capacity limitations tighten the solution space iteratively to achieve strong results and, continuously updated for each day of the entire planning horizon using the decomposition function, repeatedly. Thereby, each replication supports a sufficient change to make the planning decisions feasible and close to optimal. Neighborhood solutions are generated by a move strategy multiplying the current capacity with a random number for each day. The cooling strategy is a geometric sequence in which the temperature at each step decreases with a certain ratio. The cost efficient results are kept track and the solution with the minimum cost is presented after the stopping criterion is satisfied. The algorithm stops, if the best solution found does not improve in a limited number of consecutive changes in temperature. The following pseudo code in Algorithm is adopted by adding the decomposition function into the generic simulated annealing algorithm presented by Alizamir et al. (2008).

Decomposition Algorithm:

Input : Initial temperature t_0, Number of iterations M_p for each step p, Neighborhood structure $N(w)$, overall stopping criteria and temperature decreasing rule.

Output : Feasible solution w

1: Calculate the initial solution: the decomposition function with the initial capacity.

2: Initialize step counter: $p = 0$

3: Set current solution w to initial solution w_0 : $w = w_0$

4: **while** the stopping criteria are not met **do**

5: **for** M_p iterations do

6: compute a neighborhood solution: $w' \in N(w)$:

7: **if** $f(w') - f(w) \le 0$ **then**

8: $w \leftarrow w'$

9: **else**

10: $w \leftarrow w'$ with probability $exp\left(\frac{f(w') - f(w)}{t_p}\right)$

11: **end if**

12: **end for**

13: decrease temperature t_p

14: $p \leftarrow p + 1$

15: **end while**

16: **return** feasible solution w

Decomposition function:

Step 1: Solve the big bucket planning sub-model

Step 2: Transfer the planning decisions to the small bucket scheduling sub-model

Step 3: Solve the small bucket scheduling model for each day

Step 4: Transfer the scheduling decisions to the big bucket planning model

Step 5: Calculate the objective value

Planning decisions; The planning decisions are outputs of the planning MILP sub-model which serve as inputs of the scheduling sub-models. The equations calculating the transferred planning decisions differ in modelling approach of the scheduling sub-model as follows;

$$CmaxLine_l = CmaxLine_{il} \qquad \forall i \qquad (4.56)$$

$$CmaxProduct_j = CmaxProduct_{ij} \qquad \forall i \qquad (4.57)$$

$$binsetup_{jkl} = binsetup_{ijkl} \qquad \forall i \qquad (4.58)$$

For scheduling MILP sub-model, the solution values for the decision variables of planning MILP sub-model (*i. e.,* $CmaxLine_{il}$, $CmaxProduct_{ij}$ and $binsetup_{ijkl}$) are transferred by the proposed algorithm using Equation (56), (57) and (58). Equation (4.56) and (4.57) provides the transfer the completion times of lines and products, respectively. Equation (4.58) provides the transfer of sequence of production and changeovers.

$$Duration_j = \sum_l PT_{ijl} \qquad \forall i, j \qquad (4.59)$$

$$IncDuration_j = IncNb_{ij}.IncTime_j \qquad \forall i, j \qquad (4.60)$$

For scheduling CP sub-model, the solution values of MILP decision variables (*i. e.,* PT_{ijl}, $IncNb_{ij}$) are compiled by the proposed algorithm using Equation (4.59) and (4.60), then given to the CP model as parameter values of $Duration_j$ and $IncDuration_j$. Equation (4.59) provides that duration of product j is equal to process time of product j and Equation (4.60) calculates the incubation duration multiplying the number of incubation operation and the incubation times.

Scheduling decisions; The scheduling decisions are outputs of the scheduling sub-model which serve as inputs of the planning MILP sub-model. The equations calculating the scheduling decisions differ in modelling approach of the scheduling sub-model as follows;

For the scheduling MILP sub-model, the solution values for the decision variables of scheduling MILP sub-model (*i. e.,* $CmaxLine_l$, $CmaxProduct_j$ and $binsetup_{jkl}$) are retransferred by the proposed algorithm using Equation (4.56), (4.57) and (4.58).

$$CmaxLine_{il} = schedule_l.end \qquad \forall i,l \tag{4.61}$$

$$CmaxProduct_{ij} = endOf(Inc_j) \qquad \forall i,j : endOfTask_j \leq MaxTime_i \tag{4.62}$$

$$binsetup_{ijkl} \begin{cases} 1,\ OptTask_{jl} \rightarrow \\ OptTask_{kl}\ in\ Schedule_l \\ 0,\ otherwise \end{cases} \qquad \forall i,j,k,l \tag{4.63}$$

For the scheduling CP sub-model, the solution values for the decision variables of scheduling model (*i. e.,* $Schedule_l$, Inc_j, $Task_j$, $OptTask_{jl}$) are compiled by the proposed algorithm using Equations (4.61), (4.62) and (4.63), then given the MILP model as parameter values of $CmaxLine_{il}$, $CmaxProduct_{ij}$, $binsetup_{ijkl}$. Equation (4.61) ensures that the end of schedule for line l is equal to completion time of line l on day i. Equation (4.62) guarantees that the end of the incubation operation of product j is equal to completion time of product j on day i. Equation (4.63) shows that the binary setup variable is equal to 1 if product j precedes product k on schedule of line l and, otherwise equals 0.

It should be noted for Equations (4.56) to (4.63) that the same scheduling sub-model is called by planning MILP sub-model recursively for each day (*i. e.,* $\forall i$) and hence, the variables of the scheduling CP sub-model (*i. e.,* $Duration_j$, $IncDuration_j$, $Schedule_l$, Inc_j, $Task_j$ and $OptTask_{jl}$) and the variables of the scheduling MILP sub-model (*i. e.,* $CmaxLine_l$, $CmaxProduct_j$ and $binsetup_{jkl}$) do not include of i production day indices.

4.6 An Illustrative Case Study

In this section, an illustrative case study on production planning and scheduling of a dairy industry is considered to show applicability and effectiveness of the proposed approaches.

4.6.1 Description and Data

The production and distribution network consists of a single plant and seven DCs. The production planning and scheduling is performed for a weekly planning. Regular working time of the plant is 8 hours among 5 working days of the week. If necessary, overtime can be afforded in addition to regular working times. Available working time is limited by maximum 16 hours for each working day. The daily demand of DCs for 11 separate products is collected during working days. The plant comprises two packaging lines and one single room for incubation. The products are operated on these identical parallel lines. The processing time of a product depends on the produced quantity and the corresponding machine speed. In yoghurt production, there is a natural sequence in which the various products are to be produced in an order. It stands to reason that each product has different fat consistency and ingredients. The changeover rules arranged with data. Product 1, 2 and 3 requires 120 min changeover time and 600 € cost between each other. The corresponding changeover time and cost are 30 min - 350 € for the rest of the products. In addition, to set the packaging lines between some certain products is time consuming and costly. The changeover time and cost between the product group of product 1, 2, 3 and the other products are either 30 min - 350 € for product 4, 5, 6, 7 or 60 min - 450 € for product 8, 9, 10, 11.The setup matrix is designed symmetrically. The rest of the input data used is summarized in Table 4.2. Data collection for analysis of the proposed models took place in cooperation with research partners through interviews, industrial reports and literature. Only the most important problem parameters are given in details in order to be concise. The remaining data are available upon request from the authors.

Table 4.2 Input data for model parameters

Monetary Parameters	Value (~ between)	Unit
Cost of the decrease on shelf life	0. 1 ~ 0. 5	€ / lt per day
Variable production cost	0. 09 ~ 0. 16	€ / lt
Inventory cost	0. 01 ~ 0. 07	€ / lt per day
Operating cost of lines	0. 3	€ / min.
Production waste cost	0. 01 ~ 0. 05	€ / min.
Operation cost of incubation room	360	€ per batch
Overtime cost	1	€ / min.
Transportation cost	0. 120 ~0. 300	€/ lt
Unmet demand cost	1.4 ~ 2	€ / lt
Technical Parameters	**Value (~ between)**	**Unit**
Shelf life of product	1	week
Minimum shelf life required by the customers	66	%
Incubation time	180 ~ 240	min.
Packaging machine speeds	10 ~ 50	lt/min.
Maximum storage capacity	2000	pallets
Maximum incubation capacity	150	pallets
Minimum production lots	100	lt
Maximum production lots	10,000	lt
Factor converting quantities to pallets	0. 1 ~ 0. 05	pallets/lt

4.6.2 Analysis and Discussion

The analysis is performed with respect to changes in the demand. Since a short-term planning horizon of one week is considered, seasonal demand variations are not essential. However, depending on the time of the year, the average workload may be higher or lower. These conditions are reflected by two scenarios which assume an average workload of 75 and 90% of the available total capacity, respectively. Moreover, since the demand is driven by customer orders of various sizes, the granularity of demand elements are considered as a key factor and examined in three levels (*i.e.,* high, medium, and low). The high demand granularity implies a large number of small-sized customer orders while low demand granularity is given by a comparatively small number of large-sized orders. In particular, in a high demand granularity scenario the scheduling complexity is considerably increased because a comparatively large number of production lots have to be established. The demand figures are randomly generated according to the following procedure in line with Bilgen and Günther (2010).

1. Determine X as the total number of available operating hours: $X = 8 \cdot 5 \cdot 1 \cdot 2 = 80$ hours based on 8 hours operating time per day, five days per week, a planning horizon of one week, and two production lines.
2. Considering an average workload factor of 75% and 90%, respectively, and a capacity loss of 10 hours due to setup operations, determine Y as the effective total workload on the production system: $Y = 0.75 \cdot (X - 10) = 52.5$ and $Y = 0.9 \cdot (X - 10) = 63$, respectively.
3. The entire set of products can be produced on two lines and $N = 2 \cdot 11 = 22$ product-week assignments are achieved. In order to generate demand elements of different size, a granularity factor g taking values of 1, 3, and 5 is defined. Accordingly, $n = 1 \cdot 22 = 22$, $n = 3 \cdot 22 = 66$, and $n = 5 \cdot 22 = 110$ demand elements are generated under the three different granularity scenarios.
4. The average size of demand elements is $D = Y/n$ hours. In order to create a realistic degree of demand variability for each scenario, actual values of demand elements d are randomly drawn from the uniform distribution $d \in [0.5 \cdot D, 1.5 \cdot D]$. The detailed assignment of demand elements to products, periods, and DCs is completed by the following procedure.
   (a) Select randomly one out of the 11 products. The demand d of the selected product is doubled for two lines, *i.e.,* $d \leftarrow d \cdot 2$. The manufactured products causing a capacity load of more than 75% or 90%, respectively, can be produced with overtime reach up to 8 additional working hours. The overtime rule provides to avoid infeasible capacity loads.
   (b) Select randomly one of days 1, 2, …, 5 within the planning horizon and assign the demand element generated in the previous step.
   (c) Assign fractions of 50%, 30%, and 20% of the generated demand randomly to the three DCs.
   (d) For each DC, assign the demand to a day selected in (b), and convert the demand from hours into liters. Aggregate demand generated for the

specific product and the specific day with already existing demand, if necessary.

5. Repeat this procedure until the assigned demand equals or exceeds the effective total workload Y.

Several numerical experiments were carried out in order to evaluate the proposed models and the algorithms. Each experiment was repeated five times with different randomly generated demand data. According to the demand generation procedure, 45, 133 and 222 demand elements were generated on average per problem instance for the three granularity levels under the 75% capacity load scenario. The corresponding figures for the 90% capacity load scenario are 43, 132 and 219.

In addition, a parameter setting is performed to make the proposed decomposition heuristic more robust. From the result of some pilot experiments, the initial temperature t_0 is pre-determined as 100. The temperature reduction factor is chosen as 0. 90. The number of iterations M_p for each step p is equal to 10. The algorithm stops, if the best solution found does not improve in 100 consecutive changes in a temperature.

The numerical investigation is performed by comparing results of the integrated model, the decomposition heuristic and the hybrid MILP/CP approaches by means of both optimality and computational efforts. The IBM ILOG CPLEX optimization studio version 12.6 is used with the default parameter settings to solve the proposed models for the case study. The hybrid algorithm is developed using IBM ILOG Script. All analyses were conducted on a computer with an Intel Core i7-3630QM CPU @ 2.40GHz and 16 GB memory. The resulting integrated model contains 1245 integer, 2160 binary decision variables and 5140 constraints. All of the 30 problems are solved within the imposed CPU time limit of 18,000 seconds and evaluated with the corresponding MILP gaps.

Table 4.3 present the comparative results of the proposed approaches. The experiments show each scenario generated with the corresponding demand parameters (i.e., capacity load and granularity level). The table presents all demand scenarios together with the results, the computational times and the gap values which compare the results. First, it appears that the decomposition heuristic and the MILP/CP hybrid approaches are preferable to the integrated MILP model. Obviously, the decomposition heuristic exploits the possibility to link the planning and scheduling decisions and reach to reasonable solutions. The decomposition heuristic reach even better results than the integrated MILP results more often for the scenarios which have 90% capacity load. The decomposition heuristic is considerably fast comparing to the integrated MILP model. In addition, while the heuristic can reach the results in short computational times especially for low granularity level scenarios. The MILP/CP hybrid approach requires less computational effort due to its inherent scheduling flexibility of CP sub-model. The second observation is that the decomposition heuristic and the MILP/CP hybrid approach leads to the results with very low computational efforts when the number of the demand elements is small and at the same time the average size of the demand elements is large. The lowest demand granularity allows to a smooth plan and schedule, which balances out the lumpy demand. Hence, the proposed approaches seem to be more effective than in the cases with a higher demand granularity level.

Figure 4.2 and Figure 4.3 present the convergency charts of 75% and 90% capacity load experiments, respectively. The convergency charts show the computational time related results. The charts are used to compare the computational performance of the proposed approaches in time. Apparently, the proposed approaches start with better objective values for the initial operations. The decomposition heuristic reaches to a quite low objective value in initial iterations, and search for better solutions. The MILP/CP hybrid approach starts with a reasonable value, but the search for better solutions has a drastic improvement comparing to the decomposition heuristic. After the MILP/CP hybrid approach stops with a feasible solution, the search of the decomposition heuristic can continue for a while to reach better solutions. In general the solutions of the proposed approaches converge enough to close optimum results of integrated MILP model and can reach even better results for the low granularity scenarios. Most of the results of 90%

capacity load in the low granularity level have lower heuristic gaps than the 75% capacity load scenarios.

It should be noted that a high capacity load refers to more efficient utilization the existing manufacturing resources and a low granularity level expresses the situation of a manufacturer who faces comparatively large replenishment orders from his customers. The tendency of concentration and mergers in the retail sector cause high demand volumes. This situation gets more common in industrial sized problems. The observations show that the proposed decomposition heuristic and the MILP/CP hybrid approach are reliable and quick optimization approaches and capable of solving the industrial sized problems.

Table 4.3Comparison of the numerical results[*]

Experiment			Decomposition Heuristic Result (€)	Decomposition Heuristic Time (s)	Decomposition Heuristic H. Gap (%)	MILP/CP Hybrid Approach Result (€)	MILP/CP Hybrid Approach Time (s)	MILP/CP Hybrid Approach H. Gap (%)	Integrated model Result (€)	Integrated model O. Gap (%)
75% Capacity load	Low gran.	1	33,680	330	1.50	36,786	1,260	10. 86	33,181	14.65
		2	23,812	1,619	4.98	25,874	1,819	14.07	22,683	9.64
		3	35,634	800	-4.74	40,204	1,294	7.47	37,408	16.20
		4	26,753	1,063	0. 10	33,031	950	23.59	26,727	12.95
		5	23,948	695	4.31	25,799	764	12.37	22,958	17.45
	Avg.		28,765	902	1.23	32,339	1,217	13.67	28,591	14.18
	Medium gran.	1	34,747	17,090	15.06	36,936	569	22.30	30,200	21.28
		2	36,033	4,717	11.72	38,401	1,227	19.07	32,252	21.13
		3	35,484	414	33.78	36,533	722	37.73	26,525	17.34
		4	36,432	1,457	17.74	37,303	928	20. 55	30,943	18.58
		5	35,197	2,579	7.90	37,813	2,252	15.92	32,621	17.81
	Avg.		35,579	5,251	17.24	37,397	1,139	23.11	30,508	19.23
	High gran.	1	39,092	2,731	19.88	36,804	1,769	12.87	32,608	21.06
		2	35,883	1,233	14.57	33,959	737	8.43	31,320	22.60
		3	39,224	18,000	11.13	41,362	3,112	17.19	35,295	20. 75
		4	44,218	18,000	13.49	47,234	1,870	21.23	38,961	27.07
		5	37,333	11,242	-4.18	39,156	859	0. 50	38,961	27.04
	Avg.		39,150	10,241	10. 98	39,703	1,669	12.04	35,429	23.70
90% Capacity load	Low gran.	1	37,921	84	-10. 07	44,204	353	4.83	42,169	21.40
		2	31,179	332	-1.84	34,234	678	7.77	31,765	17.29
		3	30,369	329	-0. 70	32,359	1,995	5.81	30,582	18.42
		4	39,731	221	-6.38	42,205	2,659	-0. 55	42,436	21.50
		5	30,171	82	2.20	33,966	1,410	15.06	29,520	13.80
	Avg.		33,874	210	-3.36	37,394	1,419	6.59	35,294	18.48
	Medium gran.	1	40,108	1,829	15.32	44,972	5,294	29.31	34,779	19.11
		2	37,076	2,174	4.18	40,364	2,049	13.41	35,590	23.04
		3	32,971	730	7.83	33,075	1,338	8.17	30,577	22.02
		4	46,366	2,123	8.66	53,220	425	24.73	42,670	21.89
		5	39,000	1,731	11.89	43,538	1,532	24.91	34,855	20. 32
	Avg.		39,104	1,717	9.58	43,034	2,128	20. 11	35,694	21.28
	High gran.	1	41,129	403	4.04	47,024	1,548	18.95	39,531	30. 38
		2	44,320	9,322	22.47	45,747	516	26.41	36,188	24.15
		3	42,254	18,000	19.30	46,595	1,099	31.56	35,419	22.57
		4	48,806	18,000	16.32	51,155	647	21.92	41,957	25.81
		5	41,345	18,000	22.06	40,452	1,214	19.42	33,872	22.38
	Avg.		43,571	12,745	16.84	46,195	1,005	23.65	37,393	25.06
Overall Avg.			**36,674**	**5,178**	**8.75**	**39,343**	**1,430**	**16.53**	**33,818**	**20. 32**

[*] The current optimality gap value of the integrated MILP model is calculated by CPLEX within 18,000 seconds computational time limitation (see, User's Manuel for CPLEX / Progress reports: interpreting the node log). The gap values of the decomposition heuristics are calculated to make comparison between the results of proposed heuristics and the results of integrated MILP model. Note that a negative value indicates that the heuristic is able to reach better results than the integrated MILP model within the computational time limitation. i.e., Heuristic gap = [(Heuristic result - MILP result)/MILP result]*100

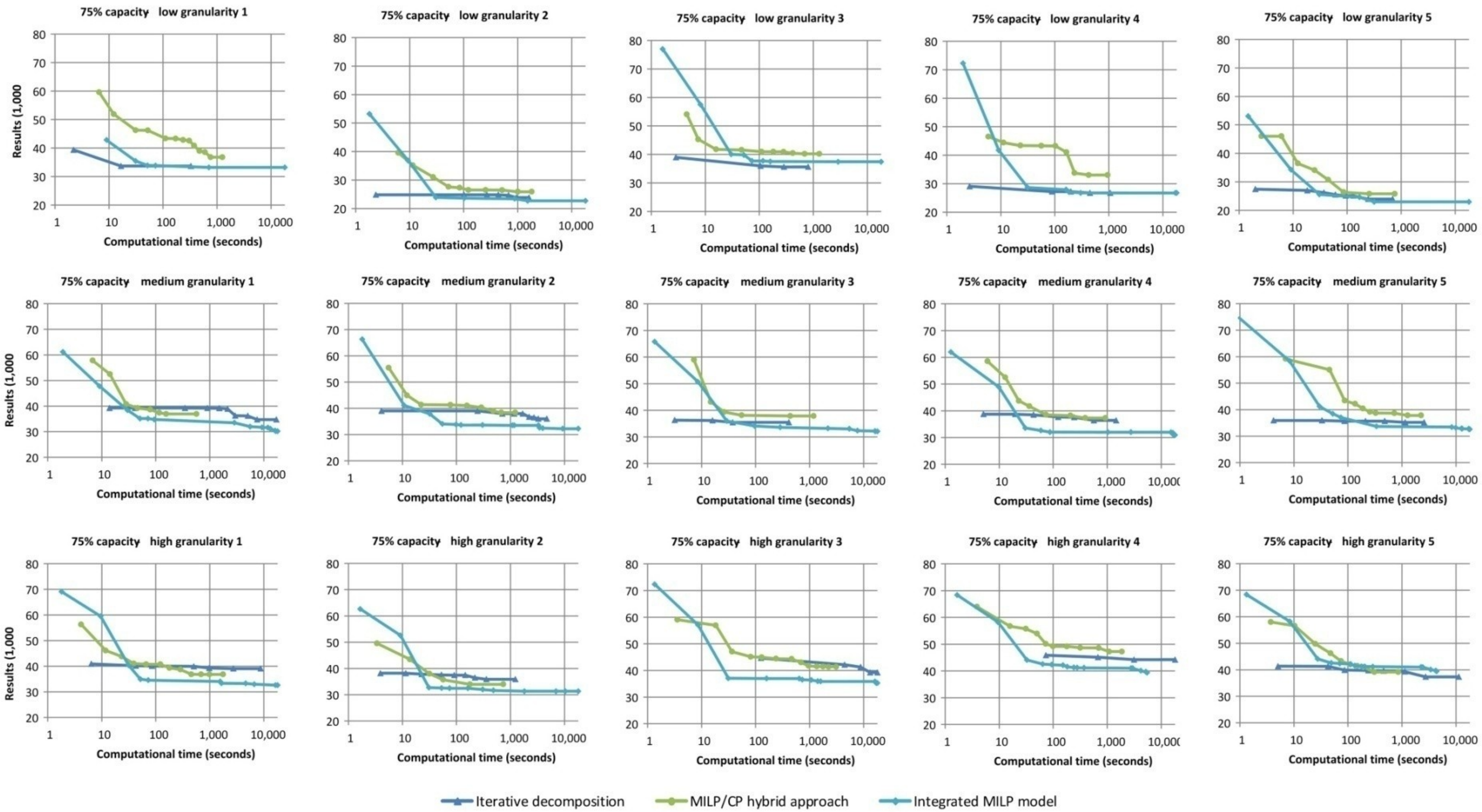

Figure 4.2 Convergency charts of 75% capacity load experiments

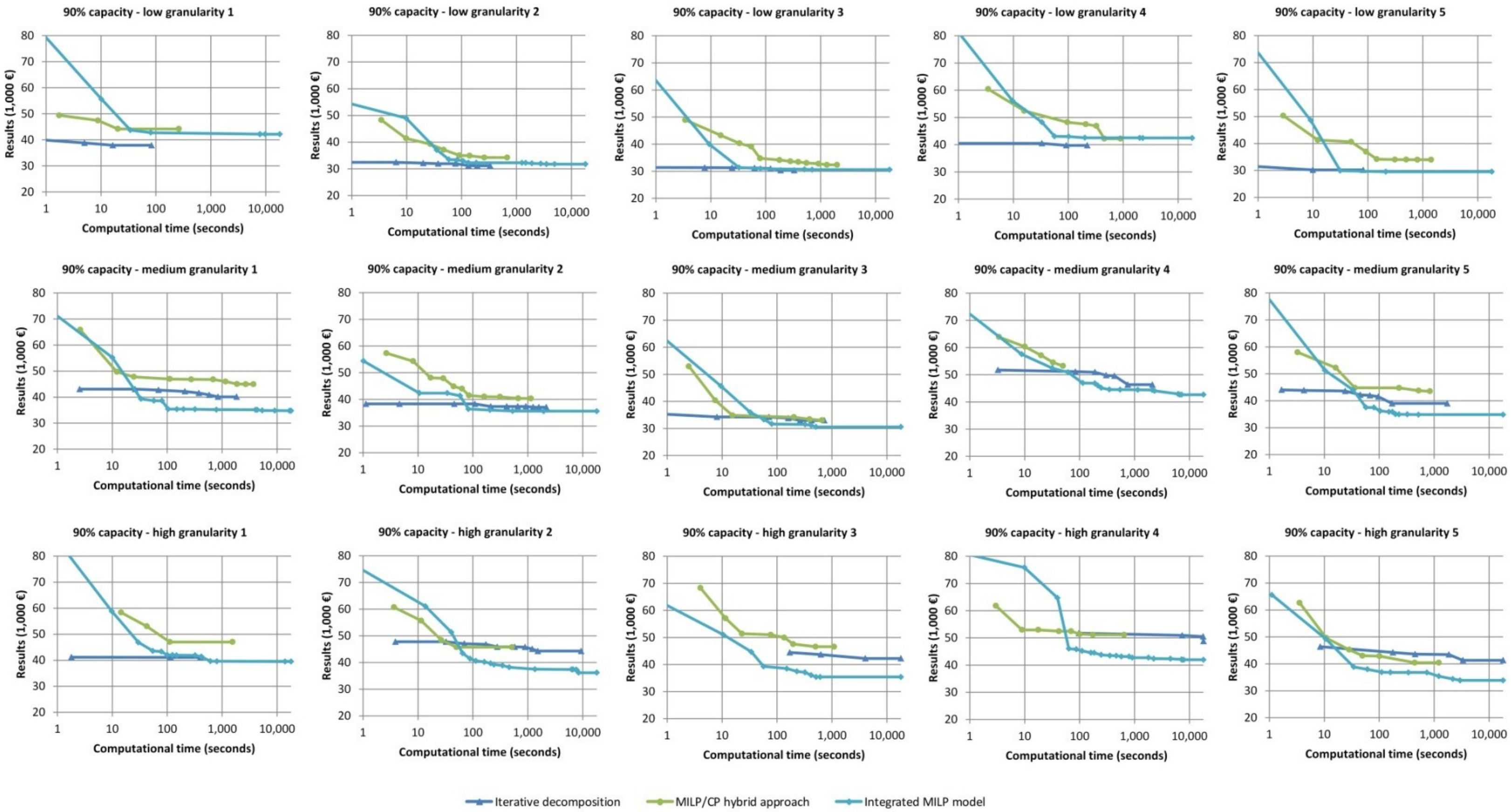

Figure 4.3 Convergency charts of 90% capacity load experiments

4.7 Conclusion

This research addresses the integrated production planning and scheduling problem within dairy industry. The problem is motivated from a two-stage semi-continuous set type yoghurt production process and formulated as a comprehensive MILP model. The objective function of the MILP model aims at minimization of the total cost by considering a shelf life dependent loss function. The model formulation is introduced to represent the planning and scheduling decisions under consideration of the shelf-life restrictions, sequence dependent changeovers, product dependent machine speeds, demand due dates, regular and overtime working hours, and delivery to the DCs. The key limitation of the overall MILP solution approach lies in the large computational times that are mainly due to large number of integer variables related with planning decisions, as well as binary setup variables triggered with big M constraints for scheduling decisions.

The integration of production planning and scheduling have been a challenging issue for a long while since it requires a comprehensive point of view on both tactical and operational level decisions. The major challenges appear in the development of computationally effective planning and scheduling formulations and, in the achievement of linkage with qualified restrictions between these two interrelated levels. In our approach, the integrated planning and scheduling problem is divided into two distinct sub-problems. The sub-problems are solved by the decomposition heuristic. A hybrid MILP/CP hybrid approach is proposed. The hybrid approach exploits complementary strengths of the MILP model on the accuracy in the planning level and, of the CP model on the computational efficiency in the scheduling level. The results show that the decomposition heuristic achieves reasonable solutions and the hybrid approach outperforms the integrated MILP model with short computational times.

The major advantages of the proposed approaches are their applicability to different dairy production processes (e.g., cheese, butter, ice cream). The flexibility originates from the integrated MILP model formulation providing an opportunity to integrate planning and scheduling horizons, as well as CP model which can easily be modified to account for process specific operating conditions. A limitation of the research is that the model is presented under assumption of all packaging lines are identical and, simultaneous production of the same product in many packaging lines is not allowed. Therefore, the line speeds and the setup times depend only on products and not on the machines.

It is possible to extend the research in several ways, which can be suggested as future research areas. The first direction for further research is to deal with the non-identical packaging line considerations. Second, the further research should address improving the computational efficiency of the proposed hybrid methodology. Another feedback mechanism aside from linkage capacity constraints can be investigated. Third, the other alternative solution techniques (e.g., stochastic programming and simulation) dealing with the stochastic and dynamic nature of dairy supply chains and various key characteristics of sustainability issues are promising directions.

The yoghurt production is a multi-stage semi-continuous process. The process characterized with make-and-pack stages. In addition to the final product which is perishable and its shelf life is restricted with a short period such as weeks, raw material milk and intermediate product milk-culture mixture is much more perishable and highly restricted with only several hours. Because of this time restriction scheduling of the make-and-pack production should be modeled to not allow the production waste.

In the next chapter, multi-stage-production planning, uncertainty and sustainability perspectives of the literature review are discussed. A scheduling problem is considered in make-and-pack production and a MILP model is introduced. The lifetime of the intermediates is represented by a probability distribution and a stochastic variant of the MILP model is developed. The production process is simulated and the proposed schedules are evaluated in terms of production waste.

Nomenclature

For the mathematical description of the models the following notation is introduced;

Indices &sets:

$i \in I^S$	days	$I^S = \{1..I\}$
$d \in D^S$	demand days	$D^S = \{1..D\}$
$j,k,t \in P^{S1}$	products	$P^{S0} = \{0..P\}, P^{S1} = \{1..P\}$
$l \in L^S$	lines	$L^S = \{1..L\}$
$a \in A^S$	distribution centers	$A^S = \{1..A\}$

Monetary parameters:

MILP models;

$Loss_j$	Cost of the decrease on the shelf life of product j, €/liter per day
$VarCost_j$	Variable production cost of product j, €/liter
$StrgCost_j$	Inventory cost of product j, €/liter per day
$SetupCost_{jk}$	Changeover cost from product j to k, €
$LineCost_l$	Operating cost of line l, € per day
$PwCost_j$	Waste cost of product j during packaging, €/minute
$IncCost$	Operating cost of incubation room, €
$OverTCost$	Overtime cost, €/minute
$TransCost_a$	Transportation cost from plant to DC a, €
$UnmDCost_j$	Unmet demand cost of product j, €

Technical parameters of:

MILP models;

$ShelfLife_j$	Shelf life of product j, day
$CrRate_j$	Minimum shelf life requirement of customer for product j, % of shelf life
$IncTime_j$	Incubation time of product j, minute

$Demand_{jda}$	Demand of DC a for product j on demand day d, liter
$QContTime$	Quality control time, day
$MchSpeed_j$	Machine speed for product j, liter per minute
$StCapacity$	Storage capacity of the plant, minute
$IncCapacity$	Incubation capacity of the plant, minute
$MinLot_j$	Minimum production lots of product j, liter
$MaxLot_j$	Maximum production lots of product j, liter
$SetupTime_{j \in P^{S0} k}$	Changeover time from product j to k, minute
$MaxTime_i$	Maximum available time on day i, minute
$RTime_i$	Regular working time on day i,minute
$Capacity_i$	Production capacity on day I, minute
γ_j	Factor for converting product quantity to storage unit, e.g., pallet
M	Scalar chosen to be huge number

CP model;

$IncDuration_j$	Incubation duration of job j, minute
T_j	The type associated with each interval variable in the sequence, a non-negative integer
$Setup$	Setup time defined as triple, hour $Setup = \{< j,k,st > \mid j,k \ in \ J^S : j \neq k : st \ in \ ST^S \}$
ST^S	Set of setup times

Decision variables of:

Integrated model and planning sub model – MILP;

x_{ijld}	Quantity of product j produced on line l on day i for demand day d, liter
y_{jda}	Quantity of product j produced for DC a for demand day d, liter
$UnmD_{jda}$	Unmet demand of product j for DC a on demand day d, liter

inv_{ij} Inventory of product j at the end of day i, liter

$overtime_i$ Overtime on day i, minute

PT_{ij} Production time of product j on day i, minute

$FT_{ij \in P^{S0} l}$ Finishing time of product j on line l on day i, minute

$CmaxLine_{il}$ Maximum completion time of line l on day i, minute

$CmaxProduct_{ij \in P^{S0}}$ Maximum completion time of product j on day i, minute

$IncNb_{ij \in P^{S0}}$ Number of incubation for product j on day i

$binsetup_{ij \in P^{S0} k \in P^{S0} l}$ Changeover from product j to k on line l on day i, binary

$IncSequence_{ij \in P^{S0} k \in P^{S0}}$ Incubation sequence of product j preceding product k in day i, binary

bin_{ijl} Production of product j on line l on day i, binary

Scheduling sub-model – MILP;

x_{jld} Quantity of product j produced on line l for demand day d, liter

PT_j Production time of product j, minute

$FT_{j \in P^{S0} l}$ Finishing time of product j on line l, minute

$CmaxLine_l$ Maximum completion time of line l, minute

$CmaxProduct_{j \in P^{S0}}$ Maximum completion time of product j, minute

$IncNb_{j \in P^{S0}}$ Number of incubation for product j

$binsetup_{j \in P^{S0} k \in P^{S0} l}$ Changeover from product j to k on line l, binary

$IncSequence_{j \in P^{S0} k \in P^{S0}}$ Incubation sequence of product j preceding product k, binary

Scheduling sub model – CP;

$Task_j$ Activities corresponding with each of job j, interval variable

$OptTask_{jl}$ Operational activities which has optional size of $Duration_j$, interval variable

Optional activities correspond with each of job j operated on line

l

$Duration_j$	Size of the $OptTask_{jl}$
Inc_j	Incubation activities which has size of $IncTime_j$, interval variable Incubation activities correspond with each of job j
$Schedule_l$	Variable represents a total order over a set of $OptTask_{jl}$, sequence variable T_j integer type is used

CHAPTER FIVE
SCHEDULING OF THE MAKE-AND-PACK PRODUCTION PROCESS WITH UNCERTAIN PERISHABILITY IN THE DAIRY INDUSTRY

5.1 Introduction

During recent decades, perishability has received increasing attention of the food processing industry. Apart from raw foods (e.g., meat, grains, legumes, nuts, fruits, vegetables), almost all foods are processed such as bakery, dairy and meat products (e.g., bread, milk, ice creams, burgers and sausages). These processed foods are inherently perishable and have mostly specific product and process characteristics such as variety in product types, contamination issues and long changeover times (Akkerman and van Donk, 2009a). Product and process characteristics of perishable food products require specific models to support decision making.

Processed foods show a wide variety of retail cup sizes or labels, contents and special ingredients with numerous flavors. A few intermediate product recipes lead to a large number of product types. Hence, product-dependent cleaning, sterilizing and re-tuning of used production units (*e.g.,* pipes, mixing tanks, packaging lines) arise to avoid contamination (Montagna et al., 1998) and, and, long sequence-dependent changeover times cause a noticeable decrease of available production times. Considering this issue, Günther et al. 2006, Bilgen and Günther (2010) introduce the block planning concept to ease make planning decisions by using a pre-defined production sequence (*i. e.* from low to high concentrations of certain content such as fat). The intermediates of the processed foods are subject to time-dependent deterioration. The possible storage time of perishable intermediates is very short and depends on varying semi-controllable parameters such as raw material characteristic (*e.g.,* pasteurized or not) and composition (*e.g.,* fat, protein, sugar content), used process equipment (*e.g.,* vessels, tanks or pipe lines), storage and transportation conditions. In addition, the available time span is uncertain due to uncontrollable parameters such as microbial load, cleaning efficiency and water activity. The time-dependent deterioration can be represented with lifetime probabilities which fit gamma distributions, Weibull, two-parameter Weibull, or exponential distributions (Pahl and Voß, 2010; Al-Kadamany et al., 2002; Al-Kadamany *et al,.* 2003). Stochastic linear programming has been developed as a useful modelling and solution paradigm to deal with such uncertainty (Charles et al. 2011; Javaid et al., 2013).

The production process of processed foods commonly consists of two stages (processing and packaging) (van Dam et al. 1993). Scheduling two-stage flow shop problems have been studied in literature (*e.g.,* Allahverdi, 1995; Bousonville 2002; Ruiz and Vázquez-Rodríguez*,* 2010). As a pioneering research, Méndez and Cerdá (2002) define the two-stage food production as make-and-pack. Akkerman et al. (2007) and Akkerman and van Donk (2009b) consider a make-and-pack production process with a batch processor in the first stage and parallel packaging lines in the second stage. They introduce explanatory studies using simulation methodology. Akkerman et al. (2007) investigate capacity and time constraints of a limited number of storage tanks (which often have to be shared by a multitude of products) using simulation. Akkerman and van Donk (2009b) extend the previous study to model possible dependencies between intermediate products and packages. They conclude that lifetime and rapid quality decay of intermediates are uncertain parameters affecting the total time needed to finish the daily production and the amount of waste during the production process.

In dairy industry, intermediates are more perishable than final products. Final products can have long shelf life from 15 days up to years, but the lifetime of the intermediates is restricted to several hours (Bylund, 1995). Besides, foods are never completely the same as time progresses and there is always variability and uncertainty in the condition of raw ingredients. Therefore, the dependency between intermediate production and packaging levels and the uncertainty in lifetime of intermediates negatively affect the makespan and the waste.

The dairy industry offers real-life production problems as in the case of yogurt production. Lütke Entrup et al. (2005) develop several MILP models. They take into account the perishability of final products with a shelf life integrated price component. The MILP models focus on flavoring and packaging stages. The integration of the fermentation process into the planning procedure, and incorporation of uncertainty are presented as the future directions of the research. Marinelli et al. (2007) present a real capacitated lot sizing and scheduling problem with parallel machines and shared buffers in the packaging stage. They introduce a discrete mathematical planning model minimizing the setup, storage and processing costs. As a solution methodology, they propose a two-stage heuristic based on the decomposition of the problem into lot sizing on tanks and scheduling on lines.

Doganis and Sarimveis (2007) propose a MILP model for production scheduling. The model considers the sequencing limitations, sequence dependent changeover times and costs in addition to material balances, inventory, machinery capacity, labor shifts and manpower restrictions. The model is limited to the single production line. Doganis and Sarimveis (2008) extend the previous MILP model to multiple parallel machines together with the different production costs of each parallel machine, the starting and finishing time for the production of each product at the machines. Doganis and Sarimveis (2009) address a new MILP model that combines the advantages of the two models. Additionally, they integrate shelf life restrictions in the constraints to keep stable the remaining shelf life on production and in the objective function to control the freshness on delivery.

Kopanos et al. (2010) study on a lot sizing and scheduling problem and introduce a mixed discrete/continuous time MILP model. They consider parallel packaging units sharing common resources and take into account the sequence-dependent times and costs. Kopanos et al. (2011b) present a MILP framework for a resource constrained production planning problem. They consider renewable resource limitations and differ from the literature by optimizing quantitative as well as qualitative optimization goals. Kopanos et al. (2012a) present a MILP framework based on a hybrid discrete/continuous time representation for the simultaneous production and distribution planning problem. In these studies, whereas timing and capacity constraints are imposed with respect to the pasteurization, homogenization and fermentation processes, the main focus is on the packaging stage.

Amorim et al. (2011) present multi-objective MIP models on a lot sizing and scheduling problem considering perishability issues. The model is analyzed for two distinct scenarios depending on make-to-order and hybrid make-to-order/make-to-stock production systems. The proposed MILP model is hybridized with a non-dominated sorting genetic algorithm. Amorim et al. (2012) present multi-objective MIP models for an integrated production and distribution planning problem integrating the economic aspects and freshness at an operational level. The models are formulated for two distinct cases with a fixed and a loose shelf life. They propose a simple hybrid genetic heuristic to solve the problem where the shelf life is loose. Amorim et al. (2013a) and Amorim et al. (2014) investigate a production planning problem with a different point of view from the existent literature. Amorim et al. (2013a) assess the suitability of financial risk measures for mitigating crucial risks, Amorim et al. (2014) consider the influence of customer purchasing behavior on the production planning of perishable goods. Amorim et al. (2013b) focus on lot sizing and scheduling decisions of the production process consisting of multi-product and multi-parallel lines with complex setup structure. They analyze the performance of existent formulations in the literature for small bucket and big bucket capacitated lot sizing and scheduling problems.

Recently, Bilgen and Çelebi (2013) consider an integrated production scheduling and distribution planning problem. They introduce a MILP model and propose a hybrid method combining MILP and simulation approaches. While in the most of the previous studies parameters are accepted as deterministic, they handle the stochastic failures on operation times to obtain more realistic solutions. Sel et al. (2015) considers an integrated planning and scheduling problem. They introduce a MILP model to integrate tactical and operational decisions and propose a heuristic approach to decompose time buckets of the decisions. Further, they combine MILP and CP methodologies with the decomposition algorithm to show their complementary strengths.

The studies considering the yoghurt production process focus on the packaging stage (*e.g.,* Lütke Entrup et al., 2015; Doganis and Sarimveis, 2007; Kopanos et al., 2010). However, the packaging stage has an interrelation with the processing or mixing stages. Honkomp et al. (2000) discuss the interrelation of these two stages with scheduling examples from consumer goods industry including food and beverage. Based on practical examples, Stadtler and Sahling (2013) present a lot-sizing and scheduling model for multi-stage flow lines and a solution approach using rolling horizon techniques. Baumann and Trautmann (2013)develop a MILP model for short-term scheduling of make-and-pack production processes. Baumann and Trautmann (2014) extend the previous study by a hybrid method linking the MILP model with a heuristic framework for large-scale instances. Nevertheless, perishability issues have been excluded from these studies.

In brief, research dealing with the yoghurt production and the perishability mostly focus on the packaging stage ignoring interrelations the processing or mixing stages and research taking into account the interrelations neglect perishability issues. The contribution of the research is to account for both of the interrelations and the perishability issues in the make-and-pack production. The summary of the related literature is presented in Table 1. Table 1 shows the characteristics of the problems, and confirms the lack of stochastic programming and simulation models.

In this research, we consider a scheduling problem accounting for the interrelation of two consecutive stages (i. e. processing and packaging). We propose a stochastic MILP model aiming at minimization of makespan. The model deals with uncertainty in quality decay of perishable intermediates. A yoghurt production case is presented to illustrate the typical structure of a two-stage semi-continuous make-and-pack process. Accordingly a simulation of the production process is introduced to evaluate the solutions of the proposed model in terms of product waste. The research helps to fill the gap pointed out by Sel and Bilgen (2015) stating the uncertain characteristic of perishable dairy products.

The reminder of this chapter is organized as follows. The structure of the considered make-and-pack production is described in Section 5.2.The MILP model and the simulation model are described in Section 5.3. An illustrative case study is presented in Section 5.4.Finally, the main conclusions are given in Section 5.5.

Table 5.1 Literature summary –two-stage & yoghurt production scheduling problem

	Reviewed literature	Problem characteristics			Modelling approaches				
		Make	Pack	Perish.	MILP	MINP	SM	SP	CP
Yoghurt production	Lütke Entrup et al. (2005)		✓	✓	✓				
	Marinelli et al. (2007)	✓	✓		✓				
	Doganis and Sarimveis (2007)		✓		✓				
	Doganis and Sarimveis (2008)		✓		✓				
	Doganis and Sarimveis (2009)		✓	✓	✓				
	Kopanos et al. (2009)	✓	✓		✓				
	Kopanos et al. (2011b)	✓	✓		✓				
	Kopanos et al. (2012a)	✓	✓		✓				
	Amorim et al. (2011)		✓	✓	✓				
	Amorim et al. (2012)		✓	✓	✓	✓			
	Amorim et al. (2013a)		✓	✓				✓	
	Amorim et al. (2014)		✓	✓	✓			✓	
	Amorim et al. (2013b)		✓		✓				
	Bilgen and Çelebi (2013)		✓	✓	✓		✓		
	Sel et al. (2015)		✓	✓	✓				✓
Two-stage production	Méndez and Cerdá (2002)	✓	✓		✓				
	Akkerman et al. (2007)	✓	✓	✓			✓		
	Akkerman and van Donk (2009b)	✓	✓	✓			✓		
	Stadtler and Sahling (2013)	✓	✓		✓				
	Baumann and Trautmann (2013)	✓	✓		✓				
	Baumann and Trautmann (2014)	✓	✓		✓				
	This research	✓	✓	✓	✓		✓	✓	

✓– Defined otherwise undefined, Perish. - Perishability, MILP – Mixed-Integer Linear Programming, MINP – Mixed-Integer Non-linear Programming, SM – Simulation, SP – Stochastic Programming, CP – Constraint Programming

5.2 Problem Description and Notations

We consider a two-stage semi-continuous make-and-pack production in line with Honkomp et al. (2000), Méndez and Cerdá (2002), Akkerman and van Donk (2007, 2009b), Baumann and Trautmann (2013, 2014). The intermediates $i \in I = \{1,...,|I|\}$ (*i.e.* variations in fat content) are processed with a mixing unit in the first stage and product types $j, j', j'' \in J = \{1,...,|J|\}$ (*i. e.* retail cups in different sizes) are packed on non-identical parallel lines $l \in L = \{1,...,|L|\}$ in the second stage during production cycles $n \in N = \{1,...,|N|\}$. Each cycle represents an interval in which processing, storage and packaging operations are performed for intermediate i. A cycle starts with mixing of the intermediate and finishes after its packaging operations (*i. e.* until the mixing tank is fully discharged). The production process is analogue with many food production processes such as candy, flour, yoghurt (see respective references in Akkerman and van Donk, 2009a). Figure 5.1 illustrates the schematic representation of the process.

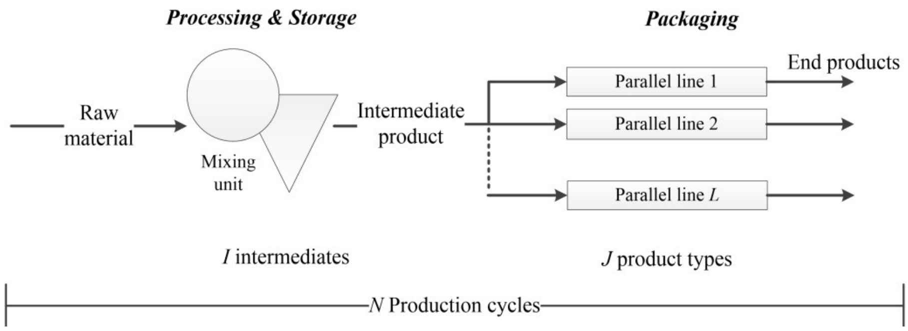

Figure 5.1The two-stage semi-continuous make-and-pack production

Each product type j packed from intermediate i has a known non-negative demand d_{ij}. To fulfill the demand, homogeneous intermediate mixtures i are produced in a certain mixing time mt_i and the processing unit can only mix one single intermediate i at the same time. The processing unit serves as temporary storage within the lifetime of the intermediate f_i. Lifetime is very limited because of rapid chemical reactions (*e.g.,* fermentation). Lifetime also has variations in reaction rate because of uncontrollable process parameters causing quality decay (*e.g.,* microbial load, cleaning efficiency and water activity). Therefore, the limited lifetime is uncertain and can be described with a non-linear continuous distribution. Each product type j requires a certain amount of intermediate. r_j is a conversion factor to translate the demand of product type j packed from intermediate i into necessary amount of intermediate i. The changeovers at the processing unit are realized in a pre-defined production sequence from low to high fat concentrations. Each product type j of intermediate i is packed in non-identical lines with different packaging speeds ls_{ij}. Changeovers require sequence-dependent setup times $st_{j'j''}$, $j'' > j'$ (*i. e., j''* is the successor of product type j'). Cleaning operations (*i. e.* automatic washing and sterilization of the product tank and the filling valves of packaging machines) are processed for each of the packaging operations based on changeover rules. The setup times include the time spent on cleaning operations. The mixing unit has a minimum production lot-size ml with maximum mixing capacity mc. The packaging lines have minimum lot-size pl and maximum packaging capacity pc.

The short-term scheduling of the make-and-pack production aims at minimization of $Makespan$. To achieve a minimum makespan, decision variables are as follows;

(i) Allocation of mixing intermediate i at production cycle n on the processing unit and allocation of product type j from intermediate i on packaging line l at cycle n by binary allocation variables M_{in} and P_{ijln},

(ii) Changeovers from product type j' to j'' on packaging line l at production cycle n by binary setup variable $S_{ij'j''ln}$,

(iii) The packaging time for product type j of intermediate i packed on line l at cycle n by continuous time variable PT_{ijln},

(iv) The required production amount of intermediate i to produce product type j on line l at production cycle n by continuous quantity variable X_{ijln},

(v) The beginning and completion times for mixing operation of intermediate i at production cycle n by $B^{M}{}_{in}, C^{M}{}_{in}$ continuous time variables,

(vi) The beginning and completion times for packaging operation of product type j of intermediate i on line l at production cycle n by continuous time variables $B^{P}{}_{ijln}, C^{P}{}_{ijln}$.

5.3 Modelling Approach

In this section, we propose a stochastic MILP model and a simulation model. The stochastic MILP model determines optimum schedules yielding minimum production makespan as an indicator of productivity of the production process. It uses a deterministic approximation of the probability distribution describing the uncertain lifetime. The simulation model provides a reasonable representation of the production process and is able to describe the uncertainty from the actual distribution. It is possible with the simulation model to mimic the proposed schedule of MILP model and to determine the waste caused by quality decay.

5.3.1 Mathematical Formulation

The stochastic MILP model and the deterministic approximation of probabilistic perishability constraints are formulated as follows.

Objective;

$$Minimise\ Makespan \tag{5.1}$$

The minimum makespan objective is given in Equation (5.1) as a performance measure of productivity.

Demand constraints;

$$\sum_{ln} X_{ijln} \geq d_{ij}.r_j \qquad \forall i, j \tag{5.2}$$

$$PT_{ijln} \geq X_{ijln} / ls_{jl} \qquad \forall i, j, l, n \tag{5.3}$$

Equation (5.2) ensures that the amount of intermediate i meets the demand of related product type j. In Equation (5.3) the packaging time for product type j of intermediate i on line l at production cycle n depends on the required amount of intermediate i to produce product type j on line l at cycle n and packaging speed of lines for product type j.

Timing constraints;

$$C^{M}{}_{in} \geq B^{M}{}_{in} + M_{in}.mt_i \qquad \forall i,n \tag{5.4}$$

In Equation (5.4), the completion time of mixing for intermediate i at cycle n should be greater than or equal to the sum of the starting time of mixing for intermediate i at cycle n and the corresponding mixing time (see Figure 5.2). Note that completion times are also assigned to empty mixing orders. In case no intermediate i is processed, the completion time of the mixing operation equals the beginning time.

$$B^{M}{}_{in} \geq C^{P}{}_{iJln-1} \qquad \forall i,l,n \tag{5.5}$$

$$B^{M}{}_{i1} \geq C^{P}{}_{i-1JlN} \qquad \forall i,l \tag{5.6}$$

Equation (5.5) and (5.6) calculate beginning times for mixing operations (see Figure 5.2). In Equation (5.5), the beginning time for mixing of intermediate i at production cycle n should be greater than or equal to completion time for packaging of the last product type J of intermediate i operated at the preceding production cycle $n-1$. In Equation (5.6), the beginning time for mixing of intermediate i at the first production cycle should be greater than or equal to the completion time for packaging of the preceding intermediate $i-1$ at the last production cycle N.

$$B^{P}{}_{ijln} \geq C^{M}{}_{in} \qquad \forall i,j,l,n \tag{5.7}$$

$$B^{P}{}_{ij''ln} \geq C^{P}{}_{ij'ln} \qquad \forall i,j',j''>j',l,n \tag{5.8}$$

Equation (5.7) and (5.8) calculate beginning times for packaging operations (see Figure 5.2). In Equation (5.7), beginning time for packaging of product type j of intermediate i on line l at production cycle n should be greater than or equal to completion time for mixing of intermediate i at production cycle n. In Equation (5.8), beginning time for packaging of product type j'' of intermediate i on line l at production cycle n should be greater than or equal to completion time for packaging of preceding product type j' of intermediate i on line l at production cycle n.

$$C^{P}_{ij'ln} \geq B^{P}_{ij'ln} + PT_{ij'ln} + \sum_{j''=j'+1}^{P} st_{j'j''}.S_{ij'j''ln} \qquad \forall i, j', l, n \qquad (5.9)$$

$$MKS \geq C^{P}_{ijln} \qquad \forall i, j, l, n \qquad (5.10)$$

In Equation (5.9), completion time for the packaging operation of product type j' of intermediate i on line l at production cycle n is calculated by summing its beginning time, processing time and the setup time required for changeover to the succeeding product type j''. When a product type is not packed, the production time and all the binary variables involved in Equation (5.9) are zero and, the completion time is the same as the beginning time. Finally, Equation (5.10) provides that the makespan is longer than the completion time of each product in the sequence.

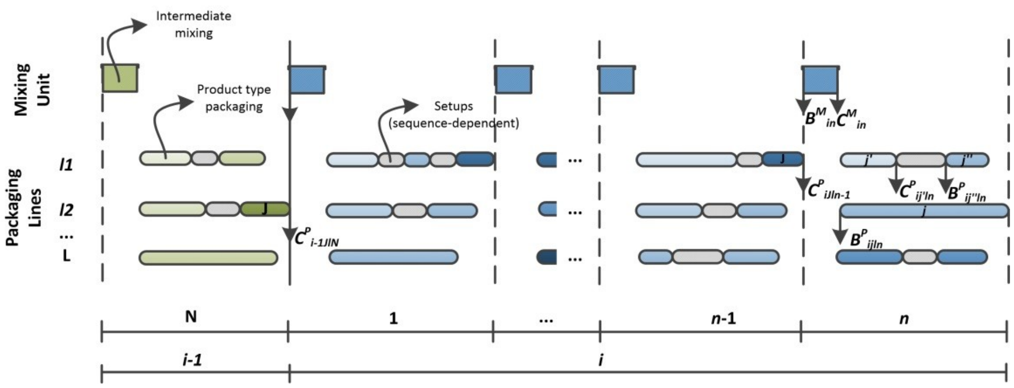

Figure 5.2 Timing decisions sequencing the mixing-packaging operations

Allocation and sequencing constraints;

$$S_{ij'j''ln} = 0 \qquad \forall i, j', j'' \leq j', l, n \tag{5.11}$$

$$S_{ij'j''ln} \leq 1 + (1 - P_{ij'ln}) + (1 - P_{ij''ln}) - \lambda . \sum_{j=j'+1}^{j''-1} P_{ijln} \qquad \forall i, j', j'' > j', l, n \tag{5.12}$$

$$S_{ij'j''ln} \geq P_{ij'ln} + P_{ij''ln} - 1 - \sum_{j=j'+1}^{j''-1} P_{ijln} \qquad \forall i, j', j'' > j', l, n \tag{5.13}$$

$$S_{ij'j''ln} \leq P_{ij'ln} \qquad \forall i, j', j'' > j', l, n \tag{5.14}$$

$$S_{ij'j''ln} \leq P_{ij''ln} \qquad \forall i, j', j'' > j', l, n \tag{5.15}$$

$$\sum_{j''} P_{ij'ln} - \sum_{j'} \sum_{j''} S_{ij'j''ln} \leq 1 \qquad \forall i, l, n \tag{5.16}$$

$$\sum_{l} P_{ijln} \leq 1 \qquad \forall i, j, n \tag{5.17}$$

Equations (5.11) to (5.16) are adopted from the allocation and sequencing constraints which are introduced by Doganis and Sarimveis (2007, 2008, and 2009) to decrease search efforts using pre-defined precedence rules of product types (*i. e.,* $j'' > j'$). Equation (5.11) prevents the transitions violating the given sequence of production. In Equations (5.12) to (5.15), binary variable equals 1 if and only if the product type packed from intermediate is allocated to line at production cycle. In addition, binary variable equals 1 if and only if there is a changeover from product type to product packed from intermediate on line at production cycle. λ represents a small number. Equation (5.16) presents a constraint accelerating the optimization process considerably. The equations always produce the correct binary values using an interaction between the binary variables representing production and setup operations. The set of constraints is examined with different cases by Doganis and Sarimveis (2007). In addition, Equation (5.17) forbids the batch splitting for packaging operations.

Capacity and lot sizing constraints;

$$\sum_{jl} X_{ijln} \geq M_{in}.ml \qquad \forall i,n \qquad (5.18)$$

$$\sum_{jl} X_{ijln} \leq M_{in}.mc \qquad \forall i,n \qquad (5.19)$$

$$X_{ijln} \geq P_{ijln}.pl \qquad \forall i,j,l,n \qquad (5.20)$$

$$X_{ijln} \leq P_{ijln}.pc \qquad \forall i,j,l,n \qquad (5.21)$$

Equations (18) to (21) state that production of product type j from intermediate i on packaging line l at production cycle n is allowed if and only if the respective binary variables M_{in} and P_{ijln} are equal to 1.The maximum and minimum allowed lot sizes are denoted by parameters ml, mc, pl and pc. Equations (18) and (19) guarantee minimum and maximum lot sizes for mixing of intermediates. Equations (20) and (21) pose minimum and maximum lot sizes for individual products.

Perishability constraints;

$$P\left(C^{P}{}_{iJln} - C^{M}{}_{in} \leq f_i\right) \geq p_i \qquad \forall i,l,n \qquad (5.22)$$

The storage duration is calculated as the difference between completion time of last product type J of intermediate i on packaging lines l at production cycle n and completion time of corresponding intermediate i on the processing unit. Equation (5.22) limits the storage duration of intermediate i with the lifetime parameter f_i where $0 < p_i < 1$ is a given probability.

Deterministic approximation of the probabilistic perishability constraints;

$$f_i = \mu_i + \alpha_i \{-\log(p_i)\}^{1/c_i} \qquad \forall i \qquad (5.23)$$

$$C^{P}{}_{iJln} - C^{M}{}_{in} \leq \mu_i + \alpha_i \{-\log(p_i)\}^{1/c_i} \qquad \forall i,l,n \qquad (5.24)$$

It is assumed that the lifetime f_i shows random variability and fits a Weibull probability distribution. It is also given that random lifetime parameter f_i has known μ_i location, α_i scale and c_i shape parameters. In Equation (5.22), the random lifetime parameter f_i can be expressed with its deterministic equivalent given in Equation (5.23), based upon Javaid et al. (2013). As a result, the stochastic model is simplified replacing Equation (5.22) with Equation (5.24).

5.3.2 Simulation

The simulation model is introduced to evaluate the proposed production schedule. The simulation model mimics the production process with the decisions made by the proposed MILP model (*e.g.,* allocation of mixing unit and packaging lines, production quantities). The aim of the simulation is to calculate the production waste. The simulation produces random lifetime values from a Weibull distribution using the same mean and scale parameters as the proposed MILP model. Then, the simulation calculates the waste by comparing production length and the produced lifetime values. In this way, the performance of the stochastic model using a deterministic approximation of the Weibull distribution is evaluated with random lifetimes produced from the actual continuous distribution. The simulation is presented within three sub-groups; (i) mixing, (ii) packaging and (iii) waste calculation.

(i) Mixing stage: The simulation starts with arrivals of entities representing intermediates produced in a cycle. The arrivals of entities are produced by a time based entity generator. Entities arrive at the beginning time of mixing operations for each intermediate. Each entity carries attributes representing a set of indices (*i. e.* intermediates i, production cycle n), lifetimes f_i and mixing times of intermediates produced in each production cycle (*i. e.,* $M_{in}.mt_i$). Lifetime values are produced from a continuous Weibull distribution. The other attribute values are taken from the proposed mathematical model using attribute setting and attribute function blocks. Finally, intermediates are produced in a mixing unit within the mixing time.

The mixing unit is represented by a single server block which has a service time equal to the mixing time. Figure 5.3 illustrates the used simulation blocks of the mixing stage.

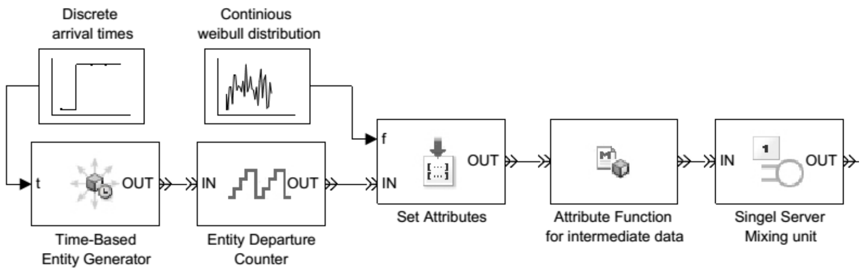

Figure 5.3 Simulation of mixing stage

(ii) Packaging stage: Entities are replicated according to the number of product types. From here, entities represent product types of intermediates. Each entity representing a product type has the same attributes as the corresponding intermediate. Besides, the new entities have additional attributes representing indices of product types j, the assigned parallel machine to each product type l and their packaging durations including corresponding setup times (*i. e.,* $PT_{ij'ln} + st_{j'j''}.S_{ij'j''ln}$). The values of new attributes are taken from the proposed mathematical model using attribute setting and attribute function blocks. The queue orders the incoming entities using pre-defined precedence rules of product types (*i. e.,* $j'' > j'$). And output switch leads entities to the allocated packaging lines. Product types are produced by two parallel packaging lines within the packaging duration. The paths are combined to lead entities to the following if-control for waste calculation. Figure 5.4 illustrates the used simulation blocks of the packaging stage.

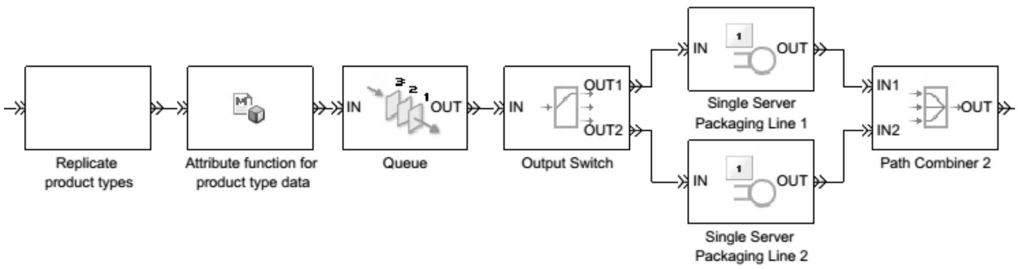

Figure 5.4 Simulation of packaging stage

(iii) Waste calculation: Each entity is controlled by an if-control statement. If packaging duration of the entity is longer than lifetime, it gets a value to attribute waste. If the entity has the attribute value of waste then $Waste$ is calculated as the proportion of the produced amount run longer than random lifetime. The waste calculation is formulated in Equation (5.25).

$$Waste = \sum_{ijln} \left[\frac{\left(C^{P}{}_{ijln} - C^{M}{}_{in} - f_i\right).X_{ijln}}{C^{P}{}_{ijln} - C^{M}{}_{in}} \right] \quad where\ C^{P}{}_{ijln} - C^{M}{}_{in} > f_i \tag{5.25}$$

Finally, entities are reported and disposed. The simulation is replicated until an average of the waste is calculated accurately. Figure 5.5 illustrates the used simulation blocks of the waste calculation stage.

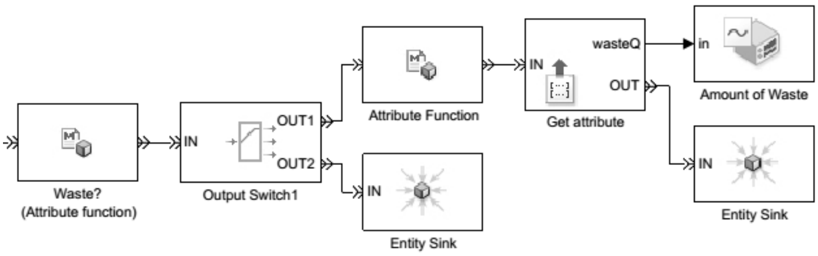

Figure 5.5 Simulation of waste calculation

5.4 An Illustrative Case Study

An illustrative case on production planning and scheduling of a dairy industry is considered to show applicability and numerical validation of the proposed model. The considered production process is a set type yoghurt production process. The yoghurt production typically starts with standardized and homogenized milk. The standardization and homogenization are pre-process operations to enhance the quality of final product. In these operations, fat and solid-not-fat content are standardized, and fat globules are granulated to a smaller diameter. Later on, the pre-processed milk is cooled to 43-45 °C and mixed with starter cultures in a tank. Filling and packaging are performed in parallel packaging machines which can pack different types of yoghurt depending on the cup sizes. Set yoghurt is fermented after the packaging stage. Interested readers are referred to Bylund (1995) for details on set type yoghurt production.

The production process consists of a mixing unit and two parallel packaging machines. The scheduling is performed over an hourly time horizon. The demands for 8 product types of 3 intermediates are produced within regular working hours (*i. e.* 8 hours). The cleaning of the processing equipment and parallel machines are performed within 2 cleaning hours in every working day after shutting down the process. The demand data is presented in Table 5.2. Each intermediate can be produced within 3 production cycles. Cup sizes of each product type are given in Table 5.3. Mixing times of intermediates are given in Table 5.4. Packaging speeds of each packaging line are given in Table 5.5. Sequence dependent setup times of changeovers between product types are given in Table 5.6. The mixing unit has a minimum level and should not be used to have a mixture less than 1,200 liters. The mixing unit has a tank capacity of 10,000 liters. The minimum production amount of any product type in any packaging unit is 150 cups. The tank capacity also limits the maximum production amount of product types in each packaging unit.

Table 5.2 Demand data (in cups)

Intermediates	**Product types**								
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**Total**
Low-fat	750	0	890	620	0	1,180	780	0	4,220
Medium-fat	0	0	3,425	3,460	0	2,700	0	0	9,585
High-fat	0	2,180	2,950	0	2,905	0	1,580	1,730	11,345
Total	750	2,180	7,265	4,080	2,905	3,880	2,360	1,730	25,150

Table 5.3 Cup sizes of product types (in liters)

	Product types							
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Cup sizes	1.5	1.25	1	0. 75	0. 5	0. 35	0. 2	0. 15

Table 5.4 Mixing times for intermediates (in hours)

	Intermediates		
	Low-fat	**Medium-fat**	**High-fat**
Mixing times	0. 33	0. 42	0. 50

Table 5.5 Packing speeds of lines (in liters/hours)

Lines	**Product types**							
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Line 1	4,615	2,640	2,013	1,710	1,350	1,230	1,150	850
Line 2	3,420	2,316	1,768	1,547	1,320	1,210	1,140	850

Table 5.6 Setup times (in hours)

		Product types							
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Product types	1	-	1.5	1.5	1.5	1.5	1.5	1.5	1.5
	2	1.5	-	1	1	0. 5	0. 5	0. 5	0. 5
	3	1.5	1	-	1	0. 5	0. 5	0. 5	0. 5
	4	1.5	1	1	-	0. 5	0. 5	0. 5	0. 5
	5	1.5	0. 5	0. 5	0. 5	-	0. 5	0. 5	0. 5
	6	1.5	0. 5	0. 5	0. 5	0. 5	-	1	1
	7	1.5	0. 5	0. 5	0. 5	0. 5	1	-	1
	8	1.5	0. 5	0. 5	0. 5	0. 5	1	1	-

The process has a time restriction between mixing and packaging stages, since bacteria growth has been started already in the mixing stage. At the end of the mixing operation, the culture added milk reaches the optimum activation. Hence, the intermediate mixture must be packed in a limited time and delivered to incubation which is a quality and temperature controlled storage process to perform fermentation. Otherwise, firmness cannot be achieved and the yoghurt product cannot get a thick texture. In the process, the temperature, the final product type and the concentration of the culture in the mixture (*i. e.* limited time depends on these process parameters) can be controlled to a certain extent. Still variations can occur because of uncontrollable parameters such as microbial loads, and temperature variations on process equipment (*e.g.,* mixing unit, pipes), cleaning efficiency, and activity of the starter culture. The uncertainty is represented by a Weibull distribution which has $p_i = 95\%$ lifetime probability and distribution parameters such as location $\mu_i = 1.5$, scale $\alpha_i = 2$, shape $c_i = 0.5$

5.4.1 Numerical Validation

The IBM ILOG CPLEX Optimization Studio version 12.6 is used with the default parameter settings to solve the deterministic approximation of the proposed stochastic model. The resulting mathematical model contains 604 continuous, 1305 binary decision variables and 4215 constraints. It takes less than one hour to get optimal solutions. The simulation model is developed using the SimEvents toolbox of Simulink/Matlab (R2013a). The simulation is replicated 1,000 times and maximum waste value is calculated. All analyses are conducted on a computer with an Intel Core i7-3630QM CPU @ 2.40GHz and 16 GB memory.

The resulting schedule of the illustrative case study is completed in a makespan of 8.97 hours and illustrated in Figure 5.6. Table 5.7 and Table 5.8 present the optimal production schedule of the two-stages. The intermediate mixtures are categorized in different fat contents. For the intermediate mixtures, mixing quantities in each cycle, beginning times and completion times of the corresponding mixing operations are presented in Table 5.7. The packaging operations follow to each mixing operation and, cleaning/changeover operations can be operated during the mixing operations in every cycle. Packing of the intermediate mixtures to the retail cups in different sizes is explained with product types. For the packaged products, packing quantities on each production line in each cycle, beginning times and completion times of the corresponding packing operations are presented in Table 5.8.

For the illustrative case, the intermediate mixing is operated in two cycles for low fat content and high fat content and three cycles for medium fat contents. The mixing operations start with 1538 liters of intermediate mixture in low fat content. Then, 1180 cups of product 6 and 750 cups of product 1 are packed on line 1 and line 2 until 0. 66 hours. After the first production cycle, mixing tank is refilled to mix 1511 liters of the same intermediate mixture. Then, 620 cups of product 4 and 890 cups of product 3 are packaged on line 1 and line 2.After product 4 is packed, line 1 is changed to produce 780 cups of product 7.Thus, all of the mixing and the packaging operations corresponding to low fat content are completed at 1.90 hours.

For medium fat content, 1200 liters intermediate mixture is mixed in the first cycle, 752 cups of product 11 and 1280 cups of product 14 are packaged on line 1 and line 2 until 2.70 hours. After the first production cycle, the same mixing operation is repeated for the second production cycle. 937 cups of product 12 and 1420 cups of product 14 are packaged on line 1 and line 2 until 3.53 hours. Then, 4565 liters intermediate mixture is mixed in the third cycle. 2623 cups of product 11 and 2523 cups product 12 are packed on line 1 and line 2.Thus, all of the mixing and the packaging operations corresponding to medium fat content are completed at 5.28 hours.

For high fat content,2965 liters intermediate mixture is mixed in the first cycle, 2950 cups of product 19 and 1223 cups of product 18 are packaged on line 1 and line 2 until. After product 18 is packed, line 2 is changed to produce 1733 cups of product 24.Thus, all of the mixing and the packaging operations corresponding to high fat content are completed at 8.97 hours. The simulation experiments result in zero waste and confirm that the proposed schedule is applicable.

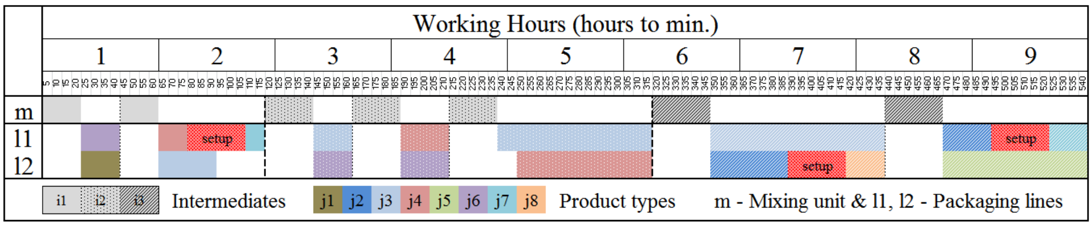

Figure 5.6 The resulting schedule of the illustrative case study

Table 5.7 Optimal mixing schedule

Intermediate	Cycle	Mixing quantity	Beginning time	Completion time
i	n	$\sum_{jl} X_{ijln}$,liters	B^{M}_{in}, hours	C^{M}_{in}, hours
Low-Fat	1	1538	0	0. 33
	2	1511	0. 66	1.00
Medium-Fat	1	1200	1.90	2.32
	2	1200	2.70	3.12
	3	4565	3.53	3.95
High-Fat	1	2965	5.28	5.78
	2	4739	7.24	7.74

Table 5.8 Optimal packing schedule

Product	P. Type	Intermediate	Line	Cycle	Packing	Beginning	Completion
	i	j	l	n	X_{ijln}/r_j cups	B^{P}_{ijln}	C^{P}_{ijln}
p6	6	Low-fat	1	1	1180	0. 33	0. 66
p1	1	Low-fat	2	1	750	0. 33	0. 66
p4	4	Low-fat	1	2	620	1.00	1.77
p7	7	Low-fat	1	2	780	1.77	1.90
p3	3	Low-fat	2	2	890	1.00	1.50
p11	3	Medium-fat	1	1	752	2.32	2.70
p14	6	Medium-fat	2	1	1280	2.32	2.70
p12	4	Medium-fat	1	2	937	3.12	3.53
p14	6	Medium-fat	2	2	1420	3.12	3.53
p11	3	Medium-fat	1	3	2673	3.95	5.28
p12	4	Medium-fat	2	3	2523	4.05	5.28
p19	3	High-fat	1	1	2950	5.78	7.24
p18	2	High-fat	2	1	1223	5.78	6.94
p24	8	High-fat	2	1	1733	6.94	7.24
p18	2	High-fat	1	2	957	7.74	8.69
p23	7	High-fat	1	2	1580	8.69	8.97
p21	5	High-fat	2	2	2906	7.87	8.97

5.4.2 Scenario Analysis

This section presents the scenario analysis for the proposed models with respect to changes in the probability distribution. The value of the shape parameter c_i and the scale parameter α_i affect the characteristics of the probability distribution and, change the shape of the function curve. Different values of the shape parameter c_i change the behavior of the probability distribution (*i. e.,* $0 < c_i < 1, c_i = 1$ and $c_i > 1$). For example, some values of the shape parameter cause the probability distribution to reduce to other distributions (*e.g.,* $c_i = 1$, Exponential distribution and $c_i = 2$, Rayleigh distribution). Increasing the value of the scale parameter α_i without changing the value of scale parameter c_i stretches the probability distribution function curve. Interested readers might consult Dodson (2006) for a broad overview.

In addition to characteristics of the probability distribution, we consider demand variations changing with the capacity load of the production process. Depending on the working period, the average workload may be higher or lower. The demand conditions are reflected by two scenarios which assume an average workload of 75% and 90% of the available total capacity. The demand figures are randomly generated for each scenario according to the following procedure in line with Bilgen and Günther (2010).

1. The total number of available operating hours X is determined: $X = 8 \cdot 2 = 16$ hours based on average 8 hours operating time per day and two production lines.
2. The effective total workload on the production system Y is determined by considering 3.75 hours of average capacity usage for the mixing operations, 1.5 hours average capacity loss due to setup operations and a workload factor of 75% and 90%, respectively: $Y = 0.75 \cdot (X - 5.25) = 8.1$ and $Y = 0.9 \cdot (X - 5.25) = 9.7$, respectively.
3. The entire set of products (*i.e.,* 3 intermediates and 8 product types) can be produced on two lines and $n = 2 \cdot 3 \cdot 8 = 48$ product assignments are achieved.
4. The average size of demand elements is $D = Y/n$ hours. In order to create a realistic degree of demand variability for each scenario, actual values of demand elements d are randomly drawn from the uniform distribution $d \in [0.5 \cdot D, 1.5 \cdot D]$.

5. One of the 24 products is selected randomly. The demand is doubled for two lines, i. e. $d \leftarrow d \cdot 2$ and assigned to the selected product until the assigned demand equals or exceeds the effective total workload Y .

The proposed model is examined with 8 scenarios under $p_i = 50\%, 99\%$ lifetime probabilities. Each scenario is formulated using different scale parameters (*i. e.,* $\alpha_i = 1, 3$) and shape parameters (i. e. $c_i = 1, 2$) of the probability distribution which has $\mu_i = 1, 1.25$ location parameters. Each scenario is repeated five times with different randomly generated demand data. Results of the scenario analysis are presented with the considered demand variations in Table 5.9.

Table 5.9 Results of the scenario analysis

Scenarios						**75% Capacity load**		**90% Capacity load**	
S	μ_i	α_i	c_i	p_i	f_i	**Makespan**	**Waste**	**Makespan**	**Waste**
1.	0. 75	1	1	50%	1.30	7.17	1.02	8.13	0. 00
				99%	1.00	7.24	0. 00	8.52	0. 00
2.	0. 75	1	2	50%	1.55	7.01	325.89	8.27	100. 50
				99%	1.07	7.06	6.11	8.57	1.11
3.	0. 75	3	1	50%	1.90	8.32	983.56	7.56	95.83
				99%	1.01	8.58	0. 00	7.92	0. 00
4.	0. 75	3	2	50%	2.65	6.58	0. 00	6.93	0. 00
				99%	1.20	6.58	0. 00	7.12	0. 00
5.	1	1	1	50%	1.55	7.17	0. 00	8.13	762.86
				99%	1.25	7.24	0. 00	8.52	0. 00
6.	1	1	2	50%	1.80	7.01	13.42	8.27	1.21
				99%	1.32	7.06	0. 00	8.57	0. 00
7.	1	3	1	50%	2.15	8.32	0. 00	7.56	33.03
				99%	1.26	8.58	0. 00	7.92	0. 00
8.	1	3	2	50%	2.90	6.58	0. 00	6.93	382.65
				99%	1.45	6.58	0. 00	7.12	0. 00

μ_i : Mean, c_i : Shape parameter and α_i : Scale parameter
p_i : Lifetime probability of intermediate i , %
f_i : Lifetime of intermediate i , hours
Makespan : Maximum completion time of the production, hours
Waste : Amount of the product waste, liters

Waste occurs in the 1st, 2nd, 3rd and 6th scenario of 75 % capacity load examples, For the 1st and 6th scenarios, the waste is at a tolerable level. To tighten the corresponding f_i lifetime values with 99 % probability level (*i. e.* the lifetime highly fits the distribution defined with given μ_i location, α_i scale and c_i shape parameters) has only limited effect on the waste. However, for the 2nd and 3rd scenarios, the results show that the waste can be drastically decreased with the proposed f_i lifetime values and a reasonable increase of makespan.

The similar results are observed from the 90 % capacity load examples. For the 6th scenario of 90 % capacity load examples, the f_i lifetime value calculated from the 50 % probability level has only limited effect on the waste. The improvement can be achieved in the 2nd, 3rd,4th,7th and 8th scenario. Besides, the 4th, 5th, 7th, 8th scenarios of 75% capacity load examples have no improvement of waste. The number of the scenarios which have no improvement is comparatively different for two distinct capacity levels. This number is lower for 90% capacity load examples (*i. e.* only 1st and 4th scenarios) than in the 75% capacity load examples. This investigation shows that the proposed solutions become more effective for high capacity load levels.

In summary, within a certain lifetime period, the intermediates have to be packed, or else the product has to be disposed as waste. In case the lifetime is considered as a wide parameter, there is a risk on packing spoiled products and transporting to customers. However, for tight lifetime restrictions, emptying the processing unit as soon as possible (*i. e.* mixing the intermediates frequently in small quantities) results in a long makespan of production which may extend lead times to customers. The proposed approach helps to analyze the uncertainty on lifetimes of intermediates, thereby optimizing the production makespan to decrease the product waste.

5.5 Conclusion

This research addresses a scheduling problem in the make-and-pack production. The problem is motivated from a two-stage semi-continuous set type yoghurt production process. The problem has been formulated as a stochastic MILP model to deal with the uncertainty in the quality decay of intermediates. The objective of the model is minimizing makespan.

The lifetime and rapid quality decay of intermediates have been a challenging issue as uncertain parameters affect the makespan and the amount of waste. In our approach, the mathematical model describing the uncertain lifetime decides optimum schedules yielding minimum production makespan as an indicator of productivity of the production process. The simulation model mimics the production process and determines the waste to evaluate the proposed schedule of the MILP model.

The major advantage of the proposed approach is its applicability to different dairy production processes (e.g., cheese, butter, ice cream). The flexibility originates from the mathematical model formulation providing an opportunity to deal the uncertain lifetime of intermediates, as well as the simulation model which can easily be modified to account for process specific operating conditions. Further research could address a make-and-pack production consisting of multiple mixing units and packaging lines combinations. Another future direction is to improve the computational efficiency of the proposed model. In this respect, MILP based heuristics as rolling horizon techniques and decomposition algorithms using the complementary strengths of different modelling techniques can be alternative solution approaches.

Nomenclature

For the mathematical description of the models the following notation is introduced;

Indices &sets:

$i \in I$	intermediates	$I = \{1,...,\|I\|\}$
$j, j', j'' \in J$	product types	$J = \{1,...,\|J\|\}$
$l \in L$	non-identical parallel lines	$L = \{1,...,\|L\|\}$
$n \in N$	production cycles	$N = \{1,...,\|N\|\}$

Parameters:

d_{ij}	demand of product type j packaged from intermediate i , cups
mt_i	mixing time of intermediate i , hours
f_i	lifetime of intermediate i , hours
r_j	amount of intermediate for product type j , liters
ls_{jl}	packaging speed of line l for each product type j , liters/hours
$st_{j'j''}$	sequence-dependent setup time between product types j' and j'', hours
ml	minimum lot-size of mixing unit, liters
mc	maximum capacity of mixing unit, liters
pl	minimum lot-size of packaging line, liters
pc	maximum capacity of packaging lines, liters
p_i	Lifetime probability of intermediate i , %
μ_i	Mean of the probability distribution, hours
c_i	Shape parameter of the probability distribution
α_i	Scale parameter of the probability distribution

Decision variables:

$Makespan$	makespan of production, hours
M_{in}	allocations for mixing of intermediate i at production cycle n on the processing unit, binary

P_{ijln}	allocations for production of product type j from intermediate i on packaging line l at cycle n, binary
$S_{ij'j''ln}$	changeovers from product type j' to j'' on packaging line l at production cycle n, binary
PT_{ijln}	packaging time for product type j of intermediate i packaged on line l at cycle n, hours
X_{ijln}	production amount of intermediate i to produce product type j on line l at production cycle n, liters
$B^{M}{}_{in}$	beginning for mixing operation of intermediate i at production cycle n, hours
$C^{M}{}_{in}$	completion times for mixing operation of intermediate i at production cycle n, hours
$B^{P}{}_{ijln}$	beginning for packaging operation of product type j of intermediate i on line l at production cycle n, hours
$C^{P}{}_{ijln}$	completion times for packaging operation of product type j of intermediate i on line l at production cycle n, hours
$Waste$	production waste, liters

CHAPTER SIX
CONCLUSION

The planning and scheduling activities brings planning and production organizations together. They start to act as one, and work as a common unit. While the proposed models improve the quantity and quality of the information, the proposed solution approaches provide faster decision making. Moreover, we can enumerate several benefits of using the proposed models and solution approaches in terms of operational and tactical level. Operational level consists of day to day activities which are repeated periodically, such as daily, weekly and monthly. The activities require be well organized because of the usage of production resources which are mostly common and shared. When it comes to achieve cutting costs, raising outputs, speeding up processes, increasing operation volumes, cycle time reduction, productivity improvement, quality improvement, it is inevitable to use the proposed reliable and quick optimization approaches. Tactical level guide control and coordination of these allocated resources. The proposed optimization approaches support the management process by providing summarized information and reports which are closely connected with better resource management, improved decision making and planning, performance improvement.

7.1 Summary and Concluding Remarks

In this thesis, we have studied planning and scheduling problems in supply chain environment within process industry. In Chapter 2, a review on quantitative operations research literature is studied to reveal major trends of process industry and to explore research opportunities. We identify the characteristics that a model should have to address adequately in dairy SCM planning needs. The reviewed research is classified by problem types based on the solution approaches. Future research directions are stated with respect to different perspectives (i.e., multi-stage production planning, sustainability, integrated production-distribution planning and scheduling, single and multi-objective, uncertainty, alternative solution techniques, postponement and decoupling point theory perspectives). According to these concluding remarks of the Chapter 2, the following studies are organized.

In Chapter 3, a production allocation and distribution planning problem is considered in the soft drink industry. We introduce a MILP model and propose the MIP based rolling horizon heuristics. For a realistic solution, operation time is taken into account as a stochastic parameter and adjusted according to a simulation model. For determining operation time, probability density of machine failures and repair times are considered in the simulation model. For the computational performance tests, randomly generated demand figures for the three granularity categories and different capacity loads are examined to compare the standard MIP procedure and MIP based heuristic approaches.

The concluding remarks of Chapter 3 are; (i) the F&O heuristic yields the best solution, (ii) hybrid method integrate the best capabilities of MILP model, (iii) simulation model leads to more realistic planning solutions, (iv) the hybrid methodology merges the advantages of these two distinct modeling techniques

In Chapter 4, an integrated production planning and scheduling problem is considered in dairy industry. The problem is motivated from a two-stage semi-continuous set type yoghurt production process and formulated as a MILP model. The objective function of the MILP model aims at minimization of the total cost considering a shelf life dependent loss function. The model formulation is introduced to represent the planning and scheduling decisions under consideration of the shelf-life restrictions, sequence dependent changeovers, product dependent machine speeds, demand due dates, regular and overtime working hours, and delivery to the DCs. The key limitation of the overall MILP solution approach lies in the large computational times that are mainly due to large number of integer variables related with planning decisions, as well as binary setup variables triggered with big M constraints for scheduling decisions. In our approach, the integrated planning and scheduling problem is divided into two distinct sub-problems. The sub-problems are solved by the decomposition heuristic. A hybrid MILP/CP hybrid approach is proposed.

The concluding remarks of Chapter 4 are; (i) the hybrid approach exploits the complementary strengths of the MILP model (the accuracy in the planning level) and the CP model (the computational efficiency in the scheduling level) (ii) the decomposition heuristic achieves reasonable solutions, (iii) the hybrid approach outperforms the integrated MILP model with short computational times.

In Chapter 5, a scheduling problem is considered in the make-and-pack production. The problem is motivated from a two-stage semi-continuous set type yoghurt production process. The problem formulated as a stochastic MILP model to deal with the uncertainty in the quality decay of intermediates. The objective function of the proposed model aims at minimization of the makespan. The model formulation is introduced to represent the scheduling decisions under consideration of the shelf-life restrictions, sequence dependent changeovers, product dependent machine speeds. The lifetime and rapid quality decay of intermediates have been a challenging issue as uncertain parameters affecting the makespan and the amount of waste. In our approach, the mathematical model describing the uncertain lifetime decides optimum schedules yielding minimum production makespan as an indicator of productivity of the production process. The simulation model mimics the production process and determines the waste to evaluate the proposed schedule as the result of MILP model. The major advantage of the proposed approach is its applicability to different dairy production processes (e.g., cheese, butter, ice cream). The flexibility originates from the mathematical model formulation providing an opportunity to deal the uncertain lifetime of intermediates, as well as the simulation model which can easily be modified to account for process specific operating conditions.

The concluding remarks of Chapter 5 are; (i) In case the lifetime is considered to be long, there is a risk on packing spoiled products and transporting to customers. (ii) Otherwise, emptying the processing unit as soon as possible results in a long makespan of production which may extend lead times to customers. (iii) The proposed approach helps to analyze the uncertainty on lifetimes of intermediates, thereby optimizing the production makespan to decrease the product waste.

7.2 Future Research

As a scope for future research, the computational efficiency of the rolling horizon heuristics proposed in Chapter 2 can be improved by integrating meta-heuristics and alternative hybrid approach using MILP and simulation techniques can be studied to deal with the stochastic characteristics of supply chain network problems. In Chapter 3, non-identical packaging lines can be considered to enhance the problem. A feedback mechanism aside from linkage capacity constraints can be investigated for the proposed hybrid methodology. Alternative solution techniques (e.g., stochastic programming and simulation) dealing with the stochastic and dynamic nature of dairy supply chains can be studied with various key characteristics of sustainability issues. In Chapter 4, a make-and-pack production consisting of multiple mixing units and packaging lines combinations can be considered to enhance the problem. MILP based heuristics (*e.g.,* rolling horizon techniques such as F&R and F&O) and decomposition algorithms (*i.e.,* using the complementary strengths of MILP and CP models) can be investigated to improve the computational efficiency of the proposed model.

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