APPLICATION OF LARGE-SCALE OPTIMIZATION METHODS IN SCHEDULING AND ROUTING PROBLEMS

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APPLICATION OF LARGE-SCALE OPTIMIZATION METHODS IN SCHEDULING AND ROUTING PROBLEMS

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To my family...

ABSTRACT

In this thesis, we consider three different applications of large-scale optimization methods. We focus on the blood donation tailoring problem under uncertain demand in the first problem. In the second one, we propose a model for hybrid manufacturing consisting of flexible manufacturing systems and typical manufacturing machines. In the last one, we consider a two-echelon vehicle routing problem for last-mile delivery of groceries.

In the first part of the thesis, we propose a stochastic scenario-based reformulation of the blood donation management problem that adopts multicomponent apheresis and utilizes donor pool segmentation as here-and-now and wait-and-see donors. The donation pool segmentation enables more flexible donation schedules than the orthodox donation approach because wait-and-see donors may adjust their donation schedules according to the realized values of demand over time. We propose a column generation approach to solve the associated multi-stage stochastic donation tailoring problem for realistically sized instances.

The Second part considers a flexible/hybrid manufacturing production setting with typically dedicated machinery to satisfy regular demand and a flexible manufacturing system to handle surged demand. We model the uncertainty in demand using a scenario-based approach and allow the business to make here-and-now and wait-and-see decisions exploiting the cost-effectiveness of the standard production and responsiveness of the flexible manufacturing systems. We propose a branch-and-price algorithm as the solution approach. Our computational analysis shows that this hybrid production setting provides a highly robust response to the uncertainty in demand, even with high fluctuations.

In the third part, we propose a *two-echelon vehicle routing problem* (2E-VRP) under consideration of a heterogeneous fleet of vehicles and different customer types. In our model, unlike the previous studies in the literature, not only do the large vehicles visit the pre-assigned points, called satellites, to refill the smaller vehicles, but they also deliver items to the customers. On the other hand, smaller vehicles are responsible for the customers

with small size demands and can get refilled whether at the depots or satellites. We propose a branch-and-price algorithm as the solution approach and obtain promising results in comprehensive numerical studies that prove its versatility.

ÖZETÇE

Bu tezde, büyük ölçekli optimizasyon yöntemlerinin üç farklı uygulamasını ele alıyoruz. İlk problemde, belirsiz talep altında kan bağışı terzilik problemine odaklanıyoruz. İkincisinde, esnek imalat sistemleri ve tipik imalat makinelerinden oluşan hibrit imalat için bir model öneriyoruz. Sonuncusunda, bakkalların son mil teslimatı için iki kademeli bir araç rotalama problemini ele alıyoruz.

Tezin ilk bölümünde, çok bileşenli aferezi benimseyen ve burada-şimdi ve bekle-gör donörleri olarak donör havuzu bölümlemesini kullanan kan bağışı yönetimi probleminin stokastik senaryo tabanlı yeniden formüle edilmesini öneriyoruz. Bağış havuzu segmentasyonu, geleneksel bağış yaklaşımından daha esnek bağış programları sağlar çünkü bekle ve gör bağışçılar bağış programlarını zaman içinde gerçekleşen talep değerlerine göre ayarlayabilirler. Gerçekçi olarak boyutlandırılmış örnekler için ilgili çok aşamalı stokastik bağış uyarlama problemini çözmek için bir sütun oluşturma yaklaşımı öneriyoruz.

İkinci bölümde, düzenli talebi karşılamak için tipik olarak tahsis edilmiş makineler ve ani talebi karşılamak için esnek bir üretim sistemi ile esnek/hibrit üretim üretim ayarı ele alınmaktadır. Talepteki belirsizliği senaryo tabanlı bir yaklaşım kullanarak modelliyoruz ve işletmenin standart üretimin maliyet etkinliğinden ve esnek üretim sistemlerinin yanıt verebilirliğinden yararlanarak burada ve şimdi ve bekle-gör kararları almasına izin veriyoruz. Çözüm yaklaşımı olarak sütun oluşturma tabanlı bir algoritma öneriyoruz. Hesaplamalı analizimiz, bu hibrit üretim ayarının, yüksek dalgalanmalarda bile talepteki belirsizliğe son derece sağlam yanıt verdiğini gösteriyor.

Üçüncü bölümde, heterojen bir araç filosu ve farklı müşteri tipleri göz önünde bulundurularak *iki kademeli bir araç rotalama problemi* (2K-ARP) önerilmiştir. Modelimizde literatürdeki önceki çalışmalardan farklı olarak büyük araçlar, daha küçük araçları doldurmak için uydu adı verilen önceden belirlenmiş noktaları ziyaret etmekle kalmaz, aynı zamanda müşterilere ürün teslim eder. Daha küçük araçlar ise, küçük boyutlu talepleri olan müşterilerin sorumluluğundadır ve ister depolarda ister uydularda dolum yapabilmektedir. Çözüm yaklaşımı olarak bir dal-ve-fiyat-kes algoritması öneriyoruz ve çok yönlülüğünü kanıtlayan kapsamlı sayısal çalışmalarda umut verici sonuçlar elde ediyoruz.

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CHAPTER I

INTRODUCTION

Operations research (OR) is a discipline that is applied to real-life problems in diverse areas such as medicine, manufacturing, transportation and supply chain, finance, politics, economics, and humanitarian and healthcare operations. In fact, OR is at service to enhance life quality. In real life, there are usually hundreds, thousands, or even millions of variables and constraints in applied fields when complex processes and phenomena are formalized. The decomposition of real-life large-scale problems into simpler ones is possible through a variety of approaches. Dantzig-Wolfe decomposition is one of the decomposition methods that incorporate column generation for improving the tractability of large-scale problems. In this thesis, we focused on implementing column generation in real-life problems. We study three different problems and propose column generation as the solution approach for these problems.

In the first part of the thesis (Chapter 2), we study the donation tailoring problem under demand uncertainty. Perishable blood products, a limited pool of donors, and an uncertain demand make managing blood donations a challenging endeavor. We are examining two aspects of blood supply chain management in this study, namely, inventory control of blood products and donors' donation schedules, under the conditions outlined. The plan is designed to meet the unpredictable demand for blood products in an efficient manner. Until now, the uncertainty of demand for blood has been neglected as a major challenge in blood donation management. Taking uncertainty into account, we propose a flexible donation scheme to the literature. Multicomponent apheresis is also employed by us as a way of providing supply when demand is uncertain. In this thesis, using a stochastic scenario-based reformulation, we apply multicomponent apheresis and divide donors into here-and-now and wait-and-see pools based on donor pool segmentation. Due to the segmentation of donation pools, donors can plan their donation schedules more efficiently than with the orthodox donation strategy since wait-and-see donors may adjust schedules according to the value of the actual demand as time progresses. As a solution to the multistage stochastic donation tailoring problem when dealing with realistically sized instances, we propose a column generation approach. Donation organizations should take advantage of multicomponent apheresis and flexible wait-and-see donations to reduce costs and maintain donation schedules. This study is presented in Chapter 2 of the thesis.

Secondly, in Chapter 3, we study production planning with hybrid manufacturing. In recent days, widespread economic disorder has been caused by an ongoing pandemic, COVID-19. On the supply side, production has been delayed across several industries. Businesses with longer supply chains were more affected by the disruption, especially those reaching East Asia. In terms of demand, sectors can be divided into three groups: i) those with a surged in demand, such as e-commerce companies; ii) those with a plunge in demand, such as hotels and restaurants; iii) and those experiencing a roller-coaster-ride business. Following mitigation efforts, the economy began to recover, which led to an increase in demand. The companies are, nevertheless, not fully back to their pre-pandemic levels, regardless of their struggles. Employing flexible/hybrid manufacturing systems is one strategy to gain resilience in its supply chain and manage disruptions. The paper examines a flexible/hybrid manufacturing production setting that typically uses dedicated equipment for satiating regular demand and a *flexible manufacturing system* (FMS) to handle surged demand. Utilizing a scenario-based approach, we model uncertainty in demand and allow the business to make here-and-now or wait-and-see choices that are as cost-effective as the standard production and responsive as the FMS. We propose a branch-and-price algorithm as the solution approach. This hybrid production setting, as showed by our computational analysis, exhibits a high degree of robustness to the uncertainty of demand, even in the presence of high fluctuations.

Thirdly, we study last-mile delivery of groceries by means of two fleets of vehicles with synchronization in Chapter 4. The urbanization rate is increasing, and the resulting tendency toward using e-commerce for grocery delivery in cities is aggravating the traffic congestion. The adverse health effects associated with augmented traffic congestion and air pollution must therefore be addressed through some mitigation measures. It is possible to use low-emission vehicles in inner-city areas, but their limited capacities make a complete transformation of city logistics unattainable. Due to this, large deliveries should still be carried out by vehicles with larger engines. Due to capacity limitations, tight delivery windows, and other limitations, it is difficult to manage these two types of fleets in an urban setting. Through integrated planning, it becomes possible to replenish smaller-sized trucks from the inventory of larger-sized trucks without the need to return to a depot. The present chapter considers a *two-echelon vehicle routing problem* (2E-VRP) under the assumption of a heterogeneous fleet of vehicles and different types of customers. The model we propose does not only involve the large vehicles visiting pre-assigned points, called satellites, to refill the smaller vehicles but also involves customers receiving products. In contrast, smaller vehicles are designated for customers with smaller needs and can be refilled both at the depots and at satellites. In comprehensive numerical studies, we obtain promising results using a branch-and-price algorithm as the solution approach that demonstrates its versatility.

CHAPTER II

COLUMN GENERATION-BASED HEURISTIC FOR MANAGING BLOOD DONATIONS UNDER DEMAND UNCERTAINTY

Managing blood donations is a challenging problem due to the perishable nature of blood products, limited donor pool, deferral time restrictions, and demand uncertainty. The problem addressed here combines two important aspects of blood supply chain management, i.e., the inventory control of blood products and donors' donation scheduling, under the above-mentioned constraints. It aims to yield an efficient plan to satisfy the uncertain demand for blood products. The biggest challenge of blood donation management is the uncertainty of the demand which has so far been neglected in the literature. We contribute to the literature by proposing a flexible donation scheme while considering demand uncertainty. We also implement multicomponent apheresis, which is an invaluable tool for providing supply for uncertain demand. In this paper, we propose a stochastic scenario-based reformulation of blood donation management problem that adopts multicomponent apheresis and utilizes donor pool segmentation as here-and-now and wait-and-see donors. The donation pool segmentation enables more flexible donation schedules than the orthodox donation approach because wait-and-see donors may adjust their donation schedules according to the realized values of demand over time. We propose a column generation approach to solve the associated multi-stage stochastic donation tailoring problem for realistically sized instances. The numerical results show the effectiveness of the proposed optimization model, which provides solutions with only less than a 7% optimality gap on average with respect to a lower bound. It also improves the operational cost of the standard donation scheme that does not use wait-and-see donors by more than 18% on average. Our study proposes an optimization method that solves the challenging donation scheduling problem in a practicable amount of time. Utilizing multicomponent apheresis and flexible wait-and-see donations are suggested for donation organizations because it yields significant cost reductions and resilient donation schedules.

2.1 Introduction

Blood is not only essential for accident/disaster victims, but it is also vital for patients who are getting cancer treatment, undergoing surgeries, or getting treatment for blood disorders. A majority of medical procedures rely heavily on an effective *blood supply chain management* (BSM) since in the U.S. only, every two seconds someone needs blood or its products [1] and one of the seven people who are hospitalized needs blood, and almost five million people in the U.S. demand blood or its products every year [2]. However, since blood cannot be manufactured, donation organizations need to satisfy the demand for blood by utilizing volunteer donors. That said, in the U.S., while 38% of the population are eligible, only around 10% actually donate blood [3], and this figure is comparatively lower in middle and low-income countries [4]. This is why utilizing repeat blood donors is crucial for health organizations to save from continuous recruitment costs and access a stable and safer source of blood [5]. Considering more than a thousand individuals, [6] show that it is essential to intensify donor retention to maintain an effective donation system. For further details on the factors affecting the retention of donors, we refer the reader to [7]. On the other hand, [8], and [9] show that only 45-60% of first-time whole blood donors are likely to return for a second donation within two years; while, donors who have two or more prior donations return with higher rates of 72-96% [10, 11], and more likely to be considered as repeat blood donors. In another study, [12] show that aged first-time donors are more likely to return, and they return faster than middle-aged donors. These observations show the importance of utilizing repeat blood donors in an effective blood supply chain management, and in this study, we focus on developing a framework that is based on repeat blood donor utilization. Notice that a sustainable blood donation system may only be achieved by utilizing repeat blood donors better since they constitute a significant part of the overall supply and are more willing to cooperate with donation centers by sticking to predefined donation schedules or complying with the urgent donation requests of donation centers.

BSM consists of the following stages: blood collection, processing, storage, and distribution of the blood to demand points [13]. The studies in the field of BSM mostly focus on donor utilization and shortage elimination [14, 15, 16, 17, 18]. There are some factors that make BSM a challenging task. Firstly, the main issue with BSM is that the supply can barely meet the demand since blood is only donated by a limited number of donors. Secondly, a donor needs a regeneration period, called *deferral time*, after each donation to be eligible for the next donation. Thirdly, blood is a perishable commodity with a limited shelf-life, and this is why if blood centers store an excessive amount of blood products, when not used in time, these valuable resources will be lost, and costly disposal processes will take place. For example, more than 200,000 units of blood and its components were disposed of after the terrorist attack on September 11, 2001, when people donated more than 500,000 units of blood [19]. We refer the reader to [20] to have a profound understanding of the probable outcomes of blood shortage or surplus. Ultimately, the limited number of donors, and the deferral time requirement, as well as the limited shelf-life of blood products make BSM a challenging task.

Managing the blood supply chain becomes more challenging when the uncertainty of the demand is incorporated into the associated problem. Even though the demand of any product is an inherently uncertain parameter because of estimation errors, the uncertainty in blood demand faces drastic fluctuations because of external factors and unforeseen incidents such as accidents, natural disasters [21], and the outbreak of pandemics [22] as well. For example, [23] report that since the convalescent plasma therapy has been proved beneficial for COVID-19 patients, the demand for that blood product has increased. When the actual demand is higher than the planned or forecasted amount, drastic outcomes will proceed as blood is a vital product, and a shortage in blood products may escalate fatality since it may cause the surgeries to be put off. While in some countries the demand is higher than the supply [4], the aggregate demand for blood products in the U.S. is feebly balanced by the supply. There are two main reasons for this: first, the supply rate is decreasing [24]; second, donors are aging, and the regulations for donor selection are very strict [25, 26, 27, 24]. On the contrary, when the realized demand is lower than the supply, the surplus amount will be disposed of, resulting in a waste of a valuable commodity. Moreover, due to the deferral time, the utilized donors would be able to donate blood in upcoming periods if blood is needed. Therefore, a method that could handle the uncertainty in the blood demand is of high importance for a better management of blood supply.

Traditionally, whole blood donation was performed in all blood donation organizations. Whole blood donation may result in some adverse effects on donors such as fatigue, vasovagal symptoms, and nausea [28, 29]. Moreover, whole blood donation may result in shortages and inefficient utilization of donors. However, recent developments allow better utilization of blood products and donors [30, 18] by proposing supply flexibility. The new method which has been utilized recently is called *multicomponent apheresis* (MCA). The importance of supply flexibility has been explored in the literature (see for example, [31], [32], and [33]. Using MCA, one or more blood components and/or more than one transfusable unit may be donated without risking safety based on the eligibility of the donor [34, 35]. Compared to whole blood donation, MCA has several other advantages as follows. *Increased donor utilization:* More than one component and/or more than one transfusable unit can be collected in a single donation. In this case, the deferral times will be based on the donation types, and it will lead to better BSM. *Reduced costs:* MCA type of donations reduce both the processing costs and the logistics costs due to transporting whole blood from the donation site to a processing center. It also results in savings due to the reduced cost of extra bags and reduced number of required tests before performing a transfusion since more transfusable units can be collected from a single donor. *Reduced infection risks:* In MCA, more transfusable units of a blood product can be collected from a single donor. Hence, patients are exposed to the blood of a fewer number of donors, which reduces the infection risks. *Better matching demand and supply:* By allowing tailored donations, MCA provides an opportunity to better match the uncertain demand and supply by reducing wastage and collecting required components only [36, 37]. In order to categorize the perks of MCA, *blood donation tailoring* is defined with the objective of minimizing the total cost of donation, holding, and disposal of blood products by utilizing the donor pool to satisfy the demand for blood [38]. According to [39] when the donors are flexible on the time and the donation type, there will be tremendous benefits. In this study, we aim to reach the highest efficiency in donation schedule. In order to achieve this goal, we combine MCA with modern optimization techniques. To customize the supply, we take advantage of MCA, and to be resilient against the uncertainty in demand, we adopt a scenario tree-based stochastic optimization model that divides the donor pool into two donor types, i.e., *here-and-now* and *wait-and-see*. A here-and-now donor follows a standard donation scheme regardless of the scenario realized and his/her donation schedule is known at the beginning of the planning horizon; a wait-and-see donor, on the other hand, is more situational/flexible and her/his donation schedule is determined/adjusted according to the realizations of the demand in the planning horizon. Regardless of the donation schemes followed by donors, i.e., wait-and-see or here-and-now, we assume that all donors are repeat blood donors who are willing to cooperate with the donation center according to the donation schemes.

Considering donor segmentation, holding and scrapping costs, as well as shelf-life and deferral times of blood products, we develop models that highlight the significance of MCA by proposing donation tailoring under demand uncertainty for blood donation organizations. To this end, the *stochastic donation tailoring problem* (SDTP) that is proposed in this paper aims to minimize the total (expected) operational donation costs while satisfying the uncertain demand. The goal of the model is to satisfy all the demand scenarios with the minimum cost. Notice that since the demand must be satisfied for all realizations in the scenario tree, a feasible solution may also yield an excessive amount of donation that results in spoilage of some of the products when a non-worst-case scenario is realized; nevertheless, the associated drawback is avoided in our setting to some extent by utilizing wait-and-see donors who are flexible in cooperating with the donation center to adjust their donation types according to the realized demand over the planning horizon. It must be noted that scenario tree-based techniques have been utilized in different domains to deal with uncertainty. [40] utilize a scenario tree-based approach to handle uncertainty in load and wind power in dynamic economic emission dispatch problems. According to the proposed scenarios, they utilize a particle swarm optimization algorithm to get the best solution. [41]

propose a scenario tree-based stochastic model for energy management to minimize the total emission and cost. [42] implement a scenario tree-based modeling approach for considering the uncertainty in elective operation duration and randomly arriving demands in order to maximize the expected profit associated with the operation rooms.

Contributions of this study can be summarized in threefold. Firstly, only a few studies propose an optimization under uncertainty framework in the donation tailoring literature; SDTP is the first problem that seeks a flexible donation scheme for MCA and provides resilient solutions against the demand uncertainty with donor segmenting as wait-and-see and here-and-now. Secondly, we propose a *column generation* (CG) based heuristic approach that solves the problem for realistically sized instances for four different cases that encompass the seasonality and variability of demand for blood, while a commercial solver cannot even create an instance of the standard model. To evaluate the performance of the proposed algorithm, we provide an efficient lower bound mechanism for the problem that is obtained by solving the linear programming (LP) relaxation of proposed mixed-integer programming models. The numerical results show that the proposed CG approach provides (on average) less than 7% optimality gap for the setting that adopts both here-and-now and wait-and-see donors for realistically sized instances. Lastly, regardless of the difficulties due to uncertain demand, deferral times, and shelf-life of the blood products, we develop effective wait-and-see and here-and-now donation schedules that improve the operational cost of standard donation schemes that do not use wait-and-see donors by (on average) 18%.

The remainder of the paper is organized as follows. Section 2.2 provides the literature survey. Section 2.3 defines the problem by proposing the mathematical model of SDTP. Section 2.4 provides the solution approaches. The numerical experiments are given in Section 2.5. In Section 2.6, we provide the conclusion of the study.

2.2 Literature Review

BSM has been widely studied by researchers in recent years. In this study, we mainly focus on the papers that consider uncertainty in demand. We refer the reader to the surveys written by [43], [13], [44], [45], and [46] that propose a detailed overview of the blood supply chain by analyzing its features from different perspectives. As pointed out in all of these surveys, one of the biggest challenges of BSM is to satisfy the demand on time by utilizing (repeat) donors that form the donation pool.

Most of the studies in BSM focus on inventory control policies to balance the shortage and disposal of the whole blood products [47, 48, 49, 50, 51, 52, 53, 54, 55, 56]. For example, [49] studies stochastic models that simulate the daily operations of a hospital blood bank inventory in a finite horizon. The numerical results show that the hospitals with larger variations in a daily transfusion must be supplied by young red blood cells while the hospitals with smaller ones must be supplied by older stocks. [52] evaluate the performance of a regional blood center in Canada by employing the two demand rate models proposed by [57]. The authors seek an optimal policy in which the objective is to minimize the cost, shortages, and expiration with multiple demand and service levels by using a queuing model and using level crossing techniques. [55] consider mismatching costs as well as holding, shortage, and spoil costs in blood platelets. Modeling the problem as a Markov Decision Process, the authors propose a heuristic algorithm in order to compare the results with near-optimal approaches in the literature.

Another aspect that has been widely studied by the researchers is the issuing policies. The most common policies in the realm of blood inventory management are FIFO (first-in-first-out), in which the oldest one is issued first, and LIFO (last-in-last-out), in which the freshest one is issued first [38]. Plenty of research is conducted to study the impacts of different issuing policies on average inventory level, shortage, and wastage rates [58, 59, 60, 61, 62, 63]. Even though a blood supply chain network consists of four different echelons, namely, collection, processing, inventory, and distribution [13], the exploited hitherto that is mainly based on inventory control is still lagging behind in integrating the two critical phases, i.e., production and inventory. MCA may help donation organizations to overcome the donor shortage and to reduce health care costs by better donor scheduling via improved and integrated management of production and inventory of blood and blood products. Nevertheless, the major positive impact of MCA on better donation tailoring has so far been neglected [64, 38]. Only a few studies have focused on the associated aspect of MCA: [65] provide donation patterns by implementing MCA in a health center in Italy; [66] propose an integer programming model to decide on the donation amounts of each blood product under a capacity constraint without the deferral time restriction; finally, [38] discuss the effectiveness of MCA in production and cost management by integrating inventory control with donation tailoring and scheduling decisions. Notice that the associated streamline of research assumes that the demand is known, and this is why the proposed donation schedules and the solutions of the models, in general, may be infeasible for the problem at hand when demand is uncertain. The proposed approach in this study is different from others in the literature due to the demand uncertainty and donor segmentation considered when using MCA to tailor donations.

Studies that focus on BSM under demand uncertainty, on the other hand, focus on different aspects of the problem without utilizing MCA or donation scheduling. [67] propose an integer programming model with uncertain demand in order to minimize the cost of purchasing, shortage cost, holding cost, and wastage cost. Some other studies deal with the allocation of blood from a center to the hospitals and health centers while minimizing the shortages and spoils as well as scheduling the blood product distributions [68, 69, 70, 71, 72, 73, 74, 75]. [76] consider a network of the central blood bank and several hospitals with uncertain demand during each review period. The validity of the proposed two-stage stochastic programming approaches for ordering from a central blood bank and transshipping to other hospitals in each period has been presented via extensive numerical experiments in their study. Our optimization methodology is also different from other studies in the BSM literature that tackle the demand uncertainty because we aim to gain resilience against the uncertainty via segmentation of donors as wait-and-see and here-and-now in donation tailoring problem while other studies such as [77], [78], [79] and [80] focus on two-stage stochastic programming to formulate the recourse decisions. Utilizing wait-and-see and here-and-now donors provides more flexible donation schedules since based on the realized values of demand over time, wait-and-see donors may adjust their donation schedules. Lastly, different than the standard parametric decision rule functions that are often used in stochastic programming [81] and robust optimization [82], we adopt scenario-based adjustable decisions.

2.3 Problem Definition

In SDTP, the main objective of the blood donation organization is to satisfy the uncertain demand while minimizing the holding, disposal, and donation costs. The donation costs include the bag, apparatus, centrifuge, technical time, medical time, filtration, labeling, and general costs [38]. We consider only one blood type, and the proposed model can be utilized for all blood types separately. Three main blood products are studied; platelets, plasma, and red blood cells (RBCs), and their shelf-lives are considered as one week, one year, and six weeks, respectively. Every time a donor performs a donation, they need to wait for an amount of time, namely *deferral time* before making another donation. Deferral times depend on both the current and following donation types, and a donor is only allowed to perform a limited number of donations depending on the donation performed during the planning horizon [83]. For example, if a donor makes a whole blood donation, they have to wait for eight weeks in order to be able to perform another whole blood donation; however, they have to only wait for four weeks to donate single-unit platelets after the whole blood donation.

In this study, we assume a multi-period and multi-product problem, the demand of which is satisfied by a limited donor pool in which all donors are repeat blood donors and are willing to cooperate with the donation center according to the preferred donation schemes. The amount of product j obtained by donation type i is denoted by a_{ij}. For instance, if a donor performs a whole blood donation, 1 unit of RBCs, 0.5 units of plasma, and 0.1 units of platelets are obtained. The total number of donations in the planning horizon is indirectly limited by blood products. According to the data collected at Martino Apheresis Facility, a donor can only donate up to four units of RBCs, sixteen units of platelets, and eight units of plasma [65]. The upper bound on the number of the units of blood product j that can be collected from a donor in the planning horizon is denoted by E_j. The sets, parameters and decision variables are presented in Table 13. It must be noted that throughout this paper, for the sake of notation simplicity, we define the sets used for the specific indices when restricted sets are used, i.e., when the set definition of a specific index is not indicated

Table 1: Nomenclature for SDTP

Sets	
$\mathcal{I}$	set of donation types ($\{1, 2, \ldots, L\}$) – indexed by i
$\mathcal{J}$	set of blood products ({red blood cells, platelets, plasma}) – indexed by j
$\mathcal{K}$	set of donors ($\{1, 2, ..., K\}$) – indexed by k
$\mathcal{T}$	set of time periods in the planning horizon ($\{1, 2, ..., T\}$) – indexed by t
$\mathcal{N}$	set of demand nodes ($\{1, 2, ..., N\}$) in scenario tree – indexed by e
Restricted Sets	
$\mathcal{N}_t$	set of nodes in period $t \in \mathcal{T}$
$\mathrm{Pd}(e, l)$	set of $l - 1$ predecessors of node $e \cup \{e\}$
$\mathrm{Pt}(e)$	set of nodes in the path from the source node to e
$\bar{N}(e, l)$	set of children nodes of e in the next l periods $\cup \{e\}$
Parameters	
c_i	cost of performing donation type i
$\tilde{h}_j$	unit holding cost of blood product j (per period)
$\tilde{d}_j$	unit disposal cost of blood product j
$s_{ii'}$	deferral time between donation types i and i'
h_j	shelf-life of blood product j
a_{ij}	units of blood product j collected when donation type i is performed
d_{ej}	demand of blood product j at node e
E_j	upper bound on the number of units of blood product j that can be collected from a donor in the planning horizon
$\mathrm{ipd}(e)$	immediate predecessor of node e
$t(e)$	period of node e
$\mathrm{pr}(e)$	probability of node e being realized
θ	percentage of wait-and-see donors in the pool
Decision variables	
x_{ike}	1 if donor k performs donation type i at node e; 0, otherwise
y_{ikt}	1 if donor k performs donation type i in time period t; 0, otherwise
I_{ej}	inventory of blood product j at the end of time period of node e ($t(e)$)
P_{ej}	amount of blood product j disposed at the end of time period of node e ($t(e)$)

in the mathematical model, the related index is assumed to belong the general (unrestricted) set.

Moreover, uncertainty in demand is modeled via a scenario tree approach. We consider two types of decision variables: here-and-now and wait-and-see decision variables. Here-and-now decision variables are decided at the beginning of the planning horizon, and wait-and-see decision variables are more situational/flexible. The donation schedule is determined/adjusted according to the realizations of the demand in the planning horizon. In Figure 1, we represent a general scenario tree with the notations used in SDTP. This figure provides a tangible representation of the demand tree structure. For example, the immediate predecessor of node e_6 is node $e_2 = \mathrm{ipd}(e_6)$. Also, set of children of node e_1 in the next period is presented by $\bar{N}(e_1, 1)$ and for the next two periods is presented by $\bar{N}(e_1, 2)$. Each node $e \in \mathcal{N}$ in the scenario tree denotes a demand realization at period $t(e)$ with its associated probability $\mathrm{pr}(e)$; and each path from the root node (0) to a leaf node $e \in \mathcal{N}$ is referred to as a *scenario* of the tree, i.e., denoted by $\mathrm{Pt}(e_{14}) = \{0, e_2, e_6, e_{14}\}$, where $\mathcal{N}_T$ denotes the set

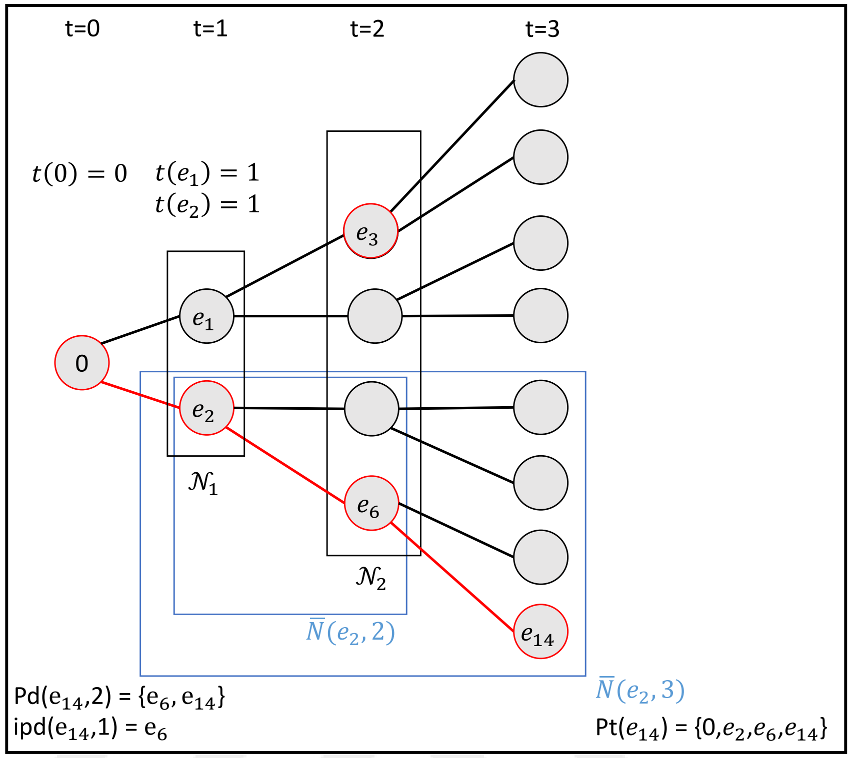

Figure 1: Problem structure for SDTP

of nodes in the last period of the planning horizon.

SDTP can be formulated considering both here-and-now and wait-and-see decisions ([MIP-WS]). It should be noted that in [MIP-WS], donation decisions are divided into two groups, namely, here-and-now ($\boldsymbol{y}$) that are scheduled at the beginning of the planning horizon and are independent of the scenario realizations; and scenario-specific wait-and-see ($\boldsymbol{x}$) decisions.We present the mathematical programming model of [MIP-WS] consisting of both here-and-now and wait-and-see donation decision variables as follows:

[MIP-WS]:

$$\min \sum_{e \in \mathcal{N}_T} \mathrm{pr}(e) \sum_{e' \in \mathrm{Pt}(e)} \left(\sum_i \sum_k \left(c_i x_{ike'} + c_i y_{ikt(e')} \right) + \sum_j \left(\tilde{h}_j I_{e'j} + \tilde{d}_j P_{e'j} \right) \right) \tag{2.1}$$

$$\text{s.t. } (M-1)x_{ike} + \sum_{i'} \sum_{e' \in \bar{N}(e, s_{ii'}-1)} x_{i'ke'} \le M \qquad \forall e, i, k \tag{2.2}$$

$$(M-1)y_{ikt} + \sum_{i'} \sum_{t'=t}^{t+s_{ii'}-1} y_{i'kt'} \le M \qquad \forall i, k, t \tag{2.3}$$

$$I_{\mathrm{ipd}(e)\,j} - I_{ej} - P_{ej} + \sum_i \sum_k a_{ij}(x_{ike} + y_{ikt(e)}) = d_{ej} \qquad \forall e, j \tag{2.4}$$

$$\sum_i \sum_{e' \in \mathrm{Pt}(e)} a_{ij} x_{ike'} + \sum_i \sum_t a_{ij} y_{ikt} \leq E_j \qquad \forall e \in \mathcal{N}_T, j, k \tag{2.5}$$

$$I_{0j} + \sum_{e' \in \mathrm{Pd}(e,h_j)} \sum_i \sum_k a_{ij} x_{ike'} + \sum_{t'=t(e)-h_j+1}^{t(e)} \sum_i \sum_k a_{ij} y_{ikt'} \geq I_{ej} \qquad \forall j, e : t(e) \leq h_j \tag{2.6}$$

$$\sum_{e' \in \mathrm{Pd}(e,h_j)} \sum_i \sum_k a_{ij} x_{ike'} + \sum_{t'=t(e)-h_j+1}^{t(e)} \sum_i \sum_k a_{ij} y_{ikt'} \geq I_{ej} \qquad \forall j, e : t(e) > h_j \tag{2.7}$$

$$x_{ike} \leq z_k \qquad \forall e, i, k \tag{2.8}$$

$$\sum_i \sum_t y_{ikt} \leq M(1 - z_k) \qquad \forall k \tag{2.9}$$

$$\sum_k z_k \leq \theta K \tag{2.10}$$

$$x_{ike}, y_{ikt} \in \{0, 1\} \qquad \forall e, i, k, t \tag{2.11}$$

$$I_{ej}, P_{ej} \geq 0 \qquad \forall e, j \tag{2.12}$$

$$z_k \geq 0 \qquad \forall k \tag{2.13}$$

The objective (2.1) is to minimize the sum of expected donation, inventory holding, and disposal costs. Constraints (2.2) enforce deferral time between successive wait-and-see donations of a donor; constraints (2.3) enforce the same deferral time restriction for the here-and-now donations. Constraints (2.4) ensure the inventory balance for each blood product and the time period overall scenarios. The upper bound on the number of units of each blood product that can be collected from a single donor in the planning horizon is enforced by constraints (2.5). Constraints (2.6) and (2.7)ensure the shelf-life limitation of blood products. Lastly, constraints (2.8) and (2.9) ensure that a donor can either appear in a wait-and-see or a here-and-now schedule but not both, and we limit the number of wait-and-see donors by constraint (2.10). As discussed in [38], the deterministic form the proposed model is related to *general lot-sizing and scheduling problem* and *cutting stock problem.* The proposed *mixed integer programming* (MIP) model is a challenging one, especially when the planning horizon is long and the number of donors and the scenarios are high. Therefore, in the next section, we propose a column generation-based heuristic approach to solve this problem effectively.

2.4 Column Generation Approach

Solving [MIP-WS] is not trivial for real-life instances because of the size of the problem that is due to the high number of donors, the high number of scenarios, and the long planning horizons. In this section, we propose a column generation-based heuristic that efficiently solves realistically sized instances. The proposed algorithm, in which we consider each donor's donation schedule as a column, starts with a feasible set of columns for the LP-relaxation of *restricted master problem* (RMP) with both here-and-now and wait-and-see decisions called [RMP-WS]. Following that, by obtaining the dual variables and solving corresponding subproblems, we add profitable columns to the model. These steps are continued until all the decision variables in [RMP-WS] are integers or the time limit has been reached. In the final step of the algorithm, by considering all the generated columns, we solve master problems with integer decision variables with here-and-now and wait-and-see decision variables ([MP-WS]). It must be noted that since in the final step of the algorithms, we solve [MP-WS] instead of branching on the decision variables, which would take a great amount of time, these algorithms are different than orthodox branch-and-price algorithms, and that is why we call them heuristics. We refer the readers to [84], [85] and [86] for detailed explanation of column generation algorithm.

The column generation-based algorithm we propose here follows a sequential order; more specifically, we introduce a column ($\boldsymbol{\alpha}$) to [RMP-WS] that is associated with a wait-and-see donor ($\boldsymbol{x}$) first, and then we introduce a column ($\boldsymbol{\beta}$) to [RMP-WS] that is associated with here-and-now donors ($\boldsymbol{y}$). Notice that in [RMP-WS], we ignore the shelf-life constraint and this sequential column generation approach shall continue until the objective function values of the subproblems [PP-x] and [PP-y] are non-negative, i.e., there does not exist any column that may improve the current solution of [RMP-WS]. Finally, [RMP-WS] is solved with the inclusion of the shelf-life constraint as an integer programming problem whose solution becomes the final solution of SDTP. The *reduced master problem* [RMP-WS] is given as follows where decision variable y_l represents the number of the donors who follow here-and-now schedule l, and x_m represents the number of the donors who follow wait-and-see schedule m, $\tilde{c}_l$ is the total donation cost of here-and-now schedule l while $\hat{c}_m$ is the total donation cost of wait-and-see schedule m. Moreover, $\beta^{l}_{jt(e)}$ is the total number of units of blood product j that is collected in time period $t(e)$ if here-and-now donation schedule l is followed and α^{m}_{ej}

is the total number of units of blood product j that is collected in node e if wait-and-see donation schedule m is followed.

$$\textbf{[RMP-WS]:} \quad \min \quad \sum_{e \in \mathcal{N}_T} \mathrm{pr}(e) \left(\sum_j \sum_{e' \in \mathrm{Pt}(e)} \tilde{h}_j I_{e'j} + \tilde{d}_j P_{e'j} \right) + \sum_m \hat{c}_m x_m + \sum_l \tilde{c}_l y_l \tag{2.14}$$

$$\text{s.t.} \quad I_{\mathrm{ipd}(e)\,j} - I_{ej} - P_{ej} + \sum_m \overset{m}{\alpha}_{ej}\, x_m + \sum_l \overset{l}{\beta}_{jt(e)}\, y_l = d_{ej} \qquad \forall e, j \tag{2.15}$$

$$\sum_l y_l + \sum_m x_m \leq K \tag{2.16}$$

$$\sum_m x_m \leq \theta K \tag{2.17}$$

$$I_{ej}, P_{ej} \geq 0 \qquad \forall e, j \tag{2.18}$$

$$y_l, x_m \geq 0 \qquad \forall l, m \tag{2.19}$$

In [RMP-WS], the objective (2.1) is to minimize the total (expected) cost of the columns, including the sum of donation, inventory holding, and disposal. Constraints (2.15) ensure the inventory flow balance for each blood product j at each node e. The total number of available donors is K, and it is imposed by constraint (2.16). Constraint (2.17) ensures that only θ fraction of total donors can follow a wait-and-see schedule. Lastly, the non-negativity of decision variables is defined in constraints (2.18) and (2.19). The dual variables (w_{je}) associated with (2.15) are used in the two *subproblems* [PP-x] and [PP-y]. [PP-y], which provides profitable here-and-now columns, can be formulated as follows:

$$\textbf{[PP-y]:} \quad \min \quad \sum_i \sum_t q_{it}(c_i - \sum_j \sum_{e \in \mathcal{N}_t} a_{ij} w_{je}) \tag{2.20}$$

$$\text{s.t.} \quad (M-1) q_{it} + \sum_{i'} \sum_{t'=t}^{t+s_{ii'}-1} q_{i't'} \leq M \qquad \forall i, t \tag{2.21}$$

$$\sum_{i,t} a_{ij} q_{it} \leq E_j \qquad \forall j \tag{2.22}$$

$$q_{it} \in \{0, 1\} \qquad \forall i, t \tag{2.23}$$

In [PP-y], q_{it} is a binary decision variable representing whether donation type i is performed at time t or not. If it is, $q_{it} = 1$; 0, otherwise. Objective (2.20) is to minimize the reduced cost of the new column. If the reduced cost is negative, it means that there exist donation patterns that can improve the value of the objective function of [RMP-WS]. In other words, when optimal objective function value of [PP-y] is negative, a column is generated corresponding to optimal q_{it} values, which is then passed to restricted master problem [RMP-WS] as a new column, say column l. More specifically, optimal q_{it} values are used to calculate β^{l}_{jt} and $\tilde{c}_l$ values as follows: $\beta^{l}_{jt} = \sum_{i=1}^{L} a_{ij} q_{it}$, $\tilde{c}_l = \sum_{i=1}^{L} \sum_{t=1}^{T} c_i q_{it}$. The whole process continues until the value of the objective function for [PP-y] is greater or equal to zero. Constraints (2.21) force the deferral times between successive donations. Upper bounds on the number of units of each blood product that can be collected from a single donor in the planning horizon are imposed by constraints (2.22). Finally, binary variable declarations are defined in constraints (2.23).

Following that, [PP-x], which is responsible for producing profitable wait-and-see columns, can be formulated as follows:

$$\textbf{[PP-x]:} \quad \min \quad \sum_{e} \mathrm{pr}(e) \left(\sum_{i} c_i z_{ie} \right) - \sum_{e} \sum_{i} \sum_{j} z_{ie} a_{ij} w_{je} \tag{2.24}$$

$$\text{s.t.} \quad (M-1) z_{ie} + \sum_{i'} \sum_{e' \in \bar{N}(e, s_{ii'}-1)} z_{i'e'} \leq M \qquad \forall e, i \tag{2.25}$$

$$\sum_{i} \sum_{e' \in \mathrm{Pt}(e)} a_{ij} z_{ie'} \leq E_j \qquad \forall e \in \mathcal{N}_T, j \tag{2.26}$$

$$z_{ie} \in \{0, 1\} \qquad \forall e, i \tag{2.27}$$

In [PP-x], z_{ie} is a binary decision variable representing whether donation type i is performed at node e or not. If it is, $z_{ie} = 1$; 0, otherwise. The objective (2.24) is to minimize the reduced cost of the new column. If it is negative, then the column formed by all z_{ie} decision variables that are equal to 1 will be added to [RMP-WS]. Constraints (2.25) force the deferral times between successive donations. Upper bounds on the number of units of each blood product that can be collected from a single donor in the planning horizon are imposed by constraints (2.26). Finally, binary variable declarations are defined in constraints (2.27). When [PP-x]'s optimal objective function value is negative, a column is generated corresponding to optimal z_{ie} values, which is then passed to master problem [RMP-WS] as a new column, say column l. More specifically, optimal z_{ie} values are used to calculate α^{m}_{je} and $\hat{c}_m$ values as follows: $\alpha^{m}_{je} = \sum_{i=1}^{L} a_{ij} z_{ie}$, $\hat{c}_m = \sum_{e=1}^{N} \mathrm{pr}(e) \left(\sum_{i=1}^{L} c_i z_{ie} \right)$. Then, [RMP-WS] is again solved with the newly added column.

After all the profitable columns are generated, in the end, we solve RMP-WS with the inclusion of shelf-life constraint and binary decision variables in order to obtain a meaningful solution, and we call the new model [MP-WS], which is presented as follows:

$$\begin{aligned}
\textbf{[MP-WS]:} \quad \min \quad & \sum_{e \in \mathcal{N}_T} \mathrm{pr}(e) \left(\sum_{j} \sum_{e' \in \mathrm{Pt}(e)} \tilde{h}_j I_{e'j} + \tilde{d}_j P_{e'j} \right) \\
& + \sum_{m} \hat{c}_m x_m + \sum_{l} \tilde{c}_l y_l \qquad (2.28) \\
\text{s.t.} \quad & (2.15) - (2.18)
\end{aligned}$$

$$I_{0j} + \sum_{e' \in \mathrm{Pd}(e,h_j)} \sum_{m} \alpha^{m}_{je'} x_m + \sum_{t'=1}^{t(e)} \sum_{l} \beta^{l}_{jt'} y_l - I_{ej} \geq 0 \qquad \forall j, e : t(e) \leq h_j \qquad (2.29)$$

$$\sum_{e' \in \mathrm{Pd}(e,h_j)} \sum_{m} \alpha^{m}_{je'} x_m + \sum_{t'=t(e)-h_j+1}^{t(e)} \sum_{l} \beta^{l}_{jt'} y_l - I_{ej} \geq 0 \qquad \forall j, e : t(e) > h_j \qquad (2.30)$$

$$y_l, x_m \geq 0 - integer \qquad \forall l, m \qquad (2.31)$$

In [MP-WS], constraints (2.29) and (2.30) are the shelf-life constraints, and constraints (2.31) define binary variable declarations. This algorithm is not a pure branch-and-price because we do not branch on the continuous decision variables; instead, we solve the associated master problem with integer decision variables ([MP-WS]). The steps of column generation-based algorithm for both here-and-now donors and wait-and-see donors are presented in Figure 2.

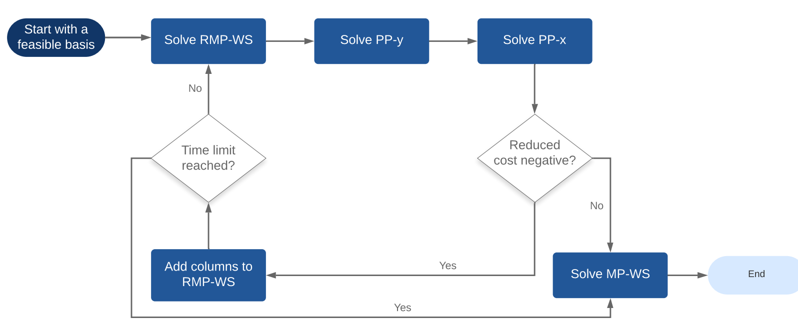

Figure 2: Steps of column generation-based algorithm for [MIP-WS]

Initial solution approach for here-and-now donations. In order to start the column generation, an initial feasible solution must be passed to the [RMP-WS] to have a feasible LP relaxation to ensure that the correct dual information is passed to the subproblems. Since the initial basis determines the initial dual variables that will be passed to the pricing problem, a good initial basis for the restricted master problem can be of high importance. We propose a simple heuristic approach for generating initial columns of [RMP-WS]. In this approach, we assume that each donor is just allowed to perform one type of donation, considering the deferral time of that specific donation type. It is clear that when only one type of donation is performed, donor tracking will be simplified as only keeping track of previous donation time will suffice for feasibility. For example, if a person performs a whole blood donation today, he/she needs to wait for eight weeks to perform another whole blood donation. Therefore, while providing the initial solution for a problem with 12 periods, we could have a person with a whole blood donation in week 1, and the second whole blood is performed in week 9. Similarly, another person can perform the whole blood donation in week 2, and the next donation is performed in week 10. Notice that if the first donation of the planning horizon is performed after week 4, then only one donation can be performed. For this given scenario, by sliding the start time of donations, we create 12 different donation patterns. We adopt the same approach for other donation types as well. In other words, we assume the number of periods between the two consecutive donations in the initial solution approach is exactly equivalent to the deferral time of the donation type.

Initial solution approaches for wait-and-see donations. Starting with a good initial solution for wait-and-see donors is at least as important as that for here-and-now because of the structure of the columns that are more complex and the higher number of decision variables. We utilize three different algorithms one by one to generate initial solutions for wait-and-see donors.

Algorithm I. A wait-and-see donation pattern may be equivalent to a here-and-now one when the same donation type is performed for all the nodes that are in the same period. Therefore, the initial solution approach for here-and-now decisions presented before may also be used for generating feasible wait-and-see patterns as we can easily translate a here-and-now pattern to a wait-and-see one. Notice that this might not yield high-quality columns for the problem, but it is still practical for the rapid generation of initial columns.

Algorithm II. We solve the problem with the column generation approach for only here-and-now decision variables by setting the value of θ equal to zero and not solving [PP-y]. We denote the associated restricted master problem by [RMP-HN]. Subsequently, we take the columns that are on the basis of the final solution of [RMP-HN] and use them as initial here-and-now and wait-and-see columns for the [RMP-WS]. Again, it is just a practical way of generating initial columns that does not necessarily guarantee high-quality columns. Notice that the updated demand values in the first constraint of [WS-In] cannot be less than zero; nevertheless, this could be the case when the demand of a node is greater than the nominal demand of the associated period. To avoid such cases, we take the maximum of zero and the updated demand $[d_{je} - \sum_{e':\ t(e')=t(e)} \mathrm{pr}'(e') d_{je'} (|\mathcal{N}_{t(e)}| K'_T)^{-1}]$. On the other hand, the updated demand may result in an instance that cannot be served by one wait-and-see donor. To yield feasibility in such cases, we include the auxiliary variable (R_{ej}) that determines the unsatisfied demand penalized in the objective. Ultimately, [WS-In] provides feasible wait-and-see columns. Like before, optimal z_{ie} values are used to obtain the columns α^m and $\hat{c}_m$ as follows: $\alpha^m_{je} = \sum_{i=1}^{L} a_{ij} z_{ie}$, $\hat{c}_m = \sum_{e=1}^{N} \mathrm{pr}(e) \left(\sum_{i=1}^{L} c_i z_{ie} \right)$. It must be noted that solving [WS-In] to optimality by a commercial solver may not be straightforward due to complexity of this mixed-integer linear programming (MILP) model. Therefore, we terminate the commercial solver with optimality gap. Moreover, in instead of adding a single feasible solution, we utilize solution pool to add more than one feasible columns.

[**WS-In**]:

$$\min \quad \sum_{e \in \mathcal{N}_T} \mathrm{pr}'(e) \left[\sum_j \sum_{e' \in \mathrm{Pt}(e)} \left(\tilde{h}_j I_{e'j} + \tilde{d}_j P_{e'j} \right) + \sum_i c_i z_{ie} \right] + M \sum_{e \in \mathcal{N}_T} \sum_j R_{ej} \tag{2.32}$$

$$\text{s.t.} \quad I_{\mathrm{ipd}(e)\,j} - I_{ej} - P_{ej} + \sum_i \sum_{e \in \mathcal{N}_T} a_{ij}\, z_{ie}$$

$$= \max \left\{ d_{ej} - \sum_{e':\ t(e')=t(e)} \mathrm{pr}'(e') d_{e'j}, 0 \right\} (|\mathcal{N}_{t(e)}| K'_T - R_{ej})^{(-1)} \qquad \forall e, j \tag{2.33}$$

$$(M-1) z_{ie} + \sum_{i'} \sum_{e' \in \bar{N}(e, s_{ii'}-1)} z_{i'e'} \leq M \qquad \forall e, i \tag{2.34}$$

$$\sum_i \sum_{e' \in \mathrm{Pt}(e)} a_{ij} z_{ie'} \leq E_j \qquad \forall e \in \mathcal{N}_T, j \tag{2.35}$$

$$I_{ej}, P_{ej}, R_{ej} \geq 0 \qquad \forall e, j \tag{2.36}$$

$$z_{ie} \in \{0, 1\} \qquad \forall e, i \tag{2.37}$$

2.5 *Computational Experiments*

In this section, we describe the results of a numerical study conducted based on random instances motivated by real-life data. The goal of our numerical study is to evaluate the performances of the proposed methods in terms of solution quality. The computational experiments are carried out on a 64-bit Windows Server with two 2.4 GHz Intel Xeon CPUs and 24 GB RAM. The algorithms are implemented using Python Programming Language and GUROBI Solver version 9.1.1.

2.5.1 Data Generation

In this study, we use instances that are motivated by real-life data [87]. Throughout this section, a period corresponds to a week, and we solve the problem for a 12-week planning horizon, which is the largest dimension that can be solved in practicable CPU times. [38] show that out of 17 possible donation types, three main donation types, namely, i) whole blood (WB), (ii) single unit platelets (SP) and double units plasma (DPLS), and (iii) double units platelets (DP), single-unit red blood cells (RBC), and single-unit plasma (PLS) are utilized more in donation schedules. We also consider these three types in this study.

Table 2: Deferral times between donation types (in terms of weeks) and collection cost ($) of each donation type

From \ To	I	II	III	Collection Cost ($)
I	8	4	8	138
II	8	8	1	364
III	8	4	8	364

I: WB; II: SP-DPLS; III: DP-RBC-PLS

As mentioned before, between two different donations, there must be a deferral time that depends on both the current and upcoming donation types. Table 2 represents the deferral times and the collection/donation costs of each donation type [88, 65]. For example, if a donor performs a whole blood donation, he/she needs to wait eight weeks to be able to perform another whole blood donation or four weeks to perform SP-DPLS donation. We consider the upper bounds on the number of the units that can be collected from a donor during a season to be equal to 1.5, 6, and 3 for red blood cells, platelets and plasma, respectively. In other words, in 12 weeks, only 1.5 units of red blood cells, six units of platelets, and three units of plasma can be collected [65]. Moreover, while as suggested by [67], the holding cost for each blood product is considered as \$1.25 per unit per day, the unit disposal costs are \$0.36, \$0.36, and \$0.06 for red blood cells, plasma, and platelets, respectively.

Table 3: Number of unit products collected from each donation type and shelf-life of the blood products

Donation Type \ Blood Products	Red Blood Cells	Plasma	Platelets
I	1	0.5	0.1
II	0	2	1
III	1	1	2
Shelf-life (in weeks)	6	50	1

Table 3 represents the number of unit products that are collected from each donation type and the shelf-life of each blood product. For example, in WB donation, a single unit of red blood cells, 0.5 units of plasma, and 0.1 units of platelets are collected.

In order to investigate the effect of uncertainty on the results, we conduct computational analysis in threefold. Firstly, in order to provide a better understanding of the problem and scenario tree-based reformulation of blood donation management problem that adopts multicomponent apheresis and utilizes donor pool segmentation as here-and-now and wait-and-see donors, we propose an illustrative example with a low number of repeat donors and time periods. Secondly, we investigate the seasonality and variability of demand. We also provide optimality gaps, and improvements the blood organizations can get through utilizing wait-and-see donors. Finally, in order to provide a profound insight toward utilizing the wait-and-see donors in real life, we propose a road map through the computational results provided.

2.5.2 Illustrative Example

This section provides an illustrative example to understand the impact of utilizing wait-and-see donors compared to the model with only here-and-now donors. In the given instance, there are 30 repeat blood donors who perform donations for three time periods. The scenario tree and the demand for different products are presented in Figure 3 and Table 4, respectively; for example, the demand for product 1 in node e_2 of period one ($t = 1$) is equal to 9 units.

We solve [MIP-HN] and present the results in Table 5. For here-and-now and wait-and-see decisions, we solve [MIP-WS] and present the results in Table 6 and Table 7.

	Products		
Nodes	1	2	3
e_1	9	8	8
e_2	1	5	5
e_3	6	6	7
e_4	4	3	2
e_5	6	6	7
e_6	4	3	2
e_7	7	7	8
e_8	2	3	2
e_9	7	7	8
e_{10}	2	3	2
e_{11}	7	7	8
e_{12}	2	3	2
e_{13}	7	7	8
e_{14}	2	3	2

Table 4: The demand of nodes for different products

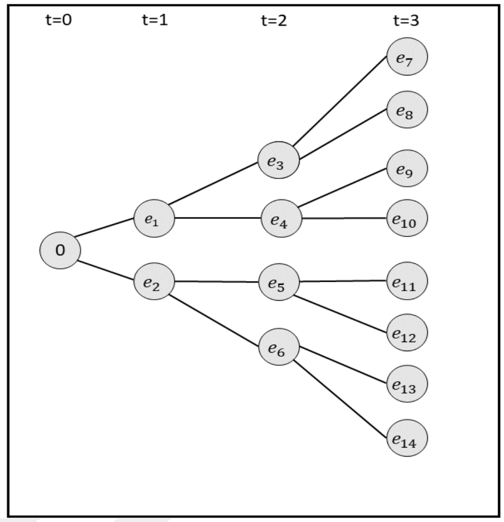

Figure 3: Scenario tree of the products in the illustrative example

In Table 5, the first column represents the periods, and the second, third, and fourth columns provide the information on the donation patterns. For example, donor 6 performs a donation type 2 in the first and donation type 3 in the third period. As another example, donor 18 only performs a donation type 1 in the first period during the planning horizon. It must be noted that donors 23 to 30 are not utilized in this setting as the demand is satisfied by fewer donors. For the model with only here-and-now donors, the total cost is equal to 6571, which is calculated using the data provided.

Table 5: The donation schedule of donors for the setting with only here-and-now donation schedules

	Donation Types		
Time Periods	**1**	**2**	**3**
1	[10,11,12,13, 14,15,16,17, 18,19,20,21,22]	[6,7,8,9]	[1,2,3,4,5]
2	-	-	-
3	-	-	[6,7,8,9]

Table 6 and Table 7 provide the donation schedules of the here-and-now and wait-and-see donors, respectively, when both here-and-now and wait-and-see donors are available. The first column in Table 7 represents the nodes, and the next columns provide the donation schedules of the wait-and-see donors according to the donation types. For example, (here-and-now) donor 10 performs a donation type 3 in the second period (see Table 6); (wait-and-see) donor 14 performs a wait-and-see donation type 1 in the first node (e_1), repeats the same donation in the eleventh node (e_{11}), and makes no donation in the other nodes (see Table 7). The total cost for the general model that contains both types of donors is 4634 using the data provided above. We set the limit for the total number of the wait-and-see donors to 13 (i.e., $\theta = 0.45$). In the optimal solution, 13 wait-and-see and 12 here-and-now donors are scheduled for donation, while five donors are not utilized since the demand is satisfied.

Table 6: The donation schedule of here-and-now donors for the setting with both here-and-now and wait-and-see donation schedules

	Donation Types		
Time Periods	**1**	**2**	**3**
1	[1, 2]	[3]	[11, 12]
2	[4, 5]	[6]	[9, 10]
3	[7]	-	[8]

The efficiency of utilizing wait-and-see donors is tangible considering the donation schedules in Table 6 and Table 7. Notice that the total cost of the donation is significantly less than that of the model with only here-and-now donations (compare the optimal objective function values 4634 and 6571). Moreover, utilizing wait-and-see donors alongside the here-and-now ones provides adjustable donation schedules. For example, donor number 24, performs donation types 1, 2, and 3 in the same period but in different nodes. It must be noted that when only here-and-now donors are considered in the system, the solutions obtained are robust as they are worst-case-oriented solutions. On the other hand, wait-and-see donors are more flexible, and they adapt their donations according to different demand realizations in the scenario tree, which yields better inventory management for the system under different scenarios. Last but not least, when only here-and-now donors are used, 22 donors are used in the optimal donation schedule—the total number of donors to satisfy the same demand increases to 25 when wait-and-see donors are utilized. In other words, it must be highlighted that even though the number of the donors utilized increases in the setting with wait-and-see donors, as these donors provide more flexible donations, the system uses more donors to reduce the overall cost and this trade off between the number of the utilized donors and the overall cost must be underlined.

Table 7: The donation schedule of wait-and-see donors

	Donation Types		
Nodes	**1**	**2**	**3**
e_1	[13, 14, 19, 21]	-	[16, 22]
e_2	-	-	-
e_3	-	-	[15, 18]
e_4	-	-	-
e_5	-	-	[23]
e_6	-	-	-
e_7	[20]	-	[17, 24, 25]
e_8	-	-	-
e_9	[18, 24, 25]	-	[15]
e_{10}	-	-	-
e_{11}	[14]	[24]	[15, 20]
e_{12}	-	[19]	-
e_{13}	[17]	[20]	[23]
e_{14}	-	-	-

2.5.3 Impact of Seasonality and Time Variability of Demand

In this section, in order to provide insight into the benefits the system can get from wait-and-see donors and to investigate the impact of seasonality and variability of demand, we propose four different settings and compare the improvements we gain when using wait-and-see donors as well as reporting the optimality gaps with respect to a lower bound. In other words, we consider two different cases for demand seasonality (late and early shocks) and two different ones for the variability of demand (low variance and high variance); therefore, there will be four different cases in total. In all of the settings, considering 100 repeat donors, the instances are generated from the data set of the study by [87] that consists of demands for 180 days in the planning horizon. We consider *low*, *nominal*, and *high* demand notes at each period. In other words, there will be 3^{12} leaf nodes in total. Moreover, we set the value of θ (percentage of the wait-and-see donors in the pool) equal to 40%. We set the probability of *low*, *nominal*, and *high* demand nodes as 0.32, 0.44, and 0.24, respectively. Furthermore, the initial inventory of each blood product is considered to be equal to the average demand of two periods. Notice that solving [MIP-WS] for these settings is impossible because of the number of decision variables and constraints, and commercial solvers are not even capable of establishing the model. The settings for four different cases as well as the obtained results are as follows:

Case 1: Seasonality with Late Demand Shocks with Low Variance: In this case, the *nominal* demand value of each product for the first period is set equal to the average demand of the data proposed by [87]. The nominal demand values for the next periods are multiplied to some coefficients to generate instances for late seasonality. Figure 4 represents the late seasonality case for *nominal* demand value of a product. The *high* demand value of a product for each period is equal to the *nominal* demand plus the standard deviation of the sampled data. That value for the *low* demand of a product in each period is equal to the *nominal* demand minus the standard deviation of the sampled data. The results for this case are summarised in Table 8. In Table 8, the first column represents the instance number, the numbers of the different here-and-now and wait-and-see patterns are presented in columns two and three, respectively; column four represents the number of here-and-now donors, and column five represents that for wait-and-see; column six represents the optimality gap of the proposed algorithm with respect to LP-relaxation of [MP-WS]; ultimately, the last column represents the improvement in objective function value of [MP-WS] over [MP-HN]. The numerical results in Table 8 show that, on average, the algorithm provides only 6.66% gaps while improving the results with only here-and-now donors for 15.85%. While the best and the worst gaps are 3.68% and 9.80%, those numbers for the improvement are 25.58% and 11.61%, respectively.

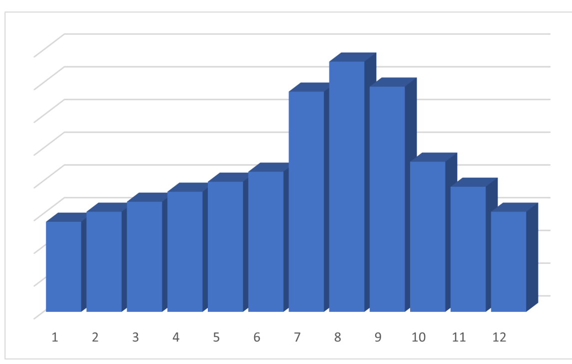

Figure 4: Demand histogram for seasonality with late demand shocks

Case 2: Seasonality with Late Demand Shocks with High Variance: In this case, the *nominal* demand value of a product is obtained using the approach explained in

Table 8: Case 1: Seasonality with late demand shocks with low variance

Instance	HN patterns	WS patterns	HN donors	WS donors	Gap	Improvement
1	15	24	55	36	9.72%	15.37%
2	7	28	54	36	8.18%	11.78%
3	10	29	60	37	3.68%	12.68%
4	10	22	58	36	5.60%	11.80%
5	8	11	52	37	5.86%	12.27%
6	11	28	59	39	3.73%	20.75%
7	10	20	57	40	8.81%	25.58%
8	12	19	58	37	9.80%	15.33%
9	12	15	60	34	4.24%	21.32%
10	7	24	56	39	6.96%	11.61%
		Average			6.66%	15.85%
		Best			3.68%	25.58%
		Worst			9.80%	11.61%

Section 2.5.3. The *high* demand value of the product for each period is equal to the *nominal* demand plus two times the standard deviation of the sampled data. That value for the *low* demand of the product in each period is equal to the *nominal* demand minus two times the standard deviation of the sampled data. The results for this case are summarised in Table 9. On average, the algorithm provides only 5.76% gaps while improving the results with only here-and-now donors for 18.78%. Comparing the results with those in Section 2.5.3, proves that the algorithm provides more quality results when the variance is higher. Generally, utilizing wait-and-see donors helps the donation organizations to satisfy demand for the blood with a high variance. Therefore, in case the demand for the blood has a high variance, the improvement of using wait-and-see donors over utilizing only here-and-now donors is more than that of the demand with a low variance. Comparing the results in Table 8 and Table 9 reveals this fact. On average, when the variance is higher, the improvement is higher for 3.31%.

Table 9: Case 2: Seasonality with late demand Shocks with high variance

Instance	HN patterns	WS patterns	HN donors	WS donors	Gap	Improvement
1	13	20	59	36	2.75%	15.11%
2	12	17	64	35	5.26%	20.11%
3	12	22	57	35	4.55%	10.66%
4	10	17	59	40	5.48%	19.67%
5	12	14	60	34	6.11%	17.68%
6	7	20	56	39	8.47%	30.62%
7	10	11	56	36	6.58%	23.09%
8	12	15	62	36	6.73%	13.80%
9	9	13	52	37	6.49%	17.45%
10	13	30	60	37	5.18%	19.65%
		Average			5.76%	18.78%
		Best			2.75%	30.62%
		Worst			8.47%	10.66%

Case 3: Seasonality with Early Demand Shocks with Low Variance: In this case, the *nominal* demand value of the product for the last period is set equal to the average demand of the data proposed by [87]. This value for the other periods is multiplied to some coefficients in order to have early seasonality for the data as it is presented in Figure 5. The *high**low* demand values of a product for each period is calculated as the *nominal* plus\minus the standard deviation of the sampled data. Table 10 presents the results for this case. On average, the algorithm provides a 7.20% gap with respect to the lower bound while the best and the worst gaps are equal to 4.48% and 10.53%, respectively. It must be noted that when the demand shocks happen in the early periods (see Case 1), because of an unforeseen calamity as an example, the donation organizations will invite more wait-and-see donors to donate blood in order to satisfy the demand for product. In other words, the utilizing wait-and-see donors will help the donation organizations reduce costs. Comparing the results in Table 8 and Table 9 also shows this fact. When the demand receives an early shock, the average improvement of utilizing wait-and-see donors over here-and-now donors is about 2% higher than the case of late shocks.

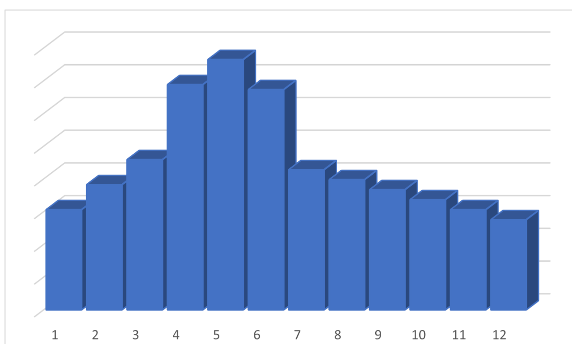

Figure 5: Demand histogram for seasonality with early demand shocks

Case 4: Seasonality with Early Demand Shocks with High Variance: In this case, the *nominal* demand value of a product for each period is calculated as it is explained in Section 2.5.3, and the *low* and *high* demand values are calculated as it is explained in Section 2.5.3. The associated results are presented in Table 11. The improvement we obtain from utilizing wait-and-see donors is the highest (on average) among the four different cases (21.04%). On average, the algorithm provides a 6.44% gap with respect to the lower bound.

Table 10: Case 3: Seasonality with early demand shocks with low variance

Instance	HN patterns	WS patterns	HN donors	WS donors	Gap	Improvement
1	13	25	58	36	10.59%	19.81%
2	15	11	57	37	6.69%	12.53%
3	8	14	55	40	9.00%	21.01%
4	11	29	57	40	7.49%	19.29%
5	12	19	61	34	7.21%	13.46%
6	14	22	54	38	7.92%	17.38%
7	11	20	61	39	5.24%	25.37%
8	13	29	58	34	6.60%	18.85%
9	11	12	60	34	6.80%	12.46%
10	13	15	58	40	4.48%	18.27%
		Average			7.20%	17.84%
		Best			4.48%	25.37%
		Worst			10.59%	12.46%

Table 11: Case 4: Seasonality with early demand shocks with high variance

Instance	HN patterns	WS patterns	HN donors	WS donors	Gap	Improvement
1	15	15	55	36	4.04%	19.78%
2	15	30	63	35	6.22%	16.91%
3	9	27	63	37	6.08%	17.03%
4	10	13	58	39	9.69%	20.66%
5	8	10	60	35	6.14%	26.69%
6	11	25	58	36	7.00%	19.07%
7	14	30	61	34	9.86%	18.48%
8	7	24	59	40	5.06%	22.29%
9	13	29	60	35	5.15%	28.60%
10	11	20	61	39	5.14%	20.86%
		Average			6.44%	21.04%
		Best			4.04%	28.60%
		Worst			9.86%	16.91%

The algorithm in this case, provides more improvement than case 2 and case 3, and the reason is the fact that utilizing wait-and-see donors helps donation organizations to deal with early demand shocks and high variances in demand for blood. It must be noted that this fact is a clear-cut manifestation of the fact that utilizing wait-and-see donors helps blood donation organizations to deal with demand uncertainty regardless of variability and seasonality of demand.

2.5.4 Utilization of Wait-and-see Donation Schedules in Real-life

Even though donations made by here-and-now donors are predetermined and independent from the realized demand, wait-and-see donors are flexible, and they adapt according to different demand realizations in the scenario tree. Nevertheless, as it may be anticipated, in practice, the actual demand will rarely be equivalent to one of the scenarios in the tree. To ensure the validity of wait-and-see decisions in such cases, we propose two approaches for donation organizations on selecting donation schedules of wait-and-see donors when the realized demand is different from the predetermined scenarios in the tree; both methods guarantee the feasibility of a donation schedule obtained from SDTP. As the first approach, one may choose the wait-and-see donation schedule of the *nearest larger demand node* (NLDN) in the decision tree with respect to the realized demand of the associated period. The NLDN approach always yields a solution that fully satisfies the demand even though it may result in excess blood product inventory under the assumption that the realized demand is always less than the "high" demand node at each period. The second approach that is referred to as *folding horizon* (FH) reoptimizes the wait-and-see donation schedules of SDTP after the demand of each period is realized, i.e., the problem is reoptimized T times in the planning horizon when the here-and-now donations are fixed to the initial plan that is decided before the uncertain demand reveals itself. The advantage of the NLDN approach is that it works much faster than FH since it is a simple selection rule and does not require solver integration; the FH approach, on the other hand, is very time consuming, and it may yield better solutions than NLDN since it uses the information of the realized demand. It is worthwhile to mention that when adjustable donation decisions must be decided immediately after the demand has occurred, FH may not be applicable in practice due to increased CPU time requirements.

Lastly, it is essential to point out that donation organizations may use adjustable decision-making in their routine process because such organizations usually satisfy demand from their donation bank inventory and refill the associated inventory with new donations after the demand has been served. Therefore, organizations have the required flexibility to wait for the demand as long as the donation plan may be promptly executed afterward, given that an extended waiting time for the new plan is not intended.

In order to analyze the optimality performance of SDTP with the NLDN approach, we use the FH approach as the benchmark that resolves SDTP for the realized data at each period. We randomly sample demand ten times for each instance and compare the objective function values of solutions gathered from FH and SDTP with NLDN in Table 12. We run the algorithms for five period instances with *low*, *regular*, and *conservative* demand

Table 12: Comparison of wait-and-see decisions and FH

Instance #	Best	Worst	Average
1	5.27%	18.86%	11.17%
2	8.84%	19.99%	13.25%
3	7.55%	18.90%	11.71%
4	4.89%	22.40%	12.57%
5	3.09%	15.16%	9.55%
6	8.27%	16.29%	12.21%
7	7.31%	13.34%	10.61%
8	6.22%	15.84%	11.45%
9	5.29%	20.24%	12.42%
10	3.21%	18.36%	8.99%
11	2.27%	21.35%	12.32%
12	2.27%	17.59%	12.10%
13	6.25%	21.35%	12.91%
14	2.20%	18.41%	10.02%
15	1.24%	15.57%	9.82%
16	8.30%	22.39%	13.23%
17	0.74%	19.53%	10.30%
18	2.81%	18.39%	10.27%
19	3.85%	18.74%	11.24%
20	4.75%	18.10%	11.79%
Best	0.74%		
Worst		22.40%	
Average			11.40%

nodes at each period (i.e., we have 3^5 leaf nodes in total). We generate our instances by randomly sampling 84 (= 7×12) daily demands from the data set of the associated study that consists of demands for 180 days in the planning horizon. Regular demand of a given period (week) is equivalent to the sum of daily demands that coincide with the associated period in the sampled data. Low demand of a given period is obtained by multiplying the regular demand with a uniformly sampled coefficient from [0.7, 0.9], and for conservative demand of a given period, the coefficient is uniformly sampled from [1.05, 1.85] and multiplied by the regular demand. Moreover, the probability of low, regular, and conservative demand nodes are randomly generated, as explained above. In the FH approach, we solve SDTP first to fix here-and-now decisions and use [MIP-WS] at each period to reoptimize wait-and-see decisions. The numerical results show that SDTP with NLDN approach has (on average) an 11.4% optimality gap with respect to FH while the best and the worst gaps are 0.7% and

22.4%, respectively.

2.6 Conclusion and Managerial Implications

In this paper, we proposed *stochastic donation tailoring problem* (SDTP) that takes into account the shelf-life, deferral times, and uncertain demand of blood and aims to minimize the total (expected) operational donation, holding, and scrapping costs while meeting the demand and utilizing *multicomponent apheresis* (MCA) technology. The numerical experiments have shown that utilizing an optimization method for the blood donation scheduling problem as well as considering uncertain demand and wait-and-see donors can be helpful in order to manage blood donations more effectively. Donation organizations can benefit from the presented research from four different aspects.

2.6.1 Importance of Optimization

Utilizing a tailored supply for the uncertain demand is of high importance. MCA is an invaluable tool that revolutionizes blood donation management. However, regardless of its advantages, utilizing MCA significantly increases the number of possible donation patterns. This, in turn, makes the blood donation management which is already a challenging task–due to the limited number of donors, deferral time requirement, limited shelf-life of blood products, and demand uncertainty–a more challenging one. Therefore, optimization methods for viable MCA donation provide significant advantages to donation organizations to manage this challenging problem much better than before. Moreover, in managing blood products, solving an optimization problem gains more importance as people's lives are at issue. In other words, implementing optimization techniques in blood donation management provides a unique opportunity to balance the supply with the demand in an uncertain environment and, more importantly, maximizes the efficiency of this high-cost operation. The proposed optimization method aims to tackle the issues mentioned above for donation organizations within practicable amounts of time while yielding near-optimal solutions.

2.6.2 Importance of Wait-and-see Donors

In a highly unstable demand pattern and its variance, customizability of the supply is very critical, and it highlights the significance of utilizing wait-and-see donors. This fact is also proven by the numerical results provided in this study. When wait-and-see donors were utilized, regardless of seasonality and variance of demand, the overall cost reduction for only here-and-now donors was high. This improvement changed between 15% and 21% on average considering the seasonality and variance of the demand. The donation organizations must show their utmost effort to convince donors to follow flexible wait-and-see donation schemes to achieve a higher quality service. Even though we limit the number of wait-and-see donors in our experiments, more significant improvements would be achieved when this percentage increases, and this must be one of the ultimate goals of donation organizations.

2.6.3 Implementation of Wait-and-see Donors in Real-life

In practice, the actual demand will rarely be equivalent to one of the scenarios in the tree. It is worthwhile to mention that when adjustable donation decisions must be decided immediately after the demand has occurred, FH may not be applicable in practice since reoptimizing the wait-and-see decisions takes several hours when the number of periods in the planning horizon is higher than ten. To this end, the proposed NLDN approach is a tractable and feasible way of selecting the wait-and-see donation schedules according to the realized demand and may be easily implemented by the donation organization according to the SDTP solution at hand. Ultimately, we suggest donation organizations adopt the NLDN approach over the SDTP solution since it is relatively more implementable in practice when demand realizes different than the scenario tree and results in very close solutions to the FH benchmark. Lastly, it is essential to point out that donation organizations may use adjustable decision-making in their routine process because they usually satisfy demand from their donation bank inventory and refill the associated inventory with new donations after the demand has been served. Therefore, organizations have the required flexibility to wait for the demand as long as the donation plan may be promptly executed afterward, given that an extended waiting time for the new plan is not intended.

2.6.4 Effects of Ignoring Uncertainty

The demand of a product is an inherently uncertain parameter, and in the case of blood products, the uncertainty is also affected by several different external factors and unforeseen incidents. Ignoring the uncertainty of blood products would indeed have drastic effects on patient lives. Therefore, it is of high importance for donation organizations to consider demand uncertainty while managing blood donations. Our study also highlights this importance by suggesting a customizable supply concept utilizing wait-and-see donors over here-and-now donors. While here-and-now donors serve the nominal demand, flexible wait-and-see donors tackle critical high-demand nodes if they are realized. This fact have been studied in two distinct settings; one with lower uncertainty and one with higher uncertainly. The results show that when the uncertainty increases, the improvement is more substantial. This is a clear-cut manifestation of the significance of providing more customizable supply patterns using MCA and state-of-the-art optimization methods.

CHAPTER III

BRANCH-AND-PRICE ALGORITHM FOR STOCHASTIC PRODUCTION PLANNING WITH FLEXIBLE MANUFACTURING SYSTEMS AND UNCERTAIN DEMAND

The ongoing pandemic, namely COVID-19, has rendered widespread economic disorder. The deficiencies have delayed production at manufacturers in several industries on the supply side. The effects of disruption were more notable for industries with longer supply chains, especially reaching East Asia. Regarding the demand, sectors can be divided into three categories: i) the ones, like e-commerce companies, that experienced augmented demand; ii) the ones with a plunged demand, like what hotels and restaurants experience; iii) the companies experiencing a roller-coaster-ride business. After mitigation efforts, the economy started recovering, resulting in increased demand. However, regardless of their struggles, the companies have not fully returned to their pre-pandemic levels. One of the strategies to gain resilience in its supply chain and manage the disruptions is to employ flexible/hybrid manufacturing systems. This paper considers a flexible/hybrid manufacturing production setting with typically dedicated machinery to satisfy regular demand and a *flexible manufacturing system* (FMS) to handle surged demand. We model the uncertainty in demand using a scenario-based approach and allow the business to make here-and-now and wait-and-see decisions exploiting the cost-effectiveness of the standard production and responsiveness of the FMS. We propose a branch-and-price algorithm as the solution approach. Our computational analysis shows that this hybrid production setting provides a highly robust response to the uncertainty in demand, even with high fluctuations.

3.1 Introduction

The COVID-19 pandemic caused havoc in all sectors worldwide. Healthcare, hospitality, and tourism were among the most affected, though almost all businesses faced inevitable disruptions. People's behavior has dramatically changed due to concerns and restrictions taking place, and this, in turn, caused several transformations for the business, employees, and consumers. Some of these transformations are relatively positive for certain businesses/people, such as e-commerce activities and customer satisfaction have increased, opportunities for working remotely arises, universities and other institutions have become more proficient in online education, less petroleum usage reduced the oil prices and carbon emissions worldwide, etc. Nevertheless, others were quite negative. Shutdowns and travel restrictions caused many businesses to struggle or even fail. Raw material deficiencies have delayed production at factories in several industries on the supply side, and so this resulted in rising input prices in subsequent industries. People lost their jobs due to the pandemic or had to be furloughed during lockdown phases [89].

On the supply chain side, the effects of disruption were more notable for industries with longer supply chains, especially reaching East Asia. The supply chain disruptions almost immediately started as the outbreak took over China in early 2020. The supply shock was then followed by extreme demand fluctuations globally. Regarding the demand, sectors can be divided into three categories:

1. The ones, like e-commerce companies, that experienced augmented demand
2. The ones with a plunged demand, like what hotels and restaurants experience
3. The companies experiencing a roller-coaster-ride business

In any of these categories, however, the consumers demand low prices as the pandemic took a toll on their household incomes, whereas businesses cannot survive for long without hiking the prices under such a disrupted supply environment.

Businesses have tried to adapt to the "new normal" since the early stages of the pandemic and started employing mitigation strategies to overcome these supply shocks. Some firms switched to local suppliers in an attempt to shorten the supply lines as all critical aspects of a supply chain, such as transportation, storage, and currency exchange rates, are affected by the pandemic. Multisourcing was another option to secure the supply by hedging the potential risks among multiple suppliers. Demand planning/smoothing was employed to reduce the peak demand, which gives the firm an edge to handle surged demand. Also, to deal with uncertainties in supply/demand matching, some firms built up extra inventories to sustain their business through prolonged periods of disruption. Here, the challenge for the firms was to make their supply chains more resilient without a toll on their competitiveness.

One of the strategies to gain resilience in its supply chain and manage the disruptions is to employ flexible/hybrid manufacturing systems. To this end, compared to its alternatives, having flexibility in manufacturing might be more cost-effective as the other options have certain downsides such as increased labor costs in local production, increased holding costs in keeping an extra inventory, and so on. As customer expectations are ever-increasing, manufacturing techniques are also evolving to keep up with those expectations. The concept of mass customization, manufacturing a highly varied product portfolio in a mass production scheme, forces the companies to seek manufacturing systems that are both flexible and can produce high-quality items at a meager cost. This, in turn, highlights the significance of designing *flexible manufacturing systems* (FMSs) that are capable of producing a variety of goods belonging to a specific class. However, the downside of the FMSs is that their initial investment is expensive, and they typically require high maintenance times.

According to [90] the idea of FMS was first proposed by David Williamson in the 1960s under the name 'System 24,' which stands for a machine that operates 24 hours a day without any need for a human operator. However, the definition of FMS, which is widely accepted nowadays, is proposed by [91]. [92] present the structure of FMS, its process, and problem views. Different aspects of flexibility are presented in this study by defining the design and operational problems. Several survey papers there are about FMS. We refer the readers to [93], [94], and [93] for the most recent and fundamental reviews of the papers about FMS.

The most significant advantage of FMSs is to provide versatility to the manufacturing environment in case of rapid changes. It mainly offers two types of flexibility: (i) machine flexibility which refers to the flexibility of machines to perform different operations, and (ii) routing flexibility which refers to the ability to change the order of operations on a part. Even though FMS's adaptability favors them in efforts to reduce response times, reduce delays, increase machine/labor productivity, and hence increase customer satisfaction, they require skilled/flexible labor, extensive initial planning, and possibly higher maintenance costs. Therefore, in most cases, it is necessary to exploit its potential benefits to the full extent; otherwise, the firms might face unnecessary inefficiencies/costs while trying to increase productivity.

[95] discuss robust supply chain strategies in the face of disruption and suggest that companies that deploy contingency plans would be less vulnerable in case of disruption. [96] consider single product procurement with two non-identical suppliers and compare different mitigation strategies such as inventory building, sourcing from the reliable high-cost supplier, and passive acceptance and discuss the optimality of these strategies under different conditions. [97] suggest a network-based modeling methodology to understand how disruptions affect the supply chains, which will lead to developing better mitigation strategies. [98] propose a series of models to study supply disruptions under different scenarios with deterministic and stochastic demand settings. [99] provide a thorough review of the models to deal with potential supply chain risks. [100] consider FMS with operation interruptions and unreliable resources. They propose an anytime graph search algorithm with an objective function that encompasses performance and risk and compare the results with another algorithm in the literature. [101] consider future production demands uncertainty on a maintenance scheduling method for a flexible multistage manufacturing system in multi-specification and small-batch production. The authors propose a load-integrated deterioration model for the flexible manufacturing system, followed by a cost-effective maintenance scheduling model. They minimize the expected total maintenance cost per unit time within the next uncertain production period to determine the optimal preventive maintenance scheme for the system in order to deal with uncertainty in the future production demands. Using the proposed maintenance scheduling model, the total maintenance cost under the full load model and average load model is always lower than that under the full load model.

[102] investigate the scheduling problem in a flexible manufacturing system with routing flexibility under uncertain parts arrival times and machine failures. In order to solve the problem, they use a genetic algorithm-based approach to minimize deadlocks and maximize overall system reliability. Their results demonstrate that the proposed genetic-based algorithm results in the best performance in terms of total profit, system productivity, and machine utilization on a heavily loaded system. [103] investigate scheduling problems for flexible manufacturing systems under uncertain machine failure disruptions, where machine allocations and job scheduling meet production due-date requirements as accurately as possible. They propose a threshold-based scenario that guarantees the due dates will be met in a robust scheduling optimization model. Their solution of a mixed-integer linear program demonstrates superiority in meeting the planned due dates under uncertainty in comparison to standard approaches. They apply their approach in the stamping industry, and the robust scheduling model shows a good performance in achieving the due dates.

[104] present a two-objective mathematical programming model for integrating flow shop scheduling and routing of automated guided vehicles in a flexible manufacturing system under demand, due dates, and processing times uncertainties. Their solution sets the uncertain parameters using fuzzy logic and then uses two meta-heuristic algorithms. On the basis of a dataset from [105], they assessed the efficiency of their solution. [106] propose applying a real options theoretical approach to modeling and analyzing various types of uncertainty involved in an operational environment of a flexible manufacturing system in a marketplace. Using the real options approach, traditional valuation methods that rely on discounted cash flow analysis often overlook investment upside potential. The authors suggest a framework for flexibility planning that incorporates production options and a pricing model for production options. Their model was applied to a refrigerator company that deals with a wide range of products and an uncertain demand.

In this study, we consider multiple companies trying to satisfy the demand for multiple products using a typical production environment. This standard production floor consists of two different machines; (i) *typical manufacturing machines* (TMM) and (ii) a limited number of FMS. A product can be produced on a TMM or an FMS. The production cost and the amount of the product that can be produced on each of them are different. This two-mode setup provides the efficiency of traditional mass manufacturing under stationary demand patterns with a potentially lower cost of production per unit and flexibility under highly volatile demand patterns with a potentially higher cost of production per unit but highly adjustable output.

Contributions of this study can be summarized in threefold. Firstly, to the authors' best knowledge, this is the first study that proposes an optimization-under-uncertainty framework in flexible manufacturing systems literature; *stochastic production planning* (SPP) is the first problem that considers FMSs and TMMs in a manufacturing company and provides resilient solutions against the demand uncertainty. Secondly, we propose a branch-and-price approach that solves the problem for medium-sized instances optimally, and for twenty different cases, while a commercial solver cannot even create an instance of the standard model, we propose a column generation-based approach. To evaluate the performance of the proposed algorithm, we provide an efficient lower bound mechanism for the problem that is obtained by solving the linear programming (LP) relaxation of proposed mixed-integer programming models. The numerical results show that the proposed *column generation* (CG) approach provides (on average) less than a 3% optimality gap for the setting that adopts both FMS and TMM for realistically sized instances. Lastly, regardless of the difficulties due to uncertain demand, we develop effective schedules that improve the operational cost of standard production schemes that do not use FMS by (on average) 14% and 18% for the cases with low and high uncertainty, respectively.

The remainder of the paper is organized as follows. Section 3.2 defines the problem by proposing the mathematical model of the proposed problem. Section 3.3 provides the solution approaches. The numerical experiments are given in Section 3.4. In Section 3.5, we provide the conclusion of the study.

3.2 Problem Definition

In this section, we define the problem formally, list our assumptions, and present the mathematical formulation of SPP. In SPP, we consider a set of companies $N = \{1, \ldots, n\}$ that

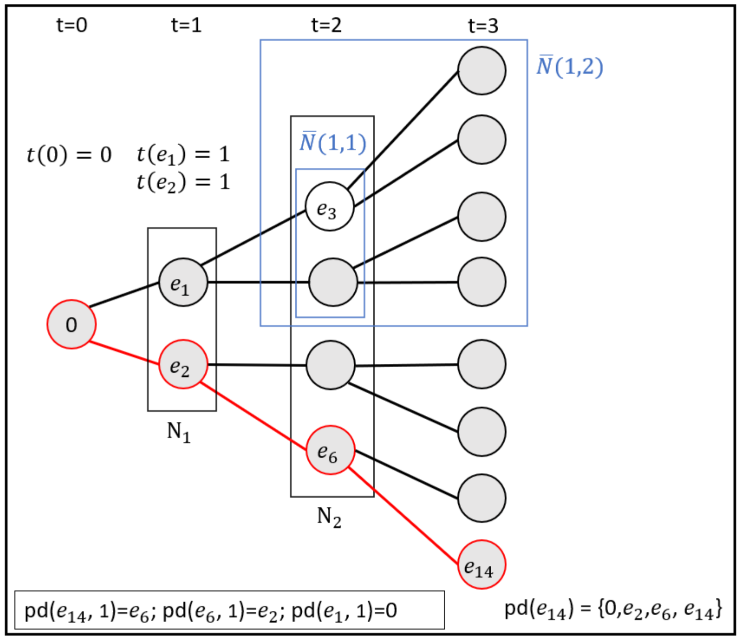

Figure 6: Problem structure of SPP

would like to cooperate in order to reduce their procurement costs. Each company is trying to fulfill the demand for multiple products ($J = \{1, \ldots, R\}$) over a finite planning horizon, T. Moreover, uncertainty in demand is modeled via a scenario tree approach. We consider two types of decision variables: here-and-now and wait-and-see decision variables. Here-and-now decision variables are decided at the beginning of the planning horizon using the typical machines, and wait-and-see decision variables are more situational/flexible and are satisfied utilizing FMSs, and their production is determined/adjusted according to the realizations of the demand in the planning horizon. It is assumed that both TMMs and FMSs are capable of producing all products, and there is a sequence-based setup time between each production. Units of product j that a TMM and an FMS can produce are denoted by a_j and a'_j, respectively. Demand of company n for product j in node e is denoted by d_{nej}. Each company meets the demand by ordering the product from a common supplier. The supplier may either manufacture or order from a third party to meet the demand of the companies. A fixed cost is incurred with each production/order, and a variable cost is incurred depending on the amount of production/order.

The fixed production cost of producing product j for TMMs for period t is denoted by

A_{tj}, while the unit variable cost for TMMs is denoted by v_{tj}. The fixed and variable costs for FMSs are denoted by A'_{tj} and v'_{tj}, respectively. When the product is ordered before the realization of the demand, the cost of keeping inventory is incurred up until the actual time of the demand, and the cost of keeping a unit product in inventory in each period for product j is denoted by h_j. The supplier has a certain production capacity for each period, and this production capacity is indicated by C_j. The supplier also has a certain inventory capacity for storing items after each period, and this inventory capacity is indicated by S. The demand of the grand coalition, where all the companies come together, in node e is indicated by d_{nej}. Finally, we assume that the unit outsourcing cost of product j in each period is denoted by β_j. The nomenclature for the SPP is presented in Table 13.

Table 13: Nomenclature for SPP

Sets	
N	set of companies ($\{1, 2, \ldots, W\}$) – indexed by n
J	set of products ($\{1, 2, \ldots, R\}$) – indexed by j
K	set of TMMs ($\{1, 2, \ldots, M\}$) – indexed by k
K'	set of FMSs ($\{1, 2, \ldots, M'\}$) – indexed by k'
$\bar{K}$	set of machines ($\bar{K} = K \cup K'$) – indexed by $\bar{k}$
T	set of time periods in the planning horizon ($\{1, 2, ..., L\}$) – indexed by t
E	set of demand scenario or node indexes ($\{1, 2, ..., S\}$) – indexed by e
N_t	set of nodes in period $t \in T$
$\bar{N}(e, l)$	set of children nodes of e in the next l periods $\cup$ $\{e\}$
Parameters	
a_j	units of product j that each TMM produces
a'_j	units of product j that each FMS produces
$s_{jj'}$	setup time between product j and j' on TMM
$s'_{jj'}$	setup time between product j and j' on FMS
d_{nej}	demand of company n for product j in node e
v_{tj}	variable cost of production of product j in period t by a TMM
v'_{tj}	variable cost of production of product j in period t by an FMS
A_{tj}	fixed cost of production of product j in period t by a TMM
A'_{tj}	fixed cost of production of product j in period t by an FMS
h_j	unit holding cost of product j
β_j	unit outsourcing cost of product j
C	production capacity of TMM during the planning horizon
C'	production capacity of FMS during the planning horizon
S	inventory capacity per period
R	a very large number
pd$(e, 1)$	immediate predecessor of node e
pd(e)	nodes in the path from the source node to e
pr(e)	probability of scenarios in path pd(e) being realized
t(e)	period of node e
Decision variables	
y_{ktj}	1 if there is a production of TMM for product j on machine k in period t & 0 otherwise
$x_{k'ej}$	1 if there is a production of FMS for product j on machine k' in node e & 0 otherwise
I_{ej}	inventory of product j at the end of node e
P_{ej}	amount of product j outsourced at the end of node e

In Figure 6, we represent a general scenario tree with the notations used in SPP. This figure provides a tangible representation of the demand tree structure. For example, the immediate predecessor of node e_6 is node $e_2 = \mathrm{pd}(e_6, 1)$. Also, set of children of node e_1 in the next period is presented by $\bar{N}(e_1, 1)$ and for the next two periods is presented by $\bar{N}(e_1, 2)$. Each node $e \in N$ in the scenario tree denotes a demand realization at period $t(e)$ with its associated probability $\mathrm{pr}(e)$, and each path from the root node (0) to a leaf node $e \in N$ is referred to as a *scenario* of the tree, i.e., denoted by $\mathrm{pd}(e_{14}) = \{0, e_2, e_6, e_{14}\}$, where N_T denotes the set of nodes in the last period of the planning horizon. SPP can be formulated considering both TMM and FMS (MIP). It should be noted that in MIP, production decisions are divided into two groups, namely, here-and-now ($\boldsymbol{y}$) that is done by TMMs and are scheduled at the beginning of the planning horizon and are independent of the scenario realizations, and scenario-specific wait-and-see ($\boldsymbol{x}$) decisions that are done by FMSs.

MIP:

$$\begin{aligned}
\min \sum_{e \in N_L} \mathrm{pr}(e) \sum_{e' \in \mathrm{pd}(e)} \Bigg(& \sum_j \sum_{k'} v'_{t(e')j} a'_j x_{k'e'j} \\
& + \sum_j \sum_{k'} A'_{t(e')j} x_{k'e'j} + \sum_j \Big(h_j I_{e'j} + \beta_j B_{e'j} \Big) \Bigg) \\
& + \sum_t \sum_j \sum_k \Big(v_{tj} a_j y_{ktj} + A_{tj} y_{ktj} \Big) && (3.1)
\end{aligned}$$

$$\text{s.t. } (R-1) x_{k'ej} + \sum_{j'} \sum_{e' \in \bar{N}(e, s_{jj'}-1)} x_{k'e'j'} \leq R, \qquad \forall j, e, k' \qquad (3.2)$$

$$(R-1) y_{ktj} + \sum_{j'} \sum_{t'=t}^{t+s_{ii'}-1} y_{kt'j'} \leq R \qquad \forall j, k, t \qquad (3.3)$$

$$\sum_j \sum_k \sum_t a_j y_{ktj} \leq C \qquad (3.4)$$

$$\sum_j \sum_e \sum_{k'} a'_j x_{k'ej} \leq C' \qquad (3.5)$$

$$\sum_{e \in N_t} \sum_j I_{ej} \leq S, \qquad \forall t \qquad (3.6)$$

$$\sum_{e \in N_t} B_{ej} \leq \mu_j, \qquad \forall t, j \qquad (3.7)$$

$$B_{\mathrm{pd}(e,1)j} - I_{ej} - I_{\mathrm{pd}(e,1)j}$$
$$- \sum_k a_j y_{kt(e)j} - \sum_{k'} a'_j x_{k'ej} + \sum_n d_{nej} - B_{ej} = 0 \qquad \forall e, j \qquad (3.8)$$

$$x_{k'ej}, y_{ktj} \in \{0, 1\} \qquad \forall e, t, j, k, k' \qquad (3.9)$$

$$I_{ej}, B_{ej} \geq 0, \qquad \forall e, j \qquad (3.10)$$

In this model, the objective (3.1) is to minimize the sum of the expected production that is done by TMM and FMS, inventory, and outsourcing costs. Constraints (3.2) enforce the setup times of FMSs, and constraints (3.3) enforce the setup times of TMMs. The total production capacity of TMMs and FMSs are enforced by constraints (3.4) and (3.5), respectively. While constraints (3.6) ensure the total inventory capacity for each period, the total amount that can be outsourced for each product in each period is ensured by constraints (3.7). Constraints (3.8) ensure the inventory balance for each product and the time period overall scenarios. Constraints (3.9) and (3.10) are binary and non-negativity constraints, respectively.

3.3 Branch-and-price Algorithm

Solving MIP is not an easy task for large instances due to the size of the problem and long planning horizons. In this section, we present our approach to solve the problem. An LP relaxation of the restricted master problem is presented in Section 3.3.1, along with the associated dual information. Utilizing the pricing problem presented in Section 3.3.2 the optimal solution in a branching node is obtained. Following that, a column generation approach is used for each node recursively, as explained in Section 3.3.3. Section 3.3.4 explains how the bases are updated if not all the variables are integers.

3.3.1 Reduced Master Problem

LP-relaxation of *restricted master problem* (RMP), in which there are two types of columns, each representing the production schedule of TMMs and FMSs, is presented in this section. The *reduced master problem* RMP is given as follows where decision variable y_l represents the TMM productions which follow here-and-now schedule l, and x_m represents the FMS productions that follow wait-and-see schedule m, $\tilde{c}_l$ is the total donation cost of TMM schedule l while $\hat{c}_m$ is the total donation cost of FMS schedule m. Moreover, $\theta^{l}_{jt(e)}$ is the total number of product j that is produced in time period $t(e)$ by production schedule l of a TMM, and λ^{m}_{ej} is the total number product j that is produced in node e if an FMS follows schedule m.

RMP:

$$\min \sum_{e \in N_L} \mathrm{pr}(e) \left(\sum_{e' \in \mathrm{pd}(e)} \sum_{j} h_j I_{e'j} + \beta_j B_{e'j} \right) + \sum_{m} \hat{c}_m x_m + \sum_{l} \tilde{c}_l y_l \tag{3.11}$$

$$\text{s.t.} \quad \sum_{e \in N_t} \sum_{j} I_{ej} \leq S \qquad \forall t \tag{3.12}$$

$$\sum_{e \in N_t} B_{ej} \leq \mu_j \qquad \forall t, j \tag{3.13}$$

$$B_{\mathrm{pd}(e,1)j} + I_{ej} = I_{\mathrm{pd}(e,1)j} - \sum_{n} d_{nej} + B_{ej} + \sum_{m} \lambda^{m}_{ej} x_m + \sum_{l} \theta^{l}_{t(e)j} y_l \qquad \forall e, j \tag{3.14}$$

$$\sum_{j} \sum_{m} \sum_{e} \lambda^{m}_{ej} x_m \leq C \tag{3.15}$$

$$\sum_{j} \sum_{l} \sum_{t} \theta^{l}_{t(e)j} y_l \leq C' \tag{3.16}$$

$$\sum_{l} y_l \leq M \tag{3.17}$$

$$\sum_{l} x_m \leq M' \tag{3.18}$$

$$y_l \geq 0, \; x_m \geq 0 \qquad \forall l, m \tag{3.19}$$

$$I_{ej}, B_{ej} \geq 0 \qquad \forall e, j \tag{3.20}$$

In RMP, the objective (3.11) is to minimize the columns' total (expected) cost, including the sum of productions by TMM and FMS, inventory holding, and outsourcing. Constraints (3.12) and (3.13) ensure the inventory and outsourcing capacities, respectively. Constraints (3.14) ensure the inventory balance. Production capacities of FMSs and TMMs are enforced by constraints (3.15) and (3.16), respectively. While constraints (3.17) enforce that the total TMM columns must be less than or equal to the number of TMMs, constraints (3.18) ensure that the total FMS columns must be less than or equal to the number of FMSs. It should be noted that the dual variables obtained from constraints (3.12) - (3.18) are denoted by δ_t, γ_{tj}, η_{ej}, ι, and ζ, respectively.

3.3.2 Pricing Problem and Solution Algorithm

In essence, the pricing problem (or Subproblem) seeks to identify the column with the lowest possible reduced cost to be added to RMP. After obtaining the dual variables from the RMP, corresponding subproblems (PP-y and PP-x) are solved, and profitable columns are added to the RMP. The sub-problems that must be solved for TMMs and FMSs are denoted by PP-y and PP-x, respectively. *Subproblem* PP-y is provided below:

PP-y:

$$\min_{q} \quad \sum_{t}\sum_{j} q_{jt}(a_j v_{tj} + A_{tj} - \sum_{e\in N_t} a_j \eta_{ej}) - \sum_{t} \delta_t - \iota \tag{3.21}$$

$$\text{s.t.} \quad (M-1)q_{jt} + \sum_{j'} \sum_{t'=t}^{t+s_{ii'}-1} q_{j't'} \leq M \qquad \forall j,t \tag{3.22}$$

$$q_{jt} \in \{0,1\} \qquad \forall j,t \tag{3.23}$$

In PP-y, the objective function (3.21) is minimizing the total production cost of a TMM, and constraints (3.22) enforce the setup times between two consecutive productions of a TMM. After solving PP-y, the following calculations must be done: $\theta^l_{tj} = a_j q_{tj}$ and $\tilde{c}_l = \sum_j \sum_t q_{tj}(a_j v_{tj} + A_t)$. *Subproblem* PP-x is given as follows:

PP-x:

$$\begin{aligned} \min_{z} \quad & \sum_{e} \mathrm{pr}(e) \sum_{j} \Big(z_{ej}(a'_j v'_{t(e)j} + A'_{t(e)j}) \Big) \\ & - (\sum_{j}\sum_{e} a'_j z_{ej} \eta_{ej}) - \sum_{t} \delta_t - \iota \end{aligned} \tag{3.24}$$

$$\text{s.t.} \ (M-1)z_{ej} + \sum_{j'} \sum_{e' \in \bar{N}(e, s_{jj'}-1)} z_{e'j'} \leq M \qquad \forall e,j \tag{3.25}$$

$$z_{ej} \in \{0,1\} \qquad \forall e,j \tag{3.26}$$

In PP-X, the objective function (3.24) is minimizing the total production cost of an FMS, and constraints (3.25) enforce the setup times between two consecutive production of an FMS. After solving PP-x, we have the following calculations: $\lambda_{ej}^{m} = a'_j z_{je}$ and $\hat{c}_l = \sum_e pr(e) \sum_j z_{ej}(a'_j v'_{t(e)j} + A'_{t(e)j})$.

3.3.3 Column Generation Algorithm

With an excessive number of decision variables such as RMP, column generation can be useful for solving linear discrete optimization problems. This algorithm starts with solving the LP-relaxation of *restricted master problem* (RMP), in which there are two types of columns, each representing the production schedule of TMMs and FMSs. Following that, after obtaining the dual variables from the RMP, corresponding subproblems (PP-y and PP-x) are solved, and profitable columns are added to the RMP. These steps are continued until all profitable columns are added to RMP. If the solution of LP-relaxation of RMP is not fractional, the optimality is guaranteed; otherwise, the branching on the fractional decision variables continues.

3.3.4 Branch-and-price Tree

For the purpose of generating an integer solution, we have to adopt branching. We start the branching with the most fractional x_m variable, i.e., its decimal part is the closest to 0.5. In case all the x_m variables are integer, we continue the branching with y_l variables until all the decision variables are integer. It must be noted that instead of directly branching on x_m and y_l variables, we branch on the production schedules of FMS and TMM, respectively. More specifically, for an FMS schedule, we branch on the production schedule of product j in node e; for a TMM schedule, we branch on the production schedule of product j in time period t.

3.4 Computational Experiments

In this section, we present the results of a numerical study conducted based on random instances motivated by real-life data. Our numerical study aims to evaluate the performance of the proposed method in terms of solution quality. The computational experiments are carried out on a 64-bit Windows Server with two 2.4 GHz Intel Xeon CPUs and 24 GB RAM. The algorithms are implemented using Python Programming Language and GUROBI Solver version 9.1.1. Throughout this section, a period corresponds to a month, and we solve the problem for a 12-month planning horizon, which is the largest dimension that can be solved in possible CPU times.

The proposed mathematical model, namely, MIP, cannot be solved because of memory problems. Even for the branch-and-price algorithm, there are many decision variables; therefore, for realistically-sized instances, instead of continuing branching, we solve the column generation in node 0, and when there are no profitable columns to be added to the column pool, we some the RMP with binary decision variables. Even in this case, we limit the CPU time of the proposed algorithm to 24 hours. In order to investigate the performance of the solutions of the column generation-based heuristics, we report the optimality gaps with respect to lower bounds in two different cases of lower and higher uncertainty levels. The lower bounds in this study are obtained by solving the *linear programming* (LP) relaxation of MIP.

3.4.1 Lower Uncertainty Experiments

The optimality gap of wait-and-see decision making (using FMS) and the improvement of having wait-and-see production schedules over only here-and-now (TMMs) are presented in Table 14. In Table 14, the first column represents the instance number, the second column represents the optimality gap of the proposed algorithm w.r.t. LP-relaxation of MIP, and the last column represents the improvement in the objective function value of MIP when the wait-and-see schedules are included over utilizing only TMMs. Notice that the system benefits from the wait-and-see production plans because they yield scenario-based inventory management flexibility to the problem. On average, the proposed column generation-based heuristic provides only 2.68% gap w.r.t. the lower bound while providing 0.72% and 4.19% gaps for the best- and the worst-case instances, respectively. Moreover, including wait-and-see schedules decreases the total cost over here-and-now only schedules case by 13.41% on average, while the lowest and the most remarkable improvements are 6.00% and 21.03%, respectively, for the reported instances.

Table 14: Optimality gaps and improvements for here-and-now and wait-and-see production schedules under low uncertainty levels

Instance	Gap	Improvement
1	3.31%	13.65%
2	3.03%	15.76%
3	3.19%	17.48%
4	2.96%	14.50%
5	3.32%	15.80%
6	3.97%	19.24%
7	0.73%	21.03%
8	2.90%	14.78%
9	4.13%	18.98%
10	3.81%	15.72%
11	3.07%	13.57%
12	1.93%	8.39%
13	1.57%	8.69%
14	0.72%	8.90%
15	4.19%	6.00%
16	2.10%	11.78%
17	1.78%	10.87%
18	2.32%	10.76%
19	2.17%	10.35%
20	2.37%	11.99%
Average	2.68%	13.41%
Best	0.72%	21.03%
Worst	4.19%	6.00%

3.4.2 Higher Uncertainty Experiments

In this section, we investigate the performance of the proposed algorithm when the mean of the high-demand nodes is more conservative. The nominal demand values at each period and variation in node demand values at high demand nodes are higher in the high uncertainty setting than they were in the previous experiment. As we have pointed out before, TMMs serve the nominal demand while FMSs tackle critical high-demand nodes if they are realized. Table 15 provides information about the optimality gap with respect to the lower bound and improvement of considering FMS production on only having TMSs.

Table 15: Optimality gaps and improvements for here-and-now and wait-and-see production schedules under high uncertainty levels

Instance	Gap	Improvement
1	3.48%	21.83%
2	4.26%	24.07%
3	3.78%	21.42%
4	2.18%	24.52%
5	1.08%	25.38%
6	4.44%	24.12%
7	1.92%	27.51%
8	2.99%	18.94%
9	5.15%	26.29%
10	5.21%	20.08%
11	3.22%	16.37%
12	2.02%	11.38%
13	1.51%	13.79%
14	1.51%	13.79%
15	1.70%	9.62%
16	2.02%	15.84%
17	1.77%	12.37%
18	7.38%	9.59%
19	2.30%	12.05%
20	2.42%	17.40%
Average	3.19%	18.32%
Best	1.08%	27.51%
Worst	7.38%	9.59%

In Table 15, the results for the instances with here-and-now and wait-and-see donors with high uncertainty are presented. The numerical results show that like the instances with low uncertainty, the results prove the efficacy of the proposed algorithm. On average, the algorithm provides only 3% gaps while improving the results with only here-and-now donors for 18%. While the best and the worst gaps are 1% and 8%, those numbers for the improvement are 28% and 10%, respectively.

3.5 Conclusion

After the COVID-19 outbreak, many companies have been forced to deal with demand disruptions. Some companies built up extra inventories to gain resilience against prolonged periods of disruption. One of the strategies to gain resilience in its supply chain and manage the disruptions is to employ flexible/hybrid manufacturing systems. To this end, in this study, we propose *stochastic production planning* (SPP) problem that takes into account the uncertain demand of products in hybrid manufacturing systems that takes advantage of a *flexible manufacturing system* (FMS) and aims to minimize the total (expected) production, holding, and outsourcing costs. We model the uncertainty in demand using a scenario tree approach. SPP is the first optimization model that yields a hybrid scheme for producing by providing resilient solutions against demand uncertainty. Utilizing FMS and *typical manufacturing machines* (TMM) provides more flexible production schedules since, based on the realized values of demand over time, FMS adjust their production schedules. Moreover, we propose a *column generation* (CG) based heuristic that solves the problem in less than 24 hours for realistically sized instances while a commercial solver cannot even create an instance of the standard model. The numerical results show that the proposed CG approach yields around 3% (average) optimality gap for realistically sized instances. Last but not least, we develop effective hybrid production schedules that improve the operational cost of a standard production scheme that uses only TMM by 14% on average for the cases with low uncertainty and by 8% for the cases with higher uncertainty.

CHAPTER IV

LAST-MILE DELIVERY OF GROCERIES BY MEANS OF TWO FLEETS OF VEHICLES WITH SYNCHRONIZATION

Due to the increasing rate of urbanization and resulting tendency toward utilizing e-commerce in grocery delivery in cities, the traffic congestion in urban areas is aggravating. Therefore, some mitigating actions must be taken in order to hedge adverse health issues associated with augmented traffic congestion and air pollution. Using lower-emission vehicles in inner-city areas is one potential solution direction though due to their limited capacities, a thorough transformation of city logistics to these vehicles seems not practical. Therefore, some larger deliveries are still supposed to be delivered by larger vehicles. It is challenging to manage these two types of fleets in an urban setting due to capacity limitations, tight delivery windows, and other planning constraints. Moreover, by virtue of integrating planning, it is possible to replenish smaller-sized trucks from the larger-sized trucks' inventory without having to return to a depot location. In this study, we propose a two-echelon vehicle routing problem (2E-VRP) under consideration of a heterogeneous fleet of vehicles and different customer types. In our model, unlike the previous studies in the literature, not only do the large vehicles visit the pre-assigned points, called satellites, to refill the smaller vehicles, but they also deliver items to the customers. Smaller vehicles, on the other hand, are responsible for the customers with small size demands and can get refilled whether at the depots or at satellites. We propose a branch-and-price algorithm as the solution approach and obtain promising results in comprehensive numerical studies that prove its versatility.

4.1 Introduction

With more than 68% of the world's population expected to live in urban areas by 2050, ongoing urbanization continues to reshape our cities and alters our way of life [107]. At the same time, the current Covid-19 pandemic and the associated mobility restrictions have changed consumer lifestyles over recent years, further accentuating the steady growth in e-commerce and grocery deliveries within cities [108]. The combination of these developments puts a strain on the available infrastructure in urban areas by increasing the total number of freight movements, aggravating traffic congestion as well as air and noise pollution [109, 110]. Adverse health effects linked to this pollution demand the implementation of appropriate countermeasures that reduce the number of vehicles and mitigate the environmental impact of logistics within cities [111].

One possible solution direction, in this context, is the use of often smaller low or zero-emission vehicles, denoted by SV in this study, such as small electric trucks or cargo bikes, within inner-city areas [112]. Logistics providers that aim to switch to these SVs face substantial challenges hindering this transition due to these vehicles' limited range and capacity. Certain deliveries, in particular larger ones, thus, still need to be transported with larger-sized trucks, denoted by BV in this study, which omit more CO_2. Managing these two types of fleets in an urban setting under consideration of capacity limitations, generally tight delivery time windows, and other planning restrictions is challenging. At the same time, an integrated planning approach presents opportunities by allowing to replenish the smaller-sized vehicles from the inventory of the larger-sized trucks without having to return to a depot location [113]. By synchronizing planning decisions and using big vehicles as moving depots for the smaller low emission vehicles, distribution companies can reduce the overall travel distance and improve capacity utilization. Planning and decision-making approaches should thus aim to incorporate these considerations in order to facilitate the logistics transition within urban environments.

In this context, this paper considers a *two-echelon vehicle routing problem* (2E-VRP) with time windows in a time-expanded network incorporating two types of vehicles responsible for two types of deliveries. The problem is formulated mathematically and a branch-and-price algorithm is proposed in order to solve more realistic instance sizes. The remainder of the paper is organized as follows. Section 2 provides the literature survey. Section 3 defines the problem by proposing the mathematical formulation of the problem. Section 4 provides the solution approaches. The numerical experiments are given in Section 5. In Section 6, we provide the conclusion of the study.

4.2 Literature Review

The continuous rise in e-commerce and the corresponding development of new city logistics concepts over recent years has also sparked interest in the research community, resulting in a growing body of scientific literature on the topic of urban logistics [114]. As city logistics is a multidisciplinary field trying to tackle the negative impacts of urban freight, many definitions of city logistics exist and other terms, such as urban (freight) distribution, last-mile logistics, urban logistics, or city distribution, may be used interchangeably ([115, 116, 117, 118]). Common to all these terms and definitions is the focus on finding efficient and effective ways of transporting goods in urban areas, while considering the adverse effects on congestion, safety, and the environment [119].

Over the last few years there has been an upward trend for utilizing delivery services for grocery items due to several reasons such as easier accessibility of the ingredients, guaranteed freshness and safety, enhanced customer satisfaction and better inventory management.This increased demand for e-commerce delivery has resulted in a sundry of research in the context of urban logistics [114]. In this section, we discuss some related studies and provide an analysis of the main concepts as well as highlighting the research gap at the end of this section.

As city logistics is a multidisciplinary field trying to tackle the negative impacts of urban freight, there are many definitions of city logistics, but common to all is that city logistics is about finding efficient and effective ways to transport goods in urban areas while considering the adverse effects on congestion, safety, and the environment [119]. City logistics is characterized by the explicit recognition that transporting goods in urban areas affects the lives of both the people in those urban areas and the goods being transported. City logistics is also referred to as urban (freight) distribution, last-mile logistics, urban logistics, or city distribution (for more discussions see, e.g., [115, 116, 117, 118]). The trend toward an on-demand economy and e-commerce is driving cities to take the freight into account with their planning processes [120, 121]. An overview and classification of these projects are presented in [122] and, more recently, in [123].

Different methods have been utilized in modeling city logistics. According to [124], two families of modeling approaches exist in city logistics literature: (i) systemic models to evaluate the impact of modifications in the flows; (ii) operational models that improve the flow management. Generally, these models consist of three different steps, namely, trip generation: the trips are estimated or derived from the economic activities in the city [125, 126], distance calculation, distances for the different trips generated are calculated via transport modelling or simulation [127, 128], and evaluation: a set of economic, environmental and/or social metrics is constructed to compare the situation as is to the proposed modifications [127, 129]. This project seeks to follow these three stages by creating trips, calculating distances, and evaluating the model with the objective of maximizing the profit that can be gain by satisfying the demand of the customers.

The deteriorating effects that freight transpiration may have on the urban environment on one hand, and the constraints such as reduced access for the vehicles within cities and deliveries with tight time-windows on the other hand, has changed the distribution patterns in city logistics [130]. One of the most commonly seen designs for handling and reducing the many freight vehicles going into cities, each delivering small quantities per drop, is to consolidate this fragmented volume at the border of the city. Then from these centers, the freight is forwarded into the city with clean and highly utilized vehicles [131, 124, 132, 117].

2E-VRP deals with more than one vehicle fleet on two echelons, and has been formally introduced in [133], [134], and [135]. In 2E-VRP, the first echelon vehicles transport goods between depots (warehouses) and satellites, which are, in general, located along the border between echelons. Satellites are used to load goods from first echelon vehicles into smaller second echelon vehicles that match customers' requirements. Next, the goods are delivered from the satellites to the customers by the second echelon vehicles. Different variants of 2E-VRP have been addressed in the literature. In this study, we mainly focus on the studies that are related to ours from different perspectives, namely, time windows, number of depots, and solution approaches. We refer the readers to the recent literature review by [136] for more details on 2E-VRP models.

Time windows are considered in the context of 2E-VRP in different ways. Most of the studies in this field, consider hard constraints for the deliveries (see for example, [137, 138, 139]); the earliest and the latest times that each delivery must be done are incorporated into the models. Flexible soft constraints are also considered for time windows [140]. In this case, when a customer's soft time window is exceeded, a penalty cost is incurred. In this study, we consider hard time windows in a time expanded network. To the best of author' knowledge, this is the first study that considers a time expanded network in a 2E-VRP problem, which can handle the time windows properly.

A typical extension of the 2E-VRP involves including multiple depots, where each depot would have its own set of first echelon vehicles. While in some studies, each depot is responsible for specific commodities [141], others consider the depots that are capable of dispatching different commodities [142]. The idea of using satellites as consolidation centers is introduced by [143]. They address planning and operation issues arising in city logistics, and investigate possible organizational and technical frameworks for an integrated management of city logistics. In this study, we analyze multiple depots from which multiple commodities are dispatched. Unlike the most of the studies in the literature, in our proposed model, SVs are not the set of vehicles that do the delivery to the costumers. BVs are responsible for delivering the items from depots to the customers with large demands (courier delivery) and the ones with small demands (parcel delivery). Moreover, BVs serve as moving depots for the SVs. SVs, on the other hand, are responsible for delivering parcels that they pick up from a depot or from a BV at a satellite point.

The planning of these types of systems is challenging due to delivery time windows and synchronisation considerations between the different types of vehicles [113]. Moreover, planning of a 2E-VRP gets more challenging when vehicles of the two echelons are allowed to deliver goods and there can be loading/unloading between the second/first echelon vehicles. Therefore, the literature on optimization methods addressing such systems in their wholeness is limited, because they are usually decomposed into a sequence of single-echelon distribution cases [144]. [114] propose preassigning all the customers to either the first echelon or the second echelon by dividing the regions to inside of the inner-city center and outside of it.

Highlighting the problems with that approach especially with the cities in the boarderline, [145] generalize the problem that decides on the customers near the boarderline. In contrast to what they propose, instead of preassigning the customers to the echelons strictly, we classify the costumers into two categories, namely parcel customers and courier customers. The demand of the parcel customers can be satisfied by both the BVs and SVs while courier customers' demands can only be satisfied by BVs. Moreover, in the proposed study, unlike the previous studies, the BVs do not only visit the satellite points to refill the SVs, but they also deliver items to the customers.

Different heuristic algorithms are proposed for 2E-VRP. Most of the research in this context propose both single solution-based (see for example, [146, 147, 148, 149, 142, 150]) and population-based (see for example, [151, 152, 153, 154, 155]) heuristics as solution methods [136]. [135] present a family of multi-start heuristics based on separating the depot-to-satellite transfer and the satellite-to-customer delivery. [156] propose a *large neighborhood search* (LNS) metaheuristic as well as an exact mathematical programming algorithm that uses decomposition techniques for enumerating promising first-level solutions, coupled with bounding functions and routes for second-level paths.

Exact algorithms and fast lower bounds are also proposed in the literature [134]. [133] propose a decomposition and an integral path approach for 2E-VRP. By demonstrating that the upper bounds presented by [133] may not be correct for the instances with more one satellites, [157] present a branch-and-cut algorithm for the symmetric version of 2E-VRP based on an edge flow model that is a relaxation and provides a valid lower bound. [158] adapt the known *vehicle routing problem* VRP inequalities to the two-echelon formulation and their proposed algorithm is effective in solving instances with up to two satellites and 32 customers. [159] propose five different valid inequalities for a 2E-VRP in which the demands of the customers are satisfied by second-echelon vehicles that leave the satellites. Their proposed method is effective for instances with 40 customers and four satellites.

Our study distinguishes from discussed studies focusing on 2E-VRP in twofold: i) We are the first to propose the two-echelon multi-trip selective capacitated vehicle routing problem under consideration of a heterogeneous fleet of vehicles and different customer type. In other words, in our model, unlike the previous studies, not only do the BVs visit the satellite points to refill the Svs, but they also deliver items to the customers. ii) We propose a branch-and-price algorithm that can solve the instances with up to ... customers and ... satellites, where commercial solvers fail to even generate the problem.

4.3 Problem Definition

In this section, we describe the scope of the problem in detail and present our notation and formulation. This study considers a two-echelon selective multiple trip vehicle routing problem with satellite synchronization and time windows. The main objective of the presented research is to satisfy as many demands of the customers as possible within the desired time window while minimizing the total transportation cost. Therefore, it is a selective VRP, and all orders/demands of the customers do not have to be satisfied. Planners have the right to accept or reject the orders. We classify customer demands into two groups, courier and parcel, based on the total volume of items they demand with corresponding sets of customer nodes V_c^1 and V_c^2. The customers' demands are considered deterministic and received at the beginning of each planning horizon. We consider a daily planning horizon between 08:00 and 22:00, divide this timetable into 30 minutes time periods and model the problem using a time-expanded network. However, we also consider instances with fewer and more time periods for benchmarking purposes. There are two homogeneous fleets of vehicles, big vehicles (trucks) K_1 and small vehicles (cargo bikes) K_2 based on their origins, V_o^1 and V_o^2 with corresponding inventory capacities Q_1 and Q_2. There two main differences between these vehicle types. The primal one is the cost of using them and their CO_2 emissions. The cargo bikes are less costly to utilize and more environmentally friendly. On the other hand, trucks consume fuel and emit significantly more CO_2, and they incur additional costs for entering the city center. However, the second main difference is that the total volume that cargo bikes can carry is way less than that of the trucks. Therefore, an order with items with a total volume larger than the capacity of the cargo bikes can only be satisfied with trucks. However, both trucks and cargo bikes can satisfy the customers with parcel demand. The trucks can carry a large inventory to satisfy all customers they visit over the planning horizon. Moreover, we consider satellite/drop-off locations V_s where trucks and cargo bikes can meet, and the cargo bikes can replenish their inventory by getting items from the trucks. These locations can be considered as parking lots or any other available spot in the city, where both trucks and bikes can stop by and stay for some time while cargo bikes replenish their inventory. There is no storage in the satellites; thus, exact synchronization is needed between the trucks and cargo bikes at the satellite nodes.

All vehicles start their journey from their origins, go to any available depot, fill their inventory, and make deliveries. As stated before, trucks have large enough inventory and do not need to refill it. However, cargo bikes can visit any depot or a satellite to replenish their inventory throughout the day if required. Finally, trucks and cargo bikes can make multiple trips between depots, satellites, and customers, and they have to go back to their origins at the end of the day.

The mathematical formulation of the problem is defined on a directed graph. Moreover, we expand this network with time and generate copies of all nodes for each discrete time step in the planning horizon, allowing us to omit time indices in our variables and easily control synchronization. However, solving the problem on a graph that contains multiple copies of each location is computationally challenging. Therefore, we preprocess our graph by removing the copies of the nodes if they are not essential for modeling the problem (e.g., customers place their orders for a specific time, and the package delivery can only be made at that time. Therefore, adding copies of the nodes other than those corresponding to the time unit in which the customers want to receive packages is unnecessary). We provide an example of the time-expanded network graph in 7. Green and blue circles are the customer nodes with demands in the third and fourth time units accordingly. Considering they can be visited only in those time units, we remove the unnecessary copies of these nodes from the graph.

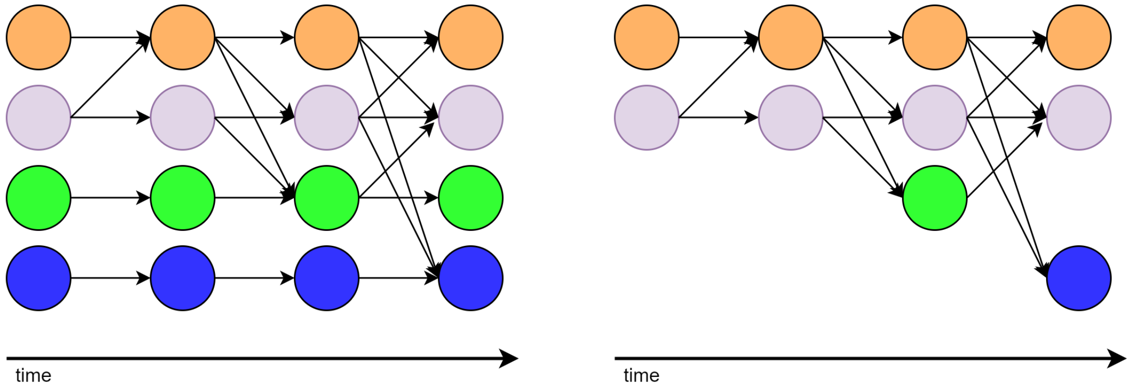

Figure 7: Example time-expanded network graph — Before (left) and after (right) preprocessing nodes.

The final form of the graph after preprocessing is $G = (V, E)$ with $V = V_o \cup V_d \cup V_c \cup V_s$ and $E = \{(i,j)|i \in V_o, j \in V_d)\} \cup \{(i,j)|i,j \in V_d \cup V_s \cup V_c\} \cup \{(i,j)|i \in V_d, j \in V_o\}$. We provide this notation in detail in Table 16.

Table 16: Nomenclature for 2E-VRP

Sets	
V	set of all nodes
V_o	set of origin nodes
V_d	set of depot nodes
V_s	set of satellites/drop-off nodes
V_c	set of customer nodes
V_{o_t}	set of origin nodes at time t
V_{d_t}	set of depot nodes at time t
$\bar{V}$	set of all nodes except the first and the last time period
K	set of all vehicles
K_l	set of vehicles of type l. For BVs, $l = 1$, and for SVs, $l = 2$
T	set of time periods
N	set of items
Parameters	
M	significantly a large number
d_i^m	demand for product m in node i
p^m	profit per unit of item m
c_{ij}^l	cost of traversing arc (i,j) by a vehicle of type l
α_{ij}	1, if there is an arc from node i to j; 0, otherwise
v^m	volume of product m
Q_l	capacity of vehicle type l
Decision variables	
x_{ijk}	1 if vehicle k arrives to node j from node i; 0, otherwise
I_{jk}	total inventory level/the volume of load of vehicle k before serving node j

[MIP]

$$\max \quad \sum_{i\in V}\sum_{j\in V_c}\sum_{k\in K}\sum_{m\in N} p^m d_j^m x_{ijk} - \sum_{l\in\{1,2\}}\sum_{k\in K_l}\sum_{i,j\in V} c_{ij}^l x_{ijk} \tag{4.1}$$

$$\text{s.t.} \quad x_{ijk} \leq \alpha_{ij} \qquad \forall (i,j) \in V, k \in K \tag{4.2}$$

$$\sum_{i\in V_{o_1}}\sum_{j\in V_{d_2}} x_{ijk} = 1 \qquad \forall k \in K \tag{4.3}$$

$$\sum_{i\in V} x_{ijk} = \sum_{i'\in V} x_{ji'k} \qquad \forall k \in K, j \in \bar{V} \tag{4.4}$$

$$\sum_{i\in V}\sum_{j\in V_{o_{|T|}}} x_{ijk} = 1 \qquad \forall k \in K \tag{4.5}$$

$$\sum_{i\in V}\sum_{k\in K} x_{ijk} \leq 1 \qquad \forall j \in V_c \tag{4.6}$$

$$I_{jk} \leq Q_l \qquad \forall j \in V, \forall k \in K_l, \forall l \in \{1,2\} \tag{4.7}$$

$$I_{jk} \leq I_{ik} - \sum_{m\in N} v^m d_i^m + M(1 - x_{ijk}) \qquad \forall i \in V_c, \forall j \in V, k \in K \tag{4.8}$$

$$I_{ik} - \sum_{m\in N} v^m d_i^m - M(1 - x_{ijk}) \leq I_{jk} \qquad \forall i \in V_c, \forall j \in V, k \in K \tag{4.9}$$

$$I_{jk} \geq \sum_{m\in N} v^m d_j^m - M(1 - \sum_{i\in V} x_{ijk}) \qquad \forall j \in V, k \in K \tag{4.10}$$

$$\sum_{i\in V}\sum_{k\in K_2} \leq |K_2| \sum_{i\in V}\sum_{k\in K_1} \qquad \forall j \in V_s \tag{4.11}$$

$$I_{jk} \in \mathbb{N} \qquad \forall j \in V, k \in K \tag{4.12}$$

$$x_{ijk} \in \{0,1\} \qquad \forall i,j \in V, k \in K \tag{4.13}$$

The objective function (4.1) is maximizing the total profit. Constraints (4.2) guarantee that the vehicles can traverse only the arcs that are available on the network. Constraints (4.3) make sure that all the vehicles leave the origin and go to an available depot when they start their trip. Constraints (4.4) and (4.5) are the network flow constraints and the latter one make sure that all vehicles will reach to an origin node of last time unit at the end of their trip. The demand of each node can be satisfied by at most one vehicle and constraints (4.6) are responsible for it. Constraints (4.7) make sure that vehicles can be loaded up to their capacities. Constraints (4.8) and (4.9) are the inventory balance constraints for the customer nodes. Constraints (4.10) guarantee that only the vehicles with inventory level at least equal to demand of a customer can visit that customer. Constraints (4.11) make sure that there is at least one BV in the satellite node where SVs replenish their inventory. Finally, constraints (4.12) and (4.13) are integrality and binary constraints, respectively.

4.4 Branch-and-price Algorithm

A branch-and-price (BP) approach is a branch-and-bound algorithm that involves creating columns in order to compute the dual bounds. Mentioned methods are iterative approaches within a decomposition framework containing a set of subproblems that are related to a restricted master problem and that contain variables with positive costs and violated inequalities. We describe below the main components of the BP algorithms we have designed to solve the MIP model.

4.4.1 Reduced Master Problem

In order to be able to solve the problem with BPC, the MIP model must be reformulated. LP-relaxation of *restricted master problem* (RMP), in which X_r and $Y_{r'}$ are decision variables which stand for choosing r^{th} route for the BVs and r'^{th} route for the SVs, respectively is presented in this section. We introduce a column ($\boldsymbol{\alpha}$) to RMP that is associated with a BV first, and then we introduce a column ($\boldsymbol{\beta}$) to RMP that is associated with an SV route. c_r denote the delivery cost of route r of a BV, and $c_{r'}$ denote the delivery cost of route r' of an SV.

[RMP]

$$\min \quad \sum_{r} c_r X_r + \sum_{r'} c'_r Y_{r'} \tag{4.14}$$

$$\text{s.t.} \quad \sum_{r} X_r \leq |K_1| \tag{4.15}$$

$$\sum_{r'} Y_{r'} \leq |K_2| \tag{4.16}$$

$$\sum_{i,r} \alpha_r^{ij} X_r + \sum_{i,r'} \beta_{r'}^{ij} Y_{r'} \leq 1 \qquad \forall j \in V_c \tag{4.17}$$

$$\sum_{i,r'} \beta_{r'}^{ij} Y_{r'} - |K_2| \sum_{i,r} \alpha_r^{ij} X_r \leq 0 \qquad \forall j \in V_s \tag{4.18}$$

$$\sum_{i,r} \alpha_r^{ij} X_r \leq 1 \qquad \forall j \in V_s \tag{4.19}$$

$$X_r, Y_{r'} \in \{0,1\} \qquad \forall r \in R, r' \in R' \tag{4.20}$$

The objective function (4.14) is maximizing the total profit. Constraints (4.15) and (4.16) guarantee that the total number of routes for BVs and SVs must be less than equal to the number of the BVs and SVs, respectively. Each customer node at any time slot can be visited by one a vehicle (whether SV or BV) and it is incorporated into the model by Constraints (4.17). Constraints (4.18) guarantee that at each satellite point, total replenishment of SVs can be up to their capacities, if there is a BV in that point. Constraints (4.19) ascertain that each satellite point in any time slot can be visited by at most one BV. Finally, constraints (4.20) are binary constraints. It should be noted that the dual variables for MP are denoted by γ, δ, ϵ, η, and θ respectively.

4.4.2 Pricing Problem and Solution Algorithm

In essence, the pricing problem (or Subproblem) seeks to identify the column with the lowest possible reduced cost to be added to RMP. After obtaining the dual variables from the RMP, corresponding subproblems (PP-y and PP-x) are solved, and profitable columns are added to the RMP. The sub-problems that must be solved for BVs and SVs are denoted by PP-y and PP-x, respectively. *Subproblem* PP-y is provided below:

[PP-y]

$$\min \quad \sum_i \sum_j c^1_{ij} z_{ij} - \sum_i \sum_j \sum_m p^m d^m_j z_{ij} - \gamma - \sum_i \sum_{j \in V_c} \epsilon_j z_{ij} \tag{4.21}$$

$$+ \sum_{j \in V} \sum_{j \in V_s} |K_2| \eta_j z_{ij} - \sum_i \sum_{j \in V_s} \theta_j z_{ij} \tag{4.22}$$

$$\text{s.t.} \quad z_{ij} \le \alpha^1_{ij} \qquad \forall (i,j) \in V \tag{4.23}$$

$$\sum_{i \in O_1} \sum_{j \in D_2} z_{ij} = 1 \tag{4.24}$$

$$\sum_{i \in V_1} z_{ij} = \sum_{i' \in V_1} z_{ji'} \qquad j \in \bar{V} \tag{4.25}$$

$$\sum_{i \in V} \sum_{j \in V_{o_{|T|}}} z_{ij} = 1 \tag{4.26}$$

$$z_{ij} \in \{0,1\} \qquad \forall i,j \in V \tag{4.27}$$

In PP-y, the objective function (4.22) is minimizing the total delivery cost of a BV, and constraints (4.23) guarantee that the BV can traverse only the arcs that are available on the network. Constraint (4.24) make sure that all the BV leave the origin and go to an available depot when it starts its trip. Constraints (4.25) and (4.26) are network balance constraints and the latter one enforces the BV to return to the origin at the end of its trip. Finally, constraints (4.27) are binary constraints. *Subproblem* PP-x is given as follows:

[PP-x]

$$\min \quad \sum_i \sum_j c^2_{ij} w_{ij} - \sum_i \sum_j \sum_m p^m d^m_j w_{ij} - \delta - \sum_i \sum_{j \in V_c} \epsilon_j w_{ij}$$

$$- \sum_{j \in V_s} \sum_{i \in V} \eta_i w_{ij} \tag{4.28}$$

$$\text{s.t.} \quad w_{ij} \le \alpha^2_{ij} \qquad \forall (i,j) \in V \tag{4.29}$$

$$\sum_{i \in O_1} \sum_{j \in D_2} w_{ij} = 1 \tag{4.30}$$

$$\sum_{i \in V_2} w_{ij} = \sum_{i' \in V_2} w_{ji'} \qquad j \in \bar{V} \tag{4.31}$$

$$\sum_{i \in V} \sum_{j \in V_{o_{|T|}}} w_{ij} = 1 \tag{4.32}$$

$$I_j \leq I_i - \sum_m d_i^m v_m + M(1 - w_{ij}) \qquad \forall i \in V_c^2, j \in V \tag{4.33}$$

$$I_i - \sum_m d_i^m v_m - M(1 - w_{ij}) \leq I_j \qquad \forall i \in V_c^2, j \in V \tag{4.34}$$

$$I_j \geq \sum_m d_j^m - M(1 - \sum_{i \in V} w_{ij}) \qquad \forall j \in V \tag{4.35}$$

$$0 \leq I_j \leq C_2 \qquad j \in V \tag{4.36}$$

$$w_{ij} \in \{0, 1\} \qquad \forall i, j \in V \tag{4.37}$$

In PP-x, the objective function (4.28) is minimizing the total delivery cost of an SV. Constraints (4.29) guaranteed that the SV can only traverse the arcs that are available to it. Constraints (4.30) enforce the SV to leave the origin and go to an available depot. Constraints (4.31) and (4.32) are network balance constraints and the latter one enforces the SV to return to the origin at the end of its trip. Constraints (4.33) and (4.34) are the inventory balance constraints for the customer nodes with parcel demands. Constraints (4.35) guarantee that the SV can visit only the nodes that it can satisfy their demands. Constraints 4.36 enforce that the SV can hold items up to its capacity and finally constraints (4.37) are sign constraints.

4.4.3 Column Generation Algorithm

With an excessive number of decision variables such as RMP, column generation can be useful for solving linear discrete optimization problems. This algorithm starts with solving the LP-relaxation of *restricted master problem* (RMP) with initial columns that are generated by the algorithm explained in Section 4.4.3. After obtaining the dual variables from the RMP, corresponding subproblems (PP-y and PP-x) are solved, and profitable columns are added to the RMP. These steps are continued until all profitable columns are added to RMP. If the solution of LP-relaxation of RMP is not fractional, the optimality is guaranteed; otherwise, the branching on the fractional decision variables continues.

Initial Solution: In this section, we propose a clustering-based algorithm that adopts clustering in Step 1 and calculates the cost of each cluster in Step 2. The steps of the algorithm are as follows:

[***Step 1***] ***Iterative cluster generation***

We generate different routing patterns for BV and SV by using an iterative clustering algorithm. In each iteration, a random point is chosen on the map as the base point, and a probability is assigned for each customer with respect to its distance from the base point. The customers on each cluster are then chosen using a roulette wheel selection approach. Since we seek to generate unique clusters when a repetitive cluster is generated, such a generation is denoted as a failure. The associated clustering approach and the probability calculation used in the roulette wheel selection are inspired by [160]. It should be noted that we limit the number of unsuccessful trials used in terminating the cluster generation to $25000 \times V$.

[***Step 2***] ***Determining the routes for BVs and SVs and the associated costs***

After the clusters are generated, considering the capacities of the vehicles, we utilize a random greedy algorithm to generate routes for BVs and SVs.

4.4.4 Branch-and-price Tree

For the purpose of generating an integer solution, we have to adopt branching. We start the branching with the most fractional X_r variable, i.e., its decimal part is the closest to 0.5. In case all the X_r variables are integer, we continue the branching with $Y_{r'}$ variables until all the decision variables are integer. It must be noted that instead of directly branching on X_r and $Y_{r'}$ variables, we branch on the routes of BVs and SVs, respectively.

4.5 Computational Experiment

An analysis based on random instances is presented in this section. The objective of our numerical study is to evaluate the quality of the solution obtained by the proposed method. The computational experiments are carried out on a 64-bit Windows Server with two 2.4 GHz Intel Xeon CPUs and 24 GB RAM. The algorithms are implemented using Python

Programming Language and GUROBI Solver version 9.1.1. We test the efficiency of the proposed algorithm by comparing the obtained results against those obtained from the commercial solver with a time limit (3 hours) for instances with different settings. The ranges from which the data is generated is presented in Table 17.

Table 17: Instance parameters for 2E-VRP

Parameters	Ranges
Volume of items	[100,700]
Demand of couriers	[5,10]
Demand of parcels	[2,4]

The setting of the instances and objective function values as well as the runtimes of the proposed algorithm and the commercial solver, for instances are presented in Tables 18.

Table 18: Comparison of the results of the proposed algorithm and the commercial solver

Instance	BV	SV	Time units	Items	MIP			BP	
					Obj. val.	Gap	CPU (in seconds)	Obj. val.	CPU (in seconds)
1	1	3	5	2	-11886.67	0.00%	120.24	-11886.67	3.65
2	1	3	5	2	-5343.15	0.00%	24.37	-5343.15	8.95
3	1	3	5	2	-9325.93	0.00%	40.53	-9325.93	8.95
4	1	3	5	2	-13562.40	0.00%	24.04	-13562.40	2.91
5	1	3	6	2	-14265.11	0.00%	172.89	-14265.11	67.73
6	1	3	6	2	-39808.55	0.00%	859.21	-39808.55	133.45
7	1	3	6	2	-7289.61	11.00%	1800.21	-7289.61	403.18
8	1	3	6	2	-11886.67	8.45%	321.53	-11886.67	7.39
9	1	3	10	2	-39838.16	3.00%	1802.54	-39838.16	72.63
10	1	3	10	2	-7289.61	12.00%	1803.22	-7289.61	234.66
11	1	3	10	2	-2779.48	14.00%	1807.00	-2781.27	158.66
12	2	4	10	2	-62071.39	0.00%	100.15	-62071.39	17.42
13	2	4	15	3	-89545.06	0.00%	1208.73	-89545.06	810.58
14	2	4	15	3	-44139.70	8.00%	1805.03	-44139.70	612.46
15	2	4	15	3	-12583.88	15.35%	1810.91	-12583.88	234.56
16	2	4	15	3	-27096.19	7.00%	1820.36	-27096.19	299.40
17	2	4	10	3	-71206.71	9.08%	1840.55	-71206.71	153.84
18	2	4	10	3	-107275.99	14.82%	1809.83	-107275.99	311.22
19	2	4	15	3	-1253.18	20.19%	1819.97	-1253.18	223.94
20	2	4	15	3	-18352.79	16.42%	1821.42	-18352.79	143.70
		Average			-	6.97%	1140.64	-	195.46
		Best			-	0.00%	24.04	-	2.91
		Worst			-	20.19%	1840.55	-	810.58

In Table 18, the first column shows the number of the instance, the number of BVs and SVs are presented in the second and the third columns, respectively. While the time units are presented in the fourth column, in the fifth column, the number of the items are presented. Objective function value, optimality gap of Gurobi and the runtime of it are presented in sixth to the eighth columns, respectively. Objective function value and the runtime of the proposed branch-and-price algorithm are presented in ninth and tenth columns. As it can be interpreted from Table 18, the proposed algorithm find the optimal solutions in more reasonable amounts of time. While the results obtained by Gurobi for the MIP have around 7% gap taking 1140 seconds (on average), the results obtained from the branch-and-price algorithm take 195 seconds. For the best and worst cases, MIP is solved in 24 and 1840 seconds, respectively. These numbers for the branch-and-price algorithm are 2 and 810 seconds, respectively.

4.6 Conclusion

Traffic congestion in urban areas is intensifying due to urbanization and the trend of e-commerce grocery delivery in cities. Due to augmented traffic congestion and air pollution, some mitigation measures must be taken to address adverse health issues. One way to reduce emissions is to use low-emission vehicles in inner-city areas – however, due to their limited capabilities, it is not practical to transform city logistics entirely to these vehicles. For that reason, delivery of some larger items is still done by larger vehicles. A combination of these two types of fleets can be challenging in an urban environment because of capacity limitations, tight delivery windows, and other planning constraints. Additionally, in the presence of integrated planning, smaller-sized trucks may be replenished by larger-sized trucks' inventory without requiring the return to a depot. We propose a two-echelon vehicle routing problem for last-mile delivery of groceries. The proposed model is distinguishable of the most of the studies in the literature since it considers the separate deliveries of big vehicles and ones to the customers in a time-expanded network. Moreover, the proposed model considers synchronization of the big and small vehicles in satellite points in which zero-emission can get loaded with the items carried by the big vehicles. We propose a branch-and-price algorithm which is very versatile in solving the problem. Finally, our proposed model can handle large-scale instances where commercial solvers cannot even produce quality solutions within a reasonable amount of time.

CHAPTER V

CONCLUSION

In this thesis, we consider three different optimization problems. After proposing the mathematical models of the problems, we propose column generation as the solution method.

Chapter 2 considers *stochastic donation tailoring problem* (SDTP) that takes into account the shelf-life, deferral times, and uncertain demand of blood and aims to minimize the total (expected) operational donation, holding, and scrapping costs while meeting the demand and utilizing *multicomponent apheresis* (MCA) technology. The numerical experiments have shown that utilizing an optimization method for the blood donation scheduling problem as well as considering uncertain demand and wait-and-see donors can be helpful in order to manage blood donations more effectively. Donation organizations can benefit from the presented research from four different aspects.

In Chapter 3, we propose *stochastic production planning* (SPP) problem that takes into account the uncertain demand of products in hybrid manufacturing systems that takes advantage of a flexible manufacturing system (FMS) and aims to minimize the total (expected) production, holding, and outsourcing costs. We model the uncertainty in demand using a scenario tree approach. SPP is the first optimization model that yields a hybrid scheme for producing by providing resilient solutions against demand uncertainty. Utilizing FMS and typical manufacturing machines (TMM) provides more flexible production schedules since, based on the realized values of demand over time, FMS adjust their production schedules. Moreover, we propose a *column generation* (CG) based heuristic that solves the problem in less than 24 hours for realistically sized instances while a commercial solver cannot even create an instance of the standard model. The numerical results show that the proposed CG approach yields quality solutions for realistically sized instances.

In Chapter 4, we propose a two-echelon vehicle routing problem for last-mile delivery of groceries. The proposed model is distinguishable of the most of the studies in the literature since it considers the separate deliveries of big vehicles and ones to the customers in a time-expanded network. Moreover, the proposed model considers synchronization of the big and small vehicles in satellite points in which zero-emission can get loaded with the items carried by the big vehicles. We propose a branch-and-price algorithm which is very versatile in solving the problem. Finally, our proposed model can handle large-scale instances where commercial solvers cannot even produce quality solutions within a reasonable amount of time.

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