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# A Column Generation-based Approach for the Adaptive Stochastic Blood Donation Tailoring Problem

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## ABSTRACT

Managing blood donations is a challenging problem due to the perishability of blood, limited donor pool, deferral time restrictions, and demand uncertainty. The problem addressed here combines two important aspects of blood supply chain management: the inventory control of blood products and the donation schedule. We propose a stochastic scenario-based reformulation of the blood donation management problem that adopts multicomponent apheresis and utilizes donor pool segmentation into here-and-now and wait-and-see donors. We propose a flexible donation scheme that is resilient against demand uncertainty. This scheme enables more flexible donation schedules because wait-and-see donors may adjust their donation schedules according to the realized values of demand over time. We propose a column generation-based approach to solve the associated multi-stage stochastic donation tailoring problem. The numerical results show the effectiveness of the proposed optimization model, which provides solutions with 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. Utilizing multicomponent apheresis and flexible wait-and-see donations are suggested for donation organizations because they yield significant cost reductions and resilient donation schedules.

## KEYWORDS

SDG 3: good health and well-being; stochastic methods; blood supply chain; column generation; multicomponent apheresis;

## 1. Introduction

Blood is not only essential for accident/disaster victims, but it is also vital for patients 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. alone, every two seconds someone needs blood or its products (American Red Cross Blood Services 2020), one of seven hospitalized people needs blood, and each year, almost five million Americans depend on blood products or blood-related services (American Association of Blood Banks 2021). 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 is eligible, only around 10% actually donate blood (American Red Cross 2021), and this figure is comparatively lower in middle and low-income countries (World Health Organization 2020). 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 (Masser et al. 2009). According to Martín-Santana and Beerli-Palacio (2013), donor retention must be intensified to keep the donation system effective. For further details on the factors affecting the retention of donors, we refer the reader to Van Dongen (2015). On the other hand, Masser et al. (2012), and Notari IV et al. (2009) 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% (Bagot et al. 2016; Whyte 1999), and are more likely to be considered as repeat blood donors. 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 urgent donation requests.

BSM consists of the following stages: blood collection, processing, storage, and distribution of the blood to demand points (Osorio, Brailsford, and Smith 2015). The studies in the field of BSM mostly focus on donor utilization and shortage elimination (Waxman 2002; Bonomo, Garozzo, and Bennardello 2004; Aubuchon et al. 2007; Ridley 2009). There are some factors that make BSM a challenging task. First, blood is only donated by a limited number of donors. Second, a donor needs a regeneration period, called *deferral time*, after each donation to be eligible for the next donation. Third, blood is a perishable commodity with a limited shelf-life. For example, more than 200,000 units of blood and its components were disposed of after the terrorist attack on September 11, 2001, when Americans donated more than 500,000 units of blood (Korcok 2002). We refer the reader to Nagurney (2017) to have an overview of the probable outcomes of blood shortage or surplus.

Managing the blood supply chain becomes more challenging when the uncertainty of the demand is incorporated into the associated problem. Even though the demand for 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 (Tabatabaie et al. 2010), and the outbreak of pandemics (Sayedahmed et al. 2020). When the actual demand is higher than the planned or forecasted amount, drastic outcomes will proceed as a shortage in blood products may escalate fatalities since it may cause surgeries to be delayed. Moreover, these unforeseen incidents have a negative effect on the fluctuation of the supply as well. According to American Association of Blood Banks (2020b), due to the COVID-19 pandemic, more than 50,000 blood drives were canceled, and blood storage was so low that it could last for about three days in New York City. When the realized demand is lower than the supply, the surplus amount will be disposed of or used for research purposes, resulting in a waste of a valuable commodity. Moreover, due to the deferral time, the utilized donors would not 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 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 (Newman 1997; Newman et al. 2003). Moreover, whole blood donation may result in shortages and inefficient utilization of donors. However, recent developments allow better utilization of blood products and

donors (Haemonetics Corporation 2008; Ridley 2009) by proposing supply flexibility. The new method that has been utilized recently is called *multicomponent apheresis* (MCA). It is worth noting that apheresis donations are not immune from donor issues, and this method is costly (Osorio, Brailsford, and Smith 2018). The importance of supply flexibility has been explored in the literature (Tachizawa and Thomsen 2007; Liao, Hong, and Rao 2010; Irfan, Wang, and Akhtar 2019). The donor can donate more than one transfusable unit and/or one or more blood components using MCA without risking safety (Infanti 2018; Burgstaler and Winters 2016). Compared to whole blood donation, MCA has several other advantages as follows. *Increased donor utilization:* In a single donation, several components or transfusable units may be included with deferral periods based on the type of donation, and this will result in better BSM. *Reduced infection risks:* With MCA, a single donor can donate more transfusable units of blood. As a result, patients receive blood from a smaller number of donors, reducing only the risk of infection. *Better matching demand and supply:* Through tailored donations, MCA helps match the uncertain demand with the supply by only collecting the required components (Ciavarella 1993; Connelly and Pink 2002). As a way to categorize the benefits of MCA, *blood donation tailoring* is defined with the objective of minimizing the overall costs of donation, holding, and disposing of blood products by utilizing the donor pool to supply the blood essential for those in need (Özener, Ekici, and Çoban 2019). According to Australian Red Cross (2021) when the donors are flexible on time and donation type, there will be tremendous benefits. In this study, we aim to reach the highest efficiency in the donation schedule. 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 it is known from the start of the planning horizon what donation schedule he/she will follow; a wait-and-see donor is more flexible and adjusts their donation schedule based on the actual needs within the planned time frame. 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. We propose donation tailoring under uncertainty for blood donation organizations based on MCA utilization, donor segmentation, holding and scrapping costs, shelf life, and deferral times of blood products. To this end, the *stochastic donation tailoring problem* (SDTP) that is proposed in this paper aims to minimize the total (expected) operational donation costs. 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 donations that result in spoilage of some of the products when a non-worst-case scenario is realized; nevertheless, the associated drawback is avoided in our setting 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. Scenario tree-based techniques have been utilized in different domains to deal with uncertainty (Aghaei et al. 2013; Niknam, Azizipanah-Abarghooee, and Narimani 2012; Freeman, Melouk, and Mittenthal 2016).

*The contribution* of this study is threefold. First, there are only a limited number of studies in the literature on donation tailoring that suggest utilizing optimization methods within an uncertain framework; the SDTP is a problem that aims to develop a flexible donation system for MCA and offers solutions to handle uncertainty

in demand through donor segmentation while considering participation ratio of the donors. The proposed approach is a column generation-based heuristic that can handle realistically sized instances that cannot be solved with commercial solvers. The algorithm's performance is assessed by using a mechanism for determining a lower bound that is efficient and achieved by solving the linear programming relaxation of the mixed-integer programming models. The findings indicate that the CG suggested method has a less than 7% average deviation from optimal for situations involving both wait-and-see and here-and-now donors. In addition, effective donation schedules are developed that incorporate wait-and-see donors and improve the operational cost of standard donation schemes by an average of 18%.

The rest of the paper is structured as follows: The literature review is presented in Section 2, the problem is defined, and the mathematical model of SDTP is introduced in Section 3; the solution methods are discussed in Section 4, the numerical results are presented in Section 5, and the conclusion and the managerial insights of the study are provided in Section 6.

## 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 Belien and Force (2012), Osorio, Brailsford, and Smith (2015), Pirabán, Guerrero, and Labadie (2019), Keskinocak and Savva (2020), Williams, Harper, and Gartner (2020), and Meneses, Santos, and Barbosa-Póvoa (2023) 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.

Research in BSM focuses primarily on inventory control policies to balance the shortage and disposal of whole blood products (Brodheim, Hirsch, and Prastacos 1976; Cohen et al. 1979; Pereira 2005; Rytla and Spens 2006; Haijema, van der Wal, and van Dijk 2007; Kopach, Balcioglu, and Carter 2008; Fontaine et al. 2009; Zhou, Leung, and Pierskalla 2011; Civelek, Karaesmen, and Scheller-Wolf 2015; Hosseinifard and Abbasi 2018). For example, Pereira (2005) 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 daily transfusion must be supplied by young red blood cells while the hospitals with smaller ones must be supplied by older stocks. Kopach, Balcioglu, and Carter (2008) evaluate the performance of a regional blood center in Canada by employing the two demand rate models proposed by Perry and Posner (1990). 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. Civelek, Karaesmen, and Scheller-Wolf (2015) consider mismatching costs as well as holding, shortage, and spoil costs in blood platelets. Modelling the problem as a Markov Decision Process, the authors propose a heuristic algorithm to compare the results with near-optimal approaches in the literature.

Another aspect that has been widely studied by researchers is issuing policies. Significant research is conducted to study the impacts of different issuing policies on average inventory level, shortage, and wastage rates (Pegels and Jelmert 1970; Ohsaka et al. 2009; Haijema et al. 2009; Haijema 2011; Abbasi and Hosseinifard 2014; Lowalekar, Ni-

lakantan, and Ravichandran 2016). Even though a blood supply chain network consists of four different echelons, namely, collection, processing, inventory, and distribution (Osorio, Brailsford, and Smith 2015), hitherto models that are mainly based on inventory control is still lagging behind in integrating the two critical phases, i.e., production and inventory. By improving and integrating production and inventory management of blood and blood products, MCA can help donation organizations to alleviate the donor shortage and to reduce healthcare costs. Despite this, donor tailoring has largely been overlooked as one of the major benefits of MCA (Pierskalla 2004; Özener, Ekici, and Çoban 2019). Only a few studies have focused on this aspect of MCA: Valbonesi et al. (2005) provide donation patterns by implementing MCA in a health center in Italy; Osorio et al. (2017) 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, to study the importance of MCA in production and cost management, Özener, Ekici, and Çoban (2019) combine inventory management with scheduling of donations. Notice that the associated stream 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.

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. To reduce the costs of purchasing, shortages, holding costs, and waste, Gunpinar and Centeno (2015) propose an integer programming model for uncertain demand. Moreover, other studies have been conducted that aim to study blood distribution while minimizing shortages and spoilage, as well as arrange the distribution of blood products (Prastacos 1981; Gregor, Forthofer, and Kapadia 1982; Federgruen, Prastacos, and Zipkin 1986; Alshamrani, Mathur, and Ballou 2007; Hemmelmayr et al. 2010; Chaiwuttisak et al. 2016; Sarhangian et al. 2018; Jafarkhan and Yaghoubi 2018).

Dehghani, Abbasi, and Oliveira (2021) 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. Ghasemi et al. (2022) consider a multi-echelon mathematical model for managing the blood supply chain in disaster situations. The proposed model aims to minimize costs while maximizing satisfaction by determining the need for reliable and unreliable distributors and central warehouses and calculating the amount of blood to be sent to distribution centres. The authors also consider pre- and post-disaster modes, investigate flow between centres, and employ a robust optimization approach for solving the proposed model, demonstrating its effective performance. Momenitabar et al. (2022) focus on the reconfiguration of a closed-loop blood supply chain network considering blood group compatibility and blood product shelf-life. A fuzzy multi-objective mixed-integer non-linear programming model is proposed to minimize network costs and maximize the minimum service level to patients.

Ghahremani-Nahr et al. (2022) present an approach for designing a blood supply chain network that considers economic and environmental factors. The proposed model aims to minimize both operational costs and logistical carbon footprint. Three multi-objective decision-making approaches are examined and ranked based on various attributes using statistical tests and the TOPSIS method. The study includes a real case study involving 21 cities in the North-West of Iran, with a 12-month implementation time window, to illustrate the trade-offs between cost and carbon emis-

sions. Xu and Szmerekovsky (2022) propose a multi-product multi-period stochastic program to optimize the integrated blood supply chain. By considering interactions between red blood cells and platelets, demand uncertainty, blood age information, blood type substitution, and multiple patient types, the objective is to minimize costs throughout the collection, production, inventory, and distribution process. The study demonstrates the cost advantages of the multi-product model compared to an uncoordinated approach, highlighting the importance of integrating red blood cell and platelet supply chains, particularly in scenarios with increased whole blood donations and a higher percentage of whole blood derived platelets pooled for transfusion. Khalilpourazari and Hashemi Doulabi (2022) present a multi-objective formulation to address the challenges faced by the blood supply chain during the COVID-19 pandemic. The authors propose two flexible uncertain models to account for parameter uncertainties and offer robust solutions for emergency blood supply chain design. The findings demonstrate that the robust model effectively handles uncertainties, resulting in lower costs and delivery time, and provides valuable managerial insights for enhancing the effectiveness of the supply chain. Xu and Szmerekovsky (2023) study a multi-stage stochastic optimization model for a platelet supply chain under centralized control. The authors investigate the impact of transshipment between hospitals on performance improvement and identify strategies such as donor recruitment, suitable inventory management, and shorter stage lengths for enhanced cost efficiency. The proposed model outperforms a two-stage stochastic program in handling random daily demand and demonstrates that transshipment helps alleviate shortages and wastage and improves stock allocation.

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 the donation tailoring problem while other studies such as Fattahi et al. (2015), Dillon, Oliveira, and Abbasi (2017), Cunha, Raupp, and Oliveira (2017) and Hamdan and Diabat (2019) focus on two-stage stochastic programming to formulate the recourse decisions. By including both wait-and-see and here-and-now donors in the donation plan, it allows for more flexibility in scheduling as the wait-and-see donors can adjust their donation schedules based on the actual demand over time. Lastly, different from the standard parametric decision rule functions that are often used in stochastic programming (Shapiro, Dentcheva, and Ruszczyński 2014) and robust optimization (Ben-Tal et al. 2004), we adopt scenario-based adjustable decisions.

### 3. Problem Definition

In SDTP, the main objective of the blood donation organization is to satisfy the uncertain demand with the supply of blood while minimizing the holding, disposal, and donation costs. The expenses associated with donation cost encompass various items such as bags, equipment like centrifuges, the time spent by technical and medical personnel, filtration processes, labelling, and general expenses (Özener, Ekici, and Çoban 2019).

We consider only one blood type, and the proposed model can be utilized for all blood types separately. This approach is predicated on the standard medical practice which, despite the technical feasibility of substituting compatible blood types, generally prefers to use blood with the same ABO type as the patient for optimal compatibility and safety (Harmening, Forneris, and Tubby 2012). Furthermore, this

strategy aligns with previous studies in the field, including the work by Özener, Ekici, and Çoban (2019). 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. Donors can only perform a limited number of donations depending on the donation performed during their planning horizon; deferral times are determined by the type of the current and upcoming donation (American Association of Blood Banks 2020a). For example, after donating whole blood, a donor has to wait eight weeks until they can donate again; however, they have to only wait for four weeks to donate single-unit platelets after whole blood donation.

**Table 1.** Nomenclature for SDTP

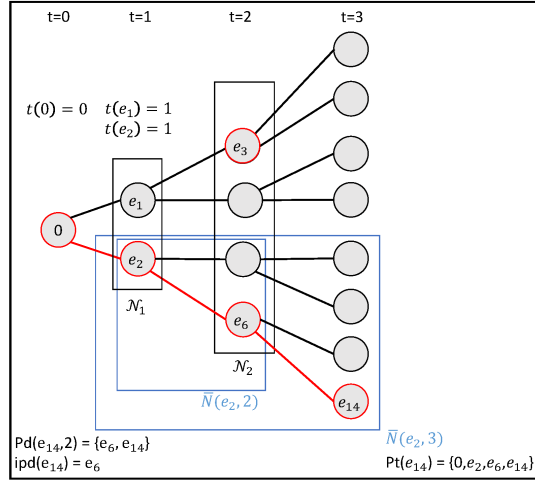
[Alt-Text: ]Sets, parameters, and decision variables used in SDTP are presented in this table.

<i>Sets</i>	
$\mathcal{I}$	set of donation types ( $\{1, 2, \dots, L\}$ ) – indexed by $i$
$\mathcal{J}$	set of blood products ({red blood cells, platelets, plasma}) – indexed by $j$
$\mathcal{K}$	set of donors ( $\{1, 2, \dots, K\}$ ) – indexed by $k$
$\mathcal{T}$	set of time periods in the planning horizon ( $\{1, 2, \dots, T\}$ ) – indexed by $t$
$\mathcal{N}$	set of demand nodes ( $\{1, 2, \dots, N\}$ ) in scenario tree – indexed by $e$
$\mathcal{N}_t$	set of nodes in period $t \in \mathcal{T}$
$\text{Pd}(e, l)$	set of $l - 1$ predecessors of node $e \cup \{e\}$
$\text{Pt}(e)$	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 $\cup \{e\}$
<i>Parameters</i>	
$c_i^{hn}$	cost of performing type $i$ here-and-now donation
$c_i^{ws}$	cost of performing type $i$ wait-and-see donation
$h_j$	unit holding cost of blood product $j$ (per period)
$o_j$	unit disposal cost of blood product $j$
$s_{ii'}$	deferral time between donation types $i$ and $i'$
$\eta_j$	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
$\text{ipd}(e)$	immediate predecessor of node $e$
$t(e)$	period of node $e$
$\text{pr}(e)$	probability of node $e$ being realized
$\theta$	percentage of wait-and-see donors in the pool
$\xi_t$	ratio of participation in a donation for a donor in period $t$
$M$	significantly a large number
$\Omega$	penalty cost for the shortage of blood
<i>Decision Variables</i>	
$x_{ike}$	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 $e$ ( $t(e)$ )
$B_{ej}$	amount of shortage of blood product $j$ at the end of time period of node $e$ ( $t(e)$ )

In this study, we assume a multi-period, multi-product, and multi-stage 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  $a_{ij}$ . The total number of donations in the planning horizon is indirectly limited by blood products. A donor can donate only a limited amount of blood product  $j$  within the planning horizon (Valbonesi et al. 2005), and that limit is denoted by  $E_j$ .



The sets, parameters and decision variables are presented in Table 1.



**Figure 1.** Problem structure for SDTP

[Alt-Text: ]This figure represents the demand structure tree for blood products.

A scenario tree approach is used to model the demand uncertainty. The here-and-now decision variables are determined at the start of the planning horizon, while wait-and-see decision variables are more flexible, and the donation plan is adjusted based on the projected needs within the planning period.

**Remark 1.** In this study, we introduce the concepts of “wait-and-see” and “here-and-now” donors to describe differing behavioral patterns observed in the donor population. These terms are not meant to suggest that donors are the primary decision-makers in the donation process. Instead, they serve as descriptive categorizations to aid in understanding variability in donor behavior. The decision-making power unequivocally remains with the blood centers. This terminology, while novel, is conceptually similar to the wait-and-see strategy commonly employed in two-stage modeling and other methodologies.

Figure 1 shows a general scenario tree with the notations used in SDTP, providing a visual representation of the demand tree structure. The immediate predecessor of node  $e_6$  is node  $e_2 = ipd(e_6)$ . Also, the set of children of node  $e_1$  in the next period is represented by  $\bar{N}(e_1, 1)$  and for the next two periods is represented 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  $pr(e)$ ; 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  $Pt(e_{14}) = \{0, e_2, e_6, e_{14}\}$ , where  $\mathcal{N}_T$  denotes the set of nodes in the last period of the planning horizon.

**Remark 2.** Donor segmentation into here-and-now and wait-and-see categories, as we have proposed, introduces a crucial aspect of flexibility and resilience to the blood donation system. The here-and-now donors with fixed schedules and predetermined quantities provide stability and facilitate the planning process, as their contributions remain unaffected by uncertainties or scenario shifts. In contrast, the introduction of wait-and-see donors adds a robust and adaptable aspect to our model. These donors serve as a contingent force, ready to respond to variable requirements as different scenarios unfold. This segmentation enables blood centers to adjust the contribution from

wait-and-see donors according to specific unfolding scenarios, significantly enhancing a more resilient and efficient blood donation system.

In the SDTP model, here-and-now decisions, represented by  $\mathbf{y}$ , are made at the start of the planning horizon and are not affected by specific scenario outcomes, and wait-and-see decisions, represented by  $\mathbf{x}$ , are specific to a particular scenario. The resulting multi-stage mathematical optimization model [MIP-WS] is presented below:

[MIP-WS]:

$$\min \sum_{e \in \mathcal{N}_T} \text{pr}(e) \left[ \sum_{e' \in \text{Pt}(e)} \left( \xi_{t(e)} \sum_i \sum_k \left( c_i^{ws} x_{ike'} + c_i^{hn} y_{ikt(e')} \right) + \dots \right. \right. \\ \left. \left. \dots \sum_j \left( h_j I_{e'j} + o_j P_{e'j} + \Omega B_{e'j} \right) \right) \right]$$

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

$$(M-1)y_{ikt} + \sum_{i'} \sum_{t'=t}^{t+s_{ii'}-1} y_{i'kt'} \leq M \quad \forall i, k, t \quad (2)$$

$$I_{\text{ipd}(e)j} - I_{ej} - P_{ej} + B_{ej} + \dots \\ \dots \sum_i \sum_k \xi_{t(e)} a_{ij} (x_{ike} + y_{ikt(e)}) = d_{ej} \quad \forall e, j \quad (3)$$

$$\sum_i \sum_{e' \in \text{Pt}(e)} a_{ij} x_{ike'} + \sum_i \sum_t a_{ij} y_{ikt} \leq E_j \quad \forall e \in \mathcal{N}_T, j, k \quad (4)$$

$$I_{0j} + \sum_{e' \in \text{Pd}(e, \min\{\eta_j, t(e)-1\})} \sum_i \sum_k \xi_{t(e')} a_{ij} x_{ike'} + \dots \\ \dots \sum_{t'=1}^{t(e)} \sum_i \sum_k \xi_{t'} a_{ij} y_{ikt'} - I_{ej} \geq 0 \quad \forall j, e : t(e) \leq \eta_j \quad (5)$$

$$\sum_{t'=t(e)-\eta_j+1}^{t(e)} \sum_i \sum_k \xi_{t'} a_{ij} y_{ikt'} - I_{ej} + \dots \\ \dots \sum_{e' \in \text{Pd}(e, \eta_j)} \sum_i \sum_k \xi_{t(e')} a_{ij} x_{ike'} + \dots \geq 0 \quad \forall j, e : t(e) > \eta_j \quad (6)$$

$$x_{ike} \leq z_k \quad \forall e, i, k \quad (7)$$

$$\sum_i \sum_t y_{ikt} \leq M(1 - z_k) \quad \forall k \quad (8)$$

$$\sum_k z_k \leq \theta K \quad (9)$$

$$x_{ike}, y_{ikt} \in \{0, 1\} \quad \forall e, i, k, t \quad (10)$$

$$I_{ej}, P_{ej}, B_{ej} \geq 0 \quad \forall e, j \quad (11)$$

$$z_k \geq 0 \quad \forall k \quad (12)$$

The objective is to minimize the sum of expected costs, which consist of donation, holding, and discarding costs. It must be noted that it is difficult to accurately determine a value for the shortage cost ( $\Omega$ ) in the general model. To mitigate this challenge, we set  $\Omega$  to a relatively large value to ensure that the model satisfies demand when supply meets demand. Constraints (1) enforce deferral time between successive wait-and-see donations of a donor; constraints (2) enforce the same deferral time restriction for the here-and-now donations. It must be noted that donors who miss their scheduled donations are still subject to the same deferral period before they can donate again. The constraints in (3) are designed to maintain inventory balance for every blood product and across all time periods' scenarios. A single donor may only donate product  $j$  of blood during the planning horizon up to a limit and that is guaranteed by constraints (4). The shelf-life of blood products is restricted by the constraints (5) and (6). Finally, constraints (7) and (8) 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 (9). As discussed in Özener, Ekici, and Çoban (2019), the deterministic form of the proposed model is related to the *general lot-sizing and scheduling problem* and the *cutting stock problem*. The proposed *mixed integer program* (MIP) is a challenging model, in particular if the planning horizon is long and there are many donor. Therefore, in the next section, we propose a column generation-based heuristic approach to solve this problem effectively.

**Remark 3.** The role of first-time or single donations in maintaining the blood supply chain is significant and we duly acknowledge this. However, gathering reliable data on these one-time donors within the strategic planning horizon is inherently challenging, particularly when compared to the more predictable pattern of repeat donors. Despite this obstacle, we propose that should reliable data on single donations become accessible, it would be feasible to incorporate this into the existing system. Under such circumstances, the demand scenarios within the planning model would need to be updated in line with single donation forecasts. Once this is achieved, the planning approach, primarily designed for repeat donors, would then be applied considering the revised scenario tree.

#### 4. Column Generation-Based Heuristic Approach

The proposed algorithm for solving the MIP-WS problem, which is a mixed-integer programming problem with a large number of donors and scenarios as well as long planning horizons, is a column generation-based heuristic. The algorithm begins by starting with a feasible set of columns for the LP-relaxation of the restricted master problem (RMP-WS) that includes both here-and-now and wait-and-see decisions. Then, by obtaining the dual variables and solving corresponding subproblems, profitable columns are added to the model. This process is repeated until all decision variables in the RMP-WS are integers or the time limit is reached. In this stage, unlike the branch and price approach, which starts branching on the decision variables, the master problem with integer decision variables and both here-and-now and wait-and-see decisions (MP-WS) is solved using all the generated columns. To clarify the procedure adopted in our methodology, we diverge from the traditional branch and price approach, where branching commences on the decision variables. In contrast, our process begins by solving the master problem incorporating both integer decision

variables and a combination of here-and-now and wait-and-see decisions (MP-WS). This is undertaken utilizing the entirety of the generated columns rather than initiating column generation in each node on the branch tree. The key advantage of the algorithm is that it is able to efficiently solve realistically sized instances of the problem. We refer the readers to Lübbecke and Desrosiers (2005), Desaulniers, Desrosiers, and Solomon (2005) and Lübbecke (2010) for a detailed explanation of the column generation algorithm.

The proposed column generation-based heuristic has a set sequence of steps to follow. First, we introduce a column, denoted as  $\alpha$ , to the reduced master problem ([RMP-WS]) that is associated with a wait-and-see donor, denoted as  $x$ . Then, we introduce another column, denoted as  $\beta$ , to the [RMP-WS] that is associated with a here-and-now donor, denoted as  $y$ . It is important to note that in the [RMP-WS], we ignore the shelf-life constraint. This method will continue until the values of the objective functions for the subproblems [PP-x] and [PP-y] are non-negative, indicating that useful columns for the [RMP-WS] have been generated or the time limit has reached. Finally, by incorporating the shelf-life constraint, the [RMP-WS], which includes binary and integer decision variables, such as  $y_l$  representing the number of donors who follow here-and-now schedule  $l$ , and  $x_m$  representing the number of donors who follow wait-and-see schedule  $m$ , will be solved. The solution of this [RMP-WS] with the shelf-life constraint will be the final solution of the SDTP. It also needs to be noted that a total donation cost of  $\tilde{c}_l$  is the cost of here-and-now schedule  $l$ , and a total donation cost of  $\hat{c}_m$  is the cost of a wait-and-see schedule  $m$ .

The total number of blood product  $j$  collected during a time period  $t(e)$  is calculated using  $\beta_{jt(e)}^l$ . Meanwhile,  $\alpha_{ej}^m$  denotes the amount of blood product  $j$  collected at node  $e$  under a wait-and-see donation schedule. [RMP-WS] is presented as follows:

[RMP-WS]:

$$\min \sum_{e \in \mathcal{N}_T} \text{pr}(e) \left( \sum_j \sum_{e' \in \text{Pt}(e)} h_j I_{e'j} + o_j P_{e'j} + \Omega B_{e'j} \right) + \dots \\ \dots \sum_m \hat{c}_m x_m + \sum_l \tilde{c}_l y_l$$

$$\text{s.t. } I_{\text{ipd}(e)j} - I_{ej} - P_{ej} + B_{ej} + \sum_m \alpha_{ej}^m x_m + \sum_l \beta_{jt(e)}^l y_l = d_{ej} \quad \forall e, j \quad (13)$$

$$\sum_l y_l + \sum_m x_m \leq K \quad (14)$$

$$\sum_m x_m \leq \theta K \quad (15)$$

$$I_{ej}, P_{ej}, B_{ej} \geq 0 \quad \forall e, j \quad (16)$$

$$y_l, x_m \geq 0 \quad \forall l, m \quad (17)$$

In [RMP-WS], donation, holding, and disposal costs should be minimized to minimize the total cost of the columns. Each node's inventory flow balance is ensured by constraints (13). Constraint (14) imposes a limit of  $K$  on the number of donors available. Constraint (15) ensures that only fraction  $\theta$  of total donors can follow a wait-and-see schedule. Lastly, the non-negativity of decision variables is defined in constraints (16) and (17). It must be noted that we handle the separation of wait-and-see and

here-and-now schedules differently in the master problem. By generating the donation schedules separately for wait-and-see and here-and-now donors, we ensure that a donor can only appear in either one of these schedules but not both. Moreover, to limit the number of wait-and-see donors, we employ constraints (14) and (15) in the master problem, which effectively control the number of donors assigned to the wait-and-see and here-and-now schedules. The dual variables ( $w_{je}$ ) associated with (13) are used in the two *subproblems* [PP-x] and [PP-y]. In the context of the proposed model, the dual variables associated with constraints (14) and (15) in the master problem may seem to be overlooked. However, due to the nature of our problem structure, these dual variables, in practice, present themselves as constants with relatively small values, leading to their marginal impact on the overall problem. In particular, during periods when the availability of donors is limited, these small discrepancies might potentially cause inaccuracies. To circumvent such instances, we add a mechanism to introduce columns with small positive costs in the subproblems. This strategy is developed to tackle the challenges that might arise from the addition of columns with negative costs, ensuring the integrity and reliability of our solution approach. [PP-y], which provides profitable here-and-now columns, can be formulated as follows:

[PP-y]:

$$\begin{aligned} \min \quad & \sum_i \sum_t q_{it} (\xi_t c_i^{hn} - \sum_j \sum_{e \in \mathcal{N}_t} \xi_{t(e)} a_{ij} w_{je}) \\ \text{s.t.} \quad & (M-1)q_{it} + \sum_{i'} \sum_{t'=t}^{t+s_{ii'}-1} q_{i't'} \leq M \quad \forall i, t \quad (18) \end{aligned}$$

$$\sum_{i,t} a_{ij} q_{it} \leq E_j \quad \forall j \quad (19)$$

$$q_{it} \in \{0, 1\} \quad \forall i, t \quad (20)$$

In [PP-y], a donation of type  $i$  at time  $t$  will be represented by this binary decision variable  $q_{it}$ . The objective is to minimize the reduced cost of the column. If the reduced cost is negative, there exist donation patterns which, if added to the basis, will improve the objective function of [RMP-WS]. In other words, if the objective function value of [PP-y] is less than zero, there exists a column ( $l$ ) related to optimal values of  $q_{it}$  which must be taken to the restricted master problem [RMP-WS].  $\beta_{jt}^l$  and  $\tilde{c}_l$  values are calculated as follows:

$$\beta_{jt}^l = \xi_t \sum_{i=1}^L a_{ij} q_{it} \quad (21)$$

$$\tilde{c}_l = \sum_{i=1}^L \sum_{t=1}^T \xi_t c_i^{hn} q_{it} \quad (22)$$

After each iteration, the process is repeated until the objective function for [PP-y] is greater than or equal to zero. The deferral times are imposed by constraints (18). For a given blood product, a donor can only donate a limited amount during the planning horizon and that is guaranteed by Constraint (19). Constraint (20) is a

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

[PP-x]:

$$\begin{aligned} \min \quad & \sum_e \text{pr}(e) \left( \sum_i \xi_{t(e)} c_i^{ws} z_{ie} \right) - \sum_e \sum_i \sum_j \xi_{t(e)} z_{ie} a_{ij} w_{je} \\ \text{s.t.} \quad & (M-1)z_{ie} + \sum_{i'} \sum_{e' \in \bar{N}(e, s_{i'}-1)} z_{ie'} \leq M \quad \forall e, i \end{aligned} \quad (23)$$

$$\sum_i \sum_{e' \in \text{Pt}(e)} a_{ij} z_{ie'} \leq E_j \quad \forall e \in \mathcal{N}_T, j \quad (24)$$

$$z_{ie} \in \{0, 1\} \quad \forall e, i \quad (25)$$

A binary decision variable ( $z_{ie}$ ) in [PP-x] represents if in node  $e$ , donation type  $i$  is performed. Minimizing the reduced cost of the column is the objective of the model. Upon a negative objective function value, the column corresponding to all  $z_{ie}$  that are equal to 1 will be added to [RMP-WS]. As a result of constraints (23), successive donations are deferred for a certain period of time. Constraints (24) limit the amount of blood products that a donor can donate during the planning horizon. Lastly, binary variables are declared in constraints (25). Optimal  $z_{ie}$  values are used to calculate  $\alpha_{je}^m$  and  $\hat{c}_m$  values as follows:

$$\alpha_{je}^m = \xi_{t(e)} \sum_{i=1}^L a_{ij} z_{ie} \quad (26)$$

$$\hat{c}_m = \sum_{e=1}^N \text{pr}(e) \left( \sum_{i=1}^L \xi_{t(e)} c_i^{ws} z_{ie} \right) \quad (27)$$

With the newly added column, [RMP-WS] is once again solved.

To obtain a suitable solution, all profitable columns are generated, and then [RMP-WS] is solved along with shelf-life constraints and binary decision variables. The new

model is called [MP-WS], which is presented below:

[MP-WS]:

$$\begin{aligned}
\min \quad & \sum_{e \in \mathcal{N}_T} \text{pr}(e) \left( \sum_j \sum_{e' \in \text{Pt}(e)} h_j I_{e'j} + o_j P_{e'j} + \Omega B_{e'j} \right) + \dots \\
& \dots \sum_m \hat{c}_m x_m + \sum_l \tilde{c}_l y_l \\
\text{s.t.} \quad & (13) - (16) \\
& I_{0j} + \sum_{e' \in \text{Pd}(e, \eta_j)} \sum_m \alpha_{je'}^m x_m + \dots \\
& \dots \sum_{t'=1}^{t(e)} \sum_l \beta_{jt'}^l y_l - I_{ej} \geq 0 \quad \forall j, e : t(e) \leq \eta_j \quad (28) \\
& \sum_{e' \in \text{Pd}(e, \min\{\eta_j, t(e)-1\})} \sum_m \alpha_{je'}^m x_m + \dots \\
& \sum_{t'=t(e)-\eta_j+1}^{t(e)} \sum_l \beta_{jt'}^l y_l - I_{ej} \geq 0 \quad \forall j, e : t(e) > \eta_j \quad (29) \\
& y_l, x_m \geq 0 - \text{integer} \quad \forall l, m \quad (30)
\end{aligned}$$

In [MP-WS], constraints (28) and (29) are the shelf-life constraints, and constraints (30) define binary variable declarations. This algorithm is not a pure branch-and-price algorithm because we do not branch on the continuous decision variables; instead, we solve the associated master problem with integer decision variables ([MP-WS]).

The suggested method of column generation begins by finding a feasible solution to [RMP-WS]. Then, the [PP-y] and [PP-x] problems will be resolved, and the corresponding columns will be incorporated into the basis of [RMP-WS]. This process will be repeated until either the reduced cost is positive or the time limit is reached. If the reduced cost is not negative, then [MP-WS] will be solved and the algorithm will be terminated. The initial solutions for here-and-now and wait-and-see donations are presented in Appendix A and Appendix B, respectively.

**Post processing algorithm for donor utilization efficiency.** To achieve optimal donor allocation, we first develop and solve an optimization model. However, recognizing the potential for further refinement and improvement, we have incorporated a post-processing stage into our approach. The primary objective of this algorithm is to address the equitable distribution of donations to the pool without affecting the overall benefits derived from the donations yielded by the optimization model. By systematically evaluating and reassigning available resources, we aim to demonstrate substantial improvements in the utilization efficiency of donors, providing valuable insights for optimizing donor allocation strategies in similar contexts. The algorithm begins with selecting an unassigned donor (referred to as “donor  $a$ ”) and identifying the donor with the highest number of donations (referred to as “donor  $b$ ”). Let the total number of donations made by “donor  $b$ ” be denoted by  $n^*$ . We randomly assign  $\lfloor \frac{n^*}{2} \rfloor$  donations from “donor  $b$ ” to “donor  $a$ ”. After this reassignment, the number of donations is updated, and these steps are iteratively repeated until all donors have

been evaluated or until each donor has performed one donation during the planning horizon. The procedure is conducted for wait-and-see and here-and-now donors separately.

## 5. Computational Experiments

We conduct a numerical study to evaluate the effectiveness of the proposed solution methods using random examples inspired by real-life scenarios. The study is run on a 64-bit Windows Server with two 2.4 GHz Intel Xeon CPUs and 24 GB RAM. The algorithms are implemented using the Python Programming Language and GUROBI Solver version 9.1.1.

### 5.1. Data Generation

Throughout this study, we analyze instances that are inspired by real-life data (Do Carmo et al. 2013). In this section, a week is referred to as a “period”, and the problem is solved over a 12-week planning horizon, which is the longest time frame that can be computed within the limitations of CPU time. Özener, Ekici, and Çoban (2019) show that out of 17 possible donation types, the following three donation types are the most utilized ones in donation schedules:

- I whole blood (WB)
- II single unit platelets (SP) and double units plasma (DPLS)
- III double units platelets (DP), single-unit red blood cells (RBC), and single-unit plasma (PLS)

We also consider these three types in this study. As mentioned before, there must be a deferral period between two different types of donations depending on the current type and the upcoming type. Table 2 represents the deferral times of each donation type (Valbonesi et al. 2005; Stanford Blood Center 2021; Özener, Ekici, and Çoban 2019).

**Table 2.** Deferral times in terms of weeks

[Alt-Text: ]This table presents the diferral times between donations in terms of

From \ To		I	II	III
weeks.	I	8	4	8
	II	8	8	1
	III	8	4	8

In the case of a whole blood donation, the donor will have to wait eight weeks before he or she can donate whole blood or four weeks before he or she can donate SP-DPLS. Moreover, we consider the donation cost of donation types I, II, and III to be equal to \$138, \$364, and \$364, respectively. It must be noted that in this study, we assume here-and-now and wait-and-see donations to have the same cost. However, our proposed model is versatile enough to consider the cases with different donation costs. Red blood cells, platelets, and plasma are each limited to 1.5, 6, and 3 units of donation per planning horizon, respectively (Valbonesi et al. 2005). Moreover, as suggested by Gunpinar and Centeno (2015), the holding cost for each blood product is considered as \$1.25 per unit per day, red blood cells, plasma, and platelets have



disposal costs of \$0.36, \$0.36, and \$0.06 per unit, respectively based on an actual regional waste management center (Özener, Ekici, and Çoban 2019).

**Table 3.** Number of unit products collected from each donation type and their shelf-life

[Alt-Text: ]This table provides information on the number of unit products collected from each donation type and their shelf-life.

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.

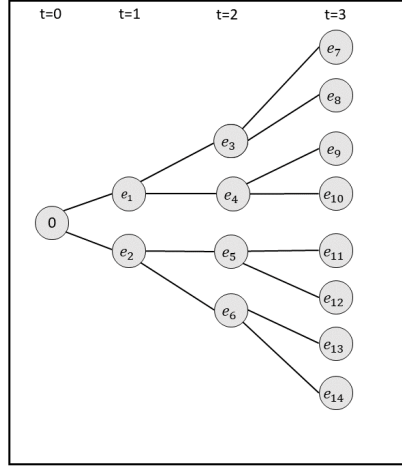
To investigate the effect of uncertainty on the results, we conduct computational analysis in three ways. First, to provide a better understanding of the problem and scenario tree-based reformulation of the blood donation management problem that adopts multicomponent apheresis and utilizes donor pool segmentation as here-and-now and wait-and-see donors, we propose an illustrative example with a low number of repeat donors and time periods. Second, 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. Third, to provide a profound insight toward utilizing the wait-and-see donors in real life, we propose a road map to the computational results.

## 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, and the deferral times of donations are relaxed. The scenario tree and the demand for different products are presented in Figure 2 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 after applying the post-processing algorithm, we present the results in Table 5. For here-and-now and wait-and-see decisions, we solve [MIP-WS] followed by the post-processing algorithm and present the results in Table 6 and Table 7. Moreover, to have a comparison of the results before and after the post-processing algorithm, we present the associated results in Appendix C.

In Table 5, the first column represents the periods, and the second, third, and fourth columns provide information on donation patterns. For example, donor 18 only performs a donation type 1 in the first period during the planning horizon. It must be noted that donors 27 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 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 and the second columns in Table 7 represent the time periods and nodes, respectively, 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



**Figure 2.** Scenario tree of the products in the illustrative example

[Alt-Text: ]This figure represents all the nodes and scenarios of the demand structure for blood products in the illustrative example.

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 ( $e_1$ ) (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 wait-and-see donors to 18 (i.e.,  $\theta = 0.60$ ). In the optimal solution, 18 wait-and-see and 12 here-and-now donors are scheduled for donation.

The efficiency of utilizing wait-and-see donors is clear 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. 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, 26 donors are used in the optimal donation schedule—the total number of donors to satisfy the same demand increases to 30 when wait-and-see donors are utilized. In other words, the number of donors utilized increases in the setting with wait-and-see donors, as these donors provide more flexible donations, and 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 highlighted.

### 5.3. *Impact of Seasonality and Time Variability of Demand*

In this section, 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

**Table 4.** The demand of nodes for different products

[Alt-Text: ]This table provides information on the demand of the nodes for different

		Products		
		1	2	3
blood products.	Nodes			
	$e_1$	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 5.** The donation schedule of donors for the setting with only here-and-now donation schedules

[Alt-Text: ]This table provides information on the donation schedule of donors for the setting with only here-and-now donation schedules.

Time Periods	Donation Types		
	1	2	3
<b>1</b>	[10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22]	[23, 7, 8, 26]	[1, 2, 3, 4, 5]
<b>2</b>			
<b>3</b>			[6, 24, 25, 9]

bound. 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, four cases in total. In all of the settings, considering 100 repeat donors, the instances are generated from the data set of the study by Do Carmo et al. (2013) and modified to be used for this study with 12 time periods as weeks. We consider *low*, *nominal*, and *high* demand nodes at each period. In other words, there will be  $3^{12}$  leaf nodes in total. In addition, in this section, we assume that all the repeat donors will be ready at the donation organization for donating though our model is versatile enough to consider participation ratio of the donors too by setting the percentage of presence of donors to a value lower than 1. Moreover, we set the value of  $\theta$  (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 for 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 results obtained are as follows:

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

[Alt-Text: ]This table provides information on the donation schedule of here-and-now donors for the setting with both here-and-now and wait-and-see donation schedules.

Time Period	Donation Type		
	1	2	3
<b>1</b>	[1, 2]	[3]	[11, 12]
<b>2</b>	[4, 5]	[6]	[9, 10]
<b>3</b>	[7]	-	[8]

**Table 7.** The donation schedule of wait-and-see donors

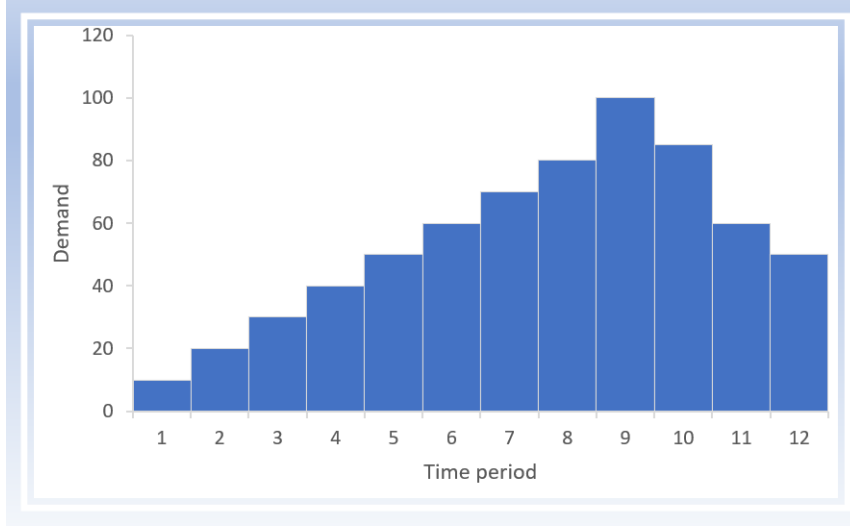
[Alt-Text: ]This table provides information on the donation schedule of wait-and-see donors for the setting with both here-and-now and wait-and-see donation schedules.

Time Periods	Nodes	Donation Types		
		1	2	3
<b>1</b>	<b>1</b>	[13, 14, 19, 21]	-	[16, 22]
	<b>2</b>	-	-	-
	<b>3</b>	-	-	[26, 18]
<b>2</b>	<b>4</b>	-	-	-
	<b>5</b>	-	-	[23]
	<b>6</b>	-	-	-
	<b>7</b>	[20]	-	[17, 24, 25]
	<b>8</b>	-	-	-
<b>3</b>	<b>9</b>	[29, 24, 25]	-	[15]
	<b>10</b>	-	-	-
	<b>11</b>	[14]	[28]	[15, 27]
	<b>12</b>	-	[19]	-
	<b>13</b>	[30]	[20]	[23]
	<b>14</b>	-	-	-

### 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 Do Carmo et al. (2013). The nominal demand values for the next periods are multiplied by some coefficients to generate instances of late seasonality. Figure 3 represents the late seasonality case for the *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. The first column indicates the instance number, followed by the number of different here-and-now donation schedules (HNP) in the second column and the number of different wait-and-see donation schedules (WSP) in the third column. The fourth column (HND) displays the count of here-and-now donors, while the fifth column (WSD) represents the number of wait-and-see donors. For all the settings, we do not apply the post-processing algorithm to get a better understanding of the utilized donors without it. Columns 6 to 8 provide contributions for different cost components, namely donation cost (Don.), inventory cost (Inv.), and

disposal cost (Dis.). Further, columns 9, 10, and 11 indicate the improvements in cost savings when utilizing only here-and-now donors. In addition, column 12 represents the total improvement achieved when utilizing wait-and-see donors along with here-and-now donors compared to relying solely on only here-and-now donors. Lastly, the final column (Gap) displays the optimality gap concerning the optimality gap of the proposed algorithm with respect to the LP-relaxation of [MIP-WS].



**Figure 3.** Demand histogram for seasonality with late demand shocks

[Alt-Text: ]This figure represents the demand histogram when there exist late demand shocks.

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

[Alt-Text: ]This table provides results for Case 1: seasonality with late demand shocks and low variance. The columns of the table are: Instance number; Number of different here-and-now donation schedules (HNP); Number of different wait-and-see donation schedules (WSP); Count of here-and-now donors (HND); Number of wait-and-see donors (WSD); Donation cost (Don.); Inventory cost (Inv.); Disposal cost (Dis.); Improvements in cost savings when utilizing only here-and-now donors; Further improvements in cost savings when utilizing only here-and-now donors; Additional improvements in cost savings when utilizing only here-and-now donors; Total improvement achieved when utilizing wait-and-see donors along with here-and-now donors compared to relying solely on only here-and-now donors; The optimality gap concerning the optimality gap of the proposed algorithm with respect to the LP-relaxation of [MIP-WS].

Ins.	HNP	WSP	HND	WSD	Contribution of Cost			Improvement			Total	Gap
					Don.	Inv.	Dis.	Don.	Inv.	Dis.		
1	15	24	55	36	90.84%	7.41%	1.75%	22.36%	16.21%	7.54%	15.37%	9.72%
2	7	28	54	36	86.28%	12.37%	1.35%	16.87%	9.83%	8.65%	11.78%	8.18%
3	10	29	60	37	93.31%	4.74%	1.95%	18.32%	10.69%	9.02%	12.68%	3.68%
4	10	22	58	36	90.80%	7.38%	1.82%	14.04%	12.14%	9.22%	11.80%	5.60%
5	8	11	52	37	90.37%	8.19%	1.44%	17.04%	11.92%	7.85%	12.27%	5.86%
6	11	28	59	39	93.18%	5.33%	1.48%	36.44%	17.72%	8.09%	20.75%	3.73%
7	10	20	57	40	89.82%	9.14%	1.04%	50.88%	18.39%	7.47%	25.58%	8.81%
8	12	19	58	37	89.38%	9.11%	1.52%	20.94%	16.48%	8.57%	15.33%	9.80%
9	12	15	60	34	90.06%	8.52%	1.42%	36.37%	18.94%	8.64%	21.32%	4.24%
10	7	24	56	39	89.10%	9.14%	1.76%	19.87%	7.78%	7.18%	11.61%	6.96%
Average					90.32%	8.13%	1.55%	25.31%	14.01%	8.22%	15.85%	6.66%
Best								50.88%	18.94%	9.22%	25.58%	3.68%
Worst								14.04%	7.78%	7.18%	11.61%	9.80%

Comparing the HNP and WSP columns, we observe that the number of different wait-and-see donation schedules (WSP) tends to be higher than the number of here-and-now donation schedules (HNP). This diversity in strategies implies a more nuanced and adaptive response to the specific circumstances of each instance. Analyzing the HND and WSD columns, the presence of both types of donors indicates a dynamic donor population with varying preferences and decision-making processes.

Examining the contribution of cost components in columns 6 to 8, we observe that

the donation cost tends to have the highest proportion in all instances. However, there are variations in the relative contributions of inventory and disposal costs across different cases. Comparing these contributions allows us to identify cost drivers and allocate resources more effectively based on their relative significance. Regarding columns 9 to 11, the improvements in cost savings achieved by incorporating wait-and-see strategies are substantial across all instances. However, there are noticeable variations in the magnitudes of these improvements. Instance 7, for example, stands out as having the greatest improvements in all three cost components. This implies that in certain scenarios, wait-and-see strategies can yield particularly significant cost savings. On the other hand, instance 10 exhibits the smallest improvements overall. This suggests that the benefits of wait-and-see strategies may be less pronounced in some instances, potentially due to factors such as demand patterns.

In terms of the total improvement (column 12), the average improvement across all instances is 15.85%. This indicates a considerable enhancement in cost savings when combining the benefits from all three cost components through the use of wait-and-see donation strategies. However, it is important to note that the best case (instance 7) achieves a total improvement of 25.58%, while the worst case (instance 10) only sees a total improvement of 11.61%. These disparities emphasize the influence of specific instance characteristics and highlight the potential for substantial cost savings in certain scenarios. Lastly, the optimality gap column shows the proposed algorithm provides high-quality solutions.

#### *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 Section 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 by 18.78%. Comparing the results with those in Section 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 satisfy the demand for the blood with a high variance. Therefore, for the case where 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 by 3.31%.

Looking at the contribution of cost components in columns 6 to 8, we can see that the donation cost remains the highest proportion in all instances, which is consistent with Case 1. The relative contributions of inventory and disposal costs also exhibit variations across different instances, highlighting the impact of demand variance on these cost components. Regarding columns 9 to 11, which represent the improvements in cost savings, we find that incorporating wait-and-see strategies still leads to substantial improvements in all instances. However, comparing these improvements with Case 1, we can observe that the magnitudes of the improvements tend to be higher in Case 2. This implies that the benefits of wait-and-see donors may be pronounced more in scenarios with high demand variance.

Examining the total improvement (column 12), the average improvement across all

**Table 9.** Case 2: Seasonality with late demand shocks with high variance

[Alt-Text: ]This table provides results for Case 2: seasonality with late demand shocks and high variance. The columns of the table are: Instance number; Number of different here-and-now donation schedules (HNP); Number of different wait-and-see donation schedules (WSP); Count of here-and-now donors (HND); Number of wait-and-see donors (WSD); Donation cost (Don.); Inventory cost (Inv.); Disposal cost (Dis.); Improvements in cost savings when utilizing only here-and-now donors; Further improvements in cost savings when utilizing only here-and-now donors; Additional improvements in cost savings when utilizing only here-and-now donors; Total improvement achieved when utilizing wait-and-see donors along with here-and-now donors compared to relying solely on only here-and-now donors; The optimality gap concerning the optimality gap of the proposed algorithm with respect to the LP-relaxation of [MIP-WS].

Ins.	HNP	WSP	HND	WSD	Contribution of Cost			Improvement			Total	Gap
					Don.	Inv.	Dis.	Don.	Inv.	Dis.		
1	13	20	59	36	91.08%	7.05%	1.87%	19.14%	16.40%	9.79%	15.11%	2.75%
2	12	17	64	35	89.23%	9.67%	1.10%	32.23%	19.80%	8.30%	20.11%	5.26%
3	12	22	57	35	93.67%	4.35%	1.98%	11.28%	13.60%	7.10%	10.66%	4.55%
4	10	17	59	40	93.02%	6.05%	0.93%	33.46%	19.10%	6.45%	19.67%	5.48%
5	12	14	60	34	91.79%	7.17%	1.04%	30.61%	14.01%	8.42%	17.68%	6.11%
6	7	20	56	39	92.96%	6.13%	0.91%	55.98%	26.40%	9.48%	30.62%	8.47%
7	10	11	56	36	93.11%	5.06%	1.83%	38.37%	14.90%	16.00%	23.09%	6.58%
8	12	15	62	36	91.65%	7.44%	0.91%	18.57%	13.10%	9.73%	13.80%	6.73%
9	9	13	52	37	92.04%	6.01%	1.95%	26.16%	16.10%	10.09%	17.45%	6.49%
10	13	30	60	37	93.34%	5.75%	0.91%	30.42%	19.40%	9.13%	19.65%	5.18%
Average					92.19%	6.47%	1.34%	29.62%	17.28%	9.45%	18.78%	5.76%
Best								55.98%	26.40%	16.00%	30.62%	2.75%
Worst								11.28%	13.10%	6.45%	10.66%	8.47%

instances is 18.78%. This indicates a significant enhancement in cost savings when combining the benefits from all three cost components through the use of wait-and-see donation strategies. However, similar to Case 1, there are notable variations in total improvement. The best case (instance 6) achieves a total improvement of 30.62%, while the worst case (instance 3) only sees a total improvement of 10.66%. Comparing Case 2 with Case 1, we can observe some differences. In Case 2, the average improvement in cost savings is slightly higher (18.78% in Case 2 vs 15.85% in Case 1), indicating that higher demand variance can lead to increased benefits from wait-and-see strategies. However, the average contributions of inventory and disposal costs are lower in Case 2 compared to Case 1. In addition, the optimality gap column shows that the proposed algorithm provides high-quality solutions in both cases. The results for Case 3 and Case 4 are presented in Appendix D and Appendix E, respectively.

#### 5.4. Impact of Uncertainty in the Presence of Donors

In this section, we study the impact of the probability of the donors not showing up at the donation center, and by varying the probability of donor presence, we aim to understand how this probability influences the overall effectiveness of the donation organization in terms of the number of here-and-now and wait-and-see donors. We consider 200 repeat donors for five time periods. We generate the demand for blood products the same way as in Case 1. Moreover, the probability of participation in a donation for a donor is considered to be the same for all periods. The value of  $\theta$  is set to 0.4. Table 10 presents the results for different values of the probability of participation in a donation for a donor ( $\xi$ ). In Table 10, the first column, labeled  $\xi$ , presents different values of the probability of participation, ranging from 0.1 to 1.0 in increments of 0.1. The second and third columns present the number of donors who perform here-and-now and wait-and-see donations, respectively. The fourth to sixth columns present the donation cost, inventory cost, and disposal cost gaps, respectively. The last column presents the gap in the total cost with respect to the case where all donors are present in the donations, represented as a percentage.

The results indicate that as the probability of donor participation decreases, there is a significant increase in the gaps, especially in donation costs. For example, when the probability is 0.1, 175 out of 200 donors are utilized, resulting in a total cost gap of 31.78% with respect to the 100% participation rate when only 50 donors are uti-

**Table 10.** Impact of the probability of participation in a donation for a donor

[Alt-Text: ]This table provides results for evaluation of the impact of the probability of participation in a donation for a donor

$\xi$	HN donors	WS donors	Utilized donors	Gap			
				Don.	Inv.	Dis.	Total
0.1	105	70	175	30.10%	0.78%	0.90%	31.78%
0.2	75	50	125	25.42%	0.43%	0.62%	26.47%
0.3	60	40	100	20.11%	0.89%	0.56%	21.56%
0.4	57	38	95	18.07%	0.17%	0.67%	18.91%
0.5	54	36	90	15.97%	0.22%	0.20%	16.39%
0.6	48	32	80	11.24%	0.43%	0.43%	12.10%
0.7	45	30	75	7.53%	0.57%	0.41%	8.51%
0.8	42	28	70	6.48%	0.63%	0.16%	7.27%
0.9	33	22	55	4.01%	1.02%	0.09%	5.12%
1	30	20	50	0.00%	0.00%	0.00%	0.00%

lized. This suggests that when there is a high likelihood of donors not showing up, the donation organization incurs higher costs to hedge against the risk of not having enough donations. On the other hand, as the probability of donor participation increases towards 100% (i.e.  $\xi = 1$ ), the gaps in costs gradually decrease. This highlights the importance of managing and mitigating uncertainties in donor turnout for blood donation organizations.

### 5.5. 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 afterwards, given that an extended waiting time for the new plan is not intended.

**Table 11.** Comparison of wait-and-see decisions and FH

[Alt-Text: ]This table provides results for comparing the results of donations with wait-and-see decisions and the folding horizon.

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%

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 11. We run the algorithms for five-period instances with *low*, *regular*, and *conservative* demand nodes at each period (i.e., we have  $3^5$  leaf nodes in total). We generate our instances by randomly sampling 84 ( $= 7 \times 12$ ) daily demands from the data set of the study by Do Carmo et al. (2013). 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 conserva-

tive 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 the 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.

## 6. Managerial Implications

Donation organizations can benefit from the presented research from four different aspects.

### 6.1. Importance of Optimization

While MCA may increase the complexity of managing blood donations, optimization techniques effectively streamline the scheduling process, increasing the efficiency of these high-stakes, high-cost operations. Our findings suggest that managing this complexity can provide considerable benefits. From a cost perspective, we observed that donation costs consistently accounted for the highest proportion of the total cost across instances. Therefore, strategies that can effectively reduce donation costs, such as better targeting of potential donors, can yield substantial savings. Inventory and disposal costs also played notable roles in several instances, emphasizing the importance of efficient inventory management and the minimization of waste.

In terms of algorithm performance, the optimization solution demonstrated high quality, with an average optimality gap of 6.66% across all instances. This reinforces the reliability and robustness of our optimization approach in providing near-optimal solutions within practical timeframes, even in the face of increased complexity introduced by MCA. In conclusion, optimization techniques for viable MCA donations offer significant benefits to blood donation organizations, allowing them to manage their resources more effectively, respond to uncertain demand patterns, and, ultimately, save more lives. Considering the unique characteristics of each instance and integrating wait-and-see donors into the donation strategy can significantly reduce costs and improve operational efficiency. By doing so, blood donation organizations can ensure they are leveraging their resources to the fullest potential in their noble mission to save lives.

### 6.2. Importance of Wait-and-See Donors

When faced with a highly unstable demand pattern and its variance, the customizability of the supply becomes paramount. This highlights the significance of utilizing wait-and-see donors, a fact further substantiated by the numerical results of this study. The introduction of wait-and-see donation schedules demonstrated a significant positive impact on cost savings. Across all instances, the average improvement in cost savings when including these donors was between 15% and 21%, with some scenarios even showing an improvement of 25.58%. This underscores the potential of adaptive, responsive strategies in the face of demand uncertainty, which can yield sizeable cost savings. It is important to note that these cost savings were derived from all three cost components, indicating that using wait-and-see donation strategies can improve

efficiency across the entire supply chain, not just in one area.

Wait-and-see donors play a pivotal role in resource management. Unlike regular donors who contribute consistently, these donors provide resources during times of unexpected or increased demand. They function as a just-in-time supply system, reducing the need for large-standing inventories. The variance in improvements between different instances emphasizes the importance of tailoring donation strategies to specific contexts. While on average, wait-and-see strategies offered significant improvements, there were instances where the benefits were less pronounced. Such scenarios could be due to certain demand patterns or unique characteristics of the donor population. It underscores the need for donation organizations to understand their unique environments, apply optimization methods accordingly, and show their utmost effort to convince donors to follow flexible wait-and-see donation schemes to achieve a higher quality service. As we limit the number of wait-and-see donors in our experiments, more significant improvements would be achieved when this percentage increases, making it one of the ultimate goals of donation organizations.

### **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 the demand realization is 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.

Moreover, using incentives for wait-and-see blood donors can be an effective way to increase the number of people who donate blood. Incentives can range from small tokens of appreciation to more significant rewards, like a cash prize. The average improvement of utilizing wait-and-see donors over here-and-now ones in Cases 1-4 are 15.85%, 18.75%, 17.84%, and 21.04%, respectively. Therefore, it can be concluded that the cost savings generated by using wait-and-see donors can then be used to provide incentives and rewards for these donors. This can help to build a stronger relationship with wait-and-see donors and increase their likelihood of making a donation in the future.

### **6.4. *Effects of the Donation Participation Ratio***

The uncertainty in blood product demand is influenced by unpredictable factors. Ignoring this can endanger patients. Blood donation organizations must consider this

uncertainty in operations. Our study suggests a strategy using both wait-and-see and here-and-now donors. In our model, here-and-now donors meet regular demand, while wait-and-see donors address high-demand situations. Results show that when donor participation likelihood is low, both donation types peak, optimizing resource use and ensuring operational efficiency. However, decreased donor participation can increase donation, inventory, disposal, and total costs. Managers must recognize the financial effects of donor uncertainty and develop strategies to reduce these costs, enhancing cost-effectiveness. Addressing donor turnout uncertainties is crucial. Our findings show cost increases as donor participation likelihood drops. Organizations can use risk management tactics like targeted engagement and marketing to reduce donor attendance uncertainty, improving performance.

Understanding donor participation probability is key for capacity planning. High absence probability may require capacity adjustments to avoid waste, while high presence probability means preparing for more donors. Long-term effects of donor probabilities should be considered. Analyzing historical data helps in decision-making regarding resources and costs. Effective donor engagement strategies, like incentives and community building, can boost attendance. The study emphasizes cost sensitivity to donor participation, so monitoring turnout and analyzing cost gaps is vital for continuous improvement.

## 7. Conclusion

In this research, we introduce the *stochastic donation tailoring problem* (SDTP), a model that considers the shelf-life, deferral times, and unpredictable demand of blood products. Our objective is to minimize associated costs while leveraging *multicomponent apheresis* (MCA) technology. Unlike previous deterministic models, SDTP is innovative in offering a flexible donation strategy for MCA. It does this by segmenting donors into two categories: wait-and-see and here-and-now. This categorization allows donation centers to dynamically adjust donation schedules based on real-time demand. To address the inherent challenges of this problem, we propose a *column generation* (CG) based heuristic. This heuristic can efficiently solve the problem in under 24 hours for realistic scenarios, outperforming commercial solvers. Our numerical results validate the effectiveness of the CG approach. Importantly, our model successfully navigates the complexities of the blood donation process, such as deferral times and uncertain demand, and offers improved operational cost savings compared to traditional donation schemes.

*Future* studies should refine the developed stochastic model to optimize blood donation management. Exploring the integration of dynamic machine learning algorithms could address fluctuating demands, enhancing the model's precision. The benefits of using multicomponent apheresis and flexible donations highlight new research avenues, especially in their practical implementation. Evaluating the integration of these strategies through a cost-benefit analysis can provide insights into both financial and health outcomes. Additionally, understanding donor behavior towards flexible schedules can reveal potential sociological barriers, aiding in smoother transitions to efficient systems. In terms of blood type management, there's an evident need for models that can incorporate various blood types, ensuring a comprehensive view of blood bank operations and promoting informed decision-making for optimal resource allocation and patient care.

## Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author.

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## Appendix A Initial solution approach for here-and-now donations

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]. Taking into account the deferral times for each specific type of donation, we assume that each donor may just make one type of donation at a time. When a single donation type is made, donor tracking will be simplified, as keeping track of previous donation dates is sufficient for keeping track of donors. As an example, if a person donates whole blood today, he/she must wait for eight weeks before donating whole blood again. To provide the first solution for the problem with 12 periods, we can have a person who donates whole blood in week 1, and the second donation in week 9. The next whole blood donation can be performed in week two by another person, and the next donation 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 2 consecutive donations in the initial solution approach is exactly equivalent to the deferral time of the donation type.

## Appendix B 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  $\theta$  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. 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 penalty in the objective. Ultimately, [WS-In] provides feasible wait-and-see columns. As before, optimal  $z_{ie}$  values are used to obtain the columns  $\alpha^m$  and  $\hat{c}_m$  as follows:

$$\alpha_{je}^m = \xi_{t(e)} \sum_{i=1}^L a_{ij} z_{ie} \quad (31)$$

$$\hat{c}_m = \sum_{e=1}^N \text{pr}(e) \left( \sum_{i=1}^L \xi_{t(e)} \hat{c}_i^{ws} z_{ie} \right) \quad (32)$$

It must be noted that solving [WS-In] to optimality by a commercial solver may not be straightforward due to the complexity of this *mixed-integer linear program* (MILP). Therefore, we terminate the commercial solver with a safe optimality gap. Moreover, instead of adding a single feasible solution, we utilize a solution pool to add more than one feasible column.

[WS-In]:

$$\begin{aligned}
\min \quad & \sum_{e \in \mathcal{N}_T} \text{pr}'(e) \left[ \sum_j \sum_{e' \in \text{Pt}(e)} (h_j I_{e'j} + o_j P_{e'j} + \Omega B_{e'j}) + \sum_i \xi_{t(e)} c_i^{ws} z_{ie} \right] + \dots \\
& \dots M \sum_{e \in \mathcal{N}_T} \sum_j R_{ej} \\
\text{s.t.} \quad & I_{\text{ipd}(e)j} - I_{ej} - P_{ej} + B_{ej} + \sum_i \sum_{e' \in \mathcal{N}_T} \xi_{t(e)} a_{ij} z_{ie} = \dots \\
& \dots \max \left\{ d_{ej} - \sum_{e': t(e')=t(e)} \text{pr}'(e') d_{e'j}, 0 \right\} (|\mathcal{N}_{t(e)}| K_T')^{(-1)} - R_{ej} \quad \forall e, j \\
& (M-1) z_{ie} + \sum_{i'} \sum_{e' \in \bar{N}(e, s_{ii'}-1)} z_{i'e'} \leq M \quad \forall e, i \\
& \sum_i \sum_{e' \in \text{Pt}(e)} a_{ij} z_{ie'} \leq E_j \quad \forall e \in \mathcal{N}_T, j \\
& I_{ej}, P_{ej}, R_{ej}, B_{ej} \geq 0 \quad \forall e, j \\
& z_{ie} \in \{0, 1\} \quad \forall e, i
\end{aligned}$$

## Appendix C Effect of the Post-Processing Algorithm on Illustrative Example

In this section, we present the detailed results and analysis obtained from the illustrative example discussed in the main report. We define two different cases (Case I and Case II). In Case I, the post-processing algorithm is not applied; however, in Case II, the post-processing algorithm is applied after solving [MIP-HN] or [MIP-WS]. The donation patterns of here-and-now donors for the setting in which only here-and-now donations are allowed are presented in Table 12 for both cases. Applying the post-processing algorithm does not provide any change for the here-and-now donations for the setting in which both here-and-now and wait-and-see donations are allowed. However, the wait-and-see donation patterns are presented in Table 13 for both cases.

**Table 12.** The donation schedule of donors for the setting with only here-and-now donation schedules for Case I and Case II

[Alt-Text: ] This table provides results for the donation schedule of donors for the setting with only here-and-now donation schedules for Case I and Case II

Time Period	Case I			Case II		
	Donation Type					
	1	2	3	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]	[10,11,12,13,14, 15,16,17,18, 19,20,21,22]	[23,7,8,26]	[1,2,3,4,5]
2						
3			[6,7,8,9]			[6,24,25,9]

In Case II of Table 12, where the post-processing algorithm is applied after solving

[MIP-HN], the donation schedule for donation Type 1 remains the same as in Case I. However, for Donation Types 2 and 3, there is a noticeable change in their donation patterns during Time Period 1 and Time Period 3, respectively.

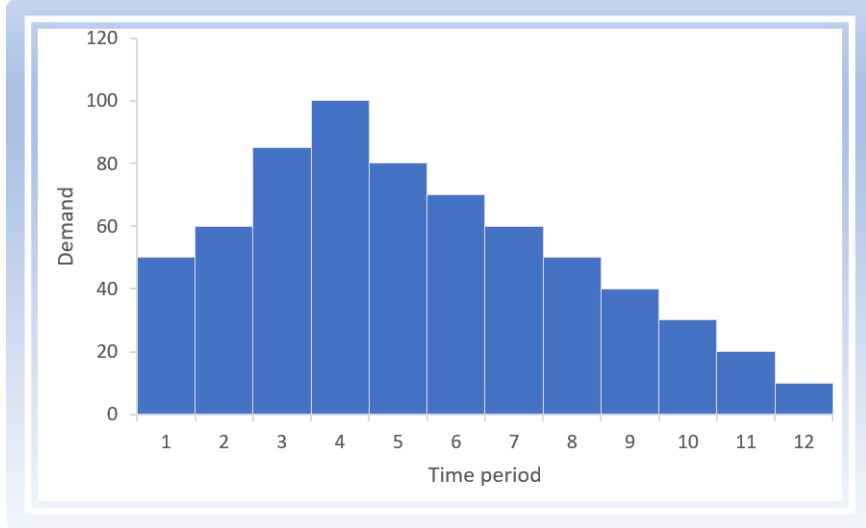
**Table 13.** The donation schedule of wait-and-see donors for Case I and Case II  
 [Alt-Text: ]This table provides results for the donation schedule of wait-and-see donors for Case I and Case

Time Periods	Nodes	Case I			Case II			
		Donation Types			Donation Types			
		1	2	3	1	2	3	
II.	1	1	[13, 14, 19, 21]	-	[16, 22]	[13, 14, 19, 21]	-	[16, 22]
		2	-	-	-	-	-	-
		3	-	-	[15, 18]	-	-	[26, 18]
	2	4	-	-	-	-	-	-
		5	-	-	[23]	-	-	[23]
		6	-	-	-	-	-	-
	3	7	[20]	-	[17, 24, 25]	[20]	-	[17, 24, 25]
		8	-	-	-	-	-	-
		9	[18, 24, 25]	-	[15]	[29, 24, 25]	-	[15]
		10	-	-	-	-	-	-
	3	11	[14]	[24]	[15, 20]	[14]	[28]	[15, 27]
		12	-	[19]	-	-	[19]	-
		13	[17]	[20]	[23]	[30]	[20]	[23]
		14	-	-	-	-	-	-

In Table 13, comparing the wait-and-see donations between Case I and Case II, we can observe that some donation patterns are changed for some wait-and-see donors in Case II due to the application of the post-processing algorithm. These changes suggest that the post-processing algorithm has influenced the decisions regarding some wait-and-see donors, leading to different donation patterns in Case II.

#### Appendix D 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 Do Carmo et al. (2013). This value for the other periods is multiplied by some coefficients to have early seasonality for the data as is presented in Figure 4. The *high*\low demand values of a product for each period are calculated as the *nominal* plus\minus the standard deviation of the sampled data. Table 14 presents the results for this case.



**Figure 4.** Demand histogram for seasonality with early demand shocks

[Alt-Text: ]This figure represents the demand histogram when there exist early demand shocks

**Table 14.** Case 3: Seasonality with early demand shocks with low variance

[Alt-Text: ]This table provides results for Case 3: seasonality with early demand shocks and low variance. The columns of the table are: Instance number; Number of different here-and-now donation schedules (HNP); Number of different wait-and-see donation schedules (WSP); Count of here-and-now donors (HND); Number of wait-and-see donors (WSD); Donation cost (Don.); Inventory cost (Inv.); Disposal cost (Dis.); Improvements in cost savings when utilizing only here-and-now donors; Further improvements in cost savings when utilizing only here-and-now donors; Additional improvements in cost savings when utilizing only here-and-now donors; Total improvement achieved when utilizing wait-and-see donors along with here-and-now donors compared to relying solely on only here-and-now donors; The optimality gap concerning the optimality gap of the proposed algorithm with respect to the LP-relaxation of [MIP-WS].

Ins.	HNP	WSP	HND	WSD	Contribution of Cost			Improvement			Total	Gap
					Don.	Inv.	Dis.	Don.	Inv.	Dis.		
1	13	25	58	36	97.92%	0.87%	1.21%	42.71%	6.73%	9.99%	19.81%	10.59%
2	15	11	57	37	94.79%	1.78%	3.43%	25.70%	5.18%	6.71%	12.53%	6.69%
3	8	14	55	40	95.23%	1.73%	3.04%	43.82%	7.34%	11.87%	21.01%	9.00%
4	11	29	57	40	96.32%	0.61%	3.07%	37.55%	6.08%	14.24%	19.29%	7.49%
5	12	19	61	34	91.99%	3.48%	4.53%	34.32%	2.17%	3.89%	13.46%	7.21%
6	14	22	54	38	95.68%	1.09%	3.23%	37.91%	6.22%	8.01%	17.38%	7.92%
7	11	20	61	39	95.26%	0.54%	4.20%	43.16%	15.21%	17.74%	25.37%	5.24%
8	13	29	58	34	95.37%	1.13%	3.50%	29.69%	11.47%	15.39%	18.85%	6.60%
9	11	12	60	34	95.22%	0.98%	3.80%	22.36%	6.86%	8.16%	12.46%	6.80%
10	13	15	58	40	94.61%	2.25%	3.14%	30.26%	10.38%	14.17%	18.27%	4.48%
Average					95.24%	1.45%	3.32%	34.75%	7.76%	11.02%	17.84%	7.20%
Best								43.82%	15.21%	17.74%	25.37%	4.48%
Worst								22.36%	2.17%	3.89%	12.46%	10.59%

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 demand shocks happen in 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 to satisfy the demand for product. In other words, 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.

Examining the contribution of cost components in columns 6 to 8, we find that the donation cost remains the highest proportion in all instances, consistent with the previous cases. However, there are variations in the relative contributions of inventory and disposal costs, highlighting the impact of demand variance on these cost components. Regarding columns 9 to 11, which represent the improvements in cost

savings, we can observe that incorporating wait-and-see strategies leads to substantial improvements across all instances. Analyzing the total improvement (column 12), we see that the average improvement across all instances in Case 3 is 17.84%. This indicates a significant enhancement in cost savings when utilizing wait-and-see donation strategies. Comparing Case 3 with Case 1, we observe that the average improvement in cost savings is higher in Case 3 (17.84% vs 15.85%), suggesting that the benefits of wait-and-see strategies may be more pronounced in scenarios with early demand shocks and low variance.

## Appendix E 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 is explained in Appendix D, and the *low* and *high* demand values are calculated as is explained in Section 5.3. The associated results are presented in Table 15.

**Table 15.** Case 4: Seasonality with early demand shocks with high variance.

[Alt-Text: ]This table provides results for Case 4: seasonality with early demand shocks and high variance. The columns of the table are: Instance number; Number of different here-and-now donation schedules (HNP); Number of different wait-and-see donation schedules (WSP); Count of here-and-now donors (HND); Number of wait-and-see donors (WSD); Donation cost (Don.); Inventory cost (Inv.); Disposal cost (Dis.); Improvements in cost savings when utilizing only here-and-now donors; Further improvements in cost savings when utilizing only here-and-now donors; Additional improvements in cost savings when utilizing only here-and-now donors; Total improvement achieved when utilizing wait-and-see donors along with here-and-now donors compared to relying solely on only here-and-now donors; The optimality gap concerning the optimality gap of the proposed algorithm with respect to the LP-relaxation of [MIP-WS].

Ins.	HNP	WSP	HND	WSD	Contribution of Cost			Improvement			Total	Gap
					Don.	Inv.	Dis.	Don.	Inv.	Dis.		
1	15	15	55	36	95.83%	1.06%	3.11%	30.39%	13.43%	15.52%	19.78%	4.04%
2	15	30	63	35	94.94%	2.19%	2.87%	34.18%	7.27%	9.28%	16.91%	6.22%
3	9	27	63	37	97.89%	0.79%	1.32%	39.45%	4.81%	6.83%	17.03%	6.08%
4	10	13	58	39	97.36%	1.20%	1.44%	40.97%	9.50%	11.51%	20.66%	9.69%
5	8	10	60	35	96.32%	1.71%	1.97%	45.81%	15.95%	18.31%	26.69%	6.14%
6	11	25	58	36	97.18%	1.19%	1.63%	45.83%	4.42%	6.96%	19.07%	7.00%
7	14	30	61	34	93.85%	2.60%	3.55%	30.86%	11.29%	13.29%	18.48%	9.86%
8	7	24	59	40	94.86%	1.30%	3.84%	41.82%	12.38%	12.67%	22.29%	5.06%
9	13	29	60	35	95.32%	1.66%	3.02%	45.83%	19.56%	20.41%	28.60%	5.15%
10	11	20	61	39	97.41%	0.72%	1.87%	48.09%	6.24%	8.25%	20.86%	5.14%
Average					96.10%	1.44%	2.46%	40.32%	10.49%	12.30%	17.84%	7.20%
Best					48.09%	19.56%	20.41%	25.37%	4.48%			
Worst					30.39%	4.42%	6.83%	12.46%	10.59%			

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. The algorithm in this case, provides more improvement than case 2 and case 3, and the reason is 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.

Looking at the contribution of cost components in columns 6 to 8, we find that the donation cost remains the highest proportion in all instances, which aligns with the findings in previous cases. However, the relative contributions of inventory and disposal costs exhibit variations across different instances, highlighting the impact of demand variance on these cost components. Regarding columns 9 to 11, which represent the improvements in cost savings, we can observe that incorporating wait-and-see strategies leads to significant improvements in all instances. Comparing these improvements with previous cases, we can observe that the magnitudes of the improvements tend to be higher in Case 4. This suggests that wait-and-see donors play a crucial role in

scenarios with high demand variance, as they enable donation organizations to better satisfy the fluctuating demand for blood products. Examining the total improvement (column 12), the average improvement across all instances in Case 4 is 17.84%, indicating a substantial enhancement in cost savings when combining the benefits from all three cost components through the use of wait-and-see donation strategies. Comparing Case 4 with previous cases, we can observe that the average improvement in cost savings is slightly higher in Case 4. This highlights the increased benefits of wait-and-see strategies in scenarios with high demand variance.