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The supply chain of blood products in the wake of the COVID-19 pandemic: Appointment scheduling and other restrictions

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ABSTRACT

In this work, we formulate the blood products supply chain problem in the wake of disasters such as the COVID-19 (SARS-CoV-2) pandemic using two-stage stochastic programming where uncertainty of both demand and supply is considered. The products considered are red blood cells (RBCs), plasma, and platelets. Age-based demand and blood type substitution are included in our model. A heuristic is developed to solve the instances a commercial optimization software failed to solve in a reasonable amount of time. To obtain managerial insight a sensitivity analysis is conducted. Results of the analysis show that bigger capacities of permanent collection facilities are favored over the mobility of temporary facilities while accounting for blood substitution and age-based demand in the planning phase reduced shortages significantly. Moreover, different objective functions were considered to ensure fairness in distribution of the products among hospitals. The fairer distribution resulted in an increase in the total unmet demand.

1. Introduction

By definition, a pandemic is a disease that spreads across several countries simultaneously at an alarming rate. Usually, pandemics have a lethal effect on the human race, especially if precautions are not immediately taken by governments to ensure the safety of their populations. On March 11th, 2020, World Health Organization (WHO) chief Dr. Tedros Ghebreyesus officially declared COVID-19 (SARS-CoV-2) as a pandemic (BBC, 2020). As a result, many countries have immediately taken several precautions to help in containing this pandemic. Some of these precautions include closing off borders, imposing nationwide or area-based lock-downs, forcing people to wear masks and maintain social distancing, forcing companies to allow their employees to work from home, shifting their education systems to online-based ones, and many other restrictions that differ from one country to another (Salcedo et al., 2020; The World Bank, 2020).

While these restrictions did indeed prove effective in partially controlling the pandemic (Zhou et al., 2020), naturally, they had their side effects. These side effects were on a national level where economies crashed and unemployment rates increased (Jones et al., 2020). In addition, other side effects were seen on an individual level in the form of a negative impact on the mental health of adults and on the social and educational health of children who were accustomed to attending schools in person (Panchal et al., 2020). It is generally accepted that these side-effects are all a direct result of pandemic-related restrictions. However, there are several indirect side effects that may have even worse implications. One of the major indirect effects of the pandemic is the disruption of supply chains because of loss of workforce, restricted access, and lack of transportation options especially for overseas deliveries.

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Table 1
Properties of the most demanded blood components (The American National Red Cross, 2018).

Component	Shelf life (days)	Storing conditions	Key uses
Red blood cells	42	Refrigerated	Trauma, Surgery, Anemia, Any blood loss, Blood disorders, such as sickle cell
Platelets	5	Room temperature with constant agitation to prevent clumping	Cancer treatments, Organ transplants, Surgery
Plasma	365	Frozen	Burn patients, Shock, Bleeding disorders

Table 2
Compatibility of the different blood types.

		Patient's blood type							
		A+	A-	B+	B-	AB+	AB-	O+	O-
Donor's blood type	A+	✓$\textcolor{red}{\checkmark}$				✓		$\textcolor{red}{\checkmark}\textcolor{green}{\checkmark}$	$\textcolor{green}{\checkmark}$
	A-	✓$\textcolor{red}{\checkmark}$	✓$\textcolor{red}{\checkmark}$			✓	✓	$\textcolor{red}{\checkmark}\textcolor{green}{\checkmark}$	$\textcolor{red}{\checkmark}\textcolor{green}{\checkmark}$
	B+			✓$\textcolor{red}{\checkmark}$		✓		$\textcolor{red}{\checkmark}\textcolor{green}{\checkmark}$	$\textcolor{green}{\checkmark}$
	B-			✓$\textcolor{red}{\checkmark}$	✓$\textcolor{red}{\checkmark}$	✓		$\textcolor{red}{\checkmark}\textcolor{green}{\checkmark}$	$\textcolor{red}{\checkmark}\textcolor{green}{\checkmark}$
	AB+	$\textcolor{red}{\checkmark}\textcolor{green}{\checkmark}$	$\textcolor{green}{\checkmark}$	$\textcolor{red}{\checkmark}\textcolor{green}{\checkmark}$	$\textcolor{green}{\checkmark}$	✓$\textcolor{red}{\checkmark}\textcolor{green}{\checkmark}$	$\textcolor{green}{\checkmark}$	$\textcolor{red}{\checkmark}\textcolor{green}{\checkmark}$	$\textcolor{green}{\checkmark}$
	AB-	$\textcolor{red}{\checkmark}\textcolor{green}{\checkmark}$	$\textcolor{red}{\checkmark}\textcolor{green}{\checkmark}$	$\textcolor{red}{\checkmark}\textcolor{green}{\checkmark}$	$\textcolor{red}{\checkmark}\textcolor{green}{\checkmark}$	✓$\textcolor{red}{\checkmark}\textcolor{green}{\checkmark}$	✓$\textcolor{red}{\checkmark}\textcolor{green}{\checkmark}$	$\textcolor{red}{\checkmark}\textcolor{green}{\checkmark}$	$\textcolor{red}{\checkmark}\textcolor{green}{\checkmark}$
	O+	✓		✓		✓		✓$\textcolor{red}{\checkmark}\textcolor{green}{\checkmark}$	$\textcolor{green}{\checkmark}$
	O-	✓	✓	✓	✓	✓	✓	✓$\textcolor{red}{\checkmark}\textcolor{green}{\checkmark}$	✓$\textcolor{red}{\checkmark}\textcolor{green}{\checkmark}$

✓RBCs $\textcolor{red}{\checkmark}$ platelets $\textcolor{green}{\checkmark}$ plasma.

Former United States President Donald J. Trump issued an executive order ensuring that essential medical supplies are made in the U.S.A. because of the disruptions that happened in March and April of 2020 (Trump, 2020). Of all the pharmaceutical ingredients used in the U.S.A., 72% are imported from outside the country including 13% from China, and as a result there were severe shortages in the early days of the pandemic (Tausche et al., 2020).

One of the supply chains severely affected in terms of shortages by the COVID-19 (SARS-CoV-2) pandemic is that of blood products. The resulting shortages are due to the fact that most regular donors are avoiding donations because of social distancing and fear of leaving their homes. Prior to the pandemic, inventory levels for blood products typically lasted one to two weeks while now they have dropped to one to two days (Stiepan, 2020). The American Red Cross has also voiced concerns over shortages in blood products because people are confusing social distancing with social engagement. In fact, to assist with the process and ensure the safety of donors, they have set up an appointment scheduling system to avoid crowding at donation centers (The American National Red Cross, 2020). Gulf Cooperation Council (GCC) countries, in addition to many countries worldwide, have started using the plasma of recovered COVID-19 patients to speed up the treatment of currently infected patients. In addition to encouraging people to donate more blood products, governments of these countries also have to encourage recovered patients to donate their plasma.

The supply chain of blood products is a highly complex one because of the many decisions involving supply collected, inventory levels, waste levels, and transfusion decisions. The COVID-19 (SARS-CoV-2) pandemic adds several layers of complexity to the already-complex problem. The pandemic results in a high uncertainty in supply. Donor behavior is highly uncertain to begin with and with all the social distancing rules some people prefer to avoid confined spaces or unnecessary trips away from their houses. This has resulted in a shortage and a very nonuniform distribution of blood availability among blood banks and collection centers. Additionally, the pandemic has resulted in restricted access to and from specific regions that have high infection rates within a city. This means that not every collection center is accessible to every resident/visitor in that city. The uncertain supplies and restricted access have resulted in shortages. On one hand, having shortages is not acceptable for obvious reasons while, on the other hand, hoarding large quantities of blood products will lead to higher wastage rates of an already scarce asset due to its short life. Therefore, optimal decisions have to be made to ensure a balance is maintained with all the above considerations in mind (the different properties of the blood products are shown in Table 1.)

Demand for blood products tends to be lower the older they get, and this is caused by two factors: (i) the shelf-life of these products after which the products will have no value and must be immediately discarded, and (ii) the evidence reported in Atkinson et al. (2012) suggests that trauma and cardiac surgery patients have seen improvements in morbidity and mortality rates when fresher RBCs are used. Further evidence by Vamvakas (2010) that suggests fresher RBCs result in lower post-surgery bacterial infections. Therefore, it is necessary to keep track of the age of the blood products in inventory to ensure that any age-based demand is properly satisfied.

To ensure further effectiveness of the considered supply chain in minimizing shortages, blood substitution has to be considered. Basically, for a given transfusion process, if the specific blood type of the patient is available only in limited quantities or completely unavailable, blood substitution may take place where the patient is transfused with the product from a compatible blood group (Duan and Liao, 2014; oneblood, 2018). The ABO compatibility chart is shown in Table 2. Including ABO substitution in the planning phase of a supply chain will result in fewer shortages and decreased mortality rates.

Considering all the above, the contributions of this work are:

1. Designing a three-echelon supply chain of blood products, depicted in Fig. 1, that includes donors, blood collection facilities, and hospitals. Donors are initially assigned to blood collection facilities through an appointment system. The collected blood

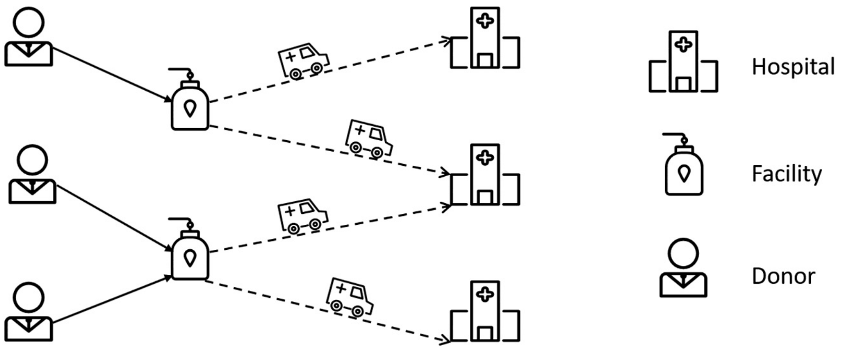


Fig. 1. The considered supply chain of blood products.

is then sent to the hospitals via specialized trucks. Blood is kept in inventory at the hospitals and transfused into patients according to the demand.
2. Formulating a mathematical model of the supply chain using two-stage stochastic programming to account for uncertainty of both supply and demand in the event that a disaster takes place. Specifically, the first stage of the model determines the locations of permanent collection facilities ahead of a disaster while the second stage determines the locations of temporary facilities, inventory levels, and transfusion decisions once a disaster takes place.
3. Accounting for multiple blood products, namely RBCs, plasma, and platelets, the three most common blood products dealt with in the health sector. The supply chain considered consists of three echelons: the donors, the collection facilities, and the hospitals.
4. Accounting for safety measures to protect the donors by assigning them to collection centers that are within an acceptable distance and through an appointment scheduling system that ensures no overcrowding happens at these centers. These safety measures are expected to encourage donors to proceed with their donations.
5. Including age-based demand for blood products and ABO blood type substitution which are both practical extensions.
6. Developing a heuristic to solve the complex problem yielded by all the considered characteristics mentioned above. The heuristic provides near-optimal solutions.
7. Providing managerial insight that discusses the different bottlenecks of the supply chain, the effect on different objective functions, and the advantages of accounting for age-based demand and blood substitution.

The remainder of this paper is organized as follows. A comprehensive literature review of the state-of-the-art is presented in Section 2. The details of the model and the mathematical formulation are presented in Section 3. Section 4 details the heuristic used to solve the model. Section 5 presents both the results of the complexity study and the sensitivity analysis conducted on the parameters. Managerial insight is also provided in that section. A conclusion and future research directions are presented in Section 6.

2. Literature review

In this section we present the state-of-the-art in literature focusing on the supply chains of blood products (Section 2.1), age-based demand of products (Section 2.2), and the effect of the COVID-19 (SARS-CoV-2) pandemic on supply chains (Section 2.3). Towards the end of each section we discuss the gaps in the literature and then we proceed in explaining how the contributions of this work fill in these gaps.

2.1. Supply chains of blood products

While there is a large body of work dealing with the supply chain of blood products, the majority of these works focus on individual echelons in the supply chain rather than on an integrated model (Osorio et al., 2015). These echelons include collection, production, storage and inventory, and distribution individually. It was not until recently that the literature started investigating integrated models and only a small portion of these works used mathematical programming to formulate their problems.

One of the main challenges in operating the supply chain of blood products is the highly stochastic nature of both the supply and the demand. Despite the importance of these considerations, many works have opted to model their supply as deterministic (Chung and Erhun, 2013; Ensafian and Yaghoubi, 2017; Haghjoo et al., 2020; Hosseinifard and Abbasi, 2018; Ma et al., 2019; Nahmias, 1982). The work of Ma et al. (2019) formulates a mathematical model using integer programming that introduces a novel method to prioritize blood substitution and substitution rates. However, both their supply and demand are considered to be deterministic. Despite only considering deterministic supply, Haghjoo et al. (2020) include a novel practical consideration in their work. Their formulations consider a lower probability of disruption for those temporary facilities that have a larger sum of money invested in their establishment, and vice versa. This adds complexity to their model because their objective function minimizes both the cost of opening facilities and disruption-related costs. The quantity of literature that has considered a stochastic supply (Fahimnia et al., 2017; Hamdan and Diabat, 2019, 2020; Jabbarzadeh et al., 2014; Osorio et al., 2018; Samani et al., 2018) is small. Jabbarzadeh et al. (2014) present a robust supply chain for blood emergencies in the case of disasters. The main decisions in their model are location, allocation, and inventory levels for different disaster scenarios over multiple periods. However, their work focused only on minimizing costs in the objective function, while, in reality, several objectives may be considered that conflict with each other. Fahimnia et al. (2017) consider a robust supply chain with an objective function that aims at minimizing both costs and delivery times. The authors account for the production process of blood by including local and regional blood centers that screen the blood before being sent to hospitals. These contradictory terms in the objective function increase the complexity of the problem which is then solved using ε-constraint and Lagrangian relaxation. Other important practical considerations were made in the work of Hamdan and Diabat (2019). While not considering disaster scenarios, the authors include multiple blood types, production, and substitution decisions for RBCs. Production involves the routing of blood from local to regional blood centers for further screening and substitution allows for the replacement of certain blood types with other compatible blood types to reduce overall costs, shortages, and outdates. Their case study considers the blood bank in the Hashemite Kingdom of Jordan and shows that the proposed model in their work manages to reduce the costs and outdated units from the current practice by more than 77%. Recently, the robust supply chain problem was revisited by Hamdan and Diabat (2020). The authors consider multiple blood products and the possibilities of disruptions at certain locations that will lead to rerouting decisions. The work of Samani et al. (2018) formulates the blood supply chain problem using two-stage stochastic programming with the addition that the blood collected can be either transported to hospitals or to established relief bases. Additionally, each facility has several capacity options which determine the cost of establishing that facility. One of the terms of their objective function also focuses on maximizing the freshness of the delivered blood, a feature missing from other supply chains of blood products.

A novel approach for collecting blood in the blood supply chain was introduced in the work of Osorio et al. (2018). The authors introduce different blood collection technologies such as apheresis that increases the yield of blood collected but at an additional cost. While they do not explicitly model their supply to be stochastic, they introduce uncertainty in the arrival of donors. Their model includes two objective functions that are conflicting in their nature. The first aims at minimizing the total costs of the system while the second aims at minimizing the total number of donors needed to satisfy the demand. To formulate the deterministic equivalent of their stochastic problem, the authors opt for Sample Average Approximation (SAA). Meanwhile, their multi-objective problem is solved using the Augmented Epsilon Constraint algorithm.

While covering a range of important practical considerations, especially in the context of disasters, none of these considerations fit the special case of the COVID-19 (SARS-CoV-2) pandemic. Although the works of Jabbarzadeh et al. (2014), Fahimnia et al. (2017), and Samani et al. (2018) impose a maximum distance allowed for donors to travel, their works do not ensure the safety of donors from infection by coming in contact with other donors. Ma et al. (2019) do not account for disasters of any nature as their model is deterministic. As far as we know, no works account for appointment scheduling under uncertainty of both demand and supply in the supply chain of blood products to ensure that only a specific number of donors are allowed at collection facilities in a given time window.

2.2. Age-based demand of blood products

Perishable products are generally classified into two categories, (i) those that are perfectly consumable until their expiration date and (ii) those whose quality deteriorates continuously with time (Alkaabneh et al., 2020). The work of age-based demand for perishable products is generally scant, and more so those that focus on blood products.

In terms of cost, the work of Fontaine et al. (2009) showed that when outdates costs were split between the responsible entities depending on the age at which platelets were shipped, the reduction in the number of outdates reached 10% within six months of implementation. Their study considered the supply chain between Stanford Blood Center and Stanford University Medical Center. Another study on platelet costs was conducted by Dalalah et al. (2018) where different storage mechanisms are considered for platelets of different ages. This mechanism resulted in decreased costs in comparison to a mechanism that does not consider product age.

In terms of patient well-being, the empirical evidence presented by Vamvakas (2010) suggests that bacterial infections are more likely to occur in patients that were transfused with "old" blood. Later, Atkinson et al. (2012) conducted a study where an age threshold of 14 days was instated in transfusion policies. Their priority would be to transfuse the oldest blood younger than 14 days and, if unavailable, the youngest blood older than 14 days. Their results show an expected annual drop of 20,000 in mortality rates.

While none of these works explicitly consider age-based demand of blood products, they all indicate the necessity to do so. A reduction is shortages (which leads to a reduction in mortality rates) and a reduction in costs is essential when critical products such as blood components are considered. This work aims at closing this gap in the literature.

2.3. Effects of COVID-19 on supply chains

When a disaster, whether natural or man-made, strikes any geographical region, it leads to severe repercussions on several sectors, especially the health and supply chain sectors. Unlike most disasters, the consequences caused by a pandemic on the scale of COVID-19 are extremely severe and dynamic in their nature since, for example, the virus can mutate without warning and the longevity of the current vaccines is still unknown. Additionally, human behavior, being uncontrollable, plays a huge role in dictating the dynamics of spreading of the virus.

In his work, Ivanov (2020a) characterizes epidemic outbreaks, such as that of COVID-19, in terms of long-term disruptions, disruption propagation, and high uncertainty. Other features framed in his work include unpredictable scaling of the outbreak, and disruptions in supply and demand. The author then uses simulation to predict the long- and short-term disruption and errors in risk mitigation practices used in supply chains. This work was expanded by Ivanov and Dolgui (2020) to include intertwined supply networks (ISN) which are collections of supply chains that operate collectively to secure the delivery of goods and services. Typically, ISNs require long-term survivability which in turn requires large-scale resilience. The authors propose a novel environment for decision-making in the case of extraordinary disruptions.

To provide a long-term solution for the effects of pandemics such COVID-19, Ivanov (2020b) develops the notion of a viable supply chain (VSC) which covers the agility, resilience, and sustainability of a supply chain. The value of this notion is to assist decision makers in the supply chain to ensure profitability during normal times while withstanding the effects of disruptions.

While these works provide an extremely valuable contribution to the literature, they neither provide specific solutions nor do they discuss specific products. The uncertainty in supply of blood products caused by the COVID-19 (SARS-CoV-2) pandemic, in addition to the restricted access to highly infected areas and regions, needs to be tackled. Thus, in our work we focus on the supply chain of blood products specifically to close these gaps.

3. The model

To formulate a mathematical model of the blood products supply chain problem during pandemics (**BSCP**) with uncertain supply and demand, two-stage stochastic programming with scenarios is used. A set S will denote the different supply and demand scenarios, each with a probability $p_s \forall s \in S$. Additionally, we are given a set of donor groups I dispersed across the city. To collect blood products from the donor groups, mobile collection facilities will be deployed at a set of candidate locations J. We consider two types of facilities: (a) temporary facilities that may be relocated and have a small capacity and (b) permanent facilities that have a fixed location and larger capacity. In the first stage of our problem, decisions on the locations of the permanent facilities are made in anticipation of any pandemic, while in the second stage decisions on the locations of temporary facilities, inventory levels, substitutions, and transfusions are made during the pandemic. To ensure the maximum safety of donor groups, two safety precautions are taken: (i) donor group i will not be allowed to travel more than a predetermined distance r_{ij} to reach blood collection facility j and (ii) each donor group should book a time slot m at the collection facility to ensure no overcrowding happens and social distancing rules are respected. It is worth noting that we consider three blood products in this work: (i) RBCs, (ii) platelets, and (iii) plasma. At the other end of the supply chain, we have a set of hospitals h with capacities and demand for each of the aforementioned blood products. The aim of this work is to deliver the blood products from donors to patients while ensuring that shortages are minimized.

The model will make decisions in two stages. Because establishing permanent collection facilities requires a long time to be accomplished, the decisions on their locations will be made in the first stage. After the demand scenarios are realized, locations of the temporary facilities are made in the second stage. The second stage decisions also include inventory decisions and the amount of each product to be delivered to each hospital.

3.1. Age-based demand

All the products considered in this work are perishable with different shelf-lives and, hence, if a product is not used and kept in inventory its value will drop with time. As a consequence of aging, demand for the products will decrease. However, given that the time horizon in this work is significantly shorter than its shelf-life, the perishability of plasma is not considered. Additionally, studies have shown that "fresh" plasma does not have a significant functional advantage over "older" plasma (Triulzi et al., 2012). Based on that, and for the sake of model simplicity, age-based demand will only be considered for RBCs. In fact, only blood that is less than three days old is accepted for specific types of surgery while in other cases the blood will be accepted as long as it is less than two weeks old. To capture age-based demand in our model, we introduce a set of blood categories C and a set of ages A_c included in each category. For $c = 1$, blood up to three days old ($a \leq 3$) is accepted, while for $c = 2$, blood up to two weeks old $a \leq 14$ is accepted. Category $c = 3$ accepts blood of all ages as long as it has not expired. Typically, when "fresh" blood is required then only category $c = 1$ can be transfused while if "older" blood is accepted then both categories $c = 2$ and $c = 3$ can be used. Fig. 2 illustrates this further and shows that blood in lower age categories can be used to satisfy demands of higher age categories.

3.2. Blood substitution

The availability of different blood types across a population is not uniform. In fact, it varies significantly from one country to another. For example, in Pakistan, O+ accounts for 26.6% of the population while in Chile this number is 85.5% (Wikipedia contributors, 2020). ABO matching can take place during transfusions and, hence, to account for shortages of plasma, platelets, and specific RBCs types, other suitable types are used as substitutes according to Table 2.

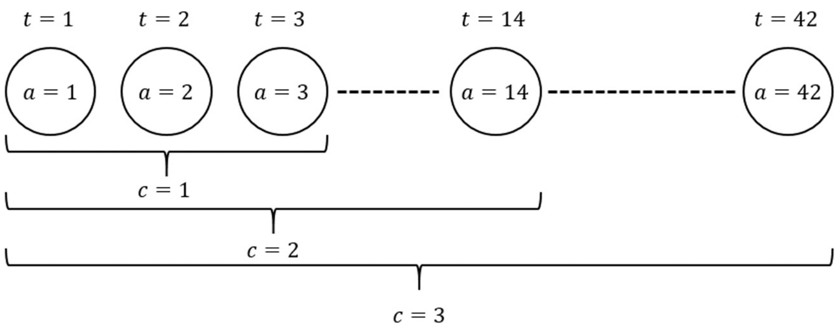


Fig. 2. The blood ages included in each category.

3.3. The formulation

The model in our work is based on the following set of assumptions:

- Donors from the same group i live within proximity of each other and the distance from all the donors of that group to any collection facility is taken to be the same.
- Trucks delivering blood products from collection centers to hospitals are well equipped for that purpose.
- Blood sent to waste may be due to outdates or capacity constraints.
- If donor group i is assigned to several collection facilities, the collected amount across all collection facilities cannot exceed the total available supply nor the capacities of the facilities.
- Any product collected by the facilities is sent to the hospitals during the same time period.
- A single time period is assumed to be one day.

The following sets and indices are used:

I: set of donor groups, indexed by i
J: set of candidate locations for collection facilities, indexed by j
M: set of appointment windows, indexed by m
H: set of hospitals, indexed by h
T: set of time periods, indexed by t or t'
B: set of blood types, indexed by b or b'
C: set of different blood categories, indexed by c
A_c: set of age groups accepted in category C, indexed by a, $\forall c \in C$
B_b: set of blood types compatible with blood type b, $\forall b \in B$
S: set of scenarios, indexed by s

The following parameters are used:

L: shelf-life of platelets
Cap^T: capacity of a temporary facility
Cap^P: capacity of a permanent facility
Cap^H: capacity of a hospital
DB_{bchts}: Demand for RBCs of type b and category c at hospital h during period t under scenario s, $\forall b \in B$, $h \in H, t \in T, c \in C, s \in S$
DP_{bhts}: Demand for plasma of type b and at hospital h during period t under scenario s, $\forall b \in B$, $h \in H, t \in T, c \in C, s \in S$
DL_{bhts}: Demand for platelets of type b and at hospital h during period t under scenario s, $\forall b \in B$, $h \in H, t \in T, c \in C, s \in S$
SB_{ibts}: supply of donor group i for RBCs of type b during period t under scenario s, $\forall i \in I, \forall b \in B, t \in T, s \in S$
SP_{ibts}: supply of donor group i for plasma of type b during period t under scenario s, $\forall i \in I, \forall b \in B, t \in T, s \in S$
SL_{ibts}: supply of donor group i for platelets of type b during period t under scenario s, $\forall i \in I, \forall b \in B, t \in T, s \in S$
r_{ij}: distance between donor group i and collection facility j, $\forall i \in I, j \in J$
r: maximum allowed distance between a donor group and a collection facility
N: maximum number of facilities to be opened during any time period
p_s: probability of occurrence for scenario s, $\forall s \in S$

The following decision variables are used:

x_j: $\begin{cases} 1 & \text{if a permanent facility is established at location } j,\ \forall j \in J \\ 0 & \text{otherwise} \end{cases}$

y^B_{ijmts}: $\begin{cases} 1 & \text{if RBCs donor group } i \text{ is assigned to facility } j \text{ and appointment slot } m \text{ during period } t \text{ under scenario } s, \\ & \forall i \in I, j \in J, m \in M, t \in T, s \in S \\ 0 & \text{otherwise} \end{cases}$

y^P_{ijmts}: $\begin{cases} 1 & \text{if plasma donor group } i \text{ is assigned to facility } j \text{ and appointment slot } m \text{ during period } t \text{ under scenario } s, \\ & \forall i \in I, j \in J, m \in M, t \in T, s \in S \\ 0 & \text{otherwise} \end{cases}$

y^L_{ijmts}: $\begin{cases} 1 & \text{if platelets donor group } i \text{ is assigned to facility } j \text{ and appointment slot } m \text{ during period } t \text{ under scenario } s, \\ & \forall i \in I, j \in J, m \in M, t \in T, s \in S \\ 0 & \text{otherwise} \end{cases}$

z_{jts}: $\begin{cases} 1 & \text{if a temporary facility moves to location } j \text{ from } j' \text{ during period } t \text{ under scenario } s,\ \forall j, j' \in J, t \in T, s \in S \\ 0 & \text{otherwise} \end{cases}$

$\mathrm{QB}_{ijmbhts}$: amount of RBCs of type b collected from donor group i during appointment m at facility j and sent to hospital h during period t under scenario s, $\forall i \in I,\ j \in J, b \in B, h \in H,\ t \in T, s \in S$

$\mathrm{QP}_{ijmbhts}$: amount of plasma of type b collected from donor group i during appointment m at facility j and sent to hospital h during period t under scenario s, $\forall i \in I,\ j \in J, b \in B, h \in H,\ t \in T, s \in S$

$\mathrm{QL}_{ijmbhts}$: amount of platelets of type b collected from donor group i during appointment m at facility j and sent to hospital h during period t under scenario s, $\forall i \in I,\ j \in J, b \in B, h \in H,\ t \in T, s \in S$

IB_{habts}: amount of RBCs of type b and age a kept in inventory at hospital h during period t under scenario s, $\forall a \in A$, $b \in B,\ h \in H,\ t \in T,\ s \in S$

IP_{hbts}: amount of plasma of type b kept in inventory at hospital h during period t under scenario s, $\forall b \in B,\ h \in H$, $t \in T,\ s \in S$

IL_{habts}: amount of platelets of type b and age a kept in inventory at hospital h during period t under scenario s, $\forall a \in A$, $b \in B,\ h \in H,\ t \in T,\ s \in S$

WB_{bahts}: waste of RBCs of type b and age a at hospital h during period t under scenario s, $\forall a \in A,\ b \in B,\ h \in H,\ t \in T$, $s \in S$

WP_{bhts}: waste of plasma of type b at hospital h during period t under scenario s, $\forall b \in B, h \in H, t \in T, s \in S$

WL_{bahts}: waste of platelets of type b and age a at hospital h during period t under scenario s, $\forall a \in A,\ b \in B,\ h \in H,\ t \in T$, $s \in S$

UDB_{bchts}: unmet demand for RBCs of type b and category c at hospital h during period t under scenario s, $\forall c \in C,\ b \in B$, $h \in H,\ t \in T,\ s \in S$

UDP_{bhts}: unmet demand for plasma of type b at hospital h during period t under scenario s, $\forall c \in C,\ b \in B,\ h \in H,\ t \in T$, $s \in S$

UDL_{bhts}: unmet demand for platelets of type b at hospital h during period t under scenario s, $\forall c \in C,\ b \in B,\ h \in H,\ t \in T$, $s \in S$

$\mathrm{TB}_{b'bahts}$: Amount of RBCs of type b' and age a used to substitute type b and transfused at hospital h during period t under scenario s, $\forall a \in A,\ b, b' \in B,\ h \in H,\ t \in T,\ s \in S$

$\mathrm{TP}_{b'bhts}$: Amount of plasma of type b' used to substitute type b transfused at hospital h during period t under scenario s, $\forall b, b' \in B,\ h \in H,\ t \in T,\ s \in S$

$\mathrm{TL}_{b'bhts}$: Amount of platelets of type b' used to substitute type b transfused at hospital h during period t under scenario s, $\forall b, b' \in B,\ h \in H,\ t \in T,\ s \in S$

The problem is formulated as follows:

$$\mathbf{BSCP}: \text{Min Unmet} = \sum_{s\in S} p_s \left(\sum_{b\in B} \sum_{h\in H} \sum_{t\in T} \Big(\sum_{c\in C} \mathrm{UDB}_{bchts} + \mathrm{UDP}_{bhts} + \mathrm{UDL}_{bhts} \Big) \right) \tag{1}$$

subject to

$$\sum_{j\in J} x_j + \sum_{j\in J} z_{jts} \le N, \qquad \forall t \in T, s \in S, \tag{2}$$

$$x_j + z_{jts} \le 1, \qquad \forall j \in J, t \in T, s \in S, \tag{3}$$

$$r_{ij} y^B_{ijmts} \le r, \qquad \forall i \in I, j \in J, m \in M, t \in T, s \in S, \tag{4}$$

$$r_{ij} y^P_{ijmts} \leq r, \qquad \forall i \in I, j \in J, m \in M, t \in T, s \in S, \tag{5}$$

$$r_{ij} y^L_{ijmts} \leq r, \qquad \forall i \in I, j \in J, m \in M, t \in T, s \in S, \tag{6}$$

$$\sum_{i\in I} \left(y^B_{ijmts} + y^P_{ijmts} + y^L_{ijmts} \right) \leq 1, \qquad \forall j \in J, m \in M, t \in T, s \in S, \tag{7}$$

Constraints (2)–(7) refer to facility location and appointment scheduling. Constraints (2) do not allow the total number of facilities at any instance to exceed a pre-specified number N. At any given location, at most one permanent or temporary facility can be placed as ensured by constraints (3). Constraints (4), (5), and (6) ensure that the distance traveled by donor group i to facility location j does not exceed r, for RBCs, plasma, and platelets donors, respectively. Any appointment slot m can at most be booked by donors of one product, as enforced by constraints (7).

$$\sum_{h\in H} \mathrm{QB}_{ijmbhts} \leq \mathrm{SB}_{ibts} y^B_{ijmts}, \qquad \forall i \in I, j \in J, m \in M, b \in B, t \in T, s \in S, \tag{8}$$

$$\sum_{h\in H} \mathrm{QP}_{ijmbhts} \leq \mathrm{SP}_{ibts} y^P_{ijmts}, \qquad \forall i \in I, j \in J, m \in M, b \in B, t \in T, s \in S, \tag{9}$$

$$\sum_{h\in H} \mathrm{QL}_{ijmbhts} \leq \mathrm{SL}_{ibts} y^L_{ijmts}, \qquad \forall i \in I, j \in J, m \in M, b \in B, t \in T, s \in S, \tag{10}$$

$$\sum_{j\in J} \sum_{m\in M} \mathrm{QB}_{ijmbhts} \leq \mathrm{SB}_{ibts}, \qquad \forall i \in I, b \in B, h \in H, t \in T, s \in S, \tag{11}$$

$$\sum_{j\in J} \sum_{m\in M} \mathrm{QP}_{ijmbhts} \leq \mathrm{SP}_{ibts}, \qquad \forall i \in I, b \in B, h \in H, t \in T, s \in S, \tag{12}$$

$$\sum_{j\in J} \sum_{m\in M} \mathrm{QL}_{ijmbhts} \leq \mathrm{SL}_{ibts}, \qquad \forall i \in I, b \in B, h \in H, t \in T, s \in S, \tag{13}$$

Constraints (8)–(13) ensure that the quantity collected by the facilities does not exceed the total supply. Constraints (8), (9), and (10) ensure that at a given appointment m, the total amount collected of RBCs, plasma, and platelets, respectively, does not exceed the supply. Meanwhile, constraints (11), (12), and (13) ensure that the total amount collected across all appointments and facilities of RBCs, plasma, and platelets, respectively, does not exceed the supply.

$$\sum_{i\in I} \sum_{j\in J} \sum_{m\in M} \mathrm{QB}_{ijmbhts} = \mathrm{IB}_{h,1,bts} + \sum_{b'\in B_b} \mathrm{TB}_{bb',1,hts} + \mathrm{WB}_{b,1,hts}, \qquad \forall h \in H, b \in B, t \in T, s \in S, \tag{14}$$

$$\mathrm{IB}_{h,a-1,b,t-1,s} = \mathrm{IB}_{habts} + \sum_{b'\in B_b} \mathrm{TB}_{bb'ahts} + \mathrm{WB}_{bahts}, \qquad \forall h \in H, b \in B, t \in T, s \in S, a \geq 2 \tag{15}$$

$$\sum_{i\in I} \sum_{j\in J} \sum_{m\in M} \mathrm{QP}_{ijmbhts} + \mathrm{IP}_{hb,t-1,s} = \mathrm{IP}_{hbts} + \sum_{b'\in B_b} \mathrm{TP}_{b'bhts} + \mathrm{WP}_{bhts}, \qquad \forall h \in H, b \in B, t \in T, s \in S, \tag{16}$$

$$\sum_{i\in I} \sum_{j\in J} \sum_{m\in M} \mathrm{QL}_{ijmbhts} = \mathrm{IL}_{h,1,bts} + \sum_{b'\in B_b} \mathrm{TL}_{b'b,1,hts} + \mathrm{WL}_{b,1,hts}, \qquad \forall h \in H, b \in B, t \in T, s \in S, \tag{17}$$

$$\mathrm{IL}_{h,a-1,b,t-1,s} = \mathrm{IL}_{habts} + \sum_{b'\in B_b} \mathrm{TL}_{b'bahts} + \mathrm{WL}_{bahts}, \qquad \forall h \in H, b \in B, t \in T, s \in S, a \geq 2 \tag{18}$$

Constraints (14)–(18) are inventory constraints for the different products in this work. Constraints (14) are balance constraints at hospitals for RBCs where any fresh incoming RBCs are either kept in inventory, used in transfusion, or sent to waste. Constraints (15) ensure the same balance but for any RBCs more than one day old. The balance of plasma at hospitals is ensured by constraints (16). Constraints (17) and (18) ensure the balance of platelets at hospitals for fresh and old platelets, respectively.

$$\sum_{i\in I} \sum_{b\in B} \sum_{h\in H} \sum_{m\in M} \left(\mathrm{QB}_{ijmbhts} + \frac{1}{2} \mathrm{QP}_{ijmbhts} + \frac{1}{10} \mathrm{QL}_{ijmbhts} \right) \leq \mathrm{Cap}^T z_{jts} + \mathrm{Cap}^P x_j, \qquad \forall j \in J, t \in T, s \in S, \tag{19}$$

$$\sum_{a\in A} \sum_{b\in B} \mathrm{IB}_{habts} + \frac{1}{2} \sum_{b\in B} \mathrm{IP}_{hbts} + \frac{1}{10} \sum_{a\in A} \sum_{b\in B} \mathrm{IL}_{habts} \leq \mathrm{Cap}^H, \qquad \forall h \in H, t \in T, s \in S, \tag{20}$$

Constraints (19) and (20) are capacity constraints at facilities and hospitals, respectively. Constraints (19) ensures that the capacity is either Cap^T or Cap^P depending on whether a permanent or temporary facility is open at location j. Typically, one unit of plasma is half the size of one unit of RBCs (The Rock River Valley Blood Center, 2018; The University of Texas Medical Branch at Galveston, 2019) while for platelets this ratio is one-tenth (Medscape, 2017; The Rock River Valley Blood Center, 2018). All hospital capacities are equal as shown in constraints (20).

$$\sum_{b'\in B_b} \sum_{a\in A_c} \mathrm{TB}_{b'bahts} + \mathrm{UDB}_{bchts} = \mathrm{DB}_{bchts}, \qquad \forall b \in B, h \in H, c \in C, t \in T, s \in S, \tag{21}$$

$$\sum_{b'\in B_b} \mathrm{TP}_{b'bhts} + \mathrm{UDP}_{bhts} = \mathrm{DP}_{bhts}, \qquad \forall b \in B, h \in H, t \in T, s \in S, \tag{22}$$

$$\sum_{b'\in B_b} \sum_{a\in A:a\leq L} \mathrm{TL}_{b'bahts} + \mathrm{UDL}_{bhts} = \mathrm{DL}_{bhts}, \qquad \forall b \in B, h \in H, t \in T, s \in S, \tag{23}$$

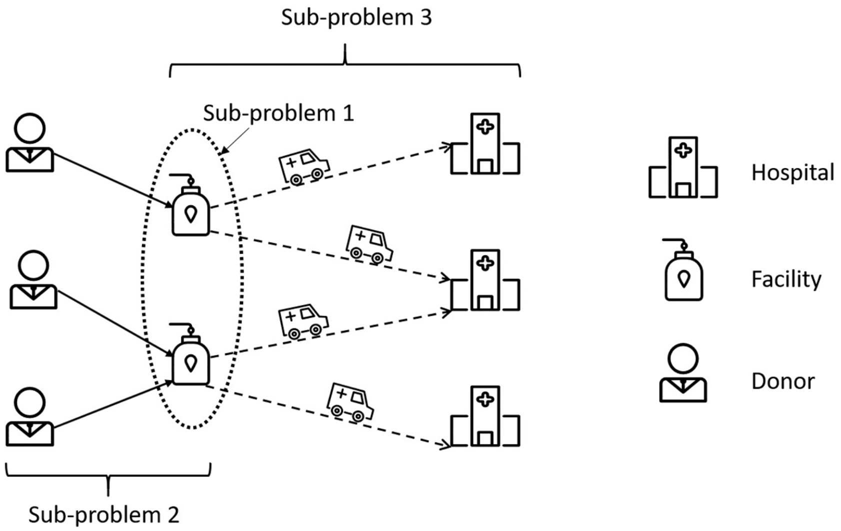


Fig. 3. Breakdown of **BSCP** into the three sub-problems.

Unmet demand is calculated using constraints (21)–(23). The constraints take into account the possible substitution of compatible blood types while ensuring that the specific required category is matched. Unmet demand for plasma is simply calculated as the difference between the transfused amounts and the demands. Constraints (23) also ensure that the transfused platelets are not past their shelf-lives.

$$x_j, y^B_{ijmts}, y^P_{ijmts}, y^L_{ijmts}, z_{jts} \in \{0,1\}, \qquad \forall i \in I, j \in J, m \in M, t \in T, s \in S, \tag{24}$$

$$\begin{aligned}&\mathrm{QB}_{ijmbhts}, \mathrm{QP}_{ijmbhts}, \mathrm{QL}_{ijmbhts}, \mathrm{IB}_{habts}, \mathrm{IP}_{hbts}, \mathrm{IL}_{habts}, \mathrm{WB}_{bahts}, \mathrm{WP}_{bhts}, \mathrm{WL}_{bahts},\\ &\mathrm{UDB}_{bchts}, \mathrm{UDP}_{bhts}, \mathrm{UDL}_{bhts}, \mathrm{TB}_{b'bahts}, \mathrm{TP}_{b'bhts}, \mathrm{TL}_{bhts} \geq 0, \qquad \forall i \in I, j \in J, m \in M, h \in H, b, b' \in B, c \in C,\\ &\qquad a \in A, t \in T, s \in S\end{aligned} \tag{25}$$

Constraints (24) and (25) are variable type constraints.

4. Heuristic

The formulated model of **BSCP** is very complex as shown in Section 5.2 and commercial MIP solvers are not effective in solving it. For this purpose, a heuristic is developed to obtain near-optimal solutions in a reasonable time. The principle behind the heuristic is to split **BSCP** into three sub-problems where the solution of one is the input of the next. The details of the sub-problems are further explained in the following subsections and Fig. 3.

4.1. Sub-problem 1

The focus of sub-problem 1 (hereinafter referred to as **SP1**) is determining the locations of permanent and temporary facilities with the objective of maximizing the total possible amount of blood products collected. The following decision variables are introduced to formulate **SP1**.

TS_s: total supply of blood products collected during scenario s, $\forall s \in S$

SP1 is formulated as follows:

$$\textbf{SP1}: \text{Max Total Supply} = \sum_{s \in S} p_s \mathrm{TS}_s \tag{26}$$

subject to

$$\sum_{j \in J} (x_j + z_{jts}) \leq N, \qquad \forall t \in T, s \in S, \tag{27}$$

$$x_j + z_{jts} \leq 1, \qquad \forall j \in J, t \in T, s \in S, \tag{28}$$

$$\mathrm{TS}_s = \sum_{j \in J} \sum_{t \in T} \min\left(\mathrm{Cap}^P, \sum_{i \in I} \sum_{b \in B} (\mathrm{SB}_{ibts} + \mathrm{SP}_{ibts} + \mathrm{SL}_{ibts}) \right) x_j +$$

$$\sum_{j\in J}\sum_{t\in T}\min\left(\mathrm{Cap}^T,\sum_{i\in I}\sum_{b\in B}(\mathrm{SB}_{ibts}+\mathrm{SP}_{ibts}+\mathrm{SL}_{ibts})\right)z_{jts}, \qquad \forall s\in S, \tag{29}$$

$$x_j, z_{jts}\in\{0,1\}, \qquad \forall j\in J, t\in T, s\in S, \tag{30}$$

$$\mathrm{TS}_s\geq 0, \qquad \forall s\in S, \tag{31}$$

The objective function (26) ensures that the expected total amount of blood products collected is maximized. Constraints (27) and (28) ensure that no more than N facilities can be open and that each location j is restricted to either a temporary or a permanent facility, respectively. During scenario s, the total amount of blood products collected is determined by constraints (29). Constraints (30) and (31) are variable type constraints.

4.2. Sub-problem 2

Once the locations of the permanent and temporary facilities are determined in **SP1** they are entered as parameters in sub-problem 2 (hereinafter referred to as **SP2**) and will be denoted as x_j^P and z_{jts}^T, respectively. **SP2** will make decisions on donor assignment to collection facilities and appointment scheduling. Naturally, the amount collected of each blood product should be determined by the demand for that particular product. Based on that, and to ensure that the decisions made in **SP2** are not completely myopic, we connect the demands at the hospitals to **SP2** through ratio multipliers in the objective function (32).

The following parameters are introduced.

RatioB_{ts}: the ratio of demand of RBCs to the total demand of all products during period t under scenario s, $\forall t\in t, s\in S$

RatioP_{ts}: the ratio of demand of plasma to the total demand of all products during period t under scenario s, $\forall t\in t, s\in S$

RatioL_{ts}: the ratio of demand of platelets to the total demand of all products during period t under scenario s, $\forall t\in t, s\in S$

$$\mathrm{RatioB}_{ts}=\frac{\sum_{b\in B}\sum_{c\in C}\sum_{h\in H}\mathrm{DB}_{bchts}}{\sum_{b\in B}\sum_{h\in H}\sum_{c\in C}(\mathrm{DB}_{bchts}+\mathrm{BP}_{bhtcs}+\mathrm{BL}_{bhtcs})}$$

$$\mathrm{RatioP}_{ts}=\frac{\sum_{b\in B}\sum_{h\in H}\mathrm{DP}_{bhts}}{\sum_{b\in B}\sum_{h\in H}\sum_{c\in C}(\mathrm{DB}_{bchts}+\mathrm{BP}_{bhtcs}+\mathrm{BL}_{bhtcs})}$$

$$\mathrm{RatioL}_{ts}=\frac{\sum_{b\in B}\sum_{h\in H}\mathrm{DL}_{bhts}}{\sum_{b\in B}\sum_{h\in H}\sum_{c\in C}(\mathrm{DB}_{bchts}+\mathrm{BP}_{bhtcs}+\mathrm{BL}_{bhtcs})}$$

The following decision variables are introduced.

ACB_{ijmbts}: amount of RBCs of type b collected from donor group i during appointment m at facility j during period t under scenario s, $\forall i\in I, j\in J, m\in M, b\in B,\ t\in t, s\in S$

ACP_{ijmbts}: amount of plasma of type b collected from donor group i during appointment m at facility j during period t under scenario s, $\forall i\in I, j\in J, m\in M, b\in B,\ t\in t, s\in S$

ACL_{ijmbts}: amount of platelets of type b collected from donor group i during appointment m at facility j during period t under scenario s, $\forall i\in I, j\in J, m\in M, b\in B,\ t\in t, s\in S$

SP2 is formulated as follows:

$$\textbf{SP2:}\ \text{Max Total Supply}=\sum_{s\in S}p_s\sum_{i\in I}\sum_{j\in J}\sum_{m\in M}\sum_{b\in B}\sum_{t\in T}\big(\mathrm{RatioB}_{ts}\mathrm{ACB}_{ijmbts}+$$
$$\mathrm{RatioP}_{ts}\mathrm{ACP}_{ijmbts}+\mathrm{RatioL}_{ts}\mathrm{ACL}_{ijmbts}\big) \tag{32}$$

subject to

$$\sum_{i\in I:r_{ij}\leq r}(y^B_{ijmts}+y^B_{ijmts}+y^B_{ijmts})\leq 1, \qquad \forall m\in M, j\in J, t\in T, s\in S \tag{33}$$

$$\mathrm{ACB}_{ijmbts}\leq \mathrm{SB}_{ibts}y^B_{ijmts}, \qquad \forall i\in I, j\in J\ :\ r_{ij}\leq r, m\in M, b\in B, t\in T, s\in S, \tag{34}$$

$$\mathrm{ACP}_{ijmbts}\leq \mathrm{SP}_{ibts}y^P_{ijmts}, \qquad \forall i\in I, j\in J\ :\ r_{ij}\leq r, m\in M, b\in B, t\in T, s\in S, \tag{35}$$

$$\mathrm{ACL}_{ijmbts}\leq \mathrm{SL}_{ibts}y^L_{ijmts}, \qquad \forall i\in I, j\in J\ :\ r_{ij}\leq r, m\in M, b\in B, t\in T, s\in S, \tag{36}$$

$$\sum_{j\in J:r_{ij}\leq r}\sum_{m\in M}\mathrm{ACB}_{ijmbts}\leq \mathrm{SB}_{ibts}, \qquad \forall i\in I, b\in B, t\in T, s\in S, \tag{37}$$

$$\sum_{j\in J:r_{ij}\leq r}\sum_{m\in M}\mathrm{ACP}_{ijmbts}\leq \mathrm{SP}_{ibts}, \qquad \forall i\in I, b\in B, t\in T, s\in S, \tag{38}$$

$$\sum_{j\in J:r_{ij}\leq r}\sum_{m\in M}\mathrm{ACL}_{ijmbts}\leq \mathrm{SL}_{ibts}, \qquad \forall i\in I, b\in B, t\in T, s\in S, \tag{39}$$

$$\sum_{i\in I}\sum_{b\in B}\sum_{m\in M}\left(\mathrm{ACB}_{ijmbts}+\frac{1}{2}\mathrm{ACP}_{ijmbts}+\frac{1}{10}\mathrm{ACL}_{ijmbts}\right)\le \mathrm{Cap}^T z^T_{jts}+\mathrm{Cap}^P x^P_j,\qquad \forall j\in J,t\in T,s\in S, \tag{40}$$

$$y^B_{ijmts},y^P_{ijmts},y^L_{ijmts}\in\{0,1\}\qquad \forall i\in I,j\in J,m\in M,t\in T,s\in S, \tag{41}$$

$$\mathrm{ACB}_{ijmbts},\mathrm{ACP}_{ijmbts},\mathrm{ACL}_{ijmbts}\ge 0,\qquad \forall i\in I,j\in J,m\in M,b\in B,t\in T,s\in S, \tag{42}$$

Objective function (32) maximizes the expected total amount of blood products collected across all the facilities and appointment slots. Constraints (33) ensure that for every appointment slot m at every facility j, only one blood product is collected from donor group i. Constraints (34)–(36) ensure that the amount collected during each appointment for each blood product does not exceed the available supply. Meanwhile, constraints (37)–(39) ensure that the amounts of blood products collected across all facilities and appointments do not exceed the available supply as well. The total amount of blood products collected at each facility must not exceed the capacity of the facility as ensured by constraints (40). Constraints (41) and (42) are variable type constraints.

Each constraint and decision variable in **SP2** is a function of t and s. Based on this, **SP2** can be split further into $(T\times S)$ sub-problems. By exploiting the structure of **SP2** the solution time is even further reduced.

4.3. Sub-problem 3

Once the amounts collected of RBCs, plasma, and platelets are determined, they are input as parameters into sub-problem 3 (hereinafter referred to as **SP3**) and denoted as ACB^P_{ijmbts}, ACP^P_{ijmbts}, and ACL^P_{ijmbts}, respectively. Inventory, RBCs substitution, and transfusion decisions are made by **SP3** to ensure that the total unmet demand is minimized. To formulate **SP3**, we introduce the following decision variables.

- QB^H_{jbhts}: amount of RBCs of type b collected at facility j and sent to hospital h during period t under scenario s, $\forall j\in J$, $b\in B$, $h\in H$, $t\in t$, $s\in S$
- QP^H_{jbhts}: amount of plasma of type b collected at facility j and sent to hospital h during period t under scenario s, $\forall j\in J$, $b\in B$, $h\in H$, $t\in t$, $s\in S$
- QL^H_{jbhts}: amount of platelets of type b collected at facility j and sent to hospital h during period t under scenario s, $\forall j\in J$, $b\in B$, $h\in H$, $t\in t$, $s\in S$

SP3 is formulated as follows:

$$\mathbf{SP3}:\ \text{Min Unmet}=\sum_{s\in S}p_s\left(\sum_{b\in B}\sum_{h\in H}\sum_{t\in T}\left(\sum_{c\in C}\mathrm{UDB}_{bchts}+\mathrm{UDP}_{bhts}+\mathrm{UDL}_{bhts}\right)\right) \tag{43}$$

subject to
Constraints (20)–(23) and

$$\sum_{j\in J}\mathrm{QB}^H_{jbhts}=\mathrm{IB}_{h,1,bts}+\sum_{b'\in B_b}\mathrm{TB}_{bb',1,hts}+\mathrm{WB}_{b,1,hts},\qquad \forall h\in H,b\in B,t\in T,s\in S, \tag{44}$$

$$\mathrm{IB}_{h,a-1,b,t-1,s}=\mathrm{IB}_{habts}+\sum_{b'\in B_b}\mathrm{TB}_{bb'ahts}+\mathrm{WB}_{bahts},\qquad \forall h\in H,b\in B,t\in T,s\in S,a\ge 2 \tag{45}$$

$$\sum_{j\in J}\mathrm{QP}^H_{jbhts}+\mathrm{IP}_{hb,t-1,s}=\mathrm{IP}_{hbts}+\sum_{b'\in B_b}\mathrm{TP}_{b'bhts}+\mathrm{WP}_{bhts},\qquad \forall h\in H,b\in B,t\in T,s\in S, \tag{46}$$

$$\sum_{j\in J}\mathrm{QL}^H_{jbhts}=\mathrm{IL}_{h,1,bts}+\sum_{b'\in B_b}\mathrm{TL}_{b'b,1,hts}+\mathrm{WL}_{b,1,hts},\qquad \forall h\in H,b\in B,t\in T,s\in S, \tag{47}$$

$$\mathrm{IL}_{h,a-1,b,t-1,s}=\mathrm{IL}_{habts}+\sum_{b'\in B_b}\mathrm{TL}_{b'bahts}+\mathrm{WL}_{bahts},\qquad \forall h\in H,b\in B,t\in T,s\in S,a\ge 2 \tag{48}$$

$$\sum_{h\in H}\mathrm{QB}^H_{jbhts}\le\sum_{i\in I}\sum_{m\in M}\mathrm{ACB}^P_{ijmbts},\qquad \forall j\in J,b\in B,t\in T,s\in S \tag{49}$$

$$\sum_{h\in H}\mathrm{QP}^H_{jbhts}\le\sum_{i\in I}\sum_{m\in M}\mathrm{ACP}^P_{ijmbts},\qquad \forall j\in J,b\in B,t\in T,s\in S \tag{50}$$

$$\sum_{h\in H}\mathrm{QL}^H_{jbhts}\le\sum_{i\in I}\sum_{m\in M}\mathrm{ACL}^P_{ijmbts},\qquad \forall j\in J,b\in B,t\in T,s\in S \tag{51}$$

$$\mathrm{QB}^H_{jbhts},\mathrm{QP}^H_{jbhts},\mathrm{QL}^H_{jbhts}\ge 0,\qquad \forall j\in J,b\in B,h\in H,t\in T,s\in S, \tag{52}$$

Objective function (43) and constraints (44)–(48) act in a very similar way to objective function (1) and constraints (14)–(18). Constraints (49)–(51) ensure that the amounts of RBCs, plasma, and platelets sent to the hospitals, respectively, do not exceed the amounts collected from donors in **SP2**. Constraints (52) are variable type constraints.

Table 3
Details of the data sets used to test the complexity of BSCP.

Instance	$\|I\|$	$\|J\|$	$\|H\|$	$\|S\|$	$\|T\|$	$\|M\|$	r	N
1	4	4	4	5	50	3	3	2
2	4	4	4	10	50	3	3	2
3	4	4	4	20	50	3	3	2
4	4	4	4	30	50	3	3	2
5	4	4	4	40	50	3	3	2
6	4	4	4	50	50	3	3	2
7	4	4	4	100	50	3	3	2
8	7	7	7	5	50	5	4	3
9	7	7	7	10	50	5	4	3
10	7	7	7	20	50	5	4	3
11	7	7	7	30	50	5	4	3
12	7	7	7	40	50	5	4	3
13	7	7	7	50	50	5	4	3
14	7	7	7	100	50	5	4	3
15	10	10	10	5	50	7	5	4
16	10	10	10	10	50	7	5	4
17	10	10	10	20	50	7	5	4
18	10	10	10	30	50	7	5	4
19	10	10	10	40	50	7	5	4
20	10	10	10	50	50	7	5	4
21	10	10	10	100	50	7	5	4
22	13	13	13	5	50	9	6	6
23	13	13	13	10	50	9	6	6
24	13	13	13	20	50	9	6	6
25	13	13	13	30	50	9	6	6
26	13	13	13	40	50	9	6	6
27	13	13	13	50	50	9	6	6
28	13	13	13	100	50	9	6	6

There are two important observations that can be made about **SP3**. The first is that all the constraints and variables are a function of s and hence the structure can be exploited to further split **SP3** into s sub-problems. The second observation is that all decision variables are continuous and hence each of the s sub-problems can be solved using linear programming. Exploiting **SP3** based on both observations significantly reduces the solution time.

5. Results and discussion

5.1. Data description

Given the extremely uncertain nature of the spread of the COVID-19 (SARS-CoV-2) among a population, the lock-down hours, restricted access areas, and donor behavior are almost impossible to predict and, therefore, a large number of scenarios may be needed to capture this uncertainty. Because of model complexity, we vary the considered number of scenarios from 5 to 100 in an attempt to achieve a balance between model complexity and tractability. The probabilities of demand and supply for any given product and quantity were assumed to be equal; these were generated using a uniform distributions $D \sim U(7, 12)$ and $S \sim U(1, 6)$, respectively. The capacities of the temporary facilities, permanent facilities, and hospitals are 40, 65, and 100, respectively. The distances between the different locations and donors are based on the distances between the centers of the 13 major areas in Abu Dhabi, United Arab Emirates. Each area is a candidate location for a location facility and hosts one donor group. There are 13 major hospitals in Abu Dhabi that are also considered in this work. The locations of the hospitals are not specified, and do not influence the decisions, as there are no restrictions on trucks delivering the products from collection facilities to hospitals. We test the complexity of the model **BSCP** on 28 data sets. The details of the data sets used in this work are shown in Table 3.

5.2. Model complexity

Commercial software GAMS 31.1/CPLEX 12.2 (CPLEX for short) was used on an AMD Ryzen Threadripper 3960X 24-core CPU with a frequency of 4.50 GHz and 128 GBs of RAM running 64-bit Windows 10 to solve **BSCP** for the 28 different instances described in Table 3. The results are presented in Table 4. It can be clearly noted, from the number of equations and variables, that the size of the problem increases exponentially as the size of the data set increases.

Only in Instance 1 was CPLEX able to solve the problem to optimality (Gap = 0%) and the smallest obtained gap afterwards was 34.33%, all within the imposed time limit of 10,800 s. Meanwhile, in thirteen other instances, the computer ran out of memory while attempting to either compile or solve the model, justifying the need for the heuristic described in Section 4. Results for the heuristic are presented in the last two columns of Table 4. In Instance 1 where CPLEX solved the model to optimality, the gap between the heuristic and GAMS 31.1/CPLEX 12.2 was 0.20%. The rest of the instances were all solved within the imposed time limit of 10,800 s.

Table 4
Comparison of CPLEX and heuristic results for the complex study on the model BSCP.

Instance	Number of variables	Number of discrete variables	Number of equations	Total time (s)	CPLEX objective value	Gap (%)	Heuristic objective value	Heuristic time (s)
1	3,328,005	37,004	801,251	7,427.28	61,930	0.00	62,056	88
2	6,656,005	74,004	1,602,501	10,800.00	73,233	37.68	62,050	175
3	13,312,005	148,004	3,205,001	10,800.00	73,205	37.72	61,963	367
4	19,968,005	222,004	4,807,501	10,800.00	73,196	37.71	61,962	712
5	26,624,005	296,004	6,410,001	10,800.00	73,190	37.71	61,946	977
6	33,280,005	370,004	8,012,501	10,800.00	73,181	37.69	61,947	1,251
7	66,560,005	740,004	16,025,001	NA	NA	NA	62,022	2,945
8	14,218,758	185,507	2,481,751	10,800.00	130,167	34.33	98,454	176
9	28,437,508	371,007	4,963,501	10,800.00	130,263	34.33	98,516	348
10	56,875,008	742,007	9,927,001	2,717.33	120,422	1,529.08	98,473	723
11	85,312,508	1,113,007	14,890,501	4,086.10	120,431	1,529.70	98,478	1,117
12	113,750,008	1,484,007	19,854,001	6,353.19	120,420	1,533.47	98,465	1,585
13	142,187,508	1,855,007	24,817,501	8,302.79	120,425	1,530.45	98,457	2,179
14	284,375,008	3,710,007	49,635,001	NA	NA	NA	98,479	5,621
15	47,875,011	527,510	5,897,751	1,888.73	177,540	1,574.13	144,033	189
16	95,750,011	1,055,010	11,795,501	4,599.34	177,456	1,573.12	143,989	377
17	191,500,011	2,110,010	23,591,001	NA	NA	NA	143,960	846
18	287,250,011	3,165,010	35,386,501	NA	NA	NA	143,975	1,378
19	383,000,011	4,220,010	47,182,001	NA	NA	NA	143,966	1,933
20	478,750,011	5,275,010	58,977,501	NA	NA	NA	143,965	2,656
21	957,500,011	10,550,010	117,955,001	NA	NA	NA	143,983	7,256
22	126,733,764	1,144,013	11,778,251	5,424.53	165,036	1,456.22	120,866	311
23	253,467,514	2,288,013	23,556,501	NA	NA	NA	120,805	620
24	506,935,014	4,576,013	47,113,001	NA	NA	NA	120,787	1,350
25	760,402,514	6,864,013	70,669,501	NA	NA	NA	120,818	2,168
26	1,013,870,014	9,152,013	94,226,001	NA	NA	NA	120,804	3,051
27	1,267,337,514	11,440,013	117,782,501	NA	NA	NA	120,820	4,107
28	2,534,675,014	22,880,013	235,565,001	NA	NA	NA	120,846	10,744

Table 5
The assignment of donor groups to blood facilities in the first period under each scenario.

	$S = 1$	$S = 2$	$S = 3$	$S = 4$	$S = 5$	$S = 6$	$S = 7$	$S = 8$	$S = 9$	$S = 10$
$I = 1$	2	1,2,3,4,5	1,3	1,4	4	4	1	2	1,4	1,2,4,5
$I = 2$	3	3,6	3	3	3	3	3,6	3	3	3,6
$I = 3$	5	2,5	5	5	5,6	5	5	5	5	5
$I = 4$	1,5,6	1	1	2,6	1	1,5	2,4	1,4	1,2	6
$I = 5$	1,2	1,4	2	3,4	1,6	2	2,4	2,3,5	4,6	2
$I = 6$	3	3	3	3	2,3	3,6	3,6	3	2,3	3,4
$I = 7$	4,5	1,4	1,4	1	1,4	1	1,4	1	1	4
$I = 8$	2	2	2	4,5	2	2,6	2	4	2	2
$I = 9$	6	5,6	5,6	5,6	3,5	3	3,5	6	3,5,6	3
$I = 10$	4	4	4	4	4	4	4	4	4	4
$I = 11$	5	5	5	5	5	5	5	5	5	5
$I = 12$	6	6	6	6	6	6	6	6	6	6

5.3. Sensitivity analysis

To understand the effect of the different components and parameters of **BSCP**, we conduct a series of experiments and sensitivity analyses and provide detailed insights to assist decision makers in the process.

5.4. Facilities locations and capacities

On March 26th 2020, the UAE announced the beginning of the National Disinfection Programme (Al Arabiya, 2020) which was followed by social distancing rules, business shutdowns, restricted working hours, limited in-office presence of employees, and the complete lock-down of some areas with high infection rates. Collectively, all these restrictions have limited the supply of blood products for a variety of reasons.

Optimally locating collection facilities is a key factor in maximizing the amount of collected products while abiding by the restrictions. Fig. 4 shows the locations at which facilities are placed during the first time period $t = 1$. Despite the facilities being located on one side of the city, each donor group is still able to access at least one facility. Table 5 shows which donors are assigned to which facilities for every scenario during the first time period in Instance 23 and, indeed, it can be observed that each facility has a donor group assigned to it. Donor group 13 ($I = 13$) was not assigned to any facility because the maximum capacities at the facilities were reached using only the first 12 groups.

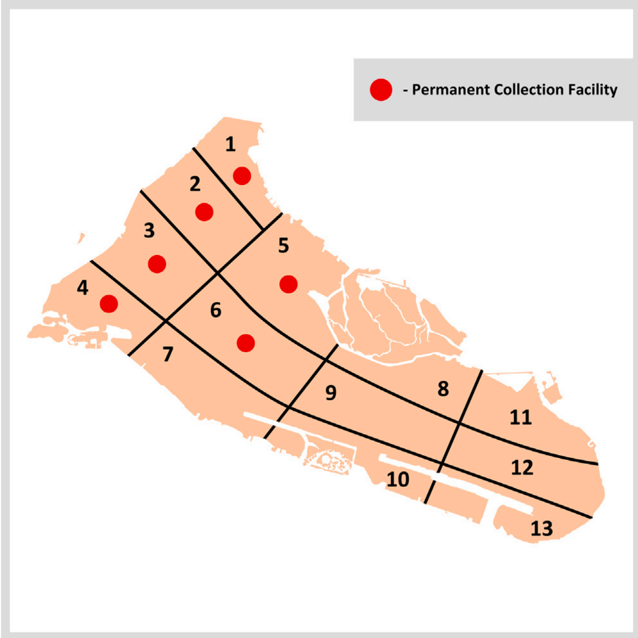


Fig. 4. Locations of established facilities.

Table 6
Effect of facilities' capacities on total unmet demand under Distribution 1.

Cap^T	Cap^P	Cap^H	No. of temp facilities	No. of permanent facilities	Total unmet demand
10	65	100	0	6	128759
20	65	100	0	6	128759
30	65	100	0	6	128759
40	65	100	0	6	128759
50	65	100	0	6	128759
55	65	100	0	6	128759
60	65	100	0	6	128759
65	65	100	6	0	122747.5
10	55	100	0	6	134402.9
20	45	100	0	6	141007.4
30	35	100	0	6	149772.5
40	70	100	0	6	127312.7
40	75	100	0	6	127073
40	65	80	0	6	128759
40	65	90	0	6	128759
40	65	110	0	6	128759
40	65	120	0	6	128759
40	65	130	0	6	128759

The main reason why permanent facilities are preferred to temporary facilities is the larger capacities they offer. To obtain a deeper understanding of when the mobility of the temporary facilities becomes advantageous over the excess capacities of the permanent facilities, we vary the capacities of the facilities and present the results in Table 6. We observe that only when the capacities of the facilities are similar will the results favor the mobility of temporary facilities. There is no instance at which a solution offers a combination of permanent and temporary facilities. Another key observation is that the capacities of hospitals do not affect the total unmet demand. This is because the supply is lower than the demand and hence capacities at hospitals do not present a bottleneck in the supply chain.

To further verify our findings, we change the distributions of the supply and demand of the blood products and run the experiment again. Hereinafter, we refer to the original distribution as **Distribution 1**. First we increase the ranges such that there is a partial overlap ($D \sim U(4,12)$ and $S \sim U(1,9)$), and refer to this distribution as **Distribution 2**. Next, we further increase the range such that there is a complete overlap ($D \sim U(1,12)$ and $S \sim U(1,12)$), and refer to this distribution as **Distribution 3**. The results are presented in Tables 7 and 8, respectively.

For Distribution 2, in all instances, permanent facilities are completely preferred over temporary facilities. On the other hand, only one instance saw a temporary facility being established in Distribution 3. This instance is when both permanent and temporary

Table 7
Effect of facilities' capacities on total unmet demand under Distribution 2.

Cap^T	Cap^P	Cap^H	No. of temp facilities	No. of permanent facilities	Total unmet demand
10	65	100	0	6	89484.72
20	65	100	0	6	89484.72
30	65	100	0	6	89484.72
40	65	100	0	6	89484.72
50	65	100	0	6	89484.72
55	65	100	0	6	89484.72
60	65	100	0	6	89484.72
65	65	100	0	6	89484.72
10	55	100	0	6	98021.48
20	45	100	0	6	107011.6
30	35	100	0	6	116011.6
40	70	100	0	6	85959.3
40	75	100	0	6	82819.76
40	65	80	0	6	89484.72
40	65	90	0	6	89484.72
40	65	110	0	6	89484.72
40	65	120	0	6	89484.72
40	65	130	0	6	89484.72

Table 8
Effect of facilities' capacities on total unmet demand under Distribution 3.

Cap^T	Cap^P	Cap^H	No. of temp facilities	No. of permanent facilities	Total unmet demand
10	65	100	0	6	57990.3
20	65	100	0	6	57992.16
30	65	100	0	6	58022.82
40	65	100	0	6	57987.46
50	65	100	0	6	57978.18
55	65	100	0	6	58025.52
60	65	100	0	6	57967.84
65	65	100	1	5	57999.46
10	55	100	0	6	64473.62
20	45	100	0	6	73167.92
30	35	100	0	6	82125.14
40	70	100	0	6	55457
40	75	100	0	6	53843.92
40	65	80	0	6	57985.64
40	65	90	0	6	57975.78
40	65	110	0	6	57962.46
40	65	120	0	6	57977.58
40	65	130	0	6	57962.46

facilities have the same capacity. The effect of the capacity of permanent facilities on the total unmet demand is much higher for Distribution 3 than it is for Distribution 2 and Distribution 1. For a 10-unit capacity decrease in Distribution 3, the increase in total unmet demand is 11.19% while for Distribution 2 it is 9.54% and for Distribution 1 it is 4.32%.

5.5. Maximum unmet demand

Minimizing the total unmet demand is indeed essential in the wake of disasters on the scale of the COVID-19 (SARS-CoV-2) pandemic. However, this objective has a major drawback: the "fairness" of distribution of the products among hospitals and patients. Consider the single product, single time period, and single scenario example in Fig. 5(a).

The total available supply is 10 units while the demands at hospitals one and two are 10 and 15 units, respectively. The optimal solution would be to completely route the supply to hospital one resulting a total unmet demand of 15 units as shown in Fig. 5(a). However, this leaves the demand of hospital two completely unmet. If we modify the objective function to minimize the maximum unmet demand, the optimal solution would be to route seven units of supply to hospital two and the remaining three units to hospital one. Although the total unmet demand remains 15 units, the unmet demand at hospital two is now reduced to eight units as shown in Fig. 5(b). To study the effect of minimizing the maximum unmet demand, we introduce the following new decision variable:

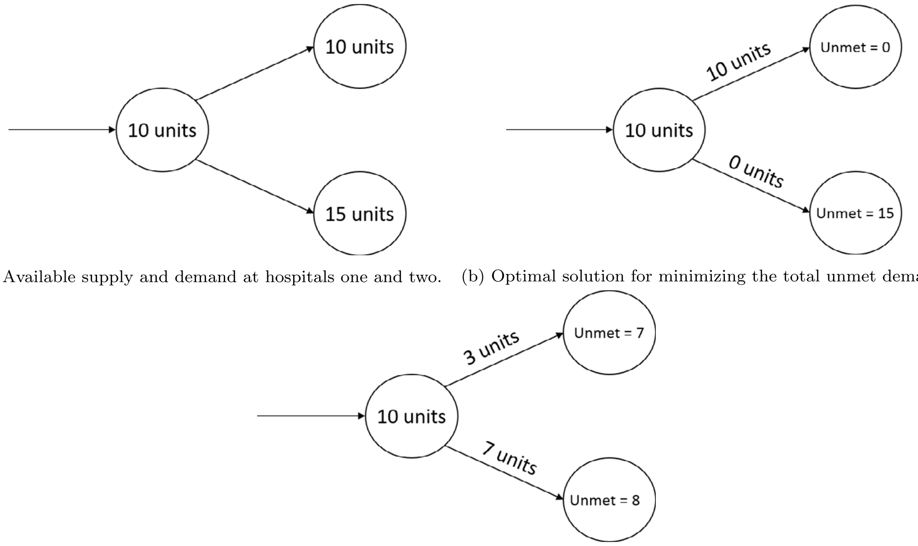
MUD_s: the maximum unmet demand under scenario s, $\forall s \in S$

Additionally, we modify BSCP as follows (we refer to the modified model as **BSCPM**):

$$\textbf{BSCPM} : \text{Min Maximum Unmet} = \sum_{s \in S} p_s \mathrm{MUD}_s \tag{53}$$

subject to

$$\mathrm{MUD}_s \geq \mathrm{UDB}_{bchts}, \qquad \forall b \in B, c \in C, h \in H, t \in T, s \in S, \tag{54}$$



(a) Available supply and demand at hospitals one and two. (b) Optimal solution for minimizing the total unmet demand.

(c) Optimal solution for minimizing the maximum unmet demand.

Fig. 5. Small example showing the difference between minimizing the total unmet demand and the maximum unmet demand.

$$\mathrm{MUD}_s \geq \mathrm{UDP}_{bhts}, \quad \forall b \in B, h \in H, t \in T, s \in S, \tag{55}$$

$$\mathrm{MUD}_s \geq \mathrm{UDL}_{bhts}, \quad \forall b \in B, h \in H, t \in T, s \in S, \tag{56}$$

$$\mathrm{MUD}_s \geq 0, \quad \forall s \in S, \tag{57}$$

and Constraints (2)–(25)

The new objective function (53) minimizes the expected maximum unmet demand. Constraints (54), (55), and (56) ensure that the maximum unmet demand is at least equal to the largest unmet demand of RBCs, plasma, and platelets, respectively. Constraints (57) are variable type constraints.

The effect of the new objective function (53) on the distribution of blood products among hospitals in presented in Fig. 6 and contrasted with the results from objective function (1). The measure used is the difference between the largest and smallest unmet demands among the hospitals (hereinafter referred to as variation). A smaller variation resembles higher levels of fairness and vice versa. The numbers at the top of the bars are the total unmet demands. For all three distributions, the variations are lower for objective function (53) than for objective function (1).

Fig. 6 shows that focusing only on fairness significantly increases the total unmet demand of all blood products. To achieve a balance between fairness and total unmet demand, we next consider an objective function that minimizes both total unmet demand and maximum unmet demand simultaneously. Once again, we modify **BSCP** as follows (we refer to the modified model as **BSCPM2**):

$$\textbf{BSCPM2:}\ \text{Min Maximum and Total Unmet} = \sum_{s\in S} p_s \mathrm{MUD}_s + \sum_{s\in S} p_s \left(\sum_{b\in B} \sum_{h\in H} \sum_{t\in T} \left(\sum_{c\in C} \mathrm{UDB}_{bchts} + \mathrm{UDP}_{bhts} + \mathrm{UDL}_{bhts} \right) \right) \tag{58}$$

subject to

Constraints (2)–(25),

and Constraints (54)–(57)

The balance achieved by simultaneously minimizing the maximum and total unmet demands is clearly presented in Fig. 6. In terms of total unmet demand (numbers on top of the bars), under all distributions, objective function (58) achieves very close values to objective function (1) and much lower values than objective function (53). As for variation levels (y-axis values), objective function (58) always outperforms objective function (1) while it only outperforms objective function (53) under two of the three distributions.

Another benchmark we use to measure the effect of the three objective functions is the number of patients that remain completely unattended. We present these results in Table 9. The only clear observation is that objective function (58) outperforms both objective function (1) and objective function (53) under Distribution 1. Under the remaining two distributions, the performance fluctuates between the different products and objective functions.

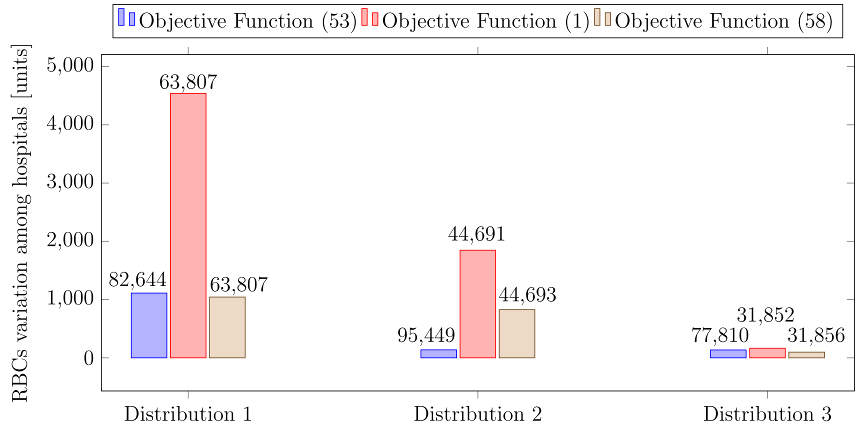


Fig. 6. The effect of the different objective functions on the RBCs unmet demand variation at the hospitals.

Table 9
Effect of the different objective functions on the number of completely unattended patients.

Objective function	Number of completely unattended patients: Total unmet demand			Maximum unmet demand			Maximum and total unmet demand		
Distribution	Distribution 1	Distribution 2	Distribution 3	Distribution 1	Distribution 2	Distribution 3	Distribution 1	Distribution 2	Distribution 3
RBCs	43,338	32,079	18,246	42,571	77,770	77,889	32,535	31,308	18,207
Plasma	24,006	26,000	26,000	20,662	26,000	26,000	21,181	26,000	26,000
Platelets	15,655	9,548	6,002	16,201	25,051	25,291	14,018	10,095	6,004

Table 10
Effect of the different demand and supply distributions on the total unmet demand in the absence of advanced planning for age-based demand.

Distribution	Total unmet demand: Distribution 1	Distribution 2	Distribution 3
Without advanced planning	64,558	46,476	37,795
With advanced planning	63,807	44,693	31,850

Table 11
Effect of the different demand and supply distributions on the number of completely unattended patients in the absence of advanced planning for age-based demand.

Distribution	Number of completely unattended patients: Distribution 1	Distribution 2	Distribution 3
Without advanced planning	41,460	31,579	21,160
With advanced planning	43,650	32,211	18,204

5.6. Age-based demand

While it is mandatory to supply the patients with the RBCs that are age-appropriate with respect to the demand, planning ahead of time for these situations is not always part of the processes in hospitals. The lack of advanced planning leads to unnecessary and avoidable deficits and emergencies. Consider a case where inventory, waste, and RBCs transfusion decisions do not account for expected age-based demands in the future but rather focus on current situations. The total unmet demands and number of attended patients are presented in Table 10.

As expected, accounting for age-based demand during the planning phases of hospitals will result in less total unmet demand under all three distributions. We can see that this difference significantly changes under the different distributions. Under Distributions 1 and 2, where the average supply is lower than the average demand, the improvement is not substantial because the deficits are already very high and can only be slightly reduced. However, under Distribution 3, where the average supply and demand are the same, planning ahead of time gives a major advantage. The importance of the distribution being considered becomes even clearer in Table 11 where it is the only case where the number of unattended patients decreases.

With a closer look at the unmet demands of the different age-categories of RBCs, we notice that category $c = 1$ always ends up with the highest levels of unmet demand. This is expected given that any fresh RBCs will last in this category for three days only. Fig. 7 shows the effect of the distributions and advanced planning on unmet demand of the different categories. As expected, in all the instances, advanced planning has led to less unmet demands for all categories.

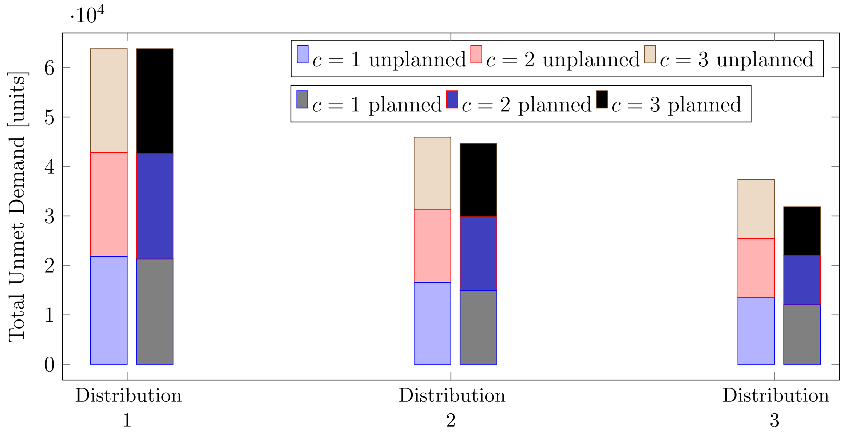


Fig. 7. Effect of advanced planning on the unmet demand of RBCs of different age categories.

Table 12
Effect of the different demand and supply distributions on the total unmet demand in the absence of advanced planning for blood type substitution.

	Total unmet demand		
Distribution	Distribution 1	Distribution 2	Distribution 3
Without advanced planning	67,090	51,431	44,267
With advanced planning	63,807	44,693	31,839

Table 13
Effect of the different demand and supply distributions on the number of completely unattended patients in the absence of advanced planning for age-based demand.

	Number of completely unattended patients		
Distribution	Distribution 1	Distribution 2	Distribution 3
Without advanced planning	41,733	32,730	27,413
With advanced planning	43,803	32,124	18,165

5.7. Blood type substitution

Despite blood type substitution being a common practice, it is not necessarily always part of the planning process of hospitals. Similar to the case with age-based demand, unnecessary shortages may be avoided with proper planning. Consider a case where inventory, waste, and RBCs transfusion decisions do not account for blood type substitution. The total unmet demands and number of attended patients are presented in Table 12.

Once again, planning in advance for blood type substitution at hospitals decreases the total unmet demand under all three demand and supply distributions. The biggest impact is seen under Distribution 3 when the average supply and demand have the same value and thus result in advanced planning having a larger impact margin. Further insight can be obtained from Table 13 where the number of completely unattended patients is measured. There is no definite trend when counting the number of completely unattended patients for all distributions. This is in line with the fact that decreasing the total unmet demand does not necessarily mean a fair distribution among patients.

6. Conclusion

The shortage in blood products amid the COVID-19 (SARS-CoV-2) pandemic is a pressing matter worldwide and the performance of their supply chain requires immediate attention. To formulate a mathematical model of the supply chain of blood products problem in the wake of such a pandemic, we use two-stage stochastic programming that captures the uncertainty in both supply and demand of the blood products. The first stage of the model will decide on the location of permanent facilities while the second stage decides on the locations of temporary facilities, the assignment of donors to these facilities, the delivery of the products to the hospitals, and inventory decisions at hospitals. Decisions on the locations of permanent facilities have to be made in advance because of their sizes and the time it will take to establish them. The deterministic equivalent of the stochastic model is formulated using scenario-based modeling where the number of scenarios was increased from 5 to 100 scenarios over 28 different data sets.

For some of the instances CPLEX fails to solve the problem in a reasonable amount of time, while for other instances it runs out of memory while compiling the model. For that purpose, we develop a heuristic. The heuristic is based on breaking down the original problem into three sub-problems where the output of each sub-problem is the input into the next sub-problem. Despite the myopic nature of the sub-problems, the heuristic reduced the solution time considerably and provided high-quality solutions. Next, we test the effect of different objective functions and conduct a sensitivity analysis on the parameters and characteristics of the model to provide managerial insight.

In all three demand and supply distributions considered in the work, the change in the capacities of the permanent facilities had the most effect on the total unmet demand since the models always favor the opening of permanent facilities over temporary facilities. To ensure fairness in distribution among hospitals, two additional objective functions are considered: (i) minimizing the maximum unmet demand, and (ii) minimizing the sum of the total and maximum unmet demands. In the former case, the supply of products to the hospitals is shown to be more uniform but the total unmet demand increases, while in the latter case a more favorable balance is achieved. The same can be observed with the number of completely unattended patients where the number decreases with the new objective functions. The importance of including age-based demand and blood substitution in the planning phase of the supply chain was reflected in both the number of unattended patients and the total unmet demand. For both benchmarks, including both age-based demand and blood substitution in the planning phase resulted in more favorable numbers.

For future work, a solution algorithm may be developed to provide guaranteed optimal solutions in a reasonable amount of time for all data sets. These optimal solutions will allow the implementation of sample average approximation (SAA) that allows us to test the quality of the obtained solution for each sample size of scenarios and determine the sample size that will accurately capture uncertainty in supply and demand.

CRediT authorship contribution statement

Nabil Kenan: Methodology, Data curation, Software, Formal analysis, Validation, Writing – original draft. **Ali Diabat:** Conceptualization, Methodology, Supervision, Funding acquisition, Validation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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