Integrating appointment scheduling and inventory management steps in the blood donation system

Luís Miguel Sousa

Department of Engineering and Management, Instituto Superior Técnico

luis.d.sousa@tecnico.ulisboa.pt

Abstract

The blood supply chain comprises several echelons, such as the collection, production, storage and usage of blood units. Blood donation systems are fundamental to ensuring the well-being of the population, and their value has been recognised for many years. Given the importance of blood in human life, the effectiveness and efficiency of the operations of this supply chain becomes a fundamental aspect for their progress. This efficiency can be achieved by optimising different processes in the various stages of the supply chain. However, by integrating processes between different stages, the efficiency level obtained can be improved. This is the aim of this work which intends to integrate two processes from two different echelons of the supply chain: appointment scheduling of blood donations and its inventory management, applied to a real case study of the AVIS Milan collection centre and the Niguardia Hospital which receives the blood units. In this sense, strategies and relations are defined through a mathematical model that allows the integration of both processes, with the concrete objectives of guaranteeing a balanced production of blood units and minimizing the total inventory costs. This is one of the first works in the literature that aims at the integration of the two described processes. Although future validation with more concrete data is needed, this work can be seen as a good starting point for a more complete integration of the two processes described.

Keywords: Blood Donation Supply Chain, Appointment Scheduling, Inventory Management, Optimization, Multi-Objective, Mathematical Programming

1. INTRODUCTION

Blood is a key resource for health care systems, as is continuously needed in the treatment of several diseases, organ transplants and surgeries. Someone needs blood every two seconds and one in seven people entering a hospital needs blood or blood products (Özener et al., 2019). The blood donation system aims to provide an adequate supply of blood units and blood products to transfusions centres and hospitals and, therefore, they have a fundamental role on the welfare of the population, since an insufficient availability of blood may result in loss of lives. Managing the BDSC is a very challenging task as blood is not an ordinary commodity. In the first place, blood can only be obtained through voluntary donations and cannot be manufactured and, secondly, blood is a perishable item, i.e., it must be discarded if not used on time. Typically, a BDSC is divided into four main echelons: collection, production, storage and distribution (Osorio et al., 2015). The donation process starts in the collection centre, being either stored as whole blood (WB) or processed into different products such as red blood cells (RBC), plasma, and platelets. Afterwards, the blood and the blood products are either stored or transported to hospitals or transfusion centres. Here, they can also be stored or used, depending on the network design of the supply chain. Even though there are different network designs for the BDSC, the management of each one of them has the common objective of being capable of meeting the demand while avoiding shortages and wasted units. To do so, several decisions must be made in all echelons, whether they are strategic, tactical, or operational. Therefore, many management tools, such as optimization tools, have been developed so far and have been applied by collection centres, blood banks and hospitals, in order to increase the effectiveness of services.

AVIS Milan, the Milan Department of the main collection centre in Italy has recently started to implement an appointment scheduling system for blood donation developed by Baş et al., 2018. This system aims to balance the production of blood units based on a demand profile while providing a constant feeding of blood to the blood donation system. Although the model reached its purpose, the inventory management of the blood units was not addressed.

Additionally, the main goal for this organisation is to supply blood units to the Niguardia Hospital which is responsible for performing the inventory management aiming to keep enough stock to fulfil the demand while minimising costs and wastages.

These two problems are separately managed since they are evaluated by two different decision-making centres.
In this context, the development of an integrated model could potentially lead to more effective and efficient management tools and contribute to improve the overall performance of the BDSC.

2. BLOOD SUPPLY CHAIN CHARACTERIZATION

Blood supply is central to the functioning of all health care systems as it is fundamental and necessary in various medical procedures, such as surgery, organs transplantation, cancer, and blood disorder treatments. The BDSC is a particular case of supply chains since blood cannot be produced and can only be acquired through volunteer donations. Furthermore, blood is a short-expiry product and a supply chain for a perishable product has specific and unique characteristics**.** By definition, a perishable product has a limited lifetime during which can be used, after which it should be discarded (Nagurney et al., 2012).
However, WB consists of several components that can be obtained from a single donation: RBC (45%), white cells and platelets (<1%) and plasma (55%). In modern medical treatments, patients may receive WB or just the particular components of the blood necessary to treat their specific condition (Hillyer et al., 2007). Consequently, as WB is perishable, blood components are also perishable although they have different shelf lives. WB can be stored for up to 35 days and is used to treat patients who need all the blood components, such as patients who have suffered a significant loss of blood due to trauma or surgery. Concerning RBC, if refrigerated, they have a shelf life up to 42 days and is mostly used on patients with blood disorders like anemia. Platelets is the constituent who presents the shortest shelf life since it can only be used for up to 5 days and are more often used during cancer treatments as well as organ transplants. On the other hand, plasma can be frozen and kept for 1 year and is commonly used in trauma, burn and shock patients.
In addition, there are four major blood groups established by the existence or absence of two antigens (A and B) on red cells: Group A has the A antigen on red cells and B antibodies in the plasma; Group B has only the B antigen on red cells and A antibodies in the plasma; Group AB has both A and B antigens on red cells; Group O has both A and B antibodies in the plasma. Furthermore, these are subdivided into two subgroups considering the presence (+) or absence (-) of the Rh factor, establishing the 8 known blood groups: A+, A-, B+, B-, AB+, AB-, O+, O- (Hillyer et al., 2007). In terms of the transfusion process, the interrelationship between these blood groups is quite complex since only some of these blood groups are compatible with each other. However, the aim is to minimize the blood substitution and use every patient's own blood type as much as possible.
According to Osorio et al. (2015), the BDSC can be divided into four echelons: collection, production, storage and distribution. The collection stage is responsible to perform donations and receive blood units from donors. In the production echelon, the blood undergoes under a testing process. Afterwards, blood units are either kept in inventory and then transported so they can be used to treat patients.
Associazione Volontari Italiani del Sangue (AVIS) is the major Italian non-profit association for blood donation. AVIS pursues an aim of public interest: to ensure an adequate availability of blood and blood components to the Italian population, through the promotion of donation in a periodic, free of charge, unpaid and anonymous method and, in some cases, the association even participates directly in the collection process. Additionally, AVIS is also responsible for the correct use of blood and its components, its quality, ensuring that all patients have the same right to receive transfusion for their treatments. In this particular case, we consider one of the largest departments of the association, the Milan department, referred to as AVIS Milan. This department has the main function of providing blood to one of the largest hospitals in Milan, the Niguarda hospital, being responsible for its collection.
In this particular case, we consider one of the largest departments of the association, the Milan department, referred to as AVIS Milan. This department has the main function of providing blood to one of the largest hospitals in Milan, the Niguarda hospital, being responsible for its collection.
This dissertation aims to optimize this specific blood donation supply chain. AVIS Milan is responsible to perform the blood donations through appointment scheduling tools and Niguardia Hospital is responsible to propper manage the inventory of these blood units. Since these are two separate decision centres, an integration of these two processes would be benefitial to the supply chain. The addressed problem will be specified with more detail upfront.

3. LITERATURE REVIEW

Since the goal of this work relies on the integration of blood collection with the inventory management, these two stages are explored in the literature review, as well as integrated models regarding other stages of the supply chain.

Blood Collection

In this echelon of the BDSC, according to Osorio et al. (2015), there are three different levels at which decisions can be made. Decisions at the strategic level have a long-term impact on the company's approach, such as the infrastructures' location, capacity, and staff definition. Moreover, these decisions influence other lower-level decisions, such as the tactical level decisions which have a middle-term impact. These decisions include the definition of policies, collection points, staff allocation and collection campaigns planning. Finally, the operational level comprises decisions that are taken daily, such as scheduling and collection methods. Therefore, this review focuses on the operational level which is directly linked to the appointment scheduling problem addressed in this work.

Many problems have been studied and many models have been developed in the literature to support decisions in the collection process among which we can highlight the quantity of blood products to be collected, collection strategies, planning for collections and donor appointments.

The study of the amount of blood to be collected is undoubtedly the most studied problem in the literature at this echelon since it is directly related to the main objective of reducing the amount of wasted blood units, being this an extremely valuable product due to its perishability and the way it is obtained. One of the pioneering studies related to this problem was carried out by Cumming et al. (1976) where a forecasting model is developed to improve blood collection by reducing shortages and preventing overstocking. However, this model does not consider some features which are essential when dealing with BDSC, making it less relevant when dealing with procurement situations (Osorio et al., 2015). Given the blood characteristics mentioned in Chapter 2, three collection policies can be considered: collect every available blood from donors, collect a particular amount or collect a specific quantity to achieve a precise inventory level (e.g., Blake et al. (2013)). According to Lowalekar and Ravichandran (2010), the first policy might lead to huge wastages and therefore, the best option might be to reduce the collected blood to a certain value to prevent over collection. Later, Lowalekar and Ravichandran (2011) develop a simulation-based model which aims to determine the optimum level of components at a blood bank in India. However, the authors conclude that it is not optimal for a blood bank to fractionate large blood quantities since this may lead to high operational costs and high levels of wastage in the system. In addition to collection policies, collection methods and their impact on supply chain performance have also been studied in the literature. For example, Madden et al. (2007) explore the impact of two different collection methods (fractionation and double RBC donations by apheresis) under different policies for RBC.

Blood Donation Appointment Scheduling

Scheduling donor appointments improves the collection process, not only from the perspective of the collection centres, in terms of the resource allocation, but also from the donor perspective, which is associated with the quality of the service provided. Alfonso et al. (2013) evaluate several scenarios and configurations of blood collection systems where Petri net models are used to describe all relevant donor flows. Additionally, Alfonso et al. (2015) present an optimization model of queue dynamics of the blood collection system for fixed-site capacity planning and blood donors' appointment scheduling in order to improve different performance measures. The authors conclude that the combination of a queuing-based approximation and mathematical programming approach is useful in order to schedule blood donation appointments. More specifically and more closely related to one of the problems addressed in the present work, Baş et al. (2018) is the first research paper that defines and proposes a framework for the Blood Donation Appointment Problem. The proposed architecture consists of two stages: an offline pre-allocation of the available time slots considering every blood type and an online assignment of each incoming donor reservation request to a slot created in the previous step, considering the donor's blood type as well. The former is based on a mixed integer linear problem and the latter is based on a prioritization policy. The main goal is to balance the blood production for each blood type, ensuring a fairly constant supply of blood units to the system. Since the parameters for this model are assumed to be deterministic, there are several uncertainty factors that are not considered such as the uncertainty arrivals of non-booked donors and random no-shows of already booked donors (Lanzarone and Yalçındağ, 2019). The integration of the Blood Donation Appointment Problem, which can be considered as a stochastic problem in its nature, with other steps of the BDSC might help to better predict parameters that cannot be assumed to be known *a priori*. The review of integrated models will be explored further ahead in section 3.3. Other earlier papers can still be considered. Pratt and Grindon (1982) study donor waiting times by varying from a 9-bed system to a 12-bed system with the number of accepted donors in three different scheduling strategies. Later, Michaels et al. (1993) also developed a computer simulation to evaluate scheduling strategies for the American Red Cross with the aim of decreasing donor transit times and increasing the staff utilization. However, in this case, the strategies scheduled donors and walk-in donors and it is concluded that having a fully scheduled system implemented with no open slots for walk-in donors would be the best option in terms of the system performance but the worse regarding the quality of the service provided since every walk-in donor would be rejected. Therefore, the identification of donor arrival patterns can play a crucial role in the functioning of the system, especially in blood centres without fixed appointments for blood collection.

Inventory Management

Inventory is the echelon of the BDSC that has received the most attention so far in the literature mainly due to the short life of the blood. As mentioned above for the collection echelon, decisions in this stage can also be categorized based on three hierarchical levels. Once more, strategic decisions are related with long-term planning such as network design and information systems. Tactical decisions are concerned with inventory policies definition and resources allocation while at the operational level the decisions are mostly associated with daily quantities to order to fulfil the demand (Osorio et al., 2015).

It can be said that more general perishable inventory theory can potentially be applied to the blood management. However, techniques implemented in more industrial backgrounds, for example, just in time, are not suitable for this type of supply chain, since it can lead to inventory shortages (Chapman et al., 2004). Therefore, the majority of the research papers related to this topic are directly associated with the BDSC. Many complex inventory policies developed so far are based on a variety of analytical and simulation techniques, with the main principle that, by improving the complexity and, consequently, the accuracy of the models, wastage can be reduced. Nevertheless, some models are focused on specific decisions and do not contemplate some constraints that might be considered as fundamental and could affect the decision in this stage. There are several problems that have been studied in the literature, among which we can highlight the following: inventory policies, issuing policies and inventory allocation. These will now be reviewed.

Regarding inventory policies, the models aim to set inventory levels and determine order quantities that consider uncertainty, but also the trade-off between cost associated to shortages and wastage and efficiency for the different collection strategies. Several general inventory policies can be found in the literature but regarding the BDSC, the majority are periodicals (Osorio et al., 2017) and are focused on fixed order intervals (order-up-to models). This means that the stock levels are evaluated periodically, usually at the end of each day (Osorio et al., 2017), and a regular fixed order is placed or not, considering the stock level. Two of the earliest studies regarding this issue are conducted by Cohen (1976) which aims at finding optimal ordering policies for any perishable product and by Nahmias et al. (1976) where two different policies are presented to meet two types of demand. More recently, many techniques have been used to address inventory policies such as simulation, mathematical programming, and dynamic programming. For example, Haijema et al. (2007) developed a combined Markov dynamic programming and simulation approach and applied it to a regional blood bank problem. This is the first work to determine the production and inventory policy to minimize both shortage and outdating of blood platelets. Later in 2009, the same authors extended their previous work. Haijema et al. (2009) modelled a stochastic dynamic programming simulation approach which included periods where no collection is performed (Christmas, New Year, Easter) and led to a reduction of the annual shortage in the blood bank.

Issuing policies which are related with the age sequence of units provided to meet the required demand have also been addressed in the literature. According to Abbasi and Hosseinifard (2014), similarly to the inventory policies, issuing policies have also a huge impact on the shortage and wastage levels, since we are dealing with a perishable inventory system. The most adopted policies within the BDSC are FIFO, which uses the oldest product first, and Last In, First Out (LIFO), which uses the freshest product first. For example, Najafi and Ahmadi (2017) presents a multi-objective integer programming to manage inventory in a hospital blood bank using FIFO which aims to study two key performance indicators, blood shortage and wastage. This paper considers uncertain supply where the blood bank does not receive all ordered blood units, the age of the blood units and two types of patients. Although Pierskalla et al. (1972) and Abdulwahab and Wahab (2014) show that FIFO usually outperforms LIFO in several key performance indicators, sometimes is not the best option to issue oldest blood first since some treatments requires fresh blood (Katsaliaki, 2008).

Inventory allocation problems are related with the most efficient location to allocate inventory in the BDSC. There are centralized and decentralized systems and Carden and Dellifraine (2006) evaluate both advantages and disadvantages associated to both types. The authors conclude that a centralized system presents a better performance regarding meeting the need in the hospitals, but decentralized systems are a better option in terms of costs. Hosseinifard and Abbasi (2018) demonstrate that the centralization of hospital's inventory can increase the sustainability and resilience of the BDSC.

Integrated Models

The BDSC has received a significant amount of attention from researchers over time, but this study is mainly focused on the analysis of each echelon of the supply chain independently. Nevertheless, due to recent advances, there is a certain tendency to increasingly integrate two or more echelons of the BDSC.

Closely related to the aim of this study, Özener et al. (2019) integrate inventory control policies with donation tailoring and scheduling decisions. These authors are the first to define the Blood Donation Tailoring Problem (BDTP) which has the aim of minimize the operational costs, including donation, inventory, and disposal cost, while satisfying the demand at the same time during a planning horizon. The objective is accomplished by developing donation schedules through heuristic methods. On the other hand, Ensafian and Yaghoubi (2017) develop a bi-objective model with the aim of maximizing the freshness of platelets and minimizing the total costs. The model considers both FIFO and LIFO policies, and two types of collection methods.

Kohneh et al. (2016) develop a bi-objective mixed integer programming (MIP) model to design a BDSC network under an emergency state. The purpose of this work is to minimize costs and maximize the covering of blood donors in order to optimize several decisions that need to be made in such case, such as the decisions related to the amount of blood donated to permanent and temporary blood donation centres, the amounts of blood products transported between different levels of the chain, among others. Similarly, Zahiri and Pishvaee (2017) study the network design of the BDSC proposing a bi-objective MIP model with the objective of minimize total costs and maximizing the unsatisfied demand among demand zones. Although blood compatibility is considered, inventory levels, the shelf time of blood products and perishability are disregarded. Finally, we can still consider the work developed by Samani et al. (2018) which is one of the most complete studies in terms of integrating several parameters such as perishability, inventory levels at both demand zones and collection centres, demand uncertainty, irregular supply, shortages and the network design. The authors develop a multi-objective MIP model to design an integrated BDSC network.

Conclusions

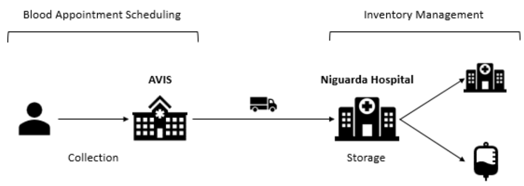
Although the frequency of integrated models has been increasing over the years, the integration of appointment scheduling and inventory management has hardly been explored. Therefore, this work should have an important contribution to the literature in this area.

4. MODEL FORMULATION

Problem Statement

Firstly, it is important to understand the supply chain functioning of the AVIS case study. In Figure 1, an operational scheme is presented in order to understand both the product flow and the processes included in each stage. In AVIS facilities, blood is collected every day and as mentioned above, many collection centres are implementing donor reservation systems and AVIS Milan is no exception. After it is collected, blood is transported twice a day to Niguardia Hospital, where it is consequently stored and used. From here, blood can either be used to treat patients in this same hospital or it is transported to be used in other clinics.

Figure 1 – AVIS Supply Chain



There are two separate decision centres. On the one hand, the blood collection process is intended to be as constant as possible, avoiding fluctuations. To balance the blood collections in terms of the total number of units produced per day and per blood type, a blood donation appointment scheduling system model was proposed by Baş et al. 2018 which is based on a profile demand. On the other hand, Niguardia Hospital intends to receive a constant and the highest amount of blood as possible, in order to avoid any type of shortage. At this level, the inventory management is performed to properly address the blood units while minimizing the inventory size and wastages.

In summing up, despite both steps are separately managed and having different objectives, these issues must be connected. Therefore, the main challenge relies on developing a model that integrates inventory management rules such as minimizing inventory costs and the utilization of blood units with the appointment scheduling for blood donors.

Model Clarification and Formulation

The following model is based on the work previously developed by (Baş et al., 2018) regarding the appointment scheduling system. In a simplistic way, this model considers an offline preallocation phase which is responsible to reserve slots for each blood type and an online allocation phase which is responsible to assign a slot to a donor whenever he/she intends to donate blood. The attribution of slots is based on a expected number of donors. It is intended now to integrate the scheduling of donors with inventory management rules in order to have a better control of the blood supply chain. A safety stock level for each blood type, as well as inventory updates according to the blood usage and blood units that were collected are now introduced.

The notation required for the model is presented in Table 1, while model parameters and decision variables are introduced in Table 2.

Table 1 – Model Notation

Sets	
$b \in B$	Set of blood types
$t \in T$	Set of time periods (days)

Table 2 – Parameters and Decision Variables

Parameters	
d_b	Expected number of booked donors over T with blood type b
φ	Flexibility degree associated with d_b
da_t^b	Number of already booked donors at period t with blood type b
dn_t^b	Expected number of non-booked donors at period t with blood type b
dm_t^b	Demand for blood type b at period t
ss_b	Safety stock level for blood type b
ii_b	Inventory level at t=0 for each blood type b
ic	cost of holding inventory
θ	maximum capacity (maximum donations per period)
$MaxInvCost$	maximum value for Inventory Cost
$MaxVariatio$	maximum value for Variation
α	weight for Inventory Cost
β	weight for Variation
Decision Variables	
y_t^b	Number of planned units for blood type b at period t
x_t^b	Number of preallocated slots for blood type b at period t
I_t^b	Inventory of blood type b at the end of period t
w_b	Variation of y_t^b

The mathematical model for the proposed integration is presented next:

$$\min Z = \alpha \frac{\sum_t Cost_t}{MaxInvCost} + \beta \frac{\sum_b w_t^b}{MaxVariation} \quad \textbf{(1)}$$

Subject to:

$$w_t^b \geq y_{t+1}^b - y_t^b \ , \qquad \forall\ b\ \in B, t\ \in T \quad \textbf{(2)}$$

$$w_t^b \geq y_t^b - y_{t+1}^b \ , \qquad \forall\ b\ \in B, t\ \in T \quad \textbf{(3)}$$

$$Cost_t = \sum_b I_t^b \times ic \ , \qquad \forall\ t\ \in T \quad \textbf{(4)}$$

$$y_t^b = da_t^b + dn_t^b + x_t^b \ , \forall\ b\ \in B, t\ \in T \quad \textbf{(5)}$$

$$\sum_b y_t^b \leq \theta, \qquad \forall\ t\ \in T \quad \textbf{(6)}$$

$$\sum_b \sum_t \left(x_t^b + da_t^b\right) \leq (1+\varphi) d_b \ , \forall\ b\ \in B \quad \textbf{(7)}$$

$$(1-\varphi) d_b \leq \sum_b \sum_t \left(x_t^b + da_t^b\right) \ , \forall\ b\ \in B \quad \textbf{(8)}$$

$$I_1^b = y_1^b + ii_b - dm_1^b, \qquad \forall\ b\ \in B \quad \textbf{(9)}$$

$$I_{t>1}^b = y_{t>1}^b + I_{t-1}^b - dm_{t>1}^b \ , \forall\ b\ \in B, t\ \in T \quad \textbf{(10)}$$

$$I_t^b \geq ss_b \ , \qquad \forall\ b\ \in B, t\ \in T \quad \textbf{(11)}$$

$$y_t^b, \quad x_t^b, \quad I_t^b \ \geq 0 \quad \textbf{(12)}$$

As previously mentioned, he proposed model intends to integrate appointment scheduling with inventory management rules. It is important to emphasize that, on the one hand, the aim is to produce a balanced number of blood units in order to avoid any kind of shortage, while also considering an appropriate inventory management of these same blood units. The objective function (1) reflects these two principles by minimizing the variation of produced units for different blood types between consecutive days (2 and 3) and the total costs related with the blood unit's storage (4). Since these two terms have different order of magnitude, the maximum values for each one of them were added in order to normalize these values and have an adequate solution. Moreover, in order to solve this bi-objective optimization problem the weighted sum method is implemented. This method has the objective of finding a unique solution, which means that combines the two terms previously defined into one scalar. These weights are defined by α and β. On the set of constraints, equation (5) defines the number of planned blood units for each day and blood type. It is assumed that there are three types of donors: donors that already have an appointment scheduled, donors that will make an appointment to donate and donors that randomly appear without any reservation to donate. Therefore, the number of planned units for each day and blood type is given by the sum of pre allocated slots (x_t^b), the number of donors that already have an appointment (da_t^b) and the number of donors that randomly appear without any appointment for each for each blood type (dn_t^b). Furthermore, equation (6) ensures that the total number of donations for each day does not surpass the maximum capacity of the collection center. Equations (7) and (8) force the total number of slots to be around the total number of expected booked donors (d_b). In a perfect scenario, the number of booked donors should be equal to the number of the slots that we want to preallocate (x_t^b) and the number of donors that already have an appointment (da_t^b) over the time horizon. However, it is not possible to know the exact number of donors that will make an appointment. Consequently, a flexibility degree ($0 \leq \varphi \leq 1$) is defined guaranteeing that the total number of available slots will be defined by a range between $(1-\varphi)d_b$ and $(1+\varphi)d_b$. The higher the value of the flexibility degree, more uncertainty is around the total expected number of donors. However, for this work we will consider the value of φ as 0. Regarding the inventory management rules, equations (9) and (10) define the inventory levels at the end of each period for each blood type which is given by the sum between the number of planned blood units (y_t^b) and the level of inventory in the previous period (I_{t-1}^b) minus the number of blood units expected to be used to treat patients in that period (dm_t^b). This also means that we are assuming that every slot will be scheduled, and every donor will not miss the appointment to donate. In order to minimise even more the possibility of any shortage, a safety stock (ss_b) is set for each blood type. Equation (11) assures that the inventory level for each blood type at the end of each period is equal or above of the safety stock level. Considering the functioning of the supply chain in section 4.1. once the blood units arrive to Niguardia Hospital either they can be used or can be transported to another hospitals or healthcare facilities. For this reason, a maximum level for the inventory was not considered. Finally, equation (12) defines the domain of the decision variables.

Assumptions and Limitations

The assumptions and limitations of the model are now presented, although some of them were already mentioned in the previous section. As mentioned above, there are two distinct objectives: assign slots per day and per blood type guaranteeing that this will generate a balanced production of blood units and minimize at the same time the inventory costs.

Regarding the collection process, it is assumed that every donor (expected donors and not expected donors) will show up and that every slot will be fulfilled on the day that was assigned. Moreover, the model previously developed by Baş et al. (2018) did not consider a fixed maximum capacity to perform donations but a penalty when the number of donations exceeded the time available by the physicians. Also, the donation process itself is considered as being a procedure to obtain a single blood unit, not considering the different donation types (Whole Blood, Plasma, Platelets and Red Blood Cells). This means that the model developed in this work is less flexible regarding the blood collection rules.

Concerning the blood usage and its inventory management, there are a few aspects that were not included. As described before, blood is a perishable product that has a shelf life. However, in the proposed model its perishability is not being considered. Furthermore, we assume that there is no wastage of blood units.

Assumptions regarding the values defined por some of the parameters were also considered, since some data was not possible to collect.

5. RESULTS

The proposed model was implemented in GAMS language, in a computer equipped with an AMD Ryzen 4700 U processor of 2.00 GHz and 8 GB of RAM. The considered scenarios to evaluate the model as well as its results are presented below.

Objective Function Values

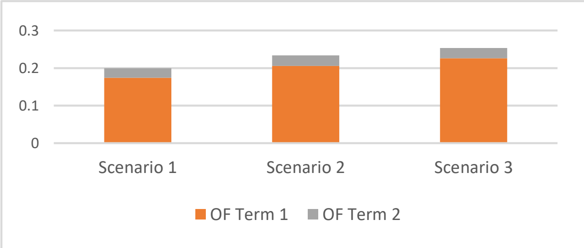


Figure 2 – Objective Function Values per Scenario

Analysing the results, it is possible to conclude that scenario 1 which considers a high level of demand (1000 blood units) performs better than scenario 2 (500 blood units) and the latter better than scenario 3 which considers a low demand (250 blood units). It is also possible to deduce that in all scenarios, the term that is related to inventory cost is the one that most contributes to the total value of the objective function and the one that most differs among the scenarios considered. This term represents 87%, 88% and 89% of the total objective function for Scenario 1 (H), 2 (M) and 3 (L), respectively. That is, considering that the value of donors expected to donate (input value) is the same for all scenarios and there is no rejection of donors, we realize that the increasing value of the inventory cost term is related to the decrease in demand. In other words, for the same number of blood units collected, the lower the demand, the more units will be stored. Thus, the inventory cost will increase as well as the value of the objective function.

In contrast, analysing the second term of the objective function that is related to balancing the production of blood units, although it presents a good performance since its values are lower, it is also possible to perceive that this value is practically unchanged in the different scenarios. For this term, scenario 1 performs better, followed by scenario 3 and lastly scenario 2. Furthermore, the values of this element represent 13%, 12% and 11% of the total value of the objective function for scenarios 1, 2 and 3, respectively.

Production of Blood Units

In this metric, it was possible to conclude that the production of blood units is fairly constant during the 28-day time horizon defined for the three scenarios. However, it was also possible to observe that each blood type has at least a major oscillation during the time horizon, being most evident in blood types *b1* and *b7*. This major fluctuation means that the system is running towards finding the lowest value possible of blood units produced in the first days of the time horizon, in order to not increase excessively the number of stored units. The results for Scenario 1 (H) are presented in Figure 3.

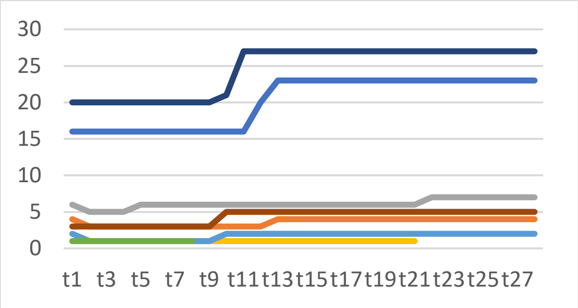


Figure 3 – Blood Units Production: Scenario 1 (H)

As previously acknowledged, the model presents a good performance for all the scenarios in terms of balancing the blood unit's production. Moreover, this constant line of production might be related with the fact that the model is not considering the blood perishability. Since these oscillations are not considerably high, is possible to state that the inventory cost presents a bigger influence in the performance concerning the three scenarios.

Inventory Cost and Inventory Levels

In Table 1 it is possible to analyse the total inventory cost as well as the final inventory level regarding all blood types for each considered scenario.

Table 1 – Inventory Cost and Final Levels per Scenario

	Inventory Cost (€)	Final Inv. Level
Scenario 1 (H)	18 373	982
Scenario 2 (M)	21 912	1 364
Scenario 3 (L)	24 009	1 561

The value for the total inventory cost is higher for Scenario 3 (L) and lower for Scenario 1 (H), which is directly related with the different level of demands defined for each scenario. Although is not possible to establish direct comparisons between the three results since they consider different demand values for the same number of expected donors, it is interesting to analyse that the gap is significantly higher between Scenario 1 and Scenario 2 (3539 €) than the difference between Scenario 2 and Scenario 3 (2097 €), considering that the demand values were decreased in 50% from Scenario 1 to Scenario 2 and from Scenatio 2 to Scenario 3. This divergence is explained by the values assigned to the safety stock levels and the initial inventory levels for each scenario, since the proportion of decrease of these parameters was not the same as that defined for the decrease in demand between the considered scenarios.

Regarding the gap between the inventory levels and the safety stock level, it can be stated that there is a trend for this gap to increase over the time horizon for every scenario, since as concluded before, the production of blood units is increased towards the end of the time horizon and the safety stock value for each blood is the same. Also, this steady increase is explained by the fact that a maximum inventory level is not being considered since the hospital can transfer blood units to another healthcare facilities and we start from an initial inventory level equal to the safety stock level. Once again, perishability is not being considered which influences this trend.

However, it can be stated that the model presents a good performance in assuring that the blood levels are above the safety stock.

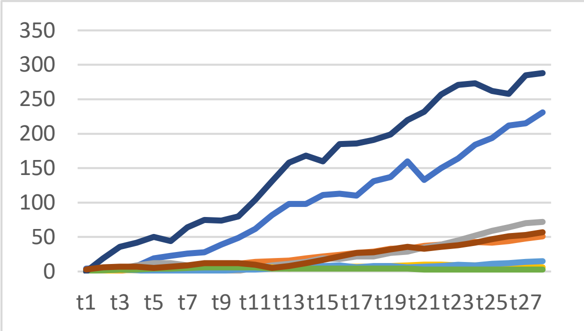


Figure 4 – Inventory gap for Scenario 1 (H)

Capacity Usage

It is possible to state that the model presents a trend towards increasing the capacity used to make donations over the time horizon. This means that the model might be prioritizing the minimization of the inventory costs over the balancing, since the first component has a higher influence in the objective function value as seen before. One can also see that the greater the demand associated with each scenario, the greater the capacity used in the first days of the time horizon. However, it is also important to mention that we are dealing with a fairly high number of expected donors (total of 1723 donors, an average of 62 per day). Considering that the collection centre has the capacity to perform 68 donations per day, it means that the maximum capacity for the time horizon would be to receive a total of 1904 donors. This implies that in total, we will use 90% of the capacity for the time horizon.

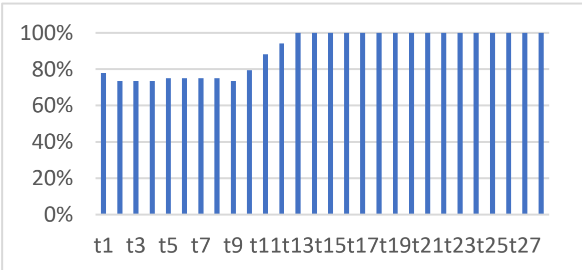


Figure 5 – Capacity Usage for Scenario 1 (H)

It was possible to conclude for all scenarios that there is a moment from which maximum used capacity is reached and is maintained until the end of the time horizon. This is supported by Figure 5 for Scenario 1 (H).

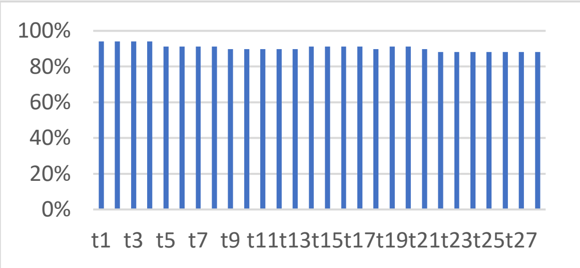
Sensitivity Analysis

Weights for the Objective Function (α and β)

This sensitivity analysis shows that with these variations there is a trade-off between the total inventory cost and the blood units' production. The higher the weight of β, the higher the inventory cost and the lower the value of the objective function since we are removing weight from the total cost. In contrast, the production of blood units gets better balanced, which is supported by the decrease of the number of days with maximum capacity usage. With the increase in the weight of β, the number of days with use of the maximum capacity (68 donations) is lower.

Considering a weight of 15% to α and 85% to β, the results on Figure 6 shows that it is possible to increase the flexibility regarding receiving more donors than the number expected with a trade-off inventory cost of 1987€ since the capacity usage per day is more balanced when compared to Figure 5. Therefore, it is possible to state that the higher the weight of β and the lower the weight of alpha, the more constant is the capacity usage, allowing the creation of a greater margin to meet unexpected donors, consequently increasing the total cost of inventory.

Figure 6 – New capacity usage for Scenario 1 (H)



Summing up, in one hand, we can increase the inventory cost and assure that there are no days with maximum capacity usage. On the other hand, we can decrease the inventory cost which results in a worse balance regarding the blood unit's production.

6. CONCLUSIONS

A more efficient supply chain management is an extremely important aspect and a common goal for all companies in the different industries. In the particular case of the blood supply chain, its efficiency is even more critical and challenging, given not only the blood characteristics, but also the importance of this product in the treatment of patients in hospitals or other healthcare facilities. This efficiency can be applied in the various stages of the supply chain and can have several dimensions, from cost reduction, waste reduction, optimization of the collection process, among many others. As seen in the literature, most of the works developed concerning this objective, focus only on the optimization of one of the echelons of the supply chain. However, although the frequency of an integrated model approach has increased in recent years, the integration of inventory management with the collection stage has been poorly explored. The idea behind this work is precisely to contribute to that end, addressing the particular case in the Italian Blood Donation System, AVIS Milan.

This dissertation aims to create the initial steps towards an integrated strategy between the appointment scheduling and inventory management rules, with the objective to have a balanced production of blood units, minimizing at the same time the inventory costs. Therefore, it is intended to carry on the work previously developed concerning the appointment scheduling decisions in AVIS Milan. To pursue this objective, it was established a relation between the produced blood units and the inventory levels, as well as defining a safety stock level for each blood type.

The model was tested and evaluated under different demand scenarios since it was not possible to collect such data and real collection data from AVIS Milan: Scenario 1 that considers a high level of demand, Scenario 2 for a medium level of demand and Scenario 3 for a low level of demand. In the first approach, in which was defined a weight of 50% for each objective (balance the production of blood units and minimize the inventory costs), the results demonstrated that the inventory cost term of the objective function was the one that presented the largest percentage in the total objective function value for all three scenarios. Regarding the blood unit's production, the production line for each blood type was quite constant presenting a major oscillation at a certain point of the time horizon in the blood types with higher demand. This demonstrates that the model is working in a way where it finds the minimum value of blood units to produce while satisfying the demand, keeping this value constant and then performs the lowest possible increase in order to perform the remaining donations, minimizing the amount of blood units that are stored and not used. This behaviour is also related to the fact that perishability for blood units is not being considered, which is actually one of the limitations for this model. Additionally, for all three scenarios, regarding the capacity used per day, the model showed an accumulation of donations in the second half of the considered time horizon which led to a maximum capacity usage in several of these days. Although we are assuming an exact number of expected donors, this represents that the model presented a low flexibility in receiving more donors than the expected ones in the referred time.

Afterwards, a sensitivity analysis was performed in some of the considered parameters. The variation of the weights defined for each one of the terms of the objective function showed that it was possible to obtain a more balanced solution in terms of capacity usage. More specifically, it was possible to conclude that the inventory cost term dominates the balance concerning the blood units' production, meaning that defining a weight of 50% for each term implies that the inventory cost is being more privileged than the balance production balance. In fact, when a weight of 85% for the balance and 15% for the inventory cost, the model was able to create a more balanced solution where the maximum capacity usage was not reached in the time horizon and consequently increasing the flexibility to receive more donors than the expected among the time horizon. However, it important to note that a trade off cost is attached to this solution.

Should this model be used as a basis for future development, it is necessary to establish some recommendations to AVIS and the hospital. Firstly, it is important to establish a rule for the definition of safety stock level. This parameter does not have to take a necessarily constant value for every time horizon and based exclusively on demand. For example, the safety stock can be higher the greater the uncertainty of the expected demand and the expected number of donors in the planning time. In addition, and as seen previously, there might exist more balanced solutions according to the variation of some parameters. However, these variations require a trade-off, and it will be up to AVIS and the hospital to assess which is the most balanced solution regarding all the aspects considered.

As a proposal for future work, it is suggested to minimise the number of assumptions and limitations that were mentioned in this work. One of the fundamental characteristics of blood is its perishability and not being considered is biasing the results of the proposed model. Moreover, taking this aspect into consideration would allow for a much more realistic inventory management than the one proposed. Another aspect that should be considered is the uncertainty associated not only to the expected number of donors, but also to the expected demand. These considerations would allow to create a much more robust and realistic integrated system.

Even though it would need further validation by comparing the results with more precise and realistic data, this model can be seen as a good starting point to increase the blood supply chain efficiency through the integration of the appointment scheduling with inventory management rules.

7. BIBLIOGRAPHY

Abbasi, B., & Hosseinifard, S. Z. (2014). On the Issuing Policies for Perishable Items such as Red Blood Cells and Platelets in Blood Service. *Decision Science*, *45*(5), 995–1020. https://doi.org/10.1111/deci.12092

Abdulwahab, U., & Wahab, M. I. M. (2014). Approximate dynamic programming modeling for a typical blood platelet bank. *COMPUTERS & INDUSTRIAL ENGINEERING*, *78*, 259–270. https://doi.org/10.1016/j.cie.2014.07.017

Alfonso, E, Xie, X., Augusto, V., & Garraud, O. (2013). Modelling and simulation of blood collection systems : improvement of human resources allocation for better cost-effectiveness and reduction of candidate donor abandonment. *VoxSanguinis*, *104*, 225–233. https://doi.org/10.1111/vox.12001

Alfonso, Edgar, Xie, X., & Augusto, V. (2015). A simulation-optimization approach for capacity planning and appointment scheduling of blood donors based on mathematical programming representation of event dynamics. *2015 IEEE International Conference on Automation Science and Engineering (CASE)*. https://doi.org/10.1109/CoASE.2015.7294167

Baş, S., Carello, G., Lanzarone, E., & Yalçındağ, S. (2018). An appointment scheduling framework to balance the production of blood units from donation. *European Journal of Operational Research*, *265*(3), 1124–1143. https://doi.org/10.1016/j.ejor.2017.08.054

Blake, J. T., Hardy, M., & Delage, G. (2013). *Déjà-vu all over again: using simulation to evaluate the impact of shorter shelf life for red blood cells at Héma-Québec*. *53*(July), 1544–1558. https://doi.org/10.1111/j.1537-2995.2012.03947.x

Carden, R., & Dellifraine, J. L. (2006). An Examination of Blood Center Structure and Hospital Customer Satisfaction. *Health Marketing Quarterly*, *22*(3), 21–42. https://doi.org/10.1300/J026v22n03_03

Chapman, J. F., Hyam, C., & Hick, R. (2004). Blood inventory management. *VoxSanguinis*, *87*(2), 143–145. https://doi.org/10.1111/j.1741-6892.2004.00472.x

Cohen, A. (1976). Analysis of Single Critical Number Ordering Policies for Perishable Inventories. *INFORMS*, *24*(4), 726–741. https://doi.org/10.1287/opre.24.4.726

Ensafian, H., & Yaghoubi, S. (2017). Robust optimization model for integrated procurement , production and distribution in platelet supply chain. *Transportation Research Part E*, *103*, 32–55. https://doi.org/10.1016/j.tre.2017.04.005

Haijema, R., Van Dijk, N., Van Der Wal, J., & Smit, C. (2009). *Blood platelet production with breaks : optimization by SDP and simulation*. *121*, 464–473. https://doi.org/10.1016/j.ijpe.2006.11.026

Haijema, R., Wal, J. Van Der, & Dijk, N. M. Van. (2007). *Blood platelet production : Optimization by dynamic programming and simulation*. *34*, 760–779. https://doi.org/10.1016/j.cor.2005.03.023

Hillyer, C., Silberstein, L., Ness, P., Anderson, K., & Roback, J. (2007). *Blood Banking and Transfusion Medicine* (2nd ed.). https://doi.org/10.1016/B978-0-443-06981-9.X5001-7

Hosseinifard, Z., & Abbasi, B. (2018). The inventory centralization impacts on sustainability of the blood supply chain. *Computers and Operation Research*, *89*, 206–212. https://doi.org/10.1016/j.cor.2016.08.014

Katsaliaki, K. (2008). *Cost-effective practices in the blood service sector*. *86*(2–3), 276–287. https://doi.org/10.1016/j.healthpol.2007.11.004

Kohneh, J. N., Teymoury, E., & Pishvaee, M. S. (2016). Blood products supply chain design considering disaster circumstances (Case study : earthquake disaster in Tehran). *Journal of Industrial and Systems Engineering*, *9*, 51–72.

Lanzarone, E., & Yalçındağ, S. (2019). Uncertainty in the Blood Donation Appointment Scheduling: Key Factors and Research Perspectives. In *Health Care Systems Engineering* (pp. 293–304). https://doi.org/10.1007/978-3-030-39694-7_23

Lowalekar, H., & Ravichandran, N. (2010). *Model for blood collections management*. 2778–2784. https://doi.org/10.1111/j.1537-2995.2010.02944.x

Lowalekar, H., & Ravichandran, N. (2011). *A model for blood components processing*. https://doi.org/10.1111/j.1537-2995.2011.03224.x

Madden, E., Murphy, E. L., & Custer, B. (2007). *Modeling red cell procurement with both double-red-cell and whole-blood collection and the impact of European travel deferral on units available for transfusion*. *47*(November), 2025–2037. https://doi.org/10.1111/j.1537-2995.2007.01426.x

Michaels, J. D., Brennan, J. E., Golden, B. L., & Fu, M. C. (1993). A simulation study of donor scheduling systems for the American Red Cross. *Computers and Operation Research*, *20*(2), 199–213. https://doi.org/10.1016/0305-0548(93)90075-T

Nagurney, A., Masoumi, A. H., & Yu, M. (2012). *Supply chain network operations management of a blood banking system with cost and risk minimization*. 205–231. https://doi.org/10.1007/s10287-011-0133-z

Nahmias, S., Pierskalla, W. P., Siam, S., Mathematics, A., May, N., & Nahmiast, S. (1976). A TWO-PRODUCT PERISHABLE/NONPERISHABLE INVENTORY PROBLEM. *Journal on Applied Mathematics*, *30*(3), 483–500.

Najafi, M., & Ahmadi, A. (2017). Blood inventory management in hospitals: Considering supply and demand uncertainty and blood transshipment possibility. *Operations Research for Health Care*, *15*, 43–56. https://doi.org/10.1016/j.orhc.2017.08.006

Osorio, A. F., Brailsford, S. C., Smith, H. K., Forero-matiz, S. P., & Camacho-rodríguez, B. A. (2017). Simulation-optimization model for production planning in the blood supply chain. *Health Care Management Science*, *20*, 1–17. https://doi.org/10.1007/s10729-016-9370-6

Osorio, A. F., Brailsford, S. C., Smith, H. K., Osorio, A. F., Brailsford, S. C., & A, H. K. S. (2015). A structured review of quantitative models in the blood supply chain : a taxonomic framework for. *International Journal of Production Research*, *53*(24), 7193–7214. https://doi.org/10.1080/00207543.2015.1005766

Özener, O. Ö., Ekici, A., & Çoban, E. (2019). *Improving blood products supply through donation tailoring*. *102*, 10–21. https://doi.org/10.1016/j.cor.2018.09.003

P . D . Cumming , K . E . Kendall , C . C . Pegels, J. . P. . S. and J. . F. . (2016). *A Collections Planning Model for Regional Blood Suppliers : Description and Validation Author (s): P . D . Cumming , K . E . Kendall , C . C . Pegels , J . P . Seagle and J . F . Shubsda Published by : INFORMS Stable URL : http://www.jstor.org/stable/26*. *22*(9), 962–971.

Pierskalla, William, & Roach, C. D. (1972). Optimal Issuing Policies for Perishable Inventory. *INFORMS*, *18*(11), 603–614. https://doi.org/10.1287/mnsc.18.11.603

Pratt, M. L., & Grindon, A. J. (1982). Computer simulation analysis of blood donor queueing problems. *Transfusion*, 234–237. https://doi.org/10.1046/j.1537-2995.1982.22382224948.x

Samani, M. R. G., Torabi, S. A., & Hosseini-Motlagh, S.-M. (2018). Integrated blood supply chain planning for disaster relief. *International Journal of Disaster Risk Reduction*, *27*(October 2017), 168–188. https://doi.org/10.1016/j.ijdrr.2017.10.005

Zahiri, B., & Pishvaee, M. S. (2017). Blood supply chain network design considering blood group compatibility under uncertainty. *International Journal of Production Research*, *7543*, 1–21. https://doi.org/10.1080/00207543.2016.1262563