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Proactive Transshipment in the Blood Supply Chain: a Stochastic Programming Approach

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Abstract

The main objective when managing inventories in blood supply chains is to establish an efficient balance between the wastage and shortage of blood units. The uncertain demand and the perishable nature of blood units can result in over- or under-stocking and increase wastage and shortage costs. In this study, we analyze how a proactive transshipment policy can avoid future shortages in addition to mitigate wastage. We consider a network of hospitals with uncertain demand in which each hospital makes decisions on the quantity to order from a central blood bank and to transship to other hospitals in each review period. We formulate the problem as a two-stage stochastic programming model. To generate scenarios, the Quasi-Monte Carlo sampling approach is employed and the optimal number of scenarios is determined by conducting stability tests. We performed numerical experiments to evaluate the performance of the proposed model and investigate its potential benefits of the outlined proactive transshipment. The developed model is used to compare the optimized policy with the current practice in some hospitals in Australia and with a no-transshipment policy. The numerical results indicate significant potential cost savings in comparison with the current policy in use and the no-transshipment policy.

Keywords: Blood supply chain; Inventory management; Lateral transshipment; Healthcare operations; Stochastic optimization.

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1. Introduction

Due to the specific characteristics of blood units such as perishability and limited donor population, managing their supply chain to make sure they are efficiently used is a highly challenging task. Blood is sourced from a semi-unpredictable supply as it is completely reliant on donations and, as yet, cannot be produced artificially. The American Blood Organization stated that 60% of the United States' population is eligible to donate blood but only about 5% actually does (America's Blood Centers, 2011). The situation is similar in Australia. According to the Australian Red Cross Blood Service, only 3.3% of Australians donate blood while 1 in 3 Australians will require blood transfusion in their lifetime. The percentage of blood donor in the population is even smaller in developing countries (Zhou et al. [90]). Nagurney and Dutta [59] noted that the average donation rate is significantly lower in developing countries than in developed countries.

In addition to the uncertain nature of supply and perishable characteristic of blood, the demand for blood products is uncertain and varies from day to day, typically presenting higher demand during weekdays. Furthermore, the demand for blood occurs at hospitals, which increases the complexity of the problem as usually there are many hospitals in the network. These facts indicate that balancing supply and demand of blood in an efficient manner requires careful planning that considers several perspectives and uncertain factors.

Keeping the balance between shortage and outdate of blood is the major challenge related to the management of the blood inventory at hospitals [41]. Due to the perishable nature of blood, having an excessive number of blood units in inventory would inevitably increase wastage [20]. Attributable to the nature of the supply of blood, wastage is not only an economic problem but also has a normative social effect, as wasting a unit of blood is a waste of the donors' time, effort, and contribution as well. Stanger et al. [77] observed that the wastage at hospitals has been significantly higher than the wastage at blood centers, which is more undesirable as an outdated item at one hospital could be used at another hospital to help save a person's life. On the other hand, an insufficient number of blood products in inventory might put human lives at a considerable risk. Therefore, blood inventory management has to take into account the trade-off between shortage and wastage.

When operating within a network of facilities (such as hospitals), one achievable opportunity to improve the performance is transshipment. Lateral transshipment consists of any stock movements between locations in the same echelon of an inventory system. This approach conventionally balances stock by reallocating the network's inventory. In other words, transshipment could be used as an effective way to adjust the existing discrepancy between the current/future demand and the inventory of blood units among hospitals. For instance, Stanger et al. [76] conducted a survey on the effect of transshipment in the United Kingdom's blood supply chain and showed that transshipment of blood between hospitals enhances flexibility in blood supply management and diminishes the number of outdated units. Moreover, transshipment supports hospitals in dealing with shortages more efficiently by using nearby hospitals' stocks. Furthermore, Abbasi et al. [3] indicated that blood transshipment in a large network of hospitals can improve the performance measures of blood supply chains and possibly help to reduce the shelf life of red blood cells to ensure that patients receive fresher units. Although transshipment has been considered in the literature [32, 83, 25], few studies have considered the effect of relying on lateral transshipment when managing inventories of perishable items, and of blood in particular. In this paper, we show how transshipment can be proactively considered in an inventory control system as a powerful mechanism to rebalance the blood inventory in a network of hospitals and ultimately to reduce costs associated with shortage, outdate, holding, ordering, and transshipment.

In the context under study, we consider that the hospitals optimally decide the amount to be ordered and transshipped every day, with the support of the proposed model. The proactive transshipment decisions are made at the same time instant in which hospitals place their orders to replenish their inventories. We assume the perspective of a centralized planner that manages several hospitals simultaneously and consider a system comprising a network of hospitals facing uncertain demand with general probability distribution. Therefore, at the beginning of each period and before demand is known (i.e., observed), the planner can decide to replenish the inventory at the hospitals either by placing orders to the blood bank or via transshipment from the other hospitals in the network.

To model the aforementioned context, we develop a mathematical model using two-stage stochastic programming (2SSP) in a rolling horizon framework to devise optimal ordering and transshipment policies for a blood inventory system. Stochastic programming is a framework that can be used to model optimization problems with uncertain input parameters, being better suited to characterize real-world problems and their inherent uncertainties. Dantzig [23] introduced 2SSP in the 50's for the first time, to handle uncertainty in mathematical programming. Since then, it has been studied extensively both in theory and computational aspects. Some examples of 2SSP applications in inventory management are discussed in the literature review section presented next.

In the standard form of a 2SSP model, decision variables are divided into two groups, namely first- and second-stage decisions. First-stage decisions must be made before the actual realization of the random (uncertain) parameters. Second-stage decisions are made when the uncertain parameters have been unveiled. The goal in this framework is to find values for the first-stage decisions that are feasible for all (or almost all, in the case where probabilistic constraints are used) scenarios and to optimize the objective function with respect to current and expected future costs.

In the 2SSP framework, uncertainty is represented by a finite set of scenarios that approximate the original stochastic phenomenon. Since most of the methods for generating scenarios involve randomness, the result must be stable with respect to the scenario sample used, meaning that if one generates several samples of scenario sets and solves the optimization problem with these sets, similar optimal values for the objective function and decision variables should be observed. We opted for a Quasi-Monte Carlo method to generate scenarios and reach stability without having to consider a prohibitive number of discrete scenarios. We performed a stability analysis to confirm the suitability of the scenario set generated. These scenarios were generated considering realistic data for the daily demand of blood, based on the average and standard deviation for one type of blood to examine the dynamics of our model.

Multistage stochastic programming is a generalization of the 2SSP that would be more naturally suitable to represent the dynamics of the problem at hand. However, to avoid problems related to having multiple decision stages and, ultimately, to make the problem computationally tractable (i.e., solvable in a reasonable time), very often multistage stochastic programming models are reformulated and approximated by 2SSP models. We achieve this by combining two central ideas. The first is that we rely on a simplified approximation of the future (i.e., second-stage) decisions. This plays a key role in the second idea, which is the use of a rolling horizon method. In this method, every decision stage (i.e., days in the planning horizon) is solved as a 2SSP model where its inputs are decisions from the previous stage (initial inventory and its age profile), and future decisions are represented by this simplified future approximation. In Section 3, we provide the details of the simplifications made and how we incorporate them in this rolling-horizon framework.

Our main contributions to the existing literature can be summarized as follows. First, we develop a new 2SSP model to obtain the optimal order and transshipment quantities using a flexible methodology to cope with the uncertain nature of demand, i.e., without any assumptions on the demand distribution. For example, our model can also consider non-homogeneous demand distribution, which is a novel feature in the related literature. This is made possible by the combination of a 2SSP framework with an rolling-horizon strategy that simulates the daily use of the proposed decision support tool, which together, allows us to benefit from the flexibility of the 2SSP approach and the computational tractability from the rolling horizon strategy. The employment of the aforementioned strategy in the context of this research is novel, to the best of our knowledge.

Second, we assess the benefits of proactive transshipment on the performance measures of blood supply chains. In addition, we are the first to provide numerical evidence of the benefits of proactive transshipment to improve the performance of a network of hospitals that is not limited to two locations only. Furthermore, we perform several numerical experiments to assess the impact of ordering frequency, enforcing the First-In-First-Out (FIFO) issuing policy in this setting, and using alternative ordering policies, which provided relevant insights concerning the importance of proactive transshipment in the management of the hospital network and the benefits that employing the proposed decision support tool could bring to the problem of managing blood inventories.

The remainder of this paper is structured as follows. Section 2 provides a review of the related literature on blood inventory management and lateral transshipment. In Section 3, we present a detailed description of the proposed model. In Section 4, we present the mathematical formulation of the 2SSP model. Section 5 contains numerical study and Section 6 offers conclusions.

2. Literature review

The literature review related to this study is presented in two categories: blood inventory management and lateral transshipment.

2.1. Blood inventory management

As blood is a precious perishable commodity, many researchers have focused on the management of blood which was initiated by Millard [57] in 1959 and van Zyl [81] in 1963. Nahmias [61] and Prastacos [71] presented a review of early research in blood inventory management and Beliën and Forcé [11] published a review paper of blood inventories and supply chain management. More recently, Osorio et al. [64] provided a comprehensive literature review of quantitative models for blood supply chain management. A variety of methodologies, such as queueing theory and Markov chains, statistical analysis, simulation, and optimization, have been used alone or in combination to analyze the supply chain of blood products. In addition, there are several recent studies considering inventory models for a general class of perishable items with deterioration rate [9, 47, 52].

Queueing theory and Markov chains have been used to model and analyze blood inventories in early research. Pegels and Jelmert [68] and Abbasi and Hosseinifard [1] investigated the effects of modified FIFO and LIFO issuing policies on the average on-hand inventory and the average age of issued blood using Markov chains. Brodheim et al. [15] proposed a fixed-order-quantity model for perishable products and formulated the problem as a Markov chain to compute the average

age of blood in inventory and the probability of blood shortage. Cumming et al. [21] proposed a Markovian population model that aimed to keep the balance between supply and demand of blood. Kopach et al. [48] applied a queuing framework to model a red blood cell inventory system with two demand levels: urgent and non-urgent demand. Hosseinifard and Abbasi [40] used a queuing theory framework with a Poisson demand distribution to evaluate the effects of inventory pooling for the blood supply chain.

Simulation has been frequently used as a method to optimize the blood supply chain due to the complexity of blood inventory problems, despite the fact that the optimality of the solution obtained could not be guaranteed. Rytilä and Spens [73] used discrete event simulation to improve blood supply chain efficiency. Duan and Liao [28] developed a new replenishment policy based on old inventory ratio for highly perishable items. They applied a simulation-optimization approach to optimize replenishment policies. Katsaliaki and Brailsford [44] used discrete event simulation to minimize costs, shortage and wastage in the blood supply chain by determining optimal ordering policies. Mustafee et al. [58] improved their model by proposing a distributed simulation approach to reduce simulation run time. Kamp et al. [43] studied the availability of blood products in pandemic situations in Germany using simulation methods. Abbasi et al. [3] and Blake et al. [13] used simulation modeling to evaluate the impact of reducing the shelf life of red blood cells in Australian and Canadian blood supply chains, respectively.

Statistical analysis methods, such as linear regression, survival analysis, and logistic regression, have been used to support decision making in the blood supply chain. Melnyk et al. [56] used survival analysis to classify blood donors and increase donor satisfaction by improving the layout of collection stations. Bosnes et al. [14] used a logistic regression model to predict blood donor arrivals. Godin et al. [33] applied a logistic regression model to obtain the main factors of repeated blood donation. Heddle et al. [37] applied logistic regression techniques to determine factors that affected red blood cells outdating. Perera et al. [69] analyzed blood stock, using the t-test and determined factors affecting stock level and wastage.

Due to the complexity of blood inventory management problems, optimization methods such as stochastic dynamic programming, integer programming and linear programming have been used less frequently. Haijema et al. [36] proposed a stochastic dynamic programming and simulation approach to design optimal order-up-to-level inventory policies for platelet production. Kendall and Lee [46] proposed a goal programming model to allocate blood units to hospitals and minimize wastage. They evaluated solutions based on stock availability, the age of blood, the outdate rate, and the availability of fresh blood. Pitocco and Sexton [70] used a data envelopment analysis model to evaluate the efficiency of seventy blood centers. Hemmelmayr et al. [38] proposed an integer programming model to determine optimal delivery days by minimizing wastage and delivery costs. They considered the known daily demand for each hospital and investigated whether switching from the current vendee-managed inventory setup to a vender-managed inventory system could be beneficial. Şahin et al. [75] developed an integer programming model to address the location-allocation decision problems in the regionalization of blood services. They considered the total population of cities as demand for blood and validated their models by using real data for Turkish Red Crescent blood services. Gunpinar and Centeno [35] applied an integer programming model to minimize the total cost including shortage cost, outdate cost, holding cost, and purchasing cost for a single level inventory system with uncertain demand.

Two-stage stochastic programming has being considered a suitable framework for inventory management problems other than blood supply chain management. Fattahi et al. [29] studied a multi-period replenishment problem under centralized and decentralized supply chain systems using two-stage stochastic programming. They assumed a safety-stock-based policy with uncertain demand for a supply chain consisting of one retailer and one manufacturer. Cunha et al. [22] developed a two-stage stochastic programming model to determine the optimal strategies of a replenishment control system considering uncertain demand and periodic review. Dillon et al. [26] proposed a two-stage stochastic programming model to manage red blood cells inventory. They considered periodic review policies with a fixed ordering point and minimized the total cost as well as shortage and wastage considering uncertain demand.

2.2. Lateral transshipment

Transshipment has been considered in the literature as a tool to balance inventory among locations in the same echelon to reduce shortage. Lateral transshipment policies can be classified into proactive and reactive transshipment [67]. Most past studies considered reactive transshipment, in which transshipment occurs when an inventory shortage is realized [8, 10, 16, 39, 54, 66, 79, 80, 84, 85, 86, 88, 89]. In these studies, the transshipment time was considered negligible to make the problem tractable.

Proactive transshipment takes place at fixed points in time before observing the demand. Most of the work on proactive transshipment considered a periodic review setting. Allen [6] presented a multi-echelon redistribution model for proactive transshipment for the first time. The author considered a single period with multiple inventory locations and obtained an optimal redistribution of stock. Agrawal et al. [5] proposed a dynamic programming formulation in which the transshipment time was determined dynamically. They developed an algorithm to obtain the optimal time of the transshipment and stock levels at retailers. Lee et al. [51] proposed a new proactive transshipment policy, called the Service Level Adjustment (SLA) policy, in which they considered the service level to determine the quantity of transshipment. Burton and Banerjee [16] used simulation to analyze and compare the cost effect of a proactive transshipment and a reactive transshipment in a two-echelon supply chain network.

Tagaras and Vlachos [78] considered a two-location system with non-negligible transshipment times and used simulation to analyze the operational characteristics of a pooling policy. They found proactive transshipment to be beneficial, especially when the demand is highly variable. Jönsson and Silver [42] studied a two-echelon distribution system with a central warehouse. They minimized the total backorders by applying limitations on the timing of transshipment. Lee and Whang [50] considered a two-period model consisting of a manufacturer and several retailers and obtained optimal stock level as well as optimal proactive transshipment policy. Rong et al. [72] considered a proactive transshipment game in a decentralized system with two demand subperiods.

Li et al. [53] considered a decentralized system with two locations and determined the optimal quantity of orders considering proactive transshipment. Glazebrook et al. [32] proposed a hybrid lateral transshipment policy such that the transshipment decisions are made when a location faces a shortage that resembles a reactive transshipment policy, however, the quantity of transshipment can exceed the current shortage to avoid future imbalance in the inventory system. Glazebrook et al. [32] employed dynamic programming to solve their model, using a heuristic to approximate the future cost of a decision. In approximating this future cost, they assumed no transshipment is performed in the future.

Recently, Abouee-Mehrizi et al. [4] proposed a proactive transshipment model to minimize the mismatch between supply and demand. They considered a finite-horizon multi-period inventory system for two locations and determined optimal joint replenishment and transshipment policies. Meissner and Senicheva [55] considered a multi-location, multi-period inventory system with proactive transshipment and used approximate dynamic programming to determine an optimal order policy and transshipment policy.

The aforementioned studies focused on applying lateral transshipment to improve the performance of a non-perishable inventory. However, a gap found in the literature is the limited number of studies that consider effects of transshipment on perishable inventory, especially on blood inventory. Cheong [19] studied the impact of proactive transshipment for perishable products. The author presented an algorithm to determine the optimal quantities of orders and transshipment for a single perishable product with a two-period lifetime ('old' or 'fresh') in a single period planning horizon, which does not allow capturing the dynamics of inventory system. The proposed model is not applicable to the blood supply chain management without considerable simplification, since the shelf life of products are greater than two; red blood cells units have a shelf life of 42 days and platelets have a shelf life of 5 days [3]. Nakandala et al. [62] considered a periodic review two-stage inventory system with compound Poisson demand for a fresh food supply chain and formulated a decision rule system to minimize the total cost considering reactive lateral transshipment. They determined the quantity of transshipment by the trade-off among expiration, purchase, backordering, transshipment and holding costs and showed that adopting lateral transshipment can be beneficial. Assuming a Poisson probability distribution for demand limits the applicability of their model to the blood supply chain as previous studies showed that the demand of blood units does not follow a Poisson distribution [34, 3]. Furthermore, they implemented reactive transshipment in their model, whereas our model considers proactive transshipment. Wang et al. [82] and Wang and Ma [83] studied transshipment of blood units between blood banks (e.g., blood banks in different regions) to remedy overstock and to respond to the observed shortages due to emergency situations such as natural disasters. Therefore, they considered reactive transshipment as the decision was to select the blood units that should be transshipped from the rescue blood banks to the affected blood bank. Dehghani and Abbasi [25] developed a model for lateral transshipment of blood products. Their model was limited to Poisson demand distribution and only works for the transshipment of perishable items between two locations, whereas, our model is not limited to any demand distribution and can be applied to a network of hospitals. Zhang et al. [87] developed a model to explore the optimal ordering and transshipment policies. However, their study was limited to transshipment decisions between two locations. Further, unlike our study, they considered reactive transshipment, in which the transshipped items were used to meet realized shortages, while we consider proactive transshipment in a network of hospitals. To the best of our knowledge, this study is the first to consider lateral transshipment of perishable items (e.g. blood) in a network of inventory locations (e.g. multiple hospitals) that is not restricted to a specific demand distribution.

3. Problem setting and modeling premises

We consider a network with N hospitals and denote them with index $i \in \mathcal{N} := \{1, 2, \ldots, N\}$. The planning horizon is divided into T periods of uniform length (generally representing days) and are denoted by $t \in \mathcal{T} := \{1, 2, \ldots, T\}$. The hospitals considered as references for this study employ a periodic inventory review policy, denoted by (R, S), meaning that at each review point (e.g., every R-th morning), the hospital reviews the inventory status and places an order to raise the inventory level to the target S. The (R, S) policy with $R = 1$ is currently used (for some small hospitals, $R = 2$ is used as well) in some hospitals in Australia due to its reasonable efficiency and simplicity [3]. However, in this study, the proposed model allows for the use of a dynamic periodic inventory policy and thus, does not enforce the (R, S) policy.

Furthermore, we assume that all hospitals place their orders with the central blood bank (CBB) for new batches of blood units at the start of each period $t \in \mathcal{T} := \{1, 2, \ldots, T\}$. We denote the order quantity of hospital $i \in \mathcal{N}$ at the beginning of period t by y_i^t. Ordering from the CBB to hospital $i \in \mathcal{N}$ costs R_i per blood unit. We do not assume fixed costs in our model, however the adaptation to include such costs is straightforward from a modeling perspective, but would require the inclusion of binary variables to capture the ordering event, as it is done, for example, in Dillon et al. [26]. We assume that each batch of blood has a shelf life of M periods. Therefore, if some of the blood units at hospital i are not used within M periods, they must be discarded, incurring an expiry cost E_i. We also assume that the orders can only be used to fulfill future demand, starting from the next day (i.e., with a lead time of one period), as it takes from a few hours to one day for the blood units to arrive in the setting under study. Hence, orders placed in period t can only be used to fulfill demands from period $t + 1$ onwards.

Hospitals can also transship blood from their inventory to other hospitals in the network. We represent the transshipment amount in period t from hospital i to hospital j, with $i, j \in \{\mathcal{N} : i \neq j\}$, by $x_{ij}^t := (x_{ij1}^t, x_{ij2}^t, \ldots, x_{ijM}^t)$, where x_{ijm}^t, $m \in \{1, 2, \ldots, M\}$, denotes the amount of transshipped blood units that have remaining shelf life m at the beginning of period t. Transshipment from hospital i to hospital j costs C_{ij} per blood unit. At the end of period t, each hospital $i \in \mathcal{N}$ observes a random demand D_i^t. If the hospital does not have enough inventory, it can place an emergency order to fulfill the excess demand. We assume that emergency order costs G_i per unit to hospital i. If hospital $i \in \mathcal{N}$ has an excess of inventory after fulfilling all its demand, a holding cost of H_i per unit is incurred for unexpired blood units at the end of period t.

We denote the inventory at hospital $i \in \mathcal{N}$ at the beginning of the first period by $B_i^1 := (B_{i1}^1, B_{i2}^1, \ldots, B_{iM}^1)$. B_{im}^1, represents the quantity of blood that has a remaining shelf life of $m \in \{1, 2, \ldots, M\}$ periods at the beginning of period 1. We assume that the inventory at the beginning of the current period (i.e., $t = 1$) is known. We represent the quantity of shortage in period $t \in \mathcal{T}$ at hospital $i \in \mathcal{N}$ by f_i^t and denote the total inventory at hospital $i \in \mathcal{N}$ at the end of period $t \in \mathcal{T}$ by v_i^t. We also denote the amount of outdated blood in period $t \in \mathcal{T}$ at hospital $i \in \mathcal{N}$ by o_i^t.

Figure 1 illustrates the dynamics of the system in the time horizon (the notation used in Figure 1 has been defined in Section 4.1). At the start of each period $t \in \mathcal{T} := \{1, 2, \ldots, T\}$, the quantity to order is set to bring the inventory position to S (represented by the dotted line)). Next, the demand ($D_i^t(\xi)$) for each period is observed (represented by the dashed line connecting two successive periods). At the beginning of the planning period, each hospital decides the transshipment quantity (x_{ijk}). We assume that the transshipped blood units arrive instantly because the transshipment time is negligible for the time scale considered (days), as it takes much less than a day for the transshipment to occur. On the other hand, the blood ordered from the CBB (y_i^1 and $y_i^t(\xi)$) arrives at the end of each period, hence being only available (in stock) for the next period. Outdated units $o_i^t(\xi)$ are discarded (i.e., discounted from the inventory level) at the end of period $t \in \mathcal{T} := \{1, 2, \ldots, T\}$.

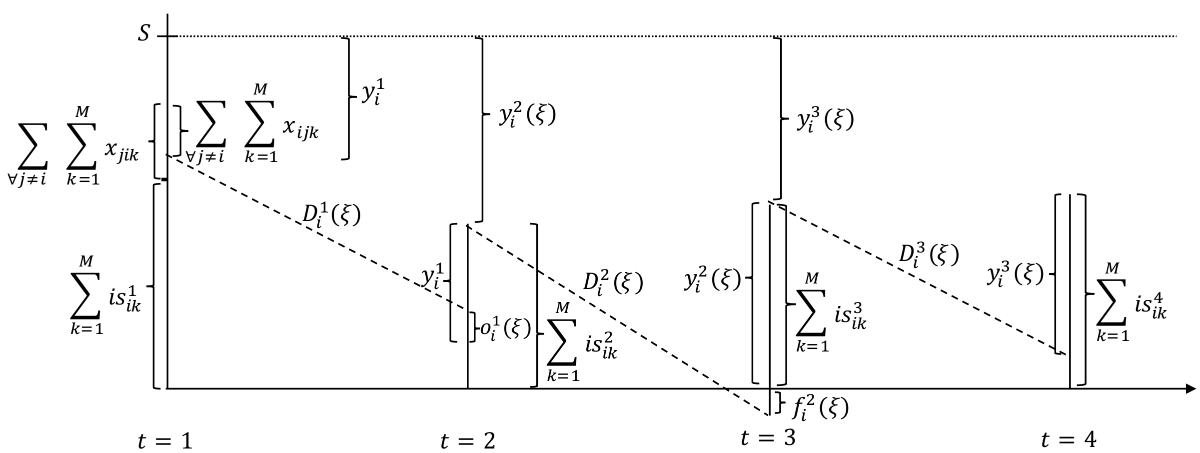


Figure 1: The dynamics of the inventory system at hospital i. The y-axis shows the inventory status at hospital i. y_i^1, S, x_{ijk} and x_{jik} are the first-stage decisions. It shows the transshipped items are available at the beginning of each period and the ordered items from the blood bank arrive at the end of the period and are practically available at the beginning of the next period. Note that only y_i^1, x_{ijk} and x_{jik} are implemented since the model is optimized at the beginning of each period t in the rolling horizon approach to decide the order and transshipment amounts at that period.

For the sake of computational tractability, we adopted a few simplifications when modeling the problem. First, we assumed that no blood substitution is considered (i.e., all patients received blood of their own ABO type and Rh factor) and that crossmatching rejection rates are negligible. We also consider that inventory capacity at each hospital is not a limitation. The combination of these aspects allows us to manage blood types individually, without having to consider multiple blood types simultaneously.

We consider the order and transshipment quantities for the current period (which is represented by $t = 1$) and target level (S) for future periods as the first-stage decisions, while the quantity of order for the remaining period ($t = \{2, \ldots, T\}$) under each of the scenarios is the second-stage decisions. To approximate the future behavior of the system, we adopted two important simplifying premises. First, we consider that no transshipment decisions are available in the second stage part of the 2SSP model. We stress that this is to preserve the non-anticipative nature of the transshipment decisions (as they must be made before observing the realization of the demand). Naturally, decisions concerning transshipment in future periods are considered in the framework, when the model is re-optimized in the next period in the rolling-horizon setting (further details are presented in Section 5), thus guaranteeing that the non-anticipativity of these decisions are preserved. We highlight that a similar approximation is also considered in previous studies that consider transshipment (e.g. [32]). Second, we assume that in future periods, the system behaves as an (R, S) system, also to enforce non-anticipativity for the decisions made in terms of ordered quantities after the future demand scenarios are observed. These two simplifications allow us to formulate the problem as a 2SSP model with a reasonable approximation of the expected future cost of the system. Otherwise, the problem would have to be posed as a multi-stage model (instead of a two-stage model), rendering it an even more computationally challenging problem, and ultimately compromising its practical appeal.

Nevertheless, to guarantee that the dynamic nature of the decision process is represented, we embed the 2SSP model into a rolling-horizon approach, meaning that while the decisions are made over a long planning horizon, only the decisions for the first period (i.e., the first-stage decisions, with the exception of S) are actually implemented. The process is successively repeated for each period in the planning horizon, at which each of the initial conditions (such as initial inventory level and age profile) are given by the decisions obtained in the previous period (Algorithm 1 in Section 5 further explains how the rolling horizon approach is implemented using the proposed 2SSP model).

4. Model formulation

We formulate the aforementioned problem as an optimization model to determine the optimal quantities of order and transshipment that minimizes the total expected cost of the system. We consider the order and transshipment quantities for the current period (which is represented by $t = 1$) and target level (S) for future periods as first-stage decisions, while the quantity of order for the remaining period ($t = \{2, \ldots, T\}$) in each of the scenarios are second-stage decisions.

The objective function is composed of five cost components: ordering, transshipment, holding, outdating, and shortage costs. The first-stage costs are associated with ordered and transshipped quantities for the first period, while the second-stage costs consist of expected holding, outdating, and shortage costs for all periods and the expected ordering cost for the second period onwards.

4.1. Mathematical notations

The mathematical notations used in the model formulation are given as follows.

4.1.1. Indices and sets

$t \in \mathcal{T} := \{1, 2, \ldots, T\}$ - time horizon;
$i, j \in \mathcal{N} := \{1, 2, \ldots, N\}$ - hospitals;
$\xi \in \Xi := \{1, 2, \ldots, \Upsilon\}$ - scenarios in scenario set Ξ;
$m, k \in \mathcal{M} := \{1, 2, \ldots, M\}$ - remaining shelf life.

4.1.2. Decision variables

$y_i^1, y_i^t(\xi)$ - order quantity of hospital $i \in \mathcal{N}$ at period $t = 1$ and $t \in \{2, \ldots, T\}$ in scenario $\xi \in \Xi$, respectively;

x_{ij}^t - quantity of transshipped units from hospital $i \in \mathcal{N}$ to hospital $j \in \mathcal{N}$ in period $t \in \mathcal{T}$;

$x_{ij}^t := (x_{ij1}^t, x_{ij2}^t, \ldots, x_{ijM}^t)$, where x_{ijm}^t represents the quantity of transshipped blood that has remaining shelf life $m \in \mathcal{M}$ at the beginning of period $t \in \mathcal{T}$;

S_i - target inventory level at hospital $i \in \mathcal{N}$;

$is_{im}^t(\xi)$ - inventory level of blood with shelf life $m \in \mathcal{M}$ at the *beginning* of period $t \in \mathcal{T}$ in scenario $\xi \in \Xi$, at hospital $i \in \mathcal{N}$;

$ie_{im}^t(\xi)$ - inventory level of blood with shelf life $m \in \mathcal{M}$ at the *end* of period $t \in \mathcal{T}$ in scenario $\xi \in \Xi$, at hospital $i \in \mathcal{N}$;

$a_{im}^t(\xi)$- quantity of blood units with shelf life $m \in \mathcal{M}$ used to fulfill demand in period $t \in \mathcal{T}$ in scenario $\xi \in \Xi$, at hospital $i \in \mathcal{N}$;

$f_i^t(\xi)$ - quantity of shortage in period $t \in \mathcal{T}$ in scenario $\xi \in \Xi$, at hospital $i \in \mathcal{N}$;

$v_i^t(\xi)$ - total inventory at hospital $i \in \mathcal{N}$ in scenario $\xi \in \Xi$, at the end of period $t \in \mathcal{T}$;

$o_i^t(\xi)$ - quantity of outdated units in period $t \in \mathcal{T}$ in scenario $\xi \in \Xi$, at hospital $i \in \mathcal{N}$.

4.1.3. Parameters

B_{im}^1 - initial inventory of units with shelf life $m \in \mathcal{M}$ at hospital $i \in \mathcal{N}$;

M- maximum shelf life;

G_i - emergency order cost at hospital $i \in \mathcal{N}$;

H_i- holding cost per unit per period at hospital $i \in \mathcal{N}$;

E_i - expiry cost per unit at hospital $i \in \mathcal{N}$;

R_i - ordering cost per unit to hospital $i \in \mathcal{N}$;

C_{ij} - transshipment cost from hospital $i \in \mathcal{N}$ to hospital $j \in \mathcal{N}$ $(i \neq j)$;

$P(\xi)$ - probability associated with scenario $\xi \in \Xi$;

$D(\xi)_i^t$ - total demand at hospital $i \in \mathcal{N}$ in period $t \in \mathcal{T}$ in scenario $\xi \in \Xi$.

4.2. Mathematical model

In this section, we present the mixed-integer linear programming (MILP) model developed to represent the problem discussed in this study. The MILP model represents the deterministic equivalent model of the 2SSP model [12]. For the sake of formulation clarity, we assume that all indices are defined within their original domain set (i.e., $\forall i$ is equivalent to $\forall i \in \mathcal{N}$, and so forth), unless otherwise specified.

$$\begin{aligned}\min.\ z = &\sum_i R_i y_i^1 + \sum_i \sum_{j \in \mathcal{N} \setminus \{i\}} \sum_m C_{ij} x_{ijm}^1 + \\ &\sum_\xi P(\xi) \left[\sum_i \left[H_i v_i^1(\xi) + E_i o_i^1(\xi) + G_i f_i^1(\xi) + \right.\right. \\ &\left.\left. \sum_{t \in \mathcal{T} \setminus \{1\}} \left(R_i y_i^t(\xi) + H_i v_i^t(\xi) + E_i o_i^t(\xi) + G_i f_i^t(\xi) \right) \right] \right]\end{aligned} \tag{4.1}$$

s.t.:

$$is_{im}^1 + \sum_{j \in \mathcal{N} \setminus \{i\}} x_{jim}^1 = \sum_{j \in \mathcal{N} \setminus \{i\}} x_{ijm}^1 + a_{im}^1(\xi) + ie_{im}^1(\xi),\ \forall i, m, \xi \tag{4.2}$$

$$is_{im}^t(\xi) = a_{im}^t(\xi) + ie_{im}^t(\xi),\ \forall i, m, t \in \mathcal{T} \setminus \{1\}, \xi \tag{4.3}$$

$$is_{im}^1 = B_{im}^1,\ \forall i, m \tag{4.4}$$

$$\sum_m a_{im}^t(\xi) + f_i^t(\xi) = D_i^t(\xi),\ \forall i, t, \xi \tag{4.5}$$

$$v_i^t(\xi) = \sum_{m \in \mathcal{M} \setminus \{1\}} ie_{im}^t(\xi),\ \forall i, t, \xi \tag{4.6}$$

$$o_i^t(\xi) = ie_{i1}^t(\xi),\ \forall i, t, \xi \tag{4.7}$$

$$ie_{i(m+1)}^t(\xi) = is_{im}^{t+1}(\xi),\ \forall i, m \in \mathcal{M} \setminus \{M\}, t \in \mathcal{T} \setminus \{T\}, \xi \tag{4.8}$$

$$is_{iM}^2(\xi) = y_i^1,\ \forall i, \xi \tag{4.9}$$

$$is_{iM}^{t+1}(\xi) = y_i^t(\xi),\ \forall i, t \in \mathcal{T} \setminus \{1\}, \xi \tag{4.10}$$

$$S_i - \sum_m is_{im}^t(\xi) = y_i^t(\xi), \ \forall i, t \in \mathcal{T} \setminus \{1\}, \xi \tag{4.11}$$

$$S_i, y_i^1 \in \mathbb{Z}_+, \ \forall i \tag{4.12}$$

$$x_{ij}^1 \in \mathbb{Z}_+, \ \forall i, j \tag{4.13}$$

$$y_i^t(\xi) \in \mathbb{Z}_+, \ \forall i, t \in \mathcal{T} \setminus \{1\}, \xi \tag{4.14}$$

$$is_{im}^1 \in \mathbb{Z}_+ \ \forall i, m \tag{4.15}$$

$$is_{im}^t(\xi) \in \mathbb{Z}_+ \ \forall i, m, t \in \mathcal{T} \setminus \{1\}, \xi \tag{4.16}$$

$$f_i^t(\xi), o_i^t(\xi), v_i^t(\xi) \in \mathbb{Z}_+ \ \forall i, t, \xi \tag{4.17}$$

$$a_{im}^t(\xi), ie_{im}^t(\xi) \in \mathbb{Z}_+ \ \forall i, m, t, \xi. \tag{4.18}$$

Objective function (4.1) consists of costs referring to ordering, transshipment between hospitals and expected costs associated with holding, outdate, and shortage. Constraint (4.2) sets the balance of blood units in the first period, while constraint (4.3) establishes the same balance for the remaining periods, in which no transshipment between hospitals is considered. Constraint (4.4) states that at the beginning of the planning horizon, the initial inventory is known beforehand (notice that (4.4) can be trivially removed via substitution in (4.2)). Constraint (4.5) models the demand fulfillment, in which the demand is fulfilled with blood of different ages (represented by $\sum_m a_{im}^t(\xi)$) and part of it is eventually not fulfilled (represented by $f_i^t(\xi)$). Constraint (4.6) accumulates the total inventory in the end of period t for cost calculation, discounting the fraction to be discarded due to outdate, as represented in (4.7). Constraint (4.8) models the aging process of the inventory. At any given period t, the total of blood units with shelf life m ($ie_{im}^t(\xi)$) is available as initial inventory with shelf life $m-1$ in $t+1$ (becoming is_{im-1}^{t+1}). Constraint (4.9) specifies that the order placed in period 1 arrives at period 2 (assuming a lead time of one period). Note that $is_{iM}^2(\xi)$ could be simplified by removing its dependency to scenarios. Similarly, constraint (4.10) models orders that arrive at period 3 onward (i.e., $t > 2$), which is assumed to follow a (R, S) policy with $R = 1$, as modeled in (4.11). Last, (4.12) to (4.18) define the domain of the decision variables.

The allocation of accessible red blood cells (RBCs) for transfusion to patients is of vital importance. Some recent medical research studies have suggested that health outcomes could be affected by the age of transfused blood, especially for trauma patients [74], as stored red blood cells undergo biochemical changes that affect their function. In response to these clinical findings, there is interest in the clinical community in designing optimal issuing policies (e.g., [7, 1]). Considering that the effect of red blood cell's age cannot be overlooked, the First-in-First-out (FIFO) policy is often employed as an issuing policy.

A non-trivial characteristic of the optimal solutions obtained from the proposed model is that they do not necessarily follow the FIFO policy (i.e., issuing blood units in decreasing order of age) to fulfill demand. As it will be shown in the computational experiments presented later, the consideration of transshipment opportunities and costs trade-offs render this simple issuing rule is not optimal in terms of minimizing overall cost. We highlight that this is a well-known fact in the perishable inventory control literature (see, for example, [31, 60, 63, 18]). Nevertheless, the current practice of hospitals is to follow the FIFO policy. To model this behavior, one can adapt the model to follow the FIFO policy by including the following constraints:

$$a^1_{i1}(\xi) = \min\{D^1_i(\xi),\ is^1_{i1}(\xi) + \sum_{j\in\mathcal{N}\setminus\{i\}} x^1_{ji1} - \sum_{j\in\mathcal{N}\setminus\{i\}} x^1_{ij1}\},\ \forall i, \xi \tag{4.19}$$

$$a^1_{im}(\xi) = \min\{D^1_i(\xi) - \sum_{j=1}^{m-1} a^1_{ij}(\xi),\ is^1_{im}(\xi) + \sum_{j\in\mathcal{N}\setminus\{i\}} x^1_{jim} - \sum_{j\in\mathcal{N}\setminus\{i\}} x^1_{ijm}\},\ \forall i, \xi, m \in \mathcal{M}\setminus\{1\} \tag{4.20}$$

$$a^t_{i1}(\xi) = \min\{D^t_i(\xi),\ is^t_{i1}(\xi)\},\ \forall i, t \in \mathcal{T}\setminus\{1\}, \xi \tag{4.21}$$

$$a^t_{im}(\xi) = \min\{D^t_i(\xi) - \sum_{j=1}^{m-1} a^t_{ij}(\xi),\ is^t_{im}(\xi)\},\ \forall i, t \in \mathcal{T}\setminus\{1\}, \xi, m \in \mathcal{M}\setminus\{1\} \tag{4.22}$$

Constraint (4.19) enforces that the demand $D^1_i(\xi)$ is, if possible, fulfilled with the net amount (current inventory $(is^1_{i1}(\xi))$ plus incoming units $\left(\sum_{j\in\mathcal{N}\setminus\{i\}} x^1_{ji1}\right)$ minus the units transshipped from hospital i $\left(\sum_{j\in\mathcal{N}\setminus\{i\}} x^1_{ij1}\right)$) of units with shelf life $m = 1$. In case the latter is not sufficient to fully satisfy the demand, the remaining demand ($D^1_i(\xi) - a^1_{i1}$ for $m = 2$, for example) is satisfied with younger units with shelf life $m = 2, \ldots, \mathcal{M}$, considered in order of age. This is enforced by constraint (4.20). Analogously, (4.21) and (4.22) enforce the same logic for the later time periods, without transshipment decision variables.

Note that constraints (4.19) to (4.22) are not linear with respect to the decision variables. However, they can be converted into linear functions by applying the subsequent constraints (where λ is a large positive number and $b^t_{im}(\xi)$ are auxiliary binary variables).

$$a^t_{i1}(\xi) \leq D^t_i(\xi), \ \forall i, t, \xi \tag{4.23}$$

$$a^1_{i1}(\xi) \leq is^1_{i1}(\xi) + \sum_{j \in \mathcal{N} \setminus \{i\}} x^1_{ji1} - \sum_{j \in \mathcal{N} \setminus \{i\}} x^1_{ij1}, \ \forall i, \xi \tag{4.24}$$

$$a^t_{i1}(\xi) \leq is^t_{i1}(\xi), \ \forall i, t \in \mathcal{T} \setminus \{1\}, \xi \tag{4.25}$$

$$D^t_i(\xi) - a^t_{i1}(\xi) \leq \lambda b^t_{i1}(\xi), \ \forall i, t, \xi \tag{4.26}$$

$$is^1_{i1}(\xi) + \sum_{j \in \mathcal{N} \setminus \{i\}} x^1_{ji1} - \sum_{j \in \mathcal{N} \setminus \{i\}} x^1_{ij1} - a^1_{i1}(\xi) \leq \lambda(1 - b^1_{i1}(\xi)), \ \forall i, \xi \tag{4.27}$$

$$is^t_{i1}(\xi) - a^t_{i1}(\xi) \leq \lambda(1 - b^t_{i1}(\xi)), \ \forall i, t \in \mathcal{T} \setminus \{1\}, \xi \tag{4.28}$$

$$a^t_{im}(\xi) \leq D^t_i(\xi) - \sum_{j=1}^{m-1} a^t_{ij}(\xi), \ \forall i, t, \xi, m \in \mathcal{M} \setminus \{1\} \tag{4.29}$$

$$a^1_{im}(\xi) \leq is^1_{im}(\xi) + \sum_{j \in \mathcal{N} \setminus \{i\}} x^1_{jim} - \sum_{j \in \mathcal{N} \setminus \{i\}} x^1_{ijm}, \ \forall i, \xi, m \in \mathcal{M} \setminus \{1\} \tag{4.30}$$

$$a^t_{im}(\xi) \leq is^t_{im}(\xi), \ \forall i, t \in \mathcal{T} \setminus \{1\}, \xi, m \in \mathcal{M} \setminus \{1\} \tag{4.31}$$

$$D^t_i(\xi) - \sum_{j=1}^{m-1} a^t_{ij}(\xi) - a^t_{im}(\xi) \leq \lambda b^t_{im}(\xi), \ \forall i, t, \xi, m \in \mathcal{M} \setminus \{1\} \tag{4.32}$$

$$is^1_{im}(\xi) + \sum_{j \in \mathcal{N} \setminus \{i\}} x^1_{jim} - \sum_{j \in \mathcal{N} \setminus \{i\}} x^1_{ijm} - a^1_{im}(\xi) \leq \lambda(1 - b^1_{im}(\xi)), \ \forall i, \xi, m \in \mathcal{M} \setminus \{1\} \tag{4.33}$$

$$is^t_{im}(\xi) - a^t_{im}(\xi) \leq \lambda(1 - b^t_{im}(\xi)), \ \forall i, t \in \mathcal{T} \setminus \{1\}, \xi, m \in \mathcal{M} \setminus \{1\} \tag{4.34}$$

$$b^t_{im}(\xi) \in \{0, 1\}, \ \forall i, m, t, \xi \tag{4.35}$$

4.3. Scenario generation and stability tests

In this study, we generate scenario sets using a quasi-Monte Carlo (QMC) sampling approach. The QMC generates samples known as low-discrepancy sequences by employing quasi-random numbers, which are intended to increase the accuracy of the estimator by generating highly uniform points. These low-discrepancy sequences are engineered to fill the sample space uniformly up to a specific density and thus have the potential to accelerate the convergence rate associated with the Monte Carlo method. The most widely used low-discrepancy sequence is the Sobol sequence, as it has proved to be more effective and produced accurate results for various problems. For further details concerning QMC sampling, we refer the reader to Caflisch [17] and Owen [65].

When relying on a sampling method for scenario generation, the most common source of instability is an insufficient number of scenarios to fully represent the uncertain phenomena. The size of scenario sets is strongly connected to the quality of the representation of the stochastic parameters, and thus, by increasing the number of scenarios, the discrete approximation (i.e., empirical distribution obtained from the generated scenarios) converges to the true distribution. However, it is important to note that the larger this set is, the more challenging the problem becomes in terms of computational effort.

The sample size in this study was determined by considering in-sample and out-of-sample stability tests. The in-sample stability test allows for defining the optimal number of scenarios to be used in the 2SSP model such that increasing the number of scenarios beyond that will not significantly change the obtained objective function value. In-sample stability was measured considering the average value and standard deviation of the optimal objective function value for each of scenarios within a given scenario set sample.

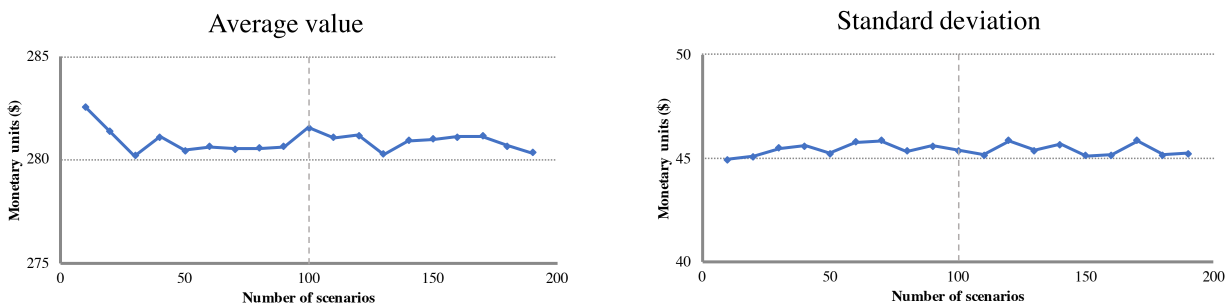
Out-of-sample stability test aims to verify whether the solution obtained is dependent on *a specific set of scenarios*. To test for out-of-sample stability, one can assess if the performance of first-stage decisions observed for a given scenario set is consistent with the performance observed for other scenario sets. The term out-of-sample refers to the fact that stability is judged on a different sample than that used to obtain the solution. In the experiments presented next, out-of-sample stability was measured by calculating the average value and standard deviation of the optimal objective function value for a given first-stage solution in a collection of 1000 scenario samples randomly drawn directly from the probability distribution (thus different from that obtained from QMC sampling and used to obtain the given first-stage solution). The steps of obtaining the results of in-sample and out-of-sample stability tests are outlined in Appendix B. For further details, the readers are referred to Kaut and Wallace [45].

We performed the stability test considering model (4.1) - (4.18). In the out-of-sample stability test as $\sum_m is_{im}^t(\xi)$ could become greater than S_i the model could become infeasible. To avoid infeasibility in the out-of-sample stability test, we substitute expression (4.11) with the following constraints:

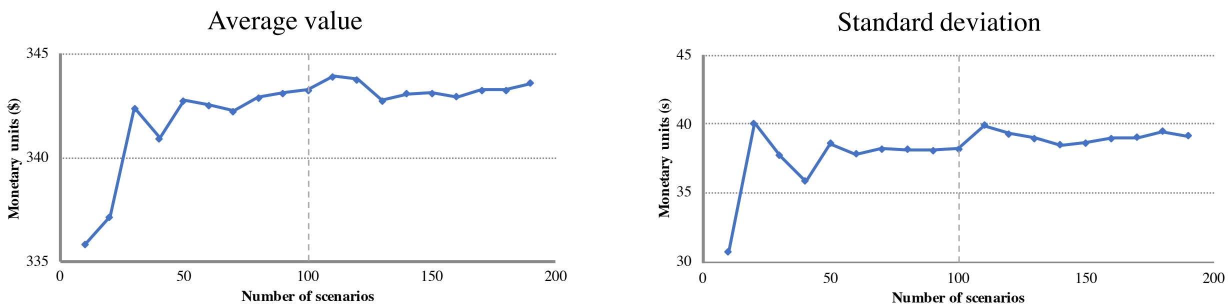
$$y_i^t(\xi) = \max\{S_i - \sum_m is_{im}^t(\xi), 0\}, \quad \forall i, t \in \mathcal{T} \setminus \{1\}, \xi \tag{4.36}$$

We used the same cost data and parameters ($T = 7$) as in Section 5 and tested 20 scenario-sets with the size varying from 10 to 200 in increments of 10. A scenario-set with 200 scenarios can be thought as 200 distinct matrices of size N by T, where each matrix represents a scenario $\xi \in \Xi$ and has entries $D_i^t(\xi)$ for $i = \{1, \ldots, N\}$ and $t = \{1, \ldots, T\}$. We highlight that the QMC method generates a unique scenario tree for each sample size since it is not randomized.

Figures 2a and 2b, depict the average and standard deviation of the objective function value for all replications performed to assess out-of- and in-sample stability. As can be observed from these figures, the scenario generation based on QMC sampling presented no significant change in the average value and/ or reduction in the standard deviation observed for scenario sets larger than 50 when analyzing in-sample stability. A similar behaviour was observed for sets larger than 100 scenarios concerning out-of-sample stability. Therefore, scenario sets with $\Upsilon = 100$ scenarios were used in the experiments presented next, as the stability assessment indicated this scenario set size as the minimal number of scenarios to achieve an acceptable level of stability.



(a) Out-of-sample stability



(b) In-sample stability

Figure 2: Scenarios sample stability results.

5. Computational experiments

We consider a network of four hospitals composed of two small and two large hospitals. The performance metrics reported are based on simulating 18500 successive days of this network (i.e., the model is solved 18500 times for each experiment). The number of simulation runs in the rolling horizon algorithm was set according to the Dvoretzky-Kiefer-Wolfowitz (DKF) inequality [49] which provides an estimate of the total number of simulations required to obtain an empirical cumulative distribution of cost components with an error less than 1% with confidence level of 95% (as used in [2]). For the sake of comparability, the same scenario sets generated at each simulation run were used in all experiments. Each simulation step (i.e., each execution of the model plus overheads with updates of values and calculation of indicators) took less than a minute on a typical personal computer. The simulation procedure was coded in Python 2.7.10 and the MILP models were solved using IBM ILOG CPLEX 12.6.2. Algorithm 1 describes the steps of each simulation run of implementing the 2SSP model using the proposed rolling horizon approach.

Note that to update the inventory, in Step 6 of Algorithm 1, demands are fulfilled from the oldest units in inventory at each hospital in the simulation runs regardless of the mathematical model used (in Step 2). That means once the results obtained from any of the models (e.g. the TS model), in the implementation/simulation phase a FIFO approach is applied to fulfill the demand. The reason is linked to the fact that at the stage of running the model (TS Model or TS-FIFO Enforcement), the demand has not been realized yet. Thus the realized demand (in the implementation/simulation phase) is not necessarily the same as the demand in the set of demand scenarios used in the models which justifies the use of a FIFO approach in demand fulfilment. In other words, the decision variables to determine the demand fulfilment were scenario indexed and are not actionable in the implementation/simulation phase.

Algorithm 1: The rolling-horizon algorithm.

for $t = 1, \ldots, 18500$ **do**

- **Step 1:** Generate Υ demand scenarios for the next T periods;
- **Step 2:** Run the 2SSP model using the initial inventories at the current period t;
- **Step 3:** Implement the orders and transshipment decisions;
- **Step 4:** Update inventory levels according to transshipment decisions;
- **Step 5:** Observe the demands at each hospital (generated according to the considered demand probability distribution functions);
- **Step 6:** Update the inventories available at the beginning of next period according to the observed demands, outdates and incoming orders. Note that demands are fulfilled from the oldest units in inventory at each hospital in all models;
- **Step 7:** Compute the actual (observed) cost of the current period. It comprises of holding, ordering, transshipment, and shortage (i.e., emergency orders) costs, according to the observed demands;

The daily demand varies during the week, with significantly less (and often zero) demand on weekends. Thus, we assumed that the uncertain demand followed a zero-inflated negative binomial distribution. The zero-inflated negative binomial (ZINB) distribution has three parameters: the inflated probability of zero (π), the number of trials (r), and the probability of success in each trial (p) [27]. The reason for assuming this distribution is that the negative binomial distribution is a flexible discrete distribution and can take the index of dispersion over one. In previous research it has been noted that the distribution of demand for blood components has the index of dispersion over one, and thus using Poisson distribution (known to have an index of dispersion equal to one) underestimates the demand variability [34, 1]. In addition, as there is often no demand on some days especially on weekends (as, with exception of emergency operations, surgeries are not scheduled on weekends), we use ZINB distribution that simply inflates the probability of observing zero demand. As the actual demand forecasts for red blood cells could not be made available, demand data for hospitals 1, 2, 3, and 4 were sampled from ZINB($\pi = 0.6, r = 4, p = 0.6$), ZINB($\pi = 0.6, r = 3, p = 0.57$), ZINB($\pi = 0.25, r = 15, p = 0.57$) and ZINB($\pi = 0.25, r = 15, p = 0.48$), respectively [24].

We set the shelf life of the blood units to 21 days as it is considered the red blood cells's shelf life at some blood services [30]. Note that in our experiments we assume that the average age of issue of red blood cells to a hospital is 10 days. It means that on average the units stay for 10 days in the collection centers, processing centers and blood banks before being issued to a hospital. Therefore, the remaining shelf life of units received by hospitals is set at 11 days. To enforce the importance of the outdate cost compared to the holding cost, we assume that the holding cost for 11 days of one blood unit is strictly less than its outdate cost. Otherwise, the model would prefer to discard rather than hold inventory to meet the demand, which is not aligned with the explicit priorities of this context. We assume that all cost components are equal at all hospitals and the value of holding cost, emergency order cost, expiry cost, order cost and transshipment cost are set at 1, 16, 13, 1, and 1.5 monetary units per unit per period, respectively.

We explore how the optimized inventory control policies obtained using the proposed approach perform when compared to the policy currently in practice at some hospitals used as reference for this study. A daily review inventory policy is applied at these hospitals, implying that the inventory status is checked every day and, if the inventory falls below a desired inventory level S, which is set to be four times the average daily demand, an order is placed to lift the inventory up to S (i.e., base stock policy). In terms of current transshipment policy, the small-sized hospitals transship their units of red blood cells that have less than a predefined residual shelf life to a given large-sized hospital within their network. Therefore, for the current policy, we assume that hospitals 1 and 2 are the two small-sized hospitals which can transship their red blood cells units with less than 6 days remaining shelf life only to hospitals 3 and 4, respectively. We stress that, contrary to the current policy observed, the proposed model allows both hospitals 1 and 2 to transship units to either of hospitals 3 and 4, as well between them. Figure 3 schematically represents the transshipment flows for current policy (left) and the optimized policy (right).

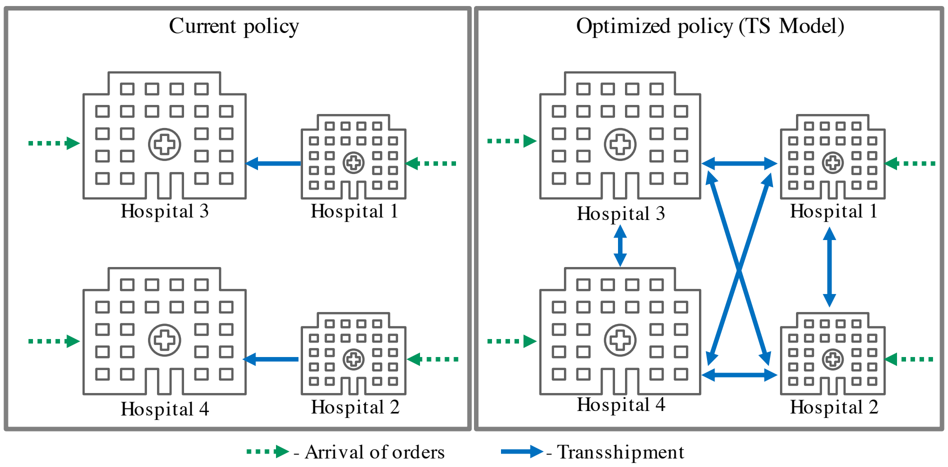


Figure 3: Schematic representation of hospital networks; solid line arrows represent possible directions for transshipment.

The numerical experiments presented in this section are threefold. First, we compare the inventory control policy devised by the proposed model with the current policy. Second, we assess the effect of enforcing the FIFO issuing policy when considering transshipment. However, as the CPU times required to solve the MILP models considering the FIFO policy for each simulation run was over 20 minutes (and thus too computationally demanding to be executed a sufficient number of times to obtain reliable results), we opted for enforcing (4.19) and (4.20) but dropping (4.21) and (4.22), as (4.21) and (4.22) enforce FIFO for future periods and do not involve the first-stage decisions. We believe that this approximation does not compromise the reliability of the policies obtained by the proposed model, as the second-stage decisions are an approximation of the future and are eventually replaced in our rolling horizon scheme. Last, as some regional and small hospitals may, in practice, place their orders every other day, we also analyze the implications of small hospitals ordering every other day.

To decide the length of the planning horizon to be considered in the two-stage model, we performed a sensitivity analysis considering distinct lengths (i.e., values of T). Trading off computational burden and quality of the solution, we opted for a seven-day planning horizon ($T = 7$). In Table 1, we compare the shortage rates (defined as the total observed shortages divided by the total observed demand) and outdate rates (defined as the discarded blood units divided by the total available inventory) for each value of T. As can be observed in Table 1, increasing the value of T does not conclusively improve the performance of the optimal policy, which lead us to believe that a seven-day planning horizon is adequate.

	Shortage	**Outdate**	**Average cost**
T=7	0.013	0.006	76.652
T=10	0.011	0.007	77.472
T=20	0.016	0.006	77.616

Table 1: Shortage rate, outdate rate and average cost for different T (the shortage cost per unit=16, the outdate cost per unit=13).

Henceforth, the name *TS Model* is used for the proposed model, described in Section 4, *TS-FIFO Enforcement* is used for the TS Model that follows the FIFO issuing policy, *Current Policy* is used for the model that simulates the current policy adopted at the hospitals, and *No Transshipment* is used when the hospitals do not use transshipment at all.

In the first set of experiments, we compared the four aforementioned models. The results obtained in terms of shortage rate, outdate rate and the total service level for each model are shown in Table 2, while Table 4 presents the average daily component costs. The total shortage rate and the total outdate rate presented in Tables 2, 5, A1, A4, A6, and A8 were calculated as follows. The total shortage rate is given by $\sum_{t=1}^{t=18500} \sum_{i \in \mathcal{N}} f_i^t / \sum_{t=1}^{t=18500} \sum_{i \in \mathcal{N}} D_i^t$ and the total outdate rate is obtained from $\sum_{t=1}^{t=18500} \sum_{i \in \mathcal{N}} o_i^t / \sum_{t=1}^{t=18500} \sum_{i \in \mathcal{N}} \sum_{j=1}^{j=M} b_{i,m}^t$, where D_i^t, $b_i^t = (b_{i,1}^t, ..., b_{i,M}^t)$, f_i^t and o_i^t denote the demand, inventory, shortage, and outdate at hospital i at period t, respectively.

Several important observations can be drawn from Tables 2 and 4. First, the four policies have comparable performance, both in terms of shortage and outdate. The Current Policy, as those obtained by the proposed model, is very efficient in regard to avoiding shortage and outdate. We also highlight the positive impact that the consideration of transshipment has when the Current Policy is compared to the No Transshipment policy in terms of wastage of blood units in the smaller hospitals (Hospitals 1 and 2). In terms of enforcing the FIFO policy, in Table 4 one can see that it causes a small reduction in the transshipment performed, at the expense of exposing the system to higher outdating costs.

Table 3 presents the average order and transshipment for each hospital. As can be seen, the average order and transshipment quantities in the Current Policy are higher than those of TS Model, specially for small hospitals. Overall, the TS Model orders and transships units more efficiently than compared to the other models, since the quantity of orders and transshipment can be coordinated to reduce the inventory level, as well as the outdate and the total costs.

Analyzing Table 4, it becomes evident that the policy devised by the TS Model is considerably more efficient in terms of expected costs. The average total cost for Current Policy is nearly 58% higher than those obtained with the TS Model. The statistical information regarding the distribution of cost also allows one to conclude that the TS Model is less affected by scenarios of high costs (as shown by the P1 and P95 values). The results of Table 4 also reveals that relaxing the FIFO constraints in the TS Model might trigger more transshipment, which leads to a lower observed outdate rate than that observed using the TS-FIFO Enforcement model.

Hospitals	TS Model		TS-FIFO Enforcement		Current Policy		No Transshipment	
	Shortage	**Outdate**	**Shortage**	**Outdate**	**Shortage**	**Outdate**	**Shortage**	**Outdate**
Hospital 1	0.024	0.014	0.023	0.025	0.006	0.000	0.000	0.387
Hospital 2	0.034	0.128	0.034	0.175	0.027	0.000	0.005	0.285
Hospital 3	0.014	0.000	0.015	0.000	0.000	0.031	0.000	0.008
Hospital 4	0.010	0.001	0.010	0.001	0.016	0.001	0.022	0.001
Total	0.013	0.006	0.014	0.008	0.010	0.010	0.012	0.047
Service level	0.986		0.986		0.990		0.988	

Table 2: Shortage and outdate rate for each hospital (the shortage cost per unit is 16; the outdate cost per unit is 13). The total figures presented in "Total" row was calculated based on the total shortage, the total outdate and the total demand at all hospitals. The total shortage is obtained as the total observed shortages divided by the total observed demand; the total outdate is computed as the total outdated units divided by the total inventory.

Hospitals	TS Model		TS-FIFO Enforcement		Current Policy		No Transshipment
Average	**Order**	**Trans.**	**Order**	**Trans.**	**Order**	**Trans.**	**Order**
Hospital 1	1.468	0.534	1.419	0.469	2.558	1.500	1.733
Hospital 2	0.819	0.124	0.820	0.094	1.813	0.912	1.289
Hospital 3	9.029	0.768	9.134	0.875	7.200	0.000	8.544
Hospital 4	11.120	0.125	11.117	0.138	11.043	0.000	11.875

Table 3: The average daily order and transshipment (the shortage cost per unit=16, the outdate cost per unit=13).

	TS Model	TS-FIFO Enforcement	Current Policy	No Transshipment
Total cost parcels				
Holding cost	45.294	45.133	87.615	85.117
Order cost	22.436	22.490	22.615	23.442
Shortage cost	4.869	4.885	3.576	4.395
Outdate cost	1.727	2.441	2.972	14.390
Transshipment cost	2.326	1.576	3.618	—
Total cost statistics				
Average	76.652	77.312	120.396	127.344
Std. dev.	22.516	22.860	28.691	34.153
Median	73.000	74.000	115.000	118.000
Skewness	4.093	3.977	4.460	3.032
P5	54.000	54.500	96.000	95.000
P95	105.500	107.500	159.000	189.000

Table 4: The average daily component costs (the shortage cost per unit is 16, the outdate cost per unit is 13). P5 and P95 denote the fifth percentile and the 95 percentile respectively.

To confirm our result, we set the shortage cost at 15, outdate cost at 12 and consider the other cost parameters as the same as the previous example. As shown in Appendix A, Table A1, we observed that changing the shortage cost and outdate cost does not affect the shortage and outdate rates of Current Policy and No Transshipment models. Table A2 in Appendix A presents the average order and average transshipment quantities for all policies. The results are consistent with those observed in previous experiment. Table A3 (Appendix A) presents the breakdown of total cost for the second experiment. Analogously to the results of the first experiment, the figures illustrate the superior performance of TS Model and TS-FIFO Enforcement over the Current Policy and No Transshipment models. Moreover, the results are consistent with those observed in previous experiment. To investigate larger variations in shortage and outdate costs, further results are presented in Appendix A (Table A4 to Table A9). The results in Appendix A also indicate a consistently superior performance of the TS Model.

Small hospitals usually have smaller order volumes than large hospitals. Therefore, it is reasonable that orders are placed every other day, as it is practiced in several hospitals [3, 90]. To apply this restriction in the TS Model, we add a constraint to set the orders of small hospitals at zero on the days that they are not allowed to order. Tables 5 and 6 present the results when small hospitals place their orders every second day.

Hospitals	**TS Model**		**TS-FIFO Enforcement**		**Current Policy**		**No Transshipment**	
	Shortage	**Outdate**	**Shortage**	**Outdate**	**Shortage**	**Outdate**	**Shortage**	**Outdate**
Hospital 1	0.020	0.004	0.021	0.007	0.010	0.000	0.001	0.376
Hospital 2	0.021	0.004	0.021	0.015	0.036	0.000	0.012	0.275
Hospital 3	0.012	0.000	0.012	0.000	0.000	0.031	0.000	0.008
Hospital 4	0.010	0.000	0.010	0.000	0.016	0.001	0.022	0.000
Total	0.012	0.001	0.012	0.003	0.011	0.010	0.012	0.045
Service level	0.988		0.988		0.989		0.987	

Table 5: Shortage and outdate rate for each hospital when small hospitals order every other day (the shortage cost per unit is 15; the outdate cost per unit is 12). The total shortage is obtained as the total observed shortages divided by the total observed demand; the total outdate is computed as the total outdated units at divided by the total inventory (considering all hospitals).

As can be observed in Table 5, the system has the lowest total outdate rate in the TS Model. The results in Table 6 show all the cost components for the TS Model are smaller than the Current Policy and No Transshipment models, except for the shortage costs. This particular effect is a consequence of the overall cost minimization perspective that model adopts, as it can be confirmed by the reductions observed in the overall costs. The trade-off opportunities exploited by this model could be straightforwardly controlled by enforcing service-level constraints (as in [26], for example). Furthermore, comparing the results of Tables A3 and 6 indicates that the restriction of ordering every other day slightly increases the total cost in all policies.

As previously discussed, the TS Model assumes an (R, S) policy for future periods to approximate the future cost of (implementable) decisions made in the current period, namely the order and

	TS Model	TS-FIFO Enforcement	Current Policy	No Transshipment
Total cost parcels				
Holding cost	47.771	47.575	86.702	84.248
Order cost	22.399	22.492	22.594	23.385
Shortage cost	4.056	4.082	3.613	4.219
Outdate cost	0.743	1.877	2.701	12.682
Transshipment cost	2.743	2.737	3.494	—-
Total cost statistics				
Average	77.712	78.399	119.103	124.534
Std.dev.	20.412	20.948	27.307	33.776
Median	75.000	76.000	114.000	115.000
Skewness	3.973	3.733	4.091	2.819
P5	56.500	56.500	94.000	93.000
P95	103.500	107.000	158.000	190.000

Table 6: The average daily component costs when small hospitals order every other day (the shortage cost per unit=15, the outdate cost per unit=12). P5 and P95 denote the fifth percentile and the 95 percentile respectively.

transshipment quantities. To investigate the impact of this simplification, we compare the order quantities obtained in each time period of the rolling horizon algorithm (i.e., the value of S_i for $i \in \mathcal{N}$) with the actual inventory level at the beginning of the time period plus the order decided for that same period (the actual dynamic inventory policy implemented by the model) for each hospital. The results obtained from the rolling horizon approach are summarized in Figure 4.

Figure 4 illustrates that, for each hospital, the average of the decided S_i values for all periods in the rolling horizon approach (represented by 'Average S') is reasonably close to the average inventory level obtained from the policy implemented by the model ('Average Inventory'). These results indicate that the simplification of using the (R, S) policy to approximate the inventory system in future periods represents the future behavior of the system reasonably well. Note that, as a consequence of having a adequate number of scenarios being generated using the QMC sampling method, the standard deviation of S_i's are considerably small, in accordance to the indications from the in- and out-of-sample stability tests performed.

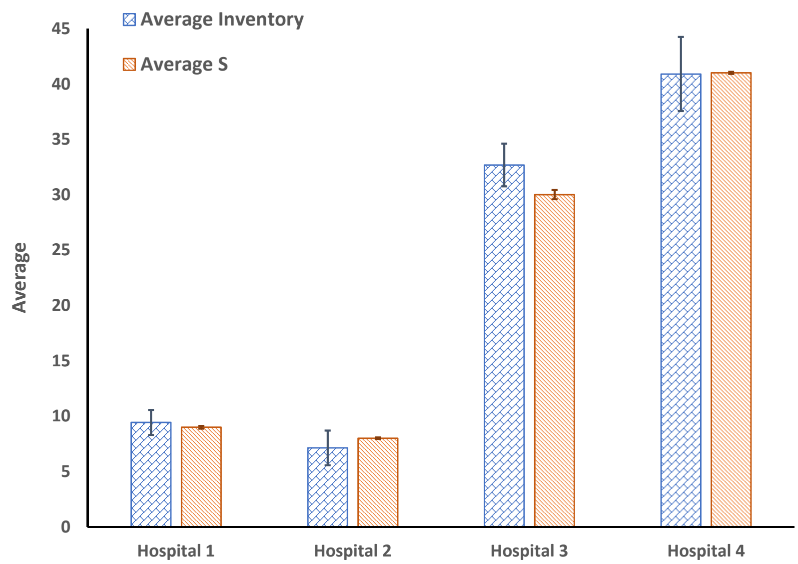


Figure 4: The average actual inventory at the begining of a period plus the actual order (shown as Average Inventory in the plot) and the average of S. The line on each bar shows mean $\pm$ standard deviation of the related quantity of the bar (the shortage cost per unit=16, the outdate cost per unit=13).

Figure 5 shows the average and standard deviation of age of blood units at transfusion time for various transshipment policies. The No Transshipment policy has the worst average age at transfusion in hospitals 1, 2 and 3 and its average age at transfusion in hospital 4 is almost same as other transshipment policies. Employing the TS and TS-FIFO Enforcement models improves the average age of transfusion in the two large hospitals (hospitals 3 and 4) in comparison to the Current policy. The Current Policy has the lowest average age at transfusion at hospitals 1 and 2 (two small hospitals), which is due to the fact that, in the Current Policy, older units are transshipped from small hospitals to large hospitals.

The aggregated average age at transfusion for all hospitals for the TS Model, the TS-FIFO Enforcement model, the Current Policy and No Transshipment policy are 11.972, 11.941, 13.812, and 14.230, respectively. These figures also show that the TS and the TS-FIFO Enforcement models outperform the Current and No Transshipment policies in terms of the overall average age at transfusion. They also indicate that the TS and the TS-FIFO Enforcement models are very similar in terms of the aggregated average age at transfusion. The reason why both TS and TS-FIFO Enforcement models provide a similar average age at transfusion is linked to the fact that the FIFO policy for fulfilling the demands is enforced for both models in the simulation runs (in Step 6 of Algorithm 1).

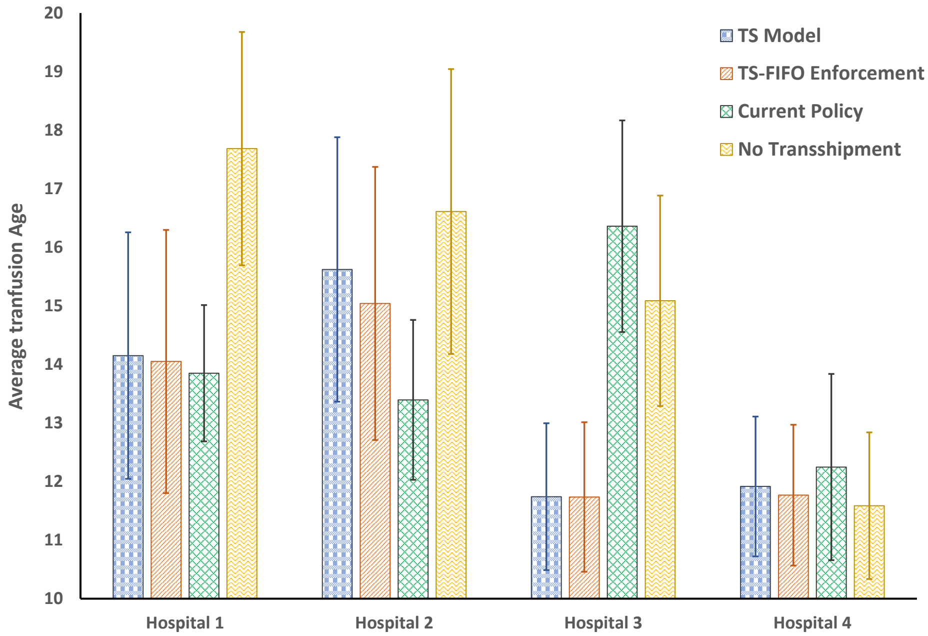


Figure 5: Average Age at transfusion in various transshipment policies. The line on each bar shows mean $\pm$ standard deviation of the age at transfusion (the shortage cost per unit is 16; the outdate cost per unit is 13).

6. Conclusion

We proposed a decision support tool to decide on proactive transshipment in order to reduce total cost as well as wastage and shortage in the blood supply chain. We considered a blood inventory system consisting of a number of hospitals with uncertain demand and developed a two-stage stochastic programming model to calculate the optimal order and transshipment quantities for each hospital that minimize the total expected cost. To tackle the uncertain nature of the demand, we generated scenarios using a Quasi-Monte Carlo sampling approach and conducted stability analysis tests to obtain a reliable number of scenarios.

We evaluated the performance of the proposed model by performing numerical experiments comparing the performance of the proposed inventory control policy with the current transshipment policy applied in the hospitals. Our numerical results showed that considerable cost benefits can be obtained through reductions in the levels of safety stock as well as wastage by using the proposed model, which also illustrated the benefits of proactive transshipment in the blood supply chain. Furthermore, the results showed that the proposed transshipment policies can also improve the age of units at transfusion, which is a desirable outcome for blood supply chains.

To the best of our knowledge, this work is the first to analyze both replenishment and proactive transshipment in a network of hospitals. Thus, for future research, we believe that significant advantages can be achieved by deployment of our model in more general networks of hospitals where proactive transshipment is applied. An initial relevant extension in this direction would be to extend our model to include different types of blood for cases when substitution (i.e., demand fulfillment using a compatible alternative blood type) is considered, as blood substitutions could improve the performance of the blood inventory management system. Also, it would be worth investigating efficient solution methods and the employment of parallel computation strategies to allow for the consideration of larger networks, more scenarios, and multiple tiers.

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References

[1] Abbasi, B., Hosseinifard, Z., 2014. On the issuing policies for perishable items such as red blood cells and platelets in blood service. Decision Sciences 45, 995–1020.

[2] Abbasi, B., Hosseinifard, Z., Alamri, O., Thomas, D., Minas, J., 2018. Finite time horizon fill rate analysis for multiple customer cases. Omega 76, 1–17.

[3] Abbasi, B., Vakili, G., Chesneau, S., 2017. Impacts of reducing the shelf life of red blood cells: A view from down under. Interfaces 47 (4), 336–351.

[4] Abouee-Mehrizi, H., Berman, O., Sharma, S., 2015. Optimal joint replenishment and transshipment policies in a multi-period inventory system with lost sales. Operations Research 63 (2), 342–350.

[5] Agrawal, V., Chao, X., Seshadri, S., 2004. Dynamic balancing of inventory in supply chains. European Journal of Operational Research 159 (2), 296–317.

[6] Allen, S. C., 1958. Redistribution of total stock over several user locations. Naval Research Logistics (NRL) 5 (4), 337–345.

[7] Atkinson, M. P., Fontaine, M. J., Goodnough, L. T., Wein, L. M., 2012. A novel allocation strategy for blood transfusions: investigating the tradeoff between the age and availability of transfused blood. Transfusion 52 (1), 108–117.

[8] Axsäter, S., 1990. Modelling emergency lateral transshipments in inventory systems. Management Science 36 (11), 1329–1338.

[9] Bakker, M., Riezebos, J., Teunter, R. H., 2012. Review of inventory systems with deterioration since 2001. European Journal of Operational Research 221 (2), 275–284.

[10] Banerjee, A., Burton, J., Banerjee, S., 2003. A simulation study of lateral shipments in single supplier, multiple buyers supply chain networks. International Journal of Production Economics 81, 103–114.

[11] Beliën, J., Forcé, H., 2012. Supply chain management of blood products: A literature review. European Journal of Operational Research 217 (1), 1–16.

[12] Birge, J. R., Louveaux, F., 2011. Introduction to stochastic programming. Springer Science & Business Media.

[13] Blake, J., Hardy, M., Delage, G., G, M., 2013. Déjà-vu all over again: Using simulation to evaluate the impact of shorter shelf-life for red blood cells at héma-québec. Transfusion 53, 1544–1558.

[14] Bosnes, V., Aldrin, M., Heier, H. E., 2005. Predicting blood donor arrival. Transfusion 45 (2), 162–170.

[15] Brodheim, E., Derman, C., Prastacos, G., 1975. On the evaluation of a class of inventory policies for perishable products such as blood. Management Science 21 (11), 1320–1325.

[16] Burton, J., Banerjee, A., 2005. Cost-parametric analysis of lateral transshipment policies in two-echelon supply chains. International Journal of Production Economics 93, 169–178.

[17] Caflisch, R. E., 1998. Monte carlo and quasi-monte carlo methods. Acta numerica 7, 1–49.

[18] Chen, X., Pang, Z., Pan, L., 2014. Coordinating inventory control and pricing strategies for perishable products. Operations Research 62 (2), 284–300.

[19] Cheong, T., 2013. Joint inventory and transshipment control for perishable products of a two-period lifetime. The International Journal of Advanced Manufacturing Technology 66 (9-12), 1327–1341.

[20] Clay, N. M., Abbasi, B., Eberhard, A., Hearne, J., 2018. On the volatility of blood inventories. International Transactions in Operational Research 25 (1), 215–242.

[21] Cumming, P. D., Kendall, K. E., Pegels, C. C., Seagle, J. P., Shubsda, J. F., 1976. A collections planning model for regional blood suppliers: description and validation. Management Science 22 (9), 962–971.

[22] Cunha, P., Raupp, F. M., Oliveira, F., 2017. A two-stage stochastic programming model for periodic replenishment control system under demand uncertainty. Computers & Industrial Engineering 107, 313–326.

[23] Dantzig, G. B., 1955. Linear programming under uncertainty. Management Science 1 (3/4), 197–206.

[24] Dehghani, M., 2018. Transshipment in supply chain networks with perishable items. PhD thesis.

[25] Dehghani, M., Abbasi, B., 2018. An age-based lateral-transshipment policy for perishable items. International Journal of Production Economics 198, 93–103.

[26] Dillon, M., Oliveira, F., Abbasi, B., 2017. A two-stage stochastic programming model for inventory management in the blood supply chain. International Journal of Production Economics 187, 27–41.

[27] Doyle, S. R., 2009. Examples of computing power for zero-inflated and overdispersed count data. Journal of Modern Applied Statistical Methods 8 (2), 3.

[28] Duan, Q., Liao, T. W., 2013. A new age-based replenishment policy for supply chain inventory optimization of highly perishable products. International Journal of Production Economics 145 (2), 658–671.

[29] Fattahi, M., Mahootchi, M., Moattar Husseini, S., Keyvanshokooh, E., Alborzi, F., 2015. Investigating replenishment policies for centralised and decentralised supply chains using stochastic programming approach. International Journal of Production Research 53 (1), 41–69.

[30] Flegel, W. A., Natanson, C., Klein, H. G., 2014. Does prolonged storage of red blood cells cause harm? British journal of haematology 165 (1), 3–16.

[31] Fries, B. E., 1975. Optimal ordering policy for a perishable commodity with fixed lifetime. Operations Research 23 (1), 46–61.

[32] Glazebrook, K., Paterson, C., Rauscher, S., Archibald, T., 2015. Benefits of hybrid lateral transshipments in multi-item inventory systems under periodic replenishment. Production and Operations Management 24 (2), 311–324.

[33] Godin, G., Conner, M., Sheeran, P., Bélanger-Gravel, A., Germain, M., 2007. Determinants of repeated blood donation among new and experienced blood donors. Transfusion 47 (9), 1607–1615.

[34] Goh, C.-H., Greenberg, B., Matsuo, H., 1993. Two-stage perishable inventory models. Management Science 39 (5), 633–649.

[35] Gunpinar, S., Centeno, G., 2015. Stochastic integer programming models for reducing wastages and shortages of blood products at hospitals. Computers & Operations Research 54, 129–141.

[36] Haijema, R., van Dijk, N., van der Wal, J., Sibinga, C. S., 2009. Blood platelet production with breaks: optimization by sdp and simulation. International Journal of Production Economics 121 (2), 464–473.

[37] Heddle, N. M., Liu, Y., Barty, R., Webert, K. E., Whittaker, S., Gagliardi, K., Lauzon, D., Owens, W., 2009. Factors affecting the frequency of red blood cell outdates: an approach to establish benchmarking targets. Transfusion 49 (2), 219–226.

[38] Hemmelmayr, V., Doerner, K. F., Hartl, R. F., Savelsbergh, M. W., 2009. Delivery strategies for blood products supplies. OR Spectrum 31 (4), 707–725.

[39] Herer, Y. T., Tzur, M., Yücesan, E., 2006. The multilocation transshipment problem. IIE Transactions 38 (3), 185–200.

[40] Hosseinifard, Z., Abbasi, B., 2018. The inventory centralization impacts on sustainability of the blood supply chain. Computers & Operations Research 89, 206–212.

[41] Hosseinifard, Z., Abbasi, B., Fadaki, M., Clay, N. M., 2019. Postdisaster volatility of blood donations in an unsteady blood supply chain. Decision Sciences.

[42] Jönsson, H., Silver, E. A., 1987. Analysis of a two-echelon inventory control system with complete redistribution. Management Science 33 (2), 215–227.

[43] Kamp, C., Heiden, M., Henseler, O., Seitz, R., 2010. Management of blood supplies during an influenza pandemic. Transfusion 50 (1), 231–239.

[44] Katsaliaki, K., Brailsford, S. C., 2007. Using simulation to improve the blood supply chain. Journal of the Operational Research Society 58 (2), 219–227.

[45] Kaut, M., Wallace, S. W., 2007. Evaluation of scenario-generation methods for stochastic programming. Pacific Journal of Optimization 3 (2), 257–271.

[46] Kendall, K. E., Lee, S. M., 1980. Formulating blood rotation policies with multiple objectives. Management Science 26 (11), 1145–1157.

[47] Kırcı, M., Biçer, I., Seifert, R. W., 2018. Optimal replenishment cycle for perishable items facing demand uncertainty in a two-echelon inventory system. International Journal of Production Research, 1–15.

[48] Kopach, R., Balcıoğlu, B., Carter, M., 2008. Tutorial on constructing a red blood cell inventory management system with two demand rates. European Journal of Operational Research 185 (3), 1051–1059.

[49] Kosorok, M. R., 2008. Introduction to empirical processes and semiparametric inference. Springer.

[50] Lee, H., Whang, S., 2002. The impact of the secondary market on the supply chain. Management Science 48 (6), 719–731.

[51] Lee, Y. H., Jung, J. W., Jeon, Y. S., 2007. An effective lateral transshipment policy to improve service level in the supply chain. International Journal of Production Economics 106 (1), 115–126.

[52] Li, G., He, X., Zhou, J., Wu, H., 2019. Pricing, replenishment and preservation technology investment decisions for non-instantaneous deteriorating items. Omega 84, 114–126.

[53] Li, X., Sun, L., Gao, J., 2013. Coordinating preventive lateral transshipment between two locations. Computers & Industrial Engineering 66 (4), 933–943.

[54] Liang, C., Sethi, S. P., Shi, R., Zhang, J., 2014. Inventory sharing with transshipment: Impacts of demand distribution shapes and setup costs. Production and Operations Management 23 (10), 1779–1794.

[55] Meissner, J., Senicheva, O. V., 2018. Approximate dynamic programming for lateral transshipment problems in multi-location inventory systems. European Journal of Operational Research 265 (1), 49–64.

[56] Melnyk, S. A., Pagell, M., Jorae, G., Sharpe, A. S., 1995. Applying survival analysis to operations management: Analyzing the differences in donor classes in the blood donation process. Journal of Operations Management 13 (4), 339–356.

[57] Millard, D. W., 1959. Industrial inventory models as applied to the problem of inventorying whole blood. Ph.D. thesis, The Ohio State University.

[58] Mustafee, N., Taylor, S. J., Katsaliaki, K., Brailsford, S., 2009. Facilitating the analysis of a uk national blood service supply chain using distributed simulation. Simulation 85 (2), 113–128.

[59] Nagurney, A., Dutta, P., 2018. Competition for blood donations. Omega In-press, 1–12.

[60] Nahmias, S., 1975. Optimal ordering policies for perishable inventory—ii. Operations Research 23 (4), 735–749.

[61] Nahmias, S., 1982. Perishable inventory theory: a review. Operations Research 30 (4), 680–708.

[62] Nakandala, D., Lau, H., Shum, P. K., 2017. A lateral transshipment model for perishable inventory management. International Journal of Production Research 55 (18), 5341–5354.

[63] Nandakumar, P., Morton, T. E., 1993. Near myopic heuristics for the fixed-life perishability problem. Management Science 39 (12), 1490–1498.

[64] Osorio, A. F., Brailsford, S. C., Smith, H. K., 2015. A structured review of quantitative models in the blood supply chain: a taxonomic framework for decision-making. International Journal of Production Research 53 (24), 7191–7212.

[65] Owen, A. B., 2003. Quasi-monte carlo sampling. Monte Carlo Ray Tracing: Siggraph 1, 69–88.

[66] Park, S. J., Lai, G., Seshadri, S., 2016. Inventory sharing in the presence of commodity markets. Production and Operations Management 25 (7), 1245–1260.

[67] Paterson, C., Kiesmüller, G., Teunter, R., Glazebrook, K., 2011. Inventory models with lateral transshipments: A review. European Journal of Operational Research 210 (2), 125–136.

[68] Pegels, C. C., Jelmert, A. E., 1970. An evaluation of blood-inventory policies: A markov chain application. Operations Research 18 (6), 1087–1098.

[69] Perera, G., Hyam, C., Taylor, C., Chapman, J., 2009. Hospital blood inventory practice: the factors affecting stock level and wastage. Transfusion Medicine 19 (2), 99–104.

[70] Pitocco, C., Sexton, T. R., 2005. Alleviating blood shortages in a resource-constrained environment. Transfusion 45 (7), 1118–1126.

[71] Prastacos, G. P., 1984. Blood inventory management: an overview of theory and practice. Management Science 30 (7), 777–800.

[72] Rong, Y., Snyder, L. V., Sun, Y., 2010. Inventory sharing under decentralized preventive transshipments. Naval Research Logistics (NRL) 57 (6), 540–562.

[73] Rytilä, J. S., Spens, K. M., 2006. Using simulation to increase efficiency in blood supply chains. Management Research News 29 (12), 801–819.

[74] Sabouri, A. B. A., 2014. Applications of stochastic optimization models in patient screening and blood inventory management. Ph.D. thesis, University of British Columbia.

[75] Şahin, G., Süral, H., Meral, S., 2007. Locational analysis for regionalization of turkish red crescent blood services. Computers & Operations Research 34 (3), 692–704.

[76] Stanger, S. H., Wilding, R., Hartmann, E., Yates, N., Cotton, S., 2013. Lateral transshipments: an institutional theory perspective. International Journal of Physical Distribution & Logistics Management 43 (9), 747–767.

[77] Stanger, S. H., Yates, N., Wilding, R., Cotton, S., 2012. Blood inventory management: hospital best practice. Transfusion Medicine Reviews 26 (2), 153–163.

[78] Tagaras, G., Vlachos, D., 2002. Effectiveness of stock transshipment under various demand distributions and nonnegligible transshipment times. Production and Operations Management 11 (2), 183–198.

[79] Tang, S.-L., Yan, H., 2010. Pre-distribution vs. post-distribution for cross-docking with transshipments. Omega 38 (3), 192–202.

[80] Tiacci, L., Saetta, S., 2011. A heuristic for balancing the inventory level of different locations through lateral shipments. International Journal of Production Economics 131 (1), 87–95.

[81] van Zyl, G. J., 1963. Inventory control for perishable commodities. Tech. rep., North Carolina State University. Dept. of Statistics.

[82] Wang, K., Ma, Z., Zhou, Y., 2012. Age-based transshipment strategy for overstock blood in emergency relief. Advances in Information Sciences & Service Sciences 4, 18.

[83] Wang, K.-M., Ma, Z.-J., 2015. Age-based policy for blood transshipment during blood shortage. Transportation Research Part E: Logistics and Transportation Review 80, 166–183.

[84] Wee, K. E., Dada, M., 2005. Optimal policies for transshipping inventory in a retail network. Management Science 51 (10), 1519–1533.

[85] Yang, J., Qin, Z., 2007. Capacitated production control with virtual lateral transshipments. Operations Research 55 (6), 1104–1119.

[86] Yao, D. D., Zhou, S. X., Zhuang, W., 2016. Joint initial stocking and transshipment—asymptotics and bounds. Production and Operations Management 25 (2), 273–289.

[87] Zhang, C., Ayer, T., White, C. C., 2018. Perishable inventory sharing in a two-location system. Available at SSRN: https://ssrn.com/abstract=3050094 or http://dx.doi.org/10.2139/ssrn.3050094.

[88] Zhang, J., 2005. Transshipment and its impact on supply chain members' performance. Management Science 51 (10), 1534–1539.

[89] Zhao, X., Atkins, D., 2009. Transshipment between competing retailers. IIE Transactions 41 (8), 665–676.

[90] Zhou, D., Leung, L. C., Pierskalla, W. P., 2011. Inventory management of platelets in hospitals: Optimal inventory policy for perishable products with regular and optional expedited replenishments. Manufacturing & Service Operations Management 13 (4), 420–438.

Appendix A - Further Numeral Results on Comparing TS Model with Current and No Transshipment policies

Hospitals	TS Model		TS-FIFO Enforcement		Current Policy		No Transshipment	
	Shortage	**Outdate**	**Shortage**	**Outdate**	**Shortage**	**Outdate**	**Shortage**	**Outdate**
Hospital 1	0.026	0.016	0.025	0.028	0.006	0.000	0.000	0.387
Hospital 2	0.034	0.122	0.034	0.167	0.027	0.000	0.005	0.285
Hospital 3	0.014	0.000	0.014	0.000	0.000	0.031	0.000	0.008
Hospital 4	0.012	0.001	0.012	0.001	0.016	0.001	0.022	0.001
Total	0.015	0.006	0.015	0.008	0.010	0.010	0.012	0.047
Service level	0.985		0.985		0.990		0.988	

Table A1: Shortage and outdate rate for each hospital (the shortage cost per unit is 15; the outdate cost per unit is 12). The total shortage is obtained as the total observed shortages divided by the total observed demand; the total outdate is computed as the total outdated units divided by the total inventory (considering all hospitals).

Hospitals	TS Model		TS-FIFO Enforcement		Current Policy		No Transshipment
	Ave.order	**Ave.trans**	**Ave.order**	**Ave.trans**	**Ave.order**	**Ave.trans**	**Ave.order**
Hospital 1	1.414	0.489	1.373	0.431	2.558	1.500	1.733
Hospital 2	0.827	0.133	0.826	0.103	1.813	0.912	1.289
Hospital 3	9.004	0.739	9.079	0.815	7.200	0.000	8.544
Hospital 4	11.162	0.129	11.182	0.139	11.043	0.000	11.875

Table A2: The average daily order and transshipment (the shortage cost per unit is 15; the outdate cost per unit is 12).

	TS Model	**TS-FIFO Enforcement**	**Current Policy**	**No Transshipment**
Holding cost	44.550	44.570	87.615	85.116
Order cost	22.407	22.462	22.615	23.442
Shortage cost	4.970	4.934	3.353	4.121
Outdate cost	1.579	2.200	2.744	13.283
Transshipment cost	1.490	1.489	2.412	—-
Total cost statistics				
Average	75.742	76.398	119.944	125.962
Std.dev.	22.126	22.195	26.986	31.868
Median	72.000	73.000	115.000	118.000
Skewness	3.953	3.871	4.297	3.005
P5	54.000	54.000	96.000	95.000
P95	104.525	106.000	156.000	182.000

Table A3: The average daily component costs (the shortage cost per unit=15, the outdate cost per unit=12). P5 and P95 denote the fifth percentile and the 95 percentile respectively.

Hospitals	**TS Model**		**Current Policy**		**No Transshipment**	
	Shortage	Outdate	Shortage	Outdate	Shortage	Outdate
Hospital 1	0.023	0.019	0.006	0.000	0.000	0.387
Hospital 2	0.032	0.170	0.027	0.000	0.005	0.285
Hospital 3	0.012	0.000	0.000	0.031	0.000	0.008
Hospital 4	0.010	0.001	0.016	0.000	0.022	0.000
Total	0.012	0.008	0.010	0.010	0.012	0.047
Service level	0.988		0.99		0.988	

Table A4: Shortage and outdate rate for each hospital (shortage cost per unit=18, outdate cost per unit=13)

	TS Model	Current Policy	No Transshipment
Total cost parcels			
Holding cost	46.210	87.615	85.117
Order cost	22.502	22.615	23.442
Shortage cost	4.990	4.023	4.945
Outdate cost	2.232	2.972	14.390
Transshipment cost	2.407	3.618	—
Total cost statistics			
Average	78.342	120.843	127.893
Std. dev.	23.948	30.416	36.074
Median	75.000	115.000	118.000
Skewness	4.437	4.684	3.361
P5	55.500	96.000	95.000
P95	108.000	161.525	190.000

Table A5: The average daily component costs (shortage cost per unit=18, outdate cost per unit=13). P5 and P95 denote the fifth percentile and the 95 percentile respectively.

Hospitals	TS Model		Current Policy		No Transshipment	
	Shortage	Outdate	Shortage	Outdate	Shortage	Outdate
Hospital 1	0.024	0.015	0.006	0.000	0.000	0.387
Hospital 2	0.033	0.169	0.027	0.000	0.005	0.258
Hospital 3	0.015	0.000	0.000	0.031	0.000	0.008
Hospital 4	0.010	0.001	0.016	0.000	0.022	0.000
Total	0.013	0.007	0.010	0.010	0.012	0.047
Service level	0.987		0.990		0.988	

Table A6: Shortage and outdate rate for each hospital (shortage cost per unit=16, outdate cost per unit=15)

	TS Model	Current Policy	No Transshipment
Total cost parcels			
Holding cost	45.251	87.615	85.117
Order cost	22.468	22.615	23.442
Shortage cost	4.875	3.576	4.395
Outdate cost	2.481	3.43	16.604
Transshipment cost	2.365	3.618	
Total cost statistics			
Average	77.440	120.854	129.558
Std. dev	22.904	30.533	36.991
Median	74.000	115.000	119.000
Skewness	3.942	4.581	2.795
P5	54.500	96.000	95.000
P95	108.000	162.000	198.000

Table A7: The average daily component costs (shortage cost per unit=16, outdate cost per unit=15). P5 and P95 denote the fifth percentile and the 95 percentile respectively.

Hospitals	TS Model		Current Policy		No Transshipment	
	Shortage	Outdate	Shortage	Outdate	Shortage	Outdate
Hospital 1	0.026	0.020	0.006	0.000	0.000	0.387
Hospital 2	0.041	0.144	0.027	0.000	0.005	0.285
Hospital 3	0.018	0.000	0.000	0.031	0.000	0.008
Hospital 4	0.013	0.001	0.016	0.000	0.022	0.000
Total	0.017	0.006	0.010	0.010	0.012	0.047
Service level	0.983		0.990		0.988	

Table A8: Shortage and outdate rate for each hospital (shortage cost per unit=14, outdate cost per unit=11)

	TS Model	Current Policy	No Transshipment
Total cost parcels			
Holding cost	42.738	87.615	85.117
Order cost	22.371	22.615	23.442
Shortage cost	5.331	3.129	3.846
Outdate cost	1.591	2.515	12.176
Transshipment cost	2.439	3.618	
Total cost statistics			
Average	74.514	119.492	124.581
Std. dev	22.051	25.308	29.606
Median	71.000	115.000	118.000
Skewness	3.741	4.107	2.967
P5	52.000	96.000	95.000
P95	105.500	153.000	176.000

Table A9: The average daily component costs (shortage cost per unit=14, outdate cost per unit=11). P5 and P95 denote the fifth percentile and the 95 percentile respectively.

Appendix B - The steps of in-sample and out-of-sample stability tests.

Algorithm 2: The in-sample stability algorithm.

for $K = 10, 20, 30, \ldots, 200$ **do**

  Step 1: Generate a set of scenarios with K demand scenarios and call in $\mathcal{D}_K$;

  Step 2: Run the 2SSP model given the set of scenarios generated in previous step;

  for i = *1 to* K **do**

    Step 2: Compute the objective function of the 2SSP model for scenario i and store the optimal objective value;

  Step 3: Compute the average and standard deviation of optimal objective value obtained in previous step. They are the average and the standard deviation of the objective function in 'in sample stability test' using K scenarios in 2SSP model.

Algorithm 3: The out-of-sample stability algorithm.

for $K = 10, 20, 30, \ldots, 200$ **do**

  Step 1: Generate a set of scenarios with K demand scenarios and call in $\mathcal{D}_K$;

  Step 2: Run the 2SSP model given set $\mathcal{D}_K$ and and obtain/store the decision variables of the first stage i.e., x_{ij}^1's, y_i^1's and S_i's;

  for i = *1 to 1000* **do**

    Step 3: Generate a scenario and solve the 2SSP model given the generated scenario by considering (fixing) the decision variables of the first stage equal to the values obtained in Step 2. Store the optimal objective value;

  Step 5: Compute the average and standard deviation of optimal objective value based on 1000 results (obtained in previous steps). They are the average and the standard deviation of the objective function in 'out of sample stability test' using K scenarios.