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Scheduling the distribution of blood products: A vendor-managed inventory routing approach

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ABSTRACT

Blood shortage may lead to immeasurable losses. But the perishable nature of blood products limits the possibility of storing a large amount of it, and the quality of blood products reduces rapidly with transportation time. Specifically, in China, the management of blood products is even more complicated due to the significant demand for clinical blood, which increases every single year because of the reformation of the health system and the resulting scale expansion of hospitals. In this research, we aim to optimize the blood product scheduling scheme by constructing a vendor-managed inventory routing problem (VMIRP) for blood products, which balances the supply and demand such that the relevant operational cost is minimized. Then a decomposition-based algorithm is developed to solve the proposed mathematical model efficiently. Based on a series of numerical experiments of platelets, we obtain and examine the distribution plan and optimal transportation path over the planning horizon. In addition to the illustrated high algorithm efficiency, the computation results show that the VMIRP scheme can considerably decrease the operational cost of the blood supply chain.

1. Introduction

Blood is an indispensable yet scarce resource. So far there are no alternative products that can entirely substitute blood and its derived products. In China, particularly, the amount of clinical blood needed has been increasing year by year due to the reformation of the health system and the expansion of the hospital scale. Also, notice that the source of blood is mainly from human donations, but research indicated that only 5% of the eligible donor population really donates (Schreiber et al., 2006; Katsaliaki, 2008). The major portion of blood donors in China are college students (Hu et al., 2019). The large mobility and poor stability of this donor group result in insufficient and unstable blood collection, which eventually leads to the seasonal and periodic characteristics of blood supply. Low blood donation rate (9‰), conservative donor selection criteria, long donation interval, and small donation volume have limited the supply of blood (Shi et al., 2014). Shortages in supply can lead to significant costs, especially immeasurable loss of lives. Take the 2018 blood shortage crisis in Beijing as an example. Around the time of Spring Festival, lots of potential donors including college students left the capital city to spend the holiday in their hometowns. This situation led to an extremely low blood supply. To make things even

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Table 1
Classification of the papers on the management of blood products.

Reference	Research problem	Methodology	Cost				Uncertainty	
			inventory holding	transportation	shortage	wastage	demand	supply
Pegels and Jelmert (1970)	issuing policies	Markov chain			✓	✓		
Kendall and Lee (1980)	rotation polices	goal programming	✓		✓	✓		
Haijema et al. (2007)	production & inventory	Markov dynamic programming & simulation			✓	✓	✓	
Katsaliaki and Brailsford (2007)	ordering polices	discrete-event simulation			✓	✓		
Hemmelmayr et al. (2009)	distribution scheduling	integer programming		✓				
Ghandforoush and Sen (2010)	production &routing	non-convex integer programming		✓		✓		
Delen et al. (2011)	blood supply chain management	analytic techniques						
Beliën and Forcé (2012)	review paper on blood supply chain							
Zhou et al. (2011)	replenishment strategies	stochastic dynamic programming	✓	✓	✓		✓	
Zahiri et al. (2015)	blood collection network design	mixed integer linear programming & robust programming		✓			✓	✓
Dillon et al. (2017)	periodic review policies	stochastic programming	✓		✓	✓	✓	
Ramezanian and Behboodi (2017)	blood collection	mixed integer linear programming & robust optimization	✓	✓	✓	✓		
Najafi et al. (2017)	ordering & issuing policies	bi-objective integer programming			✓	✓	✓	✓
Ensafian and Yaghoubi (2017)	procurement & production & assignment	stochastic robust optimization	✓	✓	✓	✓	✓	
Zahiri and Pishvaee (2017)	supply network design	bi-objective programming & robust programming		✓	✓		✓	✓
Karakoc and Gunay (2017)	blood transportation	VRP		✓				
Sarhangian et al. (2018)	threshold-based allocation policies	queuing theory			✓	✓		
Hosseinifard and Abbasi (2018)	inventory centralization	performance approximation		✓	✓	✓	✓	✓
Samani and Hosseini-Motlagh (2019)	supply network design	fuzzy analytic hierarchy process & grey rational analysis & robust model	✓	✓	✓		✓	✓
Leung et al. (2019)	blood collection	statistical analysis						
Rajendran and Ravindran (2019)	ordering policies	stochastic integer programming			✓	✓	✓	
Rajendran and Srinivas (2019)	ordering policies	stochastic mixed integer programming			✓	✓	✓	
Wang and Chen (2020)	blood distribution	robust optimization	✓	✓	✓	✓	✓	
Hamdan and Diabat (2020)	blood distribution	bi-objective robust optimization		✓				
Our study	blood distribution and routing	VMIRP	✓	✓	✓	✓		

worse, Beijing's health authorities called off family/replacement blood donations, attempting to suppress the situation of underground paid donations. This abrupt decision turned the blood shortage to blood famine and left many patients in limbo. Consequently, patients were desperate to seek help through social media, which provoked the crisis of confidence between patients and medical personnel. Ultimately, the crisis was relieved by transferring blood supplies from other provinces to Beijing, which induced exceedingly high transportation costs. The unbalanced blood supply and demand, along with the immeasurable consequences, necessitate effective and efficient management of blood products (Gao, 2018).

On the other hand, the limited life span of blood complicates the situation even further: blood and its products cannot be accumulated and stored in large quantities like ordinary commodities, and the quality of blood products reduces rapidly with transportation time. All the unique natures of blood necessitate effective and efficient management of the corresponding supply chain, which can ensure the fulfillment of demand, reduce the total cost of operation and maintain the quality of blood products.

Majority of the literature on blood product distribution (BPD) was to determine the optimal collection and production quantity at the blood center, realize the optimal inventory control, compare different allocation and distribution strategies, and plan the optimal routes for blood transportation, examples include Gregor et al. (1982), Katsaliaki (2008), Hemmelmayr et al. (2009), Fontaine et al. (2009), Zahiri et al. (2015), Zahiri and Pishvaee (2017), Dillon et al. (2017), Kaveh and Ghobadi (2017), to name a few. Only several studies, Hemmelmayr et al., 2010, Kazemi et al. (2017), Jafarkhan and Yaghoubi (2018), have examined the combination of the inventory control and distribution routes planning, and indicated the resulting significant cost savings. Despite the aforementioned efforts, so far there is no research dealing with the blood product shortage, which is an inevitable problem in the BPD in China. Therefore, all the existing research, which only minimizes either the transportation cost or inventory holding cost, is not applicable.

To overcome the drawbacks of existing research, we employ the inventory routing problem (IRP) to investigate the special situation of BPD. First defined by Campbell et al. (1998), IRP concerns how to allocate products from one warehouse to multiple customers in a pre-determined planning horizon, such that the average distribution cost in the planning period is minimized without shortage. Having been implemented to various areas, such as the distribution of gas-using tanker trucks (Campbell and Savelsbergh, 2004), the transportation of groceries (Custódio and Oliveira, 2006; Aksen et al., 2012) and maritime logistics (Christiansen et al., 2013; Song and Furman, 2013), the classic IRP cannot be directly used in BPD because of the possible wastage and shortage of the blood products. Therefore, in our proposed model, penalty costs are included to reflect the situation of wastage and shortage.

Moreover, the BPD in China is actually operated on the supply chain level, where the blood center, working as the vendor, is in charge of making the production plan for the blood products and determining the distribution scheme. Hence, in order to avoid shortage to the greatest degree, a vendor-managed policy, where the blood center monitors and manages the inventory levels at hospitals, is integrated into the inventory routing decisions. The objective of the classic inventory routing model is extended to consider not only the transportation-related cost, but also the inventory-related cost (including the penalty cost for wastage and shortage). In summary, considering multiple periods over the planning horizon, we aim to answer three questions by analyzing the inventory routing decisions: 1) Which hospitals should be provided blood product in each period? 2) What is the amount of the product that should be transported when a hospital is served in the period? and 3) What is the optimal transportation route in each period?.

The contribution of this paper is threefold. First, based on the typical structure of the blood product supply chain in China, the distribution process is examined and modeled as a VMIRP, where the blood center monitors the demands at hospitals and determines the optimal distribution scheme accordingly. To the best of our knowledge, this is the *first* attempt in applying VMIRP to blood products distribution. Secondly, a decomposition algorithm is designed to effectively solve large scale problems. The proposed mixed integer linear programming is decomposed into a distribution subproblem and a route planning subproblem, which are then solved separately and integrated to achieve the overall solution for the original model. Thirdly, numerical experiments based on a real-world platelets distribution network are conducted to illustrate the performance of our model and algorithm. A series of analyses shows that a centralized scheduling approach can improve the overall performance of the blood product supply chain. The obtained managerial insights can be adapted by blood centers or any vendors that supply perishable products in seeking practical solutions to their inventory and distribution plans.

The remainder of the paper is organized as follows. Section 2 presents a comprehensive review of relevant literature. In Section 3, we explain the operation of BPD in China and establish a mixed integer linear programming model for the VMIRP of blood products. Section 4 describes a decomposition-based method and an integrated algorithm with a detailed procedure. In Section 5, a series of numerical experiments is conducted to demonstrate the effectiveness of our model and verify the efficiency of the proposed algorithm. Section 6 provides some managerial insights regarding the VMIRP approach for the BPD in China. Finally, Section 7 concludes the paper and presents possible future research directions.

2. Literature review

This section comprehensively reviews three research areas related to the present study: management of blood products, inventory routing models for commodity distribution, and scheduling of perishable goods.

2.1. Management of blood products

Blood supply chain management is a complex and vital problem due to the rapid increase of demand, criticality of product, strict storage and handling requirements, and vastness of operations (Delen et al., 2011). In Table 1, we classify the studies on management of blood products and compare them with our study. Detailed review of each research follows.

Beliën and Forcé (2012) pointed out most of the researches on the management of blood products were focused on the inventory-related aspects. One of the inventory-related problems is blood collection. Ghandforoush and Sen (2010) presented a decision support system to determine the platelet production and bloodmobile scheduling for a regional blood center, and proposed a non-convex integer model to match the demand and supply closely. Zahiri et al. (2015) proposed a mixed integer linear programming model to determine the optimal locations of the fixed and temporary facilities, the optimal number of required facilities and assignment of customer zones to established centers in a blood collection system over a multi-period planning horizon, and applied a robust programming approach to cope with the inherent uncertainties. But they assumed the length of each planning horizon was shorter than the blood's lifetime, which guaranteed no wastage. Based on parameters, such as distance of blood donors from blood facilities and advertising budget, Ramezanian and Behboodi (2017) first formed the blood donors' utility, and proposed a deterministic location-

Table 2
Classification of the papers on inventory routing models for commodity distribution.

Reference	Model	Object		Cost		Assumptions		Uncertainty	
		perishable	nonperishable	inventory	transportation	stock-out	wastage	demand	supply
Federgruen and Zipkin (1984)	IRP		✓	✓	✓	✓		✓	
Dror et al. (1985)	multi-period VRP		✓		✓				
Lau et al. (2002)	IRPTW		✓	✓	✓	✓			
Archetti et al. (2007)	VMIRP		✓	✓	✓				
Savelsbergh and Song (2008)	IRP		✓		✓				
Hemmelmayr et al. (2010)	VMIRP	✓			✓	✓	✓	✓	
Aksen et al. (2014)	IRP		✓	✓	✓				
Coelho and Laporte (2014)	IRP	✓		✓	✓		✓		
Adulyasak et al. (2015)	PRP		✓	✓	✓	✓		✓	
Niakan and Rahimi (2015)	IRP		✓	✓	✓	✓	✓	✓	
Park et al. (2016)	VMIRP		✓	✓	✓	✓			
Jafarkhan and Yaghoubi (2018)	IRP	✓		✓	✓	✓		✓	✓
Crama et al. (2018)	IRP	✓			✓	✓	✓	✓	
Alvarez et al. (2020)	IRP	✓		✓	✓		✓		
Our study	VMIRP	✓		✓	✓	✓	✓		

allocation model to increase donors' utility and motivate blood donors to donate. The model was then extended to incorporate uncertainty by robust optimization. Since seasonal influenza epidemics posed intense pressure on blood transfusion, Leung et al. (2019) found that the blood supply in Hong Kong was affected by respiratory infections and weather conditions. Their results highlighted the importance of monitoring blood supply and demand.

Limited blood supply, uncertain demand and short shelf-life require efficient replenishment strategies in the inventory-related areas. Haijema et al. (2007) combined the Markov dynamic programming and simulation approach to study platelets production scheme and inventory rules, and found that a double-level order-up-to type replenishment policy was 'nearly optimal' when demands for platelets were distinguished into two groups based on the age of platelets. Zhou et al. (2011) analyzed a periodic review inventory system with stochastic demand, respectively, under a single-cycle model and a multi-cycle model, and determined the regular order quantity and expedited order-up-to level for each cycle when regular and emergency orderings were considered. Dillon et al. (2017) proposed a two-stage stochastic programming model to find optimal periodic review policies for red blood cells with demand uncertainty so that operational costs, such as shortage cost and wastage cost, were minimized. Najafi et al. (2017) investigated blood ordering and issuing policies in a hospital to minimize blood shortage and wastage under the scenario that the blood supply and demand were uncertain and blood transshipment was allowed. Hosseinifard and Abbasi (2018) studied the inventory centralization at the second echelon of a two-echelon blood supply chain, where hospitals in close proximity of each other maintained centralized inventories to satisfy their demands and the demands of other neighbor hospitals, and demonstrated that inventory centralization increased the sustainability and resilience of the blood supply chain. Rajendran and Ravindran (2019) proposed a stochastic integer programming model under demand uncertainty to determine ordering policies that minimized platelets wastage and shortage. Focusing on efficient blood inventory management with limited supply and uncertain demand, Rajendran and Srinivas (2019) proposed two review policies to the trade-off between the shortage and wastage cost.

Another issue highly associated with inventory is optimal allocation policies. Pegels and Jelmert (1970) applied absorbing Markov chains to study the effects of human blood issuing policies on blood shortage probabilities and the average age of transfused blood. Kendall and Lee (1980) developed a goal programming model for blood rotation policies, which specified how blood was systematically redistributed to hospital blood banks with a higher probability of transfusion, to minimize the outdated quantity and improve the quality of blood with reasonable blood shortage and regional operating costs. By carrying out a discrete-event simulation, Katsaliaki and Brailsford (2007) found the optimal blood ordering policy which reduced shortage and wastage of the whole supply chain from donors to recipients in a typical British hospital. Sarhangian et al. (2018) viewed the blood inventory in a hospital as a $M/M/1+D$ queue, and based on a mixture of two widely-used policies, First-in-First-out and Last-in-First-out, studied the performance of a series of threshold-based allocation policies for red blood cells in terms of the age of allocated units, the proportion of wastage and lost demand. Ensafian and Yaghoubi (2017) proposed two mixed integer programming model for the integrated procurement, production and distribution in platelet supply chain to determine the required whole blood units, the amount of production and the assignment quantity to hospitals with minimum total cost over the planning horizon. Also, a stochastic robust optimization approach was presented to cope with uncertain demand.

Only a few research considered the problems regarding distribution and routing in blood product management. Hemmelmayr et al. (2009) studied the delivery strategies for blood product supplies, and an integer programming model was proposed to determine the hospitals visited and the delivery quantity on each day so as to minimize the transportation cost under the assumptions that the inventory did not spoil and no stock-out occurred at hospitals. Zahiri and Pishvaee (2017) focused on the supply chain network design for a blood product with blood group compatibility, and developed a bi-objective programming model to minimize the total cost, which consisted of establishment costs of main and lab centers, locating and movement costs of the temporary centers and material flow costs when the maximum unsatisfied demand of different products was minimized. Karakoc and Gunay (2017) studied the vehicle routing problem for blood transporters and proposed a vehicle routing scheme to transport blood between hospitals or donor/client sites such that the traveling distance and number of transporters was minimized. Samani and Hosseini-Motlagh (2019) pointed out that risks in the blood supply chain originated from natural disasters, man-made incidents, and uncertainty embedded in the input data. They adopted a hybrid technique using the fuzzy analytic hierarchy process and grey rational analysis to diminish the disruption risk. Considering a two-echelon blood supply network, where blood was provided to fulfill the demands in the preparedness and disaster response stage, Wang and Chen (2020) proposed a two-stage robust optimization model to determine a blood product redistribution scheme that mitigated the blood shortage and wastage when a disaster occurred. Aiming to minimize the time and transportation cost in disaster scenarios with stochastic disruptions in blood facilities and transportation routes, Hamdan and Diabat (2020) presented a bi-objective robust optimization model and a two-stage stochastic optimization model to design a resilient blood supply chain.

Note that the aforementioned studies focused on either the inventory-related problems or merely the routing-related issues, yet overlooked the mutual influence between those two groups of problems. Realizing this interactive relationship, we herein integrate both the inventory and routing aspects, aiming to seek practical managerial insights for decision making in a blood product supply chain.

2.2. Inventory routing models for commodity distribution

The inventory routing problem (IRP), in which a supplier delivers products to a number of geographically dispersed customers, can provide integrated logistics solutions by simultaneously optimizing inventory management, vehicle routing, and delivery scheduling (Coelho et al., 2014). Table 2 summarizes the publications on the applications of inventory routing models in commodity distribution, which are reviewed in detail next.

As the first attempt to integrate the allocation and routing problems in a model, Federgruen and Zipkin (1984) studied the combined problem of allocating a scarce resource among several locations with random demands and planning deliveries to minimize the inventory holding, shortage and transportation cost. The IRP studied by Dror et al. (1985) was to minimize the annual delivery cost with the assumption that no customer ran out of the commodity at any time. Mainly focusing on periodic routing, the model was established with no consideration of any costs or constraints concerning inventory. Lau et al. (2002) considered the IRP with time windows of a single item supplied by a single supplier, and then combined the local search and network flow methods to determine the distribution plan and transportation routes such that the total cost of holding cost, backlog cost and transportation cost was minimized. Savelsbergh and Song (2008) considered an IRP with delivery and pickup, where limited product availability at facilities was considered, but they assumed that none of the customers experienced a stock-out, which was not possible for BPD in China because of the seasonal and periodic characteristics of blood supply. Aksen et al. (2014) studied a selective and periodic IRP for a biodiesel production facility to determine the raw material collection scheme and periodic routing schedule. Adulyasak et al. (2015) investigated a stochastic production routing problem (PRP), which concerned the production and distribution of a single product from a production plant to multiple customers, to minimize the total cost of fixed setup and unit costs, inventory holding costs at the plant and customers, shortage cost and transportation cost. Niakan and Rahimi (2015) focused on a healthcare IRP that medicinal drugs were distributed to healthcare facilities with minimal inventory and transportation costs as well as maximal service level, and a hybridized possibilistic method was proposed to decrease drug shortage risk. Since in China, the blood supply chain is managed by the blood center, the VMIRP is more suitable for blood distribution. Archetti et al. (2007) considered a distribution problem, where the supplier monitored the inventory at retailers and determined the replenishment policy to minimize the total cost of transportation cost and inventory cost at the supplier and retailers and guarantee no stock-out occurred at retailers. Park et al. (2016) proposed an IRP with lost sales under a vendor-managed inventory strategy to determine replenishment times and quantities as well as vehicle routes such that the profit of a two-echelon supply chain comprised of a single manufacturer and multiple retailers was maximized.

Although many studies focused on the IRP or VMIRP, very few could be applied to the blood product supply chain, because the research objectives in those papers were imperishable products, or they regarded the perishable products as normal commodities without expiration. However, when expiration is considered, a certain part of the inventory may be thrown away during the planning horizon, which not only influences the inventory flow but also incurs wastage cost. So it is necessary to consider the expired quantity caused by perishability when addressing the IRP of blood products.

Hemmelmayr et al. (2010) investigated the vendor-managed inventory resupply policies to supply blood products to hospitals under stochastic product usage, and evaluated four recourse actions to deal with possible shortages at hospitals, such as delivery quantity adjustment, out-and-back emergency deliveries, emergency delivery tours and integrated emergency deliveries. Although shortage and expiration were considered, they did not give specific formulas to calculate the expiration quantity at the blood center and the shortage quantity at hospitals. Coelho and Laporte (2014) addressed an IRP for a perishable product under three inventory management policies, *fresh first*, *old first* and *optimized priority* to maximize the total profit, which was computed as the sales revenue minus the routing and inventory holding costs. Jafarkhan and Yaghoubi (2018) analyzed a flexible and robust IRP, where a blood center distributed several types of blood cells to hospitals under uncertain demand and supply. In the model, transshipment between hospitals and substitution among compatible blood types were introduced to avoid shortage. But they treated blood cells as normal commodities that would not expire with time. Crama et al. (2018) studied an IRP for a perishable product retail chain with stochastic demand to maximize the expected net profit subject to service level constraints. They considered the situation that the unmet demand may lead to lost sales, which is assumed not to generate any other cost. But the assumption was impossible for the BPD in China due to the high demand and low supply of blood products. Moreover, inventory holding cost is a dominant part of the operational cost in

Table 3
Classification of the papers on scheduling of perishable goods.

Reference	Research problem	Cost		Transshipment		Assumptions		Uncertainty	
		inventory	transportation	allowed	not allowed	stock-out	wastage	demand	supply
Or and Pierskalla (1979)	customer assignment & routing		✓		✓				
Gregor et al. (1982)	distribution strategies	✓	✓	✓		✓	✓		
Federgruen et al. (1986)	distribution & routing	✓	✓		✓	✓	✓	✓	
Chew et al. (2014)	pricing & ordering	✓			✓	✓		✓	
Minner and Transchel (2017)	order variability & inventory policies	✓			✓	✓	✓	✓	
Devapriya et al. (2017)	production & distribution		✓		✓				
Musavi and Bozorgi-Amiri (2017)	vehicle scheduling		✓		✓				
Chua et al. (2017)	discounting & replenishment				✓				
Zhang et al. (2018)	inventory & transshipment policies	✓	✓	✓		✓		✓	
Dehghani and Abbasi (2018)	transshipment policies	✓		✓		✓			
Kouki et al. (2018)	inventory policies		✓		✓	✓			
Our study	distribution & routing	✓	✓		✓	✓	✓		

blood distribution, so excluding the inventory holding cost from the operational cost in the blood supply chain is not practical. Similar to Coelho and Laporte (2014), Alvarez et al. (2020) studied an IRP for perishable goods, where products reached the maximum age were kept separately in the inventory system and were discarded in the next period. Four mathematical formulations were introduced to maximize the total profit, which was equal to the sales revenue minus the sum of transportation and inventory holding costs at the supplier and customers. Alvarez et al. (2020) attempted to show the negative influence of perishability on the available inventory, but they did not measure the wastage cost, and the supplier was assumed to be able to fulfill the demands at customers, which indicated stock-out was not allowed.

The above papers investigated the IRP of perishable products, but either assumed no stock-out at the supplier or did not clarify the dominance of the wastage cost and inventory holding cost in blood distribution. Nevertheless, blood shortage is an inevitable concern in China because of seasonal and periodical characteristics of the blood collection. So no existing IRP can be applied to the blood supply chain management in China.

2.3. *Scheduling of perishable goods*

Blood products are perishable. For such products strongly relevant to time, scheduling becomes critical and necessary. Table 3 gives an overview of the literature on the scheduling of perishable goods.

Or and Pierskalla (1979) focused on the transportation location-allocation problem that assigned each hospital to a regional blood center and routed the periodic supply operation and emergency supply, so as to minimize the periodic delivery costs, emergency cost and system cost. Gregor et al. (1982) used a simulation model to analyze the cost and effect of different operational strategies for regional blood centers and found that the periodic redistribution of regional stock would result in a lower blood expiration rate and lower blood shortage rate. But the simulations carried out in four cases with only one element changed, this over-simplification did not clearly illustrate the benefits of combining the inventory and routing dimensions. Federgruen et al. (1986) presented an allocation model for perishable products, which distributed perishable products from a regional center to a group of sites with random demands, and studied the combination of inventory allocation and efficient deliveries to minimize the operating cost, which consisted of shortage cost, out-of-date cost and transportation cost. This paper was based on Federgruen and Zipkin (1984), they considered the influence of expiration, but they did not specify the expiration quantity. Also, shortage cost was measured by extra transportation cost instead of unmet quantity. In order to maximize the total profit of supplying a perishable product, Chew et al. (2014) investigated the optimal prices for products of different ages and the order quantity for a new product, and developed a stochastic dynamic programming model to analyze a case with two periods lifetime. Since substitution among products of different ages was allowed, the stock-out in one product of a certain age could be satisfied by an alternative source with penalty cost. Minner and Transchel (2017) measured the impact of perishability on order variability and bullwhip effect in a two-stage supply chain with stochastic demand, and found that the retailer's order variability was significantly affected by the inventory depletion policy, stock-out management and retailers' service level requirement. Devapriya et al. (2017) analyzed the integrated production and distribution scheduling problem for a perishable product to determine the production sequence, fleet size and optimal delivery routes such that the distribution cost was minimized and demands were fulfilled before the product expired. Musavi and Bozorgi-Amiri (2017) presented a sustainable hub-location vehicle scheduling problem, in which the number of transporters at hub nodes was limited and the perishability of products in a food supply chain was considered. The problem was modeled as a multi-objective mixed integer linear programming to optimize the transportation cost, the freshness of foods and carbon emissions. Chua et al. (2017) studied the discounting and

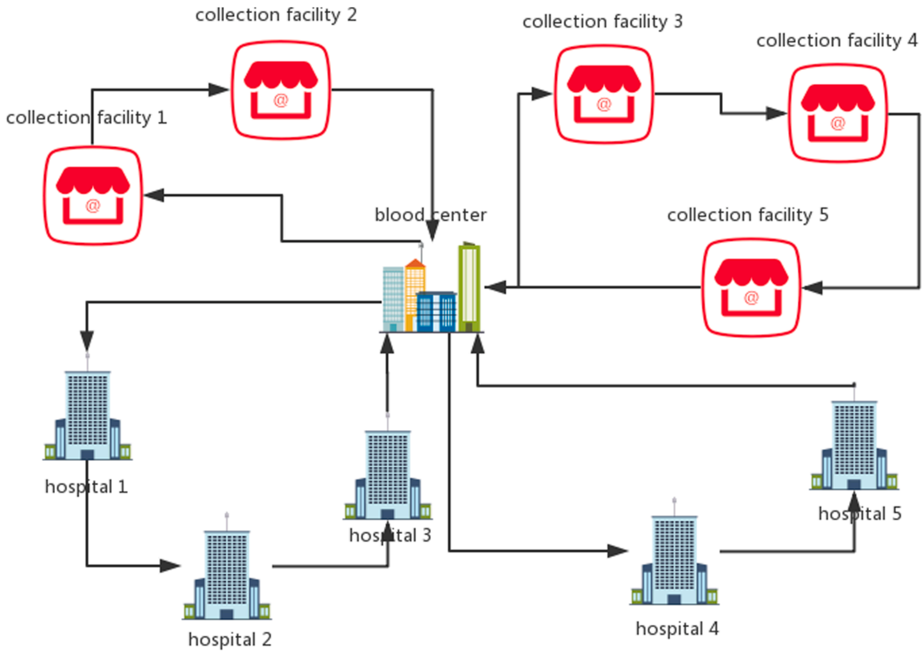


Fig. 1. A sample supply chain for blood products.

Table 4
Notation list.

Sets	
$\mathscr{T}$	Set of time periods within the planning horizon, indexed by t. $\mathscr{T} = \{1, 2, \ldots, T\}$
$\mathscr{N}$	Set of transportation nodes in the region, including the blood center and hospitals served by this blood center, indexed by i and j. Note that $i = 0$ indicates the blood center. $\mathscr{N} = \{0, 1, \ldots, N\}$
$\mathscr{K}$	Set of vehicles available at the blood center, indexed by k. $\mathscr{K} = \{1, 2, \ldots, K\}$
Parameters	
M^t	Maximal quantity of the blood product produced at the blood center in time period t.
z	The shelf life of the blood product.
w	Unit penalty cost for blood wastage.
L_i	Storage capacity of transportation node i, and L_0 represents the storage capacity of the blood center.
u_i^t	Demand of hospital i in time period t.
h_i	Unit inventory holding cost at hospital i and h_0 represents the unit inventory holding cost at the blood center.
e_i^t	Unit penalty cost for blood shortage at hospital i in time period t.
D	Maximum capacity of each vehicle.
c_{ij}	Cost of traveling form hospital i to hospital j or from the blood center to certain hospital, where $i = 0, \ldots, N, j = 0, \ldots, N$. For example, c_{0j} indicates the traveling cost from the blood center to hospital j.
Variables	
Q^t	Inventory of the blood product at the blood center in time period t after receiving the quantity produced in time period $t-1$, allocating the delivered quantity to hospitals and disposing of the expired quantity.
W^t	Quantity of expired blood product at the blood center in time period t.
I_i^t	Inventory level of the blood product at hospital i in time period t after receiving the delivered quantity and usage and $i > 0$
G_i^t	Shortage quantity at hospital i in time period t.
Decision Variables	
p^t	Quantity of the blood product produced at the blood center in time period t.
y_{ik}^t	A binary variable, if hospital i is served by vehicle k in time period $t, y_{ik}^t = 1$; otherwise, $y_{ik}^t = 0$.
d_{ik}^t	Quantity of the blood product delivered to hospital i by vehicle k in time period t.
x_{ijk}^t	A binary variable, if the delivery vehicle k travels from node i to node j in time period $t, x_{ijk}^t = 1$; otherwise, $x_{ijk}^t = 0$.

replenishment policies for a retailer, who sold a perishable product with short shelf-life and uncertain demand, to maximize the expected profit-to-go, the total expected profit from the current period to the end of the planning horizon. Zhang et al. (2018) considered a periodic-review, two-location perishable inventory system, where each location faced a stochastic demand and products could be transshipped between the two locations in each period, and developed a closed-form transshipment policy, which provided a lower bound on the optimal transshipment quantity between the two locations. Dehghani and Abbasi (2018) proposed a new transshipment policy for perishable products based on the age of the oldest items in the system to optimize the inventory cost and product freshness, and they found the transshipment policy was effective under various circumstances, such as lost sale and backlogging. Kouki et al. (2018) focused on the perishable inventory system with two supply modes, a regular mode, and an emergency mode, where the emergency source was used when the regular inventory level reached a threshold level. Given the lifetime distribution of orders, the dual-sourcing could reduce the cost substantially.

Most perishable products, such as fresh vegetables and fruits, are usually managed by the customers themselves, coordinated among customers, or can be transshipped rather freely in the supply chain network. However, blood products in China can only be supplied and managed by the blood center. This fact causes the existing research in the scheduling of perishable products not applicable. In addition, although the above-mentioned papers addressed the influence of the perishability on the scheduling strategies, an effective quantitative measure of the influence is somehow missing. Our research aims to fill in this gap in the literature.

3. Mathematical models

A commodity supply chain usually consists of a group of suppliers, retailers and customers. Herein, we consider a typical blood product supply chain, where the blood center is regarded as the supplier and retailer to determine blood collection and distribution schemes, and hospitals in this region are customers. Fig. 1 illustrates a sample supply chain for blood products with one blood center, several collection facilities and multiple hospitals. As shown, two stages, the collection and distribution stages, are depicted by the upper and lower parts respectively. More specifically, in the collection stage, blood is collected at blood collection facilities with a limited capacity in each time period, and then transported to the blood center. In the center, after a series of tests, qualified blood is used to produce various blood products, such as red cells, plasma and platelets, which are safely stored for future usage. In the distribution stage, blood products are delivered to hospitals according to each individual demand in each time period. According to the regulations regarding blood safety in China, blood products are not allowed to transport directly from collection facilities to hospitals or between hospitals. In this research, we focus on the distribution stage, aiming to optimize the time-based blood delivery scheme that reduces the total operational cost on a rolling horizon from the perspective of the blood center. The length of the rolling horizon is determined based on the shelf life of the blood product. The basic assumptions of our model are discussed next, and the notation list is presented in Table 4.

3.1. Assumptions

Blood needs to be tested and processed before being produced into blood products, so we assume the age of blood products entering the blood center inventory system is one-day-old and the blood products produced in current period are unavailable until the next period. Therefore, we define the inventory in the blood center in period t as the total quantity after receiving the quantity produced in period $t-1$, allocating the delivered quantity to hospitals, and disposing of the expired quantity. Hence, we have:

$$Q^t = Q^{t-1} + p^{t-1} - \sum_{i=1}^{N}\sum_{k=1}^{K} d_{ik}^t - W^t \quad \forall t \in \mathscr{T}$$

And we assume the initial inventory at the blood center at the beginning of the first rolling horizon is zero.

Another special issue in the blood product supply chain is about the limited shelf life. So before we establish the vendor-managed inventory routing model, we need to calculate the expired quantity in each time period. Without loss of generality, we assume that expiration can only occur at the blood center. This is because the blood product is transported from the center to hospitals according to the amount of outstanding demand. Note that additional demand may be raised during the day, which leads to the shortage issue that will be discussed next. For a specific blood product with a shelf life of z periods, the group of products that expire in period t is those being produced in period $t-z$. Consider the inventory of this product at the blood center in period $t-z, Q^{t-z}$, which contains the leftover inventory from previous periods plus the newly produced products of that period. As time goes on, Q^{t-z} is gradually moved out of the system, either through deliveries to hospitals (following a *first-in-first-out* (*FIFO*) policy) or being disposed of because of expiration. Util time period t, the remaining quantity from period $t-z$ (if there is any) is marked as "*expired*" since the expiration date is reached. Introducing a non-negative variable W^t, we can compute the expired quantity in period t as:

$$W^t = \begin{cases} \left[Q^{t-z} - \sum_{s=t-z+1}^{t-1}\sum_{i=1}^{N}\sum_{k=1}^{K} d_{ik}^s - \sum_{s=t-z+1}^{t-1} W^s\right]^+ & \forall\ z \leqslant t < T \\ 0 & \forall\ 0 < t < z \end{cases}$$

Linearizing the above equation, we have

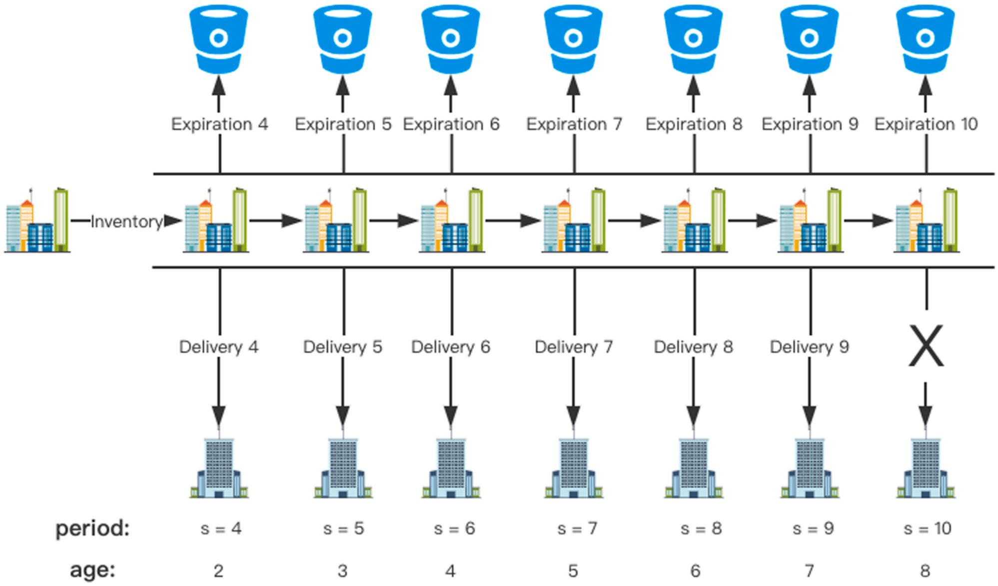


Fig. 2. A demonstration for the inventory allocation at the blood center.

$$\begin{cases} W^t \geqslant Q^{t-z} - \sum_{s=t-z+1}^{t-1} \sum_{i=1}^{N} \sum_{k=1}^{K} d_{ik}^s - \sum_{s=t-z+1}^{t-1} W^s & \forall\ z \leqslant t < T \\ W^t = 0 & \forall\ 0 < t < z \end{cases}$$

Here, we take platelets as an example. Given the shelf life of platelets is 7 days and based on the above assumption, the platelets produced in period 3 are 1-day-old, which are the youngest among the total inventory at the blood center in period 3. In time period 10, the youngest group among the platelets from time period 3 are 8-day-old, which can only be disposed of. Therefore, under the *FIFO* policy, in period 10, the total inventory in period 3 is zero. According to the inventory flow in Fig. 2, where "Expiration 4" represents the expired quantity in time period 4, "Delivery 4" represents the total delivered quantity in time period 4, and "X" means that in time period 10, the remaining quantity of the total inventory in period 3 can not be transported to hospitals since the expiration date is reached, we have:

$$\sum_{s=4}^{9} \sum_{i=1}^{N} \sum_{k=1}^{K} d_{ik}^s + \sum_{s=4}^{10} W^s \geqslant Q^3.$$

So, we can easily get the expired quantity at period 10 as

$$W^{10} \geqslant Q^3 - \sum_{s=4}^{9} \sum_{i=1}^{N} \sum_{k=1}^{K} d_{ik}^s - \sum_{s=4}^{9} W^s.$$

As mentioned before, we consider shortage in the blood product inventory routing model, so an appropriate penalty cost should be defined to signify the influence caused by shortage. As long as the demand at hospitals is not met by the existing inventory, penalty cost is generated, and this penalty cost is proportional to the unsatisfied demand. Introducing a non-negative variable G_i^t, we can calculate the shortage quantity at hospital i in time period t as:

$$G_i^t = [u_i^t - I_i^t]^+,$$

which indicates that, if $u_i^t - I_i^t > 0$, we have $G_i^t = u_i^t - I_i^t$, otherwise $G_i^t = 0$. Linearizing the above equation, we have

$$G_i^t \geqslant u_i^t - I_i^t$$

Then, the penalty cost can be computed as $\sum_{t=0}^{T} \sum_{i=1}^{N} e_i^t G_i^t$.

Besides the above assumptions about inventory, some general constraints about routing should be clarified. In each time period, each hospital can only be served by one delivery vehicle, and each vehicle can serve each hospital at most once. Moreover, vehicles are homogeneous, which means that each vehicle has the same feature, such as capacity and equipment.

3.2. The model

[P]

$$\min\sum_{t=1}^{T}(h_0Q^t+\sum_{i=1}^{N}h_iI_i^t)+\sum_{t=1}^{T}wW^t+\sum_{t=1}^{T}\sum_{i=1}^{N}e_i^tG_i^t++\sum_{t=1}^{T}\sum_{i=0}^{N}\sum_{j=0}^{N}\sum_{k=1}^{K}c_{ij}x_{ijk}^t \tag{1}$$

Subject to:

$$p^t\leqslant M^t\forall t\in\mathscr{T} \tag{2}$$

$$Q^t=Q^{t-1}+p^{t-1}-\sum_{i=1}^{N}\sum_{k=1}^{K}d_{ik}^t-W^t\forall t\in\mathscr{T} \tag{3}$$

$$W^t\geqslant Q^{t-z}-\sum_{s=t-z+1}^{t-1}\sum_{i=1}^{N}\sum_{k=1}^{K}d_{ik}^s-\sum_{s=t-z+1}^{t-1}W^s\forall z\leqslant t<T \tag{4}$$

$$W^t=0\forall 0<t<z \tag{5}$$

$$Q^t\leqslant L_0\forall t\in\mathscr{T} \tag{6}$$

$$I_i^t=I_i^{t-1}+\sum_{k=1}^{K}d_{ik}^{t-1}-u_i^{t-1}\forall i\in\mathscr{N},i\neq 0;t\in\mathscr{T} \tag{7}$$

$$I_i^t\leqslant L_i\forall i\in\mathscr{N},i\neq 0;t\in\mathscr{T} \tag{8}$$

$$G_i^t\geqslant u_i^t-I_i^t\forall i\in\mathscr{N},i\neq 0;t\in\mathscr{T} \tag{9}$$

$$\sum_{k=1}^{K}y_{ik}^t\leqslant 1\forall i\in\mathscr{N},i\neq 0;t\in\mathscr{T} \tag{10}$$

$$\sum_{k=1}^{K}y_{0k}^t=K\forall t\in\mathscr{T} \tag{11}$$

$$d_{ik}^t\leqslant L_iy_{ik}^t\forall i\in\mathscr{N},i\neq 0;k\in\mathscr{K};t\in\mathscr{T} \tag{12}$$

$$\sum_{i=1}^{N}\sum_{k=1}^{K}d_{ik}^t\leqslant Q^t\forall t\in\mathscr{T} \tag{13}$$

$$\sum_{i=0,i\neq j}^{N}x_{ijk}^t=y_{jk}^t\forall j\in\mathscr{N};k\in\mathscr{K};t\in\mathscr{T} \tag{14}$$

$$\sum_{j=0,j\neq i}^{N}x_{ijk}^t=y_{ik}^t\forall i\in\mathscr{N};k\in\mathscr{K};t\in\mathscr{T} \tag{15}$$

$$\sum_{i=1}^{N}d_{ik}^t\leqslant D\forall k\in\mathscr{K};t\in\mathscr{T} \tag{16}$$

$$\sum_{i\in S}\sum_{j\in S}x_{ijk}^t\leq\left|S\right|-1\forall S\subseteq\left\{\mathscr{N}\setminus 0\right\},\left|S\right|\geq 2;k\in\mathscr{K};t\in\mathscr{T} \tag{17}$$

$$p^t\geqslant 0\forall t\in\mathscr{T} \tag{18}$$

$$W^t\geqslant 0\forall t\in\mathscr{T} \tag{19}$$

$$G_i^t\geqslant 0\forall i\in\mathscr{N},i\neq 0;t\in\mathscr{T} \tag{20}$$

$$d_{ik}^t\geqslant 0\forall i\in\mathscr{N},i\neq 0;k\in\mathscr{K};t\in\mathscr{T} \tag{21}$$

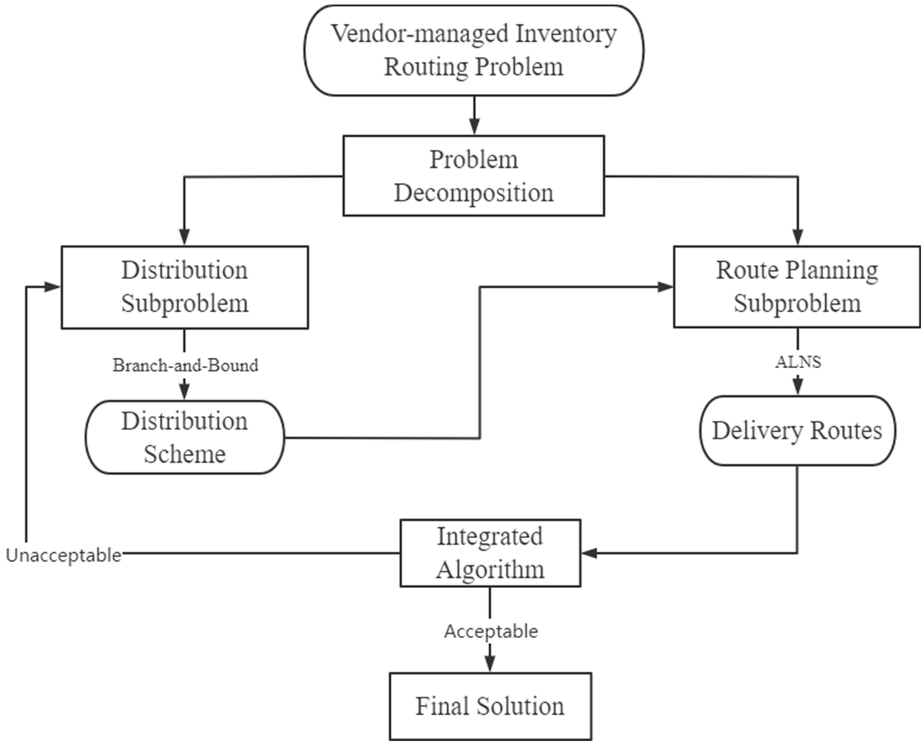


Fig. 3. The flowchart of algorithm design.

$$y_{ik}^{t} \in \{0,1\} \forall i \in \mathscr{N}; k \in \mathscr{K}; t \in \mathscr{T} \tag{22}$$

$$x_{ijk}^{t} \in \{0,1\} \forall i,j \in \mathscr{N}; k \in \mathscr{K}; t \in \mathscr{T} \tag{23}$$

Objective function (1) is to minimize the total cost of the inventory holding cost at the blood center and hospitals, wastage cost, shortage cost and transportation cost during the planning horizon. Constraints (2) are the blood collection limit. Constraints (3)–(6) are related to the inventory of the blood product at the blood center. Specifically, constraints (3) are the inventory balance at the blood center. Constraints (4) and (5) calculate the quantity of expired blood product. Constraints (6) guarantee that the inventory at the blood center never exceeds its storage capacity. Constraints (7)–(9) are related to the inventory of the blood product at each hospital. More specifically, constraints (7) ensure inventory balance at each hospital. Constraints (8) guarantee that the inventory at each hospital never exceeds its storage capacity. Constraints (9) define the shortage quantity at each hospital. Constraints (10)–(17) are related to the vehicle routing. To be more specific, constraints (10) imply that the hospital which is planned to be visited, is served by only one vehicle. Constraints (11) ensure that the number of dispatched vehicles is equal to the number of available vehicles at the blood center. Constraints (12) indicate that a positive delivery quantity occurs only when a hospital is visited. Constraints (13) guarantee that the total quantity of the blood product delivered to hospitals is available in the blood center. Constraints (14) and constraints (15) are the inflow balance and outflow balance, respectively. Constraints (16) are the capacity restriction for each vehicle. Constraints (17) guarantee the connectivity of the vehicle routes. Constraints (18)–(23) give the domains of decision variables.

4. Algorithm design

The inventory routing problem is usually very difficult to solve, and there is no exact algorithm capable of solving any type of inventory routing problem of reasonable size (Archetti et al., 2007). For our model presented in the previous section, Gurobi can only solve the 10-hospital case in an average of approximately 1800 s (over 10 random instances). When the number of hospitals reaches 20, random instances cannot be solved within 2 h. In this section, we introduce and explain a decomposition approach specially designed for the proposed mathematical model.

4.1. Problem decomposition

As one of the mostly applied methods for inventory routing models (Archetti et al., 2007), the decomposition approach decomposes the original problem to subproblems, which are smaller and easier to solve, and solutions to the original problem are obtained from the solutions to the subproblems. So by solving a series of small-scale problems, we avoid dealing with the large-scale problem, whose solution can be very hard to be found within a limited time. Hence, the efficiency of obtaining the optimal solution can be improved significantly. This approach has been implemented by many scholars, such as Dror et al. (1985), Campbell and Savelsbergh (2004), Absi et al. (2015) and Chitsaz et al. (2019).

Specifically in our case, we decompose the original problem into two subproblems, one to allocate inventory to hospitals (distribution subproblem [SP-D]); another one searching the optimal delivery routes (route planning subproblem [SP-R]). Then a branch-and-bound algorithm and an adaptive large neighborhood search algorithm are proposed to solve the subproblems sequentially. Ultimately, an integrated algorithm is used to obtain the solutions to the original problem from the solutions to the subproblems. Fig. 3 shows the overall procedure of this decomposition approach.

4.2. Distribution subproblem

In model [P], inventory allocation and route planning are solved simultaneously, which incorporates the influence of vehicle routes on the distribution schedule. So in order to retain the connection between the distribution subproblem and route planning subproblem, we use a transportation cost factor to guide the distribution subproblem to allocate inventory to hospitals with consideration of the influence of the transportation cost. Therefore, the objective of the distribution subproblem is to minimize the inventory holding cost, wastage cost, shortage cost and path-related transportation cost over the planning horizon.

[SP-D]

$$\min\sum_{t=1}^{T}(h_0Q^t+\sum_{i=1}^{N}h_iI_i^t)+\sum_{t=1}^{T}wW^t+\sum_{t=1}^{T}\sum_{i=1}^{N}e_i^tG_i^t+\sum_{t=1}^{T}\sum_{i=1}^{N}f_iR_i^t \tag{24}$$

Subject to:

$$(2), (5), (6), (8), (9), (18), (19), (20)$$

$$Q^t = Q^{t-1}+p^{t-1}-\sum_{i=1}^{N}d_i^t - W^t \quad \forall t\in\mathscr{T} \tag{25}$$

$$W^t \geqslant Q^{t-z}-\sum_{s=t-z+1}^{t-1}\sum_{i=1}^{N}d_i^s-\sum_{s=t-z+1}^{t-1}W^s \forall z\leqslant t<T \tag{26}$$

$$\sum_{i=1}^{N}d_i^t\leqslant Q^t \forall t\in\mathscr{T} \tag{27}$$

$$d_i^t\leqslant L_iR_i^t \forall i\in\mathscr{N}, i\neq 0; t\in\mathscr{T} \tag{28}$$

$$R_i^t\in\{0,1\}\forall i\in\mathscr{N}, i\neq 0; t\in\mathscr{T} \tag{29}$$

$$d_i^t\geqslant 0 \forall i\in\mathscr{N}, i\neq 0; t\in\mathscr{T} \tag{30}$$

where R_i^t indicates whether the blood center supplies blood products to hospital i in time period t or not. If hospital i is visited in time period t,$R_i^t=1$; otherwise, $R_i^t=0$. d_i^t is the quantity distributed to hospital i in time period t. A service from the blood center to hospital i generates a fixed path-related transportation cost f_i.

The distribution subproblem, which is modeled as mixed integer linear programming, can be solved by exact algorithms embedded in mathematical programming optimizers. And by solving the distribution subproblem, we can obtain the quantity of the blood product transported to each hospital in each time period. Given the distribution quantity in each period, the inventory routing problem is equivalent to a multi-period vehicle routing problem.

4.3. Route planning subproblem

The route planning subproblem with the objective of minimizing the transportation cost is a large-scale combinatorial optimization problem defined as follows.

[SP-R]

$$\min\sum_{t=1}^{T}\sum_{i=0}^{N}\sum_{j=0}^{N}\sum_{k=1}^{K}c_{ij}x_{ijk}^t \tag{31}$$

Subject to:

$$(10)-(17), (21)-(23)$$

Note that this subproblem is a multi-period capacitated vehicle routing problem (CVRP), which is *NP* hard in nature. Since the feasible region of the route planning subproblem is much bigger than that of CVRP, the widely applied methods for CVRP are not suitable for the route planning subproblem. For example, Wang et al. (2016) modified an ant colony optimization searching technique to solve CVRP, but the novel algorithm was only applicable to CVRP with a few computational limitations. Introduced by Pisinger and Ropke (2010), the adaptive large neighborhood search (ALNS) algorithm employs multiple destroy and repair operators to expand the searching neighborhood, thus this method is widely used in solving various transportation and scheduling problems. Examples include Muller et al. (2012), Belo-Filho et al. (2015), and Liu et al. (2019), among others. Algorithm 1 presents the ALNS algorithm applied to solve [SP-R] in the inventory routing problem.

Algorithm 1. Adaptive Large Neighborhood Search Algorithm

Input: initial feasible solution X
Output: the optimal solution X^*
1: Set the initial feasible solution as the optimal solution: $X^* = X$
2: Initialize the weights of destroy operators and repair operators: $\alpha^- = (1, \ldots, 1); \alpha^+ = (1, \ldots, 1)$
3: **repeat**
4: Based on weights α^- and α^+, select a pair of destroy operator D and repair operator R from the destroy operator set Ω^- and repair operator set Ω^+
5: Recall the destroy operator $D(X)$ and repair operator $R(X)$ in step 4 to obtain a new solution: $X^t = R(D(X))$.
6: **if** acceptance criteria are met **then**
7: $X = X^t$
8: **end if**
9: Calculate the objective of the new solution: $c(X^t)$
10: **if** $c(X^t) < c(X^*)$ **then**
11: $X^* = X^t$
12: **end if**
13: Update α^- and α^+
14: **until** stopping criteria are met

The basic idea of the ALNS algorithm is to find the optimal solution or near-optimal solution by neighborhood searching. Here, neighborhoods are implicitly defined by a set of destroy operators and a group of repair operators. At first, the weights of destroy operators and repair operators are initialized. And in the neighborhood search process, there are six critical procedures. First, based on the weights and roulette selection mechanism, a destroy operator D and a repair operator R are selected. Second, the destroy operator D is used to destroy a part of the current solution. Third, the repair operator R is used to reconstruct the solution destroyed by the destroy operator D. That is, by applying the destroy and repair operators, a new solution X^t is reached. Then, compare the objectives of the new solution and the current solution to determine whether to accept this new solution in the searching path or not. After that, based on the quality of the new solution, update the weights of the destroy operator D and the repair operator R. At last, check the stopping criteria to see if there is the need to make more searching. And we elaborate more on those critical procedures in the following parts.

4.3.1. Destroy operators

The destroy operator is employed to destroy the current solution and expand the search neighborhood of the current solution. The input parameters of the destroy operator are the current solution and an integer variable, which indicates the destructive degree of the solution, for example, if there are 30 nodes in the transportation network, an integer 10 means that around 30% of the nodes are deleted by the destroy operator. And the output is a part of the solution where some demand nodes have been removed. We adopt random removal, correlation removal and critical removal to destroy the solution when designing destroy operators.

Random removal is the most straightforward destroy operator, which randomly selects a part of the demand nodes and removes them from the current solution. Correlation removal is to remove some similar demand nodes since it is easier to get a better solution by removing similar demand nodes. On the contrary, if nodes with quite different demands are removed, the better solution may not be obtained when re-inserting the demand nodes, because these demand nodes can only be put back to the original position or the wrong position, resulting in infeasible solutions. And we define the correlation of two demand nodes as the difference of the distance and the distribution quantity between two demand nodes. A more complicated destroy operator is the critical removal, which is to remove some demand nodes with very high service cost, and insert these demand nodes into other locations in the repair phase to obtain a better solution.

4.3.2. Repair operators

In ALNS, various insertion heuristic algorithms are used as repair operators. Repair operators are mainly based on the greedy strategy and regret strategy.

The greedy strategy is to constantly insert demand nodes into the cheapest path. More specifically, let ΔC_{ik} denote the increase of the objective caused by inserting a demand node i at the lowest cost position in path k. If the demand node cannot be inserted into the path, then $\Delta C_{ik} = \infty$. Each iteration selects a pair of (i, k) with the minimal ΔC_{ik} and inserts the demand node i into path k at the lowest cost position. The iteration is repeated until all the demand nodes are inserted or new solutions are infeasible when inserting the next demand point.

Based on the regret value generated by not performing the current operation, regret strategy chooses to insert the demand node with the greatest regret value firstly. More specifically, let x_{ik} denote the path with the k lowest insertion cost of demand node i, and based on this concept, a *k-regret* strategy is defined. The regret value of *k-regret* strategy is defined as $\max_i\{\sum_{j=1}^{k}(\Delta C_{i,x_{ij}} - \Delta C_{i,x_{i1}})\}$. In our algorithm, we adopt a 2-*regret* strategy, which is expressed as the cost difference between inserting the demand point into the optimal path and the sub-optimal path. The formulation for the 2-*regret* strategy is $\max_i\{\Delta C_{i,x_{i2}} - \Delta C_{i,x_{i1}}\}$.

4.3.3. Update weights and select operators

The weights of destroy and repair operators are dynamically adjusted based on the performance of the operators in the previous iteration process. The performances of the destroy and repair operators used in this iteration are measured according to

$$\psi = \max\left\{\begin{array}{l} \omega_1 \text{ if the new solution is optimal} \\ \omega_2 \text{ if the new solution is better than the current one} \\ \omega_3 \text{ if the new solution is accepted} \\ \omega_4 \text{ if the new solution is rejected} \end{array}\right\},$$

where $\omega_1 \geqslant \omega_2 \geqslant \omega_3 \geqslant \omega_4$. The above formulation indicates that a greater ψ means better performance of the pair of destroy and repair operators. Based on the performance computation of each operator, the weight of each operator is updated dynamically according to

$$\alpha_i^- = \lambda\alpha_i^- + (1-\lambda)\psi, \quad \alpha_i^+ = \lambda\alpha_i^+ + (1-\lambda)\psi, \quad \lambda \in [0,1].$$

Then, the ALNS algorithm expresses the probability of operator selection based on the following calculations.

$$\phi_i^- = \frac{\alpha_i^-}{\sum_{k=1}^{|\Omega^-|}\alpha_k^-}, \quad \phi_i^+ = \frac{\alpha_i^+}{\sum_{k=1}^{|\Omega^+|}\alpha_k^+}.$$

Finally, the destroy and repair operators of the next iteration are selected based on the updated weights and the roulette selection mechanism commonly used in the genetic algorithm, where the operators with higher weights are more likely to be selected as the next ones. More designing details about the roulette selection mechanism are given in Lipowski and Lipowska (2012).

4.3.4. Acceptance and stopping criteria

In the process of neighborhood search, the acceptance criteria of solutions affect the efficiency of the algorithm. The most straightforward acceptance criterion is to accept only solutions that are better than the current solution. However, this may lead the neighborhood search to the local minimum, which reduces solving efficiency. So we adopt the acceptance criterion in the simulated annealing algorithm discussed in Van Laarhoven and Aarts (1987), that is, to accept the neighborhood solution which is not as good as the current solution with a certain probability, to reduce the risk of being stuck in the local minimum. The stopping criteria include finding the optimal feasible solution, reaching the maximum number of iteration or reaching the limited computational time. At the end of each iteration, check the stopping criteria to determine whether any termination condition is satisfied. If it is satisfied, the algorithm stops and outputs the current optimal solution.

4.3.5. The integrated algorithm

Note that a simple combination of subproblem solutions may not be optimal. So we need to design a procedure to integrate the two subproblem solutions and search for the optimal final solution. More specifically, the basic rule of such an integrated algorithm design is to retrieve another distribution scheme based on the current routes and search new routes for the new distribution scheme, iteratively. The framework of the integrated algorithm is presented in Algorithm 2.

Algorithm 2. Integrated Search Algorithm

Input: $S = (s_1, s_2)$, where s_1 and s_2 are the solutions respectively to the distribution and route planning subproblems.
Output: the optimal solution to the original VMIRP S^*

```
Set the initial feasible solution as the optimal solution: S* = S
Update the transportation cost factor proposed in the distribution subproblem based on s_2
repeat
    Solve the distribution subproblem, and thus to obtain a new distribution scheme s_1^t
    Solve the route planning subproblem based on the new distribution scheme s_1^t, and thus to obtain new routes s_2^t
    S^t = (s_1^t, s_2^t)
    Calculate the objective of the new solution: c(S^t)
    if c(S^t) < c(S*) then
        S* = S^t
        Update the transportation cost factor proposed in the distribution subproblem based on the new routes s_2^t
    end if
until Reaching the maximal computational time or the maximal number of iterations without improvement
```

First, by solving the distribution subproblem and the route planning subproblem sequentially, we obtain the initial distribution scheme s_1 and the primary routes s_2, which are regarded as the initial solution to the VMIRP. Then based on the current routes, update

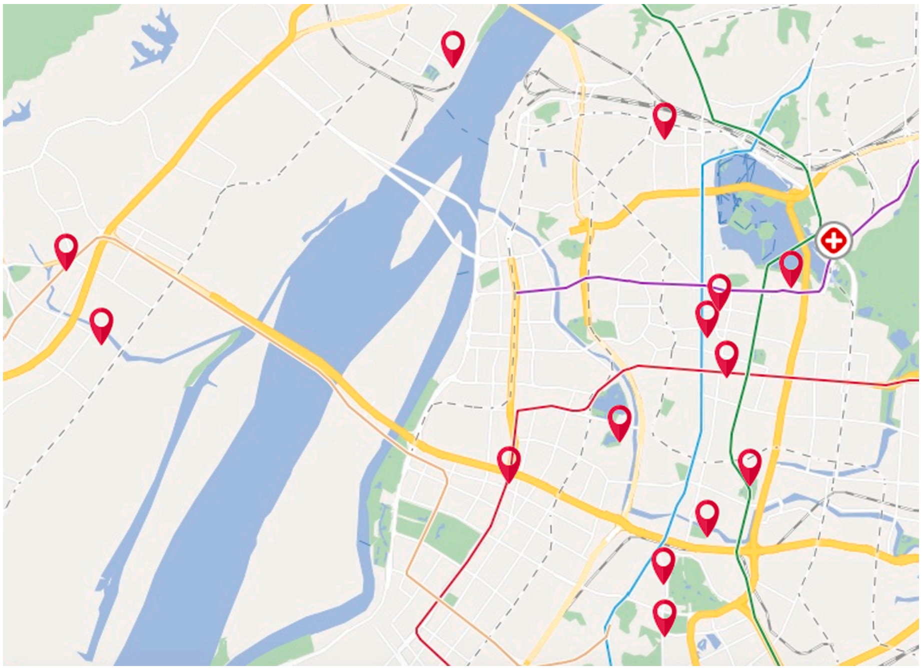


Fig. 4. A platelets distribution network.

Table 5
The comparison of performances between the original scheme and VMIRP.

# of hospitals	Performance	Original	VMIRP	Improvement
10	inventory holding cost	11572.06	6836.46	40.92%
	service level	100%	99.69%	−0.31%
	transportation cost	1450.42	408.98	71.80%
	wastage ratio	0.00%	34.27%	−34.27%
	total cost	13022.48	10653.04	18.20%
20	inventory holding cost	8126.26	6136.66	24.48%
	service level	100%	99.79%	−0.21%
	transportation cost	3023.39	668.32	77.89%
	wastage ratio	0.00%	19.75%	−19.75%
	total cost	11149.66	8778.19	21.27%
30	inventory holding cost	4769.66	5598.36	−13.18%
	service level	99.19%	98.46%	−0.74%
	transportation cost	5421.61	1374.44	74.65%
	wastage ratio	0.00%	5.80%	−5.80%
	total cost	10301.35	7555.2	26.66%
40	inventory holding cost	1742.46	2612.86	−49.95%
	service level	53.08%	51.88%	−2.24%
	transportation cost	6147.45	1644.74	73.25%
	wastage ratio	0.00%	0.00%	0.00%
	total cost	15570.12	12132.60	22.08%

the transportation cost factor proposed in the distribution subproblem to determine the new distribution scheme s_1^t. Given the new distribution scheme s_1^t, solve the route planning subproblem to generate new routes s_2^t and calculate the total cost of the new solution $S^t = (s_1^t, s_2^t)$. If the objective value of the new solution S^t is less than the previous optimal solution S^*, update S^* by S^t and update the transportation cost factor in the distribution subproblem. This search procedure is conducted iteratively until the maximal computational time or the maximal number of iterations without improvement is reached.

5. Computational results

In this section, we first compare the operational cost of blood product distribution under the VMIRP policy with the original

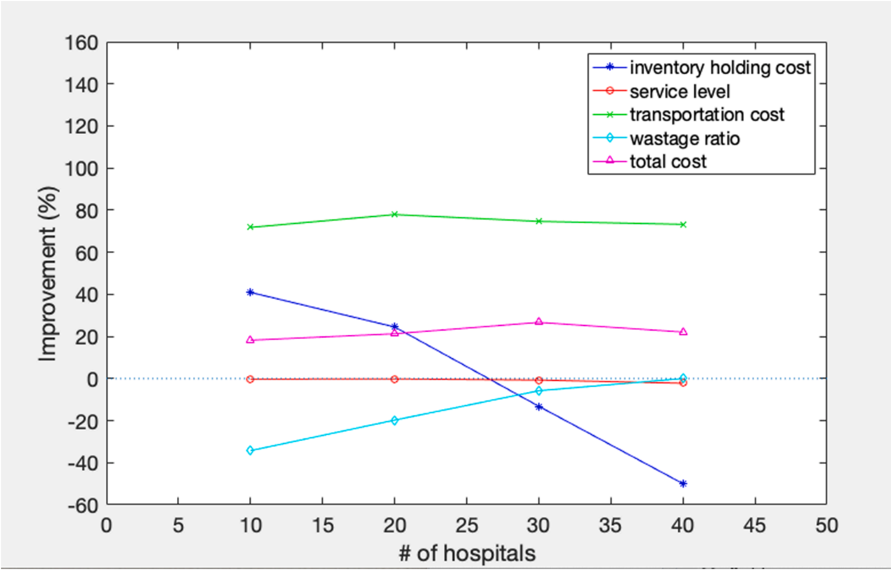


Fig. 5. Changes of the key performance measures.

scheme. Then we show the sensitivity analyses on key parameters, such as maximal production capacity, unit penalty cost for shortage and expiration and demand variation, to name a few.

5.1. Data

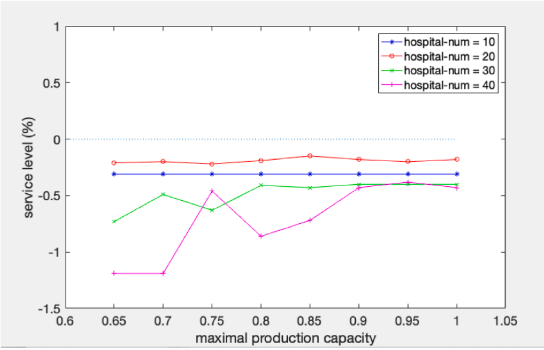
Our experiments are based on the real platelet distribution in the city of Nanjing, China. With an administrative area of 6,600 square kilometer and a total population of 8,270,500, Nanjing has 3 blood centers and 120 hospitals, but only 40% have the demand for platelets. In the present experiments, we consider the largest blood center located in the downtown area. This blood center (denoted by the red cross symbol) and the 16 hospitals covered by it are depicted in Fig. 4. Note that all data have been processed for confidentiality concerns. Given that the shelf life of platelets is 7 days, we herein take 12 days as our planning horizon. Since a 12-day period is long enough to show the influence of the perishable nature of platelets. In practice, a longer period can be used according to actual situations. Also, maximum platelet storage capacity at each hospital is set to be twice of the average demand to balance the supply and demand. The daily usage at hospitals is computed through the monthly consumption. The cost of traveling is estimated at 0.57 CNY per kilometer. For the base case, we estimate $M_t = 0.65, h_0 = 0.2, h_i = 0.3, w = 0.6$ and $e_i^t = 1$.

We use Gurobi Optimizer 8.1.1 and Python programming language to code the mixed integer linear programming and algorithms on a computer with a 3.20 gigahertz Intel-Core i7–8700 processor and 32 gigabytes of RAM, running the Windows operating system. The proposed decomposition-based algorithm is able to provide solutions to 10-, 20-, 30-, and 40-hospital cases in approximately 14, 60, 210, and 370 s, respectively.

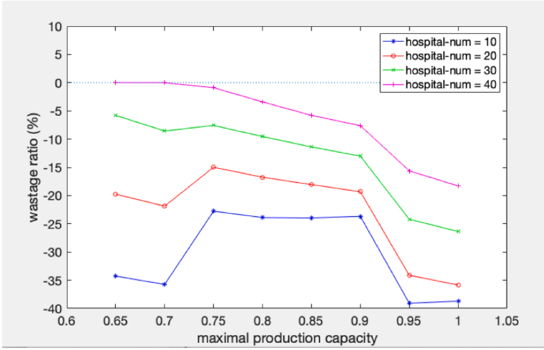
5.2. Overall performance

Herein, we aim to illustrate that the distribution scheme under the VMIRP policy can significantly reduce the operational cost. Table 5 compares the performances of the original scheme and the results from our proposed VMIRP approach, and Fig. 5 shows the changes in the inventory holding cost, service level, transportation cost, wastage ratio and total cost, respectively. The original scheme represents the situation without optimization, where the blood center directly distributes platelets according to every single hospital's order.

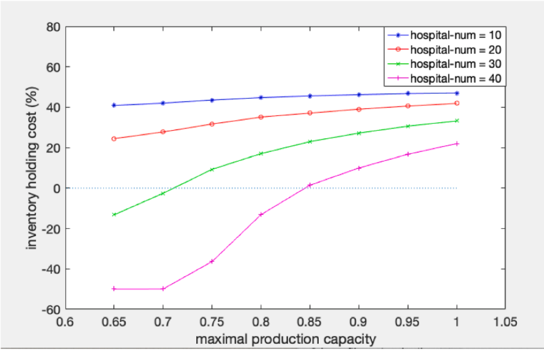
In the 10- and 20-hospital cases, the platelet quantity in the blood center is relatively sufficient. The VMIRP approach can reduce the total cost by reducing inventory holding and transportation costs significantly with keeping a 99.7% service level (percentage of demand fulfilled). But the wastage cost becomes higher, as sufficient inventory may lead to the abandonment of redundant platelets. With the expansion of the supply network (30- and 40-hospital cases), platelets becomes insufficient. So the wastage ratio converges to zero. The blood center can benefit from the VMIRP strategy by balancing the inventory holding cost and transportation cost. If the transportation cost is higher than the inventory holding cost, the blood center will distribute more platelets to the hospital at the last delivery rather than organize another distribution trip to that hospital; otherwise, the blood center prefers to conduct another delivery. This means that, under the VMIRP strategy, one delivery of platelets may cover the demand in two or more time periods, thus decreasing the frequency of delivery and then the transportation cost. Consequently, VMIRP outperforms the original scheme, especially when the platelets supply is insufficient. As shown in Table 5, VMIRP can give an average cost improvement for approximately 22% across all cases.



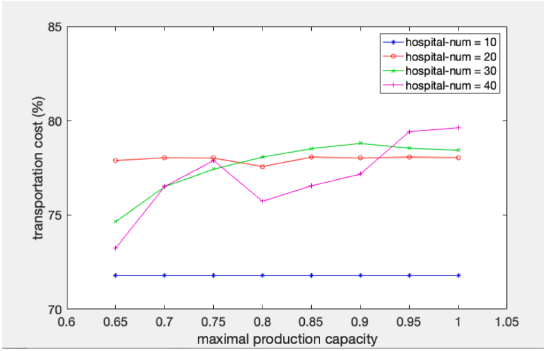
(a) Service level



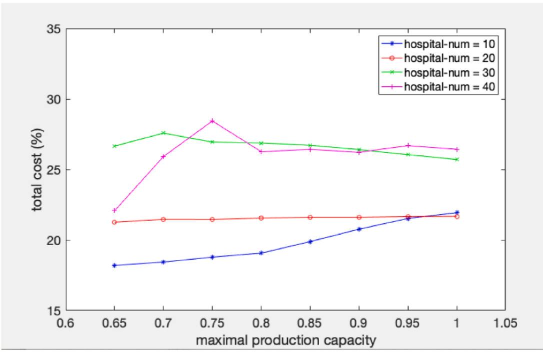
(b) Wastage ratio



(c) Inventory holding cost



(d) Transportation cost



(e) Total cost

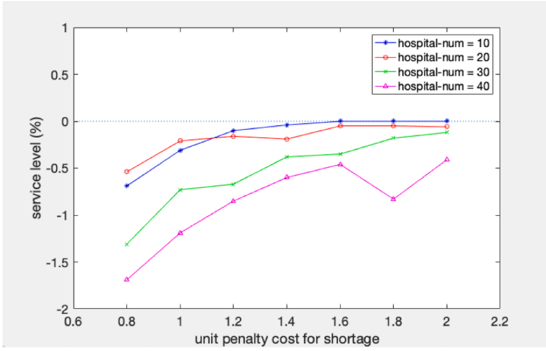
Fig. 6. Performance comparison with different maximal production capacities.

5.3. Sensitivity analyses

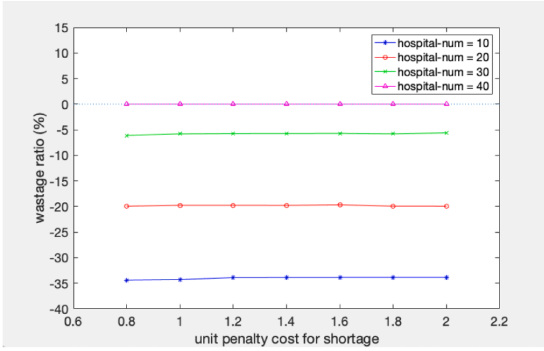
A series of sensitivity analyses is conducted based on the key parameters, namely the maximal production capacity at the blood center, unit penalty costs respectively for shortage and wastage, demand variation, average unit inventory holding cost and unit transportation cost. By varying the values of these parameters, we aim to test the corresponding influences on the main performance indicators: the service level, wastage ratio (percentage of products being abandoned due to expiration), inventory holding cost, transportation cost and total cost. To be specific, the influences are illustrated through the change ratios of the indicators computed by *[(Original Results – VMIRP Results)/Original Results]* $\times$ 100%. Note that as there may be no shortage or wastage in the original case, the comparisons of service level and wastage ratio are based on the result difference of the two schemes.

5.3.1. Maximal production capacity

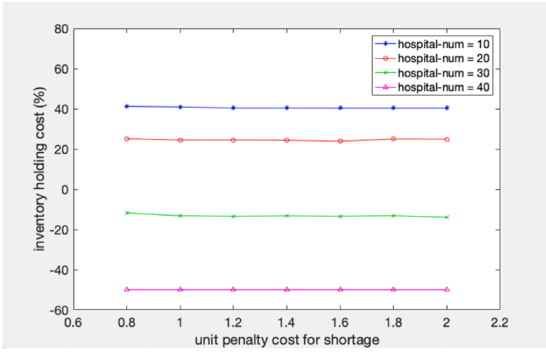
Fig. 6 illustrates the performance improvements due to employing the VMIRP scheme under different maximal production capacities, where the x-axises give the maximal production capacity ranging from 0.65 to 1.0, and the y-axises are the change ratios of



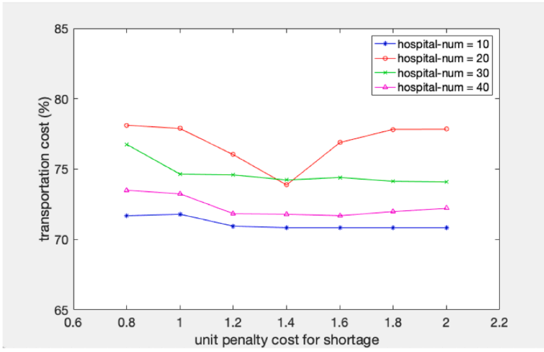
(a) Service level



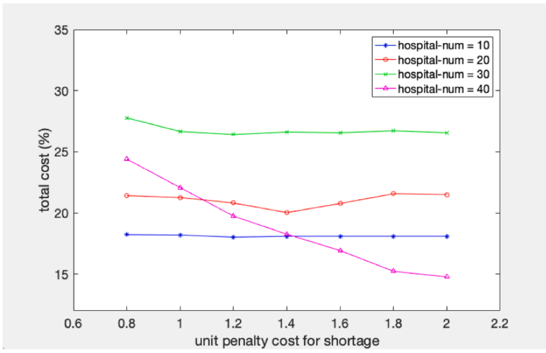
(b) Wastage ratio



(c) Inventory holding cost



(d) Transportation cost



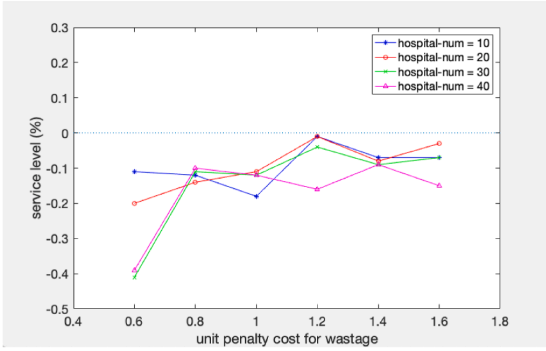
(e) Total cost

Fig. 7. Performance comparison with different unit penalty costs for shortage.

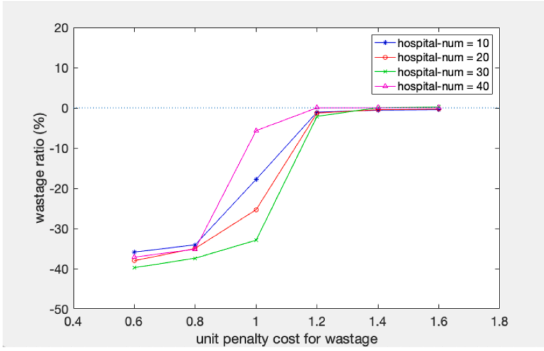
various indicators.

Observing Fig. 6(a), we notice that the service level is lower under the VMIRP scheme. This is because VMIRP tries to find the most cost-efficient solution, which sacrifices the service level. Specifically for the 10-hospital network, this difference in service level is more obvious because no shortage exists under the original scheme when the network is small enough, and large transportation cost for distant hospitals avoids deliveries to those hospitals. When 10 more hospitals are included, VMIRP can cluster similar hospitals and arrange deliveries accordingly, hence the service level may increase depending upon the network structure. Moreover, as the maximal production quantity (i.e., the supply of platelets) increases, the change of service level for small networks is relatively stable, but the service level for large networks improves dramatically. Hence, we can conclude that the amount of supply has higher impact on larger networks.

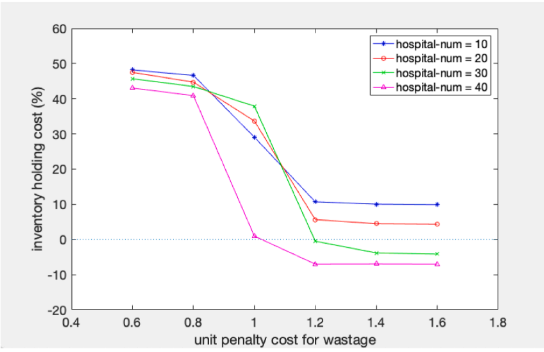
Fig. 6(b) shows that VMIRP overall causes more wastage than the original scheme, since VMIRP may abandon the redundant platelets before expiration to reduce inventory holding cost. With the expansion of the maximal production capacity, the amount of platelets being disposed of first decreases then increases. This trend is more obvious in small-network cases. It is intuitive to see higher wastage at a sufficient production quantity: exceeded supply leads to more platelets expired in the inventory. However, when the



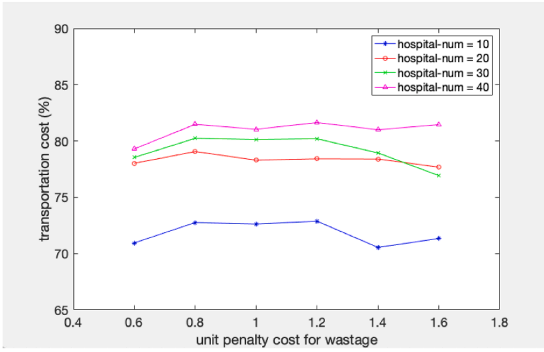
(a) Service level



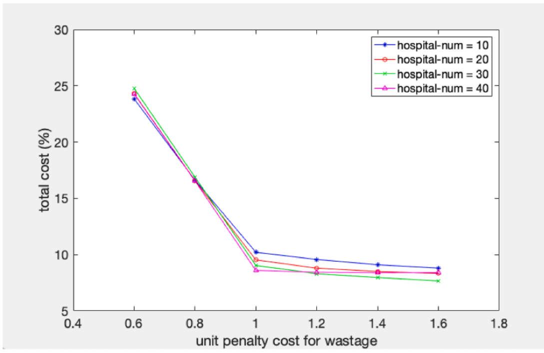
(b) Wastage ratio



(c) Inventory holding cost



(d) Transportation cost

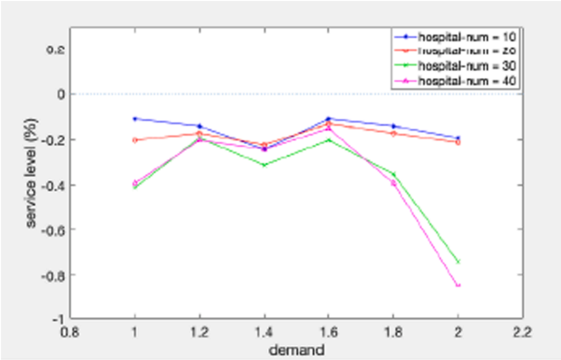


(e) Total cost

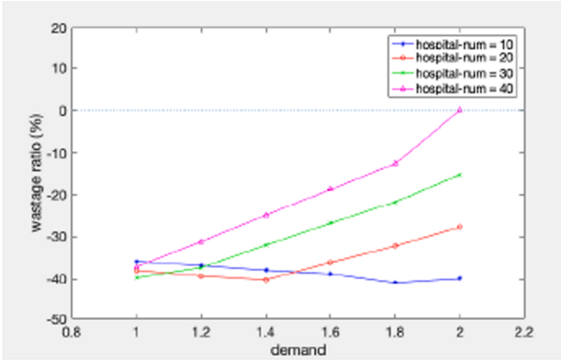
Fig. 8. Performance comparison with different unit penalty cost for wastage.

supply level is low, more delivery trips are needed to satisfy all demands. Comparing and balancing all relevant costs, VMIRP chooses to accumulate inventory to reduce the transportation cost. Higher inventory level then results in higher wastage in the blood center. The high inventory cost and low transportation cost at the insufficient production situations are also shown in the next two Figs. 6(c) and (d).

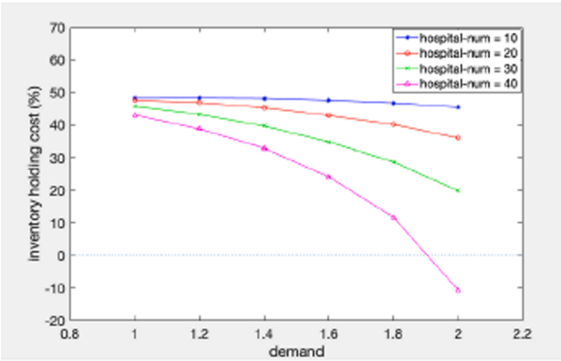
As indicated in Fig. 6(c), the change ratio of the inventory holding cost increases in terms of the maximal production quantity, and the increase is much faster in a larger-size network. In the 40-hospital case, VMIRP leads to a higher inventory cost when the maximal production quantity is very low. As the production grows, the inventory at the blood center may reach the life span before being shipped out. Thus, the disposal of redundant platelets before expiration leads to a lower inventory cost. The transportation cost (Fig. 6 (d)) can be significantly reduced by applying the VMIRP scheme (more than 70%). The improvements for small networks are relatively stable when the maximal product quantity increases, yet grow notably in larger networks. The percentage change of the total cost in Fig. 6(e) further confirms the impacts discussed in the inventory and transportation costs. The unusual peaks at a maximal production capacity of 0.75 (Fig. 6(b), (d), and (e) may be caused by the compatibility of the supply and demand.



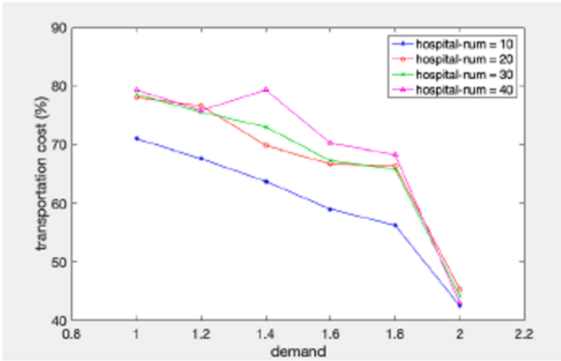
(a) Service level



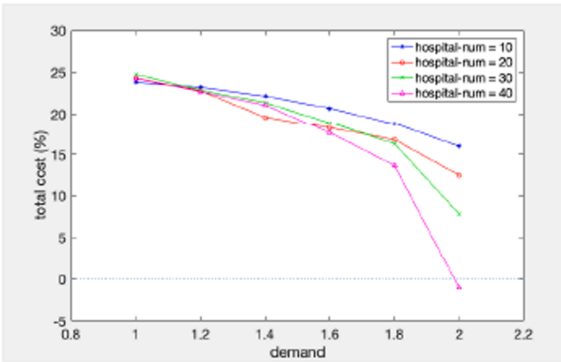
(b) Wastage ratio



(c) Inventory holding cost



(d) Transportation cost



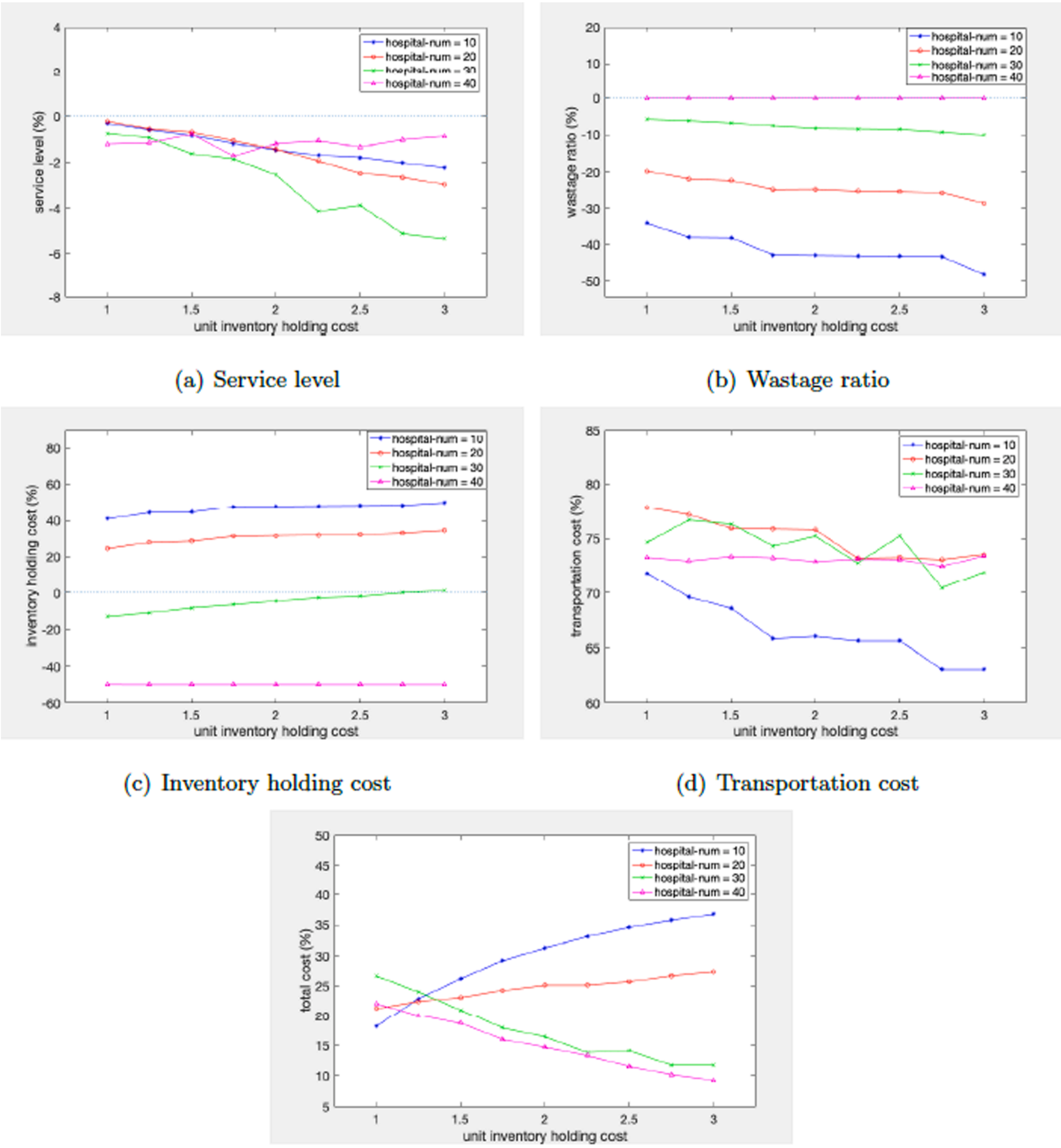
(e) Total cost

Fig. 9. Performance comparison with different demands.

5.3.2. *Unit penalty cost for shortage*

The unit shortage cost is hard to estimate when people's health is involved. Hence, it is important and necessary to examine the impact of the unit penalty cost for shortage on the distribution scheme. To show the effect clearer, the experiments are conducted under the scenario that the platelets are in great shortage (i.e., $M_t = 0.65$). The value of shortage cost varies from 0.8 to 2, and the comparison results of performance indicators are shown in Fig. 7.

From Fig. 7(a), when the unit shortage cost increases, the difference between the service levels under the VMIRP policy and the original scheme decreases accordingly. The impact of the unit shortage cost on larger networks is higher than the smaller ones, which shows no difference at a unit shortage cost of 2. This is quite intuitive, as higher penalty cost certainly leads to lower shortage, hence a higher service level. Figs. 7(b) shows the variation of unit shortage cost does not affect the wastage ratio for the same network but does have a significant impact on different sized networks. The reason is that the platelet demand in a larger network is clearly higher, which means less quantity is redundant. As shown in Fig. 7(c), the change of unit shortage cost does not affect the level of change in the



(a) Service level (b) Wastage ratio

(c) Inventory holding cost (d) Transportation cost

(e) Total cost

Fig. 10. Performance comparison with different average unit holding costs.

inventory holding cost of the same network. But a smaller sized network has higher improvement in the inventory holding cost, while the VMIRP inventory cost in a larger network can be much higher than the original scheme. To be particular, in the 10- and 20-hospital cases, where the supply of platelets is sufficient, VMIRP policy can reduce the inventory holding cost by abandoning the redundant quantity before expiration. But in the 30- and 40-hospital cases, the supply of platelets is insufficient, VMIRP chooses to deliver platelets to hospitals to avoid shortage, thus causing much more inventory holding cost at hospitals. From Figs. 7(d), as the unit shortage cost increases, VMIRP causes more transportation cost, since there are more delivery trips to hospitals to improve the service level. Finally, Figs. 7(e) shows that the improvement ratio of the total cost remains steady with the increase of unit shortage cost when platelets are relatively sufficient (10-, 20- and 30-hospital cases); but when platelets are significantly insufficient (40-hospital case), the improvement ratio drops with the increase of unit shortage cost. Even at the extreme scenario with a unit shortage cost of 2, which is about 8 times higher than the average unit inventory holding cost, the VMIRP policy still manages to reduce the total cost by approximately 15%.

5.3.3. Unit penalty cost for wastage

The impacts of unit wastage cost are studied under the scenario that the platelets are sufficient (i.e., $M_t = 1.6$), where possible wastage exists. Fig. 8 gives the changes of the five performance indicators with the unit penalty cost for wastage varying from 0.6 to 1.6.

As indicated in Fig. 8(a), a higher unit penalty cost for wastage generally improves the service level with small fluctuations, since a certain level of redundant quantity is preserved to fulfill demands. Intuitively, a higher unit penalty cost for wastage will reduce platelet wastage quantity as shown in Fig. 8(b). Because when the unit wastage cost increases and becomes dominant, the wastage ratio reduces significantly to avoid the high wastage cost.

Considering the cost aspect, the ratio of change in the inventory holding cost (Fig. 8(c)) decreases when the unit wastage cost increases, since a higher penalty cost guides VMIRP to preserve the redundant platelets until expiration. Fig. 8(d) shows that the impact of the unit wastage cost on the transportation cost maintains a similar level for the same network, while the overall improvement in transportation cost is more severe in larger networks. From Fig. 8(e), we can see that with the increase of the unit penalty cost for wastage, the improvement ratio of the total cost reduces and converges to 8%. This means that even with a much higher unit penalty cost for wastage, VMIRP can still outperform the original distribution scheme cost-wise.

5.3.4. Demand variation

This section examines the effects of variations in demand. Our experiments are carried out with the maximum production capacity $M_t = 1.6$, where the platelet supply may change from sufficient to insufficient as the demand expands gradually. Fig. 9 depicts the comparison results of performance indicators with the scale of demand varying from 1.0 to 2.0.

From Fig. 9(a), demand expansion generally lowers the service level. For the cases that the platelet supply is sufficient (10- and 20-hospital networks), the service level keeps relatively stable compared with the cases with great shortages (30- and 40-hospital networks). The reason is that platelets supply in smaller networks remains sufficient despite the increase of demand, while for the larger ones, shortage occurs as demand raises, and thus the service level tends to be lower. The fluctuations between 1.2 and 1.6 are due to the alignments between the supply and demand. As shown in Fig. 9(b), for the cases with sufficient supply, when demand increases, wastage ratio drops slightly. Demand expansion cuts down the wastage quantity under both strategies, but the positive influence on the original scheme becomes more obvious. The original scheme distributes platelets to hospitals as long as demand occurs. But VMIRP may reject some orders to reduce potential transportation cost and inventory holding cost at hospitals, which causes more wastage. When platelet supply is insufficient (30- and 40-hospital), the wastage quantity of the original scheme is zero, and demand growth reduces wastage under the VMIRP strategy, thus the wastage percentage goes up. Fig. 9(c) shows that the ratio of change in the inventory holding cost decreases with demand growth. Since more platelets are preserved in the blood center and hospitals to fulfill the large demand under the VMIRP strategy, thus incurring a higher inventory level. From Fig. 9(d), the transportation cost increases with the demand enlargement. In order to keep a relatively steady service level in Fig. 9(a), higher service frequency is organized to deliver more platelets to hospitals in the planning horizon, thus the transportation cost under VMIRP becomes higher when the demand scale expands. Considering the influence of demand variation on the total cost, Fig. 9(e) illustrates that, with the enlargement of demand, the improvement ratio of total cost drops, and the negative impact on large distribution networks is more apparent.

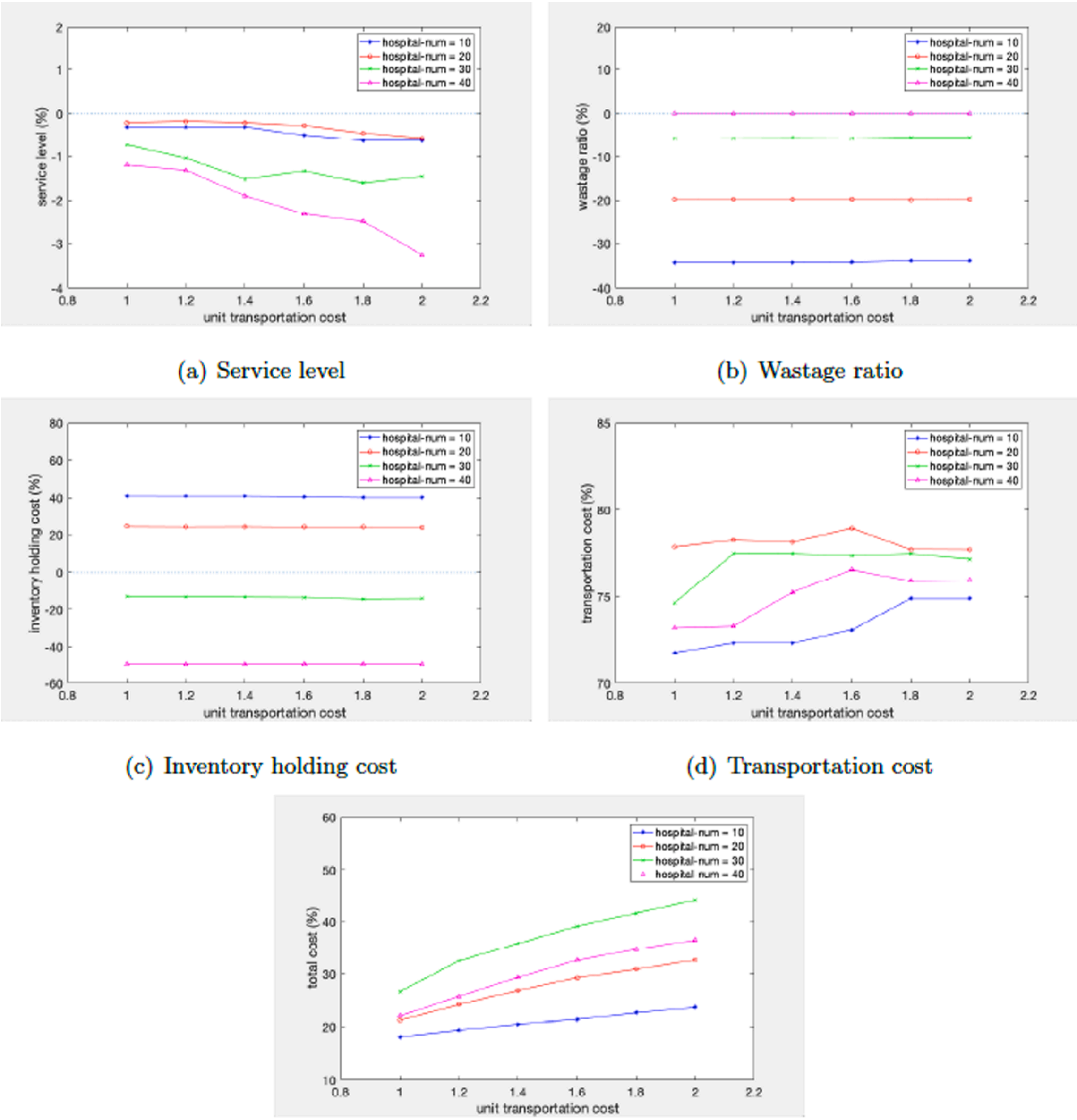
5.3.5. Average unit holding cost

We study the impacts of average unit inventory holding cost under the scenario with $M_t = 0.65$, where the platelet supply for 10- and 20-hospital delivery networks is sufficient, but are in significant shortage for the 30- and 40-hospital cases. Fig. 10 illustrates the changes of the five performance indicators when the average unit holding cost varies from 1.0 to 3.0.

From Fig. 10(a), the increase of the average unit holding cost tends to drop the service level with small fluctuations. In the original scheme, platelets are allocated to hospitals based on the demand at each hospital, so the service level remains the same. But under the VMIRP strategy, a higher average unit holding cost guides VMIRP to abandon the redundant quantity before expiration, thus resulting in a lower service level. Fig. 10(b) illustrates that with the average unit holding cost increasing, the wastage quantity under the VMIRP strategy rises. Thus, the wastage ratio is lower. In addition, the negative impact on smaller transportation networks with a large quantity of redundant platelets is more significant. Fig. 10(c) shows when the average unit holding cost rises, the proportion of change in the inventory holding cost remains smooth with rather small increase. This is because, by disposing the redundant platelets, the increase of inventory holding cost under VMIRP is less than that of the original scheme. Moreover, the improvement ratios of the 10- and 20-hospital networks are positive, as VMIRP may reduce the cost by disposing the redundant platelets before expiration. However, in the cases with 30 and 40 hospitals, where the platelets supply is in shortage, most of platelets are used to satisfy the demand, hence causing a large amount of holding cost at hospitals. From Fig. 10(d), the improvement ratio in transportation cost decreases when the average unit holding cost grows. Under the VMIRP strategy, the increase of the average unit holding cost leads to huge holding costs at the blood center and hospitals. Therefore, more visits to hospitals are scheduled to cut down the inventory holding cost at hospitals, so the transportation cost goes up. As indicated in Fig. 10(e), VMIRP outperforms the original scheme with at least 10% improvement in the total cost. In addition, the increase of the average unit inventory holding cost has a positive influence on the cases with sufficient supply (10- and 20-hospital) and a negative influence on the cases that the platelets are in shortage (30- and 40-hospital).

5.3.6. Unit transportation cost

In the base tests, unit transportation cost is estimated based on the gasoline consumption per kilometer. But many uncertainties in the transportation process, such as traffic congestion, may incur extra cost. Hence, it is necessary to investigate the impact of a higher unit transportation cost under scenarios that the platelet supply is in shortage (herein, $M_t = 0.67$), the usual state of the blood supply



(a) Service level (b) Wastage ratio (c) Inventory holding cost (d) Transportation cost (e) Total cost

Fig. 11. Performance comparison with different unit transportation costs.

chain. Fig. 11 presents the influence of the unit transportation cost on the five performance indicators.

Fig. 11(a) indicates that the service level drops with the increase of the unit transportation cost. With a higher unit transportation cost, in order to cut down the potential high transportation cost, the VMIRP strategy reduces the service frequency, which gives a lower service level. Moreover, a higher unit transportation cost causes a much lower service level in larger networks. From Fig. 11(b), the variation of unit transportation cost does not affect the wastage ratio for the same network but does have a significant impact on different sized networks. The reason is that the platelet demand in a larger network is clearly higher, which means less quantity is redundant. As shown in Fig. 11(c), the unit transportation cost has no significant influence on the proportion change in the inventory holding cost of the same network. But a smaller sized network leads to a greater improvement in the inventory holding cost; while VMIRP inventory cost in a larger network is much higher than the original scheme. The reason is the same as Fig. 7(c). Observing Fig. 11(d), we find that the improvement ratio in the transportation cost climbs as the unit transportation cost increasing. With a higher unit transportation cost, both of the transportation costs under the VMIRP strategy and original scheme tend to increase. But VMIRP is more flexible to get rid of high transportation cost by reducing the number of visits to hospitals, which causes a lower service level as shown in Fig. 11(a). From Fig. 11(e), VMIRP can reduce the total cost under the original scheme by at least 18%. In addition, with the increase of the unit transportation cost, VMIRP brings a more apparent reduction in the total cost.

6. Managerial insights

In this section, we summarize the managerial insights obtained from the previous analyses as follows.

First, the vendor-managed inventory routing approach outperforms the original distribution scheme, especially under the scenario that the platelets are insufficient to fulfill the demand. By applying the proposed VMIRP model, the overall performance of blood products distribution can be greatly improved. Specifically, the total relevant cost can be reduced by approximately 22% while keeping a rather stable service level. The most improvement lies in transportation cost, which is reduced by about 75% on average. This fact indicates that it is beneficial for the whole blood supply chain if the blood center monitors the inventory at hospitals and determines a specific distribution plan for hospitals from a centralized perspective.

Secondly, when determining the distribution scheme, the consumption rates at hospitals and the transportation distance from the blood center to each hospital should be considered simultaneously. Hence, when the blood products are insufficient, hospitals with relatively high demands or those located nearby the blood center are served with higher priorities.

Thirdly, for different sized networks, the best distribution plan in terms of various performance measures can be achieved by correspondingly adjusting the values of key parameters, such as the maximal production capacity, the penalty costs for shortage and wastage.

Last but not least, the current situation in China necessitates a series of proper management initiatives, especially optimizing the distribution schemes to align the limited supply and excessive demand. In order to maintain an adequate blood supply, several additional measures can be conducted, such as: constructing additional blood centers with sufficient production capacities; adjusting relevant public policies about blood donation, providing safety assurance for blood collections and applying certain incentives to encourage donations.

7. Conclusion

The unbalanced blood supply and demand, along with the immeasurable consequences, necessitate effective and efficient management of blood products. Focusing on the blood distribution system in China, we formulate blood products distribution as a vendor-managed inventory routing problem, where the blood center monitors and fulfills the demands in hospitals. The distribution of blood products is optimized by a mixed integer linear programming model considering possible shortage and wastage costs, in addition to the regular inventory and transportation concerns. Based on the decomposition method, an adaptive large neighborhood search algorithm and an integrated algorithm are designed to solve the optimization model effectively and efficiently. A real-world platelet distribution network in the city of Nanjing, China, is employed to conduct a series of numerical analyses. The computational results illustrate the cost reduction for different sized distribution networks and the impacts of various key parameters on service level, wastage ratio, inventory holding cost, transportation cost and total cost. Managerial insights derived from numerical tests can be also implemented by other vendors that supply perishable products in making inventory and distribution plans.

This paper conducts a preliminary exploration of the blood product distribution problem. But many additional realistic factors should be also considered, such as the stochastic nature of demand or/and travel time, possible system disruptions due to the changeable environment, to name a few. Our next step will be embedding uncertainty and disruptions into our optimization.

CRediT authorship contribution statement

Wenqian Liu: Conceptualization, Methodology, Software, Writing - original draft. **Ginger Y. Ke:** Conceptualization, Methodology, Writing - review & editing. **Jian Chen:** Methodology, Resources, Software. **Lianmin Zhang:** Conceptualization, Methodology, Resources, Supervision.

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