Decision Science Letters 12 (2023) 315–332

Contents lists available at GrowingScience

Decision Science Letters

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An integrated inventory and distribution planning problem for the blood products: An application for the Turkish Red Crescent

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C H R O N I C L E

Article history:
Received: May 24, 2022
Received in revised format: November 20, 2022
Accepted: January 13, 2023
Available online: January 13, 2023

Keywords:
Inventory planning and distribution
Perishable products
Centralized and decentralized distribution strategies
Mixed-integer linear programming
Decomposition-based heuristic algorithm

A B S T R A C T

This study considers an integrated inventory planning and distribution problem based on an applied case at the Turkish Red Crescent's Central Anatolian Regional Blood Center. We define two echelons, the first echelon being the regional blood center and the second echelon being the districts. The blood products are perishable so that the outdated products are disposed of at the end of their lives. We aim to minimize the cost of inventory keeping at both echelons, the shortage, and disposal amounts at the second echelon. We consider two distribution strategies: all deliveries are realized by the regional blood center (current implementation), and the deliveries are directly from the regional blood center or the other districts. We develop a mixed-integer linear programming model for each strategy. Our experimental results show that the decentralized strategy brings significant cost reductions over the centralized strategy. The mathematical model for the centralized distribution strategy can handle large-sized instances. On the other hand, the model for the decentralized distribution strategy is more complex and could not handle large-sized instances in our pre-specified termination limit of two hours. For large-sized instances of the decentralized distribution strategy, we design a decomposition-based heuristic algorithm that benefits from the optimal solutions of the original model and finds near-optimal solutions very quickly.

1. Introduction

Blood products play an essential role in the lives of human beings and have no substitutes. The blood supplied by human donations is centrifuged to obtain three essential products: platelets, red blood cells, and plasma. Platelets are needed for patients frequently subjected to significant blood loss and chemotherapy as a part of their cancer treatment. Red blood cells are needed in surgeries that cause blood loss in treating premature infants and anemic patients. Plasma covers blood loss and curbs surgeries, and treats burn injuries and liver disease.

The shortage of any blood product may lead to drastic consequences, including losing human lives. The blood supply is only human donations, and only a small proportion of the population donates in particular in those times of pandemic. Despite being a scarce resource, the blood demand is ever-increasing, attributed to the increases in human life and continuous advances in medical treatments involving blood transfusion. On the other hand, the blood products are perishable; for example, the platelets and the red blood cells have very limited shelf lives of 5 and 42 days, respectively. Moreover, the quality of the blood products may reduce with increased time spent while being transported. These natures of the blood products restrict their storage in large quantities.

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doi: 10.5267/dsl.2023.1.004

The scarcity of the blood products, their perishable nature and drastic consequences of their shortages, and the reduced quality due to long travel distances add to the importance of efficient and effective blood supply chain management. To effectively manage the supply chain, the health managers should ensure timely delivery of the blood products and reduce the total operation costs. Inventory planning and distribution of the blood products are two important operational problems in managing the supply chain whose successful solutions would improve the health of society and patients.

In many countries, blood supply chain management is handled by a central authority. In Turkey, the central authority is the Turkish Red Crescent (TRC), which supplies the whole blood, extracts the blood products, and regularly distributes them to the demand points via regional blood centers. Each Regional Blood Center (RBC) distributes the blood into its districts using the vehicles of the TRC. One of the major RBCs of the TRC is the Central Anatolian RBC. This RBC is located in the capital city Ankara and serves 16 districts in the neighborhood of Ankara.

In this study, we take our motivation from the planning and distribution activities of the Central Anatolian RBC of the TRC. The activities of the Central Anatolian RBC have been studied in Şahin et al. (2007), Yegül (2016), and Kurt et al. (2018, 2019). A location and allocation problem that decides the blood centers' location and the hospitals' allocation to these centers is studied by Şahin et al. (2007). Yegül (2016) defined a regional transfusion center echelon and studied the associated location and allocation problem. A single-period allocation and distribution problem for blood products at the RBC level with urgent demands and irradiation centers are studied by Kurt et al. (2018). Later on, Kurt et al. (2019) defined new transportation options that use the hospital vehicles in addition to those of the RBC.

We develop a multi-period integrated plan for the Central Anatolian RBC's inventory planning and distribution scheduling activities (single supplier) with its sixteen districts (customers) as a two-echelon inventory system. The blood center at the first echelon has a known supply quantity of the blood products. The blood products of specified ages arrive either from human donations or other RBCs. The districts at the second echelon give their orders with specified quantities and delivery times from the RBC at the beginning of the planning horizon. The blood-outdates are the products that remain unused at the end of their shelf lives are observed at the first echelon. At the second echelon, there are no blood-outdates as they have deterministic demand. The shortages of the products are observed at the second echelon. They should be avoided as the situation is directly related to the patients' lives, forcing the RBC to deliver the products to the districts at their required delivery times. We aim to minimize the total inventory-related (inventory holding, shortage, and outdates) and distribution-related (fixed and variable transportation) costs.

We consider two strategies for distributing the blood products to the districts. The first strategy, the *centralized distribution strategy*, considers direct shipment to the districts, i.e., all districts receive the blood products directly from the RBC. The second strategy, the *decentralized distribution strategy*, allows shipment among the districts keeping the inventory of other districts.

Currently, the Central Anatolian RBC employs a centralized distribution strategy. Our contribution to the RBC is two folds: First, we propose a mixed-integer linear programming model (MILP) for their current strategy that can handle any weekly operations of the Central Anatolian RBC in very short solution times. Hence, they can use the model to improve their centralized distribution and inventory plans. Second, we suggest that RBC use the new distribution strategy, i.e., a decentralized distribution strategy that would reduce their costs significantly. For the decentralized distribution strategy, we also propose a MILP model and a decomposition-based heuristic approach that makes efficient use of our mathematical model and is very effective.

The remaining sections of the paper are presented as follows. In Section 2, a brief literature review of the related works is provided. The problem definitions and MILP models for both strategies are given in Section 3 and Section 4, respectively. In Section 5, the details of our decomposition-based heuristic algorithm are presented. The results of our computational experiments are given in Section 6. The study is concluded in Section 7.

2. Review of related literature

Pierskalla (2005) and Meneses et al. (2022) reviewed the blood supply chain studies with tactical and operational concerns of supply, allocation, and distribution activities. The three most recent and most noteworthy review studies are by Belien and Force (2012), Osorio et al. (2015), Piraban et al. (2019), and Asadpour et al. (2022). Belien and Force (2012) give a literature review for blood supply chain management under the following categories: blood product types, hierarchy levels, problem types, performance measures, and solution methods. Osorio et al. (2015) discuss the quantitative models proposed for the collection, production, inventory, and delivery stages of the blood supply chains. Piraban et al. (2019) provide an updated literature review according to a new taxonomy. Asadpour et al. (2022) focus on quantitative models in disaster situations. Below we review the literature based on problem types using one of the classification categories given by Belien and Force (2012).

2.1 Location and allocation research

Bashiri and Ghasemi (2018), Ramezanian and Behboodi (2017), Zahiri and Pishvaee (2017), and Khalilpourazari and Khamseh (2019) are among some researchers who published on integrated location, allocation, and collection problems in their blood supply networks. Bashiri and Ghasemi (2018) considered an allocation problem for the mobile blood facilities and donation sites, and an inventory problem at the blood center level. They proposed a two-stage stochastic programming model to handle blood supply uncertainty. Their model defines the number of mobile blood facilities in the first stage. Ramezanian and Behboodi (2017) proposed some strategies for the location and allocation decisions of the temporary and permanent donation centers when the demand and cost are uncertain. They first presented a deterministic location-allocation model and then a robust optimization method to handle stochasticity. They implemented their results for the blood supply chain of Tehran, Iran. Zahiri and Pishvaee (2017) considered blood group incompatibility in their blood supply network. They gave a bi-objective mathematical model that minimizes the total cost and maximum unsatisfied demand. They also proposed a robust probabilistic programming approach that copes with uncertainty. Khalilpourazari and Khamseh (2019) developed a multi-objective model for the blood supply chain design to reduce the adverse effects of earthquakes. They considered the magnitude of the earthquakes and different transportation models with variable speeds and capacities. They proposed several multi-objective approaches, including the lexicographic weighted Tchebycheff method, to solve their multi-objective model.

Daskin et al. (2002), Shen et al. (2003), Yegül (2016), Şahin et al. (2007), Kaveh and Ghobadi (2017), Chaiwuttisak et al. (2016), and Fahimnia et al. (2017) are among the researchers who published on integrated location, allocation, and distribution problem. Daskin et al. (2002) introduced a distribution center location problem that incorporates working inventory and safety stock costs, and transport costs from the suppliers to the distribution centers. They developed a nonlinear integer programming model and proposed a lagrangian relaxation-based solution algorithm to find exact solutions and several heuristics to find approximate solutions. Shen et al. (2003) studied an integrated location–inventory problem for multi retailers and a single supplier case. They formulated the problem of allocating the retailers to the distribution centers as a set-covering integer-programming model and proposed a column generation method for its solution. Yegul (2016) introduced a regional transfusion center, i.e., a new echelon. They proposed decomposition-based and simulated annealing-based heuristic algorithms to solve their real-life application in the TRC. Sahin et al. (2007) studied a hierarchical location-allocation problem. They determined the location of RBC and blood centers and the allocation of the demand points to the pairs of RBC and blood centers. They developed several mathematical models to solve the problems at all levels for minimizing the total weighted distance. They tested the performance of their model using real data taken from TRC blood services. Chaiwuttisak et al. (2016) considered a location-allocation problem for donation rooms with and without a distribution center. They developed an integer programming model to reduce transportation costs and implemented their model for Thailand's blood supply chain. Kaveh and Ghobadi (2017) considered the problem of allocating BCs to hospitals to minimize the total travel distance between hospitals and blood centers. They proposed a graph partitioning-based algorithm and a metaheuristic algorithm using a new neighborhood structure. They implemented their results in Iran's blood supply chain. Fahimnia et al. (2017) considered finding the number of facilities, blood collection, and distribution amounts in case of disasters. They presented a stochastic bi-objective model of minimizing cost and minimizing delivery time. They developed a hybrid solution approach that combines the ε-constraint and lagrangian relaxation methods.

2.2 Distribution research

Several researchers studied the blood distribution problem, including but not limited to Kendall (1980), Gregor et al. (1982), Eiselt and Laporte (1989), Hemmelmayr et al. (2009), Salehipour and Sepehri (2012), and Kurt et al. (2018, 2019). Kendall (1980) and Eiselt and Laporte (1989) described frameworks for developing, designing, and implementing a regional blood distribution system and blood distribution systems as important applications with routing components, respectively. Gregor et al. (1982) considered a distribution problem to find the number of vehicles and inventory amounts and minimize the travel times and the number of postponed surgeries. The studies by Hemmelmayr et al. (2009) and Salehipour and Sepehri (2012)] aimed to minimize the total travel time and the total waiting time, respectively. Kurt et al. (2018, 2019) considered the allocation and distribution problem from the regional blood center that supplies the products to the hospitals that demand them. They considered deadlines for the urgent demands and irradiation centers where some products should be treated. They developed mixed-integer linear programs and genetic algorithm-based heuristics and implemented them in the Central Anatolian RBC of the TRC. Kurt et al. (2018) assume that all distribution should be realized by the vehicles of the RBC, and Kurt et al. (2019) considered an additional distribution option where the vehicles of the hospitals could be used to take the products directly from the RBC or via another hospital.

2.3 Inventory management research

Hosseinifard and Abbasi (2018) investigated a two-echelon inventory planning problem where a single blood center (first echelon) takes stochastic supply from their donors and the hospitals (second echelon) receive stochastic demand. They proposed to use a base stock inventory policy. They showed that a centralized inventory structure, in which some hospitals serve the demands of the other hospitals nearby, can significantly improve the blood products' supply chain performance. Dillon et al. (2017) considered the inventory problem at individual hospital levels and proposed a two-stage stochastic programming model for perishable products with uncertain demand. Their model minimizes the total cost with ordering, expected holding, and shortage costs. Ensafian and Yaghaubi (2017) studied the supply chain management problem for age-differentiated demand of the platelets. They presented a single objective model to minimize the total costs, including shortage and wastage costs, and a two objective model to minimize the total logistics cost and maximize the freshness of the blood units delivered. They developed a robust optimization model for the uncertain demand case and implemented it for a blood center in Tehran, Iran. Osorio et al. (2017) considered stochastic demand and supply case and presented a simulation model with shelf-life constraints, blood group proportions, and several collections and production methods. Their experimental results showed that their approach could reduce shortages, outdated amounts, and total cost.

Lui et al. (2021) studied integrated inventory planning and routing model where the blood center decides on the number of products to be delivered to each hospital and the visiting order of the hospitals. They presented a mixed integer program and a decomposition-based solution approach and implemented them for China's blood distribution supply chain. Lui et al. (2020) studied integrated inventory planning and routing model with multi blood centers and a single supplier. They allowed transshipment among the blood centers and assumed uncertain demand. They proposed a mixed integer program and a scenario-based robust optimization model and implemented them for the blood transfusion center of Tehran, Iran.

The most closely related study to ours is Hosseinifard and Abbasi (2018), which considered a centralized distribution strategy with stochastic supply and demand, and used a base-stock inventory planning policy. We propose mathematical models for the Central Anatolian RBC's distribution and inventory planning activities of the TRC under centralized and decentralized distribution strategies. We analyzed the models' performances and compared two distribution strategies using deterministic data (actual demand data taken from the RBC and randomly generated supply data).

3. Problem environment

The Central Anatolian Regional Blood Center (RBC) of the Turkish Red Crescent is a single supplier with sixteen districts (customers) in its territory. The RBC has a known supply quantity of blood products. The blood products of specified ages arrive either from human donations or other RBCs. The districts give their orders with specified quantities and delivery times from the RBC at the beginning of each week. The blood-outdates are the products that remain unused at the end of their shelf lives and are observed at the RBC. At the districts, there are no blood-outdates as they have deterministic demand. The shortages of the products are observed in the districts. They should be avoided as the situation is directly related to the patients' lives, forcing the RBC to deliver the products to the districts at their required delivery times.

The RBC distributes the blood products to its districts using the vehicles of the Turkish Red Crescent and has a limited supply of each product type having a specified age. The supply becomes available at the beginning of each period and is assumed to be dictated by the blood donations and the decisions of the central authorities. Two types of demand are defined: normal and urgent. The urgent demands are for emergent needs; hence their dissatisfaction is penalized at higher rates than normal demands. The vehicles with limited availability and capacity are ready at the RBC at the beginning of each period. Each vehicle departs from the RBC at the beginning of the period, visits exactly one district, and arrives back before the period ends. Arrived vehicles are made ready for the next period under the same conditions. Furthermore, each district can be visited by one RBC vehicle only. Fig. 1 illustrates the current centralized distribution in a single period for a case where there are eight districts and three RBC vehicles. Each vehicle is loaded with the demand of different districts, goes to its assigned district, unloads the demand, and returns to the RBC.

In the current *centralized distribution* strategy (Strategy 1) of the RBC, all blood products are directly distributed to each district without considering the possibility of distribution among the districts. This study considers the current centralized distribution and investigates the effect of a *decentralized distribution* strategy (Strategy 2), i.e., distribution from one district to the other districts. However, not all districts can keep the inventory of other districts due to some unavailability like a refrigerated storage area.

Fig. 2 illustrates the proposed decentralized distribution in a single period for a case where there are again eight districts, three RBC vehicles, and two vehicles belonging to two different districts. The first RBC vehicle is loaded with the demands of districts 6 and 7. It goes to district 7, unloads the demands of districts 6 and 7, and returns to the RBC. A vehicle of district 6 goes to district 7 to take the unloaded demand of district 6, and returns to district 6. The second RBC vehicle is loaded with the demands of districts 3 and 5. It goes to district 3, unloads the demands of districts 3 and 5, and returns to the RBC. A vehicle of district 5 goes to district 3 to take the unloaded demand of district 5, and returns to district 5. The third RBC vehicle is loaded with the demand of district 2. It goes to district 2, unloads the demand, and returns to the RBC.

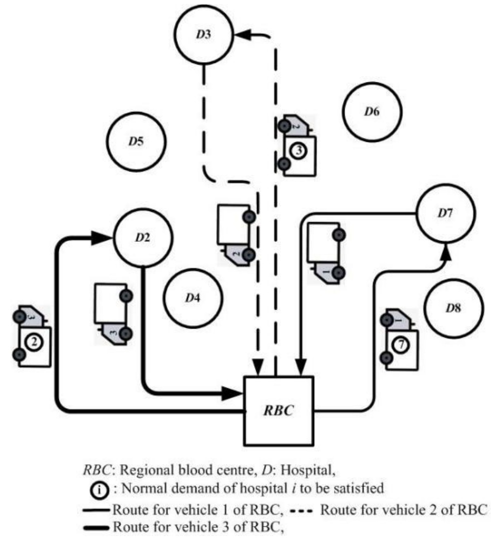

Fig. 1. The current centralized distribution in a single period

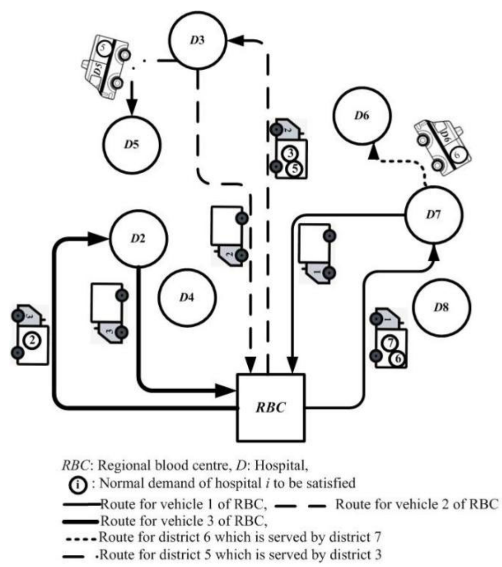

Fig. 2. The proposed decentralized distribution in a single period

The main decisions in both strategies are the amount to be sent to each district and the amount to be transferred to the next period in the RBC (first echelon) and the districts (second echelon). The districts consume products according to their ages, i.e., the oldest units are consumed earlier. The backorders attributed to the vital importance of timely demand satisfaction are avoided. The RBC loses the unsatisfied demand, so that the districts might look for other sources like other blood centers and donation campaigns. The blood products are perishable so that the outdated products are disposed of at the end of their lives at the RBC. In both strategies, we decide on the distribution quantities considering the ages, availabilities, and requirements of the products and the costs of distribution, inventory holding, lost sales, and disposal. We aim to minimize the total inventory-related (inventory holding, shortage, and outdates disposal) and distribution-related (fixed and variable transportation) costs.

4. Mathematical programming models

This section provides MILP models for the multi-period integrated inventory planning and distribution scheduling problem with centralized distribution strategy (MILP-C) and decentralized distribution strategy (MILP-D). We first introduce the parameters and indices that are common to both models.

Parameters and indices commonly used in both models

T number of periods
t index for periods ($t = 1, \dots, T$)
N number of districts
i index for districts ($i = 1, \dots, N$)
P number of product types having different ages
p index for product types ($p = 1, \dots, P$)
SL_p shelf-life of product p (i.e., the number of periods in which product p is consumed and its maximum age)
k index for the age of the products ($k = 1, \dots, SL_p$)
A_{pkt} amount (in units) of product p at age k added to the inventory of the *RBC* at the beginning of period t
I_{pk0} beginning inventory level of product p at age k at the *RBC*
ND_{ipt} amount (in units) of normal demand of district i for product p at period t
UD_{ipt} amount (in units) of urgent demand of district i for product p at period t
V number of vehicles owned by the RBC
VC capacity of each vehicle owned by the RBC

4.1 MILP model for the centralized distribution (Strategy 1)

The centralized distribution strategy's additional parameters and decision variables are stated below.

Additional parameters

FC_i fixed cost of serving district i directly from the *RBC*
HCC_p inventory holding cost per unit of product p in the *RBC* per period
HCD_{ip} inventory holding cost per unit of product p in district i per period
CLS_{ip} cost of lost sale for normal demand of district i for product p
$UCLS_{ip}$ cost of lost sale for urgent demand of district i for product p
DC_p disposal cost of product p at the *RBC* once product p reaches age SL_p

Decision variables

Y_{it} 1 if district i is served in period t; otherwise, 0
S_{ipkt} amount of product p at age k served (sent) to district i in period t
C_{ipkt} amount of product p at age k consumed by district i in period t
J_{ipkt} inventory level of product p at age k in district i at the end of period t
L_{ipt} lost sale amount (unsatisfied demand) for normal demand of district i for product p in period t
UL_{ipt} lost sale amount for urgent demand of district i for product p in period t
I_{pkt} inventory level of product p at age k in the RBC at the end of period t
$I_{p,SL_p,t}$ amount of product p disposed of by the RBC at the end of period t

The blood products supply chain associated with Strategy 1 is depicted in Fig. 3.

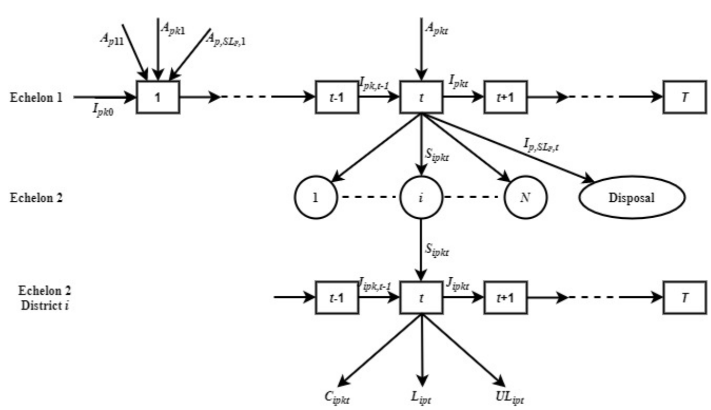

Fig. 3. The supply chain associated with Strategy 1

We now present our MILP model for the centralized distribution strategy (MILP-C).

Model MILP-C

$$\text{Minimize} \quad z_C = \sum_{t=1}^{T}\Big[\sum_{i=1}^{N} FC_i \times Y_{it} + \sum_{p=1}^{P}\sum_{k=1}^{SL_p}\big(HCC_p \times I_{pkt}\big) + \sum_{i=1}^{N}\sum_{p=1}^{P}\sum_{k=1}^{SL_p}\big(HCD_{ip} \times J_{ipkt}\big) + \sum_{i=1}^{N}\sum_{p=1}^{P}\big(CLS_{ip} \times L_{ipt} + 100CLS_{ip} \times UL_{ipt}\big) + \sum_{p=1}^{P} DC_p \times I_{p,SL_p,t}\Big] \quad (1)$$

Subject to

$$I_{p1t} = A_{p1t} - \sum_{i=1}^{N} S_{ip1t} \quad \text{for } p = 1,2,\dots,P;\ t = 1,2,\dots,T \quad (2)$$

$$I_{pkt} = A_{pkt} + I_{p,k-1,t-1} - \sum_{i=1}^{N} S_{ipkt} \quad \text{for } p = 1,2,\dots,P;\ k = 2,3,\dots,SL_p;\ t = 1,2,\dots,T \quad (3)$$

$$J_{ip1t} = S_{ip1t} - C_{ip1t} \quad \text{for } i = 1,2\dots,N;\ p = 1,2,\dots,P;\ t = 1,2,\dots,T \quad (4)$$

$$J_{ipkt} = J_{i,p,k-1,t-1} + S_{ipkt} - C_{ipkt} \quad \text{for } i = 1,2\dots,N;\ p = 1,2,\dots,P;\ k = 2,3,\dots,SL_p;\ t = 2,3,\dots,T \quad (5)$$

$$J_{ipk1} = S_{ipk1} - C_{ipk1} \quad \text{for } i = 1,2\dots,N;\ p = 1,2,\dots,P;\ k = 2,3,\dots,SL_p \quad (6)$$

$$J_{i,p,SL_p,t} = 0 \quad \text{for } i = 1,2\dots,N;\ p = 1,2,\dots,P;\ t = 1,2,\dots,T \quad (7)$$

$$\sum_{k=1}^{SL_k} C_{ipkt} + L_{ipt} = ND_{ipt} + UD_{ipt} \quad \text{for } i = 1,2\dots,N;\ p = 1,2,\dots,P;\ t = 1,2,\dots,T \quad (8)$$

$$\sum_{k=1}^{SL_p} S_{ipk1} + UL_{ip1} \geq UD_{pi1} \quad \text{for } i = 1,2\dots,N;\ p = 1,2,\dots,P \quad (9)$$

$$\sum_{k=1}^{SL_p} S_{ipkt} + \sum_{k=2}^{SL_p} J_{i,p,k-1,t-1} + UL_{ipt} \geq UD_{ipt} \quad \text{for } i = 1,2\dots,N;\ p = 1,2,\dots,P;\ t = 2,3,\dots,T \quad (10)$$

$$\sum_{p=1}^{P}\sum_{k=1}^{SL_p} S_{ipkt} \leq M_i \cdot Y_{it} \quad \text{for } i = 1,2,\dots,N;\ t = 1,2,\dots,T;\ M_i = \sum_{t=1}^{T}\sum_{p=1}^{P}\big(ND_{ipt} + UD_{ipt}\big) \quad (11)$$

$$\sum_{i=1}^{N} Y_{it} \leq V \quad \text{for } t = 1,2,\dots,T \quad (12)$$

$$\sum_{p=1}^{P}\Big(\sum_{k=1}^{SL_p} S_{ipkt}\Big) \leq VC \quad \text{for } i = 1,2,\dots,N;\ t = 1,2,\dots,T \quad (13)$$

$$S_{ipkt}, C_{ipkt}, J_{ipkt}, L_{ipt}, UL_{ipt}, I_{pkt} \geq 0 \text{ and integer} \quad \text{for } i = 1,2,\dots,N;\ p = 1,2,\dots,P;\ k = 1,2,\dots,SL_p;\ t = 1,2,\dots,T \quad (14)$$

$$Y_{it} \in \{0,1\} \quad \text{for } i = 1,2,\dots,N;\ t = 1,2,\dots,T \quad (15)$$

The objective expressed in (1) minimizes the total cost of fixed distribution cost, inventory holding at the RBC and the districts, unsatisfied demand, and disposal cost. The inventory balance equations for the products at age one and others greater than one in the RBC are given in Constraint sets (2) and (3), respectively. Constraint sets (4), (5), and (6) are the inventory balance equation for the products at age 1, ages greater than one, and period 1 in the districts, respectively. Constraint set (7) guarantees that the inventory levels for the products at the end of their shelf lives in the districts are zero. Constraint set (8) determines the amount of unsatisfied demand for each product in each district. Constraint set (9) guarantees that the total amount of each product served to a district in the first period is no less than the urgent demand for this product in the same period. Constraint set (10) guarantees that the urgent demand for each product in a district in the second and remaining periods are satisfied. Constraint set (11) makes sure that the total amount of products sent to a district in a period can be positive if the RBC serves this district in the same period. The number of visits from the RBC to the districts is limited by the number of available vehicles carrying blood products from the RBC to the districts in a period. This condition is satisfied by Constraint set (12). Constraint set (13) guarantees that the total amount of products sent from the RBC to a district in a period for serving this district cannot be greater than the vehicle capacity. Constraint sets (14) and (15) are non-negative integrality and binary restrictions.

4.2 MILP model for the decentralized distribution (Strategy 2)

In the decentralized distribution strategy, the product distribution among the districts is allowed and realized by the vehicles of the district taking the product. We introduce the following additional sets and modified parameters:

Additional sets and modified parameters

STO_i set of the districts that can serve to district i
SBY_i set of the districts that can be served by district i
FC_{ij} fixed cost of serving district i via district j, $j \neq i$
FC_{ii} fixed cost of serving district i directly from the RBC, $j = i$ ($j = i$ means direct service from the RBC to district i)

Note that FC_{ii} is the fixed cost FC_i defined in Strategy 1.

Modified decision variables

Similarly, we modified two decision variable sets of Strategy 1 as follows:

Y_{ijt} 1 if district i is served via district j in period t, $j \neq i$; otherwise, 0

S_{ijpkt} amount of product p at age k sent to district i from district j in period t, $j \neq i$

Note that Y_{iit} is the assignment decision variable Y_{it} defined in Strategy 1, and S_{iipkt} is the allocation variable S_{ipkt} defined in Strategy 1. Fig. 4 illustrates the structure of product p at district i for Strategy 2.

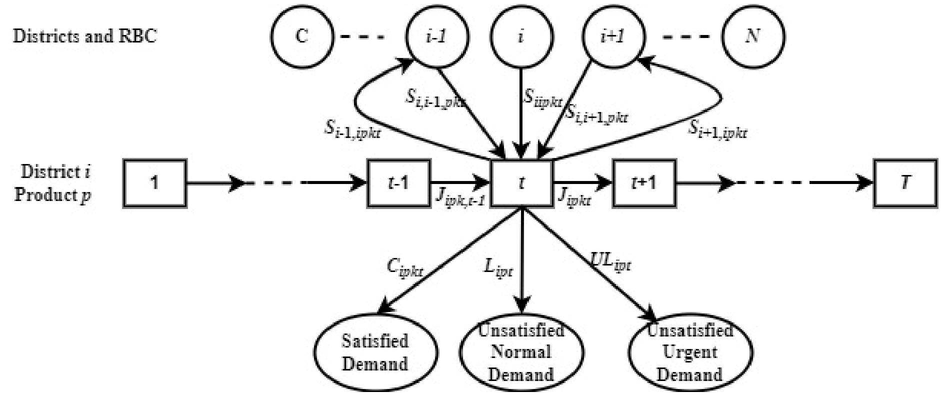

Fig. 4. The flow structure of product $p$at district i for Strategy 2

The objective function and some constraints in the MILP model for the decentralized distribution strategy (MILP-D) are similar or identical to those of the centralized distribution strategy (MILP-C) and are stated below:

Model MILP-D

Minimize $$z_D = \sum_{t=1}^{T}\Big[\sum_{i=1}^{N}\sum_{j\in STO(i)}\big(FC_{ij} \times Y_{ijt}\big) + \sum_{p=1}^{P}\sum_{k=1}^{SL_p}\big(HCC_p \times I_{pkt}\big) + \sum_{i=1}^{N}\sum_{p=1}^{P}\sum_{k=1}^{SL_p}\big(HCD_{ip} \times J_{ipkt}\big) + \sum_{i=1}^{N}\sum_{p=1}^{P}\Big(CLS_{ip} \times L_{ipt} + 100CLS_{ip} \times UL_{ipt} + \sum_{p=1}^{P} DC_p \times I_{p,SL_p,t}\Big)\Big] \tag{16}$$

Subject to $$I_{p1t} = A_{p1t} - \sum_{i=1}^{N}\sum_{j\in STO(i)} S_{ijp1t} \quad \text{for } p = 1,2,\dots,P;\ t = 1,2,\dots,T \tag{17}$$

$$I_{pkt} = A_{pkt} + I_{p,k-1,t-1} - \sum_{i=1}^{N}\sum_{j\in STO(i)} S_{ijpkt} \quad \text{for } p = 1,2,\dots,P;\ k = 2,3,\dots,SL_p;\ t = 2,3,\dots,T \tag{18}$$

$$J_{ip1t} = \sum_{j\in STO(i)} S_{ijp1t} - C_{ip1t} \quad \text{for } i = 1,2\dots,N;\ p = 1,2,\dots,P; t = 1,2,\dots,T \tag{19}$$

$$J_{ipkt} = J_{i,p,k-1,t-1} + \sum_{j\in STO(i)} S_{ijpkt} - C_{ipkt} \quad \text{for } i = 1,2\dots,N;\ p = 1,2,\dots,P;\ k = 2,3,\dots,SL_p;\ t = 2,3,\dots,T \tag{20}$$

$$J_{ipk1} = \sum_{j\in STO(i)} S_{ijpk1} - C_{ipk1} \quad \text{for } i = 1,2\dots,N;\ p = 1,2,\dots,P; k = 2,3,\dots,SL_p \tag{21}$$

$$J_{i,p,SL_p,t} = 0 \quad \text{for } i = 1,2\dots,N;\ p = 1,2,\dots,P; t = 1,2,\dots,T \tag{22}$$

$$\sum_{k=1}^{SL_k} C_{ipkt} + L_{ipt} = ND_{ipt} + UD_{ipt} \quad \text{for } i = 1,2\dots,N;\ p = 1,2,\dots,P; t = 1,2,\dots,T \tag{23}$$

$$\sum_{j\in STO(i)}\sum_{k=1}^{SL_p} S_{ijpk1} + UL_{ip1} \geq UD_{ip1} \quad \text{for } i = 1,2\dots,N;\ p = 1,2,\dots,P \tag{24}$$

$$\sum_{j\in STO(i)}\sum_{k=1}^{SL_p} S_{ijpkt} + UL_{ipt} \geq UD_{ipt} \quad \text{for } i = 1,2\dots,Np = 1,2,\dots,P; t = 2,3,\dots,T \tag{25}$$

$$\sum_{p=1}^{P}\sum_{k=1}^{SL_p} S_{ijpkt} \leq M_i \cdot Y_{ijt} \quad \text{for } i = 1,2,\dots,N;\ j \in STO(i));\ t = 1,2,\dots,T;\ M_i = \sum_{t=1}^{T}\sum_{p=1}^{P}\big(ND_{ipt} + UD_{ipt}\big) \tag{26}$$

$$\sum_{i=1}^{N} Y_{iit} \leq V \quad \text{for } t = 1,2,\dots,T \tag{27}$$

$$\sum_{j\in SBY(i)} Y_{jit} \leq |SBY(i)| \cdot Y_{iit} \quad \text{for } i = 1,2,\dots,N;\ t = 1,2,\dots,T \tag{28}$$

$$\sum_{p=1}^{P}\Big(\sum_{j\in SBY(i)}\sum_{k=1}^{SL_p} S_{jipkt}\Big) \leq VC \quad \text{for } i = 1,2,\dots,N;\ t = 1,2,\dots,T \tag{29}$$

$$S_{ijpkt}, C_{ipkt}, J_{ipkt}, L_{ipt}, UL_{ipt}, I_{pkt} \geq 0 \text{ and integer} \quad \text{for } i = 1,2,\dots,N;\ j \in STO(i); p = 1,2,\dots,P;\ k = 1,2,\dots,SL_p;\ t = 1,2,\dots,T \tag{30}$$

$$Y_{ijt} \in \{0,1\} \quad \text{for } i = 1,2,\dots,N;\ j \in STO(i); t = 1,2,\dots,T \tag{31}$$

The objective expressed in (16) minimizes the total cost of servicing the districts, inventory holding at the RBC and the districts, unsatisfied demand, and disposal cost. The inventory balance equations for the products at age one and others greater than one in the RBC are given in Constraint sets (17) and (18), respectively. Constraint sets (19), (20), and (21) are the inventory balance equations for the products at age 1, ages greater than one, and period 1 in the districts, respectively. Constraint set (22) guarantees that the inventory levels for the products at the end of their shelf lives in the districts are zero. Constraint set (23) determines the amount of unsatisfied demand for each product in each district. Constraint set (24) guarantees that the total amount of each product served to a district in the first period is greater than or equal to the urgent demand for this product in the same period. Constraint set (25) guarantees that the urgent demand for each product in a district in the second and remaining periods are satisfied. The total amount of products sent to a district in a period can be positive if this district is served by the RBC or other district(s) in the same period. This condition is satisfied by Constraint set (26). Constraint set (27) ensures that the number of visits from the RBC to the districts is limited by the number of available vehicles carrying blood products from the RBC to the districts in a period. Constraint set (28) guarantees that the service from a district to other districts is possible if a vehicle is sent to this district from the RBC. The total amount of products sent from the RBC to a district in a period for serving this district and the other districts served by this district cannot be greater than the vehicle capacity. This is achieved by Constraint set (29). Constraint sets (30) and (31) are non-negative integrality and binary restrictions.

5. A decomposition-based heuristic algorithm for the decentralized strategy

Our preliminary experiments have shown that the MILP-D model for the decentralized distribution strategy cannot handle some instances when the number of periods is high ($T = 6$ or $T = 7$in our case). We propose a decomposition-based heuristic algorithm that considers the same model with fewer binary variables to solve those instances. The smaller sized, hence lower complexity, MILP-D models are considered.

The decomposition-based heuristic first solves the first (or last) R ($R < T$) periods optimally using the MILP-D model. Then we solve the T-period model using the optimal y_{ijt}values of the R-period model as parameters. Hence, we solve a lower complexity model with binary variables only for the last (or first) $T - R$ periods.

Our preliminary experiments have shown that the performance of our heuristic algorithm is very sensitive to the R value. At one extreme, when $R = 1$, the original problem decomposes into two subproblems. The first subproblem is solved for the 1-period MILP-D model and the second subproblem is solved for the remaining $T - 1$ periods. The first subproblem is a single period problem, hence considerably easier to solve than the second subproblem. However, the second subproblem has the same difficulty level as the original problem since it differs from the original problem in only one period. The same conclusion is valid for the other extreme, i.e., when $R = T - 1$. The increase in the R value from one to the half of the T value brings the sizes of the subproblems closer to each other, and as a result, both subproblems are solved in a shorter time. Recognizing this fact, in our experiments, we set $R = \left\lfloor \frac{T}{2} \right\rfloor + 1$ where $\left\lfloor \frac{T}{2} \right\rfloor$ is the largest integer number smaller than $\frac{T}{2}$.

6. Computational experiments

This section is devoted to our experiment that is designed to assess the performances of our MILP models and heuristic algorithm. To solve the mathematical models, we use the C++ CPLEX of IBM ILOG optimization studio V12.8. We limit the run-time by 2 hours for solving each mathematical model and report the performance results at the termination time. All computations are conducted on a PC with Intel Core i7-8550U CPU at 1.8 GHz and 8 GB RAM working under operating system Windows 10.

In the following subsections, we first define our data generation scheme and discuss the results of the computational runs.

6.1 Data generation

We use the following three data types in our experiments:

1. Real data taken from the Central Anatolian RBC.
2. Real distance data taken from Google Maps.
3. Randomly generated data when the corresponding real data are not available in the Central Anatolian RBC.

6.1.1 Real data taken from the Central Anatolian RBC

There are 16 districts in the Central Anatolian RBC; hence we take $N = 16$. The RBC makes its distribution plans for 5 or 7 periods. We use three values of $T = 5$, 6, and 7 periods, where $T = 5$ and 7 are real instances, and the instances for $T = 6$ are formed by adding the demands of the last two periods. Currently, the RBC owes three vehicles, each having 300 units of capacity. In our experiments, we set $V = 2$, 3, and 4 to see the effects of using a fewer or higher number of vehicles. There are 32 blood product types in the RBC; hence we set P to 32.

The parameters taken from the Central Anatolian RBC are listed below:

- The demand figures for the normal and urgent orders (ND_{ipt} and UD_{ipt}values)

- The shelf life (SL_p) values for the platelets, red blood cells, and plasma variants are 5 days, 42 days, and 2 years, respectively. We only consider the shelf lives of platelet variants and assume that the other product types do not reach their shelf lives in our planning horizons of up to 7 periods.

6.1.2 Real distance data

The real-time distances are obtained from Google maps and are used to define sets STO_i and SBY_i. We put district j to the sets STO_i and SBY_i if the real-time distance between district j and district i is less than 3 hours. The fixed transportation costs (FC_{ij} values) are found by multiplying the real-time distance between district i (or RBC) and district j with the transportation cost (fc) per unit time distance. The fc values are set to 1 and 2.

6.1.3 Randomly generated data

We generate random data that are not available in the RBC as follows:

- The amount of product type p at age k added in the RBC at the beginning of period t (A_{pkt}values) is randomly generated from a discrete uniform distribution between 0.5 × (total demand in period t) and 1.5 × (total demand in period t), and then distributed inversely by the k values (i.e., younger products have higher additions).
- The unit inventory holding costs of product p per period in the RBC (HCC_p values) and district i (HCD_{ip} values) are randomly generated from a normal distribution *N*(0.1, 0.02) with a mean of 0.1 and a standard deviation of 0.02.
- The initial inventory levels (I_{pk0} values) are set to zero.
- For CLS_{ip}, DC_p and FC_{ij}values, three scenarios are used as in Mirzaei and Seifi (2015):

Scenario 1: CLS_{ip} and DC_p are from 5 × *N*(0.8, 0.04).
FC_{ij} = 1× (real-time distance between i and j).
Scenario 2:CLS_{ip} and DC_p are from 5 × *N*(0.4, 0.01).
FC_{ij} = 2× (real-time distance between i and j).
Scenario 3: CLS_{ip} and DC_p are from 5 × *N*(0.4, 0.01).
FC_{ij} = 1 × (real-time distance between i and j).

For urgent products, the CLS_{ip} values are multiplied by 100. In the first scenario, the cases with high lost sale and disposal costs and low transportation costs are tested. The second scenario considers the cases with low lost sale and disposal costs and high transportation costs. In contrast, the third scenario considers the cases with low lost sales and disposal costs and low transportation costs.

We take 17 instances from the RBC (7 instances with T = 5, 5 instances with T = 6, and 5 instances with T = 7). For each of these 17 instances, we use three values of V and three scenarios. Hence we consider a total of 153 (17×3×3) instances.

6.2 Analysis of the results

In this subsection, we assess the performances of our mathematical models and heuristic algorithm.

6.2.1 Performances of the mathematical programming models

We first discuss the performance of the MILP-C model designed for the centralized distribution strategy and then the performance of the MILP-D model designed for the decentralized distribution strategy. Finally, we compare the total cost values of the two models to see the amount of improvement brought by the decentralized distribution strategy.

We use the solution times expressed in CPU (Central Processing Unit) seconds as the primary performance measure. Table 1 reports the average and maximum CPU times of the MILP-C model for each number of periods (T), the number of vehicles (V), and for each scenario. As can be observed from Table 1, the MILP-C model could solve all 153 problem instances in 2 hours of termination limit. The average and maximum CPU times over all instances are 135.96 and 1623.59 seconds, respectively, i.e., less than 28 minutes. We observe that the model's performance deteriorates as Tor V increases; the most difficult instances are the ones having seven periods and four vehicles for each scenario.

Fig. 5 depicts the effect of the number of periods on the average CPU time when the number of vehicles is fixed to 3. Fig. 5 shows that an increase in the number of periods significantly increases the average CPU times for all scenarios since an increase in T increases the number of binary variables that adversely affect the complexity of the MILP-C model. Note from Table 1 that this observation is true for other T values and becomes more pronounced as V increases.

Fig. 6 depicts the effect of the number of vehicles on the average CPU time of the MILP-C model when the number of periods is fixed to 6.

Note from Fig. 6 that an increase in the number of vehicles significantly increases the average CPU times for all scenarios since any increase in V increases the number of binary variables, increasing the complexity of the MILP-C model. Note from Table 1 that the same conclusion holds for other T values, and the significance of V becomes more pronounced as T increases. We could not observe any significant effect of the scenarios on the CPU times of the MILP-C model.

The computational results of the MILP-D model are given in Table 2. The table reports the average and maximum CPU times for each value of $V$and each scenario when there are 5 and 6 periods. We did not include the results of T = 7 as no instance could be solved in two hours.

Note that the CPU times of the MILP-D model are much higher than those of the MILP-C model. 56 instances out of 108 with T = 5 and 6, all 45 instances with seven periods remain unsolved in two hours where the MILP-C model could solve all instances. The average CPU times of each combination are close to 1 and 2 hours when there are five periods and six periods, respectively.

Table 1
Performance of the MILP-C model

T	*V*	*Scenario*	*Number of instances*	*CPU Time (seconds)*	
				Average	*Maximum*
5	2	1	7	11.65	35.38
		2	7	11.51	48.26
		3	7	7.56	21.76
	3	1	7	29.33	130.32
		2	7	25.63	81.05
		3	7	26.36	71.80
	4	1	7	29.35	95.16
		2	7	23.70	69.87
		3	7	28.24	92.90
6	2	1	5	27.35	44.68
		2	5	17.30	28.93
		3	5	25.38	80.69
	3	1	5	177.27	605.55
		2	5	166.58	390.45
		3	5	221.65	602.45
	4	1	5	276.72	886.72
		2	5	286.32	1092.47
		3	5	218.69	745.40
7	2	1	5	109.05	228.94
		2	5	44.74	91.67
		3	5	45.72	88.20
	3	1	5	298.00	837.78
		2	5	177.17	397.37
		3	5	421.39	1057.62
	4	1	5	421.00	1319.61
		2	5	471.44	1623.59
		3	5	483.89	1449.35
Overall Sum & Averages			153	135.96	1623.59

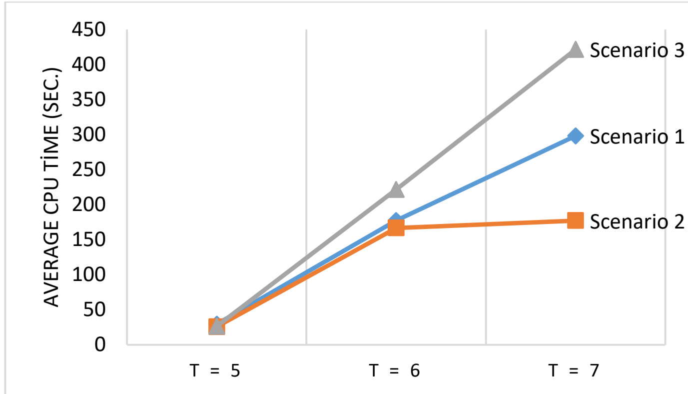

Fig. 5. Effect of T on the average CPU times for $V= 3$ (MILP-C model)

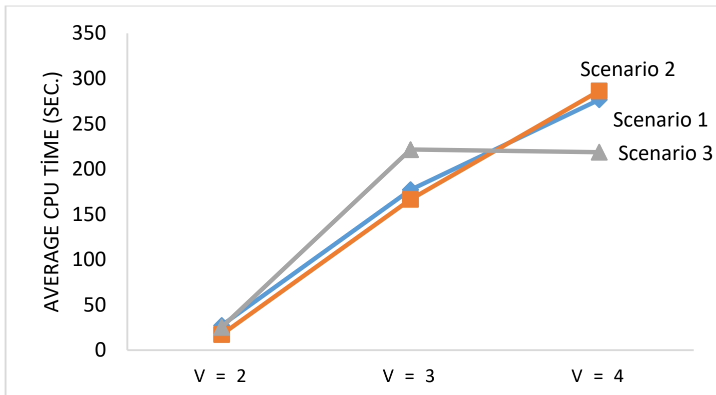

Fig. 6. Effect of V on the average CPU times for $T= 6$ (MILP-C model)

Table 2
Performance of the MILP-D model

T	*V*	*Scenario*	*Number of instances*	*CPU Time (seconds)*	
				Average	*Maximum*
5	2	1	7 (2)*	2575.24	7200
		2	7 (2)	2744.38	7200
		3	7 (2)	3307.71	7200
	3	1	7 (2)	3023.60	7200
		2	7 (2)	3864.41	7200
		3	7 (3)	5075.26	7200
	4	1	7 (2)	2587.35	7200
		2	7 (3)	4094.20	7200
		3	7 (2)	2963.10	7200
6	2	1	5 (4)	6660.12	7200
		2	5 (3)	6418.53	7200
		3	5 (5)	7200.00	7200
	3	1	5 (4)	6606.23	7200
		2	5 (5)	7200.00	7200
		3	5 (4)	6831.11	7200
	4	1	5 (3)	6018.24	7200
		2	5 (4)	6457.46	7200
		3	5 (4)	6995.35	7200
Overall Sum & Averages			108 (56) (54)(58*)	4755.61	7200

* The numbers in the parentheses give the number of instances that remain unsolved in two hours.

The effect of the number of periods on the CPU times with three vehicles is illustrated by Fig. 7. It can be observed from Fig. 7 that as T increases from 5 to 6 periods, the computational times of the MILP-D model increase due to the inflated number of binary variables. The increases are more dramatic for Scenarios 1 and 3, as the trade-offs with high (low) lost sales costs versus low (high) transportation costs become much more complex when T is higher. Similar observations are true for other values of V, as can be observed from Table 2.

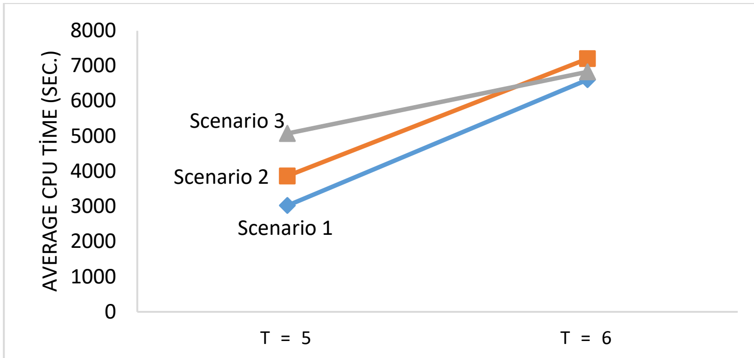

Fig. 7. Effect of T on the average CPU time for V= 3 (MILP-D model)

The effects of the number of vehicles on the complexity of the model solutions are given in Fig. 8 when the number of periods is fixed to 5 periods. As can be observed from this figure, the average CPU times increase when V increases from 2 to 3 vehicles. This result can be attributed to the increased number of binary variables adding to the complexity of the model solutions. However, when the number of vehicles is further increased from 3 to 4, the average of CPU times reduces for Scenarios 1 and 3 and increases for Scenario 2. Scenarios 1 and 3 reside low transportation cost instances that benefit from additional vehicles and make the associated assignment decisions more relaxed. Scenario 2 is a high transportation cost combination that reduces the number of vehicles used, hence spending much more time finding a low vehicle usage solution. Table 2 illustrates that the results are not compatible with those observations when there are six periods. This result is due to the many unsolved instances that prevent proper analysis.

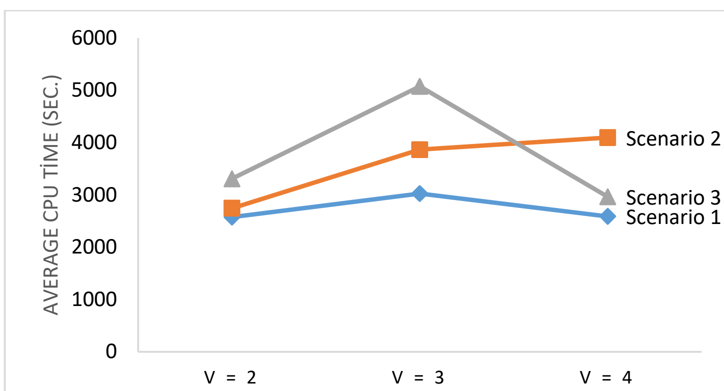

Fig. 8. Effect of V on the average CPU timefor T= 5 (MILP-D model)

The results of investigation to see the effect of the number of vehicles on the optimal/best known total cost values of the mathematical models are given in Fig. 9 and Fig. 10 for the MILP-C and MILP-D models, respectively, by fixing the number of periods to 6.

From Fig. 9 and Fig. 10, we observe that the total cost values decrease as the number of vehicles increases. The more significant decreases are observed for the first scenario, where the lost sales and disposal costs are high, and the transportation costs are low. This result is because the additional vehicle is worth using due to its low transportation cost and reductions in lost sales. The lost sales costs of the second and third scenarios are low, so the models may not prefer to use an additional vehicle to reduce the number of lost sales.

Note from Fig. 9 and Fig. 10 that the optimal total cost values of the MILP-D model are much lower than those of the MILP-C model; hence, the decentralized distribution strategy provides more economical results than the centralized distribution strategy.

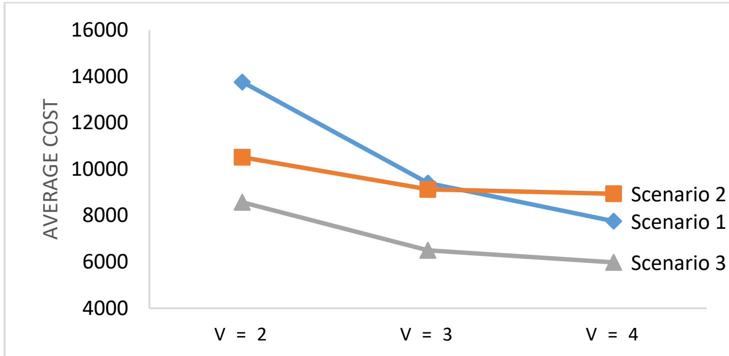

Fig. 9. Effect of V on the optimal total cost values for T= 6 (MILP-C model)

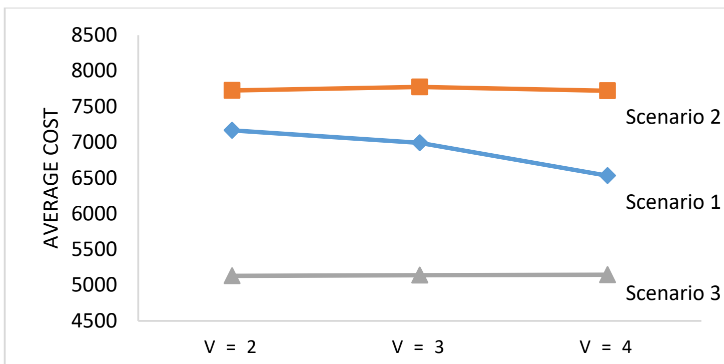

Fig. 10. Effect of V on the optimal/best known total cost values for T= 6 (MILP-D model)

To see the amount of total cost reduction brought by the decentralized distribution strategy, we define the percent improvement brought by the MILP-D model over the MILP-C model as follows:

$$\text{Percent improvement} = \frac{z_C^* - z_D^*}{z_C^*} \times 100$$

where z_C^* and z_D^* are the optimal total cost values returned by the MILP-C and MILP-D models, respectively. If the optimal solution by the MILP-D model is not available, we use the best-known total cost value that the CPLEX returns at the termination time of two hours.

Table 3 reports the percent improvement values for all T, V, and scenario combinations. The table reveals that the decentralized distribution strategy significantly reduces the optimal total costs. The average improvement brought by the MILP-D model over the MILP-C model is at least 22.93% (note that best-known solutions are used in place of the optimal solutions). The maximum improvement of 73.64% is very significant. We observe that the improvements are more significant when the transportation cost is low and lost sales and disposal costs are high, i.e., Scenario 1 is used. This result is the decentralized distribution strategy's power to help reduce the lost sales amounts. The improvements are lowest when Scenario 2 is used as longer transportations are not justified to prevent lost sales whose costs are already low.

Moreover, we observe that the improvements are most remarkable when the number of vehicles is lowest. This result is because the decentralized distribution strategy uses the vehicles to their fullest extent to prevent lost sales. When the number of vehicles is high, the centralization strategy may already prevent lost sales, and the improvement brought by the decentralized distribution strategy may not be as high.

Based on our experimental results, we suggest to the managers of the TRC to use the MILP-D model to reduce their operational costs, mainly when the number of vehicles is low and the lost sales and disposal costs are high.

Table 3
Improvements in total costs brought by the MILP-D model over the MILP-C model

T	V	*Scenario*	*Number of instances*	*Percent improvement*	
				Average	*Maximum*
5	2	1	7	41.80	73.64
		2	7	22.94	45.48
		3	7	33.17	59.29
	3	1	7	25.86	46.16
		2	7	14.32	23.56
		3	7	17.91	33.41
	4	1	7	14.94	19.77
		2	7	11.58	14.50
		3	7	13.83	19.71
6	2	1	5	46.06	56.17
		2	5	24.84	39.33
		3	5	37.92	55.02
	3	1	5	24.04	41.79
		2	5	14.53	21.19
		3	5	20.22	32.17
	4	1	5	15.91	17.37
		2	5	13.60	15.81
		3	5	13.94	18.67
7	2	1	5	50.50	63.74
		2	5	23.81	36.19
		3	5	37.59	54.43
	3	1	5	24.81	42.14
		2	5	15.34	21.99
		3	5	20.12	30.60
	4	1	5	16.25	20.44
		2	5	12.02	13.12
		3	5	15.29	23.07
Overall Sum & Averages			153	22.93	73.64

6.2.2 Performance of the decomposition-based heuristic algorithm

This subsection evaluates our decomposition-based heuristic algorithm introduced to handle large-sized instances of the decentralized distribution strategy that the MILP-D model could not solve in reasonable times.

As in measuring the performance of our mathematical models, we use the solution times expressed in CPU (Central Processing Units) seconds as the performance measure. Moreover, we define the percent deviation of the total cost obtained by our heuristic algorithm from the optimal total cost obtained by the MILP-D model. That is,

$$\text{Percent Deviation} = \frac{z_H - z_D^*}{z_D^*} \times 100$$

where z_H is the total cost obtained by the heuristic algorithm, and z_D^* is the optimal total cost obtained by the MILP-D model.

If the optimal solution is not achieved by the MILP-D model, we use the best-known total cost value that the CPLEX returns at the termination time of two hours.

Table 4 reports the average and maximum CPU times and the average and maximum percent deviation values of the heuristic algorithm for each number of periods (T), the number of vehicles (V), and the scenario. Table 4 shows that the heuristic algorithm could solve 153 problem instances in less than 844.52 seconds. The overall average CPU time of all problem instances is 114.69 seconds, i.e., less than 2 minutes. The average deviation from the objective function value (optimal or best known) is about 2%, and the associated maximum deviation is below 8%. Those results altogether reveal the excellent performance of our decomposition-based heuristic algorithm over all problem sets.

Table 4
Percent deviation of the decomposition-based heuristic algorithm

T	*V*	*Scenario*	*Number of instances*	*CPU Time (seconds)*		*Percent Deviation*	
				Average	*Maximum*	*Average*	*Maximum*
5	2	1	7	25.68	69.08	1.10	2.79
		2	7	41.33	125.53	4.00	7.08
		3	7	89.08	394.35	3.49	6.49
	3	1	7	23.34	37.98	0.94	3.09
		2	7	86.82	239.59	3.35	6.27
		3	7	65.60	214.38	2.66	5.76
	4	1	7	22.35	63.68	1.72	2.56
		2	7	63.46	209.97	4.04	7.94
		3	7	40.94	91.99	2.22	6.70
6	2	1	5	145.43	294.22	1.12	2.26
		2	5	108.16	205.41	3.45	6.18
		3	5	229.66	566.00	1.01	1.61
	3	1	5	42.52	62.59	1.37	1.99
		2	5	88.86	169.93	3.09	4.61
		3	5	133.58	197.07	0.82	1.50
	4	1	5	107.00	199.78	1.52	4.03
		2	5	101.10	162.39	2.54	4.87
		3	5	70.91	137.97	2.33	6.43
7	2	1	5	198.78	359.04	1.75	3.08
		2	5	165.10	239.75	1.56	3.38
		3	5	247.99	440.34	1.68	3.97
	3	1	5	266.25	844.52	0.53	2.80
		2	5	180.91	314.83	2.84	3.74
		3	5	206.83	546.66	1.93	3.39
	4	1	5	162.83	287.28	1.71	4.65
		2	5	161.27	254.99	2.75	5.56
		3	5	250.42	368.51	2.06	2.98
Overall Sum & Averages			153	114.69	844.52	2.19	7.94

We observe that the CPU time performance of our heuristic algorithm deteriorates as the number of the periods of the decomposed models increase. This can be attributed to the deteriorating time performance of the MILP-D model with increases in the number of the periods. As in the MILP-D model, the most complex instances have the highest number of periods for each scenario. On the other hand, we have not observed any significant effect of the number of vehicles on the time complexity of the solutions and the percent deviations.

Table 4 reveals that the percent deviations increase significantly with the increases in the objective function values. When the objective function values are higher, even a small difference from the optimal decision variable values may cause a significant deviation from the optimal objective function values. The largest objective function values are associated with Scenario 2 instances for which we observe the highest deviations. Moreover, small T values lead to higher objective function values and the largest average and maximum deviations. Note that the overall maximum deviation of all problem instances is 7.94% coming from a Scenario 2 instance with T = 5 periods. The average deviation of that combination is 4.04% which defines the highest average deviation over all problem sets.

7. Conclusions

This study addresses an integrated inventory planning and product distribution problem encountered at the Turkish Red Crescent's Central Anatolian Regional Blood Center. Two echelons are defined, the first echelon being the regional blood center and the second echelon being the districts. We aim to minimize the cost of inventory keeping at both echelons, disposal amounts at the first echelon, and the shortage at the second echelon. Centralized distribution strategy (all deliveries are from the blood center) and decentralized distribution strategy (the deliveries are from the blood center or other districts) are studied using mixed-integer linear programming models.

Our computational results have revealed that the mathematical model developed for the centralized distribution strategy can handle any weekly operation of the Central Anatolian Regional Blood Center in very short solution times. On the other hand, the model for the decentralized distribution strategy is more complex and could not handle large-sized instances in our pre-specified termination limit of two hours. To solve the large-sized instances for the decentralized distribution strategy, we design a decomposition-based heuristic algorithm that benefits from the optimal solutions of the original model and finds near-optimal solutions very quickly.

For both strategies, we notice that the number of periods, the number of vehicles, and the cost parameters are significant factors that affect the complexity of the solutions. Our computational results have shown that the decentralized distribution strategy has significantly lower total costs than the centralized distribution strategy. Especially when there are few vehicles, lost sales costs are high, and low transportation costs.

Based on the results of our experiments, our recommendation to the Turkish Red Crescent managers is to implement the decentralized distribution strategy and use our heuristic algorithm to solve their large-scale problem instances. If the managers prefer to go with the centralized distribution strategy, they can use our proposed MILP model to reduce their inventory and distribution costs.

Future research may consider the development of implicit enumeration algorithms –like a branch and cut algorithm– that deliver exact solutions for the decentralized distribution strategy.

Acknowledgments

We thank the TRC Association and especially TRC staff Derviş Ülger and Ayça Hande Kundakçı for their everlasting support.

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