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RESEARCH PAPER

The Inventory–Routing Problem for Distribution of Red Blood Cells Considering Compatibility of Blood Group and Transshipment Between Hospitals

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Abstract

This paper presents an inventory-routing problem (IRP) for Red Blood Cells (RBCs) distribution, in which -to avoid shortage- supplying the demand with compatible blood groups (substitution) and the RBC transshipments between hospitals (transshipment) are considered. The mentioned problem is investigated in four conditions: 1- allowing the transshipment and substitution, 2- allowing the transshipment, but no substitution, 3- allowing the substitution, but no transshipment, and 4- no allowing the transshipment and substitution. Since the mentioned problem is NP-Hard, the adaptive large neighborhood search algorithm (ALNS) has been used to solve all conditions. The cost in the first condition is the least one because the feasible solution space is the largest. Also, the results show that the transshipment has a more active role than the substitution in reducing the shortage. Moreover, in the first and third conditions, the O^+ blood group is used more than the other blood groups to meet the other compatible blood groups' demands.

Keywords:
Adaptive Large Neighborhood Search Algorithm;
Compatibility of Blood Group;
Red Blood Cells;
Transshipment;
Inventory Routing Problem

Introduction

Blood is one of the scarce and vital resources for human survival. RBCs, platelets, and plasma are among the most crucial blood products. RBCs are applied to treat anemia, cancer, childbirth, and thalassemia. Platelets are used for cancer treatment, and long-term surgery (such as open-heart surgery), and plasma units are taken for burn treatment [1].

Blood supply chain management is highly complex for its characteristics, such as short lifespan and blood group compatibility [2]. Therefore, minimizing the shortage and wastage is one of the most critical challenges in this field [3]. According to a review article [2], more than one hundred studies have been investigated up to September 2014 in the field of quantitative models in the blood supply chain, which the related ones to the proposed study are discussed in the following.

Federgruen et al. [4] proposed two models for the inventory-routing and allocation problem with the aims of minimizing costs of shortages, transportation, and expiration. Hemmelmayr and Doerner [5] presented an integer programming model for delivering blood products to Austrian hospitals in two different strategies. In the first strategy, the hospitals in each area can be served only by one vehicle and through a fixed route and the integer programming model aimed to schedule the delivery of blood to the hospitals. In the second strategy, routing decisions were made with a focus on regular delivery. Both strategies were implemented based on real data, revealing that about 30% of cost savings were obtained compared to the old method of blood delivery to the hospitals. Hemmelmayr et al. [6] presented an improved version of their

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previous model [5] by randomly considering the demand. Our study considers the possibility of blood transshipment between hospitals and the compatibility of blood group in addition to articles [5] and [6]. Jafarkhan and Yaghoubi [7] designed a robust mathematical model for integrated production routing inventory problem of perishable product and solved it with the adaptive large neighborhood search algorithm. Also, they used a heuristic algorithm for solving robust inventory -routing problem of red blood cells [8].

Gunpinar and Centeno [3] proposed three integer linear programming models to determine the optimal ordering in a hospital with the aims of reducing wastages and shortages. Yaghoubi et al. [9] presented a bi-objective mixed-integer linear programming model in supplying blood-platelets with the aims of minimizing total costs and delivery time simultaneously. Hospitals' priority, platelet perishability, and demand fluctuations are considered and incorporated into the mathematical model.

Since platelet extraction from whole blood must be done up to six hours, Mobasher et al. [10] presented a mixed-integer linear programming model to make coordination between collecting and processing procedures in the collection centers. Then, a heuristic algorithm named Integer Programming Based Algorithm was presented to solve the proposed model. Larimi and Yaghoubi [11] presented a mixed-integer linear programming model in a platelet supply chain to reduce the total logistics costs and increase donors' awareness. Moreover, a robust stochastic approach was applied to manage demand uncertainty. Şahinyazan et al. [12] designed a blood collection system intending to increase the collected blood at reasonable operating costs. In their model, the bloodmobiles (i.e., equipped facilities to extract blood from donors) did not return to the blood bank to prevent blood corruption, and a new device -named a shuttle- visited the mobile facilities in each period and transferred the collected blood to the blood bank. Duan et al. [13] proposed a new optimization-simulation model for managing blood inventory by considering the compatibility of blood groups in a blood bank and a hospital. The model has been evaluated in three different conditions: (1) no compatible substitutions are considered at the blood bank and hospital, (2) compatible substitution is only allowed in the hospital, and (3) compatible substitution is allowed both in the hospital and in the blood bank. The results concluded that the first condition has less waste than the other two conditions.

This study presents an inventory-routing problem for blood distribution, in which satisfying blood-demands with other compatible blood groups (substitution), and lateral transshipment between hospitals (transshipment) are considered in the mathematical model to avoid shortages. As can be seen through the classification in Table 1, no study has simultaneously focused on considering substitution and transshipment, especially in the field of optimizing routing problems. Therefore, to evaluate the efficiency of considering substitution and transshipment in the proposed healthcare system, four different conditions are proposed.

- First condition: It is allowed to consider both lateral transshipment and substitution of compatible blood groups in the supply chain.
- Second condition: It is only allowed to consider lateral transshipment between hospitals. No substitution for compatible blood groups is permitted.
- Third condition: It is only allowed to consider substitution for compatible blood groups. No lateral transshipment between hospitals is permitted.
- Fourth condition: Neither substitution nor lateral transshipment is allowed in the proposed supply chain

Table 1. Classification of related studies in the field of blood supply chain management

References	**Solution approach**			Lateral transshipment between hospitals	Blood return to blood bank	Blood compatibility	**Network**			**Decision**				**Approach**	
	Heuristic	Meta-heuristic	Exact				Multi-stage	Two-stage	Single-stage	Location	Inventory	Routing	Allocation	Simulation	Optimization
[14]					✓				✓		✓				✓
[15]			✓					✓					✓	✓	
[4]		✓						✓			✓	✓	✓	✓	
[16]	✓							✓				✓	✓	✓	
[5]		✓						✓			✓	✓	✓	✓	
[6]	✓							✓			✓	✓	✓	✓	
[13]	✓					✓		✓			✓			✓	✓
[17]			✓	✓			✓			✓			✓	✓	
[18]			✓	✓	✓				✓		✓				✓
[11]			✓						✓	✓	✓		✓		✓
[9]			✓					✓		✓	✓		✓		✓
This study		✓		✓		✓		✓			✓	✓		✓	

Problem Description and Mathematical Modeling

Inventory-Routing Problem (IRP) is an extension of the Vehicle Routing Problem (VRP) that helps decision-makers decide about vehicle routing problems and the inventory issues, simultaneously. Noteworthy, IRP ignores the possibility of transshipment between demand zones. Coelho et al. [19] presented an IRP model by considering temporary transshipment between customers. The results revealed that applying this transshipment can be beneficial for responding to demand fluctuations in a dynamic and stochastic environment. Our study is the extension of Coelho et al. [19] study, in which the possibility of responding to the demand by considering other compatible blood groups is also incorporated into the model. This strategy is added to the presented IRP model to better deal with sharp changes in RBC demands. For this purpose, a supply network with one blood center and several hospitals is presented, in which four different conditions can occur in the system (see Table 2). Table 3 demonstrates the ABO-RH matching rules. For example, blood type O^-, in the second column, can give blood to all the blood groups and only receive blood from their own blood type.

Table 2. The presented conditions for RBC distribution

Conditions	Satisfying demand with other compatible blood type		Lateral transshipment between hospitals	
	Not allowed	Allowed	Not allowed	Allowed
1		✓		✓
2	✓			✓
3		✓	✓	
4	✓		✓	

Table 3. ABO-RH matching rules for red blood cells

Donor \ Recipient	O^+	O^-	A^+	A^-	B^+	B^-	AB^+	AB^-
O^+ (1)	1	0	1	0	1	0	1	0
O^- (2)	1	1	1	1	1	1	1	1
A^+ (3)	0	0	1	0	0	0	1	0
A^- (4)	0	0	1	1	0	0	1	1
B^+ (5)	0	0	0	0	1	0	1	0
B^- (6)	0	0	0	0	1	1	1	1
AB^+ (7)	0	0	0	0	0	0	1	0
AB^- (8)	0	0	0	0	0	0	1	1

The Assumptions of the First Condition

The assumptions of the first condition can be seen as follows:

- The inventory of the blood bank and hospitals is identified and fixed at the beginning of the first period. Hospitals' demands and the replenishment amount in the blood bank are known in each period.
- The capacity of hospitals is fixed and bounded.
- The RBC demand can be satisfied by the other compatible blood groups.
- A vehicle with limited capacity is available, in which this vehicle transships in a single route to deliver the required RBC from the blood bank to a subset of hospitals. Lateral transshipment between hospitals can be added to the proposed model in the following periods. Direct transshipment between the blood bank and the hospitals is also allowed.
- The procedures of receiving and delivering RBC (transshipment) are done by an outsourcing company, and its costs depend on the distance and number of RBC transshipment.

Mathematical Formulation

The notations and the mathematical formulation of the proposed model are as follows:

Sets	
V	Set of hospitals and the blood bank $i, j \in \{0,1,2,\dots,n\}$
$V'=V\backslash\{0\}$	Set of hospitals $i, j \in \{1,2,\dots,n\}$
T	Set of periods $t \in \{1,2,\dots,T\}$
R	Set of blood type $r, u \in \{1,2,\dots,8\}$
Parameters	
h_i	Inventory costs in hospitals and the blood bank (Toman)
$F^{t,r}$	Blood bank replenishment rate for blood type *r* in period *t*
c_{ij}	Transshipment costs between different nodes based on distance (Toman)
b_{ij}	Transshipment costs between different nodes based on distance and number of transshipped RBC (Toman)
SC	Shortage costs for each unit of RBC (Toman)
Q	Maximum capacity of the vehicle (based on number of RBC units)
C_i	Maximum capacity of the hospitals (based on number of RBC units)
$d_i^{r,t}$	RBC demand at hospital *i* for each type of blood group *r* in period *t* (based on number of RBC units)

$I_i^{\cdot,r}$	Initial inventory of blood type *r* in the hospitals and blood bank (based on number of RBC units)
$MS^{r,u}$	Blood group compatibility matrixes, *r* is the recipient and *u* is the donor (Table 3)
Variables	
$I_i^{t,r}$	The inventory amount of blood type *r* at hospital *i* in period *t* (based on number of RBC units)
$sh_i^{r,t}$	The shortage amount of blood type *r* at hospital *i* in period *t* (based on number of RBC units)
$d_i^{t,r,u}$	Number of demand blood type *u* at hospital *i* in period *t* which is satisfied by the compatible blood type *r* (based on number of RBC units)
x_{ij}^t	Binary variable;1: if node *i* visits after node *j* in period t, otherwise 0.
$q_i^{t,r}$	Amount of delivered RBC type *r* to hospital *i* in period *t* (based on number of RBC units)
$w_{i,j}^{t,r}$	Amount of transshipped RBC type *r* from node *i* to *j* in period *t* (based on number of RBC units)

Model type 1

$$\text{Min} \sum_{t\in T}\sum_{r\in R} h_0 I_0^{t.r} + \sum_{t\in T}\sum_{i\in V'}\sum_{r\in R} h_i I_i^{t.r} + \sum_{t\in T}\sum_{i\in V}\sum_{j\in V} c_{ij}\, x_{ij}^t + \sum_{t\in T}\sum_{i\in V}\sum_{j\in V'}\sum_{r\in R} b_{ij}\, w_{ij}^{t.r} + SC\sum_{t\in T}\sum_{i\in V'}\sum_{r\in R} sh_i^{r.t} \quad (1)$$

The objective function 1 is to minimize the costs of holding RBC in the blood bank and hospitals, the cost of routing, the costs of transshipment between hospitals and direct delivery from the blood bank to hospitals, and the cost of shortages.

Subject to:

$$I_0^{t.r} = I_0^{t-1.r} + F^{t.r} - \sum_{i\in V'} q_i^{t.r} - \sum_{i\in V'} w_{0i}^{t.r} \qquad t \in T. r \in R \quad (2)$$

$$I_i^{t.r} = I_i^{t-1.r} + q_i^{t.r} + \sum_{j\in V} w_{j.i}^{t.r} - \sum_{j\in V'} w_{ij}^{t.r} - \sum_{u\in R} MS^{r.u}\, d_i^{t.r.u} \qquad t \in T. r \in R. i \in V' \quad (3)$$

$$d_i^{t.r} = \sum_{u\in R} MS^{u.r}\, d_i^{t.u.r} + sh_i^{r.t} \qquad t \in T. r \in R. i \in V' \quad (4)$$

$$\sum_{r\in R} I_i^{t.r} \le C_i \qquad t \in T. i \in V' \quad (5)$$

$$q_i^{t.r} \le C_i \sum_{j\in V} X_{ij}^t \qquad t \in T. r \in R. i \in V' \quad (6)$$

$$\sum_{r\in R} q_i^{t.r} \le C_i \sum_{r\in R} I_i^{t-1.r} \qquad t \in T. i \in V' \quad (7)$$

$$\sum_{r\in R}\sum_{i\in V'} q_i^{t.r} \le Q \qquad t \in T \quad (8)$$

$$\sum_{j\in V} X_{ij}^{t} = \sum_{j\in V} X_{ji}^{t} \qquad t \in T. i \in V \qquad (9)$$

$$v_{i}^{t} + v_{j}^{t} + QX_{ij}^{t} \le Q - \sum_{i\in V'} q_{i}^{t.r} \qquad t \in T. i. j \in V' \qquad (10)$$

$$\sum_{r\in R} q_{i}^{t.r} \le v_{i}^{t} \le Q \qquad t \in T. i \in V' \qquad (11)$$

$$\sum_{i\in V} X_{i0}^{t} \le 1 \qquad t \in T \qquad (12)$$

$$X_{ij}^{t} \in \{0.1\} \qquad i. j \in V'. i \ne j. t \in T \qquad (13)$$

$$I_{i}^{t.r}. q_{i}^{t.r}. w_{ij}^{t.r}. d_{i}^{t.u.r}. v_{i}^{t}. sh_{i}^{r.t} \ge 0 \qquad t \in T. r. u \in R. i. j \in V \qquad (14)$$

Constraint 2 shows the inventory balance in the blood bank for each type of blood group. The blood bank inventory in each period is equal to the inventory of each blood group at the end of the previous period, plus the amount delivered blood units from the collection centers (replenishment procedure) minus the amount that sent to hospitals through routing minus the amount sent directly to hospitals. Constraint 3 illustrates the inventory balance in the hospitals for each type of blood group. The hospital inventory in each period is equal to the inventory of each blood group at the end of the previous period, plus the amount that delivered to hospitals through routing, plus the amount delivered directly to hospitals through other hospitals and the blood bank, minus the number of blood units that shipped to other hospitals, minus the sum of the RBC demand at the hospital estimated for a compatible blood type (For instance, for recipients with blood type AB-, both blood types AB+ and AB- can be used. Therefore, in its inventory constraint, the values of $d_i^{t,8,7}$ and $d_i^{t,8,8}$ are equal to one, and the other $d_i^{t,8,u}$ $u \in \{1,2,3,4,5,6\}$ are equal to zero). Constraint 4 refers to the amount of shortage, in which the demand for each blood type can be either satisfied by its compatible blood groups (delivered RBC units) or unsatisfied (shortage amount). For example, the second blood type can only receive blood from itself (i.e. $d_i^{2,t} = d_i^{t,2,2}$). Constraint 5 ensures that the amount of inventory at the end of each period will not be more than its maximum capacity. Constraints 6 and 7 guaranty that if the hospital is visited by a vehicle, the delivery amount should not exceed the hospital's capacity. Constraint 8 refers to capacity limitation of the vehicle. Constraint 9 is applied to set tours in the proposed model, and constraints 10 and 11 delete the sup-tours [20]. Constraint 12 points to the availability of the vehicle in each period. Constraints 13 and 14 are the domain variables.

Model type 2

To obtain the second condition, first, constraint 4 is deleted. Then, the parameter $\sum_{u\in R} MS^{r,u} d_i^{t,r,u}$ (in the constraint 3) is changed and rewritten as $d_i^{r,t}$ to avoid demand satisfaction by other compatible blood groups.

Mathematical Model of Condition Three

To obtain the third condition, constraint 15 will be added to the mathematical model to prevent the lateral transshipment in the supply chain.

Mathematical Model of Condition Four

To obtain the fourth condition, all the mentioned revisions in conditions 2 and 3 should be added to the first condition.

$$w_{i,j}^{t,r} = 0 \qquad t \in T, r \in R. i. j \in V \qquad (15)$$

Solution Method

This section is divided into two parts: 1- determining the optimal routes (routing decisions), and 2- evaluating the other variables (inventory decisions). Routing decisions (x_{ij}^{t}) are assessed by the ALNS algorithm, which converts the problem to sub-flow problem to find the optimal values of $I_i^{t,r}, sh_i^{r,t}, d_i^{t,r,u}, q_i^{t,r}, w_{i,j}^{t,r}$. The sub-flow problem in the first condition can be obtained by deleting constraints 9-12 (constraints related to routing decisions) and routing costs in the objective function, as well as converting the decision variable x_{ij}^{t} to the parameter $\bar{x}_{ij}^{t}$ in constraint 6.

Adaptive Large Neighborhood Search Algorithm

Coelho et al. [19] developed an ALNS algorithm to solve an inventory-routing problem with temporary transshipment, in which in each stage of neighborhood research, only one type of operator is considered, rather than both types of operators destroy and repair. They used a set of examples [21] to evaluate the efficiency of their algorithm. The average gaps of the proposed inventory routing problem with Order-Up are in a three and six time-period are 0.24 and 0.18, respectively.

The ALNS algorithm starts with an initial answer, and then, searches for neighborhood answers in an iterative loop. Searching phases in the ALNS algorithm are divided into several sections, which in each iteration in each section, only one operator is selected among all the available operators to move to the neighborhood answer. Operator selection is chosen by the roulette-wheel mechanism and the weight of each operator (in the first section, the operators' weights are 1). Three different conditions can occur in the process of using operators which can be seen as follows,

1. The operator finds the optimal result. In this situation, the operator domain will be increased up to σ_1 (Initially, the domain of all operators is zero).
2. The operator finds a better result than the current one. In this situation, the operator domain will be increased up to σ_2.
3. The answer obtained by the operator has not improved. According to the acceptance criteria, the answer is either accepted or rejected, as a result, the operator domain will be increased up to σ_3 or remained unchanged, respectively.

So that $\sigma_1 \geq \sigma_2 \geq \sigma_3 \geq 0$, it is necessary to set all the operators' domains to zero at the end of each section. The operators' weights can also be calculated by Eq. 16.

$$w_i = \begin{cases} w_i, \text{ if } o_{ij} = 0 \\ (1-\eta)\ w_i + \eta\pi_i / v_i o_{ij}, \text{ if } o_{ij} \neq 0 \end{cases} \qquad (16)$$

where, w_i is the weight of operator i, o_{ij} is the number of operator i iteration in the last section j, $\eta \in [0,1]$ is the reaction factor, and $v_i \geq 1$ is the normalization factor (this factor depends on the computational time of the operator). π_i is total range of operator i in the last section. Fig. 1 demonstrates the ALNS algorithm structure.

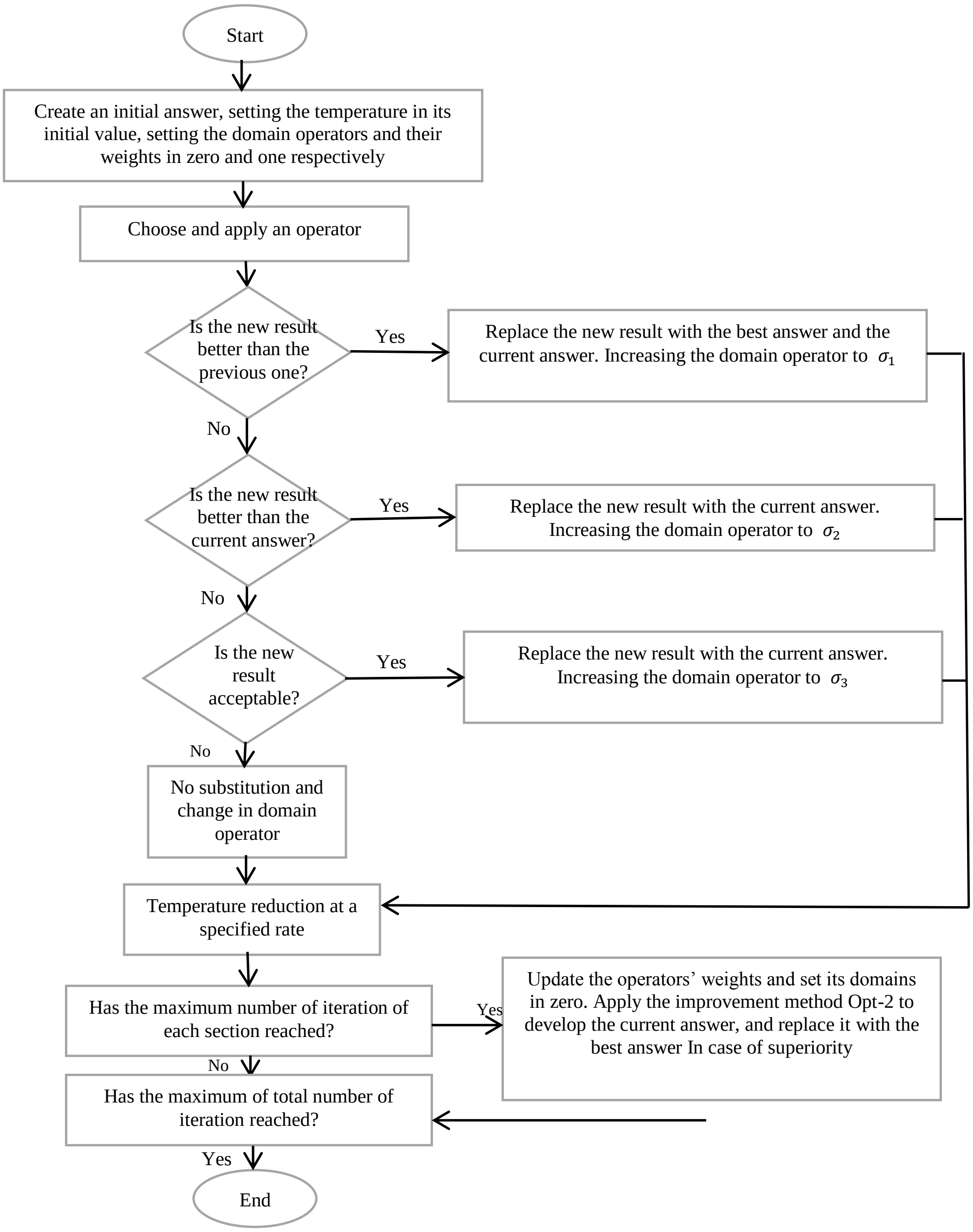

Fig .1. Structure of ALNS algorithm for routing decisions

Operators' lists

The lists of the operators are divided into eleven sections, which can be seen in the following.

1. Randomly remove ρ: This operator randomly chooses one visited customer in a single period and deletes it. This procedure iterates ρ times.
2. Randomly insert ρ: This operator randomly chooses one unmet customer in a single period and inserts it in the best position in the selected period. This procedure iterates ρ times.
3. Insert best ρ: This operator chooses all unmet customers in whole periods and inserts the customer, which has the least total costs (inventory, shortage, transportation, and routing) in comparison with other customers. This procedure iterates ρ times.
4. Remove worst ρ: This operator chooses all visited customers in whole periods and removes the customer, which has the least total costs (inventory, shortage, transportation, and routing) in comparison with other customers. This procedure iterates ρ times.

5. Remove Shaw: This operator randomly chooses one visited customer in a single period, calculates the shortest route (d_{min}) to the customer and then, deletes all the customers within distance 2d_{min}. The removal idea is for nearby customers to meet in another period.
6. Insert Shaw: This operator randomly chooses one unmet customer in a single period, calculates the shortest route (d_{min}) to the customer and then, inserts all unmet customers within distance 2d_{min}.
7. Remove ρ customers: This operator randomly chooses one customer and removes it in all routes that the customer appears.
8. Insert ρ customers: This operator randomly chooses one customer, which has not met in whole periods and then, inserts in another random period (in the best position). This procedure iterates ρ times.
9. Empty one period: This operator randomly chooses one period and deletes all the customers during that period.
10. Two-period swaps: This operator randomly chooses two periods and swaps their routes.
11. Randomly move ρ: This operator randomly chooses one visited customer in one period and removes it, then, inserts the costumer in another randomly period (in the best position).

It is noteworthy that at the end of each part of the searching in the algorithm, the 2-opt improvement method is used to develop the current response paths. The given parameters of the proposed problem are shown in Table 4. Also, the rhythmic acceptance criterion (common acceptance criterion based on n simulated annealing algorithm) has been used to accept unimproved answers.

Table 4. The value of the parameters based on the real case

Parameter	Value
max_{iter}	2000
φ	200
$\sigma_1, \sigma_2, \sigma_3$	10,5,2
Number of operators used (ρ)	1 with probability 5/9 2 with probability 3/9 3 with probability 1/9
Normalization factor (V_i)	20 for operator 3 and 4, 1 for the other operators
Reaction factor (η)	0.7
Cooling rate) T_{rate} (	0.99
Initial temperature ($T_.$)	2000

Create Initial Solution

Creating the initial solution, 75% of the hospitals are randomly selected in each period, and the routes are chosen through the selected hospitals based on the cheapest insertion rule. Then, the selected routes were used in the sub-flow problem to determine the values of other variables.

Computational Results

In this section, to measure the performance of the model and the algorithm (in terms of time and quality), a case study based on 50 main hospitals in Tehran is evaluated. The ALNS algorithm is applied and solved in MATLAB 2014. Also, to solve the flow and the sub-flow model with the exact approach, we used GAMS 24.1 in solver CPLEX on a PC with CORE i5 and 4 GB memory.

Results Discussion And The Efficiency Of The Solution Algorithm

A comparison of the results obtained from the ALNS algorithm for 4, 6, 8, 10, 12, and 14 hospitals (in three periods) in all conditions with the exact solution, shows a maximum gap of 1.3% (Table 5). This value of gap is not only in the optimal range but also is the acceptable solution to the problem in large-size, as these types of problems are not possible to be solved with exact solvers. According to Fig. 2, as the number of hospitals increases, the time to solve through the exact solution sharply intensifies, so that in large-size problems, solving with the algorithm is cost-effective.

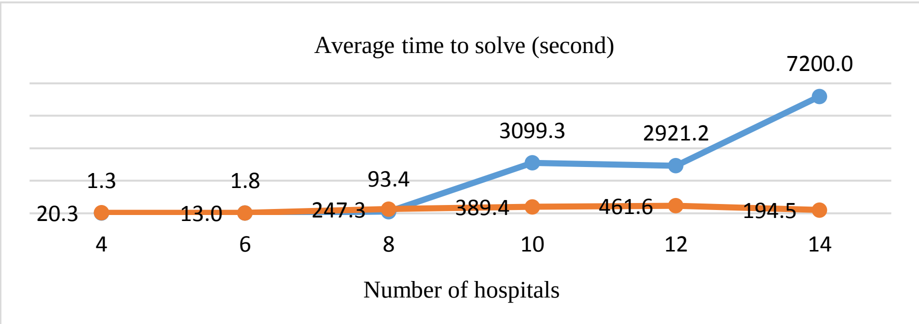

Fig. 2. Comparison between solving the problem with the algorithm and the exact approach

Table 5. Solving the problem in small and medium sizes

No. of hospitals	Condition	Solving the Algorithm			Exact solution		
		Time	Distance to optimality	Objective function	Time	Distance to optimality	Objective function
4	1	3.92	0	601.17	0.36	0	601.17
	2	7.92	0	2102.34	0.39	0	2102.34
	3	28.31	0	3659.69	2.91	0	3659.69
	4	41	0	5160.69	1.40	0	5160.69
6	1	21.78	0	4884.62	1.74	0	4884.62
	2	15.73	0	4884.78	1.60	0	4884.78
	3	2.14	0.22	6583.51	2.68	0	6583.51
	4	12.2	0	8085.29	1.26	0	8085.29
8	1	83.88	0	1133.95	2.04	0	1133.95
	2	107.45	0	2636.04	2.84	0	2636.04
	3	605.38	0.12	4242.71	360.08	0	4242.59
	4	192.4	0.05	5744.64	10.05	0	5744.59
10	1	126.75	0.4	1008.65	2559.42	0.36	1007.75
	2	533.49	0	1007.75	4293.50	0.26	1007.75
	3	41.98	0.08	4125.14	4293.50	0.05	4124.16
	4	855.52	0	4124.58	1250.73	0	4124.16
12	1	883.28	0.03	26562.66	4944.50	0.03	26562.81
	2	590.66	0	26564.04	4917.08	0.03	26564.04
	3	93.58	0.45	26662.46	1234.04	0	26662.01
	4	278.88	0.05	10609.16	589	0	26655.01
14	1	143.8	1.3	1464.79	7200	1.3	1465.28
	2	130.08	0.07	1463.95	7200	1.2	1470.67
	3	202.08	0.1	4512.41	7200	0.5	4512.41
	4	302.01	0.2	4520.24	7200	0.3	4523.58

The results obtained in Table 6 reveals that overall, the least logistics costs is in the first condition. Condition two, three, and four are respectively in the second, third, and fourth priority. This result indicates the effectiveness of the proposed solutions (lateral transshipment and substitution) to reduce RBC deficiency. A separate study of the two conditions (second condition: only lateral transshipment, third condition: only substitution), shows that lateral transshipment plays a more significant role in reducing costs (such as shortage costs) in the supply chain.

Based on Fig. 3, although the deficiency of blood group O^- happens in all conditions, this amount has decreased considerably in condition 2 (lateral transshipment is not allowed but substitution is permitted). It means that it is better not to move blood group O^- to other hospitals, but it can be used for other compatible blood types. It is a logical result because blood group O^- is a rare type, which is compatible with all blood types. Therefore, so it plays a vital role in emergencies where there is no time to check the blood compatibility between the recipient and donor. Blood group A^- has the highest amount of deficiencies after O^-. This amount is higher in the second condition than conditions one and three, where substitution is allowed. This result indicates that the supply of this blood group is less than its demand so that, using blood group type O^- can have positive effects and reduce its shortage (see Fig. 3, g2/g4 means satisfying blood demand type 4 - A^- -with blood group type 2 - O^--).

Based on Fig. 2, the fourth condition (neither substitution nor lateral transshipment is allowed) has faced the most demand shortages among all conditions.

Based on Fig. 4, in cases where substitution is allowed, the first blood group (O^+) is more likely to be used to meet the demand of blood type A^+ (g1/g3), and this situation is more observed in cases where lateral transshipment is not allowed. The number of B^+ blood group demand met by O^+ (g1/g5) is in the second place of using compatible blood types, which increases in conditions that lateral transshipment is allowed (unlike g1/g3). Although blood type O- is compatible with all blood types, it is rarely used to meet the other compatible blood demand because of the low percentage of this blood type in society.

Table 7 shows the results obtained from solving four conditions based on 50 main hospitals in Tehran.

Fig. 5 illustrates the distribution of hospitals and the location of the blood center in Tehran. Logistics costs -such as transportation and inventory- are given by actual data, and other parameters are generated according to the bed capacities of hospitals, presented in Table 8.

Table 6. logistics costs in different conditions

Condition	1	2	3	4
Logistics costs	35655.58	38665.58	497884.15	54293.32

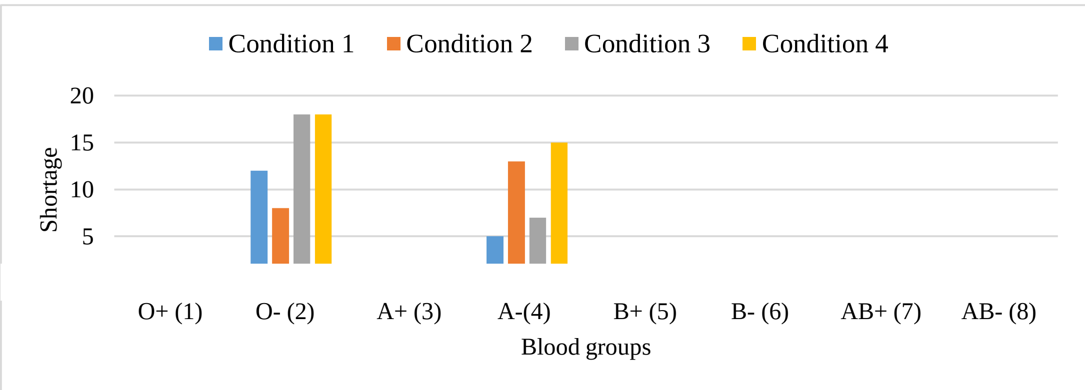

Fig. 3. Shortage amount of each blood type in different conditions

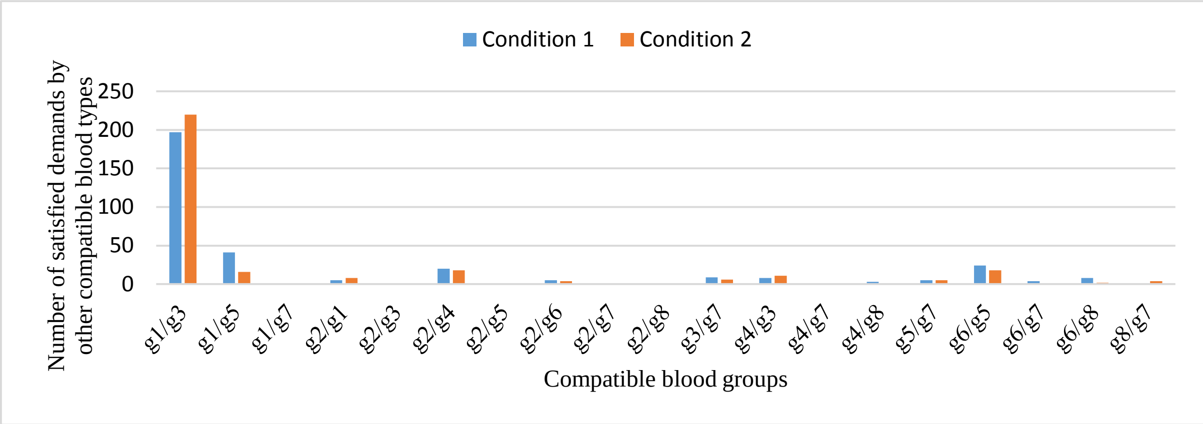

Fig. 4. Number of satisfied demands by other compatible blood types in the first and third conditions

Table 7. Solving the algorithm for 50 main hospitals

Condition	Time	Solving the algorithm
1	2795.36	62905.28
2	2862.69	63024.67
3	3415.1	64768.92
4	4817.44	64778.91

*A time limit of 2500 seconds is provided for solving the algorithm.

Table 8. parameters' value

Parameter	Creation method
$F^{t,r}$	Randomly generated in a range of $(8 * e_r)$% and $(12 * e_r)$% hospitals' bed capacity. e_r is the percentage of blood type r in Iran.
SC	A large number
Q	35% of total bed capacity limitation in hospitals
C_i	70% of bed capacity limitation in hospital i
$d_i^{r,t}$	Randomly generated in a range of $(5 * e_r)$% and $(10 * e_r)$% hospitals' bed capacity.
$I_i^{\cdot,r}$	Hospital: Randomly generated in a range of $(5 * e_r)$% and $(20 * e_r)$% hospital's bed capacity. Blood center: Randomly generated in a range of $(5 * e_r)$% and $(10 * e_r)$% total hospitals' bed capacity.

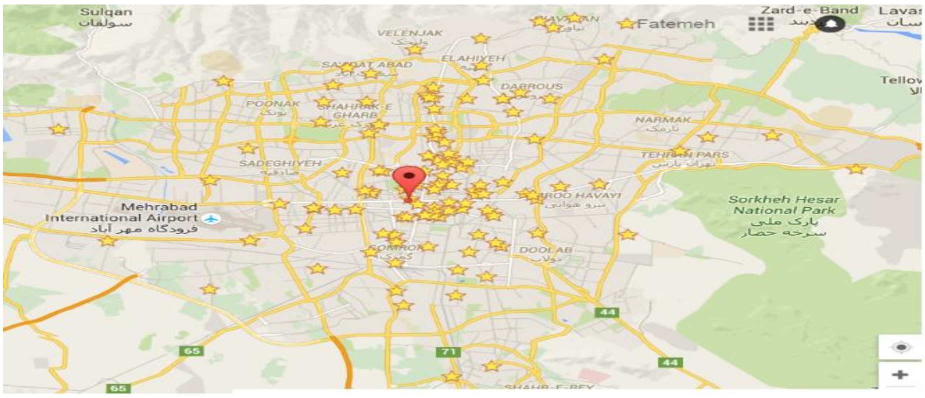

Fig. 5. Geographical location of hospitals (yellow stars) and the blood center (red point)

Conclusion and Future Researches

In this study, an inventory-routing problem for red blood cell (RBC) distribution is presented, in which it is possible to satisfy the demand with compatible blood groups (substitution) and move RBC units between hospitals (lateral transshipment) to prevent deficiency. In the proposed model, four different conditions are evaluated, namely (1) permissibility of lateral transshipment and substitution of RBCs, (2) permissibility of lateral transshipment but unauthorized substitution, (3) permissibility of substitution but unauthorized lateral transshipment, and (4) inadmissibility of lateral transshipment and substitution. For another thing, since the inventory-routing problem is NP-Hard, the adaptive large neighborhood search algorithm has been used to solve the proposed model in all conditions.

The results indicated that the deficiency amount in the first condition is the least one. Also, by separately examining the conditions two and three, it has been observed that lateral transshipment has a greater role in reducing the amount of RBC shortage than substitution. Another result revealed that that blood type O- should not be sent to other hospitals, but it can be used for other compatible blood groups in that hospital, which is quite logical for the presence of this blood type is very important in emergency situations where there is no time to diagnose the patient's blood type (O- is compatible with all blood groups). Moreover, based on conditions 1 and 3, O+ has been used more than any other blood type to meet the demand for a compatible blood type.

Unlike Duan and Liao [13], the findings of this study showed that allowing substitution is more effective in reducing deficiency than rejecting substitution. Although it is better to satisfy blood demand with its blood type, applying other compatible blood types in emergencies and shortages of that blood type can be beneficial to better manage the transshipment and time delivery, simultaneously. The differences between the present study and Duan and Liao [8] are as follows:

- Considering the cost of blood transshipment between the blood center and hospitals in the present study, which is not mentioned in Duan and Liao [13].
- Not considering the wastage cost in the present study mentioned in Duan and Liao [13]. Due to the short time planning (three days) and the longer lifespan of RBCs (three weeks) compared to the time period and to avoid complicating the mathematical model, this cost is not included.

In this study, the hospitals' demand and the rate of blood bank replenishment (supply) of each blood group are known and fixed; hence, the following items can be suggested for future researchs. (1) Considering the uncertainty in supply and demand. (2) Considering the transshipment from hospitals to the blood bank (return the unused blood). (3) Considering blood demand for unknown blood groups in emergencies.

References

[1] Hosseini-Motlagh, S. M., Larimi, N. G., & Nejad, M. O. (2020). A qualitative, patient-centered perspective toward plasma products supply chain network design with risk controlling. Operational Research, 1-46. DOI 10.1007/s12351-020-00568-4

[2] Osorio, A. F., Brailsford, S. C., and Smith, H. K. (2015). “A structured review of quantitative models in the blood supply chain: a taxonomic framework for decision-making”. International Journal of Production Research, Vol. 53, No. 24, PP. 7191-7212.

[3] Gunpinar, S., and Centeno, G. (2015). “Stochastic integer programming models for reducing wastages and shortages of blood products at hospitals”. Computers & Operations Research, Vol. 54, PP. 129-141.

[4] Federgruen, A., Prastacos, G., and Zipkin, P. H. (1986). “An allocation and distribution model for perishable products”. Operations Research, Vol. 34, No. 1, PP. 75-82.

[5] Hemmelmayr, V., Doerner, K. F., Hartl, R. F., and Savelsbergh, M. W. (2009). “Delivery strategies for blood products supplies”. OR spectrum, Vol. 31, No. 4, PP. 707-725.

[6] Hemmelmayr, V., Doerner, K. F., Hartl, R. F., and Savelsbergh, M. W. (2010). “Vendor managed inventory for environments with stochastic product usage”. European Journal of Operational Research, Vol. 202, No. 3, PP. 686-695.

[7] Jafarkhan, F., & Yaghoubi, S. (2018). An efficient solution method for the flexible and robust inventory-routing of red blood cells. Computers & Industrial Engineering, 117, 191-206.

[8] Jafarkhan, F., & Yaghoubi, S. (2017). A robust mathematical model and heuristic solution algorithm for integrated production-routing-inventory problem of perishable products with lateral transshipment. Journal of Industrial Engineering Research in Production Systems, Vol. 4, PP. 195-211.

[9] Yaghoubi, S., Hosseini-Motlagh, S. M., Cheraghi, S., & Gilani Larimi, N. (2020). Designing a robust demand-differentiated platelet supply chain network under disruption and uncertainty. Journal of Ambient Intelligence and Humanized Computing, Vol. 11, PP. 3231-3258.

[10] Mobasher, A., Ekici, A., and Özener, O. Ö. (2015). “Coordinating collection and appointment scheduling operations at the blood donation sites”. Computers & Industrial Engineering, Vol. 87, PP. 260-266.

[11] Gilani Larimi, N., & Yaghoubi, S. (2019). A robust mathematical model for platelet supply chain considering social announcements and blood extraction technologies. Computers and Industrial Engineering, 137(June), 106014.

[12] Şahinyazan, F. G., Kara, B. Y., and Taner, M. R. (2015). “Selective vehicle routing for a mobile blood donation system”. European Journal of Operational Research, Vol. 245, No. 1, PP. 22-34.

[13] Duan, Q., and Liao, T. W. (2013). “A new age-based replenishment policy for supply chain inventory optimization of highly perishable products”. International Journal of Production Economics, Vol. 145, No. 2, PP. 658-671.

[14] Cumming, P. D., Kendall, K. E., Pegels, C. C., and Seagle, J. P. (1977). “Cost effectiveness of use of frozen blood to alleviate blood shortages”. Transfusion, Vol. 17, No. 6, PP. 602-606.

[15] Sapountzis, C. (1984). “Allocating blood to hospitals from a central blood bank”. European Journal of Operational Research, Vol. 16, No. 2, PP. 157-162.

[16] Sivakumar, P., Ganesh, K., and Parthiban, P. (2008). “Multi-phase composite analytical model for integrated allocation-routing problem-application of blood bank logistics”. International Journal of Logistics Economics and Globalisation, Vol. 1, No. 3-4, PP. 251-281.

[17] Arvan, M., Tavakkoli-Moghaddam, R., and Abdollahi, M. (2015). “Designing a bi-objective and multi-product supply chain network for the supply of blood”. Uncertain Supply Chain Management, Vol. 3, No. 1, PP. 57-68.

[18] Gilani Larimi, N., Yaghoubi, S., & Hosseini-Motlagh, S. M. (2019). Itemized platelet supply chain with lateral transshipment under uncertainty evaluating inappropriate output in laboratories. Socio-Economic Planning Sciences, 68(February 2018), 100697.

[19] Coelho, L. C., Cordeau, J. F., and Laporte, G. (2012). “The inventory-routing problem with transshipment”. Computers & Operations Research, Vol. 39, No. 11, PP. 2537-2548.

[20] Desrochers, M., and Laporte, G. (1991). “Improvements and extensions to the Miller-Tucker-Zemlin subtour elimination constraints”. Operations Research Letters, Vol. 10, No. 1, PP. 27-36.

[21] Archetti, C., Bertazzi, L., Laporte, G., and Speranza, M. G. (2007). “A branch-and-cut algorithm for a vendor-managed inventory-routing problem”. Transportation Science, Vol. 41, No. 3, PP. 382-391.