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Developing multi-choice goal programming for reducing wastages and shortages of blood products at hospitals with considering cross matching ratio

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Abstract

Challenges in shortages and wastages of blood products in hospitals are the most important issues in the blood supply chain. Due to the perishability of blood products, hospitals have difficulties to determine an adequate number of blood units which led to wastages as a result of excessive orders or shortage as result of an inadequate number of blood units. Both situations lead to irreparable results since blood is a limited invaluable source that has to do with health-related activities. In this paper, we develop Multi-Choice Goal Programming (MCGP) for an integer programming model to minimize total transportation, wastage, inventory, and shortage costs, and the difference of hospitals demand from Blood Transfusion Center (BTC) and ordered amount of BTC of *m* hospitals. We focus on Red Blood Cells (RBCs) of the whole blood components. Next, a case study of real-life data of eleven hospitals in Zanjan province of Iran (ZPI), has been evaluated with the model in three demand scenarios for considering uncertainty.

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Multi-Choice Goal Programming;
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1. Introduction

Considering the large population of the world, demand for blood is immense since blood transfusion is necessary for many patients with different kinds of diseases and surgeries such as cancer, organ transplant, trauma victims and etc. Besides, blood is not an ordinary product, being an alive tissue of great concern in the medical treatment for humankind with no other alternative generation source until now which makes it a scarce resource. Carrying oxygen, nutrients and many chemicals to all over the body and taking the wastes out are of main tasks that blood does. Each unit of collected blood consists of several components, mainly of Red Blood Cells (RBCs), white blood cells (WBCs), serum, plasma and platelets which can be extracted from the blood through a series of procedures. Each individual of these components does specific tasks. Hemoglobin is the protein inside RBCs that carries oxygen. RBCs remove carbon dioxide from the body, transporting it to the lungs to exhale. White blood cells are part of the immune system and defend the body against infectious agents. The serum is a blood

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plasma neither of clotting factor, white and red blood cells. Platelets in plasma are the clotting factors which play a crucial role in coagulation that recover the body when impairs and bleeding occurs. All blood components are perishable except plasma. Perishability of blood components varies from less than a week for platelets and up to forty-two for RBCs. Blood Supply Chain Management (BSCM) is very important and critical as it deals with human lives which are drawn from volunteer donors. As shown in Figure 1, BSCM in Iran begins with the collection of blood from donors in four collection sites consisting of Blood Collection Center (BCC), Blood Collection Processing Centers (BCPCs), Mobile Teams (MTs) and Blood Transfusion Center (BTC) which we demonstrate them by two samples. Then it goes under the test of containing diseases as HIV, Hepatitis and etc. that cannot be transfused to patients. Next, it can be stored or separated into several components after taking a series of tests like typing and screening tests. Then it is transformed into hospitals as an inventory location that tries to satisfy the blood transfusion demand of patients. For each operation, the first process includes a recipient's blood test for the donor's blood. This process is called cross-matching. Then the required number of blood units is taken from blood inventory of hospital and after the operation, the unused units are taken back to inventory. The time that passes between patient's operation and the return of the unused blood units to the inventory is called *a cross-match* release period.

Blood transfusion occupies a vital position within the medical care system and efficient management of blood supplies is of great economic and social importance to both hospitals and patients (Malmir et al, 2016). Hence, its supply chain is disparate from other commodities. Gunpinar and Centeno (2015) cited four major differences considering all aspects. First, there is a monetary relationship with most of the products as the supply of blood is volunteer-based. Second, the structure of the BSCM by the living beings is mechanically separated into components. However, in the traditional supply chain, parts are manufactured and then assembled to create a finished product. Third, the price associated with the acquisition of the blood is always linear, that is, no economies of scale are present. Fourth, with receiving a blood request in hospital, the cross-matched blood is moved from unassigned inventory (free inventory) to assigned inventory (reserved inventory). Then, it is kept there until the time that blood is transfused. Blood returns to unassigned inventory if it is not transfused or cross-match release period is over. This happens as physicians overestimate the amount of needed blood to be uncertain.

Based on the patient, organizational policy and procedures, the cross-match-to-transfusion ratio (C/T ratio) will be different (Basnet et al., 2009). Considering perishable features of blood, a hospital puts effort on minimizing shortage and wastage of blood. Because of its crucial position in treatment, avoiding to save an excessive number of blood units is not possible as the inadequate number of blood units which may lead to an increment in fatality rates (see Fontaine et al. (2009) and Nagurney et al. (2012)). Gunpinar and Centeno (2015) considered only one hospital in their work; however, considering the real-life circumstances and a large number of patients with blood request; in order to address the problem with real-life conditions, we consider more than one hospital in our study.

In this paper, we present mixed integer programming (MIP) model to minimize shortage, wastage levels and total cost pertained to several procedures at *m* hospitals. The rest of the paper is structured as follows. In Section 2, we review the related literature. Section 3 discusses the model formulation is presented. The case study's computational results are reported in Section 4 which is conducted in Zanjan province of Iran (ZPI). Finally, Section 5 describes useful managerial insight tips and the conclusion of the research is given in Section 6.

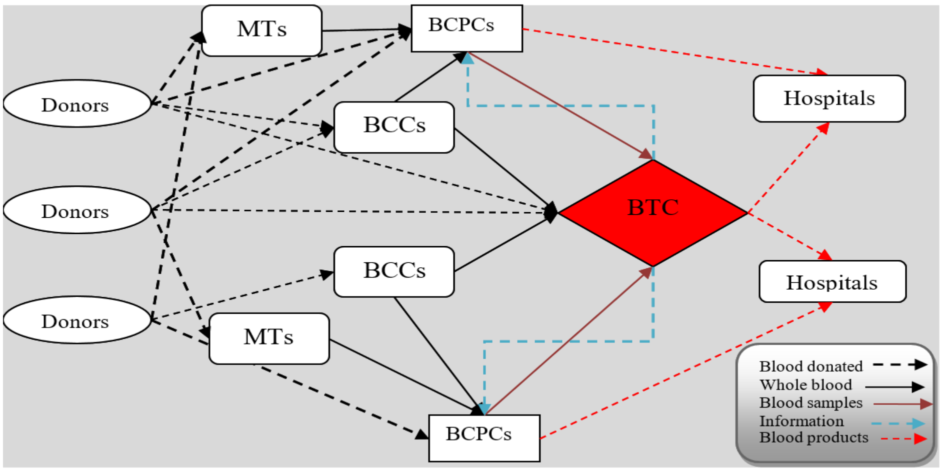

Fig. 1. General Processes involved in the blood supply chain network of Iran.

2. Literature review

BSCM has arisen to be an important area of supply chain management in healthcare problems (Jahantigh and Malmir, 2015). Two of the most well-known and detailed surveys about BSCM are given in Pierskalla (2005), and Beliën and Forcé (2012). We review the first studies on cross-matching policies in BSC. In Rabinowitz (1973), a computer model of a complete blood bank inventory system was constructed in order to determine the effects of three inventory policies on blood wastage and on workload while using inventory level to control shortages. The three policies were double cross-matching, use of older blood for patients more likely to use blood reserved for them, and use of older Rh-negative blood for compatible Rh-positive patients under limited conditions. Cohen and Pierskalla (1979) worked on inventory level for a hospital blood bank with considering daily demand level, the transfusion to cross-match ratio, the cross-match release period and the age of arriving units that determine the shortage and outdated rate. Cohen and Pierskalla (1975) considered management strategies for the administration of a regional blood bank. The techniques of management science and mathematical inventory theory were applied to construct a model for the system, to identify policy areas, and to formulate management objectives. Two simulation models and data collected from both a regional and single hospital blood bank are used in the analysis. The results presented to examine the interactions and savings associated with following optimal ordering, cross-match, and issuing policies. Jagannathan and Sen (1991), developed a model for determining outdates and shortages for cross-matched blood using generally accepted parameters, such as the proportion of cross-matched blood that is actually transfused, and the number of days after which cross-matched blood is released if not transfused. Georgsen and Kristensen (1998) work was about the country of Funen (in Denmark) transfusion service and aims were to standardize and improve the quality of blood components, laboratory procedures, and the transfusion service and to reduce the number of outdated blood units. Part of the efficiency gains was reinvested in a dedicated computer system making it possible – among other things – to change the cross-match procedures from serological to computer cross-matching according to the ABCD-concept.

Rytilä and Spens (2006) applied a discrete event simulation modeling in the health- care sector, more specifically in the area of blood transfusion services. The model has been refined in cooperation with medical expertise as it is vital that practitioners are closely involved so that the model can be tested against their understanding as it develops. The aim of their model is to improve BSCM in order to use the scarce resource of blood more efficiently. Katsaliaki (2008) did a study with the use of primary and secondary data from the National Blood Service and the supplied hospitals, and a statistical analysis was conducted and a detailed discrete event simulation model of a vertical part of the UK BSCM products was developed to test and identify good ordering, inventory and distribution practices. Delen et al. (2011) introduced a novel application of operations research, data mining and geographic information-systems-based analytics to support decision making in BSCM. Osorio et al. (2017) presented an integrated simulation-optimization model to support both strategic and operational decisions in production planning. Discrete-event simulation is used to represent the flows through the supply chain, incorporating collection, production, storing and distribution.

Cetin and Sarul (2009) used a hybrid model of discrete location approaches and center of gravity method of continuous location models, for the location of blood banks among hospitals or clinics, rather than blood bank layout in health care institutions. It is initially unknown the number of blood banks will be located within capacity, their geographical locations, and their coverage area. Jabbarzadeh et al. (2014) proposed a robust network design model for the supply of blood during and after disasters. A practical optimization model is developed that can assist in blood facility location and allocation decisions for multiple post-disaster periods. Zahiri et al. (2015) presented a MIP model to make strategic as well as tactical decisions in a blood collection system over a multi-period planning horizon. A robust possibilistic programming approach is applied to cope with the inherent epistemic uncertainty of the model's parameters. The applicability of the proposed model is demonstrated using a real case study in Mazandaran. To best of our knowledge, most similar to our work is by Gunpinar and Centeno (2015) that presented MIP models to minimize the total cost, shortage and wastage levels of blood products at a hospital within a planning horizon. Then they included uncertainty in demand rates with deterministic and stochastic models for two types of patients and cross-match-to-transfusion ratio. Chaiwuttisak et al. (2016) proposed a binary integer programming model for allocation of low-allocation locations based on objectives of improving the BSCN products while reducing costs of transportation. They evaluated their model with real-life data of 1999-2009 of national blood center of Thai Red Cross society. Fereiduni and Shahanaghi (2016) used a multi-period model for BSCM in an emergency situation to optimize the decisions related to locate blood facilities and distribute blood products after natural disasters. Considering uncertainty in disastrous situations, a robust network to capture the uncertain nature of the blood supply chain during and after disasters is proposed. Hosseini-Motlagh et al. (2016) proposed a fuzzy-stochastic mixed integer linear programming model to design a BSCN for disaster relief. To deal with uncertainty in the model parameters, a fuzzy programming approach is considered, and the combination of the expected value and the chance-constrained programming is applied to solve the proposed model. A case study with real-life data of Tehran is used as an application of the model.

Ensafian et al. (2017) developed a stochastic multi-period mixed-integer model for the collection, production, storage, and distribution of platelet in Blood Transfusion Organizations ranging from blood collection centers to clinical points. Salehi et al. (2017) proposed a new robust two-stage multi-period stochastic model for the blood supply network design with the consideration of a possible natural disaster. The demand for blood units from different types and their derivatives including plasma and platelets are uncertain variables. They consider the possibility of transfusion of one blood type as well as its derivatives to other types based on the medical requirements is considered in the optimization model. A case study related to a likely earthquake in Tehran.

Hosseinifard and Abbasi (2018) studied the significance of inventory centralization at the second echelon of a two-echelon supply chain with perishable items. The replenishment at the first echelon is considered to be stochastic. The second echelon contains hospitals receiving external demands (transfusions). Kaveh and Ghobadi (2017) proposed an efficient method for allocating a number of blood centers to a set of hospitals to minimize the total distance between the hospitals and the blood centers, based on the concept of graph partitioning (p-median methodology) and metaheuristic optimization algorithms namely colliding bodies optimization (CBO). Fahimnia et al. (2017) proposed a stochastic bi-objective supply chain network design model for blood supply in disasters. They used ε-constraint and Lagrangian relaxation methods to solve the bi-objective model. Zahiri and Pishvaee (2017) developed a bi-objective mathematical programming model to minimize the total supply chain costs and maximize unsatisfied demand. They investigated the proposed model in a case study for northern Iran. Fazli-Khalaf et al. (2017) presented a tri-objective model for five echelons blood supply chain including donors, blood collection facilities, laboratories, BCs and hospitals in emergency situations such as earthquake and tsunami. Their model contribution was to minimize costs in blood supply chain and transportation times while maximizing total testing reliability of the donated blood in the laboratories. They proposed two robust possibilistic flexible chance constraint programming and possibilistic flexible chance constraint programming model to consider uncertainty in their model. The model was investigated for Tehran. Khalilpourazari and Khamesh (2017) proposed multi-objective mixed integer linear programming model, multi-objective decision-making methods and lexicographic weighted Tchebycheff method to design efficient blood supply chain network during earthquakes with respect to the magnitude of the earthquake. They investigated their model with a case study on Tehran, Iran.

Rabbani et al. (2017) proposed multi-objective optimization models to investigate mobile blood collection system for platelets production. Maximizing the potential amount of blood collection and minimizing costs are considered in first objective function under fuzzy set. The second objective function is a vehicle routing problem with time windows that investigates the shuttles routing problem. Simulated annealing algorithm is used as a solution methodology to solve the model.

Table 1. The brief literature review.

References	Model	Uncertainty				Time period		Objective function		Solution techniques			Research scopes			Performance measure			Demand points		Shortage costs		Blood products		C/T	Case study
		D	FS	SP	RO	Single	Multi	single	multi	E	S	H	BSCN	Dis	Co	Sh	wa	ho	Single	Multi	Di	NDi	Single	Multi		
(Rytilä and Spens, 2006)	-	-	-	-	-	-	-	●	-	-	●	-	●	-	-	●	-	-	●	-	-	●	●	-	-	Canadian
(Van Dijk et al., 2009)	MDP[1]	●	-	-	-	-	●	-	-	-	●	-	-	●	-	●	●	●	-	-	-	●	●	-	-	Dutch blood bank
(Grant , 2010)	-	-	-	-	-	-	-	●	-	-	-	-	●	-	-	-	-	-	●	-	-	-	●	-	-	-
(Cetin and Sarul ,2009)	GNLP	●	-	-	-	●	-	●	-	●	-	-	-	●	-	-	-	-	-	●	-		●	-	-	-
(Zhou et al., 2011)	SDP[2]	-	-	●	-	-	●	●	-	●	●	-	-	●	-	●	●	●	●	-	-	-	●	-	-	-
(Seifried et al. 2011)	-	-	-	-	-	-	-	-	-	-	-	-	●	-	-	-	-	-	-	-	-	-	-	●	-	-
(Sha and Huang 2012)	MINLP	●	-	-	-	-	●	●	-	-	-	●	-	-	●	-	-	-	●	-	-	-	●	-	-	Beijing
(Stanger et al. 2012)	-	-	-	-	-	-	●	-	-	-	-	-	●	-	-	-	●	-	-	-	-	-	-	-	-	-
(Blake and Hardy, 2013)	-	-	-	-	-	-	-	●	-	-	●	-	-	-	●	-	-	-	-	●	-	-	●	-	-	Canada
(B. Zahiri et al., 2015)	MIP	-	-	●	-	-	●	●	-	●	-	-	-	-	●	-	-	-	-	-	-	-	●	-	-	Mazandaran
(Jabbarzadeh, et al., 2014)	MIP	-	-	-	●	-	●	●	-	●	-	-	-	-	●	-	-	-	-	●	-	-	●	-	-	Tehran
(Osorio et al., 2016)	MIP	●	-	-	-	-	●	●	-	-	●	-	-	●	●	-	-	-	●	-	-	-	●	-	-	Colombia
(Gunpinar and Centeno, 2015)	MIP	-	-	●	-	-	●	●	-	●	-	-	-	●	-	●	●	●	●	-	-	●	●	-	●	Unclear
(Zahiri and Pishvaee, 2016)	MIP	-	●	●	-	●	-	-	●	●	-	-	●	-	-	-	-	-	-	●	-	-	-	●	-	Mazandaran
(Purana7m et al., 2017)	DP[3]	-	-	●	-	-	●	●	-	-	-	●	●	-	-	-	●	●	-	-	-	-	●	-	-	Unclear
(Yates et al., 2017)	-	-	-	-	-	-	-	-	-	-	-	-	-	●	-	-	●	-	●	-	-	-	-	-	-	-
(Kazemi et al., 2017)	MIP	-	●	-	-	-	●	●	-	●	-	-	-	●	-	-	-	●	●	-	-	-	●	-	-	Mazandaran
Our work	MIP	-	-	●	-	-	●	-	●	●	-	-	-	●	-	●	●	●	-	●	●	-	-	●	●	ZPI

1 Markov Dynamic Programming

2 Stochastic Dynamic Programming

3 Dynamic Programming

It can be inferred from Table 1 that all the studies performed in the field of blood supply chain networks can be categorized by the following research areas:

- *Modeling approaches*. Different types of decision variables including continuous, binary and integer variables can be used for defining various mathematical models for BSCNs. Binary nonlinear goal programming (BNGP) approaches have been used more than other approaches for modeling MIP models.
- *Uncertainty approaches*. Different approaches like fuzzy set theory (FS), stochastic programming (SP) and robust optimization (RO) techniques have been used in literature for modeling parameters' uncertainty.
- *Time periods*. Most of the formulations considered for modeling BSCNs are presented in form of multi-period models.
- *The number of objective functions*. Different mathematical formulation developed in literature for modeling BCSNs are presented in the context of single objective and multi-objective models.
- *Solution techniques*. The methods used for solving various mathematical models can be categorized into four different groups including exact methods (E), heuristic algorithms (H), meta-heuristics (MH) and simulation techniques(S).
- *Research scopes*. Most of the scopes have been considered in literature for designing a BSCN were restricted to collecting and distributing blood and blood products. And other researchers have been focused on distribution (Dis) or collection (Co) of blood. We take into account cross-matching ratio (C/T).
- *Performance measure*. The two most general categories of performance measures are those considering the number of outdated units and the number of units short of demand. So, we divide inventory costs to Wastage (Wa), Shortage (Sh) and holding (Ho) costs.
- *Demand points*. Most of the formulations considered for modeling BSCNs have single demand point. But so far only one paper considers multiple demand points.
- *Shortage costs*. None of the previous research divided patient (ND) demand. But it can be divided (D).
- *Blood products*. In the real world, Hospitals order the package of various products but Most of the formulations considered for modeling BSCNs have single blood product.

Based on Figure 1 and other papers in the literature about blood supply chain management, the innovations of this paper can be summarized as:

- Cross-matching ratio in patient's blood demand should be considered in order to satisfy demand properly.
- In the blood supply chain, demands are more than once. Papers in literature did not consider cross-matching and reducing inventory costs for several hospitals.
- In reality, hospitals blood demand is more than what BTCs deliver to them. In this paper, we tried to reduce the gap between the real demand of hospitals and supplies of BTCs by defining the second objective function.

- In order to change our bi-objective function to one objective function, we used multi-choice goal programming that is more flexible to generate different results.
- We evaluated our model with a real-life case study.

3. Problem description and model formulation

In regard of Iranian blood supply chain, hospitals in order to satisfy patient's blood requests, ask for blood packages from BTC. Since blood products are free, hospitals usually ask for an abundant volume of blood products from BTC which leads to more blood wastages.
Consequently, both sides' further policies will strongly influence the amount of blood wastage and shortage. Considering this issue, in this paper, we try on reducing cost and minimizing the gap between hospitals blood demand and the amount that BTCs delivery to hospitals, which is proposed in second objective function in the model.
Hospitals transfer blood products to their blood bank. Operation rooms and other parts in hospitals make their requests from the hospital blood bank; blood bank starts cross-matching based on the blood sample. Then as the needed cross-matched is sent to, the cross-matched blood cannot be returned to the bank even without being used. However, cross-matched blood can be kept for further requests if it would have not sent out of blood bank (see Figure 2).

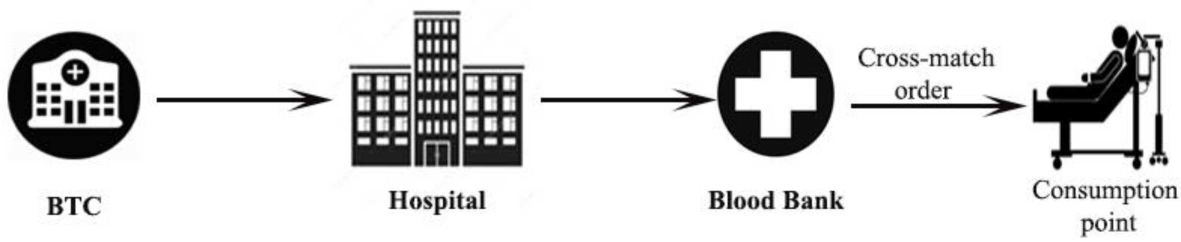

Fig 2. The supply chain of cross-matched blood

In this paper, we focus on minimizing inventory costs, wastages and shortages of hospital order levels. In this paper, the following assumptions are made:

- The capacity of BTCs is limited.
- The age of blood units received from BTC is known and varies over time.
- Lead times of blood supply are zero.
- The lifetime of blood units is limited including 5 days for platelets.
- General blood issuing policy for the hospitals is FIFO.
- If a blood unit expires, a wastage cost is incurred associated with discarding blood units.
- Testing time of blood products in BTC is assumed *P* days.
- Hospitals are not allowed to satisfy their blood demand from other hospitals.

Indices

i Hospitals; i=1,…, I

j	Age of blood product; j=1,…, J
t	Time periods; t=1,…,T
s	Demand Scenarios; s=1,…, S

Parameters

π^s	probability of scenario *s*
W_i	Unit wastage cost of blood at the hospital *i*
H_i	Unit holding cost of blood at the hospital *i*
Ca^t	Capacity of the BTC in time period *t*
M	Big M (big number)
Crp_i	Rate of cross-match at the hospital *i*
CT_i	Average C/T ratio at the hospital
B_i	Unit shortage cost of blood at the hospital *i*
C_i	Unit transportation cost of blood from BTC to hospital *i*
D_i^{ts}	Blood demand of hospital *i* in time period t for scenario *s*
P	Number of days for testing in BTC
θ_{ij}^t	Proportion of *j* days old blood in blood shipment from BTC to hospital *i* in time period *t*

Variables

u_i^{ts}	Amount of blood wastages at the end of time *t* for scenario s at the hospital *i*
x_i^t	Amount of blood ordered by hospital *i* from BTC in time *t*
y_{ij}^t	Number of *j* days old received blood by the hospital *i* in time *t*
v_{ij}^{ts}	Inventory level of *j* days old blood at the end of time *t* for scenario *s* at the hospital *i*
z_{ij}^{ts}	A binary variable which is equal to 1 if *j* days old blood used to satisfy the demand in time *t* for scenario *s* at the hospital *i*, 0 otherwise
β_{ij}^{ts}	Number of *j* days old blood returned from assigned inventory to unassigned inventory at the time *t* for scenario *s* at the hospital *i*
r_i^{ts}	Amount of blood shortage in time *t* for scenario *s* at the hospital *i*

Now, the proposed model is as follows:

$$\text{minimize } Z1 = \sum_{t=1}^{T}\sum_{i=1}^{I} C_i\, x_i^t + \sum_{i=1}^{I}\sum_{j=p+1}^{J}\sum_{t=1}^{T}\sum_{s=1}^{S} H_i v_{ij}^{ts} + \sum_{i=1}^{I}\sum_{t=1}^{T}\sum_{s=1}^{S} W_i u_i^{ts} + \sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{s=1}^{S} B_i r_i^{ts} \tag{1}$$

$$\text{minimize } Z2 = \sum_{i=1}^{I}\sum_{t=1}^{T}\sum_{s=1}^{S} (\, d_i^{ts} - x_i^t) \tag{2}$$

subject to

$$\sum_{i=1}^{I} x_i^t \leq Ca^t \qquad \forall t \in T, \tag{3}$$

$$y_{ij}^t = 0 \qquad \forall i, j = 1, \dots, P; \forall t \in T, \tag{4}$$

$$y_{ij}^t = x_i^t\, \theta_{ij}^t \qquad \forall i, j = P + b, \dots, J; \forall t \in T, \tag{5}$$

$$Z_{ij}^{ts} \geq Z_{i(j-1)}^{ts} \qquad \forall i, j = P + 1, \dots, J; \forall t \in T; \forall s \in S, \tag{6}$$

$$D_i^{ts} = \sum_{J=P+1}^{J}((v_{i(j-1)}^{(t-1)s} + y_{ij}^t)Z_{ij}^{ts} - l_{ij}^{ts}) + r_i^{ts} \qquad \forall i \in I; \forall s \in S, \tag{7}$$

$$(Z_{ij}^{ts} - Z_{i(j-1)}^{ts})(v_{i(j-1)}^{(t-1)s} + y_{ij}^t) \geq l_{ij}^{ts} \qquad \forall i, j = P + 1, \dots, J; \forall t \in T; \forall s \in S, \tag{8}$$

$$Z_{ip}^{ts} = 0 \qquad \forall i \in I, P; t \in T; \forall s \in S, \tag{9}$$

$$D_i^{ts} - \sum_{J=P+1}^{J}((v_{i(j-1)}^{(t-1)s} + y_{ij}^t) \leq r_i^{ts} \qquad \forall i \in I; t \in T; \forall s \in S, \tag{10}$$

$$v_{ij}^{ts} = \left(1 - Z_{ij}^{ts}\right)\left(v_{i(j-1)}^{ts} + y_{ij}^t\right) + \left(Z_{ij}^{ts} - Z_{i(j-1)}^{ts}\right)l_{ij}^{ts} + \beta_{ij}^{ts} \tag{11}$$
$\forall i \in I; \forall j = P + 1, \dots, J; \forall t \in T;\ \forall s \in S,$

$$v_{ij}^{ts} = \beta_{ij}^{ts} \qquad \forall i \in I; \forall j = I + 1, \dots, I + Crp;\ \forall t \in T;\ \forall s \in S, \tag{12}$$

$$v_{ip}^{ts} = 0 \qquad \forall i, j = P;\ \forall t \in T;\ \forall s \in S, \tag{13}$$

$$v_{ij}^{0s} = 0 \qquad \forall i \in I;\ \forall j \in J;\ \forall s \in S, \tag{14}$$

$$\beta_{ij}^{ts} = \left[\left(v_{i(j-Crp-1)}^{(t-Crp-1)s} + y_{i(j-Crp)}^{(t-Crp)}\right)\left(Z_{i(j-Crp)}^{(t-Crp)s} - l_{i(j-Crp)}^{(t-Crp)s}\right)(1 - CT^{-1})\right] \tag{15}$$
$\forall i, j = P + Crp, \dots, I + Crp;\ \forall\, t = Crp + 1, \dots, T,$

$$\beta_{ij}^{ts} = 0 \qquad \forall i, j = P + Crp, \dots, I + Crp, t = 1, \dots, Crp \tag{16}$$

$$\beta_{ij}^{ts} = 0 \qquad \forall i, j = 1, \dots, P + Crp - 1; \forall\, t \in T, \tag{17}$$

$$u_i^{ts} = \sum_{n=0}^{Crp} v_{i(J+n)}^{ts} \qquad \forall i \in I;\ \forall\, t \in T;\ \forall s \in S, \tag{18}$$

$$x_i^t \in Z^+ \qquad \forall i \in I;\ \forall\, t \in T, \tag{19}$$

$$r_i^{ts}, u_i^{ts} \in Z^+ \qquad \forall i \in I, t \in T, s \in S, \tag{20}$$

$$y_{ij}^t \in Z^+ \qquad \forall i \in I, j \in J, t \in T, \tag{21}$$

$$\beta_{ij}^{ts}, v_{ij}^{ts}, l_{ij}^{ts} \in Z^+ \qquad \forall i \in I; \forall j \in J; \forall t \in T;\ \forall s \in S, \tag{22}$$

$$Z_{ij}^{ts} \in \{0,1\} \qquad \forall i \in I;\ \forall j \in J; \forall t \in T;\ \forall s \in S. \tag{23}$$

The objective function (1) minimizes total transportation, wastage, inventory and shortage costs. The objective function (2) seeks to minimize the difference between hospitals real demand from BTC and the amount they order from BTC. Eqn. (3) guarantees that the number of blood units ordered is less or at least equal to the blood center (supplier) capacity. Eq. (4) claims that blood product with one to *P* days old will be tested in BTC and will not be delivered to hospitals. Eq. (5) determines the ratio of *j* days old blood to be delivered to hospitals. Eq. (6) guarantee FIFO blood issuing policy. Eq. (7) ensures that demand should be fully satisfied when blood supply exceeds demand and make a balance between demand and shortage. Eq. (8) determine the number of available blood units in inventory with *p* days old and newly received blood units to be transferred to the next day. Eq. (9) *P* days old blood are not used to satisfy demands. Eq. (10) states that total yesterday, new period inventory levels and shortage for each hospital are more than demand. Eq. (11) updates the inventory level of the current day with considering blood from the day before and unused cross-matched blood. Eq. (12) updates inventory level based on orders and assigned blood. Eqn. (13) there is no *P* days old blood in hospitals inventory section. Eq. (14) states that there is no available inventory at the beginning of the period. Eq. (15) calculates the amount of assigned blood inventory for cross-match. Eq. (16) states that the rate of cross-match in hospital *i* at the beginning of the period is zero. Eq. (17) states that the inventory of young blood with *P+Crp* days old is zero. Eq. (18) calculates wastage at the end of period *t*.

3.1. Linearization

Due to the interaction between binary and discrete variables, the optimization problem includes nonlinear terms in our model. A linearization technique is focused on the interactions between binary and discrete variables and assigns new discrete variables to replace the products of interacting variables. Then in the second linearization technique focuses on the floor function ($x = [y]$) to determine the number of blood units returned to unassigned inventory.
In our model, Eqs. (7), (8) and (11) are modified to Eqs. (24)-(51).

$$D_i^{ts} = \sum_{j=P+1}^{J} (\gamma_{ij}^{ts} + \alpha_{ij}^{ts} - m_{ij}^{ts}) + r_i^{ts} \qquad \forall i \in I;\ \forall s \in S, \tag{24}$$

$$\gamma_{ij}^{ts} + \alpha_{ij}^{ts} - \mu_{i(j-1)}^{ts} - \psi_{ij}^{ts} \geq m_{ij}^{ts} \qquad \forall i \in I;\ \forall j = P+1, \dots, J;\ \forall t \in T;\ \forall s \in S, \tag{25}$$

$$v_{ij}^{ts} = v_{i(j-1)}^{(t-1)s} + y_{ij}^{t} - \gamma_{ij}^{ts} - \alpha_{ij}^{ts} + \lambda_{ij}^{ts} - \delta_{ij}^{ts} + \beta_{ij}^{ts} \quad \forall i \in I; \forall j = P+1, \dots, J;\ \forall t \in T;\ \forall s \in S, \tag{26}$$

$$Z_{ij}^{ts} v_{i(j-1)}^{(t-1)s} = \gamma_{ij}^{ts} \qquad \forall i \in I; \forall j = P+1, \dots, J; \forall t \in T;\ \forall s \in S, \tag{27}$$

$$\gamma_{ij}^{ts} \leq Z_{i(j-1)}^{(t-1)s}.M \qquad \forall i \in I; \forall j = P+1, \dots, J; \forall t \in T;\ \forall s \in S, \tag{28}$$

$$\gamma_{ij}^{ts} \leq v_{i(j-1)}^{(t-1)s} \qquad \forall i \in I; \forall j = P+1, \dots, J; \forall t \in T;\ \forall s \in S, \tag{29}$$

$$\gamma_{ij}^{ts} \geq M.\left(Z_{ij}^{ts} - 1\right) + v_{i(j-1)}^{(t-1)s} \qquad \forall i \in I; \forall j = P+1, \dots, J; \forall t \in T;\ \forall s \in S, \tag{30}$$

$$\alpha_{ij}^{ts} \leq Z_{ij}^{ts}.M \qquad \forall i \in I; \forall j = P+1, \dots, J; \forall t \in T;\ \forall s \in S, \tag{31}$$

$$Z_{ij}^{ts}\ y_{ij}^{t} = \alpha_{ij}^{ts} \qquad \forall i \in I; \forall j = P+1, \dots, J; \forall t \in T;\ \forall s \in S, \tag{32}$$

$$\alpha_{ij}^{ts} \leq y_{ij}^{t} \qquad \forall i \in I; \forall j = P+1, \dots, J; \forall t \in T;\ \forall s \in S, \tag{33}$$

$$\alpha_{ij}^{ts} \geq M.\left(Z_{ij}^{ts} - 1\right) + y_{ij}^{t} \qquad \forall i \in I; \forall j = P+1, \dots, J; \forall t \in T;\ \forall s \in S, \tag{34}$$

$$Z_{ij}^{ts}\ m_{ij}^{ts} = \ \lambda_{ij}^{ts} \qquad \forall i \in I; \forall j = P+1, \dots, J; \forall t \in T;\ \forall s \in S, \tag{35}$$

$$\lambda_{ij}^{ts} \leq Z_{ij}^{ts}.M \qquad \forall i \in I; \forall j = P+1, \dots, J; \forall t \in T;\ \forall s \in S, \tag{36}$$

$$\lambda_{ij}^{ts} \leq m_{ij}^{ts} \qquad \forall i \in I; \forall j = P+1, \dots, J; \forall t \in T;\ \forall s \in S, \tag{37}$$

$$\lambda_{ij}^{ts} \geq M.\left(Z_{ij}^{ts} - 1\right) + m_{ij}^{ts} \qquad \forall i \in I; \forall j = P+1, \dots, J; \forall t \in T;\ \forall s \in S, \tag{38}$$

$$Z_{i(j-1)}^{ts} m_{ij}^{ts} = \ \delta_{ij}^{ts} \qquad \forall i \in I; \forall j = P+1, \dots, J; \forall t \in T;\ \forall s \in S, \tag{39}$$

$$\delta_{ij}^{ts} \leq Z_{i(j-1)}^{ts}.M \qquad \forall i \in I; \forall j = P+1, \dots, J; \forall t \in T;\ \forall s \in S, \tag{40}$$

$$\delta_{ij}^{ts} \leq m_{ij}^{ts} \qquad \forall i \in I; \forall j = P+1, \dots, J; \forall t \in T;\ \forall s \in S, \tag{41}$$

$$\delta_{ij}^{ts} \geq M.(\ Z_{ij}^{ts} - 1) + m_{ij}^{ts} \qquad \forall i \in I; \forall j = P+1, \dots, J; \forall t \in T;\ \forall s \in S, \tag{42}$$

$$Z_{i(j-1)}^{ts} y_{ij}^{t} = \psi_{ij}^{ts} \qquad \forall i \in I; \forall j = P+1, \dots, J; \forall t \in T;\ \forall s \in S, \tag{43}$$

$$\psi_{ij}^{ts} \leq \ Z_{i(j-1)}^{ts}.M \qquad \forall i \in I; \forall j = P+1, \dots, J; \forall t \in T;\ \forall s \in S, \tag{44}$$

$$\psi_{ij}^{ts} \leq y_{ij}^{t} \qquad \forall i \in I; \forall j = P+1, \dots, J; \forall t \in T;\ \forall s \in S, \tag{45}$$

$$\psi_{ij}^{ts} \geq M.\left(\ Z_{i(j-1)}^{ts} - 1\right) + y_{ii}^{t} \qquad \forall i \in I; \forall j = P+1, \dots, J; \forall t \in T;\ \forall s \in S, \tag{46}$$

$$Z_{i(j-1)}^{ts} v_{i(j-1)}^{(t-1)s} = \mu_{i(j-1)}^{ts} \qquad \forall i \in I; \forall j = P+1, \dots, J; \forall t \in T;\ \forall s \in S, \tag{47}$$

$$\mu_{i(j-1)}^{ts} \leq Z_{i(j-1)}^{ts}.M \qquad \forall i \in I; \forall j = P+1, \dots, J; \forall t \in T;\ \forall s \in S, \tag{48}$$

$$\mu_{i(j-1)}^{ts} \leq v_{i(j-1)}^{(t-1)s} \qquad \forall i \in I; \forall j = P+1, \dots, J; \forall t \in T;\ \forall s \in S, \tag{49}$$

$$\mu_{i(j-1)}^{ts} \geq M.\left(Z_{i(j-1)}^{ts} - 1\right) + v_{i(j-1)}^{(t-1)s} \qquad \forall i \in I; \forall j = P+1, \dots, J; \forall t \in T;\ \forall s \in S, \tag{50}$$

$$\gamma_{ij}^{ts}, \alpha_{ij}^{ts}, m_{ij}^{ts}, \mu_{i(j-1)}^{ts}, \psi_{ij}^{ts}, \lambda_{ij}^{ts}, \delta_{ij}^{ts} \in \ Z^{+} \qquad \forall i \in I; \forall j = P+1, \dots, J; \forall t \in T;\ \forall s \in S. \tag{51}$$

Eqn. (15) is also modified to Eqns. (52) and (53):

$$\beta_{ij}^{ts} \geq \left(\left(\gamma_{i(j-Crp-1)}^{(t-Crp-1)s} - \alpha_{i(j-Crp)}^{(t-Crp)s}\right) - m_{i(j-Crp)}^{(t-Crp)s}\right).(1 - CT^{-1}) - 1 + TOL$$
$$\forall i = P + 1 + Crp + \cdots, I + Crp;\ \forall t = Crp + 1, \ldots, T, \tag{52}$$

$$\beta_{ij}^{ts} \leq \left(\left(\gamma_{i(j-Crp-1)}^{(t-Crp-1)s} - \alpha_{i(j-Crp)}^{(t-Crp)s}\right) - m_{i(j-Crp)}^{(t-Crp)s}\right).(1 - CT^{-1}) - 1 + TOL$$
$$\forall i = P + 1 + Crp + \cdots, I + Crp;\ \forall t = Crp + 1, \ldots, T. \tag{53}$$

3.2. Converting model to a single-objective model

A MCGP approach is used in this section to convert proposed model into a single objective one. The main purpose of this technique is to minimize positive deviations of the model's objectives (Bankian-Tabrizi et al., 2012). Single objective version of linearized model is presented as follow:

$$\text{minimize } Z3 = W_1(d_1^+) + a_1(e_1^+) + W_2(d_2^+) + a_2(e_2^+) \tag{54}$$

subject to

$$Z1 - d_1^+ = y_1, \tag{55}$$

$$Z2 - d_2^+ = y_2, \tag{56}$$

$$y_1 - e_1^+ = b_{1.min}, \tag{57}$$

$$y_2 - e_2^+ = b_{2.min}, \tag{58}$$

$$b_{1.min} \leq y_1 \leq b_{1.max}, \tag{59}$$

$$b_{2.min} \leq y_2 \leq b_{2.max}, \tag{60}$$

Eqns. (3)-(6), (9), (10), (12)-(23)-(47),

$$d_1^+, d_2^+, e_1^+, e_2^+ \in Z^+. \tag{61}$$

where Z3 is the summation of Z1 and Z2.

4. Case study

In this section, we present the data driven from a real case and applied in our computational results. The data includes eleven hospitals in ZPI. Table 2 shows more detailed data obtained from ZPI.

Table 2. Blood products frequency and percentage.

Blood products	RBC	PLT	FFP	Cryo	washed RBC	whole blood
Frequency	49673	28780	14264	860	121	87
Percentage	0.53	0.30687	0.152093	0.00917	0.00129018	0.000927654

Here, we present data related to hospitals of ZPI. In Table 2, the frequency and percentage of the blood products are stated. Red blood cells (RBC) consist over half of the blood products with high frequency than others. Two other main blood products are platelets and FFP with 30% and 15%, respectively.

Table 3 and Figure 3 present the number and percentage of ABOs for hospitals in ZPI. O+ and A+ compromise over 60% of blood type in the hospitals' blood bank. It is obvious that A^- and B^- constitute a little proportion of hospitals blood bank.

Table 3. Blood types frequency and percentage.

ABO	A+	A-	B+	B-	AB+	AB-	O+	O-
Frequency	28260	4000	17453	3168	7032	1031	28686	4155
Percentage	0.301	0.04	0.186096	0.03	0.075	0.01	0.3059	0.04

Table 4. Blood products demands.

Hospitals	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11
Frequency	321	2218	6514	1418	3912	25706	2315	4335	654	648	45744
Percentage	0.003	0.024	0.069	0.015	0.042	0.274	0.025	0.05	0.007	0.007	0.488

In Table 4, we present blood products demand for 11 hospitals in ZPI. The 11^{th} hospital with 45744 demands compromising almost 49% and the 6^{th} hospital with 25706 demands compromising for approximately 28% are with most high demands in this list. Rest of the hospitals mostly have demands with percentages under 10% overall.

In Table 5, the number of blood products in the hospitals' blood bank is represented for 12 months within 3 subsequent years. Average numbers of blood products in two first years are nearly close to each other. For 2014 and 2015 in most months, the number of blood products in hospitals is more than 3000; however, for quite a few numbers of months in 2014 and 2015 and especially 2016, it is less than 3000.

4.1. Numerical results

Most of the cost parameters that are used in our model are obtained from Nagurney and Masoumi (2012), Ghandforoush and Sen (2010), Haijema et al. (2007), Zhou et al. (2011), Gunpinar and Centeno (2015). Demand values of eleven hospitals in ZPI are used for RBC which are gathered in 2015 for each month (t=12). Three scenarios are considered for demand values. The first scenario includes real demand values (s_1), second scenario's demand values are 10 percent lower than real demand values (s_2) and third scenario's demand values are 10 percent more than real ones (s_3). The first scenario happens with the possibility of 0.5, the possibility of two others are same.

Table 5. Blood products information.

Month	Number of blood products		
	2014 (Year 1)	2015 (Year 2)	2016 (Year 3)
1	3226	3184	2903
2	3295	3441	2972
3	3279	3605	2981
4	3354	3135	2828
5	3204	3310	2796
6	3489	3076	2577
7	3046	2861	-
8	2728	3237	-
9	2663	3204	-
10	3471	3225	-
11	3436	3276	-
12	2958	3025	-
Sum	38149	38579	17057
Average	3179.1	3214.917	2842.833
Standard deviation	264.66	183.6493	136.9153

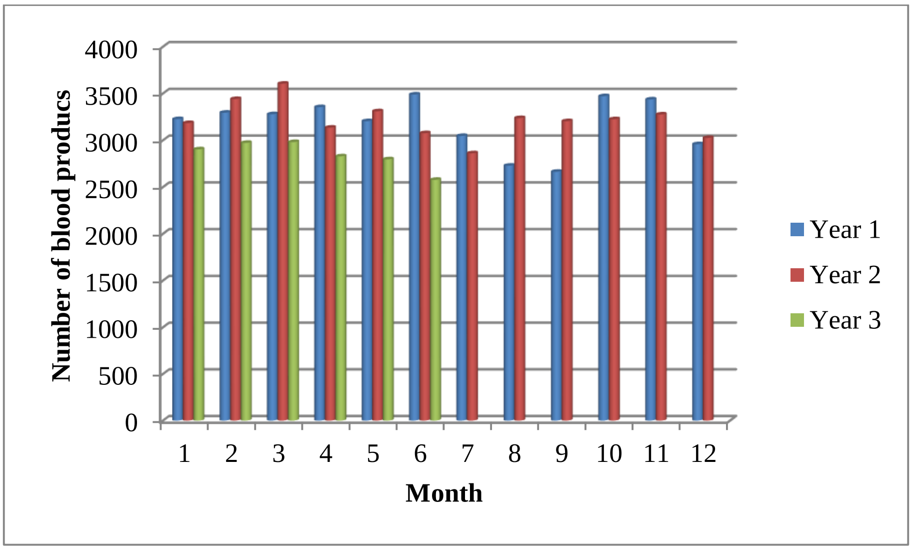

Fig. 3. Blood products frequency and percentage.

The computational results are obtained using CPLEX 12.2.0.1 on a personal laptop with Core (TM) i7- 4500U 1.80 Hz and 8 GB RAM.

For deterministic model W_1, W_2, α_1, α_2, e_1, e_2 are chosen to be 2/6, 4/6, 0.3, 0.7, 0.25, 0.75 respectively. The cross-match ratio (C/T) is 4/3, obtained from Gunpinar and Centeno (2015).

The followings results are obtained for the deterministic model. The described model was solved with real-life data including RBC demand values in eleven hospitals. The outcomes for objective function (1), objective function (2) and Objective function (48) are 5.941499E+7, 62234.186 and 1.984649E+7, respectively. Runtime (seconds) of the model is 10.152.

Table 6. Cost-related parameters.

Parameters	**Values**	**Units**
Purchase cost of RBC	180	\$/unit
Shortage cost	1500	\$/unit
Wastage cost	150	\$/unit
Holding cost	1.25	\$/unit per day

Hospital #11, Valiasr hospital, has the most blood demand between the hospitals of the province and play important role in satisfying the blood orders by patients in ZPI. As it is driven from the model's results, the values for the number of blood units ordered by hospital #11 are $X_{(11,1)} = 128, X_{(11,2)} = 168,\ X_{(11,3)} = 105, X_{(11,4)} = 132, X_{(11,5)} = 120\ , X_{(11,6)} = 112,\ X_{(11,7)} = 123,\ X_{(11,8)} = 167,\ X_{(11,9)} = 151,\ X_{(11,10)} = 171,\ X_{(11,11)} = 133,\ X_{(11,12)} = 155.$

The number of blood units shortages for real-life demand values (S_1) in this hospital are

$r_{(11,1,1)} = 444,\ r_{(11,2,1)} = 515,\ r_{(11,3,1)} = 594,\ r_{(11,4,1)} = 456,$
$r_{(11,5,1)} = 584,\ r_{(11,6,1)} = 475,\ r_{(11,7,1)} = 454,\ r_{(11,8,1)} = 568,$
$r_{(11,9,1)} = 536,\ r_{(11,10,1)} = 574,\ r_{(11,11,1)} = 553,\ r_{(11,12,1)} = 594.$

For scenario S_1 and S_2, this value slightly increases and decreases.

Table 7 represents the results for the number of blood units ordered by hospitals in different time periods. Hospitals #3, #5, #6, #8 and #11 have more blood ordered from BTCs. A high number of orders shows the high blood demand in these hospitals.

Table 7. Number of blood units ordered by hospital *i* from BTC in time *t*.

	T1	**T2**	**T3**	**T4**	**T5**	**T6**	**T7**	**T8**	**T9**	**T10**	**T11**	**T12**
H1	9	4	18	16	21	17	11	13	10	7	31	9
H2	7	8	6	5	7	8	9	3	4	5	8	5
H3	145	135	123	123	0	169	109	157	109	136	170	142
H4	42	54	58	53	45	40	56	78	54	39	31	58
H5	143	102	169	131	141	110	102	64	138	118	98	91
H6	125	152	173	175	162	136	161	128	119	177	144	146
H7	60	106	86	69	101	105	51	78	68	62	95	90
H8	98	110	129	112	91	50	69	104	124	59	60	80
H9	16	24	25	28	33	24	32	26	21	12	19	23
H10	43	25	41	20	16	38	11	33	28	21	21	8
H11	128	168	105	132	120	112	123	167	151	171	133	155

4.1. Sensitivity analysis

To evaluate the effect of parameters on outcomes, a variety of circumstances are considered to determine the sensitivity of outcomes. We considered the effect of W_1, W_2, α_1, α_2, e_1, e_2 and cross-match ratio on the objective function.

Weights of each objective function play important role in the value of the objective function in the MCGP model. Figure 4 shows the results of sensitivity analysis by the changes in the weights, the value of MCGP objective function increases in a certain trend as the weight of objective function (1) and the objective function (2) increases and decreases, respectively. Weights increases and decreased with the rate of 0.1 each time. The model was run for nine times to obtain the new objective function (1) and the objective function (2) values with respect to different W_1 and W_2 values.

Table 8 shows that weight of objective function (1) (W_1) contributes greatly to the total objective function of MCGP model rather than the weight of objective function (2). As the W_1 increases each time, the value of objective function increases, too.

Table 8. Numerical results of MCGP model.

W_1	W_2	Z3	GAMS Runtime (seconds)
0.1	0.9	5997510	12.468
0.2	0.8	11932790	15.201
0.3	0.7	17868060	15.624
0.4	0.6	23803340	14.328
0.5	0.5	29738610	12.580
0.6	0.4	35673890	13.021
0.7	0.3	41609160	13.632
0.8	0.2	47544440	12.201
0.9	0.1	53479710	11.980

Figure 4 shows the changes in the objective function of MCGP model by under the changes in the transportation cost of blood from BTC to hospitals. As the transportation cost of blood from BTC to hospitals increases, the objective function value of MCGP model noticeably increases, too. For this, we did test our model for five different transportation cost values.

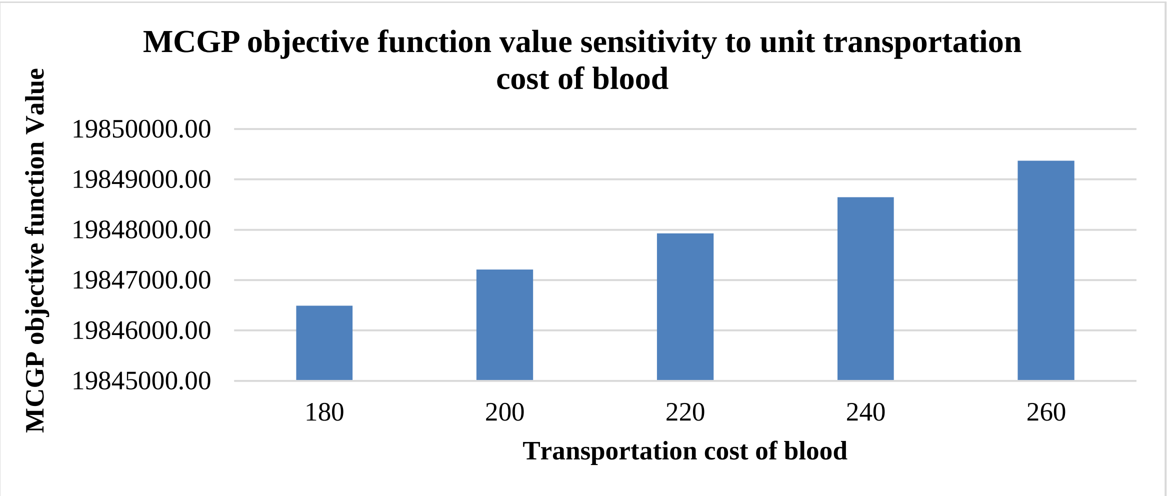

Fig. 4. MCGP objective function value sensitivity to transportation cost of blood from BTC to hospital.

5. Managerial insight

Based on the results and real-life conditions, BTCs and hospitals managers are recommended to consider followings in their strategies for blood demand and supply. Considering high blood shortage cost and its close relation with patient's vital conditions, it is strictly suggested that hospitals demand slightly more blood than it is needed to satisfy all needing patients. Besides, another reason for this is that the probability of unpredictable blood transfusion demands is always high. In comparison to the many benefits of higher orders, the significance of an increase in the blood wastages and holding costs is minor. On the other hand, the managers of BTCs are recommended to ask donors through several different voluntarily programs to donate blood regularly so that BTCs would be able to satisfy all the hospitals' demands. Managers of BTCs are also recommended to approximately satisfy the exact hospitals demand orders. As the gap between the hospitals orders and BTCs supply reduces, the transportation costs drop noticeably which contribute greatly to a decrease in objective function value.

6. Conclusion

In this paper, we developed optimization models for blood management in the hospitals to manage blood resources more efficiently with minimizing total transportation, wastage, inventory, shortage costs and the difference of hospitals demand from BTC and ordered amount of BTC. We mainly focused on red blood cells in our model due to their high demand ratio in comparison to other blood components. We present, a multi-objective model so we developed a multi-choice goal programming to solve our model. Then, we evaluated the model with real-life red blood cells demand data of eleven hospitals in ZPI. Following this, we analyzed the model's sensitivity to the effect of factors such as cross-match ratio, objective functions weights and transportation cost of blood from BTC to hospital.

The model in this paper can be expanded in a number of ways in future studies. Demand uncertainties models such as hose and hybrid models can be applied to the model to address the fluctuations in demand. Besides, meta-heuristic algorithms can be used to solve the problem as its size become larger. Another consideration would be to expand the model to analyze the blood supply chain where BTCs fail to perform or are disrupted during disasters when the significance of BTCs performance is great to medicine the patients.

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