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Optimizing Red Blood Cells Consumption Using Markov Decision Process

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Abstract *– In healthcare systems, one of the important actions is related to perishable products such as red blood cells (RBCs) units that its consumption management in different periods can contribute greatly to the optimality of the system. In this paper, main goal is to enhance the ability of medical community to organize the RBCs units' consumption in way to deliver the unit order timely with a focus on minimizing total costs of the system. In each medical center such as hospitals or clinics, decision makers consider a one-day period for their policy making about supply and demand of RBCs. Based on the inventory status of the previous day, decisions are made for following day. In this paper, we use Markov decision process (MDP) as a sequential decision-making approach for blood inventory problem considering red blood cells consumption. The proposed MDP model for RBCs consumption management is solved using sequential approximation algorithm. We perform a case study for the proposed model using blood consumption data of Zanjan, Iran. Results for several blood types are discussed accordingly. In terms of total cost of the system, LIFO-LIFO policy is best policy for RBCs consumption among all other policies. In order to analyze the importance of some parameters in the model, a sensitivity analysis is done over shortage cost.*

Keywords *– Red Blood Cells, Markov Decision Process, Blood Supply Chain, Sequential Approximation Algorithm*

I. INTRODUCTION

Collecting, testing, processing and distributing blood products from the donor to the recipient are most important processes of blood supply chain network (BSCN). As part of an ordinary medical treatment process, blood products are delivered to patients for different kinds of diseases such as organ transplant surgery as well as emergency situations. The availability of different blood products is essential in medical centers since it has a direct relationship with life of patients and fatality rate that would bring huge costs for the system. With respect to an official report from American Red Cross report in 2014, just 10% of eligible people donate blood which far lowers in countries with lower wages based on another report from World Health Organization. This shows that the decision-making process to satisfy the blood units' demand in a BSCN is challenging with respect to an increase in donor population and blood units' demand (Seifried et al., 2011). Although blood donation is made as a voluntary activity in most of the countries, blood donation is affected by different costs such as testing, segmentation (derivation of different blood products) that involves a series of actions related to the storage and distribution. An efficient BSCN must have several important characteristics such

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as the ability to satisfy the demands considering all involved costs and the ability to deliver the blood products at the right time considering their expiration date. Thorough several permanent processes for blood collection and with respect to many factors such as donation convenience, risky incidents during the donation, incentive facilities and accessibility to resources can affect donor's decision. The balance between supply and demand in the BSCN needs the development of number of infrastructures for collection, process, and distribution of blood units. Decision-making process for critical systems such as BSCN is of great significance due to its high complexity and its direct relationship with life of human beings of the system. Katsaliaki and Brailsford (2007) stated that over 100 products types are derived out from each blood units such as plasma, red blood cells, platelets, etc. Approximately 63% of blood transfusion includes RBCs, 18% consists of plasma and 14% includes blood platelets (Fanoodi et al., 2019). RBCs are required in the treatment of anemia, where platelets are used for cancer diseases, and plasma is utilized for the treatment of burning.

Due to the presence of different supply chain configurations in real-world, different policies in domestic blood banks affect several systems, most importantly hospitals as well as blood processes such as collections, processing and distribution of multiple demand units. Strategies taken in each healthcare center can be different according to policies and regulations in different countries. However, the goal of all healthcare systems in all countries is to supply adequate blood products with a focus on minimization of cost and perishability. Moreover, specific factors of blood products such as blood types, adaptation and storage time of blood products should be taken into consideration in order to make a balance in blood supply and decision processes. There are eight main blood groups as A, B, AB, O+ and O- with a specific ratio in each human. Platelets have a life span of 5 days with a minimum useful life, where best-lasting plasma has a life span of one year which is highest among all blood types. This shows that all blood products have a specific life span and should be used during that time. This denotes that if a blood product is not consumed before its useful life, it should be eliminated.

Optimal management of blood products as a valuable product can have a great contribution to the health of the human community. Therefore, the main purpose of this paper is to contribute to the medical and the human community by developing a reliable decision-making tool to provide fast and timely blood products at the minimum cost. In this study, we developed a MDP model for blood bank inventory problem with a focus on RBCs inventory problem and minimizing total costs of the system.

In section 2, we review the literature of BSCN. MDP Model formulation is presented in next section. Case study and computational results are reported and discussed in section 4. Finally, we conclude in section 5.

II. LITERATURE

Operations research is one of the frequently used methodology for health problems for the recent two decades (Papageorgiou, 1978; Rais and Viana, 2011). Syam and cote (2010) presented a location-allocation mathematical model for specialized health systems considering three important factors such as the degree of centralization of services, the role of patient retention as a function of distance to a treatment unit and the geographic density of the patient population. Recently, Pirabán et al. (2019) did a state-of-art literature review for supply chain management in blood industry in terms of proposed models and methods in the literature which are published between 2005 and 2019.

A. Simulation and MDP

Pegels and Jelmert 1(970) initially used Markov chain models for blood inventory problems. Their model was aimed at two important things; to determine the effects of the issuing policies on average inventory levels which highly counted on determining blood shortage probabilities, and on the average age of blood at a certain time. Brodheim et al. (1975) proposed Markov chain models for perishable products like blood to obtain shortage rate, the inventory life span and approximate amount of outdated products. A shortage-based simulation model was proposed by Rabinowitz (1973) for the inventory system of a blood bank to show the influences of several inventory policies. Cohen and Pierskalla (1975) presented experimental and mathematical models to do an analysis for management strategies in inventory that can be implemented for a regional blood bank. A simulation model was presented in order to determine outdated products as well as blood shortages for cross-matching based on number of parameters such as transfusion information of cross-matching blood units (Jagannathan and Sen, 1991). In another similar study, Rytilä and Spens (2006) proposed a discrete event simulation model to organize blood transfusion services. Considering production cost and inventory management of platelets, Haijema et al. (2007) utilized dynamic programming, MDP, and simulation to model blood inventory management problem for a real case study in Holland. With a focus on minimization of outdate rate for blood products, Duan and Liao (2013) developed a simulation model for supply chain of platelet. Blake and Hardy (2014) presented a simulation model which was focused on investigating demand and supply policies in blood regional network in order to optimize number of RBCs orders. Zahraee et al. (2015) used an integrated method consisting of dynamic programming and Taguchi method to design a robust blood supply chain using donor-related parameters as arrival rate, inventory level and policy used for blood delivery system. Selvakumar et al. (2019) proposed Zonal network and pull system models for blood supply chain with a focus on maximizing the availability of blood and minimizing wastage of blood at the same time using Arena software. Attari et al. (2019) developed Markov decision process to optimize the policy of red blood cell consumption for type A+ for a real case study of Iran.

Fanoodi et al. (2019) used artificial neural networks and ARIMA models to forecast daily blood platelet demands with an aim to decrease the uncertainty in the supply chain of type O+ and A+ for a real case study in Iran. They showed the superiority of the proposed artificial neural network by the improvement in prediction of uncertainties in daily demands. Dharmaraja et al. (2019) proposed a model to forecast blood demand in blood banks, optimally allocate blood units to blood banks with a focus on surplus and shortage amounts and finally select the best path to deliver the demands to blood banks for a real case study in India.

B. Mixed-integer programming

A robust BSCN was developed by Jabbarzadeh et al. (2014) in disasterous situations which determines blood facility location and allocaion of products. In another similar study, a possibilistic MIP was presented to make managerial decision in a blood collection system (Zahiri et al., 2015). Osorio et al. (2017) proposed a simulation-optimization approach to help the decision-making process in blood production planning. Supply chain flow, collection, production, storing and distribution are analyzed using discrete-event simulation model. An integer linear programming was used to determine the required number of donors, collection methods and production amount. Yousefi Nejad Attari et al. (2017) proposed a constrained bi-objective programming model for a BSCN where the model was focused on minimization of blood wastage and shortage costs as well as increasing unsatisfied demand of blood products in hospitals. Salehi et al. (2017) presented a two-stage robust stochastic model for blood supply chain during a crisis such as an earthquake. Dillon et al. (2017) considered a policy-based two-stage stochastic programming model with an aim to minimize the operational costs of BSCN like shortage and wastage costs. Najafi et al. (2017) proposed a bi-objective integer programming for blood inventory management with the main focus on minimization of shortage and wastage of blood considering the uncertainty in supply and demand of blood units as well as blood transshipment. A chance-constraint programming approach was applied to address this problem. Samani et al. (2018) developed a two-stage stochastic programming for an integrated blood supply chain in disaster relief network. In order to solve the model, they proposed a two-stage mixed possibilistic-stochastic programming for minimization of maximum unsatisfied demand, perishability and shortage of blood products. Rajendran and Ravindran (2019) proposed an improved stochastic genetic algorithm for inventory management of platelets in a blood supply chain considering the uncertainty in demand. Their model is focused on the minimization of wastage and shortage of blood product. Özener et al. (2019) presented a mixed-integer programming model for blood donation tailoring problem which is focused on finding optimal donation schedules to satisfy the demand units completely. The proposed model is based on minimizing holding and wastage costs of inventory. A column generation-based heuristic and rule-of-thumb heuristic approach were proposed to solve the problem for larger data sets. Hosseini-Motlagh et al. (2019) proposed a bi-objective two-stage stochastic programming model for location-allocation and inventory management of red blood cells with an aim to minimize the transportation, wastage and holding costs. In order to take the uncertainty of parameters into account, they applied a robust optimization method to deal with it. The proposed decision-making frame was performed for a real-life case study in Iran.

According to Table I, we categorize studies related to BSCN in following research areas:

- Modeling approaches. Mathematical models for BSCN problems can be using several kinds of variables such continuous, integer and binary. Using these variables, several mathematical methods such as linear programming (LP), mixed integer programming (MIP), goal programming (GP), bi-objective mathematical programming, dynamic programming (DP), Markov decision process (MDP) and multi-criteria decision methods (MCDM).

- Uncertainty sets. Mathematical models proposed for BSCN problems can be either based on deterministic models (M) or uncertain models such as fuzzy set theory (FS), stochastic programming (SP) and robust optimization (RO), etc.

- Time periods. Problems can be formulated in either single or multiple time periods.

- Objective functions. Proposed mathematical models for BSCN problems can have either single objective function or multi-objective functions.

- Solution approaches. Several solution algorithms are used for BSCN problems in the literature. We categorize these approaches as exact methods (E), heuristic and meta-heuristics algorithms (H/MH) and simulation techniques(S).

- Research scopes. BSCN problems are mostly based on a number of important scopes such as distribution (Dis), collection (Co), cross-matching ratio (C/T).

- Inventory performance analysis. We categorize inventory costs as wastage (Wa), shortage (Sh) and holding (Ho) costs. Besides, reliability of donated blood (RDB) and freshness of blood (FB) are other noticeable performance measures that can be investigated within inventory systems.

- Demand points. Mathematical formulations for BSCN problems either have single or multiple demand point.

- Shortage costs. Shortage costs in BSCN is either based on the patient (D) or not on a patient (ND)

To best of our knowledge, there were no studies which aimed to optimize the red blood cells consumption policy using MDP. Based on Table I, we see that there was only a study that considered the dynamic feature of the blood supply chain problem. In real-life problems, demand is not crisp and changes over the time horizon. The best way to take into account the probability of demand occurrence in each day is by using dynamic programming methods such as MDP. The findings of the model would help managers at blood transfusion and health centers to efficiently control their inventory problems.

III. PROBLEM DESCRIPTION AND MODEL FORMULATION

Considering inventory management problem in BSCM, most of the studies are focused on developing tools that can enhance their ability to determine optimal blood production and make a balance for blood products and outdate products. Two important problems in BSCM are amount order and tools that can help managers in health sector to determine them in order to not having excessive or shortage in blood products in *m* period. Equally important, managers take into account situations where unsatisfied demands can be considered for emergency cases. In this paper, we develop a mathematical model for an inventory management problem in the storage of hospitals and blood banks. Most important issue in BSCM is to come up with a decision-making tool that can analyze inventory risks and try to minimize the shortage of blood units as well as outdated products.

RBCs are categorized mostly based on age of the donor. Each age group is along with the status quo of the systems at that time period. Therefore, the number of states in each blood inventory system is equal to the number of products in each dimension which finally becomes extensive when used for real-life large scale data set is. We can illustrate this by the example that considers the maximum product life expectancy is 21 days with 35 products in the inventory so that there exist 35 states in the inventory system. Hopkins Medical Institute has reported that RBCs which stay more than 21 days in the inventory bring up issues related to flexibility that would need the re-acquisition of tiny capillaries throughout the body, nevertheless, and then RBCs cannot transfer oxygen to where they need it (Frenk et al., 2013).

MDP is a system that decision maker can take a sequence of decisions over a time horizon which is denoted as status. As transition happens and we move from one state to another, statuses change. Best set of alternatives are chosen by decision maker in each iteration (stage). The selection of best set of alternatives in each iteration leads to an effect on the probability of the next transition and makes a sudden increase or decrease in current and next statuses of the system.

The outcome in MDP model is calculated by the status of the inventory system at each iteration, previously taken decisions, the transition probabilities from one state to another considering different involved parameters. Most important problem that a decision maker deals with in MDP, is to select the sequence of activities that happen in the system in order to maximize the total profit. In this study, we first aimed to formulate RBCs as a MDP model for a real case study in Iran.

In the next step, in order to take into account, the age of blood products in inventory system, a series of policies for order considering optimal inventory time are required. This also applies for outdated blood products in the inventory that should be considered within the inventory system. For this problem, the maximum life span of RBCs is considered as *m* day. A *m*-dimensional vector is considered to store the information on the number of RBCs in inventory for each age group. The set $X \in N^m$ consists of x_r that denotes number of RBCs products with *r* remaining life at the beginning of each time period. At the beginning of each time period (day), RBCs production amount is determined. In MDP model, it is assumed that production amount that is determined at the beginning of the day does not change through the end of the day. At the end of the day, RBCs produced on that day is added to the inventory, and then a new decision is made for the next day.

As we move from day *d* to day *d + 1*, a sequence of events happen as follows:

- RBCs in the inventory are used to satisfy demand at day *d* and previous days.
- As old RBCs from inventory are used to satisfy demand at day *d*, a mismatch cost happens in the system.
- Considering inventory level, blood bank or hospital faces a shortage cost when inventory level is lower than the demand.
- As a time period finishes, RBCs get one-day-old.
- Inventory level can be more than demand.
- At the end of the day, released products are added to the inventory level.

Abbreviations: RBCs = Red Blood Cells; BSCN = Blood Supply Chain Network; BSCM = Blood Supply Chain Management; MDP = Markov Dynamic Programming; MCDM = Multi-Criteria Decision-Making; BNGP = Binary Nonlinear Goal Programming; FS = Fuzzy Set; SP = Stochastic Programming; M = Deterministic model; E = Exact algorithms; H/MH = Heuristic/Meta-Heuristic; S = Simulation; Dis = Distribution; Co = Collection; C/T = Cross-match; Wa = Wastage; Sh = Shortage; Ho = Holding; RDB = Reliability of Donated Blood; FB = Freshness of Blood

Table I. Recent BSCM studies

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/MH	BSCN	Dis	Co	Sh	wa	ho	FB	RDB	single	Multi	Di	NDi	single	Multi		
(Rytilä & Spens, 2006)	-	-	-	-	-	-	-	●	-	-	●	-	●	-	-	●	-	-	-	-	●	-	-	●	●	-	-	Canada
(Van Dijk et al.,2009)		●	-	-	-	-	●	-	-	-	●	-	-	●	-	●	●	●	-	-	-	-	-	●	●	-	-	Dutch blood bank
(Grant,2010)	-	-	-	-	-	-	-	●	-	-	-	-	●	-	-	-	-	-	-	-	●	-	-	-	●	-	-	-
(Cetin & Sarul, 2009)		●	-	-	-	●	-	●	-	●	-	-	-	●	-	-	-	-	-	-	-	●	-	-	●	-	-	-
(Zhou et al., 2011)		-	-	●	-	-	●	●	-	●	●	-	-	●	-	●	●	●	-	-	●	-	-	-	●	-	-	-
(Sha and Huang, 2012)		●	-	-	-	-	●	●	-	-	-	●	-	-	●	-	-	-	-	-	●	-	-	-	●	-	-	Beijing
(Stanger et al., 2012)	-	-	-	-	-	-	●	-	-	-	-	-	●	-	-	-	●	-	-	-	-	-	-	-	-	-	-	-
(Zahiri et al., 2015)	MIP	-	-	●	-	-	●	●	-	●	-	-	-	-	●	-	-	-	-	-	-	-	-	-	●	-	-	Mazandaran
(Jabbarzadeh et al., 2014)	MIP	-	-	-	●	-	●	●	-	●	-	-	-	-	●	-	-	-	-	-	-	●	-	-	●	-	-	Tehran
(Fahimnia et al., 2015)	MIP	-	-	●	-	-	●	-	●	●	-	-	-	-	●	-	-	-	-	-	-	●	-	-	●	-	-	Unclear
(Osorio et al., 2016)	MIP	●	-	-	-	-	●	●	-	-	●	-	-	●	●	-	-	-	-	-	●	-	-	-	●	-	-	Colombia
(Gunpinar & Centeno, 2015)	MIP	-	-	●	-	-	●	●	-	●	-	-	-	●	-	●	●	●	-	-	●	-	-	●	●	-	●	Unclear
(Zahiri & Pishvaee, 2017)	MIP	-	●	●	-	●	-	-	●	●	-	-	●	-	-	-	-	-	-	-	-	●	-	-	-	●	-	Mazandaran
(Kaveh & Ghobadi, 2016)	MIP	●	-	-	-	-	●	●	-	-	-	●	●	-	-	-	-	-	-	-	●	-	-	-	●	-	-	Tehran
(Cheraghi et al. 2016)	MIP	-	-	-	●	-	●	●	-	-	-	●	●	-	-	-	-	-	-	-	-	●	-	-	●	-	-	-
(Cheraghi & Hosseini-Motlagh, 2016)	MIP	-	-	●	-	-	●	●	-	●	-	-	-	●	-	-	-	●	-	-	-	●	●	-	●	-	-	Tehran
(Fereiduni & Shahanaghi, 2016)	MIP	-	-	-	●	-	●	●	-	●	-	-	●	-	-	-	-	-	-	-	●	-	-	-	●	-	-	Tehran

Continue Table I. Recent BSCM studies

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/MH	BSCN	Dis	Co	Sh	wa	ho	FB	RDB	single	Multi	Di	NDi	single	Multi		
(Puranam et al., 2017)	DP	-	-	●	-	-	●	●	-	-	-	●	●	-	-	-	●	●	-	-	-	-	-	-	●	-	-	Unclear
(Yates et al., 2017)	-	-	-	-	-	-	-	-	-	-	-	-	-	●	-	-	●	-	-	-	●	-	-	-	-	-	-	-
(Kazemi et al., 2017)	MIP	-	●	-	-	-	●	●	-	●	-	-	-	●	-	-	-	●	-	-	●	-	-	-	●	-	-	Mazandaran
(Khalilpourazari & Khamesh, 2017)	MIP	●	-	-	-	-	●	-	●	●	-	-	-	●	●	●	-	-	-	-	-	●	●	-	-	●	-	Tehran
(Dillon et al., 2017)	MIP	-	-	●	-	-	●	-	●	●	-	-	●	●	-	●	●	-	-	-	-	●	●	-	-	●	-	Australia
(Salehi et al.,2017)	MIP	-	-	-	●	-	●	●	-	●	-	-	●	-	●	●	-	-	-	-	-	●	-	-	-	●	-	Tehran
(Yousefi Nejad Attari et al., 2017)	MIP	-	-	●	-	-	●	-	●	●	-	-	-	●	-	●	●	●	-	-	-	●	●	-	-	●	-	Tabriz
(Fazli-khalaf et al., 2017)	MIP	-	-	-	●	-	●	-	●	●	-	-	●	-	-	-	-	●	-	●	-	●	-	-	●	-	-	Tehran
(Ramezanian & Behboodi, 2017)	MIP	-	-	-	●	-	●	●	-	●	-	-	●	-	-	-	-	-	-	-	●	-	-	-	●	-	-	Iran
(Sharma et al., 2017)	MCDM	●	-	-	-	●	-	●	-	●	-	●	●	-	-	-	-	-	-	-	●	-	-	-	-	-	-	India
(GhatrehSamani et al., 2017)	MIP	-	-	●	-	-	●	-	●	●	-	-	●	●	-	●	-	●	-	-	-	●	-	-	●	-	-	Unclear
(Ensafian & Yaghoubi, 2017)	MIP	-	-	-	●	-	●	-	●	●	-	-	●	●	●	●	●	●	●	-	-	●	-	-	●	-	-	Tehran
(Habibi-Kouchaksaraei et al., 2018)	MIP	-	-	-	●	-	●	-	●	●	-	-	●	-	-	●	-	-	-	-	●	-	-	-	-	-	-	Qaemshahr
(Attari et al., 2018)	MIP	-	-	●	●	-	●	-	●	●	-	-	●	-	-	●	●	●	-	-	-	●	●	-	-	●	-	East Azerbaijan
(Yousefi Nejad Attari & Ebadi Torkayesh, 2018)	MIP	-	-	●	-	-	●	-	●	●	-	-	●	●	-	●	●	●	-	-	-	●	●	-	-	●	●	Zanjan
(Attari & Jami, 2018)	MIP	-	-	●	-	-	●	-	●	●	-	-	-	●	●	-	-	-	-	-	-	●	-	-	-	●	-	East Azerbaijan
(Heidari-Fathian & Pasandideh, 2018)	MIP	-	-	-	●	-	●	-	●	●	-	-	●	●	●	●	●	-	●	-	-	●	-	●	-	●	-	-
Our study	MDP	-	-	●	-	-	●	●	-	-	-	●	●	-	-	●	-	-	-	●	-	●	-	●	-	●	-	Zanjan

A. Notations

m	Maximum life span of RBCs product
r	Remaining product life of RBCs products
$\boldsymbol{x_r}$	Number of RBCs with *r* remaining life
X	System status at the beginning of each day
Y	System status at the end of day
n	Denotes number of days that are repeated
a	Decision in each state with respect to policy *I*
I	Supply policy
J	Fresh RBCs demands
K	Old demands
$\boldsymbol{i_r^y}$	Fresh RBCs demand that are met by RBCs with *r* remaining life and depends on (*n*,*X*,*J*,*K*,*I*) and demand type
$\boldsymbol{i_r^A}$	Old demands that are met by RBCs with *r* remaining life and depends on (*d*,*X*,*J*,*K*,*I*) and demand type
$\boldsymbol{i^y}$	Number of RBCs that are released for satisfying new RBCs demands
$\boldsymbol{i^A}$	Number of RBCs that are released for satisfying old demands
$\boldsymbol{C^H}$	Unit holding cost of each product in the inventory at the beginning of each time period
$\boldsymbol{C^O}$	Unit cost fir outdated products
$\boldsymbol{C^S}$	Unit shortage cost for lost orders
$\boldsymbol{C^{S'}}$	Unit shortage cost for delayed orders
$\boldsymbol{C_r^Y}$	Mismatch cost for products with *r* day-old that failed for demand of young group
$\boldsymbol{P_d^A(k)}$	Possible demand probability for other RBCs products
$\boldsymbol{P_d^Y(j)}$	Possible demand probability for new RBCs
$\boldsymbol{P^a_{(d.x).(d+1.y)}}$	Probability of transmission from day *d* to day *d+1*
$\boldsymbol{C(d.X.j.k.I)}$	Direct costs related to each policy at the beginning of each day with respect to type of demand, order and inventory status
$\boldsymbol{EC^I(d.X)}$	Expected direct cost with respect to policy *I*, inventory status and *d* repetition

B. MDP model

The proposed MDP model considers that events happen at a level that is higher orders. Therefore, production amount for demand of day *d+1* is considered as a constant parameter. Moreover, RBCs supply amount is determined based on demand category of RBCs products. Using notation, a MDP model is developed for number of outdated RBCs, shortage and mismatch as following:

- In order to calculate the number of outdated RBCs that would be disposed out of inventory at the end of the time period, we can use the following equation: $x_m - i_m^y - i_m^A$
- We calculate the shortage amount for RBCs as: $(J - i^y) + (k - i^A)$
- Mismatch amount is calculated based on: $\sum_{r=1}^{l-1} i_r^y$

Only uncertain parameter in the proposed model is related to RBCs demand that is considered within normal distribution for fresh and old demands. With respect to defined notations and assumption, the proposed model is formulated as follows:

$$C(d, X, j, k, I) = \begin{cases} C^O\left(x_m - i_m^y - i_m^A\right) & \text{outdated products cost} \\ \quad +C^S(j + k - i^y - i^A) & \text{Shortage cost} \\ \quad +C^H.x & \text{Holdig cost} \\ \quad + \sum_{r=1}^{m} C_r^y r_i^y & \text{Mismatch cost} \end{cases} \tag{1}$$

In equation (1), we calculate the total cost including outdated products cost, shortage cost, inventory cost for holding blood products and mismatch cost for blood types for each day *d*. Expected cost for situation *(d,x)* for each policy *I* is calculated as:

$$EC^I(d.x) = \sum_{j.k} P_d^y(j) P_d^A(k) C(d.x.j.k.y) \tag{2}$$

Next, we calculate the expected cost for each policy *I* using equation (2). In this equation, we compute the expected cost by summing over total cost that we calculate using equation (1) and possible demand for fresh RBCs products.

A sequential approximation algorithm (SA) is utilized for solving the proposed MDP model for RBCs. Sequential approximation can be formulated as equation (3) to obtain:

$$V^n(x) = min\left[EC^I(x) + \sum_{j.k} P^Y(j) P^A(k)\, V^{n-1}\big(Y(x.j.k.I)\big)\right] \quad \forall (x) \in X \tag{3}$$

Termination criteria for the sequential approximation algorithm is based on equation (4).

$$|V^n(x) - V^{n-1}(Y(x.j.k.I))| < \varepsilon \tag{4}$$

IV. CASE STUDY

Here, we investigated our model for a real-life case study. For this, we used the real data of eleven hospitals and also blood transfusion centers of Zanjan Province of Iran. Then, we used our method for several blood groups and analyzed the results obtained from each one. At the end, we do a sensitivity analysis for the parameters, shortage cost; holding cost and mismatch cost. We reported results in several tables and then discussed the optimal consumption policy of each one of the blood groups.

In order to solve the value function of MDP, we used sequential approximation algorithm. Sequential algorithms are broadly used in many optimization-related research areas. They are mostly for partition and sequential problems like MDP where the structure of the model is based on a sequence of decision over an infinite time-horizon. Generally, sequential algorithm is used in finding an order in which items are processed, and processing the items sequentially to build the solution. Proposed MDP model is solved in an unlimited number of iteration for all $x \in X$ so in case problem does not meet termination criteria, we terminate the problem when it reaches to iteration 278256 with respect to RAM of the personal computer that was used.

A. Data

We investigated the proposed methodology for a real-life case study in blood banks of Zanjan, Iran. RBCs that are kept between 1-6 degrees are supposed to have maximum life span of 35 days. In this study, we considered RBCs with less than 21 days-old and more than 21 days-old up to 35 days-old as fresh RBCs and old RBCs, respectively.

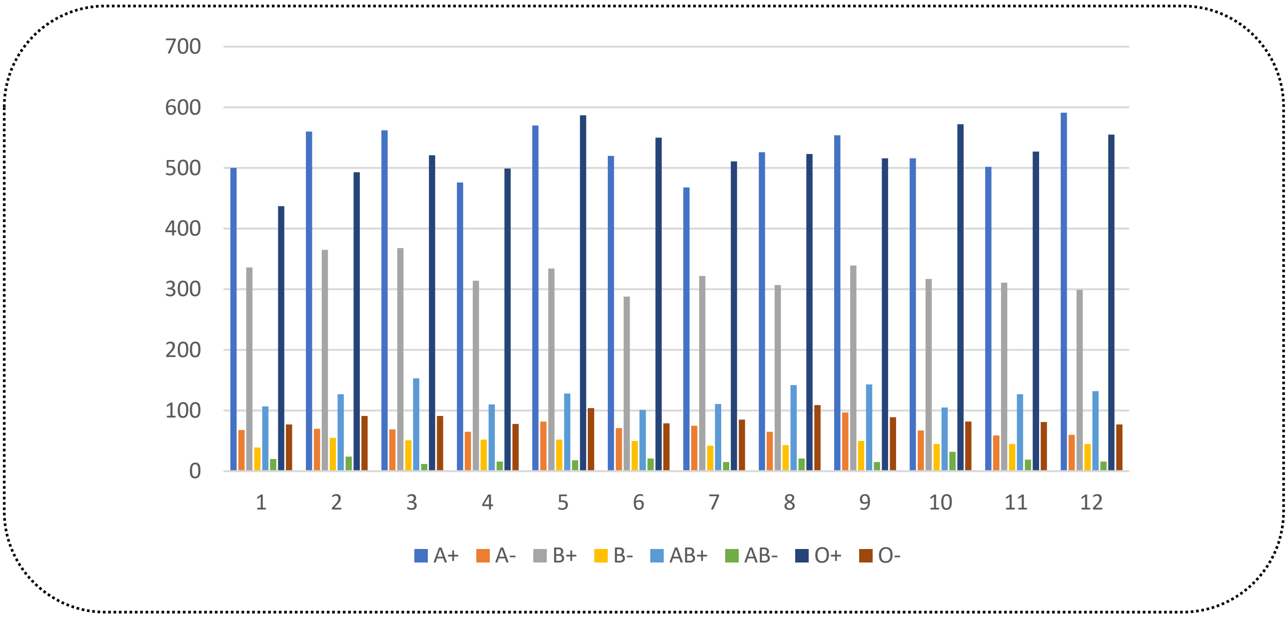

Fig. 1. Average demand of different blood types in Zanjan, Iran for one year

Supply policy: In traditional process of the system, RBCs orders are supplied using FIFO policy which means that old RBCs in the inventory are supplied first, and then fresh products would be supplied. In order to analyze different supply policy for blood banks, in this study, we aimed to show the way that a combined supply policy can meet fresh and old demands. Therefore, we considered three supply policies for RBCs product that are illustrated by details as follows:

(FIFO-FIFO): In this supply policy, inventory level is enough to meet all RBCs demands.

Table II. Parameter values

Parameters	Value (IRR per day)
C^O	600,000
C^S	2,000,000,000
C_r^Y	100,000,000
C^H	10,000

(LIFO-LIFO): In this supply policy, RBCs demands are satisfied by fresh RBCs in the inventory.

(LIFO-FIFO): In this combined supply policy, LIFO is used for fresh RBCs and FIFO is used for old RBCs.

Demand: In order to consider demands for RBCs, we tried to come up with an approximation average for demands from previous time periods that are represented in Fig. I. Annual demands are calculated based on normal distribution and are considered as $P_d^A(k)$ and $P_d^Y(j)$ in the MDP model.

Cost: As shown in Table II, real data are used for different involved costs such as holding cost, outdate product cost, shortage cost and mismatch cost.

Real data are under the influence of many situations that can happen within the system. We decided to use a specific scale for parameters in order to deal with the complexity of the problem. In terms of $\mathrm{x_r}$, we aimed to categorize the data into several groups in order to show the status of inventory. Categories for the data include following groups: $\mathrm{B_1} = (\mathrm{x_1})$, $\mathrm{B_2} = (\mathrm{x_2}.\mathrm{x_3}.\ldots.\mathrm{x_8})$, $\mathrm{B_3} = (\mathrm{x_9}.\mathrm{x_{10}}.\ldots.\mathrm{x_{14}})$, $\mathrm{B_4} = (\mathrm{x_{15}}.\mathrm{x_{16}}.\ldots.\mathrm{x_{21}})$, $\mathrm{B_5} = (\mathrm{x_{22}}.\mathrm{x_{18}}.\ldots.\mathrm{x_{28}})$ and $\mathrm{B_6} = (\mathrm{x_{29}}.\mathrm{x_{25}}.\ldots.\mathrm{x_{35}})$. Groups B_4 , B_5 and B_6 are considered for fresh blood units and old bloods are considered within other groups. Average demand in normalized scale (in range of 1-35 days) are utilized to determine the storage capacity. All of these consideration related to scale of the problem leads to a good situation where the MDP model can be solved in a logical CPU time. With respect to three proposed policies, (FIFO-FIFO), (LIFO-FIFO) and (LIFO-LIFO), we solve MDP with sequential approximation algorithm using MATLAB 2016b software.

Managers in blood banks and hospitals aim to develop strategies which have lowest possible cost due to the fact that cost is a very important parameter in BSCN. This is the reason that many researchers have contributed in BSCN and aimed to come up with models that are supposed to minimize costs of the system. Collection cost is one of the important cost that is really hard to minimize due to the fact that donors most of the times donate blood in a random manner; however, other costs such as production costs, holding costs and mismatch costs, as well as outdate products cost can be an interest of many research articles. In order to analyze the costs of the system with details, we considered blood into two groups as fresh (young) and old (other). All in all, we can state that total involved costs in BSCN are very important and a misleading strategy or decision can cause disastrous consequences for the system since it has a direct relation with mortality. This is where MDP can provide a reliable decision-making tool which at each iteration tries to come up with a decision that is not independent and is related to a previous decision that is made.

B. Results

We solve the proposed MDP model in order to calculate the optimal value of each policy with MATLAB 2016b for different blood types using a real data of Zanjan, Iran. As shown in Table III, we presented the results of optimal value of each policy and their related costs for O+ type. We considered costs of policies in cumulative form. Table III illustrates the fact that there is a noticeable gap among all involved costs. In comparison to all policies, the results indicate that (LIFO - FIFO) policy is more effective. In other words, LIFO is suitable for fresh (young) RBCs while FIFO works better for old RBCs orders.

We used the proposed model to investigate the value function, LF, LL and FF costs for other blood groups to analyze the difference between them. As shown in Table IV, results for blood group O- show lower value function cost which based on Fig. 1 is a consequence of its lower demand in comparison to O+. As same as O+, LIFO-LIFO is the best policy; however, LIFO-FIFO policy's percentage has increased in comparison to O+. Results for blood group A+ are represented in Table V where associated costs are reported for the same number of iterations. As Fig. 1, demand for A+ is very similar to the demand of the O+ so that their costs are very close to each other. High demand of these two groups shows that hospitals should invest most of their budget based LIFO-LIFO policy in order to optimally supply the blood units to the patients. LIFO-FIFO policy is not a reliable policy for these two and can let too many drawbacks such as shortages.

Table III. Computations for O+

Iteration	$V^n(x)$	LF (%)	LL (%)	FF (%)	LF cost value	LL cost value	FF cost value
0	43456546882	0.332	0.332	0.337	64000	64000	65000
1	24563785937	0.33	0.33	0.338	128000	128000	131000
2	37153357107	0.33	0.33	0.34	192000	192000	198000
3	27639759115	0.329	0.329	0.342	256000	256000	266000
4	23699663650	0.328	0.328	0.343	320000	320000	335000
5	28997709044	0.327	0.327	0.345	384000	384000	405000
6	34792152134	0.328	0.328	0.343	448000	448000	469000
7	25807728284	0.329	0.329	0.342	512000	512000	533000
8	28354736649	0.329	0.329	0.341	576000	576000	597000
9	29606354685	0.33	0.33	0.34	640000	640000	661000
…	…	...	...	...	...	...	...
18919	50259271981	21.46	39.82	38.72	106435162	197495254	205480371
…	…	...	...	...	...	...	...
278255	1.44739E+11	13.68	44.89	41.43	14784250420	48513523493	44774232085
278256	1.44518E+11	13.19	45.13	41.68	14254931318	48773696011	45045150670

Table IV. Computations for O-

Iteration	$V^n(x)$	LF (%)	LL (%)	FF (%)	LF cost value	LL cost value	FF cost value
0	28258846132	0.329	0.329	0.342	51000	51000	53000
1	24000785937	0.33	0.33	0.34	98000	98000	101000
2	27255452169	0.314	0.329	0.357	122000	128000	139000
3	28109239005	0.309	0.319	0.371	155000	160000	186000
4	25413657358	0.309	0.32	0.371	212000	220000	255000
5	28997709044	0.319	0.322	0.359	269000	271000	302000
6	28191180514	0.322	0.322	0.357	308000	308000	342000
7	28007005201	0.307	0.319	0.374	344000	358000	420000
8	29535790564	0.324	0.338	0.337	4006000	4176000	4167000
9	29006444174	0.309	0.315	0.376	440000	449000	536000
…	…	…	…	…	...	...	...
18919	39999275230	0.302	0.32	0.378	92433177	97882452	115442375
…	…	…	…	…	...	...	...
278255	1.02669E+11	0.291	0.369	0.339	9884331742	12542523471	11522298434
278256	1.03089E+11	0.282	0.37	0.349	9884331742	12963783852	12222298434

Table V. Computations for A+

Iteration	$V^n(x)$	LF (%)	LL (%)	FF (%)	LF cost value	LL cost value	FF cost value
0	41283719538	0.332	0.332	0.337	59520	59520	60450
1	23335596640	0.331	0.331	0.339	119040	119040	121830
2	35295689252	0.330	0.330	0.340	178560	178560	184140
3	26257771159	0.329	0.329	0.342	238080	238080	247380
4	22514680468	0.328	0.328	0.344	297600	297600	311550
5	27547823592	0.327	0.327	0.345	357120	357120	376650
6	33052544527	0.328	0.328	0.344	416640	416640	436170
7	24517341870	0.329	0.329	0.342	476160	476160	495690
8	26936999817	0.329	0.329	0.341	535680	535680	555210
9	28126036951	0.330	0.330	0.341	595200	595200	614730
…	…	…	…	…	...	...	...
18919	47746308382	0.209	0.388	0.403	98984701	183670586	191096745
…	…	…	…	…	...	...	...
278255	137501584068	0.137	0.449	0.414	13749352891	45117576848	41640035839
278256	137292034246	0.132	0.451	0.417	13257086126	45359537290	41891990123

Table VI. Computations for B+

Iteration	$V^n(x)$	LF (%)	LL (%)	FF (%)	LF cost value	LL cost value	FF cost value
0	34765237506	0.319	0.319	0.361	50560	50560	57200
1	19651028750	0.318	0.318	0.363	101120	101120	115280
2	29722685686	0.318	0.318	0.365	151680	151680	174240
3	22111807292	0.317	0.317	0.367	202240	202240	234080
4	18959730920	0.316	0.316	0.368	252800	252800	294800
5	23198167235	0.315	0.315	0.370	303360	303360	356400
6	27833721707	0.316	0.316	0.368	353920	353920	412720
7	20646182627	0.316	0.316	0.367	404480	404480	469040
8	22683789319	0.317	0.317	0.366	455040	455040	525360
9	23685083748	0.317	0.317	0.365	505600	505600	581680
…	…	…	…	…	...	...	...
18919	40207417585	0.200	0.371	0.430	84083778	156021251	180822726
…	…	…	…	…	...	...	...
278255	115790807636	0.131	0.429	0.441	11679557832	38325683559	39401324235
278256	115614344628	0.126	0.431	0.443	11261395741	38531219849	39639732590

Table VI shows the results obtained for blood group B+. Fig. 1 indicates that demand for B+ is somehow consistent over a year and its deviations from the average demand are not that much. On the other hand, the demand for this blood group is very lower than O+ and A+ which would strongly affect the value function cost and also costs for the three policies that we considered in this paper. Another point has to do with the fact that costs for all of the policies are very close to each other in LIFO-LIFO and FIFO-FIFO. FIFO-FIFO is slightly better than other policies. Unlike the results obtained in the previous tables, FIFO-FIFO policy shows higher efficiency for the supply of B+. As same as other blood groups, LIFO-LIFO shows more effectiveness for the AB+ group as well. However, we should mention that due to lower demand of AB+ in comparison to other, the value function cost and policies' cost are way lower than other blood groups, especially O+ and A+.

Table VII. Computations for AB+

Iteration	$V^n(x)$	LF (%)	LL (%)	FF (%)	LF cost value	LL cost value	FF cost value
0	21293707972	0.332	0.332	0.337	29440	29440	29900
1	12036255109	0.331	0.331	0.339	58880	58880	60260
2	18205144982	0.330	0.330	0.340	88320	88320	91080
3	13543481966	0.329	0.329	0.342	117760	117760	122360
4	11612835189	0.328	0.328	0.344	147200	147200	154100
5	14208877432	0.327	0.327	0.345	176640	176640	186300
6	17048154546	0.328	0.328	0.344	206080	206080	215740
7	12645786859	0.329	0.329	0.342	235520	235520	245180
8	13893820958	0.329	0.329	0.341	264960	264960	274620
9	14507113796	0.330	0.330	0.341	294400	294400	304060
…	…	…	…	…	...	...	...
18919	24627043271	0.209	0.388	0.403	48960175	90847817	94520971
…	…	…	…	…	...	...	...
278255	70921869677	0.137	0.449	0.414	6800755193	22316220807	20596146759
278256	70813786085	0.132	0.451	0.417	6557268406	22435900165	20720769308

C. Sensitivity analysis

We did a sensitivity analysis for parameters used in our model. We investigated the model for blood group A+ and compared value function, LF cost, LL cost and FF cost under the changes in parameters. As shortage cost is a very high value in blood supply chain, we did a sensitivity analysis for the value function and policies. Shown in Fig. 2 and Fig. 3, we see the new solutions obtained for the value function cost and percentage of policies in a scale of 10^6. It is understandable that they are highly sensitive to the shortage cost as it counts more than other costs in the proposed model.

Fig. 2 illustrates that value function cost is much relied on the shortage cost and as it increases, the value function increases as well. By this we can see that with proper blood supply chain management and prevention of shortage occurrence, manager can definitely have much lower costs in their system. Fig. 3 shows the changes costs in three different policies that we considered in our study. There is not much difference in the ratio in costs of the policies. However, as shortage cost increases we see a smooth increase in LIFO-LIFO policy's cost ratio in comparison to other two. On the other hand, we see a minor decrease in LIFO-FIFO policy's cost as shortage cost increases in the model. This indicates that LIFO-FIFO policy could not act as a reliable policy when we have very high shortage cost.

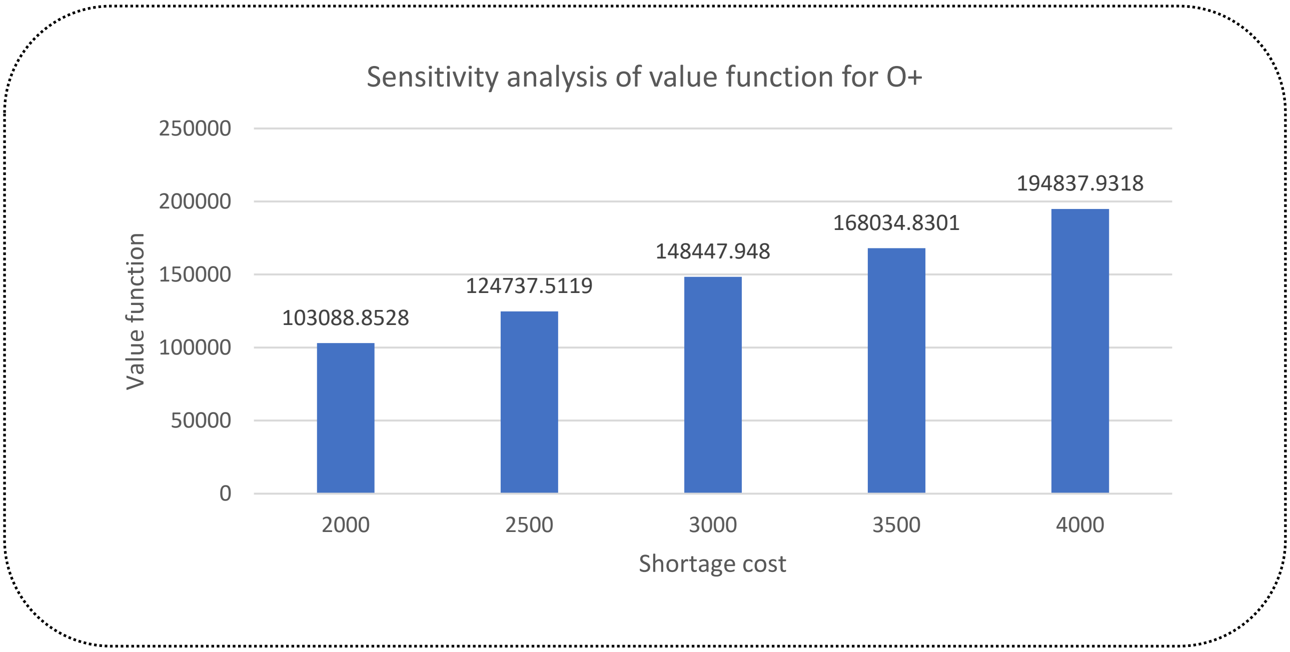

Fig. 2. Sensitivity analysis of value function for O+ considering shortage cost

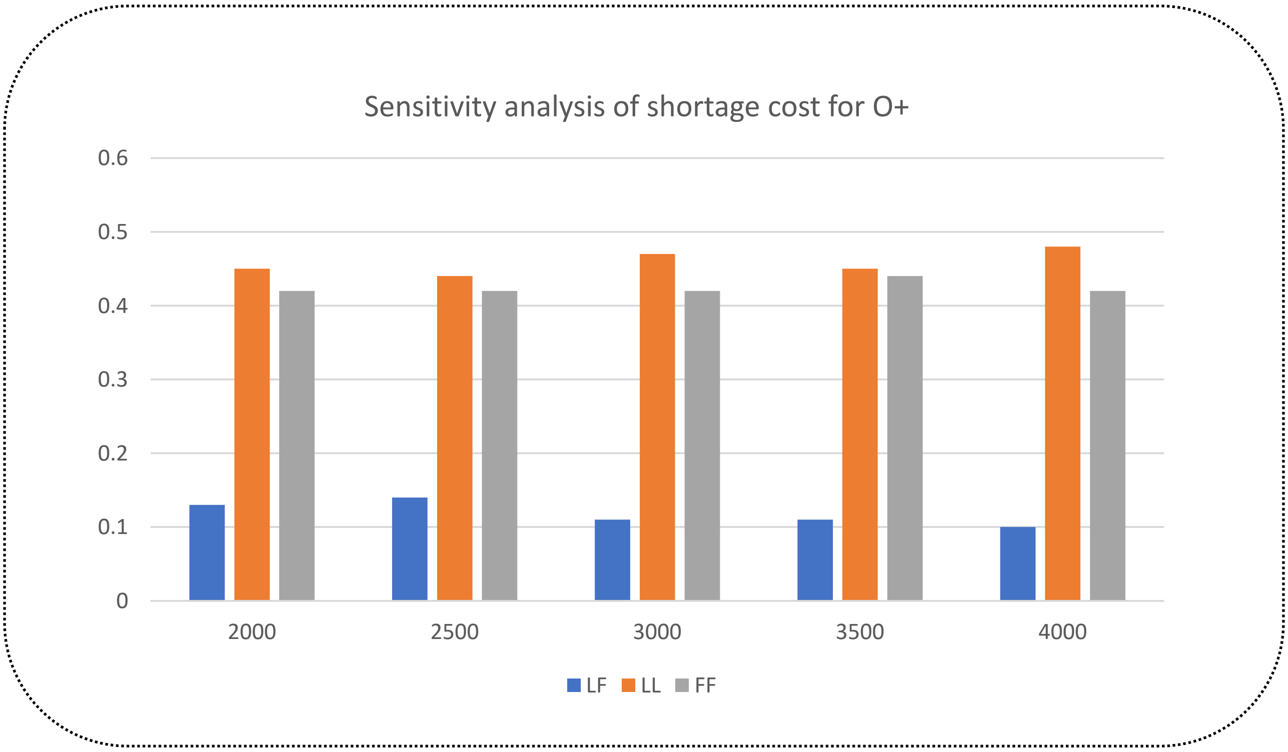

Fig. 3. Sensitivity analysis policies for O+ considering shortage cost

V. CONCLUSION

RBCs consumption policy is one interesting and important problems in health systems. Different supply policies have different performance with respect to several involved parameters like holding cost, shortage cost, wastage cost and mismatches cost. In this study, we analyzed the performance of inventory systems in terms of three supply policies (LIFO-LIFO) and (FIFO-FIFO) and (LIFO-FIFO). Results obtained from the model states that (LIFO-LIFO) and (FIFO -FIFO) policies are better than (LIFO-FIFO) policy in terms of total costs of the system. Several computational experiments were done for different blood groups, and results obtained showed that value function and also costs associated with each of the policies are strongly affected by the demand of that blood group. A sensitivity analysis for this model and its optimal solutions for different shortage cost values is performed. Decision-making process for blood supply policies in terms of the inventory costs such as outdate, shortage, holding and mismatch are main focus of this study. A MDP model is formulated for blood supply chain problem in a dynamic environment and solved the value function using a sequential approximation algorithm.

This study can be improved in several ways for future directions. MDP model can be used for other blood products such as platelets. Multi-criteria decision methods can be applied for selection of best supply policy in terms of different criteria that are involved. MDP can be used for inventory problem of other perishable products such as foods. At the end, we think MDP can be a good method to use for other blood blank problems such as blood flow, blood pressure and etc.

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