Proceedings of the 2020 Winter Simulation Conference
K.-H. Bae, B. Feng, S. Kim, S. Lazarova-Molnar, Z. Zheng, T. Roeder, and R. Thiesing, eds.

SCENARIO-BASED SIMULATION APPROACH FOR AN INTEGRATED INVENTORY BLOOD SUPPLY CHAIN SYSTEM

Mohammad Arani
Xian Liu

Department of Systems Engineering
University of Arkansas at Little Rock
2801 S., University Ave.
Little Rock, AR 72204, USA

Saeed Abdolmaleki

Department of Industrial Management
University of Shahid Beheshti
District 1, Daneshjou Blvd.
Tehran, 19839 69411, IRAN

ABSTRACT

This study conducts a comparison between a newly proposed integrated inventory blood supply chain (BSC) and the current practice of the blood product distribution system. The importance of a well-designed blood supply chain is indisputable when it comes to human lives and the valuable blood products of the BSC. Our discrete event simulation approach and scenario discussion encompass a set of operational decisions to manage the complexity of the system. Applying the Arena simulation package, we model a carefully designed blood supply chain to provide a critical comparison of the two primary Key Performance Indicators shortage and outdated units of the BSC. We conclude that the proposed method would bring straightforward improvement with respect to the indicators under study.

1 INTRODUCTION

The conventional Blood Supply Chain (BSC) system embraces four prominent components: (a) donors, (b) blood centers (BCs) and bloodmobiles (BMs), (c) blood banks (BBs), and eventually (d) hospitals. In brief, the responsibilities of the BSC are collecting, processing, screening, fractionating, preserving, distributing, and administering blood products. The vital blood products of this system require a well-designed and efficient BSC since the supplies of many blood products are scarce. For example, in the U.S. approximately 10 % of the eligible population donates, but many low-income and medium-income countries face lower percentages of donors. Therefore, from a systematic point of view, one small step towards the improvement of the two crucial KPIs (shortage and outdated units) results in a tremendous impact on the BSC system.

There are two methods to donate blood, which are either in a BC or a BM: the whole blood donation method and the apheresis method. In the first method, an individual donates about 450 ml of his or her blood collected in a blood bag. In the second method, a donor decides which component of the blood could be extracted and the residue returns to his or her vein (Katsaliaki and Brailsford 2007). Essentially, the alternative method enables a withdrawal of blood components in the BCs and BMs, which is technically called fractionation. Although a higher cost is imposed on the system along with the increased service time at the donation facilities, the number of blood product units obtained by the method is greater than that of the first method. For instance, donating plasma by the apheresis method yields three units. In the medical field, more than one hundred variations of blood products have been developed and used. Only the flow of four of them, nevertheless, drives the BSC system in real-world practice, since the accumulation of them – in terms of product units – is more than 95 % of the total (Yousefi Nejad Attari et al. 2017). In Table 1, the attained blood products from each donation method are listed, and the four main blood product donation options are (a) whole blood, (b) red blood cells (RBCS), (c) plasma, and (d) platelets. Therefore, an individual who wishes to donate can opt for one of the four options.

Table 1: Standard and apheresis methods (Yuan et al. 2010).

Process	RBCs	Plasma	Platelets
Quadruple bag	1	1	1
RBCs by apheresis	2		
Plasma by apheresis		3	
Platelets by apheresis			6

Given the shelf lives of the aforementioned blood products – whole blood is 21 days, RBCs 35 days, plasma is 12 months, and platelets 5 days – the donated whole blood units are fractionated in the BB into its components contributing to one unit of RBCs, one unit of plasma, and one unit of platelets. In addition to the preservation of the blood products, crossmatching, which is the ability to use one type of blood product in place of another, is of paramount importance to meet the urgent demand. For instance, a patient with blood type A negative can receive RBC units from either O negative or A negative (for more information about the compatibility of each blood product considered in this paper, see Australian Red Cross 2020).

In this paper, we present a discrete event simulation (DES) model to support decision making from an operational point of view in managing the blood supply chain. This model considers the shelf lives and crossmatching of blood product units. It contains several novelties that expand the existing body of knowledge in this discipline. For instance, it includes (a) two methods of blood donation in general, the whole blood donation method and the apheresis method, (b) interchangeability of blood products while either RBC units or plasma units are administered, and (c) the possibility of hiring a fifth echelon called Integrated Inventory System (IIS) manifested through a vehicle depot to facilitate the flow of blood product units at the hospitals' echelon. By a vehicle depot as means of facilitating the transportation of blood units among the hospitals, an integrated system of inventory is considered. Hence, hospitals have access to information about the inventory level, and they can place an order not only submitted to a BB, but also to other hospitals. We analyze the KPIs of the BSC under various sensible scenarios.

We analyzed the generated standard random problem against the KPIs. A medium-sized random problem was generated, which is described in Section 3. As mentioned earlier, the DES approach is preferred over other methods to address the operational level, micro-level, and maximum detailed characteristics of the studied problem (Borshchev 2015). DES studies realistically outfit our problem statement and give us access to an analyzing tool for better evaluation of the wide spectrum of proposed schemes. Taking into account the merits and disadvantages of the four simulation methods and their applications (Pirabán et al. 2019) – which are (1) Monte Carlo, (2) System Dynamics Simulation, (3) Agent-based Modelling and Simulation, and (4) DES – we have selected DES (Borshchev 2015) for our work. In particular, we propose an integrated inventory system within the hospitals.

The paper is organized as follows: Section 2 provides an overview of the most relevant and recent studies presenting the problem statements that have been explored in terms of mathematical modeling and simulation modeling. Section 3 describes the full details of our simulation model implemented in the Arena software (version 14), a scenario analysis, and a discussion. Finally, Section 4 is dedicated to the conclusion and our recommendations for future pathways.

2 LITERATURE REVIEW

There are many literature studies oriented towards Supply Chain Management (SCM) and Supply Chain Network Design (SCND), and specifically for the BSC. However, a large number of them concentrate on strategic decisions through mathematical modeling. On one hand, when it boils down to *strategic* decisions to be made, several areas of studies are of interest, for instance, location-allocation of the chain's components, the product assignment problem, scheduling of the operations, the vehicle routing problem, and so on. On the other hand, the *operational* decisions predominantly pertinent to micro-scale management or day-to-day business – for instance, dealing with registered donors, the variety of orders and service times dedicated to each order, the maximum number of order placements, and inventory policy investigations – have been completely neglected.

Only limited research has appeared in recent years on the operational level of making decisions by virtue of employing the four stated simulation modeling approaches, in particular, by utilizing the DES approach. The following two sections are dedicated to understanding the mathematical modeling approach and the simulation modeling approach. The final section discusses where our work stands in terms of research contributions.

2.1 Optimization Approach

As emphasized earlier, mathematical modeling is one of the tools that a decision-maker (DM) can employ. Operations research models naturally concern different strategic aims reflecting on the specific objective functions and problem statements that are under study. Cheraghi and Hosseini-Motlagh (2018) studied a disaster relief problem considering how responsive and reliable a BSC could be to supply critical blood products. To measure the responsiveness and reliability of the BSC, three criteria are accounted for: (1) urgency of demand, (2) fairness and equity of distribution among demand points, and (3) risk factors associated with disruption occurrence throughout the network. A robust bi-objective mixed-integer programming is proposed that investigates the trade-off between the total cost of the supply network and the maximum number of blood unit shortages at the demand points. A model that captures the risk of disruptions was proposed by Rahmani (2019). The author considers the discontinuation of service due to the disruption aftermath in two levels of the chain, the permanent BC and the BB. This interruption is incorporated by the reliability factor, ρ, inspired by Snyder and Daskin (2006), which allows the objective function to deviate by $(1+\rho)\%$ of the goal decreed by the network's DM.

Salehi et al. (2019) proposed a three-echelon blood supply chain consisting of donors, permanent and temporary blood facilities, and BCs. They applied two-stage stochastic optimization, adapted from Aghezzaf et al. (2010), which is a method to deal with uncertainty and falls under the class of robust optimization. Robust optimization can be applied in other settings than that of the proposed method by Aghezzaf et al. (2010). For instance, Haghjoo et al. (2020) considered a new design for a reliable BSC in the face of random occurrences of disruptions. The robust optimization formulation is adapted from Yu and Li (2000), which is a deviation of scenario-based stochastic optimization. Haghjoo et al. (2020) applied two meta-heuristic algorithms: (a) a self-adaptive imperialist competitive algorithm (SAICA), and (b) an invasive weed optimization (IWO) algorithm.

2.2 Simulation Modeling Approach

The simulation approach is another equally potent and effective tool in decision-making. A real-world example was proposed by Katsaliaki and Brailsford (2007) to improve a UK blood supply chain network consisting of donors, BCs, one BB, and one medium-size hospital. The authors of that paper compare different inventory policies with that of the actual system, which is called the "Baseline Scenario", applying the Simul8 software. Suggested inventory polices are considered and tested against four target measurements: (1) outdated units, (2) shortage units, (3) mismatch incidents, and (4) the number of unplanned unit deliveries to hospitals. Selvakumar et al. (2019) studied the whole blood supply chain in Chennai (India) embracing one BC and 152 large- and medium-size hospitals, using the Arena software. In their proposed system, the hospitals are clustered into four regions (also named zones) according to their distance from the BC. The four established regions share whole blood within them and two performance indicators – the number of shortage units and wastage – are compared. The new re-configured system reported improvements over the prior one.

According to recent medical studies, the older an RBC unit is, the greater is the chance of adverse issues. This problem encouraged Sarhangian et al. (2018) to consider an inventory policy called the threshold-based allocation policy. In this Queuing Modelling (QM) method, both supplies and demands are considered stochastic and follow the Poisson distribution. Another paper that considers the inventory policies in the RBCs unit supply chain is that of Clay et al. (2018), who considered two echelons comprising a BB and a hospital. They applied System Dynamics Simulation (SDS) to show that even without taking into account the uncertainties in supply and demand, the system is prone to drastic changes due to having short shelf lives for the RBCs units. Therefore, constant supply and demand are maintained until minor changes are applied to the blood requirements. One unique and interesting approach in the literature plays an important role in Lowalekar and Ravi (2017), who utilize "Theory of Constraints (TOC)" accompanied by "Thinking Process (TP)" methodology. In TOC, most of the attainable goals are adversely affected by a single minor reason that could be identified and improved. The authors found that the levels of shortage and waste dramatically decreased in the cited research in which the DES model is built based on the R language.

In Table 2, we present a comparison among the most relevant and recent publications. The closest and most-recent study was conducted by Selvakumar et al. (2019). However, our paper is distinguishable by the following main points:

1. Our model considers the entire BSC system, while Selvakumar et al. (2019) consider only two echelons.
2. Our model takes into account the four known blood units, whereas the other considers only one.
3. We extensively consider the cross-matching compatibility, as well.

2.3 Our Contributions

The literature review reveals that the DES modeling approach is utilized only sparingly, to the best of our knowledge. However, the approach is recommended to be investigated more thoroughly in the context of the BSC (Marques et al. 2019). In the following, the contributions of the current research are highlighted:

- A simulation approach is utilized to comprehensively build the problem statement, embedded in the simulation modeling with the Arena package. Perishability of blood products and crossmatching compatibility are considered.
- The concept of robustness to deal with uncertainties in supplies and demand is considered in the simulation modeling.
- A scenario-based analysis is accommodated to test the suggested alternatives.
- The consumption of less-commensurate products is prioritized by priority rules. For instance, the demand for RBCs type O negative is prioritized to consume those units first.
- Equity and fairness are taken into consideration to respond to the hospitals' demand.

3 PROBLEM STATEMENT AND SIMULATION PROCEDURES

This paper addresses the current practice and suggested improvements in the BSC network. First, a comprehensive description of the current practice is portrayed. The BSC includes the four major blood products consisting of whole blood, RBCs, plasma, and platelets, accumulating 32 distinct products as a result of four major blood products and eight blood types. To begin with the network, we reviewed and inspected the actual BSC system and modeled it as the baseline scenario. We consider a medium-size city comprising four counties and three major hospitals performing special treatments that require blood products. The state government intends to establish a BC, two BMs, and a BB to support the clinical facilities as demand points. The procedure commences from collecting whole blood by the standard technique and the three other blood products by the apheresis method, taking into account the donors' arrival preference every day from 8:00 am to 4:00 pm. In the simulation model, while donors are randomly generated, three attributes are assigned to them (Rahmani 2019): (a) location coordinates, (b) blood type, and (c) the method of donation according to Table 1. All three attributes are uniformly distributed. The collection and preliminary screening tests are among the responsibilities of the BC and BMs. The system informs the new donor to schedule a convenient time to donate based on the preference of expected earliest possible service time obtained from either (1st

priority) BMs that traverse certain routes and are known to the donors or (2nd priority) the BC, which is at a fixed location. The pseudocode is provided in Table 3.

At the end of the BC's and BMs' working hours, the collected blood units are sent to the BB for advanced testing, decomposing the whole blood into the three other blood products, storing, and distributing. As an alternative option, we also examined the possibility of capacitated BM's. In one scenario, a capacitated BM is only able to collect blood products *once a day* until the entire storage capacity is occupied. In contrast, *each time* a BM is filled with blood products, it drives to the BB and unloads its storage, and after that continues its specified route.

Table 2: Literature overview.

Author(s)	Modeling Approach (Math. Or Sim.)	Objectives Functions or KPI	# of Echelons	Uncertainty	Blood Product	Contribution	Case Study	Comments
Cheraghi and Hosseini-Motlagh (2018)	MILP	Total cost, fairness/ equity	4	Disruption, Supply, Demand	RBCs	Priority rule to treat patients, Fuzzy VIKOR	Iran	Disaster relief problem
Rahmani (2019)	MILP	Total cost	4	Disruption	RBCs	Robust and reliable model	Test problems	Lagrangian relaxation algorithm
Haghjoo et al. (2020)	MILP	Total cost	3	Disruption	RBCs	SAICA algorithm, IWO algorithm	-	Two-stage stochastic optimization
Katsaliaki and Brailsford (2007)	DES	Outdated, shortage units, mismatch incidents	4	Supplies and demand	RBCs	Inventory policies	The UK	Simul8
Clay et al. (2018)	SDS	Shortage and outdated units	2	Supplies and demand	Whole Blood	Lead time discussion	-	Shelf lives
Sarhangian et al. (2018)	QM	Outdated and transfused units	2	Supplies and demand	RBCs	Inventory policy called threshold-based allocation	-	-
Selvakumar et al. (2019)	DES	Shortage and wastage units	2	Supplies and demand	Whole Blood	Clustering hospitals	India	Arena
Current Study	**DES**	**Outdated, and shortage units**	**4**	**Supplies, and demand, service time**	**Whole blood, RBCs, plasma, platelet**	**Pair-wise comparison, scenario-based analysis, priority rules**	**Test problems**	**Cross-matching, inventory policies, equity**

Hospitals place blood product orders early in the morning taking into account their operative and non-operative scheduled treatments for patients, prediction of demand for the day, and their short-term inventory of blood products. According to the status of its inventory, the BB determines whether they need to dispatch a number of limited-capacity vehicles – with either the required blood product units or crossmatched units – to the hospitals. While a crossmatched unit is sent to a hospital, the hospital acknowledges the changes in its order. Naturally, the BB may encounter a shortage (and may not be able to fully respond to a demand) or outdated units in the inventory (since each kind of product has a finite shelf life).

In the current practice of the BSC system shown in Figure 1, hospitals operate separately without any relevant information of their counterparts. On the contrary, in the proposed system, hospitals are connected to an integrated inventory system that notifies them about any excess of blood product units at the other hospitals. By being informed of their counterparts' inventory levels, one way to satisfy the remainder of their demand is to place an order to a hospital in the vicinity and consider crossmatching rules in the new set of orders. After that, in case a required demand remained unmet after two calls, it is designated as a shortage unit. Moreover, the day a hospital encounters a shortage, neither the BB nor the other hospitals will consider the shortage as a backorder. Finally, the vehicle depot containing capacitated vehicles is to facilitate the flow of the blood product units between hospitals. The inventory policy associated with both the BB and the hospitals is first-in-first-out (FIFO). The FIFO policy is considered the best approach to decrease the number of outdated units (Pérez Vaquero et al. 2016). Every day, the inventory departments in both the BB and the hospitals monitor the expiration dates of the units respecting the donation date. This information is recorded in a DSTAT variable in the Arena simulation. While bearing in mind the cross-matching compatibility, it is of crucial importance to first fulfill the demand of those products that have no substitutes available for them. For instance, in the considered ranking, the RBC type O negative has the highest priority to become out of stock. Hence, among all demand points, we first attempt to fill the basket of RBCs type O negative demands. Conversely, dealing with plasma units, type AB has the highest priority to respond to its demand first.

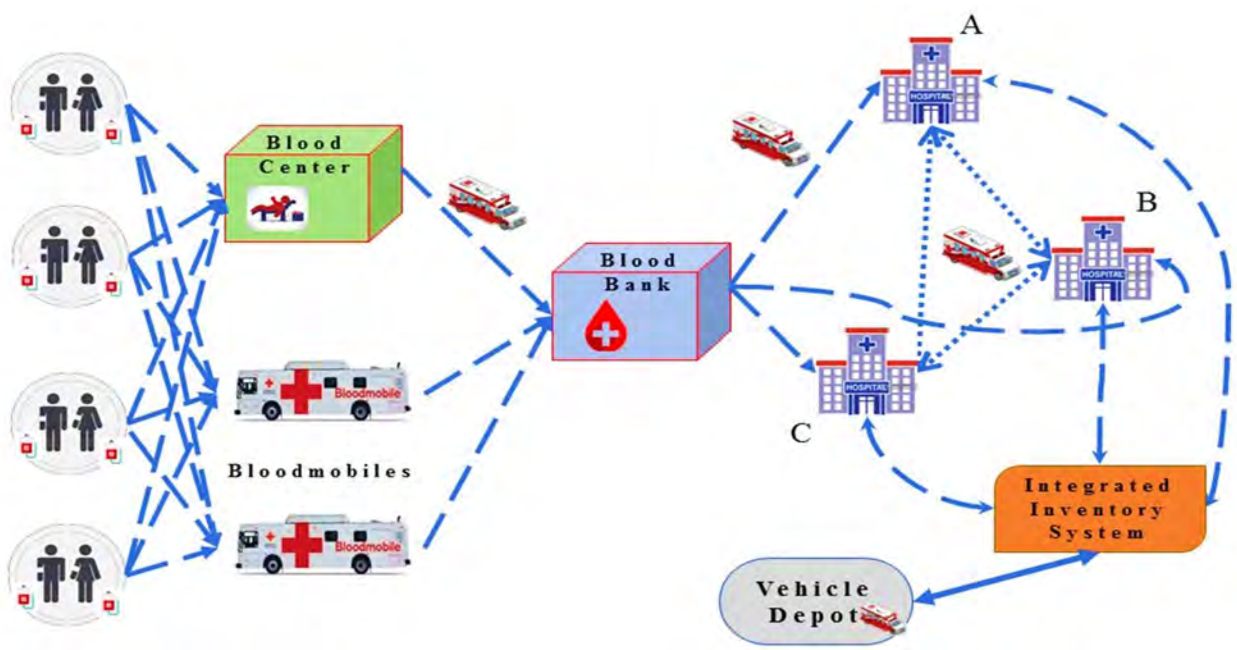

Figure 1: Proposed BSC system.

Table 3: Pseudocode for donor's enrollment in either one of the BMs or the BC.

Step	Description
1	Initialization: - BMs' paths are defined - BMs' service time window at each county is defined - Two queues of enrolled donors are established for two BMs at each stop or county - One queue of enrolled donors is created for the BC
2	A donor with the assigned attributes is entered
3.1	BMs are positioned - The distance and time to travel to stationed BMs and BC are calculated - If the travel time is not in the service time window of any BM, go to *3.2* - By knowing the number of people in queues to donate, the earliest expected service time is calculated (assuming the donor is registered to that blood facility) - If the donor's travel time $\geq$ earliest expected service time * *service time* = donor's travel time to that blood facility * (As soon as a donor arrives, she or he receives service) - If donor's travel time $<$ earliest expected service time * *service time* = earliest expected service time − donor's travel time * (donor will be considered as another person in the line to receive service)
3.2	At least one BM is on the way to its next stop - BM's arrival time to its next stop is known → If there is no one registered to the queue * If BM's travel time $\geq$ donor's travel time ** *service time* = BM's travel time − donor's travel time ** (donor waits until BM arrives) * If BM's travel time $<$ donor's travel time ** *service time* = donor's travel time ** (donor registers as the first one in the queue) → If there are some people already registered to the queue - By knowing the number of people in queues to donate, the earliest expected service time is calculated (assuming the donor is registered to that blood facility) * If (BM's travel time) + (the earliest expected service time) $\geq$ donor's travel time ** *service time* = (BM's travel time) + (the earliest expected service time) – (donor's travel time) * If (BM's travel time) + (the earliest expected service time) $<$ donor's travel time ** *service time* = donor's travel time − [(BM's travel time) + (the earliest expected service time)]
4	According to the priority mentioned and the *service time*, either a BM or BC is designated to the donor to enroll.

3.1 Simulation

As stated earlier, DES is the proposed method to make a comparison between the current practice and the recommended system of BSC regarding feasible scenarios. Considering the behavior of the system, two KPIs are assessed. The following steps are taken to be sure that the simulated models are accurate.

- The conceptual framework is prepared as the experts and literature suggested.
- A detailed version of the conceptual framework is modeled by Arena; and the embedded Visual Basic for Applications (VBA) is used, where a module does not exist, e.g., crossmatching.
- A verification assessment step is performed to observe the expected behavior of the conceptual framework (for more information, refer to Chung 2004).

- The validation assessment step is performed to examine the adaptability of the constructed model's output with the real system at a meaningful significant level of *0.05*.
- Along with the validation assessment step, we ran 150 simulation replications of 60 days to obtain confidence intervals (CIs) via Equation (1).

$$\text{Half Length of Confidence Interval} = \frac{t_{1-\frac{\alpha}{2},(n-1)} \times s}{\sqrt{n}} \tag{1}$$

where:
t : is the $100\times(1-\alpha/2)$ quantile of the t distribution with $(n-1)$ degrees of freedom
s : is the standard deviation of the replication means
n : number of initial replications.

In Figure 2, four flowcharts are designed to present the simulation scenario study, the donor's arrival policy, the BMs' decision rule, and the inventory policy update.

3.2 Scenarios

There are four simulation models examined in Arena. The first is the current practice of the BSC, in which no integrated inventory system exists and BMs are allowed to traverse through their assigned routes as long as room is left to preserve blood units only once a day. This model is designated as W_1. The second is the proposed system which offers the components of the integrated inventory system in addition to the first model and is called I_1. The third model is denoted W_2 and is an extension of the W_1 model that differs in the BMs' navigation rules throughout the system. In this model, the BMs are operational and constantly visit the BB to release their storage capacity when they are fully occupied, from 8:00 am to 4:00 pm every day. The last model is denoted I_2 and is an alternative to the W_2 model in which the integrated inventory system is implemented. We note that the entrance rate of donors to the four models remains unchanged.

We provide two scenarios not only to analyze the four developed simulation models against the two critical KPIs – the number of shortage units and outdated units – but also to validate them with regard to the declared KPIs. The first scenario is fundamentally designed to depict the nature of the two conflicting KPIs. In other words, it is expected when the Average Total Shortage (ATS) decreases as a result of attempting to retain a higher level of inventory, the Aggregated Total Outdated Units (ATO) over the planning horizon increases. The second scenario is designed to understand the behavior of the models influenced by considerable changes in demand. Figures 3 and 4 depict results from the two scenarios; and discussion takes place in the following section.

3.3 Discussion

In this section, we provide an in-depth analysis of the two trials. For the first scenario (in which we compare ATS vs. ATO as hospitals are allowed to order more than anticipated demand), we consider that hospitals are permitted to order 5 %, 10 %, 15 %, and 20 % more than their expected overall demand. It is clear from Figure 3 (a) that there is a wide gap in the amount of ATS between the two different strategies – integrated inventory system and its absence – over the studied scheme: The more orders are placed, the less ATS occurs, although both sets of lines decrease only moderately. The more hospitals placed their orders into their inventory baskets, the fewer units of shortage are experienced; however, the number of ATO increased, as illustrated in Figure 3 (b). More precisely, in the W_1 model, the expired units (ATO) went up abruptly, whilst in the I_2 model, it remains relatively constant. The main reason for the constant trend is that in the proposed model, products are consumed within the hospitals echelon prior to their expiry dates.

The aim of Figure 4 is to validate our models. By increasing the demand parameters for all products, we drew a comparison to study and validate their behaviors. The first quadruple bar chart in Figure 4 (a), shows that the ATS for all investigated models increases as the corresponding demand rate increases.

Furthermore, in the I_2 model, the volume of ATO is noticeably lower than the volume of W_1 – virtually by 50 percent, as depicted in Figure 4 (b). In Figure 4 (b), the right-most bar associated with W_1 shows that the higher the demand, the lower the volume of ATO; the same observation is made at the other models, as well. To that end, under the studied circumstances, the I_2 model performed significantly better than the rest of the models in terms of the two KPIs.

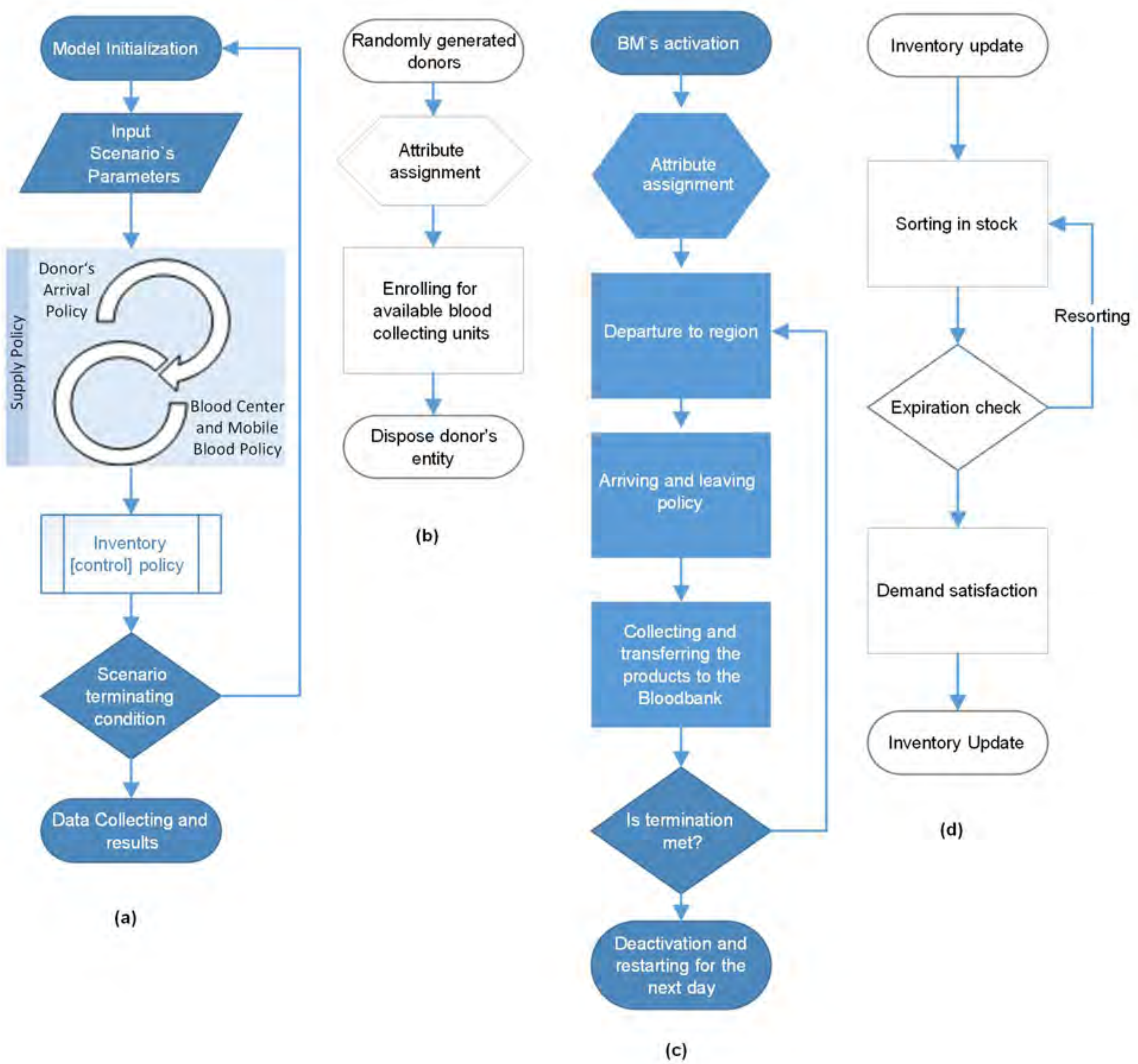

Figure 2: Flowcharts for (a) simulation scenario study, (b) donor's arrival policy, (c) BMs' decision rule, and (d) inventory policy update.

4 CONCLUSIONS AND FUTURE WORK

Although the BSC is a dynamic and vibrant area of research, the simulation approach manifestly lacks its presence in the literature. Our research serves the purpose of extending the literature. Our contributions regarding the scenario analysis provided in this study carry insights not only for interested readers but for the BBs' and hospitals' managers. The proposed integrated inventory system on the last echelon (hospitals as demand points) successfully exceeded the current practice of the BSC in terms of the number of shortages and outdated units.

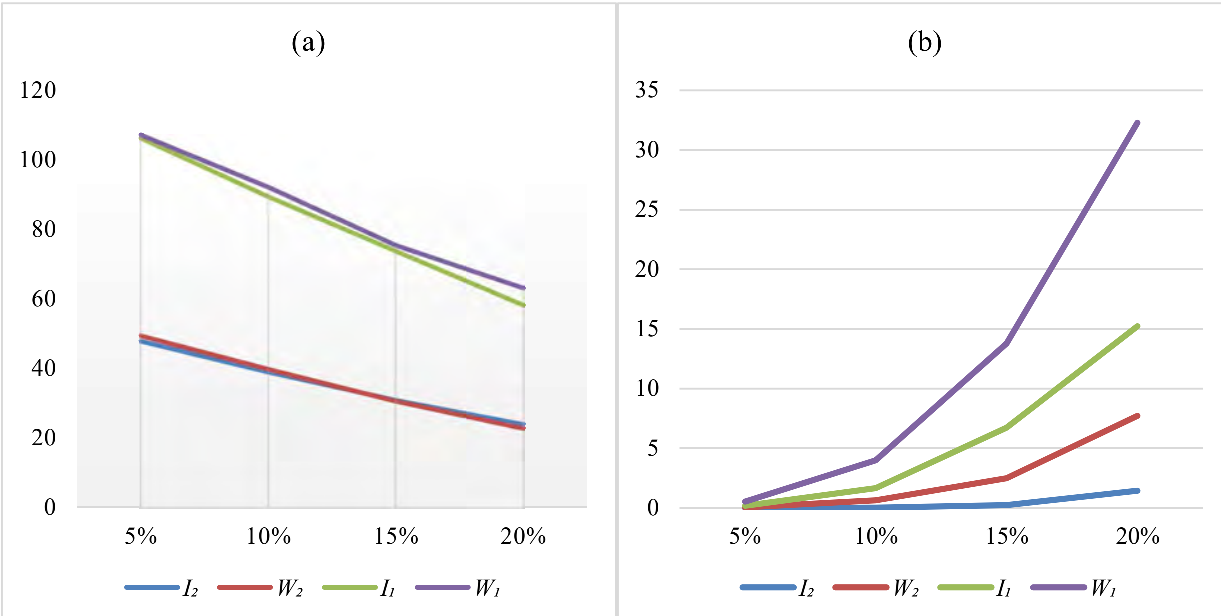

Figure 3: Key performance indicators for the first scenario (comparing ATS vs. ATO as hospitals are allowed to order more than anticipated demand) (a) Average Total Shortage, (b) Aggregated Total Outdated.

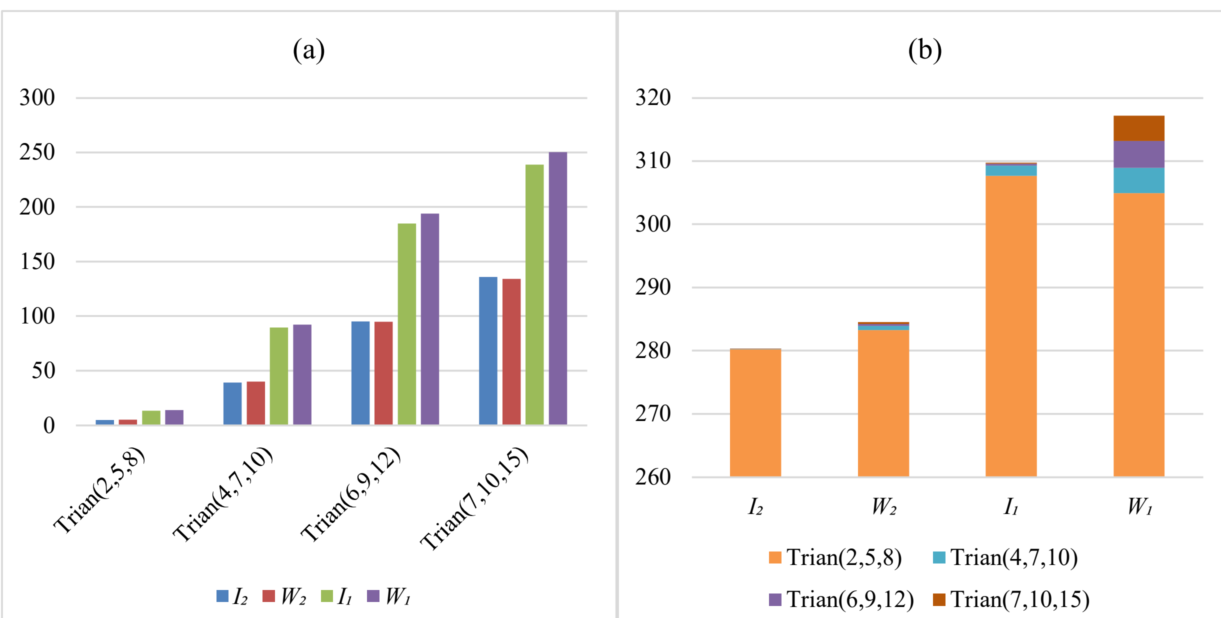

Figure 4: Key performance indicators for the second scenario (involving significant demand changes) (a) Average Total Shortage, (b) Aggregated Total Outdated.

In terms of future recommendations, simulation optimization is a further step to take. For instance, one might consider the use of the embedded optimization toolkit OptQuest in the Arena software (Abdolmaleki et al. 2019). Another approach is taken by Osorio et al. (2017) to model the BSC and responds to strategic and operational decision variables concurrently employing an operations research model and a simulation model (Table 1). Other influential approaches merged with simulation are the exercise of heuristics and meta-heuristics algorithms, which are highly recommended for future research and for which we could not find relevant papers.

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AUTHOR BIOGRAPHIES

MOHAMMAD ARANI is a Ph.D. candidate of Systems Engineering / Engineering Science from the University of Arkansas at Little Rock (UA Little Rock). He earned a Masters's degree in Industrial Engineering from Azad University in Qazvin, Iran in

2011. His research interest is in Operations Research Mathematical Modeling, Optimization, and Simulation, and he has oriented his studies towards the applications of Systems Engineering and Industrial Engineering in healthcare, logistics, manufacturing, and transportation. He has been serving as a teaching assistant and instructor of several classes at UA Little Rock for several engineering courses since Fall 2017. His email address is mxarani@ualr.edu.

SAEED ABDOLMALEKI is a graduated alumnus of industrial management from Shahid Beheshti University, Iran, in 2015. He also holds a bachelor degree in industrial engineering from Qom University of Technology (QUT), Iran, in 2009. His research interests include automation and modeling under uncertainty through simulation studies. Moreover, he is currently focussing on data science practices through the Internet of Things (IoT), within integrated concepts like condition monitoring of equipment. His email address is saeedmaleki31@gmail.com.

XIAN LIU received the Ph.D degree in Electrical and Computer Engineering from the University of British Columbia, Canada, in 1996, and the M.Math degree in Optimization from the University of Waterloo, Canada, in 1992. From 1995 to 1999, he worked in NORTEL Networks, Canada, as a software researcher and developer. In 1999, He joined the Department of Electrical and Computer Engineering at the University of Alberta, Canada. In 2001, he joined the University of Arkansas at Little Rock, USA. He became a full professor in 2010. Currently, his main research interests include optimization theory and methods, applied to communication networks and electrical power systems. Dr. Liu and his research collaborators have had more than 200 papers published or officially accepted. He has been a senior member of IEEE since 2009. His email address is xxliu@ualr.edu.