Analysis of inventory strategies for blood components in a regional blood center using process simulation

Felipe Baesler, Matías Nemeth, Cristina Martínez, and Alfonso Bastías

BACKGROUND: The storage of blood components is an important concern in the blood supply chain. Because these are perishable products, the definition of good inventory policies is crucial to reduce shortages and spills.

STUDY DESIGN AND METHODS: To analyze and propose inventory policies in a regional blood center, a discrete event simulation model was created using simulation software (Arena 12.0, Rockwell Software). The model replicates the activities that are performed along the supply chain including donation arrivals, testing, production, inventory management, and dispatching.

RESULTS: Twelve different scenarios were analyzed, with each one representing different inventory policies composed of a combination of an optimal inventory, a reorder point, and a level of extra donations. The best scenario demonstrates that it is possible to decrease unsatisfied demand and wastage of red blood cell units by 2.5 and 3%, respectively, when compared to current practices.

CONCLUSIONS: This study shows that simulation is an alternative that can be used to model inventory components in blood centers. A responsible selection of inventory variables can improve the capability of the system to respond to the final patient requirements.

From the College of Engineering, Universidad del Desarrollo, Concepción Blood Centre, Concepción, Chile; and the College of Engineering, Universidad Diego Portales, Santiago, Chile.

Address reprint requests to: Felipe Baesler, College of Engineering, Universidad del Desarrollo, Av. Sanhueza 1750, PO Box 4030000, Concepción, Chile; e-mail: fbaesler@ingenieros.udd.cl.

Received for publication January 22, 2013; revision received April 18, 2013, and accepted April 29, 2013.

doi: 10.1111/trf.12287

TRANSFUSION 2014;54:323-330.

The supply chain for blood and its components, starting from the donor until the blood reaches the patient, can be considered a traditional logistic chain. Blood is first collected from donors, and then the blood units are transported to the production center where the blood is separated into its major components through a complex process. These components are stored and finally sent to hospitals. The synchronization of each of these subprocesses is of vital importance because blood components are perishable. Additionally, from a production standpoint, synchronization can reduce bottlenecks, which in turn reduces waiting times and in-process inventories and improves resource utilization. For this synchronization, it is essential to use process analysis tools and methods to reduce operating costs and improve the quality of service provided to the patient.

Figure 1 shows a diagram of the logistic supply chain for blood, indicating each of the stages that are associated with the process.

An acceptable inventory policy seeks to maximize demand satisfaction and minimize the amount of units that expire. However, the two goals are conflicting because a larger amount of stored product can better meet the changes in demand but would result in an increased storage time for the products, thus increasing losses due to shelf life. Another aspect that makes this a complex problem is the randomness that exists during the different stages of the process, in particular, the amount of daily blood donations, the demand for blood components by each hospital, and the intrinsic randomness of the production process that can generate variable production times due to the formation of bottlenecks, among other issues. Equally important is the uncertainty in the response time to requests for replenishment of the blood supply, the number of donors, and the blood type groups that can be obtained during collection. All of these factors ultimately result in variability in the amount of time required to replenish all of the components that fell below the critical level.

The majority of the approaches found in the literature address the problem using inventory theory, where the problem is analyzed as if it were isolated from the rest of

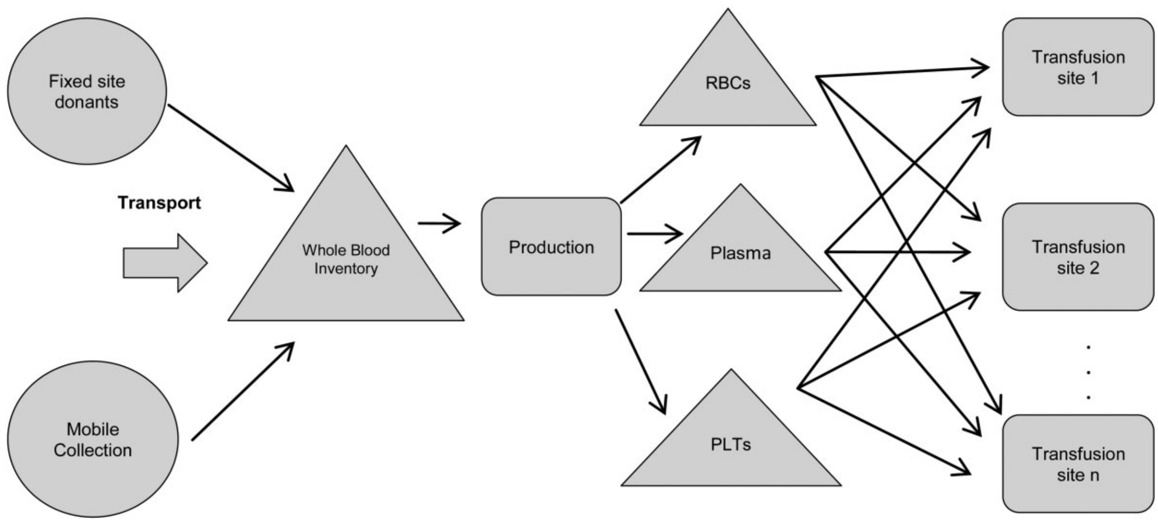

Fig. 1. Blood logistic supply chain.

the process, assuming that demand, replenishing time, and the number of shipped units are black boxes represented by random variables, underestimating the complexity of the process inside these black boxes, such as interrelated activities, machine failures, personnel and machine productivity, and product discharges. The general objective of the present work is to develop a method to determine the best inventory policy by analyzing the situation as an integrated process as shown in Fig. 1, minimizing the number of assumptions that simplifies the whole system. This analysis implements a simulation model that incorporates the randomness of each single activity that forms part of the main steps of the whole process and then analyzes alternatives to determine the optimal stock inventory and reorder point for each component and blood group. This approach improves the ability to satisfy demand levels while reducing loss due to expiration of the components and their associated inventory costs. The Concepción Blood Center in Chile is used as a case study, which considers the results of this study as paramount for its operating performance and will use them to guide research in this area. However, this methodologic approach is a mechanism that can be implemented by any blood center.

CURRENT PROGRESS

In the field related to the inventory management of blood products, the literature contains studies highlighting the contribution of Prastacos.[1] This work explains, in detail, the various decisions that must be taken into account while handling blood products and alternative approaches in the field of operations research that are designed to minimize the probability of failing to satisfy the demand and the perishability of the products. More recent studies have reported important approaches to reduce the cost and loss of blood products. In one example, a mathematical optimization method was implemented by treating the products differently according to age, which provided interesting results from a theoretical perspective.[2] In Haijema and colleagues[3] and Van Dijk and colleagues[4] the results were validated by their implementation and monitoring in blood centers. Both works suggest inventory models; the first describes a dynamic programming model, and the second study is described from the point of view of stochastic programming integrated to a simulation model. Both studies were applied in a regional blood center in Holland and implementation resulted in a less than 1% loss of platelets (PLTs) compared to an average of 20% before the implementation. Another study demonstrated similar results. This study was conducted by Transfusion Services at Stanford University Medical Center.[5] The results indicate that it is possible to reduce the loss of blood products by 50% if supply chain tools are implemented. For the specific case of using a simulation technique as a modeling tool for blood bank inventory it is possible to highlight a project that simulates a simplified inventory process for only PLTs, which leads to a reduction in losses due to perishability from 5% to 2%.[6,7] A more recent case used the simulation technique called system dynamics.[8] The authors simulated 11 scenarios that took place in a blood center in Finland and applied different inventory policies and practices. The results demonstrate that it is possible to achieve significant savings in costs that are primarily associated with the perishability of blood components. There are additional studies in which no modeling techniques were used; however, important results were obtained. Simple practices such as the use of products according to the order of their expiration date can significantly reduce losses and the management costs of blood products.[9] Similar conclusions can be found in references.[10-13]

MATERIALS AND METHODS

To address this problem, we propose using a discrete simulation to model the complete blood center process. The simulation starts from the initial donation stage and includes the production stage up to distribution to requisitioning hospitals. The simulation accurately represents each activity that occurs during the process using statistical representations. Once the model is constructed and validated, evaluation of the scenarios begins. Each scenario represents a different inventory policy, which is subsequently evaluated and compared with other policies to determine which alternative results in the best performance.

Inventory strategies

Inventory theory introduces different type of models that can be used to aid the decision makers. One classical model, widely used, that considers stochastic demand is called (s,Q).[14] When the level of inventory declines to some specified reorder point, s, an order is placed for a lot size, Q. The reorder point variable is widely used in inventory theory and it is a better strategy than just using a permanent level of inventory, because it allows the amount of time a product remains in inventory to be decreased. On the other hand if the reorder point is set at a very low value there is a risk of reducing the quality of service. In other words, the reorder point and the lot size are the variables that control the behavior of the inventory. In a traditional system containing a supplier, this system works by requesting Q units from the supplier to replenish the inventory. However, in our case, the suppliers are the donors, which is why a simple request for inventory replenishment is not easy. However, it is possible to make additional efforts to increase donation levels, thus gradually replenishing the inventory to the desired level. For this reason a different set of variables was defined to accommodate the classical inventory philosophy to the blood case.

- Optimal inventory: Number of units of the blood component that should ideally be kept in inventory.
- Reorder point: The inventory level that triggers the need to replenish inventory stock to an optimal inventory level.
- Extra donation effort: The percentage of additional donations that have to be obtained to refill the inventory.
- The combination of optimal inventory and extra donations replaces the Q variable of the classical (s,Q) model.

Figure 2 shows the schematic for this process. This diagram shows that when the inventory level of a specific blood type reaches the reorder point, a special campaign for extra donations begins. The idea is to keep this additional effort up until the optimal inventory is reached.

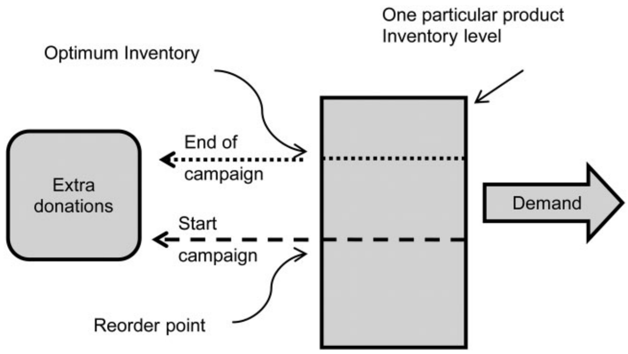

Fig. 2. Inventory replenishment schematic.

Objectives

The combination of these three variables, optimum inventory, reorder point, and extra donations, has an effect on the two indicators, number of expired units and unsatisfied demand. Both objectives are of great interest; however, they conflict with each other. For example, if high levels for optimal inventory and reorder point are defined, the unsatisfied demand will be low because high inventory levels will be in place to respond to changes in demand. However, the expiration indicator will increase because maintaining high inventory levels will cause each unit to remain in the inventory for a longer period and to therefore have a greater probability of expiring. What is the combination of variables that allows equilibrium between these two objectives? The answer is not simple because subjectivity is present in the solution that depends on the particular point of view of the decision maker. In this study the concept of Pareto Frontier is used to face this subjectivity in the decision making. This concept is explained in the Analysis section.

CASE STUDY

In recent years, the Ministry of Health of Chile created the National Blood Service, which aims to centralize the production of blood components in three regional centers. The Concepción Blood Center is one of them and concentrates its production in an important geographic area in Chile, and the numbers of donations reached 35,000 a year in 2011, approximately 20% of the national donations. Less than 10% correspond to altruistic donors, complicating the collection of specific group types. These donations are received at the Center and are processed into three primary components, red blood cells (RBCs), plasma, and PLTs. The simulation model was created to represent what actually happens at the blood center. The model consists of three main steps, blood donation, components production, and components distribution. Each one of these steps was disaggregated in different activities that represent the blood center operation. Each step is explained next.

Blood donation

All the donations that arrive at the Center come from one of five different sources, the cities of Concepción, Los Angeles, Chillán, and Talcahuano and from the mobile collection as shown in Table 1. Historical data were gathered from each one of these sources to estimate the amount of blood donation units collected per day, differentiating by altruistic or replenishment donors. Statistical distributions representing the number of units that arrive at the center on each day were fitted for each case.

For example, the first row in Table 1 indicates that the number of blood units sent to the blood center on 1 day from altruistic donors in Concepción can be represented by the expression 0.5 + GAMMA (4.22, 1.65). It is important to mention that the donations follow the Chilean population blood type percentages. So that despite the fact that the additional donation campaign was triggered by the low stock of a particular blood group, the collected blood will be from different groups, which could generate unwanted stock in some inventories, increasing the number of expired units.

Blood components production

Once the blood arrives at the center, the production blood components production process begins. The list of activities of the production process that are considered in the model as well as its time duration are presented in Table 2.

A data collection process, consisting of measuring the actual duration of each activity, was performed to fit statistical distributions that could represent the behavior and randomness of each activity. For example, the duration of the activity "RBCs labeling" was set to a gamma distribution with variables: alpha equal to 1.36, beta equal to 1.18, and a constant equal to 12 seconds. It is important to mention that the model additionally considers the interaction among the activities, personnel and machine availability, machine failures, discarded blood, discarding of products due to expiration, storage, and so forth.

Components distribution

The Concepción Blood Center ships blood components to 22 different locations including hospitals and clinics in the region. Each location has different demands for each component and blood group. For this reason, it was necessary to perform statistical analyses to adjust for the probability distributions that represent the daily demand for each site and each blood type. Some sites present a very low or null demand for some of the products. In those cases the demand was represented as a constant value or an empirical distribution. For the rest, since more data were available, a more exhaustive statistical analysis was performed, being possible to fit a total of 67 theoretical distributions for RBCs and 39 distributions for PLTs. As an example, Table 3 shows the distribution of demand for RBCs for one of the 22 requesting sites.

For example, the number of RBCs that are A– and that are shipped to a particular facility is normally distributed with a mean of 2.42 and a standard deviation of 0.4. This type of analysis was performed for the 22 sites that make requests to the Conception Blood Center, both for RBCs and for PLTs. Due to space constraints, the complete list of distributions is not shown.

The distributions used in the three steps of the model were validated by applying the Kolmogorov-Smirnov

TABLE 1. Daily donations per site

Donation site	Statistical distribution
Concepción	
Altruistic	0.5 + GAMM (4.22, 1.65)
Replenishment	NORM (29.4, 13.6)
Los Angeles	
Altruistic	0.5 + LOGN (1.68, 2.35)
Replenishment	NORM (26.7, 9.94)
Chillán	
Altruistic	0.5 + LOGN (11.7, 15.7)
Replenishment	0.5 + WEIB (16.3, 2.05)
Talcahuano	
Altruistic	0.5 + LOGN (0.957, 0.769)
Replenishment	NORM (16.3, 7.49)
Mobile collection	0.5 + GAMM (13.4, 2.32)

TABLE 2. Activities and time duration in the production step

Activity	Time (sec)
Blood bag weighing	TRIA (6.27, 7.14, 12)
Blood centrifugation preparation	19 + WEIB (11, 1.79)
Blood bag loading centrifuge	NORM (4.18, 0.812)
Blood centrifugation	600
Blood bag unloading centrifuge	NORM (4.17, 0.709)
Blood bag loading separation machine	21 + ERLA (2.65, 3)
Blood separation	173 + EXPO (66.3)
Blood bag unloading separation machine	NORM (26.3, 3.13)
RBCs weighing	6.36 + LOGN (2.15, 1.41)
Plasma weighing	6.52 + LOGN (1.34, 0.823)
Buffy coat centrifugation preparation	9 + 5.71 * BETA (1.26, 1.77)
Buffy coat bag loading centrifuge	NORM (3.82, 0.825)
Buffy coat centrifugation	600
Buffy coat bag unloading centrifuge	2.13 + 3.24 * BETA (2.93, 2.66)
Buffy coat bag loading separation machine	TRIA (15, 20.2, 26)
Buffy coat separation	43 + 8 * BETA (2.39, 1.59)
Buffy coat bag unloading separation machine	12 + GAMM (1.57, 2.81)
RBCs labeling	12 + GAMM (1.18, 1.36)
PLTs labeling	9.09 + 6.89 * BETA (2.43, 2.54)
Plasma labeling	18 + 5 * BETA (0.912, 0.93)
Microbiologic exams	359 + 363 * BETA (1.39, 2.46)

TABLE 3. Daily demand for RBCs at a particular hospital

	O	A	AB	B
+	2 + ERLA (6.2, 3)	1 + 37 * BETA (0.83, 2.4)	1 + 9 * BETA (0.55, 2.3)	1 + 28 * BETA (0.6, 4.4)
–	1 + EXPO (1.38)	NORM (2.42, 0.4)	1 + 1.2 * BETA (0.59, 0.6)	1 + EXPO (0.98)

goodness-of-fit test, with a confidence level of 0.95, obtaining p values greater than 0.1 for all cases, concluding that it was not possible to reject the hypothesis that the data sets can be represented by the selected theoretical distribution.

TABLE 4. Factor levels for the experimental design

Factor	Low level	High level
Optimum inventory	5 days of demand	7 days of demand
Reorder point	5 days of demand	7 days of demand
Extra donation	10%	20%

Simulation model

The simulation method executes the model for a continuous amount of time to simulate the behavior of the actual system. First, it is necessary to validate the model, which means verifying that the simulation results match the indicators produced by the actual process. In this project three indicators were chosen, total production of each component, the number of expired units, and the unsatisfied demand during a year. The validation was performed comparing the historical data with the simulated results for each indicator using a statistical test to compare their means. The results demonstrated that there is no significant evidence that the simulation model behaves differently than the actual process.

Once the simulation model is validated, it can be used for hypothetical experiments to assess the actual system behavior against changes to the model. More details about the simulation technique can be found in Banks and colleagues.[15] For example, it is possible to modify the number of centrifuges in the model, which are part of the production process, and analyze what effect it has on the amount of daily production. In this study, we are interested in modifying inventory management policies. However, if the reader is interested in the simulation results from the Concepción Blood Center, which are focused on evaluating and proposing solutions for the production stage process, these can be found in Baesler and coworkers.[16]

Simulation experiments

The experiments that were performed correspond to inventory policies that include different levels for the following three variables: the optimal inventory level, the reorder point, and the extra donations needed for replenishment. Fixing these variables at different levels should have an effect on the two main indicators, unsatisfied demand and expired units. Both objectives have a negative correlation, making it difficult to find a point at which both exhibit acceptable values. To better understand the relationship between the variables in the problem, a full factorial experimental design with two levels was created. Table 4 shows the levels for each factor.

The variable “days” corresponds to the number of units of a specific component and group type requested during a certain number of days. In the model this must be set as number of units. For example, mean historical daily demand for RBCs O+ is 50.6 units. This means that 5 days of demand corresponds to 253 units, and 7 days of demand corresponds to 354 units.

Table 5 presents the resulting design for RBCs consisting of a total of eight experiments with another four added as central points for a total of 12. Each was modeled on simulation software (Arena 12.0, Rockwell Software, McGraw-Hill Higher Education, Burr Ridge, IL) and ran for 1 year of operation to obtain results for the indicators corresponding to unsatisfied demand and expired units. To obtain statistically valid results, it was necessary to replicate each experiment 90 times. This value was determined by estimating the sample size needed to obtain confidence interval for both objectives with a width of at least $\pm$1% relative to its mean value. The simulation of the 90 replications of each of the 12 scenarios required approximately 30 minutes of computational execution time.

The first row of Table 5 represents the current variables that are used by the blood center. With these variables, a number of units equal to 7 days of predicted demand for RBCs is held in inventory, and when the inventory decreases below this level, replenishment donation increases by 10% until it reaches 7 days of demand. This framework generates 453 expired units and 1091 units of unsatisfied demand.

ANALYSIS OF RESULTS

The results of the 12 scenarios permitted an experimental design that enabled specific conclusions to be drawn, which are different for each of the targets under analysis. Figures 3 and 4 show the results for both targets. For unsatisfied demand, the following factors are noteworthy: the principal factor, extra donations, and the interaction between the factors corresponding to extra donations and the reorder point. In contrast, for the number of expired

TABLE 5. Simulation results

Experiment	Optimum inventory	Reorder point	Extra donation	Units outdated	Unsatisfied demand
7-7-10 (as is)	7	7	10%	453	1091
7-7-20	**7**	**7**	**20%**	**476**	**934**
6-6-10	6	6	10%	450	1110
6-6-20	**6**	**6**	**20%**	**461**	**964**
5-5-10	5	5	10%	452	1069
5-5-20	5	5	20%	465	1002
7-6-10	**7**	**6**	**10%**	**441**	**1058**
7-6-20	7	6	20%	480	1029
7-5-10	7	5	10%	449	1076
7-5-20	7	5	20%	489	1033
6-5-10	6	5	10%	444	1074
6-5-20	6	5	20%	497	1042

Rows in bold font represent nondominated solutions.

units, only the factor corresponding to extra donations was significant. These results were obtained from an analysis of variance in which significant effects have a p value of less than 0.05, indicating that they are significantly different from zero with a confidence level of 0.95.

Figure 3 shows that when considering the factor corresponding to extra donations at its high level (20%), the target corresponding to unsatisfied demand decreases, which is a favorable effect. The same applies to the interaction between the reorder point and extra donations. Instead, Figure 4 shows the opposite effect; when extra donations increase, the number of expired units increases, which is an adverse effect.

The interaction between extra donations and the reorder point is better explained in Figure 5. Here, it is clear that the reorder point by itself has no effect on the target; however, when both factors reach a high level, there is a reduction in the objective, even more significant than the effect obtained with the "extra donations" factor alone.

Clearly, a scenario that minimizes both objectives is best, that is, a low number of expired units and a low amount of unsatisfied demand. However, this is not possible because the objectives are conflicting, as seen in the above analysis. For this reason, it is necessary to analyze both objectives from a multiobjective perspective in which the decision maker defines his or her position when confronting the conflict between these two objectives. For example, Scenario 7-6-10 results in fewer expired units; however, it is not the best in terms of unsatisfied demand. In the same way, Scenario 7-7-20 results in the lowest amount of unsatisfied demand but not the lowest number of expired units. For this reason, the decision maker must decide, based on his or her own priorities, when to sacrifice one objective to improve the other. Thus, two different decision makers may prefer alternatives that better fit to

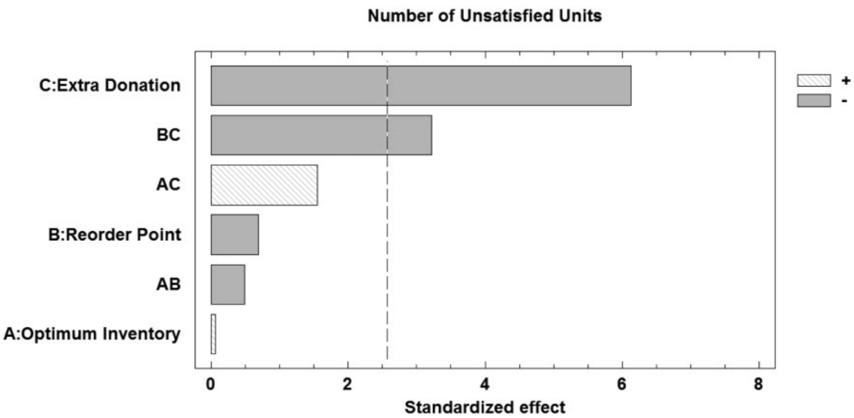

Fig. 3. Target variance analysis of unsatisfied units. AC, AB, and BC represent the interaction between factors.

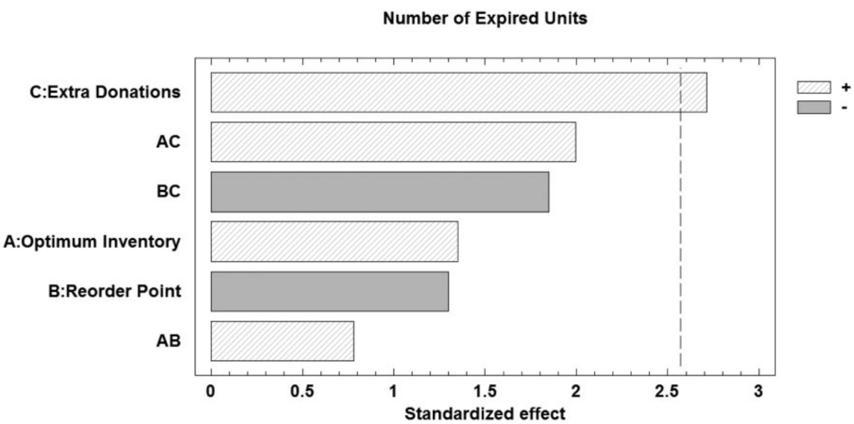

Fig. 4. Target variance analysis of expired units. AC, AB, and BC represent the interaction between factors.

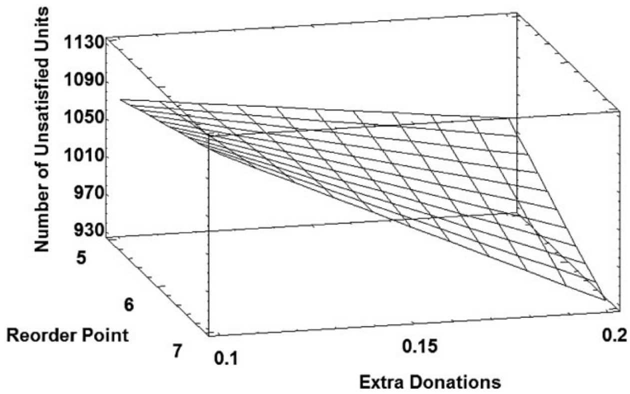

Fig. 5. Reorder point–extra donations dependence.

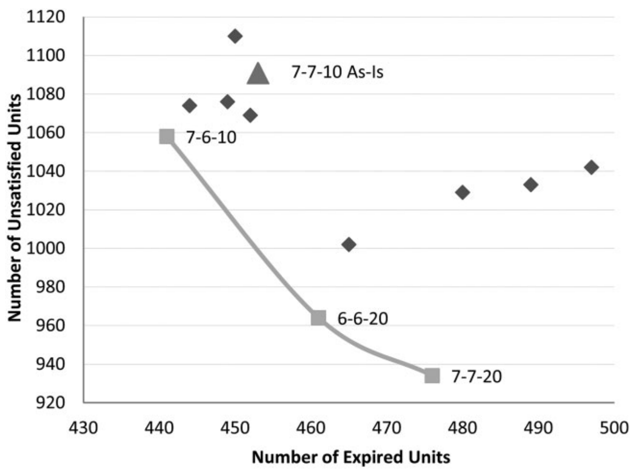

Fig. 6. Pareto frontier. (◆) Dominated; (—■—) Pareto frontier; (▲) as is.

their priorities. Despite this lack of objectivity in regard to the final decision, as shown in Table 5, it is possible to identify scenarios that are objectively better than others. These scenarios are represented in bold font and are considered nondominated solutions. This means that they are preferred over other alternatives because there is no other solution that is better than this one in both objectives. Therefore, this study focuses on finding "nondominated" solutions to present alternatives to the decision makers so that they can make an educated choice depending on their perspective. One way of representing this set of nondominated solutions is to use the Pareto frontier plot as shown in Figure 6.

In Figure 6, the solutions represented with squares are the nondominated alternatives and form part of the Pareto frontier. This type of analysis does not require assigning subjective weights to each objective before the analysis; the decision maker makes his or her choice from the Pareto frontier solutions.

Now, if we compare the actual situation with the solutions in the Pareto frontier, we can see that Scenarios 6-6-20 and 7-7-20 have better indicators of demand satisfaction. However, their actual implementation results in more expired units in the corresponding target. Moreover, the alternative 7-6-10 outperforms the actual situation for both objectives and exerts complete dominance over this inventory management strategy. For this reason, one recommendation of this study is the use of the 7-6-10 strategy as a viable solution for this problem. In other words, use 7 days of optimal inventory, a reorder point of six days, and extra donations of 10%. The results of this scenario indicate that it is possible to improve both the unsatisfied demand and the losses due to the expiration of RBCs in relation to the actual situation by 2.5 and 3%, respectively.

The decision regarding implementation of the proposed solution is not final; it is a recommendation and just one point of view of the problem. There is a significant degree of subjectivity in the selection of the best alternative, and each decision maker should apply his or her own criteria. Indeed, the results of this study conclusively indicate that apart from the particular point of view of the decision maker, the best inventory alternative must be selected from one of the three alternatives that are part of the Pareto frontier.

CONCLUSIONS

This article presents a method based on discrete simulation to model the complete blood supply chain that can be used for any blood center in the world. The general structure is the same; however, the model must be adapted to the reality of each center, considering particular variables such as demand, supply, and distribution of blood groups in each country, productive variables, and so forth. For this reason the results will differ from center to center. In this study the method was shown to be useful in evaluating different inventory policies; however, it could be used to perform other studies associated with the behavior of the blood supply chain. It is possible to study the production process to optimize costs, assess the process capacity when significant changes in demand occur, or analyze product flow and bottlenecks. In general the simulation model can be used for any purpose, allowing the studying of the behavior of the supply chain against any change that the decision maker would like to discuss.

The case study presented in this article is different from what happens in other countries where most donors are altruistic and the blood obtained would be mainly from the requested groups, simplifying the model building, besides reducing the randomness in the supply step of the chain. In these cases the uncertainty is still present, since the randomness in the production and demand steps of the supply chain has not been removed, so the decision making is still a complex issue. The model can be adapted to represent what actually happens in each society.

It should be clear that the construction of a model of this type is not a small-scale project. It is required to collect and analyze a large amount of information in addition to understand every aspect of the center operation. For this reason this method is used mainly for strategic decision making and not for decisions to be taken daily, requiring maintenance on a yearly basis or when a major change in the operation conditions occurs.

This study also used a multiobjective approach for the analysis of solutions, showing its utility to filter the non-dominated options, eliminating the need to define subjective weights by the decision maker before the analysis and letting him choose from the best alternatives based on his or her own needs.

CONFLICT OF INTEREST

The authors have no conflicts of interest.

REFERENCES

1. Prastacos G. Blood inventory management: an overview of theory and practice. Manag Sci 1984;30:777-800.
2. Goh C, Greenberg B, Matsuo H. Two-stage perishable inventory models. Manage Sci 1993;39:633-49.
3. Haijema R, Van der Wal J, Van Dijk N. Blood platelet production: optimisation by dynamic programming and simulation. Comput Oper Res 2007;34:760-79.
4. Van Dijk N, Haijema R, Vander Wal J, Sibinga C. Blood platelet production: a novel approach for practical optimization. Transfusion 2009;49:411-20.
5. Fontaine M, Chung Y, Rogers W, Sussmann HD, Quach P, Galel SA, Goodnough LT, Erhun F. Improving platelet supply chains through collaborations between blood centers and transfusion services. Transfusion 2009;49: 2040-7.
6. Sirelson V, Brodheim E. Computer-planning model for blood platelet production and distribution. Comp Methods Prog Biomed 1991;35:279-91.
7. Katz A, Carter C, Saxton P, Blutt J, Kakaiya RM. Simulation analysis of platelets production and inventory management. Vox Sang 1983;44:3-6.
8. Rytila J, Spens K. Using simulation to increase efficiency in blood supply chains. Manag Res News 2006;29:801-19.
9. Kaur R, Sinha P, Kaur G. Blood utilization and inventory management in a blood centre. Asian J Transfus Sci 2008;2: 35.
10. Custer B, Johnson E, Sullivan S, Hazlet TK, Ramsey SD, Murphy EL, Busch MP. Community blood supply model: development of a new model to assess the safety, sufficiency, and cost of the blood supply. Med Decis Making 2005;25:571-82.
11. Fontaine M, Chung Y, Rogers W, Sussmann H, Quach P, Galel S, Goodnough L, Erhun F. Improving platelet supply chains through collaborations between blood centers and transfusion services. Transfusion 2009;49:2040-7.
12. MacPherson J. Better blood recipient, inventory & supply chain management—session 5 questions and answers. Transfusion 2007;47(Suppl 2):201S.
13. Sussmann H, Fontaine M, Geary D, Quach P, Mebane W, Galel S, Erhun F. Maximizing platelet inventory from a 6 days per week draw schedule with 5-day products based on supply chain approach. Transfusion 2008;48(Suppl 2):63A.
14. Elsayed E, Boucher T. Analysis and control of production systems. 2nd ed. Englewood Cliffs (NJ): Prentice Hall; 1994.
15. Banks J, Carson J, Nelson B, Nicol D. Discrete-event system simulation. 5th ed. Englewood Cliffs (NJ): Prentice Hall; 2010.
16. Baesler F, Martinez C, Yaksic E, Herrera C. Proceso Logístico Productivo de un Centro de Sangre Regional: Modelamiento y Análisis. Rev Med Chil 2011;139:1150-6.