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# Designing A Mathematical Model For Solving The Blood Units Management Problem In The Case Of Hospital

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***Abstract:***

Blood is one of the most critical perishable substances in nature, closely related to humans' lives. The most important reasons for the importance of blood are their human origin and that they cannot be produced artificially. Thus, given the constant need that always exists for blood and blood products, there is a need for blood inventory management as a vital part of blood supply chain, and the impossibility of responding to the demand of this product has a high risk that may lead to the death of a human. On the other hand, the increase in the blood supply may lead to the loss of blood products and high costs. Hence, the purpose of this study is to present a mathematical programming model for determining the optimal policies of periodic review for managing blood supplies available to minimize the operational cost, shortage cost and waste cost of blood due to blood spoilage and transport, where the perishability and uncertainty of demand are considered. To show the potential benefits of using the proposed model and determining the optimal blood-inventory control policies, a case study was presented, considering actual data showing the daily demand for blood, which data analyzed with meta-heuristic algorithms.

***Keywords:*** *blood supply chain, inventory management, perishability, simulated annealing algorithm, Imperialist Competitive Algorithm (ICA)*

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# I. INTRODUCTION

Blood inventory management is one of the specific human problems (Dillon et al., 2017) and one of the main challenges of health systems (Gunpinar & Centeno., 2015). Despite the extensive advances in various medical fields, scientists have still not found a complete and suitable blood supply replacement for human blood (Augusto et al., 2015; Dillon et al., 2017) thus the only source for the replacement of a person's blood is the donation of blood by other people (Augusto et al., 2015). Two remarkable points here are that the demand for blood is completely random and the supply of the donated blood by individuals is irregular (Dillon et al., 2017). The rate of consumption of blood products in hospitals is a function of the number of daily accidents and the uncertain nature of it that usually leads to lack of match between the predictions of the exact daily demand of hospitals and their actual demand (Filho et al., 2013). Under such circumstances, the hospitals prefer to order more blood products to save storage to cope with the probable shortages (Fontaine et al., 2010). If the ordered blood products by hospitals are not consumed before they reach their shelf life, they expire and the expiration of each blood unit will incur a lot of cost (Ghandforoush et al., 2010).

One of the concepts of interest to researchers in recent years in healthcare systems is the supply chain management with the main challenge of balancing storage and waste of blood units. Given the perishable nature of this product, storing a large number of blood units may result in loss of this resource. On the other hand, facing deficiencies may lead to catastrophic outcomes. Human life may be lost if there is no available stock of blood in case required (Dillon et al., 2017).

Thus, the purpose of the blood supply chain is to provide adequate blood for hospitals. In the blood supply chain, re-filling blood in a blood bank is not entirely in control of decision makers because blood recollection and supplying the blood needed by the blood bank depend on the blood donors. This important feature has made the supply chain differentiated from other supply chains (Hosseinifard & Abbasi., 2016). The blood supply chain involves collecting, testing, processing and distribution of blood (and its related products) from the donors to customers, so that the blood can be available for emergency procedures, surgical procedures or routine medical treatments. Overall, blood supply chain is divided into four layers. The blood supply chain begins with collection, where blood is collected from donors. The blood is then stored as a single unit or mechanically processed to separate and store red blood cells from other lateral products such as plasma and platelets. When available for use, blood products are allocated to blood storages (in places such as blood banks and hospitals) to get ready for distribution and use (Dillon et al., 2017). Osouri et al. (2015) designed the main levels of blood supply chain, which is shown in Figure 1.

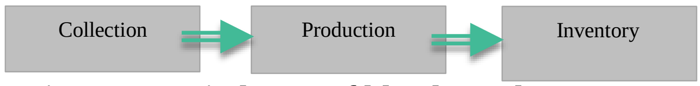


**Figure 1: Main layers of blood supply chain (Osorio et al., 2015)**

Therefore, what is significant is that an effective blood supply chain must be fully able to supply the demand, and minimize waste and costs. Several costs, such as labor costs, experiments, breakdown, division (dividing blood into its lateral products, which are widely available), storage, distribution and transportation to the supply chain are imposed. However, achieving a productive and economic operation for the supply chain needs a very complex challenge, as the uncertain nature of the demand is limited to a very limited useful life and most of the blood products are combined imposing very tight constraints on the problem, which increases the risk of shortage and expiration. Considering the connection and the complexity of the system, the need to develop a reliable methodology to support decision making at all levels of the supply chain is clear. This issue can be placed on the third level of Figure 1, i.e. in an inventory, and involves making optimal decisions to minimize operational costs, lack of blood, blood expiry, and the uncertain nature of blood (Dillon et al., 2017).

According to the points stated, the study tries to present a framework for determining inventory control policies (R, S) for blood supply chain, which by using a single-objective planning model, can consider the perishable nature of the inventory used and the complex random nature of the product demand to determine optimal inventory control policies.

The developments in this paper are two. In the first case, a mathematical programming model is proposed to determine the optimal review period (R, S) policies considering the demand and product perishability and to optimize the cost of transport (at operational costs). So far, none of the previous studies has addressed this issue with this tool, which is much more general compared to the other methodologies in the literature. Second, the article discusses how the proposed framework can be used for a real application that represents a case study rather than an important insight into how the activity of inventory management of blood units can use this framework.

Other sections of the paper are as follows: Section 2 is the literature review and the research background. Section 3 provides some explanations of the case study and the modeling assumptions. Section 4 shows a case study where the model is used along its results. Finally, Section 5 presents conclusions and suggestions for future studies.

## II. THEORETICAL BASICS AND BACKGROUND

Since 60 years ago, blood supply chain has been of interest to the researchers and some methodologies have been used to examine those (Dillon et al., 2017). Wayne Zill first conducted research on the supply chain of perishable materials in 1960 (Zyl & Gideon., 1963). So far, many studies have been conducted on the distribution and maintaining blood products. The studies in this regard, besides their use regarding blood, play a great role in the development of effective methods for managing the inventory of other perishable products (Nahmias., 1982). Pirsecala (2005), Blin & Forcé (2012) and Oserio et al. (2015) are among the researchers who have helped identify key issues in this regard by studying blood chain. Pirsecala (2005) reviewed some of the tactical and operational aspects of collection, production, inventory control, delivery of blood products and delivery decisions (Pirsecala, 2005). Blaine et al. (2012) proposed a comprehensive review of the blood supply and its management. This review paper has mentioned a variety of blood products, planning levels, and solution methods (Beliën & Forcé., 2012). Oseriou et al. (2015) paid little attention to the relationship between different stages of the supply chain and studied many single-level papers. In this paper, optimization is used less in blood inventory management issues.

By reviewing the literature, a variety of solutions can be presented for blood supply. Thus, one can state that a large number of papers are in the simulation branch (this branch includes both discrete events and Monte Carlo simulations) and statistical analysis (linear regression, survival analysis, logical regression, ANOVA, and so on). Other papers are in the field of operations research such as integer programming, linear programming, and dynamic random planning, and some papers are in queue scheduling the majority of which use Markov chain. In addition, the field of performance evaluation is used as well.

Haijema et al. (2007) designed a model using the Markov dynamic planning and simulation method for the Dutch Blood Bank. They examined optimizing the production and maintenance of platelets in blood banks, considering the costs of different parts and the criteria for freshness of blood in their problem. Kopach et al. (2008) creates a red blood cell (RBC) storage system with two demand rates. They use a queuing model for emergency and non-emergency techniques and use simulation to compare the results of the model with current control techniques, which uses data from Canadian blood services. Fenonten et al. (2010) used a simulation model to analyze the effect of shortening of the useful life of RBCs in the supply Chain. Blake et al. (2013), Devan and Liao (2014), Abbasi et al. (2016), Rhythea and Spense (2006), and Caste Lucky and Bryce Ford (2007) are among the scholars with studies regarding simulation in blood supply chain (Blake et al., 2013; Duan et al.,2014).

Hosseini Fard and Abbasi (2016) examined the significance of having a centralized inventory control system at the health care center level. In this paper, inventory control policy is considered as (s, s-1), and the results show that having a centralized supply system in the blood supply chain has led to an increase in sustainability and a reduction in the waste and loss in hospitals.

Queuing theory and Markov's chain have widely been used in the early approaches to researching the blood supply chain. The paper by Pelges et al. (1970) is the theoretical application of Markov chain modeling. They evaluated the different policies of blood consumption in hospitals and concluded that the use of FIFO consumption policy with the prioritization of consumption of products with a lower life span would reduce the amount of blood loss in hospitals and improve the hospitals function.

Statistical analysis approach has also been used in blood supply problems. Frank Footer et al. (1974) used exponential smoothing techniques to predict the levels of blood transfusion in hospitals. Pink et al. (1994) and Hedel et al. (2009) examined the factors that led to the expiration. Bossens et al. (2005) used a logical regression model to predict the arrival time of blood donors.

Jacobs et al. (1996) presented two integer-programming models to examine the problem of locating equipment for the American Red Cross, and provided tips on current planning activities for blood collection and distribution. Hammmer et al. (2009) used integer programming to deliver blood products to Austrian hospitals in cost-effective ways. They also developed their previous study for the condition of accidental use of blood products in 2010, and used external sampling to turn the problem into a definite optimization problem (19) (20). Ghandforush et al. (2010) developed a nonlinear integer-programming model to minimize platelet production for the regional blood center.

Bi-level randomized programming has been used to model capital supply systems in areas other than supply chain management. Van Dekik et al. (2009) used a combination of dynamic randomization and simulation programming to provide a new method for solving the problem of storage of blood platelets. Fattahi et al. (2015) proposed bi-level randomized programming for the multi-period refilling problem and used the policy of dependence on the supply chain to examine the supply chain with a retailer and a producer. Konha et al. (2016) also proposed bi-level randomized programming for developing refilling control system. They used periodic review system for the control system for the single-layer logistic network and then used the average sample-amplification method to obtain optimal recreational solutions. Esfen et al. (2017) suggested a randomized multi-period and integer model to collect, produce, store and distribute platelets sent

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from blood collection centers to demand points.

Among the papers using bi-level randomized programming for modeling inventory supply systems in blood supply-chain management, one can cite Fahimnia et al. (2017) and Dylon et al. (2017). Dylon et al. (2017). Fahimnia et al. (2017) examined a randomized bi-purpose network design model whose purpose was to minimize sending time. They considered a hybrid solution including the Epsilon and Lagrange limitations.

Dylon et al. (2017) proposed a two-stage randomized-programming model to determine the optimal period review guidelines for managing RBCs inventory, focusing on minimizing operational costs, as well as the cost of shortage of blood and the cost of the waste resulting from spoiled blood. They also considered perishability and uncertainty in demand.

Another method to solve problems is using heuristic and meta-heuristic methods. Hamelmayer et al. (2010) have used heuristic methods for integer programming problems (Hemmelmayr et al., 2009; 2010). Additionally, Dawn and Liavo (2014) have proposed a new simulation framework for supply chain management compatible with ABO blood type. Their purpose was to minimize the rate of expiry considering a certain tolerable level of shortage. He used the meta-heuristic method of annealing simulation algorithm to find near optimal policies with acceptable computational time.

According to the literature and to the most relevant studies described, it became clear that the problem of inventory management in blood supply chain is completely random and imprecise and cannot be addressed by conventional solving methods such as linear programming, so it is necessary the researcher should use probabilistic, random or meta-heuristic methods.

Gonpire and Santo (2015), Abdulvahab (2014), and Dylon et al. (2017) in the field of blood and methods used are the most relevant and closest studies to this study. As stated in the literature review, Dylon et al. (2017) presented the bi-level programming model, and Abdulvahab (2014) proposed the dynamic, approximate, randomized, and definitive preparation model for eight types of blood, but this paper examines platelets and does not consider RBCs. Fattahi et al. (2015) and Konha et al. (2016) developed the randomized bi-level programming model slightly similar to the methodology of this study, but they did not use blood supply chain. Moreover, Hamelmaye et al. (2010) have used heuristic methods in the integer programming problems but have focused on the delivery of blood products that is not within the scope of this study.

According to the studies by Gonpire and Santo (2015), Abdulvahab (2014), and Dylon et al. (2017), where probabilistic methods were used, their suggestions that were based on using other methods to solve them, and considering the literature, this chain has not yet been solved using a meta-heuristic approach. Thus, the study tries to solve this problem by using meta-heuristic algorithms. However, in sum, the main features of the meta-heuristic methods and the reasons for using this method can be summarized as follows.

- Unlike heuristic methods, the purpose of these methods is to find effective and efficient response space instead of finding optimal or near optimal solutions
- Meta-heuristic methods are policies and strategies guiding the search process
- Meta-heuristic methods are approximate and often non-deterministic (random)
- These methods may prevent using the mechanisms of trapping the search process in topical optimizations
- Unlike heuristic methods, meta-heuristic algorithms are not problem-dependent. In other words,

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they can be used to solve a wide range of optimization problems
- More advanced meta-heuristic methods use the experience and information obtained during the search process as memory to direct search to more promising areas of the response space

In short, one can state that meta-heuristic algorithms are the advanced and general strategies for searching, proposing steps and criteria very effective in escaping local optimal traps. An important factor in these methods is the dynamic balance between diversification and power generation strategies. Diversification refers to widespread searches in the response space, and strengthening means exploiting the experiences gained in the search process and focusing on the vast areas of the response space. According to the described characteristics of these methods, one can state that the validity of multi-purpose models using meta-heuristic methods is much more than random and probabilistic methods.

## III. MATHEMATICAL MODELING

In this section, the mathematical model of the problem is presented. For better designing of the mathematical model, after expressing the model hypotheses, the symbols, parameters and variables are defined and then the objective function and its constraints are presented. Many assumptions, sets, variables, and parameters are used in the mathematical model, with their definitions presented in Table 1:

**Table 1: Assumptions, sets, parameters**

| Sets | |
|---|---|
| Periods | $j$ |
| Review intervals $\gamma \in \Gamma$ | Γ |
| Blood types i,i′ ∈ i | i |
| **Parameters** | |
| The cost of shortage of each unit of blood | Sρ |
| Ordering cost | Oρ |
| Is 1 if the demand for the β blood group can alternatively be met with the blood group β'; otherwise, it is 0. | $C_{\beta',\beta} = 1$ |
| The i blood unit demanded in period j | $D_{i,j}$ |
| The maximum amount of the expired blood | $E_{\varepsilon}$ |
| Minimum service level (percentage of confidence) | F |
| The cost of maintaining each blood unit | Hρ |
| The cost of expiration of each blood unit | Kρ |
| Time to prepare | L |
| RBC useful life | M |
| Maximum amount of blood unit i | $\bar{S}_i$ |
| Transportation cost | TP |
| **Decision variables** | |
| The amount of blood in the blood group i received during period χ and should be used in scenario S. | $C_{x,i,j}$ |
| Expired blood from group i received in period i. | $e_{i,j}$ |
| Shortage | $f_{i,j}$ |
| Available inventory in period ρ in scenario β of β-type blood | $I_{i,j}$ |
| The status of the whole inventory (available and on the way inventory) at the end of period j in scenario S of i blood type | $it_{i,j}$ |
| The number of blood units of type i' used to satisfy the demand for type i blood type in period j | $p_{j,i',i}$ |
| The amount of order of i blood type in the period j | $q_{i,j}$ |
| The contingency inventory of i blood type | $\bar{S}_i$ |
| The zero and one variables indicate whether the order of the unit of blood has been issued in period j | $v_j$ |

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The term 1 contains the objective function of the problem that must be minimized. The objective function consists of the cost of ordering and the costs of maintenance, transportation, shortage and expiry. In this paper, the cost of each unit of shortage, ordering, maintaining each goods unit, and the expiration date of each unit of goods, the transport cost is shown with ρ in the model, so that the model is as general as possible. Limitation 2 states that only a period can be selected from the set of possible intervals for Γ review. The limitation 3 links the appropriate ordering pattern to $v_i$, which determines whether an order should be issued in period j or not.
Limitation 4 is used to calculate the daily order quantity consumed determined by the difference between the amount of demand that exists and the total current inventory, and sets a limit on the minimum level of service, with the minimum proportion of total demand to be satisfied shown with (F). The limitations from 4 to 8 are the limitations related to the second-stage decisions, so S ∈ Ξ so is represented for each scenario. Using limitation 4, management policy (R, S) is imposed on the problem. Limitation 5 specifies that the value available to complete the order in a certain period.
However, limitation 6 is obtained from the total amount of demand in a given period from the sum of the amount of the blood group i (received in period x and used in scenario S), the amount of blood is not provided and the available inventory.
Limitation 7 specifies that the available inventory must always be greater than or equal to the target inventory level.
Limitation 8 is obtained from available inventory and daily order (or inventory on the way).
Limitation 9 determines that the difference in daily order quantity from the total inventory must be smaller or equal to the target inventory level. Limitation 10 stated that the demand for the blood type i in the given period should be less than or equal to the total amount of the stock not to face shortage. Limitation 11 states that expired blood should be less than the maximum blood donation date in the order of type I blood order in period j. Limitation 13 states that there should be a unit of blood from each blood type.

$$min\, z = \sum_{j=1}^{3} \sum_{i=1}^{8} [O_{ij}(v_{ij} + T_{ij}) + H_i I_{ij} + K_{ij} e_{ij} + s_{ij} f_{ij}] \qquad (1)$$

$s.t.:$

$$\sum_{\gamma} u_{\gamma} = 1$$

$$0 \le s_i \le \overline{S}_i, \forall i$$
$$q_{ij} = F(S_i - it_{i,j})$$
$$\sum_{j} C_{x,i,j} = \sum_{i'} C_{i',i} C_{i',i,j}$$
$$o_{i,j} = D_{X,i,j} - f_{i,j} + I_{i,j}$$
$$I_{ij} \ge \overline{S}_i$$
$$it_{i,j} = I_{i,j} + q_{i,j}$$
$$q_{i,j} - it_{i,j-1} \le \overline{S}_i$$
$$q_{i,j} \le it_{i,j-1}$$
$$e_{i,j} \le E_{\varepsilon} q_{i,j-L}$$
$$V_{\rho} \epsilon \{0,1\}, \forall_{\rho}$$
$$\sum_{i=1}^{8} v_j = 8$$
$$\sum_{i=1}^{8} S_{i,j} \le \overline{S}_i$$

# IV. METHODOLOGY

In terms of data collection method, the study was descriptive-analytic. Since the model of blood-inventory management units is complicated in accordance with what was described in the previous sections, due to memory constraints and increasing solving time, the response cannot be reached using the exact solution method. Thus, simulated annealing algorithms and colonial competition were used, for analyzing data in this study, described below.

### 4.1. Simulated annealing algorithm

Simulated annealing is a well-known meta-heuristic search method used in numerous

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continuous and discrete optimization problems. The key characteristic of the simulated annealing is that it provides a similar search for elevations and height-level cues for local searches, to achieve the optimal result. The annealing simulation algorithm has been used extensively as a meta-heuristic algorithm as well as an approach to improve the performance of other meta-heuristic algorithms, and this explains the importance of learning it.

In the simulated annealing algorithm, selecting the appropriate initial temperature is critical. For the given value of $\Delta f$, if $T$ is too large $(T \to \infty)$, the probability of accepting the new answer tends towards one $(p \to 1)$. This means that almost all the new changes (new answers) will be accepted. If $T$ is very small $(T \to 0)$, any $\Delta f > 0$ (inappropriate answers) will rarely be accepted, as the likelihood of accepting the new answer tends to zero $(p \to 0)$. Thus, the variety and of the answers is limited, but any answer that improves the objective function $(\Delta f < 0)$, it will always be accepted. In fact, the special mode $T \to 0$ is the same as the gradient-based search method as it only accepts the best answers and the system essentially climbs or descends around a hill (local minimum). Therefore, if $T$ is too large, the energy system is high and the optimal answer to the minimum will not be easily achieved. If $T$ is very low, the system will be trapped at a local minimum, which will not necessarily be minimal, and it will not have enough energy to jump from the local minimum to achieve the minimum requirements, including minimum global standards.

According to the above, an appropriate initial temperature that can search for almost the entire solvent space at the start of the system, and then a suitable cooling rate that reduces the temperature of the system at a good rate to achieve a suitable convergence in proportion to the increasing number of repetitions is essential. The lower the temperature of the system, the lowering of the motor energy decreases the range of motion, and the system converges to the region with the lowest energy level.

Figure 2 presents the pseudo-code of simulated annealing algorithm.

1. Defining the objective function and setting parameters of the algorithm
Defining the initial temperature $T_0$ and the initial value $x^{(0)}$
Defining the final temperature and the number of iterations N
Defining the temperature drop rate *a*.
2. As long as $(n < N, T > T_f)$, neighborhood production and creating new answers $x_{n+1} = x_n + rand$, and calculating $\Delta f = f_{n+1}(x_{n+1}) - f_n(x_n)$
3. If the new answer is better, it is accepted; otherwise, a random number r is generated, if $p = \exp\left(\frac{-\Delta f}{T}\right) > r$, the new answer is accepted.
The end of the loop
Updating $x^*, f^*$
$n = n + 1$
The end of the loop

**Figure 2: Pseudo-annealing simulation algorithm**

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### 4.2. Imperialist Competitive Algorithm (ICA)

The various stages of ICA have been developed, as follows.

First, we produce $N_{country}$ primary country. This is done like the production of initial solutions in the simulated annealing algorithm except that, here we use four methods to produce $\bar{x}_{jklp}$. These four methods are similar to the approaches presented in the production of $x_{ijlp}$ and are as follows:

1. Using equivalent cost matrix $CF_{jkl}$
2. Use variable cost matrices $C_{jklp}$
3. Use fixed cost matrix $F_{jkl}$
4. Randomly

We produce the first three populations from $\bar{x}_{jklp}$ with the first three approaches and for other countries ($N_{country} - 3$), we produce the population using the fourth approach. Similarly, $x_{ijlp}$ values are obtained according to their $\bar{x}_{jklp}$ respective values.

We select $N_{imp}$ number of the best members of this population (the countries with the least cost function) as the imperialists. The remnants of the nations $N_{col}$ are composed of colonies, each of which belongs to an empire. To divide the initial colonies between the imperialists, we give some colonies to each imperialist that is proportional to its strength. To do this, having the expense of all imperialists, we consider the normalized cost as the Equation (1):

$$C_n = \max_i\{c_i\} - c_n \quad (1)$$

Here, $c_n$ is the cost of the n-th imperialist, $\max_i\{c_i\}$ is the maximum cost among the imperialist and $C_n$ is the normalized cost of this imperialist.

Any imperialist with a higher cost (a weaker imperialist) will have a lower normalized cost. With the normalized cost at hand, the normalized normal power of each imperialist is calculated as Equation (2) and based on that colonial countries are divided between imperialists.

$$p_n = \left| \frac{C_n}{\sum_{i=1}^{N_{imp}} C_i} \right| \quad (2)$$

On the other hand, the normalized power of an imperialist is the colonial proportions that the imperialist is managed. Thus, the number of primary colonies of an imperialist will be equal to:

$$N.C_n = round\{p_n.(N_{col})\} \quad (3)$$

Here, $N.C_n$ is the number of primary colonies of an empire and $N_{col}$ is the number of colony counties in the population of the original countries. Considering $N.C_n$ for each empire, we select this number of colonial countries randomly and give to the n-th imperialist. With the initial state of all empires at hand, ICA begins. The evolution process is in a loop that continues until a stop condition is fulfilled.

The power of an empire equals the power of a colonial country, plus a percentage of the power of its colonies. Thus, for the whole cost of an empire, we have:

$$T.C_n = Cost(imperialist_n) + \xi \; mean[Cost(colonies \; of \; imperialist_n)] \quad (4)$$

Here, $T.C_n$ is the cost of the whole n-th empire and $\xi$ is a positive number less than one and close to zero.

In the algorithm presented in this study, the movement of colonies to the empire has been accomplished by a two-point intersection. For each empire and colony, we generate a random number. If this random number is less than 0.5, we will perform the intersection, so that we produce two columns of the colony randomly and the values of these two columns are equal

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to the values of the corresponding columns of the corresponding empire.

The revolutionary operator in the proposed ICA is similar to that of mutation in simulated annealing operators. For each colony for each empire, if the random number generated is less than the revolution rate, then the revolution occurs.

During the colonial movement towards the colonial country, some of these colonies may find themselves in a better position than the imperialist (they reach points in the cost function that produce less cost than the cost function in the imperialist position). In this case, the colonial country and the colonial country have changed their place together and the algorithm continues with the colonial country in a new position. First, the best colony of each empire is specified, and by comparing the imperial cost function and the best colony, if the cost of the best colony is less than that of the empire, the two are replaced and the best colony becomes the empire.

The algorithm continues until a convergence condition is met or until the total number of iterations is completed. After a while, all the empires topple, we will have only one empire, and the rest of the nations will be under the control of this single empire.

## V. DATA ANALYSIS

As stated, the proposed math model is specific to blood management, as described in the previous section. In the proposed model, the goal is to estimate the costs of inventory management in a case study. The blood values entering the system are set based on the ratios shown in the following table. Thus, if you enter 100 units of blood into the system, about 33 units of it have O blood type and a positive type antigen. In this paper, all the blood entering the system is divided based on blood groups and type D antigen.

**Table 2: Demand ratio of each blood group to the total demand in one day**

| Blood group | O+ | O- | A+ | A- | B+ | B- | AB+ | AB- |
|---|---|---|---|---|---|---|---|---|
| Demand percentage | 33.5 | 4 | 27 | 3 | 22 | 2.5 | 7 | 1 |

In addition, in this paper, hospital demands were randomly selected in the interval (80, 15) for seven days a week, which are shown in Table 3.

**Table 3. Demand ratio of each blood group to the total demand in one day**

| | Period 1 | Period 2 | Period 3 | Period 4 | Period 5 | Period 6 | Period 7 |
|---|---|---|---|---|---|---|---|
| Loghman Hospital | 50 | 50 | 70 | 50 | 77 | 65 | 41 |

In addition, the capacity of blood banks is 80, the contingency inventory for the blood bank is 20 and for the hospital 25 and the consumption in the hospital for each period is a random number in the interval (5, 25). The initial values at the blood bank at the beginning of the course are 20 units, for the hospital, 70 units are considered, and all the deficiencies and other variables are taken positive values.

**Setting the parameters of the algorithms used**

Various factors affect an algorithm reaching acceptable and desirable responses. One of the most effective factors is to set parameters of the algorithm. Taguchi method is used to estimate the optimal parameters affecting a model and is based on mathematical calculations and experimental design. In this approach, the

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Taguchi experimental design method is used to evaluate the different levels of the parameters. In this method, first, the parameters affecting the algorithm are identified and investigated based on input parameters (usually the value of the objective function). This study, based on orthogonal arrays, determines the combinations of different levels of the parameters and solves the problem in the appropriate size, and according to the optimal solutions, it is recommended to adjust the parameters. For more efficiency, each problem is executed five times and average values are considered.

The parameters levels for the simulated annealing algorithm for small and large dimensions are shown in Table 4, respectively.

**Table 4: The parameters levels for the simulated annealing algorithm for small and large dimensions**

| Parameters | Level 1 | Level 2 | Level 3 |
|---|---|---|---|
| *Mutation rate* | 0.1 | 0.3 | 0.5 |
| *Max sub-iteration* | 10 | 15 | 20 |
| $T_0$ | 400 | 500 | 600 |
| $\alpha$ | 0.8 | 0.83 | 0.85 |

The levels of ICA parameters are given in Table 5 for set up.

**Table 5: Levels of ICA parameters in small dimensions**

| Parameters | Level 1 | Level 2 | Level 3 |
|---|---|---|---|
| *Pop size* | 100 | 150 | 200 |
| *Imp number* | 10 | 15 | 20 |
| *Revolution rate* | 0.1 | 0.3 | 0.5 |
| *Deflection rate* | 0.1 | 0.3 | 0.5 |

Figure 3 shows Taguchi signal-to-noise diagram of the simulated annealing algorithm. According to this graph, for the neighborhood productions 0.1, for the maximum number of sub-iterations 20, for the initial temperature 400 and for a 0.85 are selected.

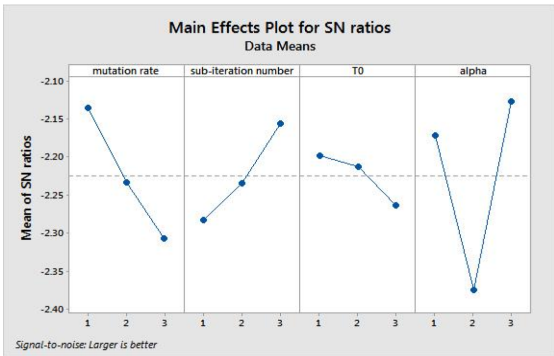


**Figure 3: Signal-to-noise diagram in the Taguchi method for the SA algorithm**

Figure 4 shows the Taguchi signal-to-noise diagram of ICA. According to this chart, for a population of 200, the number of empires is 20, revolution rate of 0.1, and deflection value is 0.5.

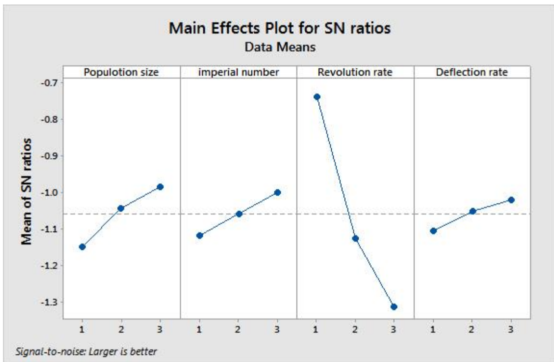


**Figure 4: Signal-to-noise diagram in the Taguchi method for ICA**

**Table 6: The values selected for the parameters of simulated annealing algorithm and ICA**

| Algorithm | Parameter | Value | Algorithm | Parameter | Value |
|---|---|---|---|---|---|
| SA | *Mutation rate* | 0.1 | ICA | *Population size* | 200 |
| | *Max sub-iteration* | 20 | | *Imperial number* | 20 |
| | $T_0$ | 400 | | *Revolution rate* | 0.1 |

| | | | |
|---|---|---|---|
| $\alpha$ | 0.85 | *Deflection rate* | 0.5 |

In this section, the efficiency of the annealing algorithm is simulated and the ICA compared to the problem solution is compared with the exact method.

The percentage of the error of the best response in each problem is calculated from the following equation, where $f_{Best}$ is the best value of the objective function of the algorithm in 5 runs and $f_{GAMS}$ is the value of the objective function obtained from the solution with GAMS software.

$$RPD = \frac{f_{\text{Algoritm}} - f_{Best}}{f_{Best}} \times 100 \qquad (6)$$

(5)

$$BSE = \frac{f_{Best} - f_{GAMS}}{f_{GAMS}} \times 100$$

The average percentage deflection of each run of the algorithm in each problem is calculated from Equation 6. In this equation, $f_{\text{Algorithm}}$ is the value of the objective function of the algorithm at each run, and $f_{Best}$ is the best value of the objective function in 5 runs, and the average RPD for 5 runs shows the average error percentage of the algorithm in each problem.

**Table 7: Results of simulated annealing algorithm and comparison of results with GAMS solution**

| Scenario | Problem specifications | | | | Solution method | | | | RPD objective function | BSE objective function |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Exact | | SA | | | |
| | Available inventory of ABO | Contingency inventory of ABO | Service level | Average consumption in each period | The value of objective function | Solution time (seconds) | The best objective function | Average solution time | | |
| **1** | 3 | 1 | 90 | 5 | 827 | 0.27 | 827 | 0.12 | 0 | 0 |
| **2** | 4 | 1 | 90 | 7 | 1055 | 0.32 | 1055 | 0.11 | 0 | 0 |
| **3** | 5 | 1 | 90 | 9 | 911 | 0.31 | 911 | 0.23 | 0 | 0 |
| **4** | 6 | 1 | 90 | 11 | 3846 | 0.5 | 3900 | 0.32 | 0.02 | 0.01 |
| **5** | 7 | 2 | 90 | 13 | 3602 | 0.3 | 3602 | 0.13 | 0 | 0 |
| **6** | 8 | 2 | 90 | 15 | 8104 | 3 | 8743 | 1.22 | 0.08 | 0.08 |
| **7** | 9 | 3 | 95 | 17 | 12300 | 5 | 13169 | 4 | 0.003 | 0.07 |
| **8** | 10 | 3 | 95 | 19 | 2270 | 0.4 | 2270 | 0.07 | 0 | 0 |
| **9** | 11 | 4 | 95 | 21 | 2717 | 0.3 | 2717 | 0.09 | 0 | 0 |
| **10** | 12 | 4 | 95 | 23 | 5680 | 4 | 5799 | 1 | 0.002 | 0.02 |
| **11** | 13 | 5 | 95 | 25 | 6144 | 3 | 6665 | 2 | 0 | 0.08 |
| **12** | 14 | 7 | 95 | 25 | 10522 | 6.5 | 11270 | 10 | 0 | 0.07 |
| **Total average** | | | | | 4831 | 6.9 | 5077 | 1.6 | 4831 | 6.9 |

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**Table 8: The results of running ICA and comparing the results with GAMS solution**

| Scenario | Problem specifications | | | | Solution method | | | | RPD objective function | BSE objective function |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Exact | | ICA | | | |
| | Available inventory of ABO | Contingency inventory of ABO | Service level | Average consumption in each period | The value of objective function | Solution time (seconds) | The best objective function | Average solution time | | |
| **1** | 3 | 1 | 90 | 5 | 827 | 0.27 | 827 | 0.12 | 0 | 0 |
| **2** | 4 | 1 | 90 | 7 | 1055 | 0.32 | 1055 | 0.11 | 0 | 0 |
| **3** | 5 | 1 | 90 | 9 | 911 | 0.31 | 911 | 0.23 | 0 | 0 |
| **4** | 6 | 1 | 90 | 11 | 3846 | 0.5 | 3846 | 0.32 | 0 | 0 |
| **5** | 7 | 2 | 90 | 13 | 3602 | 0.3 | 3602 | 0.13 | 0 | 0 |
| **6** | 8 | 2 | 90 | 15 | 8104 | 3 | 8153 | 1.22 | 0 | 0.006 |
| **7** | 9 | 3 | 95 | 17 | 12300 | 5 | 12368 | 4 | 0.005 | ~ 0 |
| **8** | 10 | 3 | 95 | 19 | 2270 | 0.4 | 2270 | 0.07 | 0 | 0 |
| **9** | 11 | 4 | 95 | 21 | 2717 | 0.3 | 2717 | 0.09 | 0 | 0 |
| **10** | 12 | 4 | 95 | 23 | 5680 | 4 | 5713 | 1 | 0.006 | 0.006 |
| **11** | 13 | 5 | 95 | 25 | 6144 | 3 | 6144 | 2 | 0 | 0 |
| **12** | 14 | 7 | 95 | 25 | 10522 | 6.5 | 10900 | 10 | 0.003 | 0.04 |
| **Total average** | | | | | 4831 | 6.9 | 4867 | 2.67 | 4831 | 6.9 |

Based on the results of Table 7 and 8, Figure 5 shows the comparison of objective functions in the exact method, the simulated-annealing algorithm, colonial competition, and the average percentage error of the algorithms used.

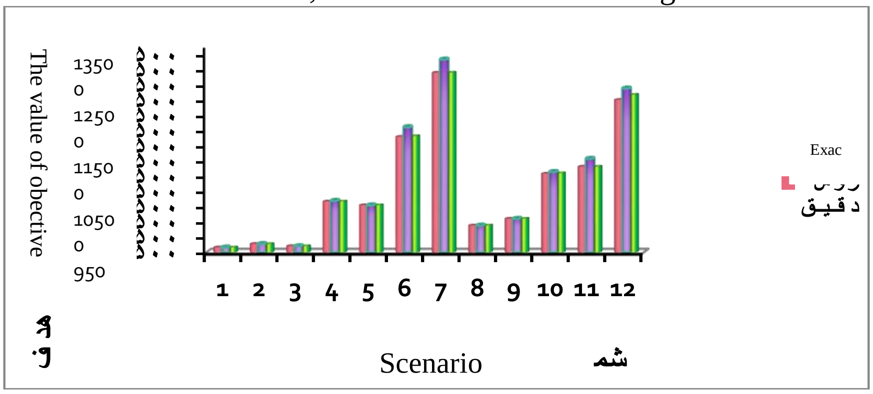


**Figure 5: Comparison of objective function values for 12 scenarios in three precise methods, SA and ICA**

As is seen in Figure 5, in most problems, the values of the objective function calculated by the annealing algorithms are simulated and ICA are consistent with the optimal target value values obtained from the GAMS software. In other problems, the differences between the values of objective functions in two methods are very small, showing the efficiency of the simulated annealing algorithm and ICA.

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Comparison of two simulated annealing algorithms and colonial competition developed for 12 problem scenarios, simulated annealing algorithms and ICA, each 5 runs and the results are shown in the table. To compare two algorithms, two PRBS% PRBS and PRAS% were used. The percentage of PRBS index shows the best solution, and PRAS% represents the percentage reduction in the target function.

These two indicators are defined as Equations (7) and (8).

$$\%PRBS = \frac{Best_{SA} - Best_{ICA}}{Best_{SA}} \times 100 \qquad (7)$$

$$\%PRAS = \frac{Average_{SA} - Average_{ICA}}{Average_{SA}} \times 100 \qquad (7)$$

**Table 9: Results of running and comparing the performance of simulated annealing algorithms and ICA**

| Scenario | Problem specifications | | | | Solution method | | | | % PRBS of the objective function | %/PRAS of the objective function |
|---|---|---|---|---|---|---|---|---|---|---|
| | Available inventory of ABO | Contingency inventory of ABO | Service level | Average consumption in each period | SA: The value of objective function | SA: Solution time (seconds) | ICA: The best objective function | ICA: Average solution time | | |
| **1** | 3 | 1 | 90 | 5 | 827 | 0.12 | 827 | 0.12 | 2.72 | 2.73 |
| **2** | 4 | 1 | 90 | 7 | 1055 | 0.11 | 1055 | 0.11 | 6.94 | 7.61 |
| **3** | 5 | 1 | 90 | 9 | 911 | 0.23 | 911 | 0.23 | 0.47 | 0.47 |
| **4** | 6 | 1 | 90 | 11 | 3900 | 0.32 | 3846 | 0.32 | 2.33 | 1 |
| **5** | 7 | 2 | 90 | 13 | 3602 | 0.13 | 3602 | 0.13 | 1.18 | 1.18 |
| **6** | 8 | 2 | 90 | 15 | 8743 | 1.22 | 8153 | 1.22 | 0.39- | -0.83 |
| **7** | 9 | 3 | 95 | 17 | 13169 | 4 | 12368 | 4 | 1.88 | 2.06 |
| **8** | 10 | 3 | 95 | 19 | 2270 | 0.07 | 2270 | 0.07 | 4.41 | 3.48 |
| **9** | 11 | 4 | 95 | 21 | 2717 | 0.09 | 2717 | 0.09 | 8.92 | 9.47 |
| **10** | 12 | 4 | 95 | 23 | 5799 | 1 | 5713 | 1 | 7.83 | 8.87 |
| **11** | 13 | 5 | 95 | 25 | 6665 | 2 | 6144 | 2 | 4 | 4 |
| **12** | 14 | 7 | 95 | 25 | 11270 | 10 | 10900 | 10 | -0.4 | -0.04 |
| **Total average** | | | | | 5.77 | 1.6 | 4867 | 2.67 | 5.77 | 1.6 |

Figure 6 shows the comparison of the solution results by the two proposed algorithms. As is seen in the figure, in most cases, ICA performs better than SA algorithm

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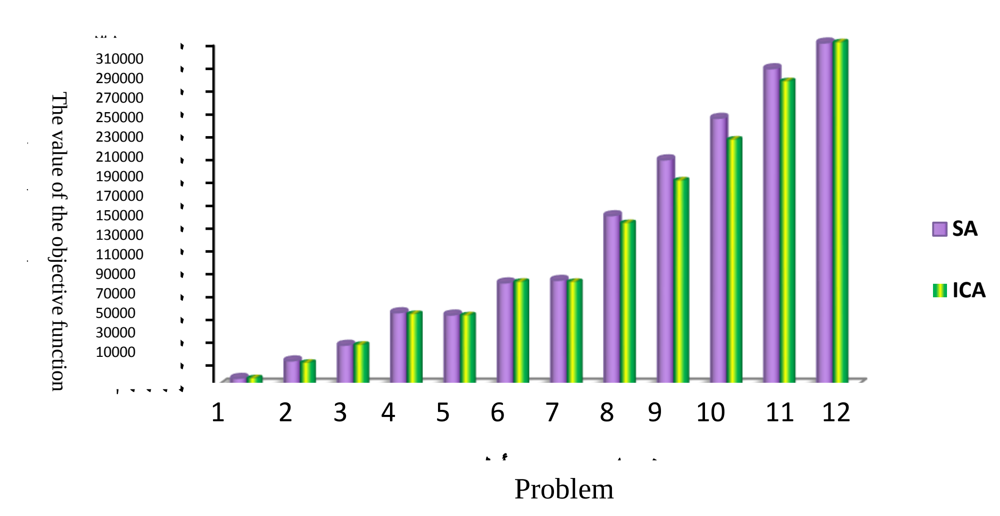


**Figure 6: Comparison of objective function values for 12 problems in the SA and ICA**

Finally, using the results of the ICA algorithm, the priority of each blood group was calculated for ordering in a periodic review period, the results are presented in Table 10.

**Table 10: The type of blood group demand in terms of their priority**

| Blood groups | Demand percentage | Period 1 | Period 2 | Period 3 | Period 4 | Period 5 | Period 6 | Period 7 | Period 8 |
|---|---|---|---|---|---|---|---|---|---|
| O+ | 33.5 | O+ | | | | | | | |
| O- | 4 | O+ | O- | | | | | | |
| A+ | 27 | O- | O- | A- | O+ | | | | |
| A- | 3 | O- | A+ | | | | | | |
| B+ | 22 | O+ | B- | O+ | | | | | |
| B- | 2.5 | O- | O- | O- | O- | | | | |
| AB+ | 7 | O- | B- | A- | A+ | O+ | O+ | B+ | A- |
| AB- | 1 | O- | A- | A- | B- | O+ | | | |

## VI. CONCLUSION

The study presented a single-objective linear programming model for inventory management in blood supply chain. These models include making decisions about the optimal blood-inventory control policies, and determining the optimal amount of inventory, and shortage and perish of blood in different periods. The objective function of this problem is to reduce the cost of demand and maintenance costs, transportation, shortages and expiration. As the blood inventory supply-chain management is NP-Hard in terms of computations, it is coded and accurately collated by the GAM software and the comprehensive meta-analysis of annealing simulation techniques. In order to analyze the results, a case study was conducted in Tehran's Bashar Hospital based on seven days of the week.
Then, Taguchi experimental design method has been used to evaluate the various levels of parameters of the meta-heuristic algorithms. Then, 12 different scenarios were proposed, designed, and solved. Two criteria of

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the solving time to analyze the results and for optimal value of the function and PRRS and PRAS% were used for comparing the two algorithms. As the results of solving meta-heuristic algorithms show, regarding the value of the objective function, ICA performs better than the annealing simulation algorithm. Nevertheless, at solution time, the annealing simulation algorithm gets optimal response in less time. Moreover, the importance and prioritization of blood groups and inventory management based on the importance of blood groups can be considered for future studies.

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