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Periodic blood inventory system with two supplies and two priority demand classes

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A B S T R A C T

Managing blood inventory is challenging due to the perishable and unstable nature of the product needed for transfusions in healthcare facilities. In this paper, we consider a periodic review blood inventory model with two priority demand classes, namely emergency and regular patients. We propose a dynamic programming model for determining the optimal ordering policy at the hospital given the uncertainty regarding received donated blood units. The optimal policy deals with placing orders for blood units that will expire within a fixed period. The objective is to minimize total expected costs within a planning horizon while maintaining a specified expected service level. Our model considers uncertain demands and donated blood units with discrete probability following known distributions. A tabu search algorithm is developed for large-scale problems. The performance of these ordering policies is compared against the optimal fixed order quantity and the order up-to-level policies using real-life data. The numerical results show the benefit of our model over the optimal fixed order quantity and the order up-to-level policies. We measure the total expected cost and the expected service level obtained from the optimal and near-optimal policies and provide a sensitivity analysis on parameters of interest.

1. Introduction

The need for blood continues to be high and urgent for many reasons. Serious medical conditions requiring blood transfusions include surgeries, accidents, and illnesses that cause anemia. The American Red Cross reported that every 2 seconds, someone in the United States needs blood and/or platelets (American Red Cross, 2021). However, although the demand is present, the supply is unpredictable. Since blood cannot be manufactured, its supply relies on volunteer donations. However, the number of blood donors is small and variable. According to the American Red Cross, about 3% of age-eligible people donate blood yearly (American Red Cross, 2021). The low number of blood donors seems to be an issue for many countries worldwide, especially during the COVID-19 pandemic. The demand for blood increased, while the supply declined, due to shortages of blood occurring more frequently than under normal circumstances (Gupta et al., 2021). Moreover, Blood inventory also has a limited shelf life because it is a perishable product. Blood inventory must be stored until required by a hospital or healthcare facility that provides blood transfusion services. Units of blood are received from a central blood bank or a repository in the form of packed red cells (PRC), which comprise red blood cells (RBCs). These PRC units must be stored from the time of receipt until the time of transfusion, and the viability and functionality of stocked PRC depend on the preservative solutions used. Generally, PRC can be stored for up to 21–42 days in suitable anticoagulant and preservative solutions (Ng et al., 2018).

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This research was motivated by the blood inventory problem at the hospital of the Suranaree University of Technology (SUT), Nakhon Ratchasima, Thailand. To maintain a scenario reflective of the real problem and account for the unique features of the problem, we conducted experiments based on a realistic case study. The blood inventory is collected in the form of PRC units and reserved for transfusion to the patient. Collected fresh blood can be stored for up to 35 days. The patients are classified into two types, namely emergency and regular patients. Emergency patients need an immediate transfusion. Thus a shortage of blood is not permitted in the model in the case of emergency patients. The PRC units are assigned with priority to emergency patients, with the remaining units being reserved for transfusions among regular patients. Healthcare departments at the hospital can request units of blood that are completely tested for compatibility. In the case of blood shortage, the healthcare department immediately requests PRC units from an outsourcing provider, namely the Thai Red Cross in Bangkok, which provides a direct donation service and serves as the National blood bank. A diagram of the problem with blood supply chain network components is shown in Fig. 1.

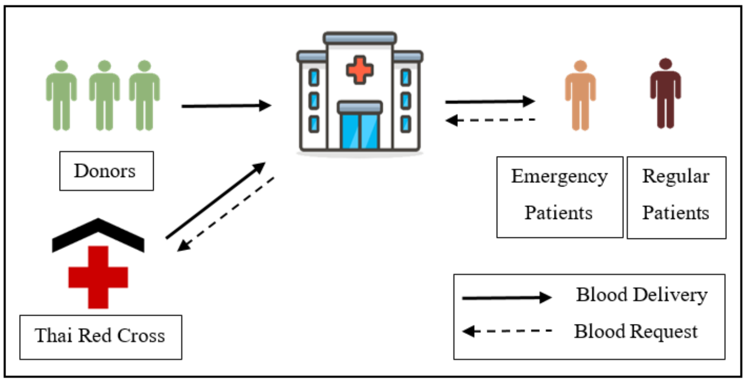


Fig. 1. A schematic diagram of the case study of this research problem

The challenge in blood inventory management is that blood is usually urgently required, whereas its supply is not constant, limited, and perishable. Thus, it is difficult for the supply to meet the demand in uncertain situations. To address this problem, we proposed a stochastic blood inventory model for perishable products with two suppliers, including donation at the SUT hospital and order placement to the Thai Red Cross. We formulated a dynamic programming (DP) model considering the periodic review. The model can be classified into two cases, one with and one without a shortage of regular patients. Furthermore, the replenishment decision must consider two suppliers and two priority demand classes even before the demand is realized. The initial blood inventory given at the start period of the model is based on the initial blood inventory at the SUT hospital. We focused on emergencies: when a shortage occurs, the universal donor, type O Rh-negative, is administered for emergency transfusions. Thus, the management of type O Rh-negative blood is significant in the blood inventory system. The proposed DP model was tested using real data from the case study. To solve the problem on a large scale, we also proposed a tabu search algorithm (TABU). Moreover, we compared the optimal policy suggested by the proposed model and the current policy regarding important criteria, namely the total expected cost and the expected service level.

The rest of this paper is organized as follows. Section 2 presents the relevant literature, and Section 3 describes the model and DP formulation for the periodic blood inventory system. Section 4 presents TABU, and Section 5 presents the computational results. Finally, Section 6 presents the conclusions of the study and avenues for future work.

2. Literature Review

Early research related to perishable inventory focused on a single product with deterministic conditions. The seminal work was conducted by Piarskalla (1972), who studied the periodic perishable inventory problem with deterministic demand in cases of backlogging and lost sales. Replenishment could be achieved for items of any age, where the demand for a given freshness level could be satisfied for items with higher levels of freshness. The stochastic perishable inventory model was presented by Nahmias (1975) with the cases of a fixed two-period lifetime and an *m*-period lifetime. The author considered the effects of outdated units in a one-period model and determined the probability distribution for outdating newly ordered units. Next, Nahmais (1978) considered the fixed-charge perishable inventory problem, analyzing and constructing by approximation a one-period model with backlogging. Thereafter, several improvements were made to the models to account for the fixed lifetime, considering the optimal replenishment policy of perishable products at the point of hospitals, by Nahmias (1982, 2011), Prastacos (1984), Karaesmen et al. (2011), and Bakker et al. (2012).

Later, some works were extended to consider more factors in models such as components of the blood supply chain and uncertainty. Dai et al. (2020) optimized a two-multi-echelon inventory system for a perishable product with price- and stock-dependent demand in the supply chain. The objective was to maximize the average profit per unit of time by determining the optimal replenishment cycle, frequency, and quantity. Sohrabi et al. (2021) proposed multi-objective inventory management for blood banks, which considered the patient’s condition. Heidari-Fathian and Pasandideh (2018) presented a green-blood supply chain network design whose objective was to minimize the total cost of the supply chain network and the total environmental impact of the activities of the supply chain network, considering the uncertainty of demand and supply. Zahiri et al. (2015) presented a mixed-integer linear programming model in the blood supply chain. They addressed the blood collection and distribution network and assumed that the quantities of donations and demand were uncertain. Hosseinifard and Abbasi (2018) studied the impact of inventory centralization on the sustainability of the blood supply chain, where the first echelon included a single blood bank that received a stochastic supply from donors and the second echelon contained hospitals receiving external demands. The results revealed that centralizing the hospitals improved the outdated quantities at hospitals and the shortage of quantities in hospitals and the blood bank. Related research on designing blood supply chain systems was also conducted by Dillon (2017), Lowalekar and Ravic (2017), Liu et al. (2020), and Gitinavard et al. (2019).

Due to the uncertainty in both demand and supply, several works focus on the issue of blood shortage and wastage. Gunpinar and Centeno (2015) formulated a stochastic integer programming model whose objective was to minimize the shortage and wastage of platelet blood, with the lifetime limited to 5 days. Rajendran and Ravindran (2017) considered blood platelets with demand uncertainty. Their objective was to minimize blood wastage while limiting the lower bound on the service level. In the area of dynamic policy, most studies formulated models of the blood platelet inventory in which the shelf life was 3–5 days. Civelek et al. (2015) considered blood platelets with discrete-time inventory where demand existed for blood platelets of different ages with respect to the inventory costs of holding, outdated, and shortage. They formulated a Markov decision process to determine the order quantity. Meng et al. (2021) considered uncertainties in emergency demand quantity and occurrence time to mitigate expiration wastages for emergency perishable inventory systems using the distribution-free newsboy model. They showed that the controversial sale strategy may be effective in both expiration mitigation and cost reduction. Arani et al. (2021) studied an integrated inventory system called lateral resupply, permitting a hospital to satisfy its demand via other hospitals' inventories in the absence of the required product at the blood center and its excess in any hospital. They measured two performance indicators, namely cross-matching and outdated units.

It is difficult to apply the inventory policies of the considered blood inventory problems to real scenarios because the determination of optimal ordering quantities (y) is required for every period. Hence, there is a need to develop policies that have characteristics of other inventory problems such as (R, q), (R, S), or (R, s, S) policies or single critical number policies. Cohen (1976) studied the single critical number policy for perishable inventory with m period lifetimes in the backlogging case. He derived an explicit closed-form solution of the optimal order-up-to quantity S for the $m = 2$ case. A Markovian model for perishable inventory was proposed by Chazan and Gal (1977), who analyzed the age distribution as a finite Markov chain in each period. They considered Poisson demand, and their model assumed a fixed number of units on hand. The objective function was to minimize the expected outdated cost. Nahmais (1977) considered the minimum total expected outdated cost related to perishable inventory with random demand and lifetime in backlogged cases. He assumed the lifetime to be a discrete distribution and showed critical number approximations. Nahmias and Schmidt (1986) analyzed perishable inventory by considering the theory of a weak convergence problem with discrete demand. They assumed continuous demand that converged weakly to a discrete distribution. Williams and Pattuwo (1999) considered the perishable inventory problem with a positive lead time in a single-period model with lifetime = 2. Their model considered the lost sales case, and they extended the model to multiple periods. Their model showed convexity with respect to y, and the optimal quantity depended on lead time. Haijema, van der Wal, and van Dijk (2007) considered blood platelets with respect to the demand for young platelets and platelets of any age. The rule for platelets of any age was that the oldest platelets were used first. For young platelets, those with a remaining lifetime of at least r were considered first. This was a case of the two-stage perishable inventory. The two classes of demand require blood units as inventory. Kouki et al. (2010) studied the periodic review model for perishable inventory with a random lifetime in the case of lost sales and fixed lead time. They used a Markov process to analyze the order-up-to-level (OUL) by dealing with discrete time monitoring. Their results showed a steady-state probability. Minner and Transchel (2010) considered the periodic review model for perishable inventory under service-level constraints and fixed positive lead time. Their model analyzed an OUL policy under first-in-first-out (FIFO) and last-in-first-out (LIFO) methods. They showed dynamic order quantities. Olsson and Tydesjö (2010) studied perishable items using the order-up-to-S policy ($S-1$, S) with the Poisson demand, fixed lifetime, lead time, and a single product in backlogging.

Since the problem is complex, many solutions have been proposed. Dillon et al. (2017) formulated a two-stage stochastic programming model of the RBC supply chain. The first-stage decision considered the reorder point and up to level (R, S) prior to the demand being realized. The second-stage decision considered the maximum service level and the minimum fraction of outdated units. Most previous works focused on the fixed policy as a finite periodic review. In the area of approximation, the myopic approximation was studied by Nahmias (1976), who considered the m period lifetime and backlogged case. Namdakuma and Morton (1993) considered near-myopic heuristics for perishable inventory in infinite-horizon DP. Their work analyzed the lost sales case with the m period lifetime. Cooper (2001) studied the perishable inventory problem under a fixed critical number order policy to determine a bound on the expectation and distribution of the number of outdated products. His model analyzed the transition matrix of a lifetime by using the Markov chain in a multi-period with lost sale cases. Chiu (1995) studied a heuristic in policy (R, T) with an order OUL R and an interval T, whereas the interval T is a decision variable in a periodic review perishable inventory problem with positive lead time. He obtained the approximated expected outdating cost and its resulting bounds. Mokhtar et al. (2021) considered an optimal supply inventory strategy under uncertain supply disruption. The problem was formulated as a DP and solved by a least squares Monte Carlo simulation technique. Zhou et al.

(2021) used a simulation technique to solve the blood supply chain operation problem with the consideration of lifetime and transshipment under an uncertain environment, as did Janssen et al. (2018), who developed a stochastic micro-periodic age-based inventory replenishment policy for perishable goods using a simulation study. For large-scale problems, metaheuristics are inevitable. Yavari et al. (2020) developed a genetic algorithm (GA) to solve a multi-period inventory problem of perishable products. Daroudi et al. (2021) developed a non-dominated sorting genetic algorithm (NSGA) to solve a multi-period model with three main objective functions.

In this research, blood with a limited lifetime of the *m* period is considered. The goal is to determine the optimal ordering policies, detailing quantities to be ordered for each period for a blood inventory problem, using finite-horizon DP. The objective is to minimize the total expected cost in a finite horizon. This work differs from that of Cohen (1976) in that multiple classes with uncertain demand are considered instead of a single class with known demand. The perishable blood inventory problem is examined under two types of stochastic demand: emergency and regular patients. For the allocation of blood units, priority is given to emergency patients. In addition, products with different lifetimes are studied in this paper rather than the outdating of unused inventory in a known fraction in each period, as in Cohen (1976). TABU is also developed for large-scale problems.

3. Mathematical Model

The main goal of this study is to decrease the risk of patient mortality while minimizing the significant financial cost associated with the blood inventory system. The risk of shortage of blood units for regular patients is a function of the number of blood units in the stock. The model is formulated to determine the replenishment order and the allocation of units to patients. Therefore, the goal is to determine the optimal policy with respect to minimizing the total expected cost and the expected service level for regular patients. Decisions on replenishment orders will lead to an increase in the rate of transfusions for both emergency and regular patients. To address this issue, an inventory management problem that considers the number of blood units to order is required. Therefore, the objective of this study is to develop an optimal policy for blood inventory aiming to minimize the total expected cost and maintain a high expected service level.

3.1 Problem descriptions

The inventory system model with a single blood type is proposed. The model deals with two random priority demand classes: emergency and regular patients. Both types of demand follow a discrete and known distribution. Priority is given to emergency patients. The perishable blood inventory is examined under stochastic demand for two types of demand: emergency patients requiring d_E^n blood units following the discrete probability ($p_E(d_E^n)$) and regular patients requiring d_R^n blood units following the discrete probability ($p_R(d_R^n)$). The allocation of blood inventory is prioritized for emergency patients with a decision variable ($z_{E,i}^n$). The model assigns blood units to regular patients with a decision variable ($z_{R,i}^n$). The goal is to find the optimal ordering policies featuring quantities to be ordered in each period. The problem of the minimum total expected cost is formulated and solved. The expected service level for regular patients given the optimal solution of the minimum total expected cost is investigated over a finite horizon. A model with a single product of the remaining lifetime (*m* periods) is considered. It is assumed that the product has an *m* fixed lifetime ($i, j = 1, 2, \dots, m$). Suppliers can periodically replenish orders with zero lead time. Two types of suppliers are considered: Thai Red Cross order placement (y^n) and received donated (q^n) blood units that follow a discrete probability ($p_G(q^n)$). The ordering costs consist of variable ordering cost (r_1) per unit, fixed ordering cost (r_2) per replenishment order, and machine cost (r_3) per donated unit. In each period, any unit left in stock with zero remaining lifetime will be outdated, which is represented as the outdated cost (o) per unit. Two model formulations are studied. In the first model formulation, unsatisfied demand is lost for regular patients. It is assumed that the shortage cost of emergency patients is the potential loss of life, which does not allow for the shortage. A shortage cost of regular patients (s_R) per unit is incurred when demand cannot be met. In the second model formulation, it is assumed that there is no allowance for lost sale cases (100% of service level). The excess of issued units after demand realization will be held in stock, and their remaining lifetime will be decreased by one period, which is represented as the holding cost (h) per unit. The model is formulated as finite-horizon dynamic program with N periods ($n = 0, 1, 2, \dots, N$). The model is described in Fig. 2.

Notations

Indexes

i, j	Useful lifetime of i, j periods remaining
m	Remaining lifetime of the product (in periods)
E	Emergency type of demand
R	Regular type of demand
n	Period
N	Maximum number of periods
M	Maximum lifetime of the product

Parameters

s_R Shortage cost per unit of the regular type of demand
r_1 Variable ordering cost per unit
r_2 Fixed ordering cost per time
r_3 Machine cost per unit for the preparation process of the donated blood units
r_4 Transfusion cost per unit
h Holding cost per unit
o Outdating cost per unit
$MaxQ$ Maximum replenish order quantity of blood unit accounting to equation (10)
SS Maximum number of blood units in stock for lifetime accounting to equation (9)
d_E^n Demand of emergency patients in period n according to a known discrete distribution, $p_E(d_E^n)$
$p_E(d_E^n)$ The discrete probability distribution of d_E^n in period n is specified by the possible values along with the probability of each.
d_R^n Demand of regular patients in period n according to a known discrete distribution, $p_R(d_R^n)$
$p_R(d_R^n)$ The discrete probability distribution of d_R^n in period n is specified by the possible values along with the probability of each.
q^n The units of donation given in period n according to a known discrete distribution, $p_G(q^n)$, for use in period n with lifetime m periods remaining
$p_G(q^n)$ The discrete probability distribution of q^n in period n is specified by the possible values along with the probability of each.
$f^n(y^n, x_i^n, q^n, z_{E,i}^n, z_{R,i}^n, d_E^n, d_R^n)$ Function of current cost in period n with the current state being (x_i^n) and actions $(y^n, z_{E,i}^n, z_{R,i}^n)$ if the realized demand is (d_E^n, d_R^n) and donation blood unit is (q^n)

State Variables
x_i^n Amount of inventory on hand with i periods useful of life at the beginning of period n

Decision Variables
y^n Units of "new" blood ordered (has remaining lifetime of m periods) in period n
u^n = 1 if $y^n > 0$, place the units of "new" blood ordered in period n
= 0 otherwise
$z_{E,i}^n$ Units of blood with lifetime i remaining periods allocated to fulfill the demand of emergency patients in period n
$z_{R,i}^n$ Units of blood with lifetime i remaining periods allocated to fulfill the demand of regular patients in period n

3.2 Dynamic Programming Model

At the start of each period n, the initial stock on hand is made up of units that are on hand (and not assigned) in the previous period and the units from the excess of issued units after depleted demand in the previous period, x_i^n. Before demand is realized, order y^n is placed and units arrive with no delay along with receipted donated blood units q^n. The $z_{E,i}^n$ is assigned for emergency patients and $z_{R,i}^n$ is assigned for regular patients after demand is realized, where i represents the remaining lifetime of the product. Then, the demand is realized by fulfilling the needs of emergency patients and the needs of regular patients when possible. Units with less remaining lifetime are allocated first. At the end of the period, the holding cost, the outdating cost, and the shortage cost are calculated. In addition, the variable ordering cost per unit (r_1), fixed ordering cost per replenish order (r_2), and machine cost per unit (r_3) for donated blood units are included in the model. The model is formulated as a finite-horizon DP model. The planning horizon has a total of $N>1$ period. The DP model decomposes the problem into a series of subproblems. The stages are the review period $n=1, 2, \ldots, N$. The DP stage is given by the current period $(n = 1, 2, 3, \ldots, N)$. The state of the system is given by the inventory on hand in period n, made up of a vector of inventory on hand in period n with i remaining lifetime (x_i^n). This is observed after satisfying the demand and holding excess units from the previous period. In each period, the current inventory on hand is observed and an ordering decision for new blood units is made along with an allocation decision for both emergency and regular patients $(y^n, z_{E,i}^n$, and $z_{R,i}^n)$. The system dynamics are given by the two recursive equations in (1)–(2).
The decision variables can be further constrained by the following upper bounds,

$$x_{m-1}^{n+1} = y^n + q^n - z_{E,m}^n - z_{R,m}^n \qquad \forall i = 1, 2, 3, \ldots, m-1 \tag{1}$$

$$x_{i-1}^{n+1} = x_i^n - z_{E,i}^n - z_{R,i}^n \tag{2}$$

where

$$z_{E,j}^n - \left(d_E^n - \sum_{i=1}^{j-1} z_{E,i}^n \right)^+ = 0 \qquad \forall j = 2, 3, 4, \ldots, m \tag{3}$$

$$z_{R,j}^{n} - \left(d_R^n - \sum_{i=1}^{j-1} z_{R,i}^{n} \right)^{+} = 0 \qquad \forall j = 2, 3, 4, \ldots, m \tag{4}$$

$$y^n + q^n - z_{E,m}^{n} \geq z_{R,m}^{n} \tag{5}$$

$$x_i^n - z_{E,i}^{n} \geq z_{R,i}^{n} \tag{6}$$

$$\text{As } \left(d_R^n - \sum_{i=1}^{j-1} z_{R,i}^{n} \right)^{+} = \max\left(\left(d_R^n - \sum_{i=1}^{j-1} z_{R,i}^{n} \right), 0 \right)$$

Case 1: Allowance for shortage situation

$$d_E^n \leq \sum_{i=1}^{m-1} x_i^n + y^n + q^n \qquad \forall\, n = 1, 2, 3, \ldots, N \tag{7}$$

Case 2: No allowance for shortage situation

$$d_E^n + d_R^n \leq \sum_{i=1}^{m-1} x_i^n + y^n + q^n \qquad \forall\, n = 1, 2, 3, \ldots, N \tag{8}$$

Recursive Eq. (1) refers to the inventory level of units with a full remaining lifetime *(y^n)* and the donated blood units (q^n). After the model assigns blood units for demand depletion, x_{m-1}^{n+1}units will be left after referring to the inventory level of units with the remaining lifetime of *m* periods. The recursive Eq. (2) is similar to Eq. (1); however, it refers to the inventory level of units with a remaining lifetime of less than *m* periods. The constraint in Eq. (3) computes the total quantity of issued units in period *n*. Units with less remaining lifetime are assigned first to emergency patients, while excess units are held in the inventory (from period *n*) for use in period *n+1*. The constraint in Eq. (4) calculates the number of issued units used to deplete the demand of regular patients, ensuring that "older" units (with less remaining lifetime) are allocated first. The constraint in Eq. (5) calculates the number of units from the excess of those issued units after depleting the emergency type of demand. This is performed to ensure the implementation of the FIFO policy, wherein older units are depleted first with a full remaining lifetime. The constraint in Eq. (6) is similar to that in Eq. (5); however, it refers to units with a remaining lifetime of less than *m* periods. The constraints in Eqs. (7-8) are required for the situation of shortage allowance and no shortage allowance, respectively. The decision variables can be further constrained by the following upper bounds.

$$y^n + \sum_{j=n}^{\min(n+m-1,N)} \min\left(q^n\right) \leq \sum_{j=n}^{\min(n+m-1,N)} \max\left(d_E^j + d_R^j\right) \tag{9}$$

$$x_i^n \leq \sum_{j=n}^{\min(n+i-1,N)} \max\left(d_E^j + d_R^j\right) \quad \forall\, i = 1, 2, 3, \ldots, m-1 \tag{10}$$

Constraints (9)–(10) are defined to limit the number of units assigned to both demand types and enforce priority based on the demand of emergency patients. Eq. (9) is used for the inventory with the full remaining lifetime, and Eq. (10) is used for others. Enforcing the upper bounds in (9)–(10) reduces the feasible region and, therefore, the computational time, in the following numerical case study. *MaxQ* is the maximum y^n obtained from Eq. (9). Further, SS is the maximum of x_i^n, which is obtained from Eq. (10).

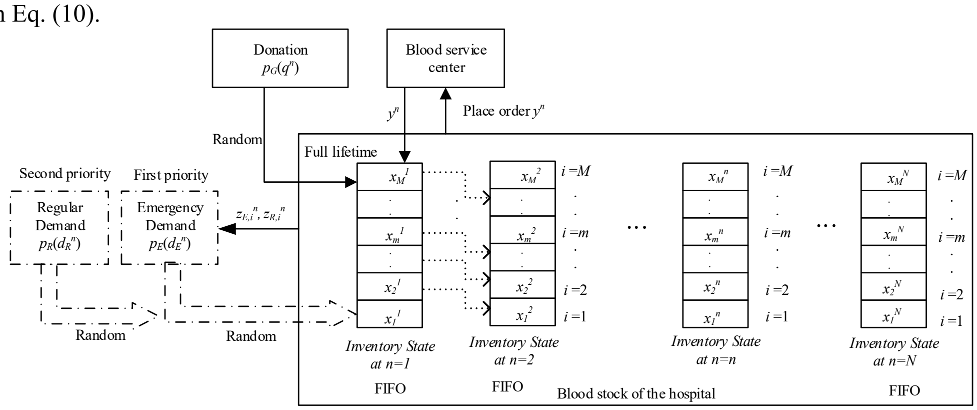


Fig. 2. Model of a periodic blood inventory system with FIFO policy, two supplies and two priority demand classes

3.3 Reward Function

In particular, the problem is to identify a balance between shortage, outdated, and holding costs by placing an order and assigning blood units while considering future costs. If the policy places an order larger than the requested demand, a large amount of remaining stock will result in high holding costs and forthcoming outdating costs. If the number of blood units is lower than the requested demand, a high shortage cost will ensure regular patients. Thus, the model will allocate units with a lower remaining lifetime before units with a high remaining lifetime to decrease the potential outdating cost. This policy is commonly referred to as FIFO. The two objective functions of minimizing the total expected cost and maximizing the expected service level are considered. In the first objective function, a two-formulation model considering the allowance for a shortage for regular patients and no allowance for a shortage for both types of patients is proposed. The DP formulation model will result in an optimal policy. In the first case, all costs (ordering, holding, shortage, and outdated costs) are calculated. In the second case, the total expected cost based on ordering, holding, and outdated costs is considered. The single-period cost for a given demand realization is calculated using Eq. (11), where F^n denotes the current cost of stage n. The first and second terms are the ordering costs, while the third term is the machine cost for the received donated blood units. The fourth term is the transfusion cost of issued units. The fifth term is the outdating cost of unissued units with only one remaining lifetime. The sixth term is the shortage cost of the regular type of demand, and the seventh term refers to the holding cost resulting from the total inventory, newly arrived orders, and donation of blood units; holding costs are incurred at the end of the period. Eq. (12) is similar to Eq. (11); however, it refers to the objective function with no allowance for the lost sale of both patients. The optimal solution is investigated from the calculation of a single-period service level, as provided in Eq. (13), given the demand realization and minimum total expected cost. Eq. (13) calculates the ratio between the total blood units assigned to regular patients and the total blood units required by regular patients.

First objective function (Total expected cost):

Case 1: Allowance for shortage scenario for regular patients

$$\begin{aligned} &F^n\left(y^n, z^n_{E,i}, z^n_{R,i} : x^n_i, d^n_E, d^n_R, q^n\right) \\ &= r_1 y^n + r_2 u^n + r_3 q^n + r_4\left(z^n_{E,i} + z^n_{R,i}\right) + o\left(x^n_1 - (z^n_{E,1} + z^n_{R,1})\right)^+ + s_R\left(d^n_R - \sum_{i=1}^{m} z^n_{R,i}\right)^+ \\ &+h\left(\sum_{i=2}^{m-1} x^n_i + y^n + q^n - \left(\sum_{i=2}^{m} z^n_{R,i} + \sum_{i=2}^{m} z^n_{E,i}\right)\right)^+ \end{aligned} \tag{11}$$

Case 2: No allowance for shortage scenario

$$\begin{aligned} &F\left(y^n, z^n_{E,i}, z^n_{R,i} : x^n_i, d^n_E, d^n_R, q^n\right) \\ &= r_1 y^n + r_2 u^n + r_3 q^n + r_4\left(z^n_{E,i} + z^n_{R,i}\right) + o\left(x^n_1 - z^n_{E,1} + z^n_{R,1}\right) \\ &+h\left(\sum_{i=2}^{m-1} x^n_i + y^n + q^n - \left(\sum_{i=2}^{m} z^n_{R,i} + \sum_{i=2}^{m} z^n_{E,i}\right)\right)^+ \end{aligned} \tag{12}$$

where if $y^n > 0$, then $u^n = 1$

Second objective function (Expected service level):

Case 1: Allowance for shortage scenario for the regular patients

$$F\left(y^n, z^n_{E,i}, z^n_{R,i} : x^n_i, d^n_E, d^n_R, q^n\right) = \sum_{i=1}^{m} z^n_{R,i} \Bigg/ \sum_{i=1}^{m} z^n_{R,i} + \left(d^n_R - \sum_{i=1}^{m} z^n_{R,i}\right)^+ \tag{13}$$

Dynamic programming recurring for the first objective functions:

$$V^n\left(x^n_i\right) = \min \sum p_E(d^n_E) \sum p_R(d^n_R) \sum p_G(q^n) F\left(y^n, z^n_{E,i}, z^n_{R,i} : x^n_i, d^n_E, d^n_R, q^n\right) + V^{n+1}\left(x^{n+1}_{i-1}\right) \tag{14}$$

The optimal total expected cost function depends on the state of the system given by the vector $x^n = (x_1^n, x_2^n, ..., x_i^n, \ldots, x_{m-1}^n)$. The minimum total expected cost from periods n to N is given by the current cost plus the future cost and it is defined by $V^n(x_i^n)$. The expected recursive optimality equation can be written as in Eq. (14). $p_E(d_E^n)$ represents the probability mass function for the emergency type of demand. The $p_R(d_R^n)$ characterizes the regular type of demand, and $p_G(q^n)$ represents the probability mass function for donated blood units. Fig. 3 presents the procedure to solve for the optimal replenishing order quantity of blood units using the DP method described above.

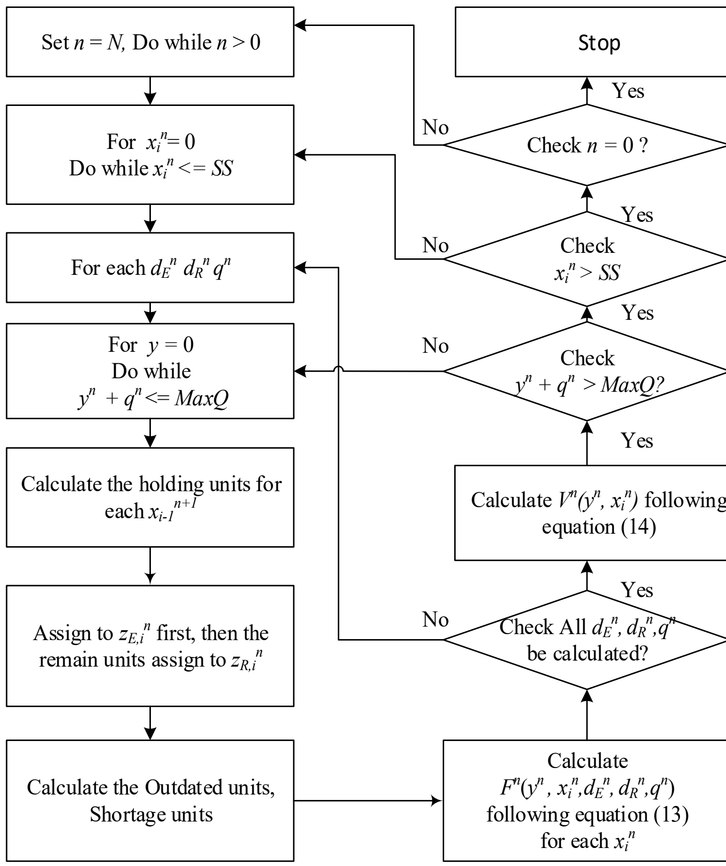


Fig. 3. Process flow to solve periodic blood inventory problem with two supplies and two priority demands by using DP model

4. Tabu Search Approach

4.1 TABU Procedure

This problem is complex, and optimal solutions are obtained via exact formulation, making it difficult to solve large problem sizes. The exact formulation requires a long computer running time for large-scale problems (real-world problems). Therefore, an algorithm is developed to solve the problem addressed in this study. The algorithm is based on the specific problem of ordering a quantity of blood units for each period. To realize the solution, TABU is employed. The idea behind the algorithm is to apply the local search method with a wrapping pair of the quantity ordered in each period to obtain a better solution. The decision on whether to accept a non-improvement solution depends on the candidate solution that is not in the tabu lists. The components of the tabu search approach are described in Fig. 4. The process flow of TABU for each inventory held in each period is provided.

Notation	Description
Indices	
k	Neighborhood solutions as $k = 1, 2, \ldots, K$
Parameters	
F^n	Current of the best fitness value based on equations (11), (12), and (14)
V^n	Minimum total expected cost from periods n to N is given by the current cost plus the future cost, based on equation (14).

X Fitness value of the neighborhood based on equations (11), (12), and (14)
X"$_k$ Fitness values of neighborhood *k* based on equations (11), (12), and (14)
X' Fitness value of the candidate neighborhood based on equations (11), (12), and (14), which is the better of all fitness values of neighborhoods

Decision variables
[B] Set of the current of better solutions of replenish order for each period for the periodic blood inventory system
[X] Set of initial solutions and neighborhood solutions
[X"$_k$] Set of each neighborhood solution *k*
[X'] Set of candidate neighborhood solutions
[Tabu] Set of tabu lists
[y^n] Set of each neighborhood of replenish order quantity of blood units for each period *n*

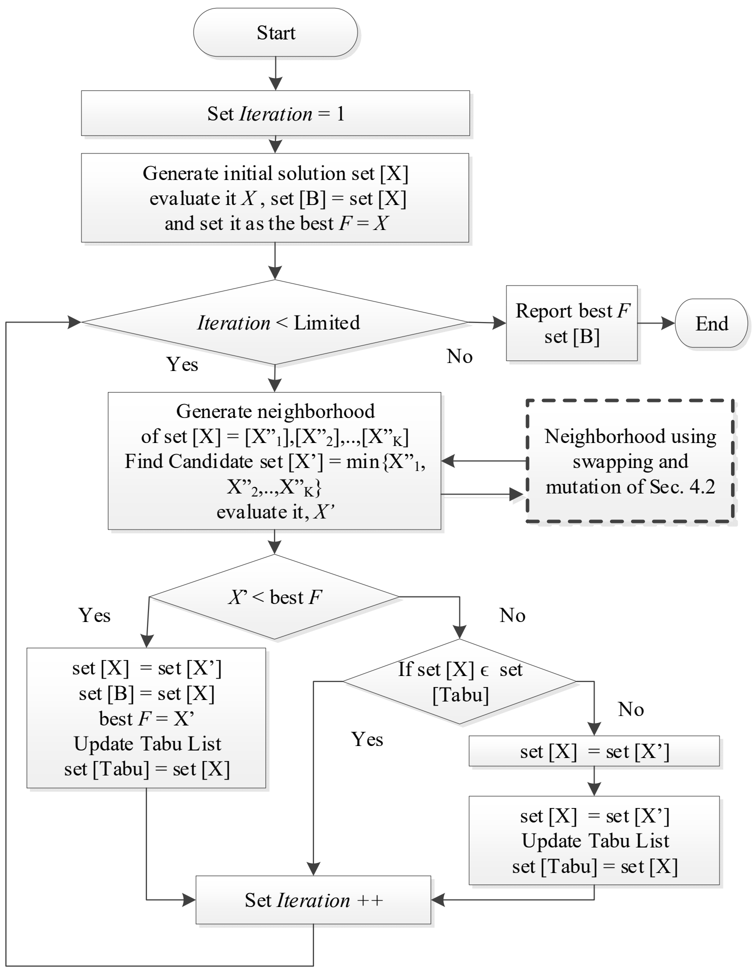


Fig. 4. Process flow of the TABU

4.2 Solution Representation

The first procedure is employed in TABU. The present work uses the idea of an integer representation. In an encoding process establishment, the state of the inventory on hand for each period is considered the encoding model, where x_i^n denotes the state of the inventory on hand. Each solution denotes an integer vector $[X]$ by length $m \times n$, fitted by each y^n of the inventory on hand. The model uses a representation of the replenishing order quantity of blood units of length *n* for each inventory on hand. The replenishing units for each inventory on hand for each period are presented in Fig. 5.

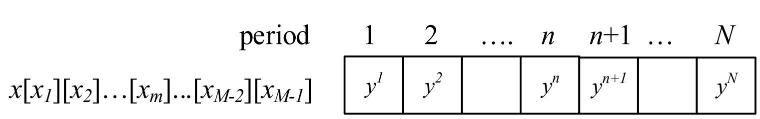


Fig. 5. Solution representation of TABU

4.3 Infeasible solution

An infeasible replenishing order quantity may be generated when generating initial solutions or during mutation operators. Infeasibility can occur because of the shortage of emergency demand, excess holding blood units, or excess order quantity. Thus, a function to check for an infeasible solution is developed. If the function finds an infeasible solution, a procedure is applied to increase or decrease the units of replenishing order quantity to meet the restriction requirements. When the total number of infeasible replenishing units, holding blood units, and donated units does not meet the emergency demand for each period, the units of replenishing order quantity must be increased to at least meet the emergency demand. If the decision to replenish the order quantity exceeds *MaxQ* from the maximum value y^n of Eq. (9), the units of replenishing order quantity must be decreased to meet the requirement. If the remaining total blood units exceed the *SS* from Eq. (10) after demand realization in the end period, the units of the replenishing order quantity must be decreased to satisfy the requirement. The reorder point (γ) is defined based on Eq. (15), which can be calculated by the summation of the maximum demands from both emergency and regular patients subtracted by the minimum donated unit for each period. The replenishing order quantity will be zero if the remaining total blood units exceed the reorder point (γ).

$$\text{Reorder} = Max[d_E^n] + Max[d_R^n] - Min[q^n] \tag{15}$$

4.4 Initial solution

The replenishing units for each inventory on hand for each period are generated randomly. The replenishing order quantity decisions are computed by applying the economic order quantity (EOQ). The reorder point (γ) is based on Eq. (15). The procedure follows these steps: the initial replenishing order quantity units for each inventory on hand for each period defined by $y^n[X]$ are calculated based on the EOQ. The vector $[X]$ is a set of inventory units for each useful lifetime of blood units at the beginning of period n. The possible maximum emergency demand and possible maximum regular demand are denoted by $Max\ [d_E^n]$ and $Max[d_R^n]$, respectively. The possible minimum donation unit is denoted by $Min\ [q^n]$. Based on Eq. (15), the solution will then add the reorder units and subtract the remaining total blood units in the starting period. The initial replenishing order quantity unit is shown in Eq. (16).

$$y^n[X] = \left(\sqrt{\frac{2 \cdot FixC \cdot (Max[d_E^n] + Max[d_R^n] - Min[q^n])}{Holding}} + \text{Re}\,order \right) - \sum_{i=1}^{m-1} x_i^n \tag{16}$$

A value in the range of $[0$, the reorder point $(\gamma)]$ defined by $\hat{u}$ is randomly generated. To create a randomly different replenishing order quantity value of $y^n[X]$ for each period, $y^n[X]$ is revised by increasing or decreasing $\hat{u}$. Next, the algorithm will check for the limited solution by using the steps of restrict infeasible solutions described in Section 4.3.

4.5 Improving process

The basic improving solution operates by selecting the current replenishing order quantity solution of randomly n periods for each inventory on hand with integer vector $[X]$ as one of all neighborhoods $[X_k'']$. The neighborhood solution is obtained by mutation, and the candidate solution is the minimum fitness of all neighborhoods $[X']$. Better candidates are selected to be the next current solution in the next iteration. In this section, the creation of a neighborhood using mutation operation is discussed. The basic mutation operation is used in the replacement step with a swapping value at a specific position n with a random position n+1. After the swapping procedure, a value A in the range of [0, the reorder point (γ)] is generated to add or subtract the current replenishing order quantity randomly at position n. The improvement process considers the limited value by investigating these constraints based on Section 4.2. Fig. 6 shows the swapping and mutation procedure. The mutation operation is implemented, and a better solution is obtained.

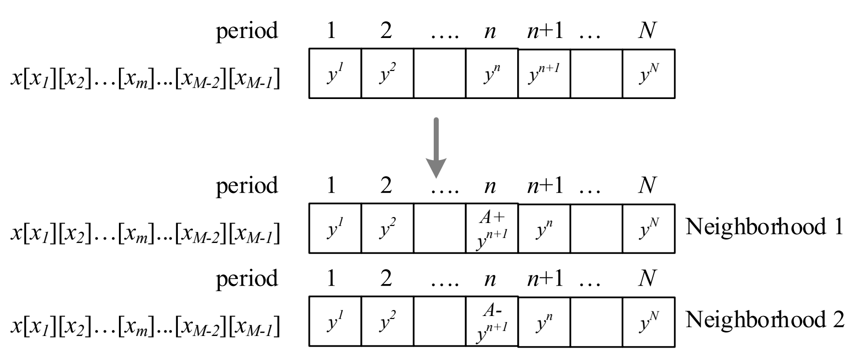


Fig. 6. Mixed swapping and mutation operations of TABU

5. Computational Results

In this section, the comparison of the optimal solutions obtained using the DP and the proposed TABU is presented. NetBeans IDE 7.3.1 software is used to implement the models. The dynamic model of the periodic blood inventory problem with two demand classes discussed in the previous section is formulated. The periodic blood inventory problem with two supplies and two priority demands is illustrated using small cases based on real-world data from the SUT hospital in Thailand. The data used in both the small and real-world case studies represent the actual PRC demands of emergency and regular patients. Data on all incoming PRC units obtained over a 12-month period were collected from September 2018 to October 2019.

5.1 Small-size Case Study

5.1.1 Data

The worst case involving both the cost of urgent transportation from the National Blood Center to the local hospital and contact cost is considered. The demands follow discrete distributions randomly, as shown in Table 2. The model is solved by varying the number of initial inventories as described in equation (10). Further, it is assumed that there is no allowance for the shortage of emergency demand. It is assumed that the blood system is implemented based on the first-come-first-serve policy. The system operates by dispatching the smallest remaining lifetime units. The discrete distribution of the two priority demands is summarized in Table 1.

The raw data for a small-size case study can be categorized as follows:
(1) Time unit used is per day.
(2) Outdating lifetime of blood units is 3 periods.
(3) The small cases are solved for 10 periods (10 days) under emergency and regular demands, with priority given to emergency patients.
(4) No lead time is considered for stock replenishment.
(5) Seven types of costs are considered. The information on all costs is collected, including fixed ordering, variable ordering, holding, outdating, machine, transfusion, and shortage costs. The major costs are as follows:
- The fixed ordering cost per time of 1,532 Thai Baht (THB) is the cost of transportation from Thai Red Cross, Bangkok, to the local hospital.
- The variable ordering cost per unit of 500 THB is the blood preparation cost when using the spinning method and infection test.
- The holding cost per unit of 275 THB is the operation cost of the blood center system, which includes official's salary and depreciation of machines (e.g., blood warmers, plasma machines, automatic blood chemistry analyzers, and blood coagulation analyzers).
- The outdated cost per unit of 600 THB is composed of the blood unit cost and blood destruction cost.
- The donation cost per unit of 360 THB is the machine cost for blood unit preparation.
- The transfusion cost per unit of 112 THB is the cost for preparing blood unit transfusions to recipients.
- The shortage cost per unit of 2,032 THB is the shortage cost of blood units for some demand cases of regular patients.

Table 1
Demand of blood unit per day and donation of blood unit per day data for a small-size case study

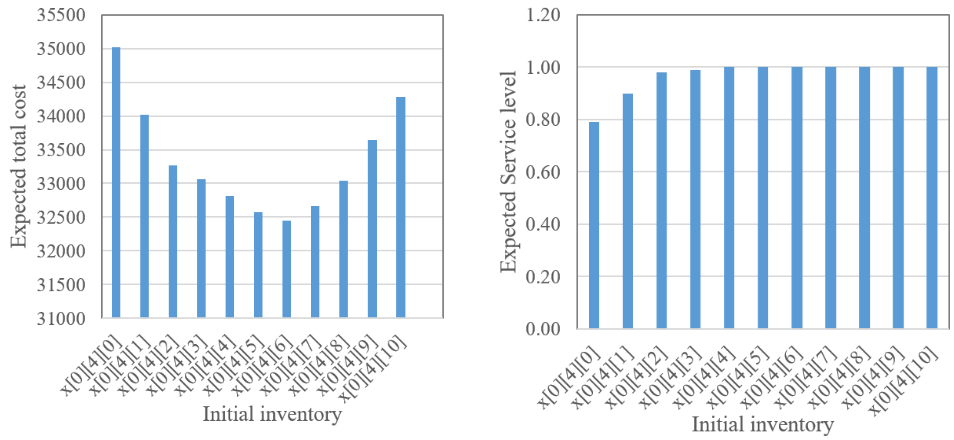
d_E^n (units)	0	1	3
$p_E(d_E^n)$	0.22	0.66	0.12

d_R^n (units)	0	2	3	5
$p_R(d_R^n)$	0.24	0.22	0.12	0.42

q^n (units)	0	1	2
$pG(q^n)$	0.88	0.07	0.04

5.1.2 Performance evaluations of the DP and TABU approaches

Fig. 7(a) shows that the optimal DP model is a convex function given the maximum shelf life of the blood units (m = 3). The results show the optimal total expected cost given the initial on-hand inventory at n = 0 with a fixed shelf life of $m - 2$ period (4 units) and varying the number of the initial on-hand inventory (from 0 to 10 units) with a shelf life of $m - 1$ period. The results indicate that the optimal policy depends on the initial stock. The curve is a convex function of the number of initial inventories. The exact point at which the curve switches depends on the maximum demand. It is believed that the convexity of the total expected cost is a function of the replenishing order quantity (y^n) with respect to the initial stock (x_i^n). In an example with the maximum demand (including emergency and regular demands) of 8 units, the exact point would be the point of initial stock plus order quantity (y^n) of approximately 8. An upper bound can be defined by searching for the optimal point of stochastic DP. In addition, the results of the expected service level based on the number of initial stocks are derived at the minimum total expected cost. Fig. 7(b) shows an increase in the expected service level in a concave function given the number of initial inventories.



(a) The total expected cost (in THB) (b) The expected service level

Fig. 7. Performance of the DP model by evaluating the total expected cost (in THB) and expected service level based on varying the number of initial inventories

Table 2 summarizes the numerical examples of the DP model investigated in cases both with and without shortage allowance. The results show the comparison of benefits between the optimal solution from the DP with shortage allowance and the optimal fixed order quantity (FOQ) with allowance for the shortage of blood units based on the total expected cost (E[Cost]) function given the number of the initial stock. Note that to find the optimal solution for FOQ, the simulation is run to find the best order quantity with the lowest total expected cost. The $x[n][m-2][m-1]$ defines the initial on-hand inventory at n period, with a fixed shelf life of $m-2$ period and $m-1$ given the maximum shelf life of the blood units (m = 3). The results indicate that DP both with and without shortage allowance provided better solutions than the FOQ (with shortage allowance, with a reduction in the overall total expected cost (E[cost]) of 25%–34% and 2%–4%, respectively. The results show that the optimal policy of FOQ with shortage allowance depends on the initial stock. It is observed that as the initial stock increases, the optimal FOQ will decrease in a monotone fashion. In addition, the expected overall service level of the optimal DP with and without shortage allowance and optimal FOQ with shortage allowance are investigated. The results show that DP with shortage allowance provides expected service levels (E[SS]) of higher than 90%, except in the case of $x[0][2][2]$, which achieves a service level of 79%, while DP without shortage allowance provides expected service levels of 100%. The FOQ with shortage allowance policy provides expected service levels (E[SS]) between 90% and 100% in all cases. The results imply that the optimal DP with shortage allowance model determines the replenished order quantity (FOQ) with shortage allowance at the smallest unit. When the initial stock is equal to the maximum requirement of emergency demand, the minimum total expected cost (E[Cost]) is obtained. In current practice, the staff of the hospital implements the OUL policy with shortage allowance. Table 3 shows the results of a comparison of the DP model and the OUL policy with shortage allowance. The DP with a shortage allowance provides a better solution than OUL with shortage allowance based on an objective of the total expected cost (E[Cost]) of 28%, while the DP without shortage allowance provides a better total expected cost (E[Cost]) than OUL with a shortage allowance of 4%.

Table 2

Comparison of the optimal policy (in THB) given the initial stock, and Short-FOQ with and without shortage allowance

Initial inventory	E[Cost]: Short-DP	E[Cost]: No Short-DP	Short-FOQ: E[Cost]				%Deviation of Short-DP and Short-FOQ				%Deviation of No Short-DP and Short-FOQ			
			y=3	y=4	y=5	y=6	y=3	y=4	y=5	y=6	y=3	y=4	y=5	y=6
x[0][2][0]	35,459	43,521	46,839	44,362	51,926	63,905	32	25	46	80	8	2	19	47
x[0][2][1]	34,998	43,068	45,531	44,230	52,862	65,143	30	26	51	86	6	3	23	51
x[0][2][2]	34,310	42,656	44,569	44,379	53,975	66,347	30	29	57	93	4	4	27	56
x[0][2][3]	33,361	42,262	43,842	44,827	55,145	67,502	31	34	65	102	4	6	30	60
x[0][2][4]	32,625	41,918	43,400	45,437	56,297	68,599	33	39	73	110	4	8	34	64
x[0][2][5]	32,309	41,685	43,250	46,193	57,420	69,653	34	43	78	116	4	11	38	67

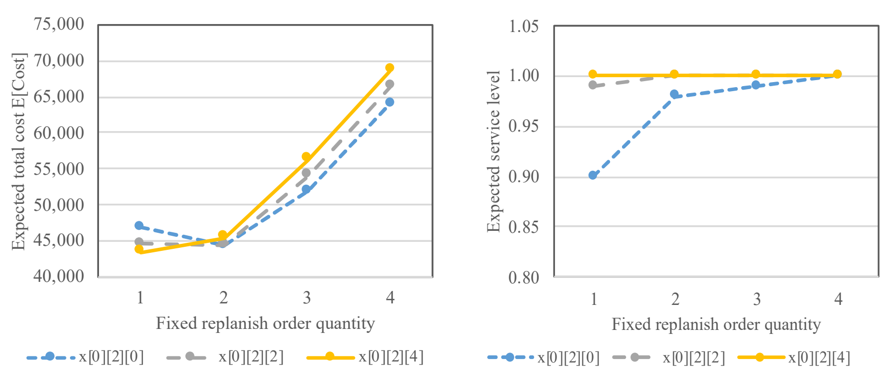
Initial inventory	E[SS]: Short-DP	E[SS]: No Short-DP	Short-FOQ: E[SS]				%Deviation of Short-DP and Short-FOQ				%Deviation of No Short-DP and Short-FOQ			
			y=3	y=4	y=5	y=6	y=3	y=4	y=5	y=6	y=3	y=4	y=5	y=6
x[0][2][0]	1.00	1.00	0.90	0.98	0.99	1.00	10	2	1	0	10	2	1	0
x[0][2][1]	1.00	1.00	0.98	0.99	1.00	1.00	2	1	0	0	2	1	0	0
x[0][2][2]	0.79	1.00	0.99	1.00	1.00	1.00	-25	-27	-27	-27	1	0	0	0
x[0][2][3]	0.90	1.00	1.00	1.00	1.00	1.00	-11	-11	-11	-11	0	0	0	0
x[0][2][4]	0.98	1.00	1.00	1.00	1.00	1.00	-2	-2	-2	-2	0	0	0	0
x[0][2][5]	0.99	1.00	1.00	1.00	1.00	1.00	-1	-1	-1	-1	0	0	0	0

Table 3
Comparison of the optimal policy (in THB) given the initial stock, short-FOQ, and short-OUL with and without shortage allowance

Initial inventory	E[Cost]: Short-DP	E[Cost]: No Short-DP	E[Cost]: Short-FOQ	E[Cost]: Short-OUL	%Deviation of Short-DP and Short-FOQ	%Deviation of Short-DP and Short-OUL	%Deviation of No Short-DP and Short-FOQ	%Deviation of No Short-DP and Short-OUL
x[0][0][6]	32,201	41,544	43,153	41,679	34	29	4	0.32
x[0][1][5]	32,339	41,733	43,263	41,867	34	29	4	0.32
x[0][2][4]	32,625	41,918	43,400	42,052	33	29	4	0.32
x[0][3][3]	32,912	42,128	43,585	42,262	32	28	3	0.32
x[0][4][2]	33,272	42,462	43,959	42,595	32	28	4	0.31
x[0][5][1]	33,724	42,864	44,505	42,998	32	27	4	0.31
x[0][6][0]	34,303	43,352	45,326	43,486	32	27	5	0.31

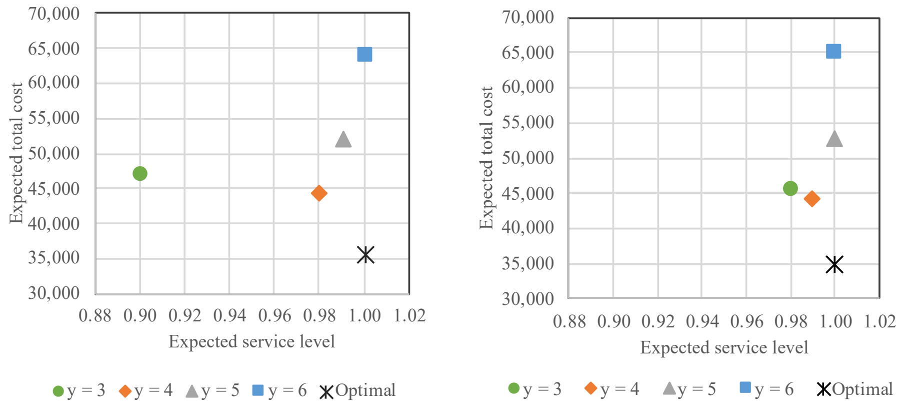
Fig.8(a) shows the results of the FOQ. We observe the effect of varying the initial on-hand inventory with a shelf life of $m-2$ periods (0, 2, and 4 units) and a fixed shelf life of $m-1$ period (2 units). Further, the results show a convex function based on an increase in replenishing order quantity. The point of the optimal FOQ depends on the number of initial inventories. A higher initial inventory provides the optimal FOQ at a higher value than a smaller initial inventory. Fig. 8(b) presents the results of the expected service level in relation to the values varying between 1 and 4 units. The results indicate that the maximum expected service level of the FOQ depends on the initial inventory. In addition, a higher initial inventory provides better results regarding the expected service level than a lower initial inventory. Figs. 9(a) and (b) show the Pareto optimization chart with the expected service level E[SS] on the x-axis and the total expected cost E[Cost] on the y-axis. Figs. 9 (a) and (b) show the results for the specific initial inventory values of *x*[0][2][0] and *x*[0][2][1], respectively. From Figs. 9(a) and (b), the same results are obtained when the expected service level is over 95%. When the minimum total expected cost is required under the FOQ policy, the best solution is to place blood orders at 4 units per period. A comparison of the minimum total expected cost when the expected service level is kept high indicates that the DP model provides a better solution than the FOQ policy in both cases of the initial inventory, that is *x*[0][2][0] and *x*[0][2][1].

Table 4 lists the results for the small data case of the SUT hospital. The sixth column shows the result of the tabu search approach with shortage allowance for each initial stock. The percent gap reported in the seventh column of Table 4 indicates the comparison between the total expected cost (E[Cost]) obtained using the DP model with shortage allowance (in the third column) and the better solutions found by implementing TABU (in the sixth column) to solve the periodic blood inventory problem with two supplies and two priority demands. The %gap value indicates that the tabu search approach can provide different results of the total expected cost (E[Cost]) depending on the number of initial solutions, which is around 10%. The eighth column shows that TABU offers an improvement in the overall expected cost (E[Cost]) by an average of 16% over the optimal solution (DP) with no shortage allowance (in the second column). The ninth column shows that TABU provides more benefits than the optimal of the FOQ (in the fourth column), with an average of 18%. The performance of the tabu search is illustrated by its comparison with the current practice (OUL). The results indicate that the proposed tabu search provides more benefits than the current practice (OUL).



(a) The expected total cost (in THB) (b) The expected service level

Fig. 8. Comparison of the total expected cost (in THB) and the expected service level under each fixed replenishing order quantity



(a) Initial inventory at $x[0][2][0]$ (b) Initial inventory at $x[0][2][1]$

Fig. 9. Comparison of the total expected cost (in THB) and the expected service level under the DP model and the optimal fixed replenishing order quantity

Table 4

Optimal policy (in THB) given the number of initial inventories with and without shortage allowance

Initial inventory on hand	Optimization policy				E[cost]: Short-TABU	Comparison of Short-TABU with others			
	E[Cost]: No Short-DP	E[Cost]: Short-DP	E[Cost]: Short-FOQ	E[Cost]: Short-OUL		%Imp. (Short-DP)	%Imp. (No-Short)	%Imp. (Short-FOQ)	%Imp. (Short-OUL)
x[0][3][1]	42,887	34,585	44,416	43,022	38,807	9	10	13	10
x[0][3][2]	42,491	33,612	44,101	42,625	36,781	5	13	17	14
x[0][3][3]	42,128	32,912	43,584	42,262	37,425	8	11	14	11
x[0][3][4]	41,881	32,635	43,393	42,015	36,030	6	14	17	14
x[0][3][5]	41,680	32,318	43,416	41,815	35,336	7	15	19	15
x[0][3][6]	40,037	32,225	43,645	40,172	35,670	11	11	18	11
x[0][3][7]	40,282	32,388	44,078	40,417	35,266	10	12	20	13
x[0][3][8]	40,569	32,605	44,605	40,704	35,528	11	12	20	13
x[0][3][9]	40,384	33,029	45,222	40,519	35,963	13	11	20	11
x[0][3][10]	40,834	33,637	45,899	40,969	36,220	13	11	21	12
x[0][3][11]	41,259	34,277	46,589	41,394	36,884	14	11	21	11
x[0][7][1]	46,356	34,466	45,213	43,561	38,804	16	16	14	11
x[0][7][2]	47,064	34,312	44,875	41,748	38,816	14	18	14	7
x[0][7][3]	47,772	34,249	44,774	41,650	37,183	4	22	17	11
x[0][7][4]	48,480	34,061	44,959	41,692	37,095	5	23	17	11
x[0][7][5]	49,188	33,723	45,309	41,822	36,975	6	25	18	12
x[0][7][6]	49,896	33,676	45,809	42,062	37,440	10	25	18	11
x[0][7][7]	50,603	34,235	46,471	42,493	36,851	11	27	21	13
					Average	10	16	18	12

5.2 Real-World Problem

5.2.1 Input data from the SUT hospital, Thailand

In this section, the computational results of the proposed TABU are presented based on real-world data. A case study with a dataset from a medical laboratory, the SUT hospital, is used to investigate the proposed TABU. Fresh PRC stored in an approved anticoagulant preservative solution may be stored in a bag for up to 35 days; thus, the time periods used are weekly. The lifetime of blood inventory is 5 weeks ($m = 5$). The emergency demand, regular demands, and donated units follow a discrete distribution. The probability mass functions for 12 weeks are listed in Table 5. Based on equation (9), a solution can be created by determining the order quantity for ($m - 1$) multiplied by $MaxQ$ and the number of periods (N). The program is tested to determine the maximum period of 12 weeks. The objective function is to minimize the total expected cost while providing the appropriate expected service level. The input parameters of the costs collected are summarized in Table 6. The ordering costs are classified into variable ordering cost (r_1) per unit, fixed ordering cost (r_2) per replenishment order, and machine cost (r_3) per donated unit; the outdated cost is cost (o) per unit. A lost sale cost of regular patients (s_R) per unit is incurred when demands cannot be met. The holding cost is cost (h) per unit. The algorithm is developed in the Java programming language. The NetBeans IDE 11.2 is used to implement TABU. The number of iterations is used as the stopping criterion of the program.

Table 5
Emergency demand, regular demand, and donation quantity based on their discrete probability distributions

Time period	Demand of emergency patients (units)		Demand of regular patients (units)		Donation quantity (units)
	$p_E(d_E^n) = 0.6$	$p_E(d_E^n) = 0.4$	$p_R(d_R^n) = 0.6$	$p_R(d_R^n) = 0.4$	$p_q(q^n) = 1.00$
1	4	10	18	22	8
2	2	4	14	24	4
3	2	4	10	20	2
4	2	4	10	14	6
5	2	4	10	16	6
6	4	10	16	20	0
7	4	10	16	20	4
8	4	10	14	16	2
9	6	8	20	24	6
10	2	4	10	16	2
11	2	4	10	16	4
12	2	4	12	16	6

Table 6
Major costs based on operation costs from medical laboratory at the SUT hospital

ID	Major costs	THB
1	Holding cost per unit (THB per unit): h	275
2	Outdating cost per unit (THB per unit): o	600
3	Shortage cost per unit (THB per unit): s_R	2,032
4	Variable ordering cost per unit (THB per unit): r_1	500
5	Fixed ordering cost per time (THB per time): r_2	1,532
6	Donation cost per unit, which is the machine cost for preparing blood unit (THB per unit): r_3	360
7	Transfusion cost per unit (THB per unit): r_4	112

5.2.2 Parameters of the tabu search approach for blood inventory system

The parameters of the tabu search are set using the central composite design (CCD) method. The objective is to minimize the total expected cost. The algorithm needs to calculate the initial replenishing order quantity units and limit the restricting infeasible solutions based on the value of the reorder points. The reorder points are considered one of the factors that can be calculated using Eq. (15). The levels of reorder points are varied from 8 to 16 units, as shown in the combination of factors for CCD in Table 7. Another factor to be determined is the number of iterations. The CCD was applied according to Montgomery (1997). Each combination of factors requires two replications. Table 7 summarizes 13 cases of factor combinations in which combination cases 7 to 13 are the reference points.

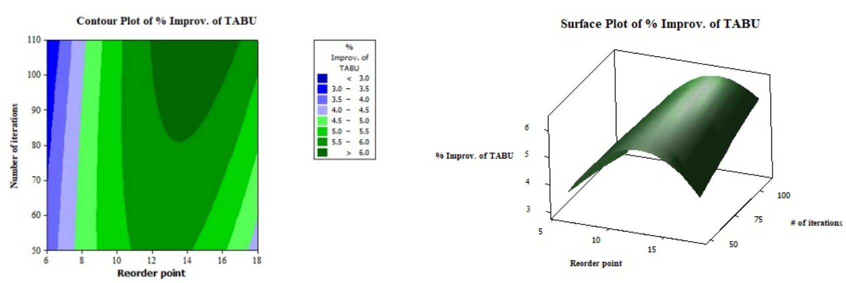
Table 7
Combination of factors for CCD experimental design

Case	Set up value	
	Reorder points	Number of iterations
1	8	60
2	16	60
3	8	100
4	16	100
5	6	80
6	18	80
7	12	50
8	12	110
9	12	80
10	12	80
11	12	80
12	12	80
13	12	80

The results of the analysis of variance in Table 8 show the significance of the reorder point at *p*-value 0.001, and the significance of the interaction between the reorder point and the reorder point at *p*-value 0.000 using Minitab 16. The R-square (adjusted) is 66.03%. Figs. 10(a) and (b) show the contour and surface plots, respectively. The plots indicate the optimal point of maximum and the percent improvement of tabu search over the current practice (OUL) of higher than 6%.

Table 8
Results of an analysis of variance (ANOVA) for the parameters setting of the tabu search approach

Estimated Regression Coefficients for % Improv. of TABU				
Term	Coef	SE Coef	T	P
Constant	−0.62550	3.44857	−0.181	0.858
Reorder point	1.02426	0.27786	3.686	0.001
Number of iterations	−0.01868	0.06069	−0.308	0.761
Reorder point*Reorder point	−0.04679	0.00830	−5.640	0.000
Number of iterations*Number of iterations	−0.00007	0.00033	−0.200	0.844
Reorder point*Number of iterations	0.00299	0.00239	1.254	0.224
S = 0.540301 PRESS = 10.6043				
R-Sq = 72.83% R-Sq(pred) = 50.65%				
R-Sq(adj) = 66.03%				



(a) Contour plot (b) Surface plot

Fig. 10. Results of the % improvement of tabu over the current practice (OUL) according to the parameters setting of the tabu search approach

The box plot and optimal function are analyzed using Minitab. The box plot in Fig. 11 shows the results of the CCD experiment. This corresponds to the combination of factors for the percent improvement of TABU over the current practice (OUL) based on the optimizations. The results of the 13 combinations of factor levels show the best overall performance in case 8, with a reorder point of 12 and several iterations of 110. It is necessary to ensure that the parameters of the tabu search approach are set using the optimal function of Minitab. Fig. 12 shows the optimal point of the percent improvement of the tabu search over the current practice (OUL). The results show an optimal point of 6.3%, with a reorder point of 14 units and 110 iterations.

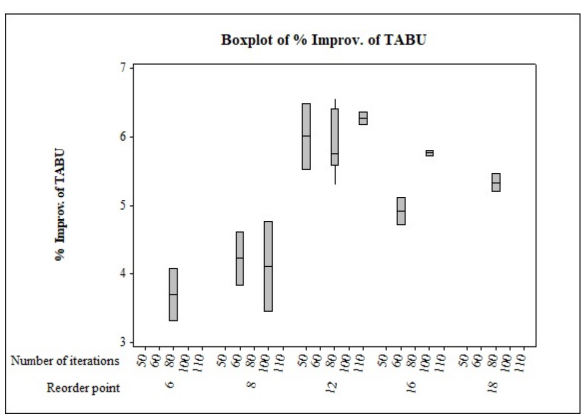


Fig. 11. Result of box plot for % improvement of tabu over the current practice (OUL) according to the parameters setting of the tabu search approach

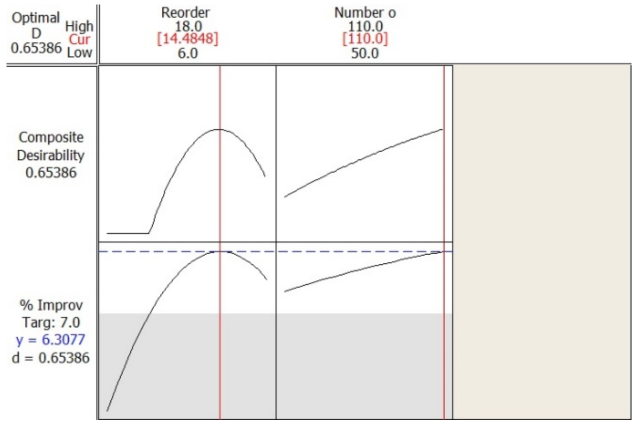


Fig. 12. Optimal point of the % improvement of tabu over the current practice (OUL) according to the parameters setting of the tabu search approach

5.2.3 Performance of tabu search approach

The goal of this section is to assess the effect of the proposed dynamic policy using the tabu search compared to the fixed policy (OUL). The real-world data from the SUT hospital are used to compare the proposed tabu search approach and current practice (OUL). Parameters are set following the discussion above, with a reorder point of 14 units and a number of iterations of 110. Table 9 summarizes some results of the total expected cost with varying numbers of initial blood inventory. The initial blood inventory is determined as the combination of the remaining lifetime of blood inventory ($i = 1, \ldots, m - 1$) within the range of 0–18 units. These results indicate a 6.5% improvement of TABU over the current practice (OUL). The results also indicate that the percent improvement of the dynamic policy using the tabu search approach is slightly less beneficial compared to the OUL when the initial blood units are small. If the initial blood units are larger, the results show an increase in percentage improvement over the OUL. In addition, there is no dependence on the number of initial blood units for each remaining lifetime of the blood inventory ($i = 1, \ldots, m - 1$). The benefit of the proposed dynamic policy based on the tabu search approach can be shown in terms of the expected service level. The results show a slight difference between solutions of the tabu search approach and solutions of the OUL policy, with an average expected service level of 98%. When the number of initial blood units is varied, the benefit in terms of improvement in the expected service level may seem small. However, recall that the expected service level is not related to the initial blood units.

Table 9
Comparison of the solutions of tabu search and the solutions of the OUL with varying number of iterations

Initial blood inventory	OUL (Fixed policy)		Tabu search (Dynamic policy)		% of deviation between OUL and tabu search	
	E[Cost] (in THB)	E[Service level]	E[Cost] (in THB)	E[Service level]	E[Cost] (in THB)	E[Service level]
x[0][0][0][0][0]	164,742	0.98	155,783	0.98	5.44	0.00
x[0][0][0][0][4]	162,742	0.98	153,783	0.98	5.50	0.00
x[0][0][0][0][8]	160,742	0.98	151,783	0.98	5.57	0.00
x[0][0][0][0][12]	158,742	0.98	149,783	0.98	5.64	0.00
x[0][0][0][0][16]	156,742	0.98	148,496	0.97	5.26	1.02
x[0][0][0][16][0]	156,742	0.98	148,496	0.97	5.26	1.02
x[0][0][0][16][4]	153,137	0.98	143,989	0.98	5.97	0.00
x[0][0][0][16][8]	151,283	0.98	142,135	0.98	6.05	0.00
x[0][0][0][16][12]	150,383	0.98	141,347	0.98	6.01	0.00
x[0][0][0][16][16]	149,384	0.98	139,986	0.98	6.29	0.00
x[0][0][16][0][0]	156,742	0.98	148,496	0.97	5.26	1.02
x[0][0][16][0][4]	153,137	0.98	143,989	0.98	5.97	0.00
x[0][0][16][0][8]	151,283	0.98	142,135	0.98	6.05	0.00
x[0][0][16][0][12]	150,383	0.98	141,347	0.98	6.01	0.00
x[0][0][16][0][16]	149,384	0.98	139,986	0.98	6.29	0.00

Table 10
Sensitivity analysis of the efficiency of TABU for different shortage costs

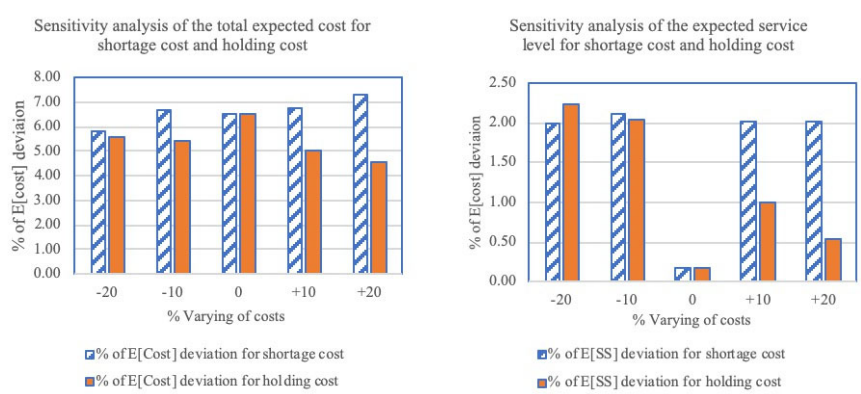
ID	% of varying the shortage cost per unit	E[Cost] (in THB)		% of deviation for E[Cost] between OUL and TABU	E[SS]		% of deviation for E[SS] between OUL and TABU
		OUL	TABU		OUL	TABU	
1	−20	147,631	139,075	5.80	0.960	0.979	1.98
2	−10	149,496	139,508	6.68	0.960	0.980	2.11
3	0	149,931	140,122	6.54	0.980	0.981	0.17
4	+10	153,219	142,813	6.79	0.960	0.979	2.00
5	+20	155,085	143,787	7.28	0.960	0.979	2.00

Table 11
Sensitivity analysis of the efficiency of TABU for different holding costs

ID	% of varying the holding cost per unit	E[Cost] (in THB)		% of deviation for E[Cost] between OUL and TABU	E[SS]		% of deviation for E[SS] between OUL and TABU
		OUL	TABU		OUL	TABU	
1	−20	146,577	138,375	5.60	0.960	0.981	2.22
2	−10	148,967	140,885	5.43	0.960	0.979	2.04
3	0	149,931	140,122	6.54	0.980	0.981	0.17
4	+10	153,748	146,052	5.01	0.960	0.969	0.99
5	+20	156,138	148,999	4.57	0.960	0.965	0.53

5.2.4 Sensitivity analysis of the tabu search approach

Table 10 summarizes the results of the sensitivity analysis for different shortage costs. The results of the proposed policy using the tabu search approach are compared to the policy using OUL under various shortage costs. The tabu search is observed to provide better outcomes for the total expected cost, with a slight difference in the percentage of deviations. The benefit in terms of improvement in the expected service level is slightly greater compared to the results of the OUL policy. Similarly, Table 11 shows the sensitivity analysis results for different holding costs. The proposed policy based on the tabu search approach and the policy based on OUL show the same benefit in terms of improvement in the total expected cost. On the other hand, the tabu search approach presents better outcomes in terms of the expected service level under various holding costs. The performances of the policy based on the tabu search approach are shown in Figs. 13(a) and (b) regarding the total expected cost and the expected service level, respectively. A graphical overview of the sensitivity analysis under different shortage costs and holding costs is presented. Fig. 13(a) shows the benefit in terms of improvement in total expected cost. While the shortage cost is increased or decreased, the tabu search approach still provides greater benefits in terms of the total expected cost. However, either an increase or a decrease in the holding cost results in a slightly reduced benefit in terms of the total expected cost. Fig. 13(b) shows the same results as in Fig. 13(a) from the perspective of the expected service level. The results indicate that the benefit in terms of improvement in the expected service level decreases more when varying the holding cost than when varying the shortage cost.



(a) Total expected cost (in THB) (b) Expected service level

Fig. 13. Sensitivity analysis of the efficiency of tabu search for varying shortage and holding costs

6. Conclusion and Future Research

In this paper, a periodic blood inventory system with the minimum total expected cost under the appropriate expected service level is proposed. The two priority demands (emergency demands and regular demands) are assumed, with an allowance for shortage for regular patients and no allowance for shortage for emergency patients. Two supplies, namely donated blood units with uncertainty and order quantity to the outsourcing provider, are considered. A DP model is developed to determine the solution of the dynamic policy in small case problems for each period over a finite horizon. TABU is developed to determine the solution of the dynamic policy in a real-world problem. The SUT hospital in Thailand is the case study subject. The optimal decision variables, including the order quantity to the outsourcing provider for each remaining lifetime of blood inventory for each period, are determined throughout the tabu search method. The results indicate that the proposed TABU yields better total expected cost under the appropriate expected service level than the current practice (OUL) of the hospital. The results of the computational study suggest that the efficiency of the proposed TABU does not depend on the shortage and holding costs. To benefit from the managerial insight of the TABU, the user should carefully implement the model in a fluctuating demand scenario. The control chart of demands needs to be operated concurrently. The most realistic blood inventory problem considers the complex substitutability between donor blood and recipient requests. In future work, we will consider some binary variables to make a decision given many choices of blood type for transfusion (AB+, AB-, A+, A-, B+, B-, O+, and O-). We will address the substitution so that the excess demand class can be satisfied using other blood type products.

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