Robust Multi-Objective Supply Chain Optimization of Surgical Supplies Considering Costs and Satisfaction of Surgeon, and ranking Suppliers Using ARAS Method

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Abstract

Operating rooms serve as costly wards of hospitals, so any cost reduction, directly affects the total costs. Operating room consumable items are received from the supplier in sterile and nonsterile forms and then sent to the operating room before surgery. If the surgeon requests nonsterile items, these items are sent first to the sterile core, and then the sterilized items are transferred to the operating room. This research reduces logistics costs and increase surgeons' satisfaction in conditions of uncertainty. There may be request during operation due to the patient's condition or other emergencies, like heavy bleeding and items breakdown which statistical distribution estimations are impossible. Hence, a robust approach was used for demands. Also, the parameters affecting supply chain costs and surgeons' satisfaction and the impact of different criteria on the selection of suppliers have been investigated. Moreover, suppliers are different in terms of cost and quality which have a direct effect on the satisfaction of surgeons. Therefore, in this paper, First, the Additive Ratio Assessment (ARAS) method was employed to rank suppliers, Then the augment ε-constraint was used to minimize costs and maximize surgeons' satisfaction. Results indicated purchase cost and demand as the most effective parameters.

Keywords: Surgical Supplies, Robust Optimization, Ranking Suppliers, Sterile Core

1. Introduction

Nowadays, the health chain has received considerable attention concerning cost and its direct connection with human lives. A hospital is one of the most critical parts of the health system, where operating rooms are the most vital wards. Hospitals are generally complex systems in which, policies and decisions are made to ensure providing services and reducing costs [1]. Although the health supply chain has received much attention, few used mathematical models for the health supply chain in the context of surgical items. Furthermore, conflict of interests among beneficiaries' results in Multi-Criteria Decision Making (MCDM) techniques in hospitals. Therefore, the extant study aimed at reducing the cost of the supply chain, including purchase and procurement costs, by modeling the problem of operating room consumable items under uncertainty. On the other hand, this study added to suppliers' levels to allow surgeons to rank suppliers by providing their comments about delivered items to be satisfied with demanded items. In fact, what distinguishes this research from the previous papers are 1. presentation of a two-phase approach for suppliers' selections and planning operating rooms and sterile core, and 2. simultaneous attention to the two issues of auction surgeons' satisfaction with consumable items based on suppliers' ranking and reducing supply chain costs under uncertain conditions. In this research, a purchase capacity was set to buy from suppliers to purchase from the next prior supplier if it is impossible to buy from a supplier with high priority. Moreover, pharmacy capacity, operating rooms, and sterile core were considered for various items to model the real-world situation. Additionally, intraoperative demand is indefinite for each patient. Therefore, there is not any certain distribution of demand regarding patient-specific conditions. Hence, the robust method was used to overcome the uncertainty aspect of the problem.

The present study has been structured as follows: the second section presents a literature review on the related papers. The third section provides the statement of the problem. Mathematical modeling and solution method are given in Section 4. The fifth section includes numerical examples and various analyses. Finally, the last section presents results and further recommendations.

2. Literature review

The hospital supply chain faces some issues, including complexity, uniqueness, operational challenges, difficult inventory tracking, and unpredictable medical supplies request [2] and supplier selection. In this case, Dellaert and Poel [3] extended the EOQ model to a so-called (R,s,c, S) model for inventory control in an academic hospital. Bijvank and Vis [4] assume that most inventory management systems at hospital departments are characterized by lost sales, periodic reviews with short lead times, and limited storage capacity. Zheng [5] compared certain and uncertain inventory systems. The internal supply chain of hospitals links logistic procedures to care services provided for patients. In this case, Agra et al. [6] used a mathematical model and branch-and-cut algorithm to distribute medical products from a warehouse to nursing wards. Bélanger et al. [7] employed a heuristic method for storing items required for the nursing unit. Lapierra and Ruiz [8] presented an approach for improving hospital logistics by coordinating the procurement and distribution operations while respecting inventory capacities. Mojarradi and Mozaffari [9] carried out a study to manage inventories in the medicine supply chain using system dynamics simulation. Hashemi et al. [10] presented a mathematical model for the health supply chain, including production and distribution centers, clinics, and age groups. Ahmadi et al. [11] developed a robust stochastic model for logistic actions in the operating room to minimize costs. Abedini et al. [12] presented a two-stage stochastic optimization model to deal with the uncertainty of patients entering the operating room. On the other hand, expansion of operating room capacity is lower than demand rise, so intrinsic uncertainty of surgical methods and patient entrance complicate the decision-making process. Diamant et al. [13] developed a discrete-time Markov chain model for inventory management of reusable surgical instruments in the operating room and suggested the hospital could reduce the number of these items by using on-site sterilization techniques.

Rossetti and Selandari [14] studied the performance improvement of inventory delivery systems of the hospital, and they used the AHP method to evaluate the replacement of human-based delivery systems with automation by employing economic, technical, and qualitative indicators. Supeekit et al. [15] presented a framework for the measurement of effectiveness and efficiency of healthcare logistics performance. Supeekit et al. [16] employed DEMATEL-modified ANP to investigate the relationships among performance groups by describing the causal relationships among criteria and calculating weights for performance aspects. They determined the most crucial aspects of performance to improve it. Ahmadi et al. [17] had a review paper on inventory management of surgical supplies and sterile instruments in hospitals. They analyzed the literatures and identified the future research directions leading to operating room inventory cost reduction. Mahmoud et al. [18] investigated Access to surgical care as an efficiency issue: using lean management in French and Australian operating theatres. They considered different types of waste in operating theatres and a series of successful tactics to increase efficiency and eliminate wastefulness. Lonner et al. [19] optimized surgical trays to improve operating room efficiency and reduce costs in instrument processing in total joint arthroplasty. Their results showed that lean methodology was useful to eliminate redundant or underutilized instruments in total joint arthroplasty, improving surgical efficiency and generating substantial cost savings. Bhosekar et al. [20] developed a discrete event simulation model for coordinating inventory management and material handling in hospitals and operating rooms. Numerical analysis showed that coordination of inventory management of surgical instruments and material handling decisions could improve the service level provided by operating rooms. O'Mahony et al. [21] used lean six sigma to redesign the supply chain to the operating room department of a private hospital. They reduced costs and release

nursing time to care. Li et al. [22] presented a robust multi-objective mathematical model for scheduling the operation room for emergency surgeries, considering the priority of surgeries to minimize the costs associated with elective and emergency surgeries and maximize the number of scheduled surgeries. Yalamanchi et al. [23] verified association of operating room costs and hospital waste with head and neck surgical instrumentation optimization. For this purpose, they used the data of a 3-years period for instrument processing, utilization, and associated institutional direct costs. Humphreys et al. [24] had an Overview of Hospital Capacity Planning and Optimization and identified the state of the art and gaps in the body of research. Then they created a holistic framework for understanding hospital capacity planning and optimization, in terms of physical elements, process, and governance. Furthermore, they presented several directions for future research. Neve and Schmidt [25] developed two models, optimizing either cost or service level for a periodic-review, base-stock inventory policy for a hospital, and considered actual net inventory and recorded net inventory for system performance measures.
In the context of supply chain management, supplier selection can be defined as the process by which organizations score and evaluate a range of alternative suppliers [26]. Therefore, Stević et al. [27] developed the multi-criteria method of MARCOS o select sustainable suppliers in healthcare industries. They conducted a case study (a polyclinic) that included a ranking of eight alternatives concerning 21 criteria for all aspects of sustainability. Orji and Ojadi [28] employed MCDM approaches to analyze the relationships between response strategies to the COVID-19 Pandemic and used Triple-Bottom-Line criteria for sustainable supplier selection (SSS). Quality, cost, use of personal protective instruments, and IT were particularly introduced as the most significant factors for customer demand prediction while performing SSS during COVID-19 Pandemic. Moreover, the efficiency of the proposed method was approved based on the comparative analysis of other MCDM methods. In this regard, during the Covid period Biswas and Das [29] examined five obstacles of restrictions such as other human resources, implementation of local laws, carrying out transportation, carrying out raw materials and cash flow for the manufacturing sectors of India during the quarantine period. They proposed a method for analyzing fuzzy hierarchical analysis (Fuzzy-AHP) using triangular fuzzy for pairwise comparison matrices. It has been seen that human forces have a higher weight barrier than others. In addition, they also examine management concepts that will be useful for manufacturing departments to make appropriate decisions. Fazlollahtabar and Kazemitash [30] represented the relation between information systems and green supplier selection. They used best worst method, eight criteria, and 31 sub-criteria for decision-making.
To the best of our knowledge, there is no paper which presented a two-phase approach for supplier selection of consumable items and planning the operating rooms and sterile core to minimize total cost and maximize the surgeon's satisfaction under uncertain conditions. Therefore, we consider to this issue, and use a MCDM method for supplier selection for the first phase, and develop a new robust bi-objective mathematical model for the second phase to have better results.

3. Problem Description

In this research, a supply chain, including suppliers, Central Storage (CS), pharmacy, sterile core, and operating rooms is considered. There are different suppliers in terms of cost and quality of items, and the difference directly affects the satisfaction of surgeons. Hence, suppliers are ranked based on the various indicators and surgeons' ranks.
In this research, the required equipment for the operating room includes necessary consumables for surgeries that do not return to the sterile and reuse a cycle after they were consumed. These items are purchased within two factories, sterile and nonsterile items. Only the sterile items are used in the operating rooms to protect the health of the patient; hence, the sterile core is before the operating room, regarding sterilization of purchase nonsterile items.

The items purchased from suppliers are stored in the central store next to the pharmacy in this study. Then the items were transferred to pharmacy shelves (you can forgo the cost and displacement distance of items between CS and pharmacy). The required items are prepared based on a list called preferred card and surgeon order, then sent to operating rooms before surgery (the nonsterile items are sterilized before being sent to the operating room). There may be some shortcomings during operations in the real world. The shortcomings are caused by item breakdown, errors of operating room staff, or emergency need for more items. In this case, a nurse brings the items from the pharmacy during the operation and then takes them to the operating room after were sterilized. Figure 1 shows more details of the studied supply chain. In this figure, black-colored arrows indicate the displacement of items before operation. Dotted arrows show the case of more items required during the operation.
A maximum inventory capacity is considered per item entered at the locations. Moreover, a maximum rate is considered for purchase from each supplier, which is called purchase capacity. The problem under consideration here includes different operating rooms that their demands are met by sending items to each operating room based on the surgeon's request in the form of a pre-operating preferred list. In case of an intraoperative emergency (e.g., sudden bleeding, items breakdown, error of operating room staff, etc.) and more need for items, the nurse goes to the pharmacy to get the required items. If the items are primary nonsterile items, they must be sent to the sterile core and then transferred to the operating room. The intraoperative requests do not have a certain statistical distribution. On the other hand, procurement costs are different between pre-operation and intraoperative steps, so the latter is more costly. To solve the problem, pessimistic, probabilistic, and optimistic scenarios were designed based on Mulvey's robust method. Figure 1 depicts an overview of the case.

Figure 1. Overview of Problem

4. Modeling and Solution Method

In this section, assumptions, indices, parameters, and variables are expressed and introduced, and then a mathematical model is proposed. The model was designed based on the following assumptions:

- The purchase items are divided into sterile and nonsterile groups. The factory sterile items do not require sterilization in the sterile core.
- All of the items required for an operation are kept in one cart.
- The items are kept in the pharmacy and then sent to operating rooms.
- The items are prepared before operation based on the surgeon-preferred card and then sent to operating rooms. The required intraoperative items are taken from the pharmacy by a nurse.
- Purchase from each supplier is based on a certain capacity.
- Demand is in two categories: pre-action demand is definite and intra-demand demand is indefinite.
- Purchasing from each supplier has a specific ceiling for each item.
- Supplier evaluation criteria include purchase cost, item quality, after-sales service, item delivery time.
- Orders from suppliers are made under definite conditions.
- Items are delivered to the operating room after sterilization.
- A specific type of surgery is unconsidered in this study and is generally considered.

4.1. Mathematical Modeling

The model of the study was developed for robust optimization of multi-objective supply chain problems of surgical supplies by consideration of surgeon satisfaction and ranking suppliers. The following symbols were used in the model:

Indices and Sets:

i: The index of sterile items purchased from the factory (e.g., syringe, sterile gas) $i \in I$

i': The index of nonsterile items purchased from the factory (e.g., sampling swaps, bone-repair pins) $i' \in I'$

k: The index of operating room $k \in K$

v: The index of suppliers $v \in V$

0: Pharmacy

$0'$: Sterile core

s, s' : Indices of scenarios $s', s \in \Omega$

Parameters:

D_{ik}: Demand for sterile item i in operating room k

$D_{i'k}$: Demand for a nonsterile item i' in operating room k

D'_{ik}: Demand for intraoperative item i in operating room k

$D'_{i'k}$: Demand for an intraoperative item i' in operating room k

CL_{ik}: Cost of supply and sending sterile item i from the pharmacy before the operation to operating room k

$CL_{i'0'}$: Cost of supply and sending the nonsterile item i' from the pharmacy before the operation to sterile core

$CL_{i'k}$: Cost of supply and sending the item i' after sterilization and before operation from sterile core to operating room k

FP_{0k}: Fixed price of transferring a sterile item from factory to pharmacy, and operating room k during operation

$\mathrm{FP}_{00'}$: Fixed price of transferring a nonsterile item from pharmacy to sterile core during operation

$\mathrm{FP}_{0'k}$: Fixed price of transferring a sterile item from sterile core to operating room k during operation

CAP_{i0}: Capacity of pharmacy for sterile items i

$CAP_{i'0}$: Capacity of pharmacy for nonsterile item i'

$CAP_{i'0'}$: Capacity of sterile core per nonsterile item i'

CAP_{ik}: Capacity of operating room k per sterile item i

$CAP_{i'k}$: Capacity of operating room k per nonsterile item i'

C_{iv}: Purchase capacity of sterile item i from supplier v

$C_{i'v}$: Purchase capacity of the sterile item i' from supplier v

CB_{iv} : Cost of buying sterile item i from supplier v

$CB_{i'v}$: Cost of buying the sterile item i' from supplier v

UP: Variable cost of urgent preparation of items for the shortage per unit of product

CE: Cost of emergence preparation of items for the shortage per unit of product

p_s and $p_{s'}$: Probability of scenario s and s' for the demand of operating room k

A_v: Coefficient of surgeon satisfaction with products provided by supplier v

M: Very large positive number

Variables:

Y_{ik} : Number of sterile items i that are sent to operating room k before operation based on the surgeon-preferred list through pharmacy items cart

Q_{iv}: Quantity of buying sterile item i from supplier v

$Q_{i'v}$: Quantity of buying the primary nonsterile item i' from supplier v

$T_{i'0'}$: Number of primary non-sterile items i' sent from pharmacy to sterile core before the operation

$O_{i'0'k}$: Quantity of item i' taken from the sterile core before the operation for operating room k
$W_{i0k}{}^{s}$: Quantity of sterile item i taken from the pharmacy during operation for operating room k under the scenario s
$W_{i'0'k}{}^{s}$: Quantity of primary nonsterile item i' from sterile core operating room k during operation for under the scenario s
$N_{i'0'}{}^{s}$: Quantity of primary non-sterile item i' sent from pharmacy to sterile core under the scenario s
$B_{i0k}{}^{s}$: 1, if the sterile item i must be taken from the pharmacy during operation in operating room k, 0, otherwise under the scenario s
$B_{i'00'}{}^{s}$: 1, if primary non-sterile item i' must be taken from the pharmacy during operation in operating room k, 0, otherwise under the scenario s
$B_{i'0'k}{}^{s}$: 1, if sterile item i' must be taken from the sterile core during operation in operating room k, 0, otherwise under the scenario s
θ: Positive number

$$min\, F_1 = OC + BC + EC_s \tag{1}$$

$$OC = \sum_{i \in I}\sum_{k \in K} CL_{ik} \times Y_{ik} + \sum_{i' \in I'} CL_{i'0'} \times T_{i'0'} + \sum_{i' \in I'}\sum_{k \in K} CL_{i'k} \times O_{i'0'k}$$

OC: Cost of preparation and transferring items from pharmacy to operating room before operation

$$BC = \sum_{i \in I}\sum_{v \in V} CB_{iv} \times Q_{iv} + \sum_{i' \in I'}\sum_{v \in V} CB_{i'v} \times Q_{i'v} \tag{2}$$

BC: Cost of buying items from suppliers

$$EC_s = \sum_{s \in \Omega}\sum_{i \in I}\sum_{k \in K}\left(FP_{0k}\, B_{i0k}{}^{s} + UPW_{i0k}{}^{s}\right) + \sum_{s \in \Omega}\sum_{i' \in I'}\left(FP_{00'}\, B_{i'00'}{}^{s} + CE\, N_{i'0'}{}^{s}\right) \tag{3}$$

$$+ \sum_{s \in \Omega}\sum_{i' \in I'}\sum_{k \in K}\left(FP_{0'k}\, B_{i'0'k}{}^{s} + CE\, W_{i'0'k}{}^{s}\right)$$

EC_S: Cost of preparation and transferring items from pharmacy to operating room during operation

$$\max F_2 = \sum_{v}\sum_{i}(A_v \times Q_{iv}) + \sum_{v}\sum_{i'}(A_v \times Q_{i'v}) \tag{4}$$

The second objective function maximizes surgeon satisfaction.

$\boldsymbol{s.to}$ (5)

$$\sum_{v \in V} Q_{iv} \le CAP_{i0} \qquad \forall i \in I$$

$$\sum_{v \in V} Q_{i'v} \le CAP_{i'0} \qquad \forall i' \in I' \tag{6}$$

$$N_{i'0'}{}^{s} + T_{i'0'} \le CAP_{i'0'} \qquad \forall i' \in I', s \in \Omega \tag{7}$$

$$Y_{ik} + W_{i0k}{}^{s} \le CAP_{ik} \qquad \forall k \in K, s \in \Omega, i \in I \tag{8}$$

$$O_{i'0'k} + W_{i'0'k}{}^{s} \le CAP_{i'k} \qquad \forall k \in K, i' \in I', s \in \Omega \tag{9}$$

Constraints (5)-(9) indicate the maximum capacity of locations, including pharmacy, sterile core, and operating room.

$$Y_{ik} + \ge D_{ik} \qquad \forall i \in I\ , k \in K \tag{10}$$

$$W_{i0k}{}^{s} \ge D'^{\,s}_{ik} \qquad \forall i \in I\ , k \in K, s \in \Omega \tag{11}$$

$$O_{i'0'k} \ge D_{i'k} \qquad \forall i' \in I', k \in K \tag{12}$$

$$W_{i'0'k}{}^{s} \ge D'^{\,s}_{i'k} \qquad \forall i' \in I', k \in K, s \in \Omega \tag{13}$$

Constraints (10)-(13) express the demand estimation based on the sum of items entered into the operating room before and during operation.

$$\sum_{k \in K} (Y_{ik} + W_{i0k}{}^{s}) \le \sum_{v} Q_{iv} \qquad \forall i \in I \ , s \in \Omega \tag{14}$$

$$T_{i'0'} + N_{i'0'}{}^{s} \le \sum_{v} Q_{i'v} \qquad \forall i' \in I', s \in \Omega \tag{15}$$

$$\sum_{k \in K} (O_{i'0'k} + W_{i'0'k}{}^{s}) = T_{i'0'} + N_{i'0'}{}^{s} \qquad \forall i' \in I', s \in \Omega \tag{16}$$

Constraints (14)-(16) are used to ensure the number of items (primary sterile and nonsterile) taken from the pharmacy and sterile core does not exceed the pharmacy and sterile core inventory.

$$B_{i0k}{}^{s} \le W_{i0k}{}^{s} \le B_{i0k}{}^{s} D'_{ik}{}^{s} \qquad \forall i \in I \ , k \in K \ , s \in \Omega \tag{17}$$

$$B_{i'00'}{}^{s} \le N_{i'0'}{}^{s} \le B_{i'00'}{}^{s} M \qquad \forall i' \in I', k \in K, s \in \Omega \tag{18}$$

$$B_{i'0'k}{}^{s} \le W_{i'0'k}{}^{s} \le B_{i'0'k}{}^{s} D'_{i'k}{}^{s} \qquad \forall i' \in I' \ , k \in K, s \in \Omega \tag{19}$$

$$B_{i0k}{}^{s} \ , B_{i'00'}{}^{s} \ , B_{i'0'k}{}^{s} \in \{0,1\} \qquad \forall s \in \Omega, i \in I \ , i' \in I', k \in K \tag{20}$$

Constraints (17)-(18) are used to model the fixed cost of walking distances traveled by nurses to pick up an item from other locations during operation.

$$Q_{iv} \le C_{iv} \qquad \forall i \in I, v \in V \tag{21}$$

$$Q_{i'v} \le C_{i'v} \qquad \forall i' \in I, v \in V \tag{22}$$

This constraint indicates the purchasing capacity of buying from each supplier

$$EC_{s} - \sum_{s \in \Omega} p_{s} \ EC_{s} + \theta_{s} \ge 0 \qquad \forall s \in \Omega \tag{23}$$

$$\begin{aligned} &\sum_{s \in \Omega} \sum_{i \in I} \sum_{k \in K} \left(FP_{0k} \ B_{i0k}{}^{s} + UP \ W_{i0k}{}^{s} \right) + \sum_{s \in \Omega} \sum_{i' \in I'} \left(FP_{00'} \ B_{i'00'}{}^{s} + CE \ N_{i'0'}{}^{s} \right) + \\ &\sum_{s \in \Omega} \sum_{i' \in I'} \sum_{k \in K} \left(FP_{0'k} \ B_{i'0'k}{}^{s} + CE \ W_{i'0'k}{}^{s} \right) - \sum_{s \in \Omega} P_{s} \Big(\sum_{i \in I} \sum_{k \in K} \left(FP_{0k} \ B_{i0k}{}^{s} + UP \ W_{i0k}{}^{s} \right) + \\ &\sum_{i' \in I'} \left(FP_{00'} \ B_{i'00'}{}^{s} + CE \ N_{i'0'}{}^{s} \right) + \sum_{i' \in I'} \sum_{k \in K} \left(FP_{0'k} \ B_{i'0'k}{}^{s} + CE \ W_{i'0'k}{}^{s} \right) + \ \theta_{s} \Big) \ge 0 \end{aligned} \tag{24}$$

$$\theta_{s} \ge 0 \qquad \forall \ s \in \Omega \tag{25}$$

We use robust modeling to deal with uncertainty.

4.1.1. Robust Modelling

The scenario-based robust approach was introduced by Mulvey et al. [31]. They developed a model in which the indeterministic parameters were defined with a set of scenarios. In this optimization, if the solution is close to an optimal solution based on all defined scenarios, then the solution will be robust. In addition, the model is called a robust model if it is feasible based on all defined scenarios. The expressed definition indicates the robustness of the solution and quality. In other words, quality robustness means problem feasibility and not leaving the response space.

Consider a linear programming model with the following stochastic parameters:

$$\min C^{T} x + d^{T} y \tag{26}$$

$s.to$

$$Ax = b \tag{26.1}$$

$$Bx + Cy = e \tag{26.2}$$

$$x \ge 0, y \ge 0 \tag{26.3}$$

Finally, the stochastic robust programming model is formulated as follows:

$$min \sum_{s \in \Omega} p_{s} \left(\xi_{s} \right) + \lambda \sum_{s \in \Omega} p_{s} \left[(\xi_{s} - \sum_{s' \in \Omega} p_{s'} \xi_{s'}) + 2\theta_{s} \right] + \omega \sum_{s \in \Omega} p_{s} \eta_{s} \tag{27}$$

$$s.t$$
$$Ax = b, \tag{27.1}$$
$$B_s x + C_s y_s + \eta_s = e_s \qquad \forall s \in \Omega \tag{27.2}$$
$$\xi_s - \sum_{s\in\Omega} p_s \xi_s + \theta_s \ge 0 \qquad s \in \Omega \tag{27.3}$$
$$\theta_s \ge 0, \quad x \ge 0, \; y_s \ge 0, \; \eta_s \ge 0, \qquad s \in \Omega \tag{27.4}$$

Study the paper written by Mulvey et al. (1995) for more details.
Equation (3) converts to the following form based on Mulvey's mode:

$$min \sum_{s\in\Omega} p_s \left(\xi_s\right) + \lambda \sum_{s\in\Omega} p_s \left[(\xi_s - \sum_{s'\in\Omega} p_{s'} \xi_{s'}) + 2\theta_s \right] \tag{28}$$

Then, we will have

$$min \sum_{s\in\Omega} p_s \left(EC_s\right) + \lambda_1 \sum_{s\in\Omega} p_s \left[\left(EC_s\right) - \sum_{s'\in\Omega} p_{s'} \left(EC_{s'}\right) + 2\theta_s \right] \tag{29}$$

Finally, we will have

$$\begin{aligned} EC_s = & \sum_{s\in\Omega} p_s (\sum_{i\in I}\sum_{k\in K} \left(FP_{0k}\, B_{i\,0k}{}^{s} + UPW_{i\,0k}{}^{s} \right) + \sum_{i'\in I'} \left(FP_{00'}\, B_{i'00'}{}^{s} + CE\;N_{i'0'}{}^{s} \right) + \\ & \sum_{i'\in I'}\sum_{k\in K} \left(FP_{0'k}\, B_{i'0'k}{}^{s} + CEW_{i'0'k}{}^{s} \right)) + \lambda (\sum_{s\in\Omega} p_s \Big(\sum_{i\in I}\sum_{k\in K} \left(FP_{0k}\, B_{i\,0k}{}^{s} + UPW_{i\,0k}{}^{s} \right) + \\ & \sum_{i'\in I'} \left(FP_{00'}\, B_{i'00'}{}^{s} + CE\;N_{i'0'}{}^{s} \right) + \sum_{i'\in I'}\sum_{k\in K} \left(FP_{0'k}\, B_{i'0'k}{}^{s} + CEW_{i'0'k}{}^{s} \right)) - \\ & \sum_{s'\in\Omega} p_{s'} (\sum_{i\in I}\sum_{k\in K} \left(FP_{0k}\, B_{i\,0k}{}^{s'} + UPW_{i\,0k}{}^{s'} \right) + \sum_{i'\in I'} \left(FP_{00'}\, B_{i'00'}{}^{s'} + CE\;N_{i'0'}{}^{s'} \right) + \\ & \sum_{i'\in I'}\sum_{k\in K} \left(FP_{0'k}\, B_{i'0'k}{}^{s'} + CEW_{i'0'k}{}^{s'} \right)) + 2\theta_s) \end{aligned} \tag{30}$$

Robust modeling is shown as follows:

$$\min F_1 = OC + BC + EC_s$$

Then, we consider constraints (5)-(25).

4.2. Solution Method

Figure 2 illustrates the solution stages of the considered problem.

Figure 2. Solution stages

4.2.1. Additive Ratio Assessment (ARAS) Method

The decision-making ARAS method was introduced by Zavadskas and Turskis [32]. The best alternative in this method is far from negative factors while close to positive factors. ARAS ranks alternatives through six stages:

Stage 1) forming a decision-making matrix

To form a decision table, options, indicators (criteria), indicators of weight indicators and the status of each option in each of the indicators must be determined. The decision matrix is shown below.

$$X = \begin{pmatrix} x_{01} & \cdots & x_{01} & \cdots & x_{0n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mj} & \cdots & x_{mn} \end{pmatrix} \quad i = \overline{0,m};\ j = \overline{1,n} \tag{31}$$

In Equation (31), the X decision matrix, m the number of options, and n the number of criteria describing each option x_{ij} represent the performance of option i in terms of criteria j.

Stage 2) normalization or un-scaling decision-making matrix.

At this stage, the decision matrix should be normalized based on the gender of the criteria. The normalized decision matrix is shown below.

$$\bar{X} = \begin{pmatrix} \overline{x_{01}} & \cdots & \overline{x_{0j}} & \cdots & \overline{x_{0n}} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \overline{x_{i1}} & \cdots & \overline{x_{ij}} & \cdots & \overline{x_{in}} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \overline{x_{m1}} & \cdots & \overline{x_{mj}} & \cdots & \overline{x_{mn}} \end{pmatrix} i = \overline{0,m};\ j = \overline{1,n} \tag{32}$$

Stage 3) weighing the normalized decision-making matrix

In this step, the balanced normalized decision matrix must be calculated. The weighted normalized decision matrix is shown as follows:

$$\bar{X} = \begin{pmatrix} x_{01} & \cdots & x_{0j} & \cdots & x_{0n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mj} & \cdots & x_{mn} \end{pmatrix} i = \overline{0,m};\ j = \overline{1,n} \tag{33}$$

In the above matrix (x_{ij})ˆis the weighted normal value of the criteria, the relationship of which is defined below.

$$\sum_{j=1}^{n} W_j = 1 \tag{34}$$

It is possible to evaluate the criteria with a weight of $0 < W_j < 1$, weights are a subjective criterion that is determined by the decision maker. In this study, the weight of the criteria was determined by Shannon entropy method.

The normalized normalized values of the criteria are calculated using the following equation:

$$x_{ij} = \overline{x_{ij}} W_j;\quad i = \overline{0,m} \tag{35}$$

Stage 4) calculating the optimal value

Using the following equation, we calculate the optimal value:

$$S_i = \sum_{j=1}^{n} x_{ij} \qquad ; i = \overline{0,m} \tag{36}$$

Where Si is the value of the optimization function of option i .
Stage 5) measuring degree of optimality and utility of alternatives
After calculating the optimal value of each of the options in this step, the degree of usefulness or desirability of the options is calculated using the following equation.

$$K_i = \frac{S_i}{S_0}; \ i = \overline{0,m} \tag{37}$$

Which is S_0 actually the most ideal value among the optimization values calculated in the previous step.
Stage 6) ranking alternatives
In this step, using the degree of usefulness of each option, they are ranked. In fact, the options are ranked in descending order of their usefulness values.

4.2.2. Augment ε-constraint method

Interactive methods used to solve multi-objective problems differ based on the stage in which the decision-maker enters the decision-making process. In this case, the Augment ε-constraint method is the most widely used [33]. To solve the multi-objective model based on the Augment ε-constraint method in this research, the first objective of the model, which is cost minimization, is taken into account as the main objective, while the second objective is added to the constraint.

5. Sensitivity Analysis

This part of the study analyzed the sensitivity of parameters. To do this, an example with small dimensions was examined regarding the effect of various parameters, including the cost of purchase, operating expense, demand, purchase capacity, and coefficient of surgeons' satisfaction. In the first phase, suppliers were ranked based on the ARAS method. In the examined sample, three suppliers were considered, and the augment ε-constraint method was used within two phases.
According to the stages mentioned in section 3.2.1, the ranking was done for three suppliers and three criteria. The weight of suppliers was measured by using the Shannon entropy weighting technique. The considered criteria included cost, quality, delivery time, and after-sales services, of which cost and delivery time were negative while quality and after-sales services were positive. Table 1 reports the alternative and indicators of the problem, as well as the material and weight of indicators. The cost and delivery time indicators were negative, while the other indicators were positive.

Table 1. Decision-making table

The optimal value is measured for each indicator based on the first stage, and the obtained value is reported in Table 2.

Table 2. Decision-making matrix by determining the optimal value

As shown in Table 3, the normalized decision-making matrix is calculated in the second stage.

Table 3. Normalized decision-making matrix

In the third stage, the weighted normalized matrix is calculated, and the results are reported in Table 4.

Table 4. Weighted normalized decision-making matrix

Optimal value and optimality degrees of alternatives are calculated through stages 5-6, and results are reported in Table 5. Ranking results have been proposed herein.

Table 5. Matrix of optimal value and optimality degrees of alternatives

Suppliers were ranked as follows:

$$v_3 > v_2 > v_1$$

In the second phase, the problem was solved by using Augment ε-constraint method. It is worth noting that the considered example included i=2, t=2, v=3, k=2 dimensions. Table 6 reports different objective values of this example.

Table 6. Different objective values of Example 1 using Augment ε-constraint method through

For better understanding, the example has been illustrated in figures 2, 3, and 4 before performing sensitivity analysis. The mentioned example included three scenarios that are presented in a separate figure. The probability of occurrence of each scenario is randomly selected so that the optimistic scenario with probability ($p = 0.25$) is considered probable scenario with probability ($p = 0.50$) The pessimistic scenario with probability ($p = 0.25$) is considered.

Figure 3. The first scenario of solving an example of the problem with small dimensions

Figure 3 shows the inventory flow from suppliers to the operating room. As mentioned before, we have two operating rooms with different demands. The pre-operation demand of operating room 1 for sterile items equals $D_{i1} = \begin{pmatrix} 8 \\ 12 \end{pmatrix}$, in which the first row represents the demand for type 1 sterile items and the second row indicates the demand for type 2 sterile items. Moreover, the pre-operation demand of operating room 1 for factor nonsterile items is shown as $D_{i'1} = \begin{pmatrix} 5 \\ 4 \end{pmatrix}$ in which the first row represents the demand for type one nonsterile item and the second row indicates the demand for type-two nonsterile items. Demand for sterile items type one and two during operation in an operating room k_1 equaled 2 and 2, respectively ($D'_{i1} = \begin{pmatrix} 2 \\ 2 \end{pmatrix}$), while demand for primary nonsterile items type one and type two equaled 1 and 3 ($D'_{i'1} = \begin{pmatrix} 1 \\ 3 \end{pmatrix}$), respectively during operation for operating room k_1.

The pre-operation demand for type one and type two items in the operating room is estimated to be 8 and 12, respectively ($Y_{ik} = \begin{pmatrix} 8 \\ 12 \end{pmatrix}$) in which the first row represents the estimated demand for item type one, and the second row indicates the demand for item type twp. The demand for primary nonsterile items equaled 4 and 5, respectively ($O_{i'0'1} = \begin{pmatrix} 5 \\ 4 \end{pmatrix}$). The estimated demand for sterile items during operation equaled $W_{i'01} = \begin{pmatrix} 2 \\ 2 \end{pmatrix}$ in operating room 1, and the estimated demand for nonsterile items during operation equaled $W_{i'0'1} = \begin{pmatrix} 1 \\ 3 \end{pmatrix}$ in operating room 1. In the vectors mentioned above, the first and second rows represent the estimated demand for items type one and type two, respectively. In this case, the demand for operating room k_2 was indicated based on the following indices: $D_{i2}, D_{i'2},\ D'_{i2},\ D'_{i'2};\ N_{i'0'} = \begin{pmatrix} 3 \\ 6 \end{pmatrix}$ indicates the estimated sum of primary nonsterile items, required during operation in both operating rooms, transferred from pharmacy to sterile core for sterilization; $T_{i'0'} = \begin{pmatrix} 11 \\ 9 \end{pmatrix}$ indicates an estimated sum of pre-operation primary nonsterile items, required in both operating rooms, transferred from pharmacy to sterile core for sterilization. The following figures indicate further details. Figures 4 and 5 depict scenarios 2 and 3, respectively.

Figure 4. The second scenario of solving an example of the problem with small dimensions

Figure 5. The third scenario of solving an example of the problem with small dimensions

Different sensitivity analyses have been proposed for the considered problem.

Figure 6. The effect of changes in purchase costs on objective function' values

As seen in Figure 6, an increase in purchase cost makes the first objective function ascending since it minimizes costs, so an increase or decrease in costs affects this function directly. However, a decline in costs leads to ascending direction of the second objective. As seen in the figure, a 100% decline in this value causes a high rise in cost. However, an increase in costs does not lead to any considerable rise in changes in the second objective function. The reason stems from the requirement of operating room items that must be accessible for surgeons even if they are expensive.

Figure 7. The effect of changes in operating expenses on objective functions' values

Figure 7 illustrates the effect of changes in operating expenses (cost of commuting to sterile core or pharmacy during the operation) on two objective functions. As seen in this figure, a rise or decline in the considered parameter cause no change in the first and second objective functions. It can be explained based on the impressibility of operating expenses compared to purchase costs.

Figure 8. The effect of changes in demand values on objective functions' values

Figure 8 indicates the effect of changes in demand on both objective functions. In the mentioned changes, the demand for both items is increased or decreased simultaneously. As can be seen in this figure, a decline in demand leaves a linear effect on values of the objective function, while an increase greater than 25% in demand leads to the unfeasibility of the problem. The case seems logical since the demand exceeds the items inventory in the pharmacy.

Figure 9. The effect of changes in purchase capacity on objective functions' values

Figure 9 shows the impact of changes in purchase capacity on both studied objective functions. The changes occurred in both items provided by all suppliers simultaneously. Purchase cost means a limitation in the number of items sent by the supplier. According to Figure 9, an increase in purchase capacity leads to a rise in the numbers of first objective functions, while a decline greater than 25% in this parameter makes the problem infeasible. The case seems logical since the inventory of items becomes less than demand. In this case, surgery cannot be performed.

Figure 10. The effect of changes in satisfaction of the second supplier on objective functions' values

Figure 10 shows the effect of changes in the coefficient of satisfaction with the second supplier on both objective functions. The coefficient of satisfaction with suppliers has been assumed as a number within the 1-100 scale based on the ARAS ranking method. For instance, Figure 10 indicates the second rank of the second supplier with an assigned coefficient of 70. According to this figure, an increase of greater than 40% in satisfaction with the second supplier makes the problem infeasible.

Figure 11. The effect of changes in satisfaction of the third supplier on the objective functions' values

According to Figure 11, increased or decreased satisfaction with the third supplier directly affects the reduction of surgeons' satisfaction. However, this effect on the first objective function is minor because a decline in satisfaction with a third supplier makes other suppliers prior, so customers prefer to buy items from other suppliers.

Table 7. Comparison between values of the first objective function in different scenario probabilities

Table 7 reports five cases calculating Pareto front values of the first objective function, minimum value, maximum value, standard deviation, and mean value based on the different probabilities of scenarios. In the five cases, (p1=0.25, p2=0.5, p3=0.25), (p1=0.33, p2=0.33, p3=0.33), (p1=1, p2=0, p3=0), (p1=0, p2=1, p3=0), and (p1=0, p2=0, p3=1) modes have been defined for each case, respectively. Accordingly, the least value of the first objective function is seen in the third mode of (p1=1, p2=0, p3=0). Moreover, the higher value of the first objective function is associated with the fifth mode. It means that if the whole demand for items during the operation occurs in the optimistic scenario, then the lowest cost is imposed on the system, while the highest cost is imposed if the case occurs in the pessimistic scenario. The shortest distance from the mean value is seen in the first mode, while the longest distance is in the third mode. Additionally, the standard deviation rate was constant in all Pareto points.
Table 8 compares the deterministic and non-deterministic modes for different samples. Accordingly, values of the objective function in the deterministic sample are less than the robust mode in each sample. In robust cases, the model responds to the non-deterministic demand under different scenarios and assigns those amounts to prepare and purchase these values, which results in higher costs. Meanwhile, the second objective function depends also on the same values, so there is also an increase in the second objective function as in the first one. In the deterministic case, the solution time of the fourth example onwards has been extended drastically. Moreover, in the non-deterministic mode of the third example, solution

time has been dramatically extended compared to the deterministic model. The larger the size of the problem, the more complicated the model will be. The case occurs sooner in non-deterministic problems since several constraints and parameters are added to these problems. It should be noted that the computer used is with the processor Intel(R)Core (TM) i5– 5005U CPU@2.00GHz and Microsoft Windows 10 operating system.

Table 8. Comparative results of deterministic and non-deterministic methods

6. Conclusions and Recommendations

The extant study examined a two-objective supply chain programming for surgical supplies by considering suppliers' rank under uncertainty. The studied items were divided into sterile and nonsterile items sent to the operating room at the surgeon's request. All items should be sterilized and then sent to the operating room. Therefore, a sterile core must exist in the hospital. The nonsterile factory items are sterilized in the sterile core and then sent to the operating room. Under emergency conditions, some items must be sent to the operating room during the operation. The emergency case may occur due to patients' needs, items breakdown, staff error, bleedings, and unpredicted problems, which may be different per case. Hence, there is not a certain distribution for demand. Mulvey's robust method was used to encounter uncertainty and discreet non-deterministic data of the problem.

The problem was programmed within two-phase by using the multi-criteria decision-making method of ARAS and Augment ε-constraint. Regarding the conflict between logistic managers and surgeons, the present study strived to reduce the costs of surgical supplies and minimize the second objective function of surgeons' satisfaction simultaneously by ranking suppliers. From the viewpoint of surgeons, suppliers are distinguishable in terms of quality and cost, so these differences directly affect their job. Therefore, it can be concluded that the managerial perspective of this study is from the perspective of operating room management and efforts to address the challenges of providing items and surgeons' satisfaction. Results obtained from numerical examples and sensitivity analysis indicated that the model assigned higher value to objective functions in non-deterministic mode rather than in the deterministic case. Moreover, sensitivity analysis showed the higher sensitivity of the model to the demand and cost values that leave the highest effects on the values of objective functions. Solution time was extended from the fourth example onwards in both deterministic and non-deterministic modes concerning the effect of enhanced dimensions of the problem on the solution time. Further studies can consider the following recommendations:

- Considering other operating room supplies to define new problems, such as surgical instruments that can be reused or reversible in a sterile cycle
- Adding the number of storage warehouses to maintain surgical equipment
- Integrating the problem of sterilization timing and consumables of the operating room to understand the importance of the surgery ward
- Considering temporary storage warehouses for rapid access of staff to intraoperative equipment
- Considering the emergency operations to develop uncertain conditions

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Captions of tables:

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Table 1. Decision-making table

Option- Criteria	After-sales service	Delivery time	Quality	Cost
Criteria type	Positive	Negative	Positive	Negative
Weight criteria	0.20522	0.31714	0.43716	0.0429
Supplier 1	1	36	1	15
Supplier 2	3	72	3	18
Supplier 3	5	24	1	18

Table 2. Decision-making matrix by determining the optimal value

Option-Criteria	After-sales service	Delivery time	Quality	Cost
Criteria type	Positive	Negative	Positive	Negative
Weight criteria	0.20522	0.31714	0.43716	0.0429
Optimal value	7	12	10	15
Supplier 1	1	36	1	15
Supplier 2	3	72	3	18
Supplier 3	5	24	1	16

Table 3. Normalized decision-making matrix

Option-Criteria	After-sales service	Delivery time	Quality	Cost
Criteria type	Positive	Negative	Positive	Negative
Weight criteria	0.20522	0.31714	0.43716	0.0429
Optimal value	0.14793617	0.1153981	0.18181818	0.174880763
Supplier 1	0.021276596	0.1153981	0.01818182	0.058293588
Supplier 2	0.063829787	0.0961651	0.05454545	0.029146794
Supplier 3	0.106382979	0.1081857	0.01818182	0.087440382

Table 4. Weighted normalized decision-making matrix

Option- Criteria	After-sales service	Delivery time	Quality	Cost
Criteria type	Positive	Negative	Positive	Negative
optimal value	0.030654681	0.0554617	0.07948364	0.004950578
Supplier 1	0.004366383	0.0184882	0.00794836	0.004950578
Supplier 2	0.013099149	0.0092436	0.02384509	0.004125481
Supplier 3	0.021831915	0.0277308	0.00794836	0.004641166

Table 5. Matrix of optimal value and optimality degrees of alternatives

Option- Criteria	The optimal value of options	The degree of usefulness of the options
optimal value	0.17046058	0.9999999
Supplier 1	0.035752553	0.2097409
Supplier 2	0.050313335	0.2951611
Supplier 3	0.062152288	0.3646138

Table 6. Different objective values of Example 1 using Augment ε-constraint method through

Iteration	First Objective Function (Cost)	Second Objective Function (Satisfaction)
1	2043.660	5480
2	2086.660	6180
3	2155.660	6870
4	2261.660	7570
5	2466.660	8260
6	2688.660	8950
7	2936.660	9650
8	3202.660	10340
9	3483.660	11050
10	3784.660	11730
11	4084.660	12420

Table 7. Comparison between values of the first objective function in different scenario probabilities

Pareto point	case 1	2 case	case 3	4 case	case 5	Min	Max	Average	Stdev
1	2043.66	2043.57	2037.11	2043.91	2049.71	2037.11	2049.71	2043.592	3.99
2	2086.66	2086.57	2080.11	2086.91	2092.71	2080.11	2092.71	2086.592	3.99
3	2155.66	2155.57	2149.11	2155.91	2161.71	2149.11	2161.71	2155.592	3.99
4	2261.66	2261.57	2255.11	2261.91	2267.71	2255.11	2276.71	2261.592	3.99
5	2466.66	2466.57	2460.11	2466.91	2472.71	2460.11	2472.71	2466.592	3.99
6	2688.66	2688.57	2682.11	2688.91	2694.71	2682.11	2694.71	2688.592	3.99
7	2936.66	2936.57	2930.11	2936.91	2942.71	2930.11	2942.71	2936.592	3.99
8	3202.66	3203.57	3196.11	3202.91	3208.71	3196.11	3208.71	3202.592	3.99
9	3483.66	3483.57	3477.11	3483.91	3489.71	3477.11	3489.71	3483.592	3.99
10	3784.66	3784.57	3778.11	3784.91	3790.71	3778.11	3790.71	3784.592	3.99
11	4084.66	4084.57	4078.11	4084.91	4090.71	4078.11	4090.71	4084.592	3.99

Table 8. Comparative results of deterministic and non-deterministic methods

Example	Dimensions of the problem				certain		Solving time(s)	Robust		Solving time(s)
	Sterile item	Non-sterile item	Operation room	Suppliers	First Objective Function	Second Objective Function		First Objective Function	Second Objective Function	
1	2	2	2	3	1436.890	5070	3578	2155.660	6870.000	2.765
2	12	5	10	9	39955	139830	3078	44550.600	149940	3.937
3	22	10	20	15	137390	489045	4.437	203840	103326	1004.32
4	30	15	25	20	139721	308658	1003.094	234777.050	502922	1334.437
5	40	20	28	22	286496	233141	1002.078	483137.300	437016	1332.969

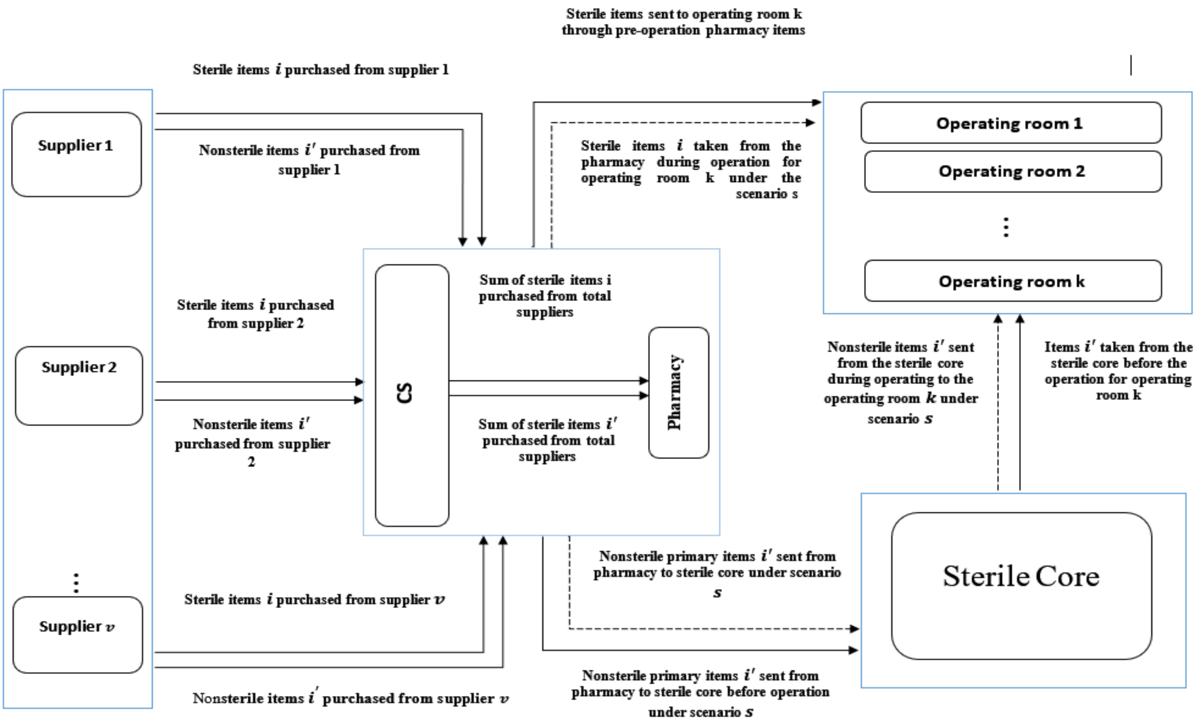

Figure 1. Overview of Problem

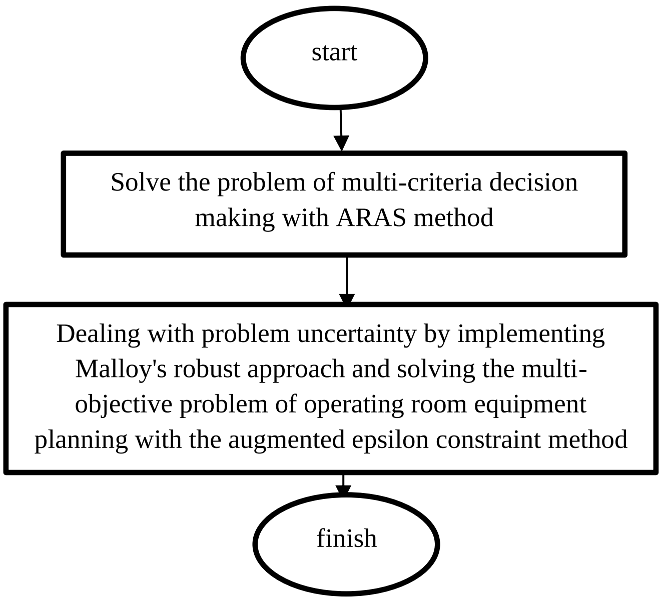

Figure 2. Solution stages

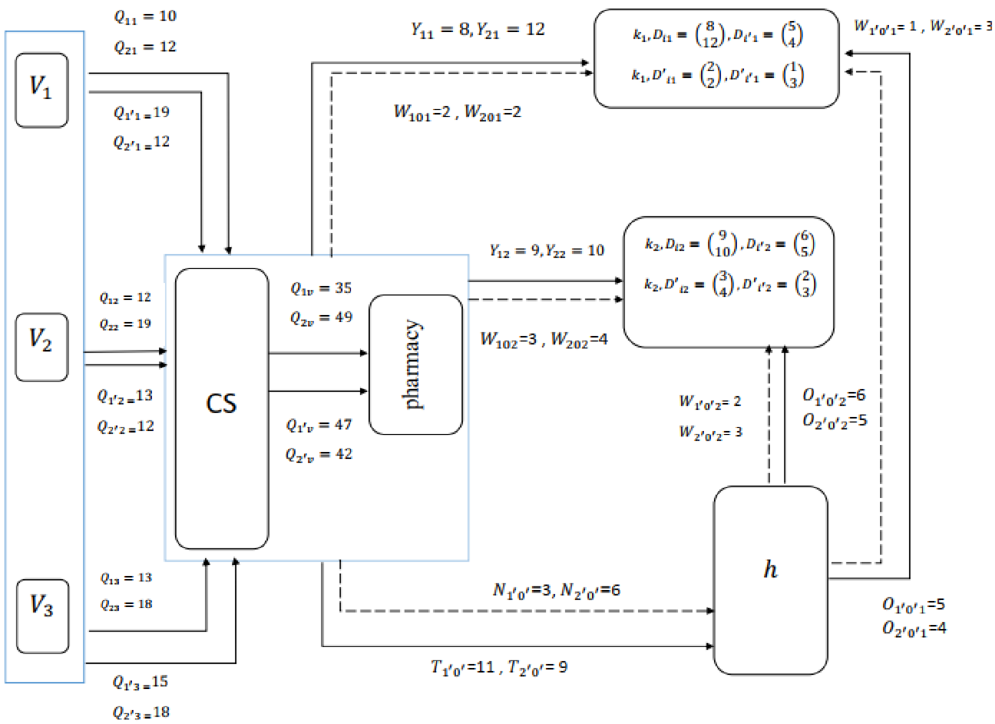

Figure 3. The first scenario of solving an example of the problem with small dimensions

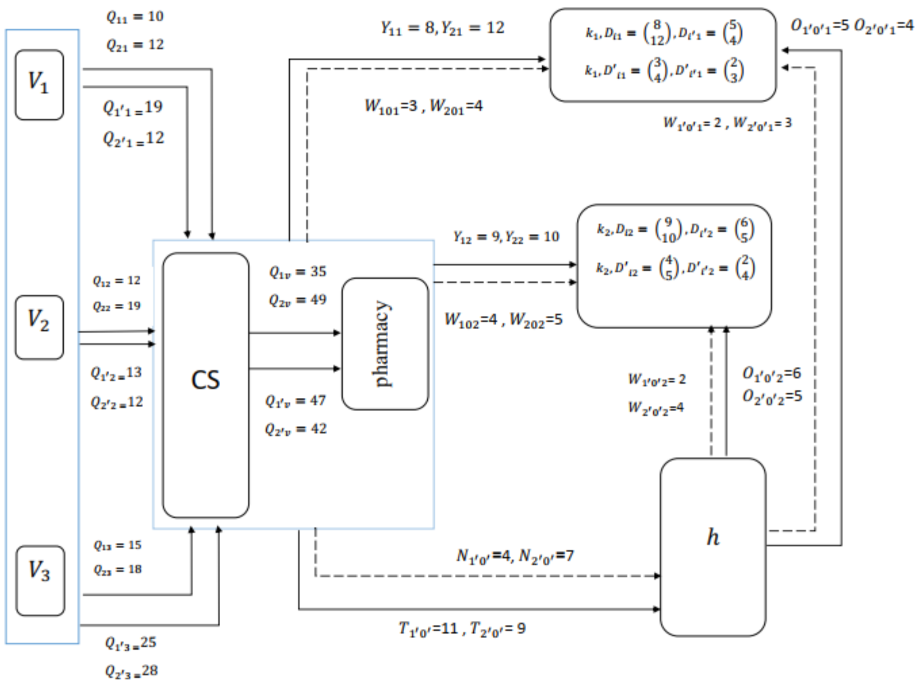

Figure 4. The second scenario of solving an example of the problem with small dimensions

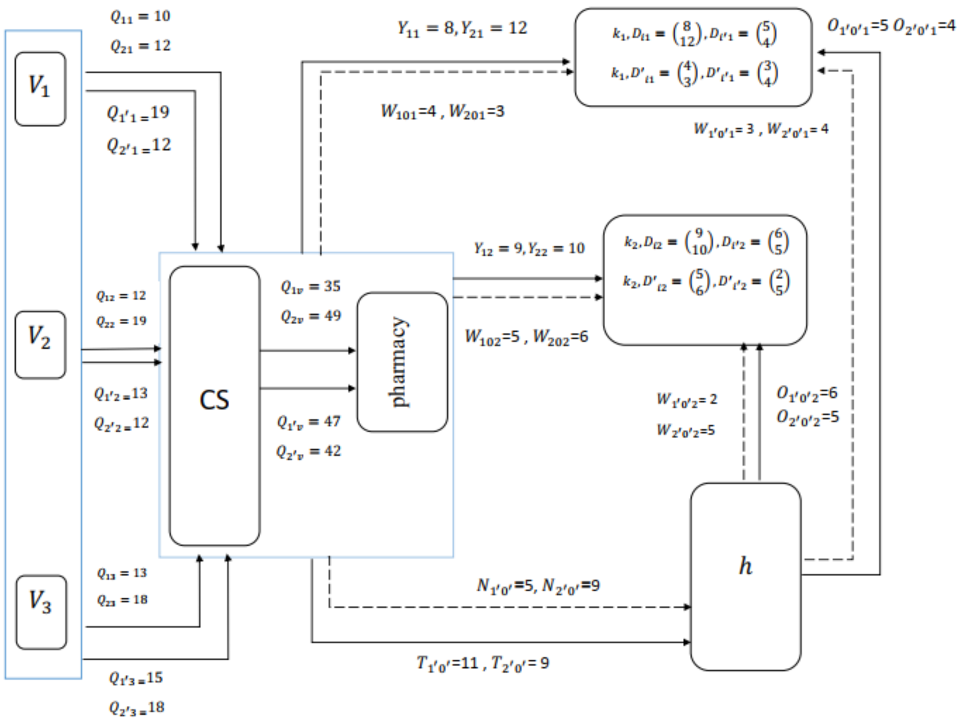

Figure 5. The third scenario of solving an example of the problem with small dimensions

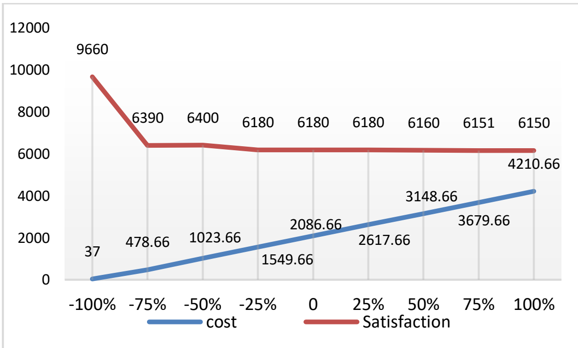

Figure 6. The effect of changes in purchase costs on objective function' values

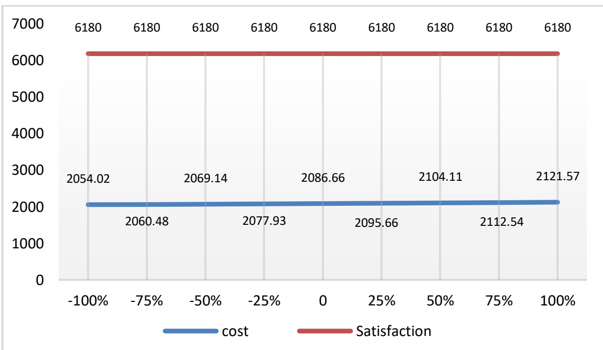

Figure 7. The effect of changes in operating expenses on objective functions' values

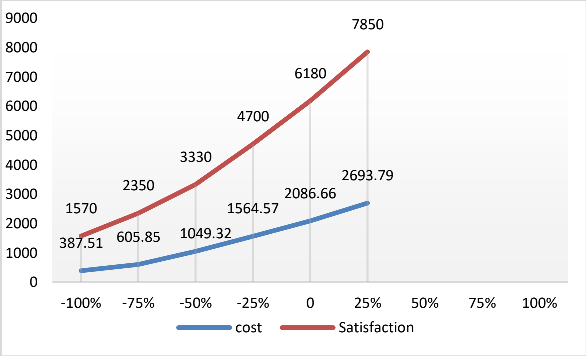

Figure 8. The effect of changes in demand values on objective functions

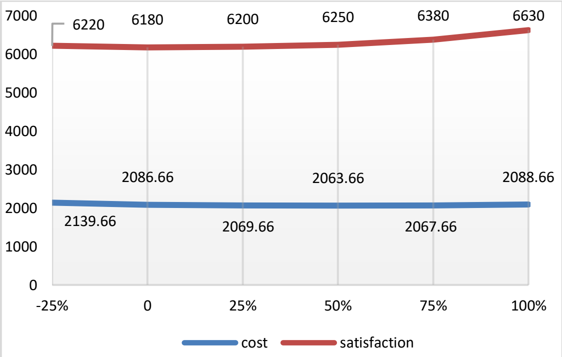

Figure 9. The effect of changes in purchase capacity on objective functions' values

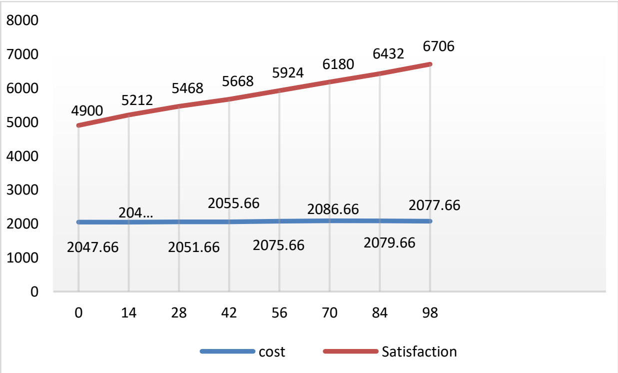

Figure 10. The effect of changes in satisfaction of the second supplier on objective functions' values

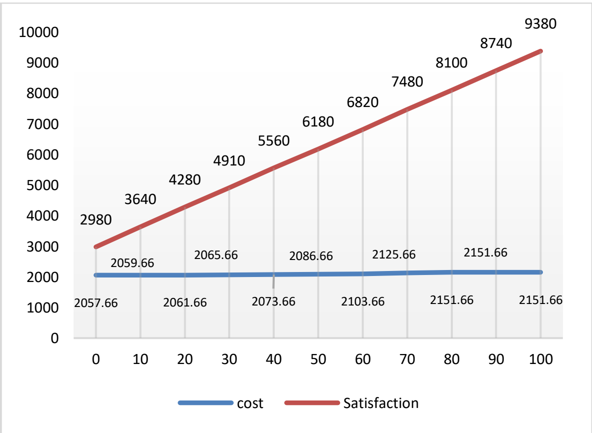

Figure 11. The effect of changes in satisfaction of the third supplier on the objective functions' values

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