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RESEARCH ARTICLE

Efficient Surgical Kit Configuration via MILP and Graph-Based Clustering Heuristics

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ABSTRACT The formation of surgical kits is essential for efficient resource management in hospitals. This problem involves determining the appropriate items and quantities to ensure that kits meet the demands of surgical procedures without shortages. A key challenge is designing shared kits that fulfill overlapping demands across procedures without including excess items, which may be discarded once deemed contaminated. Unlike existing approaches that allow oversupply, we propose optimization-based methods, including a mixed-integer linear programming model (MILP) and a two-stage heuristic, to minimize surplus in shared kits. The first stage applies a biclique enumeration framework from bipartite graph clustering. Computational experiments using real data from a Brazilian hospital demonstrate that the proposed methods effectively identify shared kit compositions. Although the heuristic yielded lower-quality solutions than the solver for larger instances, it successfully uncovered meaningful patterns that offer valuable insights and warrant further exploration. In addition, tests conducted with a commercial solver using the proposed mathematical model and the heuristic results as initial solutions revealed alternative solutions with a higher number of shared kits in certain instances.

INDEX TERMS Hospital planning, surgical kits, mixed-integer linear optimization, maximal bicliques, constructive heuristic.

I. INTRODUCTION

Well-elaborated hospital planning is essential to ensure high-quality care for patients. Effective planning plays a fundamental role in the surgical context. The surgical sector is often among the hospital units that require the most financial resources, significantly impacting the institution's revenue [1]. Within this scope, the most substantial expenses are generally associated with surgical supplies [2]. Proper management and administration of supplies allocated to the operating rooms lead to a considerable cost reduction, as demonstrated by [3].

The literature on drug management in hospital pharmacies, in the context of standardization, addresses predictive control and decision support systems to meet future demand [4], [5]. Literature is scarce on works that define medication kits.

In this context, optimizing the design of surgical kits is deemed relevant in hospital planning. A custom package surgical kit can be defined as a unique, sterile, and disposable package containing medical items for performing a surgical procedure [6]. Once a surgical kit is opened during surgery, its items become exposed, and when not used, they can no longer be considered sterile. They may end up being discarded [7]. For use in various procedures, kits may contain subsets of items tailored to specific surgeries and, as a result, may become excessive for some procedures, leading to wastage.

The design of these kits aims to enhance inventory control by grouping items in a single package, facilitating the retrieval process, reducing the time required to organize items before surgery, and minimizing waste. Furthermore,

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it promotes efficient resource sharing, contributing to a more effective operation of the surgical sector and, consequently, to a more sustainable management of hospital resources. The study by [8] demonstrates the benefits of personalized surgical kits in hospitals. Some works in the literature utilize mathematical models to configure packages composed of instruments, as seen in [9], [10], and [11], as well as disposable supplies in [1].

The personalized package decision problem extends the classical set cover optimization problem, as it allows for surplus items in personalized packages. In [1], the authors proposed a mixed-integer linear programming model to minimize physical contact between materials and staff, also referred to as contact points. The authors demonstrated that creating packages for various procedures can help identify which and to what degree excess items are worth allowing. The study proposes an objective function that minimizes the number of contact points of items used in the procedures performed in a time horizon of one year. Similarly, in the pharmaceutical sector of certain Brazilian hospitals, there is a requirement to discard unused items from opened kits due to the risk of contamination. Given these losses, kits that allow for surplus items, as proposed by [1], could lead to undesirable waste of medical supplies, which is unacceptable for Brazilian hospitals. Therefore, kits with a more limited number of items, which can be shared among procedures, are expected to be more suitable for these facilities.

In this paper, we present a mixed-integer linear programming model to determine the optimal allocation of surgical kits among different types of procedures. The goal of the model is to ensure that kits meet common demands across procedures without including excess items that may go unused. The proposed formulation minimizes the maximum number of items provided for each procedure not included in personalized packaging, such as individual items outside the kits. Compared to the previous study, which focused on minimizing the number of contact points between kits and procedures, our approach introduces a distinct and novel optimization objective: minimizing the maximum number of individual items that remain outside of kits. This surplus-minimization criterion ensures that all items included in the kits are indeed used in every procedure where the kits are shared. In contrast, the previous approach encourages the inclusion of additional items to promote shared use across procedures. However, these items are not consistently required in all cases, which can result in kits containing unused items. This leads to unnecessary waste. Our model explicitly avoids this inefficiency by ensuring that shared kits include only items essential to all associated procedures, thereby eliminating the problem of surplus. As a result, the proposed kits offer greater flexibility across distinct procedures while guaranteeing full item utilization. Furthermore, by reducing the number of items left outside kits, our approach promotes more effective and coherent grouping of components, improving overall kit standardization and resource efficiency.

In addition to an exact solution approach, we propose a heuristic method that decomposes the problem using a bipartite graph clustering strategy. Graph clustering is an unsupervised machine learning technique widely used to identify strong patterns in relational data. It is commonly applied to analyze processes involving heterogeneous elements, providing deeper insights into the underlying structures and relationships [12], [13], [14]. The first step of the proposed heuristic applies a framework from the literature for enumerating maximal bicliques. In this step, we map the items and procedures into a graph and enumerate their maximal bicliques. The second step involves a constructive method for determining item quantities and kit filling. To enumerate maximal bicliques, we use the iMBEA algorithm, an enhanced implementation of the Maximal Biclique Enumeration Algorithm (MBEA) introduced by [15]. In this study, we use data on medical supplies and medications to compose kits. However, it is essential to emphasize that we do not differentiate items based on medication classes. Our primary focus is to evaluate the efficiency of the proposed approaches in defining kits that can be shared across different procedures. The computational experiments are conducted in test scenarios that allow for the evaluation of up to thirty distinct and most frequently performed types of procedures in the partner hospital.

More specifically, the contributions of this paper are enumerated as follows:

- We propose an optimization model for the item clustering problem in the configuration of surgical kits. Our model can determine shared surgical kits for different procedures while preventing wastage by avoiding allocating excess items, a distinctive feature compared to previous studies. The objective function promotes the composition of kits by minimizing the maximum quantity of individual items in procedures, i.e., items without standardized packaging. Our constraints ensure that all items, whether provided in kits or individually, will be utilized in the procedures, fully meeting the demand.
- We employ an alternative solution approach using a literature-based framework for clustering bipartite graphs, allowing us to identify relationship groups between items and procedures. This approach has not been applied in studies with similar characteristics. We propose a constructive heuristic method that determines the quantities of items for kit fulfillment based on the groups identified by the framework.
- The computational experiments, using real data on medical supplies and medications provided by *Santa Casa da Misericórdia* in São Carlos, SP, Brazil, demonstrated that the proposed approach effectively determines shareable kits without including surplus items to facilitate sharing, contrasting with approaches found in the literature.

The rest of the paper is organized as follows: Section II provides a brief review of studies addressing similar problems. Section III describes the research problem, including the proposed mathematical model. Section IV describes the heuristic approach, divided into two solution steps. In Section V, we present the tests conducted, where initially the data is described, and then the results are shown for each approach. Finally, Section VI concludes this paper and outlines future research perspectives.

II. LITERATURE OVERVIEW

In this section, we present a summary of related works on surgical tray optimization and personalized package problems. The goal of this section is to describe how organizing items for procedures has been addressed in the literature.

A surgical tray is a rectangular, stainless steel container used to accommodate instruments such as scissors and forceps, among others. These instruments need to be selected and organized so that they are readily available for use before performing a surgical procedure. In [2], the authors developed a linear programming model to minimize storage and usage costs of trays while meeting instrument availability requirements and surgeons' preferences and schedules. In a case study proposed in [16], a comparative analysis of mathematical formulations to produce trays with redundant items and trays with a reduced number of instruments identified material and cost savings through item reduction. The problem has also been addressed through mixed-integer linear programming models and heuristics, as demonstrated by [17], with a bi-objective approach, in [3], with a stochastic programming model, as seen in [18], and through the use of consumption lists, as applied in the works of [19] and [20].

Regarding the assembly of items into surgical kits, some studies emphasize advantages such as reduced costs associated with purchasing individual items and a decrease in the time required for organizing surgical procedures, as highlighted by [6]. In [8], the authors also underline the importance of minimizing individual item storage, reducing waste, and lowering the risk of product contamination. To reduce sterilization costs, optimization models for grouping surgical instruments into packages were proposed in [9] and [10], demonstrating cost savings achieved through efficient package configuration. To ensure quality and efficiency, in [21], the authors identified the advantages of using a pre-assembled kit supply system for procedures based on the concept of a circulating inventory. The works of [22] and [23] investigated the use of surgical kits to assist in emergency procedures. Analyses and interviews with suppliers, surgeons, and hospital administrators demonstrated the safety and feasibility of their approach.

In [1], the problem of grouping disposable supplies into personalized packages to minimize points of contact was formulated as a mixed-integer linear programming model. To combine surgical supplies and optimize costs with procedure packages, in [11], the authors used a strategy that combined non-linear programming, statistical analysis to identify instrument patterns, and group analysis. Table 1 provides an overview of the related studies identified in the literature and highlights the techniques used in each work. Depending on the nature of the problem being addressed, its characteristics may vary. For example, when dealing with surgical instruments, sterilization for reuse must be considered in the formulation.

TABLE 1. Literature overview on the strategies for surgical kit composition.

Reference	Approach	Supplies	Instruments	Medications
[9]	MILP		✓	
[10]	NLP		✓	
[2]	BLP		✓	
[1]	MILP	✓		
[16]	DA		✓	
[11]	NLP		✓	
[17]	MILP		✓	
[3]	MILP		✓	
[19]	DA		✓	
[18]	SP	✓		
[20]	DA		✓	
Our approach	MILP	✓		✓

Optimization Approaches: Mixed-Integer Linear Programming (MILP), Data Analysis (DA), Nonlinear Programming (NLP), Binary Linear Programming (BLP), Stochastic Programming (SP).

III. PROBLEM DEFINITION

The problem of forming shared surgical kits among procedures consists of a strategy for grouping items to meet the demand shared among different types of surgical procedures. We proposed a mathematical formulation that ensures all items grouped in kits are utilized in each procedure, thereby preventing shortages or waste due to excess quantities. Specifically, the goal of the problem is to form shared surgical kits in a way that minimizes the number of individual items added separately to the procedure that requires the highest number of individual items. The following characteristics must be considered:

- There exists a maximum quantity of surgical kits.
- The demand for items for surgical procedures must be fully met.
- There are two different forms to obtain surgical items: grouped in a customized surgical kit or as individual items without standardized packaging.
- Each type of item must be assigned to only one surgical kit. Thus, if an item is in a kit shared among procedures, it cannot be reassigned to another kit.
- We do not allow excess items in the configured kits. Therefore, all surgical items in the kits are intended for use in the procedures.
- There is no upper limit on the quantities of items that belong to surgical kits.
- The worst-case scenario must be minimized, meaning that the highest quantity of items to be assigned individually in each procedure should be kept as low as possible.

TABLE 2. Item needs for the illustrative example.

Item	Procedure 1	Procedure 2	Procedure 3
Disposable Needle 14 x 7	3	2	2
Disposable Needle 20 x 55	1	-	1
Disposable Needle 40 x 12	-	3	3
Surgical Compress 25 x 28	2	3	-
Scalpel Blade	-	4	3
Surgical Glove size 7	1	1	3
Surgical Glove size 8	-	-	1
Disposable Syringe 3 ml	2	-	2
Disposable Syringe 5 ml	1	1	-
Disposable Syringe 10 ml	-	2	2

Based on these characteristics, the following illustrative example demonstrates the practical application of the proposed strategy before presenting the detailed mathematical formulation. Consider a set of ten types of items and three types of procedures. Each procedure requires different quantities of items without shortages, as shown in Table 2. Kits composed of groups of items that simultaneously meet distinct types of procedures must be determined. Fig. 1 represents a viable solution for the illustrative example, where four kits were formed with the following configurations: one kit shared among the three procedures, one kit common to procedures 1 and 2, one kit for procedures 1 and 3, and one kit shared between procedures 2 and 3. Each shared kit encompasses items from the intersection of the demands of the procedure set. Note that, although not presented in the example, the number of surgical kits can be determined in advance, providing alternative patterns of kits. This example offers an intuitive understanding of the methodology and configurations that align with the defined characteristics.

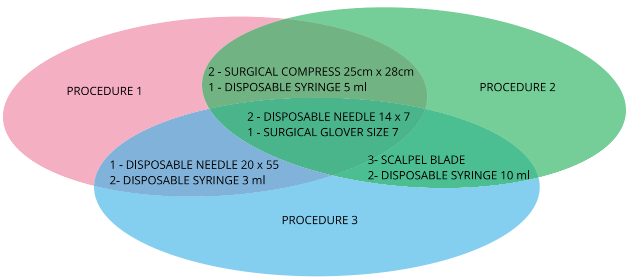


FIGURE 1. A viable solution to the illustrative example.

A. MATHEMATICAL MODEL

In this section, we propose a mathematical optimization model to represent the shared surgical kit configuration problem among procedures.

The notation used in the model formulation is presented next.

Sets:

I: Set of items, $i \in I$

J: Set of procedures, $j \in J$

P: Set of surgical kits, $p \in P$

Parameters:

N_{ij}: Quantity of items i required for procedure j

M: Sufficiently large number

Decision Variables:

Z: Number of individual items added to the procedure that demanded the largest number of individual items

x_{ip}: Number of units of item i in kit p

y_{pj}: Assumes the value 1 if kit p is used in procedure j and 0, otherwise

g_{ip}: Assumes the value 1 if item i is in kit p, and 0, otherwise

z_{ij}: Number of units of item i added individually in procedure j

v_{ipj}: Number of units of item i in kit p used in procedure j

The proposed model for configuring surgical kits shared among procedures is defined by the objective function (1) and constraints (2) to (13).

$$min \quad Z \tag{1}$$
$$s.t. \quad \sum_p g_{ip} \leq 1 \qquad \forall i \in I \tag{2}$$
$$x_{ip} \leq M \cdot g_{ip} \qquad \forall i \in I, p \in P \tag{3}$$
$$\sum_p v_{ipj} + z_{ij} = N_{ij} \qquad \forall i \in I, j \in J \tag{4}$$
$$\sum_i z_{ij} \leq Z \qquad \forall j \in J \tag{5}$$
$$v_{ipj} \leq x_{ip} \qquad \forall i \in I, p \in P, j \in J \tag{6}$$
$$v_{ipj} \leq y_{pj} \cdot M \qquad \forall i \in I, p \in P, j \in J \tag{7}$$
$$v_{ipj} \geq x_{ip} + M(y_{pj} - 1) \qquad \forall i \in I, p \in P, j \in J \tag{8}$$
$$y_{pj} \in \{0, 1\} \qquad \forall p \in P, j \in J \tag{9}$$
$$g_{ip} \in \{0, 1\} \qquad \forall i \in I, p \in P \tag{10}$$
$$x_{ip} \in \mathbb{N} \qquad \forall i \in I, p \in P \tag{11}$$
$$z_{ij} \in \mathbb{N} \qquad \forall i \in I, j \in J \tag{12}$$
$$v_{ipj} \in \mathbb{N} \qquad \forall i \in I, p \in P, j \in J \tag{13}$$

The objective function (1) minimizes the maximum quantity of individual items in each procedure. Constraints (2) ensure the assignment of each type of item i to only one kit p. This requirement aims to avoid solutions that require multiple kits for dedicated surgical procedures. Constraints (3) ensure that if item i is in kit p, the quantity of this item in the kit does not exceed a predefined large value M. Constraints (4) are essential to ensure demand satisfaction. Constraints (5) set a lower bound for Z, representing the number of individual items for each procedure. The infimum, or greatest lower bound, corresponds to the maximum number of individual items across all procedures. Since the objective function seeks to minimize Z, it will converge to the infimum value. Constraints (6) ensure that the amount of items assigned to the procedure does not exceed the quantity of items i available in kit p, thus preventing shortages during the procedure. Constraints (7) ensure that the amount of items in kit p assigned to procedure j does not exceed a predefined value M. Constraints (8) are necessary to ensure that the quantity of items in the kit used during the procedure is at least equal to the number of items available in the kit. Finally, constraints (9) - (13) define the domain of the variables.

IV. CONSTRUCTIVE HEURISTIC

To illustrate the heuristic, let $G = (U \cup V, E)$ be a bipartite graph, where U represents item units and V represents surgical procedures. An edge $(u, v) \in E$ indicates that the unit represented by node u is required for the procedure associated with node v. Fig. 2 shows the bipartite graph constructed from the data presented in Table 2, in Section III.

In Fig. 2, red vertices denote three procedures types, while green vertices labeled as *i_j*, correspond to the j-th unit of item i. An edge between a procedure and unit j of item i signifies that the procedure requires that unit.

In a bipartite graph, structures as bicliques consist of a particular feature defined in Definition 1.

Definition 1: [Biclique] Let $G = (U \cup V, E)$ be a bipartite graph. $B = (U', V')$, where $U' \subseteq U, V' \subseteq V$, is said a biclique if $G[U', V']$ is the subgraph of G spanned by U' and V', where every node from U' is adjacent to any node of V'. The proposed constructive heuristic is a two-step method based on bipartite graph clustering. In the initial step, the problem is modeled as a bipartite graph from which maximal bicliques (also referred to as groups) are enumerated. In the second step, starting from the obtained groups, a constructive procedure is initiated to determine the ideal quantities of item types for assembling surgical kits to meet procedure demand. Algorithm 1 presents a general pseudocode of this heuristic.

Algorithm 1 Surgical Kit Bipartite Graph Heuristic (SKBGH)

Stage 1: Enumeration of Maximal Bicliques
Require: $G = (U \cup V, E)$;
$A \leftarrow$ Edge List of Bipartite Graph G
$Bicliques \leftarrow$ Enumerate Maximal Bicliques(A)
Stage 2: Constructive Procedure
Require: *Bicliques*
$Solution \leftarrow$ ConstructiveHeuristic(*Bicliques*)

The following section provides a more detailed explanation of how the first stage of the heuristic works.

A. STAGE 1: ENUMERATION OF MAXIMAL BICLIQUES

Bicliques are important to various applications, such as identifying common associations between sets of genes, discovering patterns in epidemiological research, and integrating functional genomic data [24]. According to [25], one may also observe applications in web data mining, social network analysis, database correlation discovery, data compression, and more. More recently, one can find bicliques giving important insights in the field of oncology [26], [27]; in compound-protein interaction prediction [28]; and in regulatory circuit identification [29]. Definition 2 describes the meaning of a maximal biclique.

Definition 2: [Maximal Biclique] Let $G = (U \cup V, E)$ be a bipartite graph and $B = (U', V')$ a biclique. B is said maximal if there is no biclique (U'', V''), where $U' \subset U''$ and $V' \subset V''$.

Consider the bipartite graph in Fig. 2. The maximal bicliques in this bipartite graph are B_1 = ({1_1, 1_2, 1_3, 2_1, 4_1, 4_2, 6_1, 8_1, 8_2, 9_1}, {P_1}), B_2 = ({1_1, 1_2, 4_1, 4_2, 6_1, 9_1}, {P_1, P_2}), B_3 = ({1_1, 1_2, 6_1}, {P_1, P_2, P_3}), B_4 = ({1_1, 1_2, 2_1, 6_1, 8_1, 8_2}, {P_1, P_3}), B_5 = ({1_1, 1_2, 3_1, 3_2, 3_3, 4_1, 4_2, 4_3, 5_1, 5_2, −5_3, 5_4, 6_1, 9_1, 10_1, 10_2}, {P_2}), B_6 = ({1_1, 1_2, 3_1, 3_2, 3_3, 5_1, 5_2, 5_3, 6_1, 10_1, 10_2}, {P_2, P_3}), B_7 = ({1_1, 1_2, 2_1, 3_1, 3_2, 3_3, 5_1, 5_2, 5_3, 6_1, 6_2, 6_3, 7_1, 8_1, 8_2, 10_1, 10_2}, {P_3}). Note that, considering the biclique B_3, surgical items 1 and 6 are the only ones common to procedures P_1, P_2, and P_3. Furthermore, no additional procedure or surgical item can be added to this biclique. This implies that if a surgical kit were designed based on these procedures, it would include only items 1 and 6 to ensure zero waste.

In the SKBGH, to identify the relationships among items shared among procedures, we use the concept of maximal bicliques. The reasoning is that these structures will provide a set of procedures with common items and their respective number of units of the items. The maximal bicliques are not guaranteed to be exclusive, i.e., overlapping of vertices from two different maximal bicliques is not necessarily empty. For this reason, after enumerating the maximal bicliques, we process them to provide feasible kits for the introduced mathematical formulation.

The implementation used to list all maximal bicliques was found in the biclique package proposed in [15]. This package invokes the MBEA/iMBEA algorithms proposed by [24] that enumerate all maximal bicliques in bipartite graphs. The maximal biclique enumeration step has a theoretical time complexity of $O(eB)$, with e denoting the number of edges and B the number of maximal bicliques. The detailed proof and scalability analysis are presented in [24]. Empirically, we observed that runtime grows smoothly with the number of procedures $|P|$, confirming that the heuristic scales well for hospital-scale data.

B. STAGE 2: CONSTRUCTIVE PROCEDURE

In this stage, kits are formed based on the groups identified in the set of maximal bicliques, as described earlier. Algorithm 2 presents a pseudocode for the constructive heuristic step.

According to Algorithm 2, surgical kits must be assembled based on each biclique in the list of bicliques, which are sorted in descending order by the number of associated procedures and, subsequently, by the number of items. This prioritization ensures that bicliques with the highest levels of shared usage across different procedures are given precedence, as well as those containing the largest intersections of common items. The method guarantees that no item type from the biclique list is included in more than one surgical kit assembled during previous steps, thereby ensuring that each type of item is uniquely assigned to a single surgical kit.

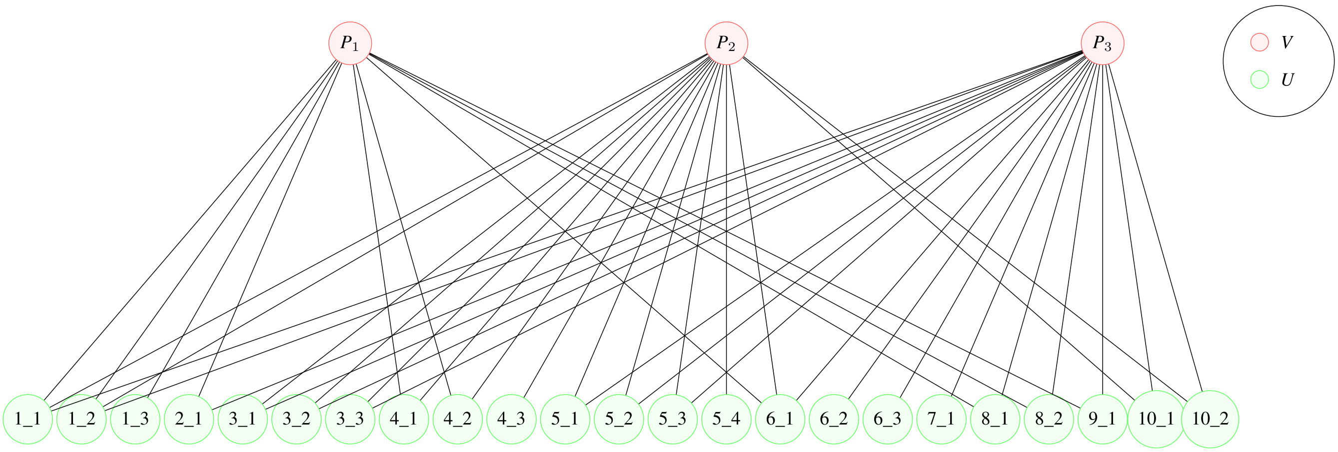


FIGURE 2. **Bipartite graph of the illustrative example.**

Algorithm 2 Constructive Heuristic for Surgical Kits

Require: L = list of maximal bicliques

Sort L by descending number of procedures, then by number of items;
Initialize $P \leftarrow \emptyset$ (set of packages);
Initialize package identifier $p \leftarrow 1$;
Initialize variables $x_{ip}, y_{pj}, z_{ij}, v_{ipj} \leftarrow 0, \forall i, p, j$;
while $L \neq \emptyset$ **do**
  Select the first biclique b from L;
  Create a new package p with all units of items from b, updating all corresponding x_{ip}, y_{pj} and v_{ipj} accordingly;
  Add p to P;
  $p \leftarrow p + 1$;
  for each item $i \in b' \cap b \in L$ **do**
    for each procedure j associated with b' **do**
      $z_{ij} \leftarrow \max\{N_{ij} - v_{ipj}, 0\}$;
    end for
    Remove all units of item i from b';
  end for
  Reorder L;
end while
$Z \leftarrow \max_{i,j} z_{ij}$;
return Z // Objective Value;

It is important to emphasize that any item not included in a surgical kit must be provided individually for the procedure. Specifically, if additional units of an item are required for a procedure, and some units have already been included in another kit for the same procedure, these extra units should be supplied as individual items.

To avoid surplus items, the quantities of items in the bicliques are adjusted to account for units already allocated to previous kits for the procedure. Only the remaining required units are considered within the biclique before assembling the next kit. When an item is already included in a package p' in P, the original number of units of that item is observed before vertex removal. It is then evaluated whether it is beneficial to move the item from p' to package p. If the number of units of the item is larger in package p', package p' is updated by removing all units of the item and inserting the maximum possible number of units in package p.

V. COMPUTATIONAL EXPERIMENTS

This section presents an analysis of computational experiments conducted to evaluate the solutions obtained by the proposed heuristic, SKBGH, and the solutions achieved by the Gurobi 9.5.1 optimization solver under an academic license in the Python programming language. We implemented the constructive procedure in the Python programming language. To enumerate maximal bicliques, we used the biclique package proposed by [15] in the R programming language.

The tests were performed on a computer equipped with an Intel(R) Core(TM) i7-4790 CPU at 3.60 GHz, 16 GB of RAM, and running the Windows 10 Pro operating system. The experiment compares the results achieved by the commercial solver, which is limited to 3,600 seconds per instance, with the solutions generated by SKBGH. All other Gurobi parameters, including the number of threads, were maintained at their default values. Furthermore, no specific preprocessing rules were applied to the utilized datasets. In the experiments, we utilized a dataset provided by a hospital in São Carlos city, which is discussed in the next section.

A. DATASET

We conducted experiments on a real dataset provided by the Santa Casa da Misericórdia hospital in São Carlos, SP, Brazil. The dataset comprises records of material and medication movements from the surgical center pharmacy over 18 months, from 2017 to 2018, totaling 563,625 entries, where each entry corresponds to an item used in a procedure. During the period, the hospital performed over 12,000 surgeries across 36 different specialties, encompassing more than 700 types of procedures.

To define the test scenarios, we selected the 30 most frequently performed types of surgical procedures, as listed in Table 3, arranged in descending order of frequency. The third column of the table indicates the number of times the procedure was performed and registered in the database. We selected the required items for each procedure by considering those used in at least 40% of cases per surgery.

In an initial study, we proposed instances containing data on materials and medications. However, the items were divided into two distinct scenarios due to the necessity of considering temperature constraints associated with medications. It is important to emphasize that the mathematical model does not account for distinctions regarding whether an item is a medication or not. Nevertheless, to better align the problem with practical applications, we opted to test both previously described scenarios.

Each instance defines a number of j procedures, corresponding to the j most frequent procedures listed in Table 3. The first scenario includes materials and medications, while the second scenario comprises only medical supplies. Tables 4 and 5 show the number of item types, total quantity, and distinct procedures per instance for the first and second scenarios, respectively. We observe that the quantity of each item type in each procedure (N_{ij}) is determined by considering the median plus the standard deviation.

For the tests on the mathematical model, we set a predefined maximum value of $|P| = 100$ for the number of kits that can be configured in each instance. This value was determined empirically to allow the model greater flexibility in assembling the maximum possible number of kits. Fig. 7, provided in Appendix, presents an analysis of the variation in the parameter $|P|$ for instance 7, which is one of the instances with the largest size among those defined for the tests. The results indicate that the objective function tends to stabilize as $|P|$ increases, suggesting that the chosen value used in the experiments does not compromise solution quality. In contrast, the heuristic does not have an upper limit on the maximum number of kits that can be configured. The heuristic explores the bicliques in an attempt to assemble shared kits, and this number tends to be large, as seen in Table 6, where one may notice that instance 7 presented 179 bicliques. Therefore, adopting a sufficiently large value for the number of kits provides greater flexibility for the model and ensures a more consistent basis for comparison with the heuristic method. We conducted additional tests on the model using a reduced value for the parameter. Table 13 in Appendix reports the results for $|P| = 60$. The objective value remained the same as that obtained with the higher limit, while the computational time was lower across all instances. Additionally, Table 13 indicates that, for some instances, the model solved with the heuristic initial solutions becomes infeasible. This infeasibility arises from the solutions generated by the heuristic because larger instances involve a greater number of bicliques that are not taken into account when applying the $P = 60$ threshold.

B. RESULTS OF THE EXPERIMENT

In this section, we present the results obtained by the proposed heuristic, contrasting them with the solutions achieved by Gurobi. Besides reporting the primal and dual bounds, we present the gap between them, calculated as $Gap = 100 \times |z_p - z_d|/|z_p|$, where z_p is the primal bound and z_d is the dual bound. To further assess the quality of the heuristic, we report the gap relative to the MILP solution as $Gap_h = 100 \times |z_h - z_d|/max(|z_h|, |z_d|)$, where z_h represents the heuristic solution. We use the value of M as the highest demand value for the quantity of items, which is determined by first identifying the maximum number of item types required in each procedure. Among these, the highest value is then assigned to M for that instance.

Table 6 reports the solution values obtained for the set of instances that encompass medical supplies and medications. The first column lists the instance names. For the mathematical model, this table reports, respectively, the number of variables and constraints, the number of individual items added to the procedure that demanded the largest number of individual items, i.e., the objective function value, the gap, the number of shareable kits, and execution time in seconds required by the commercial solver to achieve the best solution. Regarding the columns of SKBGH, the table reports the objective value, the heuristic gap, the number of bicliques, the number of shareable kits, and the time necessary to obtain such kits. Additionally, in the last columns, the table presents the results obtained by the Gurobi solver, using the SKBGH solutions as initial solutions.

Upon analyzing the results, we found that the solver was unable to prove optimality within the time limit only for instance 10. The number of variables and constraints in the MILP increases with the instance size, resulting in a direct impact on computational time. The constructive heuristic produced solutions in a short computational time, demonstrating strong performance. Additionally, to determine the bicliques in stage 1, an average of 9.58% of the total computational time was consumed, while configuring the kits required only 0.49%. In the biclique enumeration phase, a high number of possibilities were observed for each instance, especially in the largest ones. However, the heuristic did not employ all possible groupings to assemble shared kits.

Regarding solution quality, gaps below 20% were obtained in seven instances, while the others exhibited considerably higher discrepancies, ranging from 55.55% to 98.83%. The worst performance occurred in instance 10, where the heuristic gap was especially elevated. However, this does not necessarily imply poor solution quality, but rather reflects the absence of a reliable benchmark, since Gurobi failed to reach optimality within the time limit, reporting a 98.83% duality gap.

Based on the analysis of the results obtained with the initial solutions from SKBGH, we observe that the objective

TABLE 3. List of procedures.

j	Surgical Procedures	Freq.
1	SINGLE FETUS CESAREAN	2254
2	NORMAL BIRTH	818
3	CARDIAC CATHETERIZATION	680
4	VIDEO CHOLECYSTECTOMY	419
5	CARDIAC CATHETERIZATION AND LEFT OR RIGHT HEART CATHETERIZATION WITH CINEANGIOCORONARYGRAPHY AND VENTRICULOGRAPHY	384
6	CURETTAGE AFTER ABORTION	320
7	FEMUR FRACTURE - SURGICAL TREATMENT	247
8	CORONARY ANGIOPLASTY WITH INTRALUMINAL STENT IMPLANTATION	246
9	PERIDURAL OR SUBARACHNOID NEUROLITIC BLOCKADE	242
10	CESAREAN SECTION - MULTIPLE FETUS	214
11	EXPLORATORY LAPAROTOMY	205
12	PERCUTANEOUS TRANSLUMINAL MULTIPLE VESSELS ANGIOPLASTY WITH STENT IMPLANTATION	193
13	PLACEMENT OF DOUBLE J URETEROSCOPIC STENT	159
14	DEBRIDEMENT	158
15	APPENDECTOMY	157
16	UNILATERAL FLEXIBLE URETERORENOLITHOTRIPSY	144
17	ABDOMINAL HYSTERECTOMY	144
18	EYELIDS	128
19	ABSCESS - INCISION AND DRAINAGE	125
20	ANKLE FRACTURE/DISLOCATION - SURGICAL TREATMENT	125
21	WRIST/CARPAL FRACTURE/DISLOCATION - SURGICAL TREATMENT	122
22	ENDOSCOPIC PLACEMENT OF DOUBLE J URETERAL STENT	109
23	UMBILICAL HERNIORRHAPHY	106
24	TIBIAL FRACTURE	103
25	BREAST PROSTHESIS IMPLANTATION	98
26	REMOVAL OF SYNTHESIS MATERIAL	95
27	INGUINAL HERNIORRHAPHY	95
28	ARTERIOVENOUS FISTULA OF THE LIMBS	89
29	SEMIOTIC CURETTAGE WITH OR WITHOUT DILATION	89
30	LAPAROTOMY WITH BIOPSY	89

TABLE 4. Main characteristics of instances considering medical supplies and medications.

Instances	1	2	3	4	5	6	7	8	9	10
Procedures	3	4	5	6	7	10	15	20	25	30
Items	42	56	58	60	72	83	92	101	111	118
Total items	321	410	630	644	714	1135	1552	1796	2090	2355

TABLE 5. Main characteristics of instances considering tests with medical supplies.

Instances	1	2	3	4	5	6	7	8	9	10
Procedures	3	4	5	6	7	10	15	20	25	30
Items	32	40	42	42	54	58	64	69	74	78
Total items	157	195	218	227	285	427	563	700	878	1032

TABLE 6. Results of the experiment considering the instances with medical supplies and medications.

	Gurobi solver						SKBGH					Gurobi solver with SKBGH			
Instance	Number of Variables	Number of Constraints	Objective Value	*Gap*	Shared Kits	Time	Objective Value	*Gap*	Bicliques	Shared Kits	Time	Objective Value	*Gap*	Shared Kits	Time
1	42,171	21,427	2	0.00	4	3.09	9	77.77	6	3	6.80	2	0.00	5	3.34
2	73,084	34,225	4	0.00	10	32.48	9	55.55	11	7	5.65	4	0.00	10	27.77
3	93,153	41,391	34	0.00	8	6.58	37	8.10	10	9	5.22	34	0.00	8	6.28
4	114,426	48,961	34	0.00	9	9.85	37	8.10	23	10	6.28	34	0.00	10	6.76
5	158,983	66,005	34	0.00	17	40.21	37	8.10	30	14	5.59	34	0.00	12	23.51
6	258,223	101,431	43	0.00	21	1,522.77	50	14.00	62	19	5.35	43	0.00	13	377.74
7	424,687	159,281	72	0.00	18	736.31	86	16.27	179	34	5.21	72	0.00	15	592.63
8	618,241	226,221	72	0.00	9	1,783.94	86	16.27	336	44	5.11	72	0.00	6	2,080.15
9	846,511	304,976	72	0.00	21	2,484.50	86	16.27	586	56	4.99	72	0.00	10	3,600.00
10	1,077,488	384,141	72	100.00	7	3,600.00	86	98.83	856	56	5.12	72	100.00	22	3,600.00

value remained the same across all instances, with reduced computational time in some cases. Additionally, alternative solutions were identified, yielding more shareable kits. These findings demonstrate the performance of the Gurobi solver, highlighting its ability to efficiently refine initial solutions provided by SKBGH while maintaining optimal results.

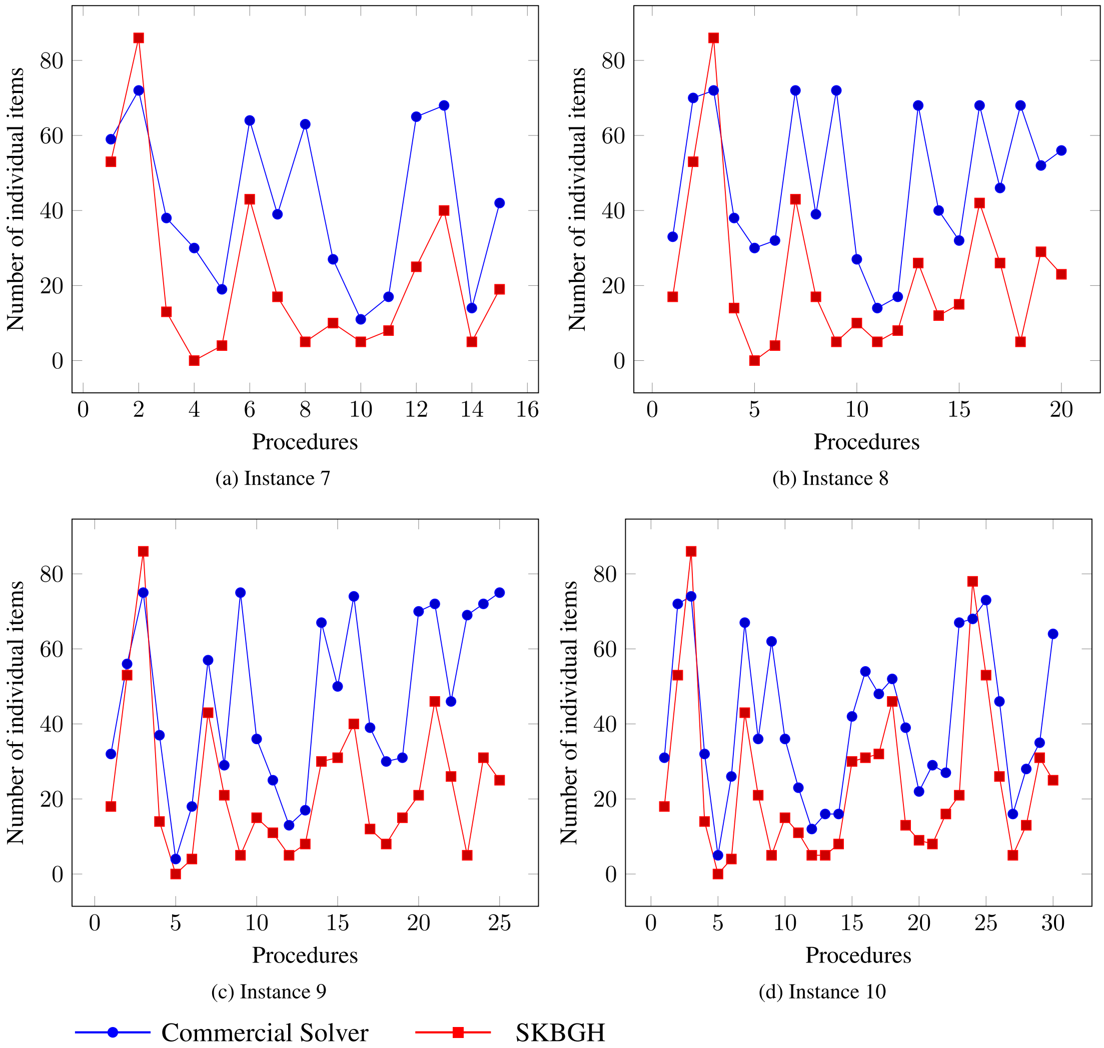


FIGURE 3. **Individual items by procedures.**

Concerning the maximum number of individual items for the procedure that demanded the highest number of individual items, which is the model objective function, the highest values were observed in the larger instances, particularly in instances 7 to 10. For each of these instances, we plotted graphs comparing the solutions obtained by Gurobi and the heuristic.

Fig. 3 illustrates a similar behavior of the solutions obtained by the SKBGH and the solver. On the one hand, the solver achieved the best solutions in all cases. On the other hand, when considering the number of individual items for each procedure, we observe an interesting behavior of the heuristic. In the four instances, the heuristic solutions had fewer individual items in the vast majority of the procedures. More specifically, the heuristic achieved a higher number of individual items in only a single procedure (which provided the maximum number of individual items) across instances 7 to 10. This outcome can be explained by the fact that the number of units of an item allocated to a kit corresponds to the minimum quantity required by one or more procedures. Moreover, this item cannot be placed in another kit to satisfy the demand of a procedure that does not use that kit. Since the heuristic considers individual items during the constructive phase, some procedures may accumulate a comparatively larger number of individual items, depending on how demands are distributed across procedures.

Regarding the quantities of shared kits determined by each method, the heuristic achieved higher values in most cases. This is attributed to the heuristic's ability to distribute more kits, whereas the model opted to consolidate the demand into fewer kits containing a larger number of items. To evaluate this behavior in a small instance, Table 7 presents the contents of the kits for comparison. It can be seen that only one kit, common to the three procedures considered, was identical for both methods, while the remaining kits were assembled differently. For the shared kits between the procedures "Cardiac Catheterization and Single Fetus Cesarian", the model selected a kit containing only one type of item.

TABLE 7. Contents of the kits for instance 1 that include supplies and medicines.

Kit ID	Origin of kits	Procedures	Quantity and Item Type
1	Common	CARDIAC CATHETERIZATION SINGLE FETUS CESARIAN NORMAL BIRTH	2 x Item Type 2
2	Heuristic	CARDIAC CATHETERIZATION SINGLE FETUS CESARIAN	1 x Item Type 8 1 x Item Type 38 1 x Item Type 40
3	Solver		1 x Item Type 40
4	Heuristic	SINGLE FETUS CESARIAN NORMAL BIRTH	3 x Item Type 3 1 x Item Type 5 1 x Item Type 10 1 x Item Type 20 2 x Item Type 35 2 x Item Type 36
5	Solver	SINGLE FETUS CESARIAN NORMAL BIRTH	3 x Item Type 3 1 x Item Type 5 1 x Item Type 20 2 x Item Type 35 2 x Item Type 36
6	Solver		1 x Item Type 10

TABLE 8. Results of the experiment considering the instances with medical supplies.

	Gurobi solver						SKBGH					Gurobi solver with SKBGH			
Instance	Number of Variables	Number of Constraints	Objective Value	*Gap*	Shared Kits	Time	Objective Value	*Gap*	Bicliques	Shared Kits	Time	Objective Value	*Gap*	Shared Kits	Time
1	32,131	16,397	2	0.00	5	2.61	9	77.77	6	3	4.77	2	0.00	5	2.44
2	52,204	24,561	4	0.00	11	14.53	9	55.55	11	7	4.65	4	0.00	10	18.00
3	67,457	30,111	5	0.00	9	95.22	10	50.00	17	9	8.04	5	0.00	15	66.48
4	80,100	34,453	5	0.00	11	42.14	10	50.00	22	10	5.05	5	0.00	13	37.28
5	119,239	49,679	6	0.00	13	97.24	14	57.14	28	12	6.23	6	0.00	13	1,512.76
6	180,448	71,181	7	14.30	23	3,600.00	15	53.33	60	16	4.63	7	0.00	18	2,154.77
7	295,439	111,261	10	60.00	32	3,600.00	22	54.54	171	27	5.17	9	44.44	32	3,600.00
8	422,369	155,181	10	80.00	30	3,600.00	23	56.52	291	34	5.17	10	80.00	31	3,600.00
9	564,349	204,151	17	94.11	27	3,600.00	26	34.61	475	40	5.22	15	93.33	31	3,600.00
10	712,248	254,941	15	100.00	29	3,600.00	43	65.11	673	42	5.82	18	94.44	24	3,600.00

In contrast, the heuristic created a larger kit comprising all items in the intersection. For the procedures ''Single Fetus Cesarian and Normal Birth'', the model divided the item demand into two kits, whereas the heuristic placed all items into a single kit.

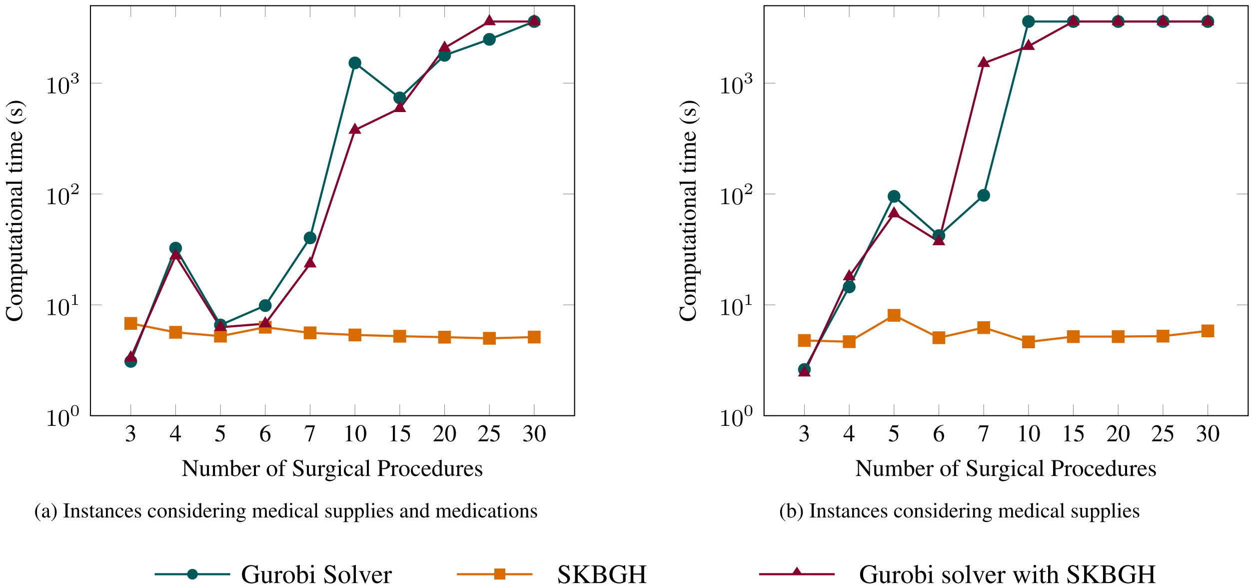
Table 8 presents the results for the instances that only include medical supplies. One may observe that, from Instance 6 on, the model fails to achieve optimality within the time limit and exhibits high gap values. The heuristic obtained solutions with a larger number of individual items in most instances. However, in Instance 9, this was not the case, as the solver's solution did not achieve optimality. Moreover, it produces results with better computational times. It is noteworthy to emphasize the average computational time consumption relative to the total execution time for the instances. In the first stage, determining the bicliques accounted for an average of 10.1% of the total time. In contrast, the second stage, which involved assembling kits that could be shared between procedures, required only 0.39% of the total time. Regarding the shared kits, it is noted that the heuristic achieved larger quantities in instances where the model did not reach optimality. In contrast, in the other instances, both methods determined similar quantities.

Examining the heuristic gap results, for instances 6 to 10, the MILP approach did not reach optimality, limiting the analysis due to the absence of reliable reference solutions. Nevertheless, even in instances where the MILP approach returned optimal solutions, the heuristic produced substantially inferior results, with gaps ranging from 50% to 77.77%. This highlights the relatively low performance of the heuristic when a strong benchmark is available.

To analyze the sensitivity of Gurobi's optimality gaps for the largest instances—specifically instances 6 to 10—we conducted an additional experiment with a two-hour time limit. Table 10 presents the results, including a column showing the percentage reduction relative to the gaps obtained with the one-hour time limit, for instances related to the medical

TABLE 9. Characteristics of test instances for SKBGH heuristic execution time evaluation.

Procedures	40	50	60	70	80	90	100
	Medical supplies and medications						
Items	134	148	154	173	184	242	252
Total items	3362	3995	4731	5248	5738	6878	7511
	Medical supplies						
Items	85	89	90	105	113	143	146
Total items	1318	1582	1863	2181	2430	2920	3176



(a) Instances considering medical supplies and medications

(b) Instances considering medical supplies

FIGURE 4. Computational time vs. number of procedures.

TABLE 10. Gurobi optimality gaps under a 2-hour time limit for the largest medical supplies instances.

Instance	Objective Value	*Gap*	Reduction %	Shared Kits	Time
6	7	0.00	100.0	18	1,966.66
7	9	33.33	44.45	32	7,200.00
8	10	80.00	0.00	31	7,200.00
9	14	85.71	8.93	31	7,200.00
10	18	94.44	5.56	24	7,200.00

supply dataset. The percentage reduction is calculated as: $100 \times (Gap_{1h} - Gap_{2h}/Gap_{1h})$. A more significant reduction was observed in the first two instances, while the remaining instances showed only minor improvements.

Upon analyzing the results of the Gurobi solver tested with initial solutions from SKBGH, we observe that the solutions improved for instances that did not achieve optimality, resulting in smaller gaps. Regarding the number of shareable kits, the results were highly similar to those obtained by the solver without initial solutions, presenting a slight increase in the number of shareable kits. Additionally, computational times were reduced in some instances, demonstrating the efficiency of the Gurobi solver in refining the provided initial solutions.

For better visualization of the results, Fig. 4 presents a graphical summary of the data reported in Tables 6 and 8, illustrating the computational time as the instances increase. These charts are directly related to the outcomes of the experiments conducted and aim to enhance the interpretation and understanding of the tabulated results.

An additional analysis was conducted to evaluate the execution time of the SKBGH heuristic on larger instances, considering the number of procedures. Each instance defines a number j of procedures, corresponding to the j most

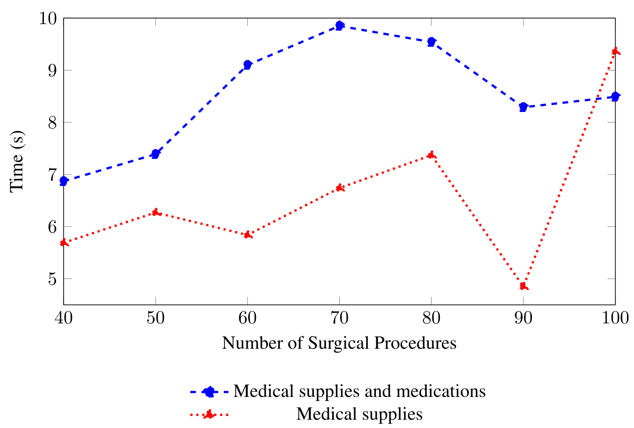


FIGURE 5. Execution time with increasing number of surgical procedures.

frequently performed surgical procedures. Instances with $j = 40, 50, 60, \ldots, 100$ were tested to analyze the time required as more frequent procedures are added and the total number of related items grows. Table 9 presents the detailed data for each instance. Fig. 5 shows a comparison between the execution times for instances that include both medical supplies and medications and those with only medical supplies. The results confirm that SKBGH maintains fast solution times, remaining under 10 seconds even as instance size increases, which demonstrates its scalability and applicability to larger hospital datasets.

The SKBGH heuristic was compared with a baseline heuristic that employs a greedy strategy for kit formation. Specifically, the baseline uses a different criterion to sort the maximal bicliques, sorting them in ascending order of the number of vertices. The results are presented in Tables 11 and 12, and it was observed that this greedy approach consistently produced higher (i.e., worse) objective values

TABLE 11. Comparative analysis between heuristics considering the instances with medical supplies and medications.

Instance	Baseline Heuristic Objective Value	Shared Kits	Time	SKBGH Objective Value	Shared Kits	Time
1	9	3	0.23	9	3	6.80
2	9	7	6.50	9	7	5.65
3	37	9	8.97	37	9	5.22
4	37	10	6.25	37	10	6.28
5	37	14	7.34	37	14	5.59
6	50	19	7.76	50	19	5.35
7	233	32	6.47	86	34	5.21
8	307	39	11.57	86	44	5.11
9	214	45	10.74	86	56	4.99
10	222	46	13.49	86	56	5.12

TABLE 12. Comparative analysis between heuristics considering the instances with medical supplies.

Instance	Baseline Heuristic Objective Value	Shared Kits	Time	SKBGH Objective Value	Shared Kits	Time
1	9	3	9.59	9	3	4.77
2	9	7	4.36	9	7	4.65
3	22	9	6.29	10	9	8.04
4	14	10	7.56	10	10	5.05
5	34	12	9.52	14	12	6.23
6	27	15	14.52	15	16	4.63
7	33	24	13.78	22	27	5.17
8	113	29	11.00	23	34	5.17
9	94	32	9.87	26	40	5.22
10	136	30	16.72	43	42	5.82

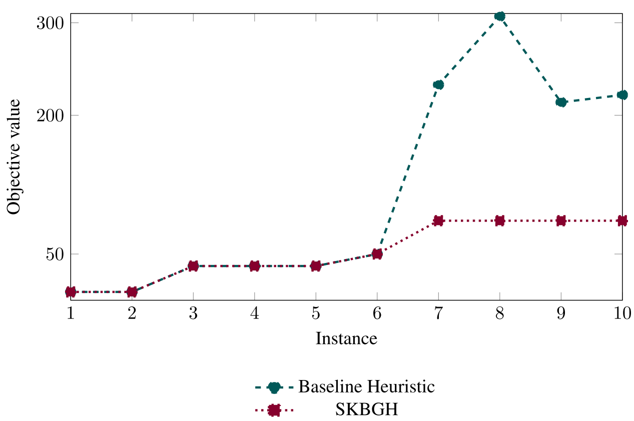


FIGURE 6. Comparative evaluation of heuristics based on objective values for instances with medical supplies and medications.

compared to the current method proposed in this paper. To improve visualization, Fig. 6 presents a comparative plot of the objective values based on the results shown in Table 11, highlighting the performance differences between the proposed method and the baseline heuristic. Furthermore, the SKBGH heuristic generates a larger number of shareable kits and achieves lower computational times for most instances.

VI. CONCLUSION AND FUTURE RESEARCH

This paper investigates the problem of configuring surgical kits to be shared across different procedures. We first introduce a mixed-integer linear programming model to minimize the maximum number of items required by a procedure that is not included in the kit. Additionally, a key constraint of this formulation prevents items from being included in multiple kits, thereby avoiding an excessive number of dedicated kits. To heuristically solve this problem, we propose a two-stage graph-based heuristic. In the first stage, groups of items related to procedures are identified using bipartite graph clustering. Subsequently, a constructive procedure generates the kits with the necessary quantities of items to meet the demand.

The experiments were conducted using real data collected from a Brazilian hospital, resulting in 20 instances. A commercial solver was employed to assess the quality of the SKBGH heuristic. The results indicate that, while the commercial solver achieved better objective function values within the imposed time limit, the heuristic produced a similar number of kits with notable characteristics and good computational time. Specifically, when analyzing the contents of the kits obtained, both methods efficiently identified the items from the shared demand. What differentiates the two approaches is the way they divide the kits, which can result in a higher or lower number of kits when compared. This characteristic allows the demand to be supplied either separately, using smaller kits, or collectively, in a larger kit. In general, the shared demand is satisfied by both approaches. However, one drawback of the heuristic approach is that, for the larger instances, it leaves a higher number of individual items to be allocated to a single procedure. It is also important to highlight that using initial heuristic solutions in the Gurobi solver enabled alternative solutions with variations in the quantities of shared kits, improved optimality gaps, and reduced computational times.

Future research directions include reformulating the model to incorporate a limit on the kit size, to account for the physical storage limit per kit, based on real data from the partner hospital, and exploring the potential for excess items in the kits by considering a permissible excess percentage. Additionally, analyzing the problem from the perspective of medications, which must meet specific requirements for drug classes and temperature, presents another avenue for investigation. Although the proposed model does not distinguish between different classes of items, it can be extended to do so—for example, by adding constraints to ensure that certain items are grouped only with similar ones, or that some items are packaged separately. Incorporating sterilization protocols may also be a valuable direction, as such considerations are typically addressed in practice when grouping items. Enhancing the heuristic approach to propose new groupings and determine subkits with the identified individual items is also possible. The maximal biclique enumeration phase could be further improved through a comparative study involving alternative enumeration algorithms. We also suggest the validation and customization of the proposed methods for hospitals in different countries or healthcare systems, to confirm their generalizability and practical relevance across

TABLE 13. Computational results obtained with the Gurobi solver for the model with a reduced parameter $|P| = 60$ (compared to $|P| = 100$).

	Instances with medical supplies and medications							Instances with medical supplies						
Instance	Number of Variables	Number of Constraints	Objective Value	*Gap*	Shared Kits	Time	with SKBGH	Number of Variables	Number of Constraints	Objective Value	*Gap*	Shared Kits	Time	with SKBGH
1	25,371	12,907	2	0.00	4	1.26	2	19,331	9,877	2	0.00	8	1.25	2
2	43,964	20,625	4	0.00	8	10.24	4	31,404	14,801	4	0.00	10	5.16	4
3	56,033	24,951	34	0.00	6	7.28	34	40,577	18,151	5	0.00	14	126.91	5
4	68,826	29,521	34	0.00	3	13.26	34	48,180	20,773	5	0.00	12	47.15	5
5	95,623	39,805	34	0.00	7	11.94	34	71,719	29,959	6	0.00	16	256.72	6
6	155,303	61,191	43	0.00	9	386.50	43	108,528	42,941	7	0.00	19	856.81	7
7	255,407	96,121	72	0.00	7	69.79	72	177,679	67,141	9	44.44	27	3,600.00	-
8	371,801	136,541	72	0.00	4	183.73	-	254,009	93,661	10	60.00	32	3,600.00	-
9	509,071	184,096	72	0.00	7	1,112.49	-	339,389	123,231	13	84.61	26	3,600.00	-
10	647,968	231,901	72	100.00	9	3,600.00	-	428,328	153,901	18	72.22	26	3,600.00	-

diverse contexts. Finally, it is recommended that experts validate the results to identify improvements and further refine the proposed approaches. As a practical recommendation, hospitals should implement the proposed kits before surgical procedures to enhance operating room organization, reduce preparation time, and minimize the risk of missing or excess items. A pilot phase involving surgical and sterilization staff is recommended to validate and fine-tune the kits before full-scale adoption. Hospitals could implement the proposed model as a decision-support layer within their existing surgical inventory systems. The optimization results can be exported as configuration tables and incorporated into management modules. This integration would enable periodic re-optimization based on updated procedure records, minimizing excess supplies and streamlining kit assembly processes.

APPENDIX

ADDITIONAL EXPERIMENTS

This appendix provides supplementary results for the analysis of the parameter $|P|$. Fig. 7 illustrates the variation in $|P|$ for Instance 7, while Table 13 reports the results obtained with a reduced limit of $|P| = 60$.

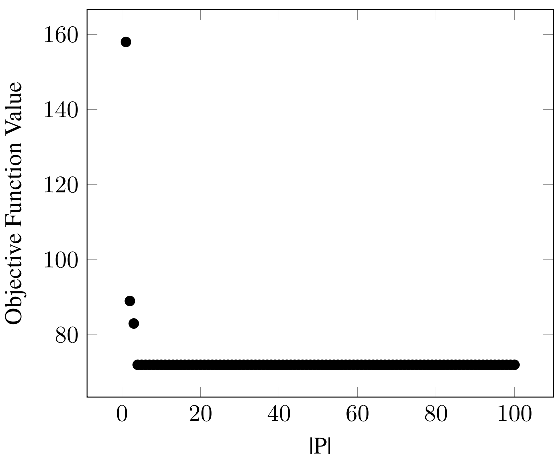


FIGURE 7. Decline in objective function value due to kit inclusion - instance 7.

DECLARATIONS

The authors contributed to the conception and design of the study. The first draft of the manuscript was written by Shayane da Silva Carvalho. They commented on previous versions of the manuscript. They read and approved the final manuscript. They have no relevant financial or non-financial interests to disclose.

A. AVAILABILITY OF DATA AND MATERIALS

The datasets analyzed during this study are not publicly available to preserve the privacy of the data provided by the partner hospital for this research project. The test instances generated for the current study are available upon request to the corresponding author.

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