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A Data-Driven Decision-Making Model for Configuring Surgical Trays Based on the Likelihood of Instrument Usages

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Abstract: In order to perform a surgical procedure, substantial numbers of sterile instruments should be readily available to surgeons through the containers referred to as surgical trays and peel packs. After the procedure, all instruments in the opened containers, regardless of whether they have been used or not, must go through the labor-intensive re-sterilization process. Empirical studies have shown that the utilization rate of instruments within trays is very low due to not having optimized tray configurations. Additionally, surgical trays often include instruments that are not likely to be used but are included "just in case", which imposes an additional cost on hospitals through unnecessary instrument re-sterilization. This study is the first analytical attempt to address the issue of configuring surgical trays based on the likelihood of instrument usage through formulating and solving a probabilistic tray optimization problem (PTOP). The PTOP model can serve as a decision support for surgeons by providing them with the tray's probability of being used for optimally configured trays and its associated reprocessing costs. The PTOP is constructed upon an integer non-linear programming model. A decomposition-based heuristic and metaheuristic method coupled with two novel local search algorithms are developed to solve the PTOP. The application of this model can be illustrated through a case study. We discuss how hospitals could benefit from our model in reducing the costs associated with opening trays unnecessarily before a procedure. Additionally, we conducted a risk analysis to estimate the level of confidence for the recommended solution.

Keywords: healthcare operations; surgical instruments; probabilistic tray optimization problem; operations research; meta-heuristics; decision support systems

MSC: 90C90

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1. Introduction

In the United States, health expenditures are projected to grow by 5.4 percent annually to reach $6.2 trillion by 2028 [1]. Hospitals account for about one-third of health expenditure [1], and operating rooms are the main cost drivers within hospitals [2,3]. An improvement in managing sterile instruments and disposable surgical supplies is one area where operating rooms could reduce costs. Surgeons request these items on their preference cards for performing procedures. The surgeons' preference cards also indicate which surgical supplies must be opened before a procedure. Several recent studies have introduced methodologies for managing disposable surgical supplies based on historical data and determining the quantity to include in a surgeon's preference card to be opened before procedures [4,5]. For sterile instruments, the ones that surgeons require to perform a procedure must have already been packed into surgical trays and peel packs. However, the trays are not surgeon specific, and a tray type may contain instruments requested by multiple surgeons, which leads to some instruments remaining unused during a procedure. After the procedure, if a tray is opened, all instruments in the tray, regardless of whether the instruments are used or not, must proceed to the Sterilization Processing Department (SPD) for cleaning, inspections and grouping into trays. Our research focuses on managing sterile instruments.

There is evidence that shows a high proportion of instruments in trays are not used during the procedures, which causes millions of dollars of cost burden on hospitals. Stockert and Langerman [6] observed that about 82.9% of instruments had not been used across four busy surgical services (i.e., Bariatric Surgery, Plastic Surgery, Otolaryngology, and Neurosurgery). In another study, Mhlaba et al. [7] reported that the utilization rate for the plastic soft tissue tray and the major laparotomy tray was 14% and 29%, respectively. Koyle et al. [8] have also indicated a utilization rate of 42% for the pediatric inguinal hernia repair tray.

A direct observation of tray usage has been conducted by the authors of this manuscript at the SPD of Geisinger Health System for the Laparoscopic and Plastic major trays. The Geisinger Health System is an integrated healthcare organization located in Pennsylvania, USA that has 12 hospitals serving more than three million people. For a single observation of Laparoscopic and Plastic trays, the utilization rates were 25% and 18%, respectively. Figure 1 illustrates a Plastic tray with 14 of the 79 instruments used during a procedure. Since the operations of the SPD are very labor-intensive, the cost associated with the unnecessary processing of instruments is significant. Farrokhi et al. [9] reported an annual cost saving of $60,000 by reducing 70% of instruments in the trays for two procedures. Then, they projected that the institution could achieve a $2.8 M annual saving by similar instrument reductions in all trays. Harvey et al. [10] also reported that two procedures of the female pelvic medicine and the minimally invasive gynecologic could annually save $151,691 by safely removing unused instruments from their surgical trays. Nast and Swords [11] indicated that improvements in the management of surgical trays in a way that more than 50% of their instruments could be reduced could lead to at least 20% of cost savings.

Figure 1. Illustration of used and unused instruments for the Plastic tray. The used instruments are listed on the towel, and the unused instruments are collected in the tray.

Better management of surgical trays would not only result in immediate cost savings but also allow for indirect cost reductions. The frequent handling of the trays in the SPD and operating rooms is the main reason for the development of Work-Related Musculoskeletal Disorders (WRMSDs) among Perioperative Nurses and Technicians (PNT) [12–15]. The occurrence of WRMSDs diminishes the productivity of the PNTs, which has financial implications for hospitals through the absenteeism of PNTs from work. In addition, improved surgical trays could allow for cost savings through a reduced setup time required for counting the instruments before and after the procedures [8,11], as the average cost of running an operating room is estimated to be $63.64 per minute [16].

For improving the management of surgical trays and their sterile instrument components, a hospital has to make three types of decisions: (1) determine the configuration of the trays regarding the type and the number of instruments; (2) assign the configured trays to surgeons and procedures; and (3) determine the quantity of each tray type [2,17,18]. The two former decisions depend on the surgeon's preferences in the type and quantity of requested instruments. The last decision is driven by the frequency and scheduling of the cases. This problem of configuring surgical trays is known as the *tray optimization problem* (TOP).

Despite the importance and significant impact of managing surgical trays on hospital costs, there have been relatively few studies devoted to addressing it. Van De Klundert et al. [19] developed an integer linear programming model for the TOP and proved that the TOP is an NP-hard problem. Florijn [20] focused on developing an optimization model for the TOP with the objectives of minimizing the number of trays, the handling of trays, and the number of instruments. Reymondon et al. [21] developed a non-linear mathematical model to solve the TOP. Dobson et al. [22] designed a heuristic for solving the TOP and showed that the optimal solution of the TOP depends on both the surgeon's preferences and the operation rooms' schedules. Dollevoet et al. [17] also formulated the TOP and defined capacity constraints to incorporate the capacity of trays into modeling. They proposed three solution methodologies: row and column generation, greedy heuristics, and genetic algorithm. Ahmadi et al. [2] designed a bi-objective optimization model for the TOP to concurrently enhance the utilization rate of the instruments and decrease the tray types required for each procedure. They took the weight of the trays into account to avoid composing overweight trays to decrease the risk of WRMSDs. They also developed an iterated local search heuristic for solving the designed model. For a comprehensive review of sterile instrument management papers, readers are referred to Ahmadi et al. [18] and Dos Santos et al. [23]. Harris and Claudio [24] formulated the TOP using a goal programming approach. Most recently, Deshpande et al. [25] developed an integer programming model and used real instrument usage data to address the TOP.

All aforementioned papers developed deterministic models for the TOP based on the assumption that the instances of instruments required for performing a procedure are precisely known in advance. However, this is not true in practice. Even if an instrument is requested by a surgeon for a procedure, it may be unneeded for a specific patient. Instruments are included to ensure the quality of care, which leads to having to reprocess instruments that were not used during a procedure, which imposes a high cost on the system.

A recently published paper utilized the empirical usage distributions of disposable surgical supplies to determine the optimal quantity to be included on the surgeon's preference cards and to be opened before the procedure [4]. The authors used a newsvendor approach to formulate the problem of designing surgeons' preference cards and evaluated their model under different service levels. However, this research does not address the configuration of surgical trays. In our research, we considered the fact that the true usage of instruments highly depends on the surgeon's preferences, as well as the condition of patients during the procedure. Therefore, we extended the conventional deterministic TOP to the *probabilistic tray optimization problem* (PTOP), which enabled us to configure trays based on the likelihood of instrument usage. To this aim, the cost components (i.e., the cost associated with inventory, sterilization, and processing of instruments), along with the historical data about instrument usage, could be incorporated to configure trays. To solve the PTOP, we constructed a heuristic algorithm based on the well-known p-median problem. In addition, we developed an empowered genetic algorithm with two local searches to solve the PTOP. The performances of different solution approaches were investigated through a case study.

The designed probabilistic optimization method captures instruments that are never (or rarely) used and has them grouped separately from the instruments with a high chance of usage. It provides surgeons with the tray's probability of being used and the associated costs. This information, along with case consideration, enables surgeons to better decide whether to open a tray before a procedure or to only open the tray if it is needed during a procedure. Since hospitals incur high costs for the supplies and instruments to function properly, and a great quantity of these items are left unused, the implementation of the proposed model is expected to have a broad financial impact by eliminating unnecessary healthcare costs.

The rest of this paper is organized as follows. In Section 2, the PTOP is described in detail. In Section 3, the mathematical model describing the PTOP is formulated, followed by solution methods presented in Sections 4 and 5. In Section 6, the incorporated case study, along with the computational results, are reported. In Section 7, managerial insights are discussed. Finally, the conclusion and discussion about implementing our model are covered in Section 8.

2. Problem Description

In order to perform a procedure in an operating room (OR), surgeons request a list of sterile instruments, which have already been grouped into trays and peel packs, to be available in the OR. The trays and peel packs associated with these sterile instruments are included on the surgeons' preference cards. A collection of surgeons' preference cards can be shown using a matrix whose rows and columns represent surgeon procedures and instruments, respectively. The elements of this matrix indicate the number of each instrument a surgeon has requested to perform a given procedure. A sample of the matrix constructed based on two surgeons and three procedures (i.e., six surgeon-procedure combinations) and five instruments has been shown in Table 1. For example, surgeon-procedure 5 requested one instance of instrument 3, while surgeon-procedure 6 requested two instances of instrument 3. Therefore, if two instances of instrument 3 are placed in the same tray type, and the tray type is assigned to surgeon-procedure 5 and surgeon-procedure 6, every time surgeon-procedure 5 performs that particular procedure, one instance of instrument 3 that was not requested would be sent in the tray. These unrequested instruments cause unnecessary reprocessing such as inspection, re-sterilization, packaging, and handling, all of which can be reduced through an improved tray configuration.

Table 1. An example of surgeons' preference cards.

Surgeon-Procedures	Instrument				
	1	**2**	**3**	**4**	**5**
1	0	2	0	3	1
2	0	1	3	0	1
3	2	3	2	1	2
4	1	1	1	0	2
5	2	2	1	0	2
6	2	0	2	1	0

In addition, not all of the instruments requested by surgeons are used. Whether an instrument is used for a procedure depends on the patient's condition during the procedure, so surgeons often request extra instruments to be included in the trays just in case. By grouping instruments that are unlikely to be used in separate trays from those that are frequently used, surgeons can decide whether to open the trays before or during the procedure. Not opening the trays that contain less frequently used instruments before the procedure can lead to the decreased reprocessing of unused instruments.

The above-discussed issues can be addressed by solving the probabilistic tray optimization problem (PTOP), which consists of two decisions: configuring surgical trays based on the likelihood of instrument usage and then assigning the configured trays to the surgeon procedures. In order to formally describe the PTOP, we can define the usage of the jth copy of instrument i for surgeon-procedure k as a random variable with P_{ijk} probability of being used. In other words, there is a P_{ijk} chance that the jth copy of instrument i will be used during surgeon-procedure k, and $1 - P_{ijk}$ chance that the instrument will not be used. Throughout the rest of this paper, for the sake of simplicity, the *procedure* is used instead of the tuple *surgeon-procedure* so that each surgeon performing a given procedure is treated as a unique procedure.

To show the probability of usage associated with each instance of instruments, the matrix describing the PTOP (i.e., Table 1) is converted to a zero-one matrix, namely a procedure-instrument incidence matrix (PIIM), with the same number of rows as the original PTOP matrix. Each column i in the original PTOP matrix is converted to N_i columns in the PIIM, where $N_i = \max_k \{A_{ik}\}$ and A_{ik} is the requested quantity of item i for procedure k. The entries in the PIIM, a_{ijk}, are equal to "1" if the jth copy of instrument i is requested for procedure k and 0 otherwise, where $a_{ijk} \geq a_{ij'k}$ if $j < j'$. The PIIM corresponding to the PTOP example shown in Table 1 is provided in Table 2.

Table 2. The binary representation of the surgeons' preference cards.

Surgeon-Procedures	Instrument												
	1		2			3			4			5	
1	0	0	1	1	0	0	0	0	1	1	1	1	0
2	0	0	1	0	0	1	1	1	0	0	0	1	0
3	1	1	1	1	1	1	1	0	1	0	0	1	1
4	1	0	1	0	0	1	0	0	0	0	0	1	1
5	1	1	1	1	0	1	0	0	0	0	0	1	1
6	1	1	0	0	0	1	1	0	1	0	0	0	0

Each column of the PIIM stands for an instance of an instrument, which can be treated as a single instrument. For example, the first column of PIIM stands for the first instance of instrument 1, the second column stands for the second instance of instrument 1, the third column stands for the first instance of instrument 2, and so on. One of our assumptions in this study is that each surgeon performed a procedure only one time in a given day, and therefore, instruments are not reused within a day. Given this assumption, it is obvious that for each instrument i, at least N_i instances needed to be stocked in an inventory to ensure that what surgeons requested on their preference cards would be available within a tray in the OR. For the instruments and procedures in the PIIM, we could show the probability of each instrument's usage, denoted by P_{ijk}, as presented in Table 3, where $P_{ijk} \geq P_{ij'k}$ if $j < j'$. For example, Table 3 shows that the first instance of instrument 1 had an 80% chance of being used during procedure 3, while its second instance had a 15% chance of usage during the same procedure.

Table 3. The probability distribution of instruments' usage.

Proc.	Instrument												
	1		2			3			4			5	
1	0.00	0.00	0.95	0.70	0.00	0.00	0.00	0.00	0.76	0.25	0.18	0.95	0.00
2	0.00	0.00	0.56	0.00	0.00	0.48	0.26	0.12	0.00	0.00	0.00	0.80	0.00
3	0.80	0.15	0.70	0.53	0.01	0.60	0.18	0.00	0.45	0.00	0.00	0.75	0.14
4	0.90	0.00	0.40	0.00	0.00	0.68	0.00	0.00	0.00	0.00	0.00	0.85	0.12
5	0.45	0.15	0.15	0.05	0.00	0.19	0.00	0.00	0.00	0.00	0.00	0.65	0.20
6	0.85	0.20	0.00	0.00	0.00	0.39	0.25	0.00	0.78	0.00	0.00	0.00	0.00

The specific question to be answered in this research is how to cluster instruments into containers (i.e., trays and peel packs) to decrease the expected number of instruments that were reprocessed without being used. A container is defined as a "peel pack" if it holds a single instrument by itself; otherwise, the container can be referred to as a "tray type". The next section describes the formulated mathematical model followed by a solution approach for answering this question.

3. Mathematical Formulation

We assumed that instrument usages were mutually independent and did not account for correlated instruments that are often used together. In the absence of data, we were not able to directly verify this assumption.

- **Indices**

i: Index for instrument, $i \in \{1, 2, 3, \ldots, I\}$.
i^j: Index for jth copy of instrument i, $j \in \{1, 2, 3, \ldots, N_i\}$ where N_i is the maximum number of instruments of type i that can be required in one procedure.
k: Index for procedure, $k \in \{1, 2, 3, \ldots, K\}$.
t: Index for container (i.e., tray or peel pack), $t \in \{1, 2, 3, \ldots, T\}$.

- **Parameters**

a_{i^jk}: The elements in the PIIM.
P_{i^jk}: The probability that jth copy of instrument i will be used during procedure k.
W_i: Unit weight of instrument i.
F_k: Frequency of procedure k performed in a year.
L: Weight limit for each tray type established by AAMI and AORN.
C_1: The unit cost of reprocessing an instrument in a tray.
C_2: The unit cost of reprocessing an instrument in a peel pack.
C_3: The unit cost associated with administration and handling of a tray type.
C_4 : The unit cost associated with administration and handling of a peel pack.
M: A big number.

- **Objective function**

$$Min\ f = f_1 + f_2 + f_3 + f_4$$

$$f_1 :\ C_1\left[\sum_{t=1}^{T}(1-e_t)\sum_{k=1}^{K} y_{tk}F_k\left(\sum_{i=1}^{I}\sum_{j=1}^{N_i} z_{i^jt}\right)\left(1-\prod_{i=1}^{I}\prod_{j=1}^{N_i}(1-z_{i^jt}P_{i^jk})\right)\right] \tag{1a}$$

$$f_2 : C_2\left[\sum_{t=1}^{T} e_t \sum_{k=1}^{K} y_{tk}F_k \sum_{i=1}^{I}\sum_{j=1}^{N_i} z_{i^jt}P_{i^jk}\right] \tag{1b}$$

$$f_3 :\ C_3\sum_{t=1}^{T}\sum_{k=1}^{K} F_k x_t y_{tk}(1-e_t) \tag{1c}$$

$$f_4 :\ C_4\sum_{t=1}^{T}\sum_{k=1}^{K} F_k x_t y_{tk} e_t \tag{1d}$$

This is subject to:

$$\sum_{i=1}^{I}\sum_{j=1}^{N_i} z_{i^jt}W_i \le x_t L, \quad \forall t \in \{1, \ldots, T\}, \tag{2}$$

$$\sum_{t=1}^{T} y_{tk}z_{i^jt} \ge a_{i^jk},\ \forall\ i \in \{1, \ldots, I\},\ j \in \{1, \ldots, J\}, k \in \{1, \ldots, K\}, \tag{3}$$

$$\sum_{i=1}^{I}\sum_{j=1}^{N_i} z_{i^jt} \le (1-e_t)M + 1, \quad \forall t \in \{1, \ldots, T\}, \tag{4}$$

$$\sum_{i=1}^{I}\sum_{j=1}^{N_i} z_{ijt} \geq 2 - 2e_t, \quad \forall t \in \{1,\ldots,T\}, \tag{5}$$

$$\sum_{t=1}^{T} z_{ijt} = 1, \quad \forall i \in \{1,\ldots,I\}, j \in \{1,\ldots,J\}, \tag{6}$$

$$\begin{aligned} z_{ijt} \in \{0,1\},\ x_t \in \{0,1\},\ y_{tk} \in \{0,1\},\ \forall\, k \in \{1,\ldots,K\}, i \in \{1,\ldots,I\}, \\ e_t \in \{0,1\}, t \in \{1,\ldots,T\},\ j \in \{1,\ldots,N_i\}. \end{aligned} \tag{7}$$

In the first component of the objective function, the term $\prod_{i=1}^{I}\prod_{j=1}^{N_i}\left(1 - z_{ijt}P_{ijk}\right)$ indicates the probability that none of the instruments in tray type t are used for procedure k, i.e., the probability that tray type t remains unused. Therefore, $\left(1 - \prod_{i=1}^{I}\prod_{j=1}^{N_i}\left(1 - z_{ijt}P_{ijk}\right)\right)$ describes the likelihood of tray t being used during a procedure k. Multiplying this expression by the total number of instruments in the tray (i.e., $\sum_{i=1}^{I}\sum_{j=1}^{N_i} z_{ijt}$) yields the expected number of instruments that are exposed during the procedure. Likewise, $\sum_{i=1}^{I}\sum_{j=1}^{N_i} z_{ijt}P_{ijk}$ describes the expected number of instruments in peel packs that are exposed during the procedure. Thus, component (1a) is the total expected reprocessing cost of the instruments in trays, including the cost of re-sterilization, the cost of inspection, and the cost of packing instruments into trays. Component (1b) is the total expected reprocessing cost of instruments in peel packs. Component (1c) is the total administrative cost associated with handling and stocking tray types. Creating more tray types as a result of separating the existing trays into additional smaller trays induces higher logistics costs that are related to stocking and transporting them. Finally, component (1d) is the total administrative cost of peel packs. It should also be noted that the model assumes that the reprocessing costs only depend on whether an instrument is in a tray or a peel pack, and the costs associated with instruments that are in the same tray are the same. Even though the sterilization time varies with the type of instrument, it is very difficult to quantify the time and, therefore, the cost of sterilizing every single instrument.

Constraint set (2) imposes a weight limit for trays to not exceed a user-specified value. In order to prevent or reduce ergonomic, sterilization, and drying issues, the Association for the Advancement of Medical Instrumentation (AAMI) recommends that the weight of surgical trays not exceed 25 pounds [26]. Constraint set (3) respects the surgeons' preferences in the type and quantity of instruments. Constraint sets (4) and (5) can determine whether an instrument is in a peel pack or placed in a tray. It can be recalled that the peel packs and tray types are distinguished by the number of instruments in the container. If two or more instruments are grouped together to be placed in a container, this is referred to as a tray, but if a single instrument is placed in a container by itself, this is defined as a peel pack. Constraint set (6) ensures that each instrument has only been assigned to one tray. Constraint set (7) imposes binary conditions of decision variables. Since the objective function (1) and constraint set (3) involve non-linear terms, this model is an integer non-linear programming model (INLP).

Lemma 1. *The PTOP described by (1)–(7) is NP-hard.*

Proof of Lemma 1. Karp [27] proved that the set-covering problem is an NP-hard problem. Here, we showed that the set-covering problem was not more complex than the deterministic version of the PTOP. This meant that the set-covering problem was reducible to PTOP in polynomial time complexity.

We defined an instance of a set-covering problem by a universe $\mathcal{U} = \{1, \ldots, n\}$ and a set $\mathcal{S}$ containing subsets of $\mathcal{U}$. The objective was to find the cover $\mathcal{C}$, where $\mathcal{C} \subseteq \mathcal{S}$, had the smallest cardinality such that its union was $\mathcal{U}$. Then, we defined $\mathcal{U}$ as the set of instruments, $\mathcal{S}$ as the collection of all possible containers, and a single procedure $K = 1$.

For simplicity, instruments of the same type were assumed to be indexed sequentially. For example, the first copy of instrument 1 was indexed 1, the second copy was indexed 2, and so on. We also set $C_3 = C_4 = 0$, $C_1 = C_2 = 1$, and $a_{i1} = 1$ for $i \in \mathcal{U}$. For a given container $t \in \mathcal{S}$, $z_{it} = 1$ if $i \in t$. Thus, for a given container $t \in \mathcal{S}$, z_{it}, e_t , and x_t become a parameter instead of a variable.

We also assumed that $P_{i1} = 1$ for all instruments $i \in \mathcal{U}$ (i.e., deterministic version of the PTOP), and $F_1 = 1$. The PTOP can be written as:

$$Min f = \sum_{t \in \mathcal{S}} (1 - e_t) y_{t1} \sum_{i \in \mathcal{U}} z_{it} + \sum_{t \in \mathcal{S}} e_t y_{t1} \sum_{i \in \mathcal{U}} z_{it}$$

For a given $t \in \mathcal{S}$ if $|t| = \sum_{i \in \mathcal{U}} z_{it} = 1$ then $e_t = 1$ (i.e., the container is a peel pack), and if $|t| = \sum_{i \in \mathcal{U}} z_{it} \geq 2$ then $e_t = 0$ (i.e., the container is a tray). Thus, the objective function becomes:

$$Min f = \sum_{t \in \mathcal{S}} y_{t1} \sum_{i \in \mathcal{U}} z_{it}$$

This is subject to:

$$\sum_{t \in \mathcal{S}} y_{t1} z_{it} \geq 1, \forall i \in \mathcal{U},$$

$$y_{t1} \in \{0, 1\}, \forall t \in \mathcal{S}.$$

This matches the ILP formulation of the set-covering problem. □

Lemma 1 implies that the PTOP cannot be solved in a reasonable time with any INLP solver, even for small sizes. Given this challenge, a heuristic and a metaheuristic algorithm were developed to solve the formulated PTOP. To this aim, the PTOP can be decomposed into two sub-problems, namely the probabilistic tray configuration problem (PTCP) and the probabilistic tray assignment problem (PTAP).

The PTCP deals with the problem of grouping instruments into trays and/or peel packs. More specifically, the PTCP determines which instruments and in what quantities should be grouped into the same tray, as well as which instruments should be wrapped as a peel pack. In the next step, the PTAP utilizes the solution of the PTCP and determines which tray types and peel packs should be assigned to each surgeon and procedure to provide all the instruments listed on the preference card. In the following sections, we design and discuss a heuristic and a metaheuristic for dealing with PTCP. These approaches determine the values for three out of four decision variables of the PTOP (i.e., $z_{i^j t}$, x_t, and e_t). In order to cope with PTAP, which is the problem of determining values of the y_{tk} decision variables, the solution generated by solving the PTCP can be fixed to the PTOP so that the PTAP becomes the trivial problem of solving an integer linear programming with objective function (1) subject to the constraint set (3).

4. Heuristic for Solving PTCP

The clustering heuristic provides an approximate solution to the PTCP by formulating the PTCP as a p-median model. The p-median model has a long history of use in several problems, such as location-allocation problems [28,29] and cell formation problems [30,31]. In this approach, the PTCP is formulated as an undirected graph, where each node represents an instrument, and each arc represents the expected number of exposed instruments when the respective two instruments in an arc are placed in the same tray. We wish to select some of the instruments as *median vertices* (to represent containers) and assign other instruments to these containers in such a way that can minimize the total distance between the selected containers and other instruments. We can define an undirected complete graph $G = (V, E)$, where the set of vertices V is the set of instances of the instruments ($|V| = \sum_{i=1}^{I} \max_k \{A_{ik}\}$). Additionally, there are $|V|$ potential containers to which instruments can be assigned. Two vertices i^j and m^n (i.e., jth copy of instrument i and nth copy of instrument m, respectively) are connected by an arc $(i^j, m^n) \in E$. Associated with each arc (i^j, m^n), there is a distance $d_{i^j m^n}$. The $d_{i^j m^n} = \sum_{k=1}^{K} F_k 2\big(1 - (1 - p_{i^j k})(1 - p_{m^n k})\big)$ which indicates the expected number of instruments i^j and m^n that are exposed in the required procedures—and therefore need to be re-sterilized—when two instruments i^j and m^n are placed in the same container and are assigned to all procedures. It should be noted that if the container holding two instruments i^j and m^n is assigned to a procedure k, for which these instruments are not requested (i.e., $p_{i^j k} = 0$ and $p_{m^n k} = 0$), then it contributes a value of 0 in the $d_{i^j m^n}$ calculation. The PTCP decides which instruments are stored in each of the predetermined P containers, which might be trays or peel packs, and assigns instruments to these P containers. The formulated integer programming model for solving PTCP in the p-median context is provided below.

$$Min \sum_{i=1}^{I} \sum_{j=1}^{N_i} \sum_{m=1}^{I} \sum_{n=1}^{N_m} d_{i^j m^n} h_{i^j m^n} \tag{8}$$

$$\sum_{m=1}^{I} \sum_{n=1}^{N_m} h_{i^j m^n} = 1, \;\; \forall\, i \in \{1, \ldots, I\},\, j \in \{1, \ldots, N_i\}, \tag{9}$$

$$\sum_{m=1}^{I} \sum_{n=1}^{N_m} h_{m^n m^n} = P \tag{10}$$

$$\sum_{i=1}^{I} \sum_{j=1}^{N_i} h_{i^j m^n} W_i \leq h_{m^n m^n} L, \;\; \forall\, m \in \{1, \ldots, I\}, n \in \{1, \ldots, N_i\}. \tag{11}$$

where $h_{i^j m^n}$ is a binary decision variable, which is equal to one if the jth copy of instrument i and the nth copy of instrument m are placed in the same tray type and is equal to 0. The set of decision variables $\{h_{i^j m^n}\}_{m=i,n=j}$ indicates the candidate containers that need to be created. The $d_{i^j m^n}$ values can be collected into a symmetric distance matrix whose diagonal values $\{d_{i^j m^n}\}_{m=i,n=j}$ indicate the expected number of instruments to be re-sterilized when the instrument is placed in a container by itself (i.e., peel packed). The objective function (8) minimizes the sum of the expected number of instruments to be re-sterilized. The constraint set (9) ensures that each instrument is assigned to exactly one potential container. The constraint set (10) ensures that P containers are assembled, and constraint set (11) prevents tray configurations that violate the weight limit.

Solving the formulated p-median problem provides an approximate solution to the PTCP, and in the next step, by fixing the decision variables corresponding to the PTCP in the model described in Section 3, we can solve the PTAP. However, the p-median model only accounts for a pre-specified number of containers. Therefore, the p-median model and then PTAP can be solved iteratively by choosing the extreme value for $P = \sum_{i=1}^{I} \max_k \{A_{ik}\}$, which implies that all instruments are peel-packed and decreases the value of P by one in each iteration until no feasible solution can be generated for the selected P. A summary of the proposed p-median based heuristic is presented in Algorithm A1 of Appendix A.

In order to show how the p-median-based heuristic works, let us consider the PTOP example presented in Table 1. According to the PIIM (see Table 2), there exist 13 instances of instruments, each of which can be a candidate for a container. Therefore, the highest possible value for P is 13. Using the probabilities of instrument usage presented in Table 3, the values for $d_{i^j m^n}$ by assuming $F_k = 1$ for all procedures k are shown in Table A1 of

Appendix A. In the following, the results of solving the p-median model are reported, where the instruments have a unit weight ($W = 1$ pound) and the capacity of the tray is restricted to not exceed 5 pounds. Therefore, each container can hold a maximum of five instruments, which implies that at least three containers are needed to be able to generate a feasible solution. It should be noted that the values of the weight of the instruments and the capacity of the trays for this small example were chosen arbitrarily just to show the applicability of the p-median model when solving the PTCP.

Figure 2 illustrates the obtained solution for the PTCP when four containers are considered (i.e., $P = 4$). As Figure 2 shows, the instruments are clustered into three tray types and one peel pack. The capacities of tray type 1 and tray type 2 are fully utilized as each contains five instruments. Tray type 3 contains two instruments of {1, 6}, and instrument 12 is placed in a peel pack.

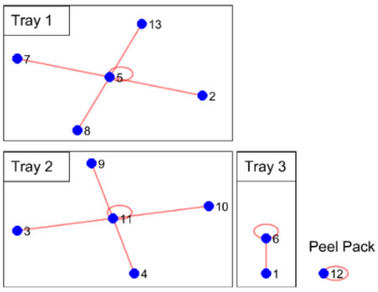

Figure 2. The solution of PTCP obtained from p-median heuristic.

5. Metaheuristic for Solving PTCP

The Genetic Algorithm (GA) is a kind of evolutionary algorithm that can solve intractable optimization problems based on stochastic search. Researchers have reported the successful application of GA to many different large space optimization problems, such as the shortest path [32,33] and inventory management [34–36]. The first step in implementing a GA is to encode a solution to the problem, denoted either as a chromosome or individual. Each chromosome is composed of genes, and each gene carries some information. The GA starts by generating a group of initial chromosomes. This group constitutes the population of the first generation. Each individual in the population is evaluated through the objective function and receives a fitness value. Individuals with a better fitness value have a higher chance of surviving for the next generation. Individuals are selected for removal to the mating pool for reproduction based on their fitness values. Reproduction is performed by the use of the crossover operators so that the generated child inherits some information from their parents. Mutation operators are incorporated to increase diversity among generations. In addition, to avoid the traditional GA from being stuck in a local optimum, we designed two local search algorithms called combining local search (CLS) and decomposing local search into the GA to improve its exploration capability.

5.1. Solution Encoding

A solution to the PTCP is encoded as a vector of integer numbers defining the index of containers to which instruments are assigned. The cardinality of the vector is equal to the total number of instances of instruments stocked in an inventory (i.e., $\sum_{i=1}^{I} \max_k \{A_{ik}\}$, which is the number of columns in the PIIM). The instruments are also presented in the order of the columns of the PIIM. For example, given the PIIM of Table 2 and 13 possible containers, including trays and peel packs, the vector [4,12,4,3,4,2,6,2,4,6,2,3,3] means that the first, the third, the fifth, and the ninth instruments are placed in container 4. The second instrument is in container 12 by itself. The fourth, twelfth and thirteenth instruments are placed in container 3. The sixth, eighth and eleventh instruments are in container 2. Finally, the seventh and the tenth instruments are in container 6. Therefore, containers 4, 3, 2, and 6 can be labeled as trays of instruments since they contain more than one instrument, while container 12 is a peel pack since it holds a single instrument. Thus, the above vector indicates that the instruments can be grouped into four tray types and one peel pack. A sample of solution encoding is illustrated in Figure 3.

Instrument	1	2	3	4	5	6	7	8	9	10	11	12	13
Container index	4	12	4	3	4	2	6	2	4	6	2	3	3

Figure 3. Solution encoding for a sample PTCP.

5.2. Fitness Function

The fitness function can be used to assess the quality of chromosomes, of which chromosomes with better fitness values are more likely to survive. For a given chromosome which is a solution to the PTCP and determines values of $z_{ij't}$, x_t, and e_t, the PTAP is solved to determine the values of the y_{tk} decision variables. It can be recalled that the PTAP is an integer linear programming model of the objective function (1) subject to the constraint set (3). Finally, the fitness value corresponding to each chromosome is defined as $\frac{1}{f}$, where f is the value of the objective function (1).

5.3. Genetic Operators

5.3.1. Selection Operator

This operator selects individuals in the current population for reproduction. There exist various selection operators such as tournament selection, random selection, and roulette-wheel selection. In this study, the roulette-wheel selection operator was chosen, in which the chance of individuals being selected for reproduction was proportional to their fitness value.

5.3.2. Crossover Operators

Two cut-point crossover operators: this operator randomly selects two genes as the cut-points within the selected parents and then interchanges the sections before and after these points to produce two new solutions [37]. The mechanism of this operator is shown in Figure 4.

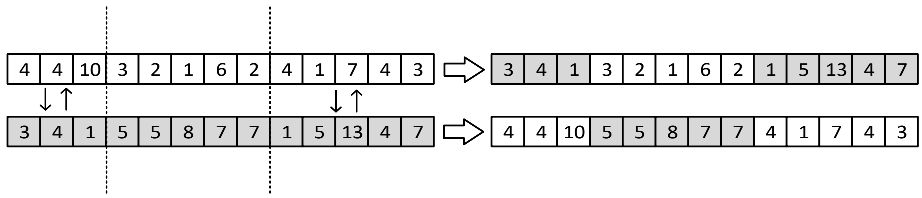

Figure 4. Two cut-point crossover operator.

Uniform crossover operator: this operator fills each gene of the offspring by copying the corresponding gene from one or the other parent with a 50% probability [38]. To do so, a binary vector with the same length as the parents can be generated using a uniform distribution. Each gene's value in the offspring is copied from the first parent if the value of the corresponding gene in the binary vector is "1"; otherwise, the gene's value of the offspring is copied from the second parent (see Figure 5).

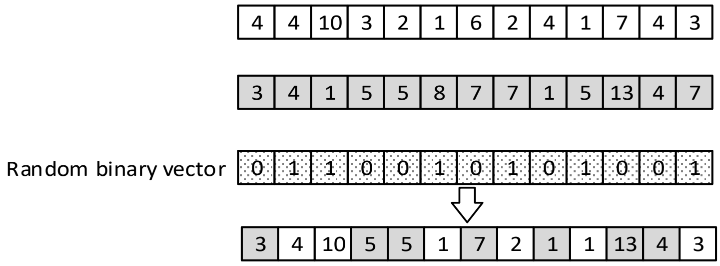

Figure 5. Uniform crossover operator.

5.3.3. Mutation Operators

Swap Operator: As illustrated in Figure 6, this operator swaps two arbitrary genes in a parent.

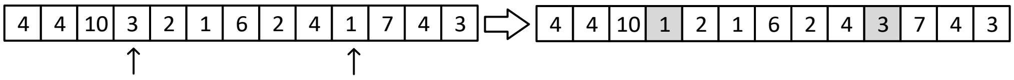

Figure 6. Swap mutation operator.

Inversion operator: this operator randomly selects two genes and then reverses the sequence of the section between the selected genes (Figure 7).

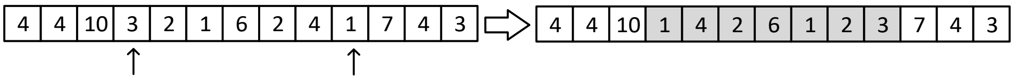

Figure 7. Inversion mutation operator.

Shifts operator: this operator selects one gene to transfer it from its current position to the first position and shifts the rest of the genes forward (Figure 8).

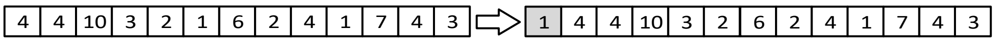

Figure 8. Shifts mutation operator.

Shuffle operator: this operator randomly selects two genes in a solution and then randomly updates the values of the section between these two genes (Figure 9).

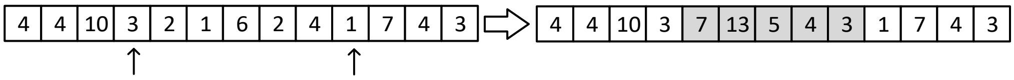

Figure 9. Shuffle mutation operator.

If any of the mutation and crossover operators result in an infeasible solution by violating the weight limit constraint, a repairing mechanism can be performed to bring the solution into the feasible region. In the repairing mechanism, as long as there are trays that exceed the weight limit, the lightest instruments from those trays can be moved to the lightest trays to ensure that the weight limit constraint is met.

5.4. Combining Local Search (CLS)

The CLS attempts to reduce the number of containers in a given solution. For this purpose, some containers should be selected, and then their instruments should be combined together to become a single container. The selection of containers occurs based on their contribution to the objective function. Given that a container t holds I instruments, its contribution to the objective function is equal to the cost component f_1 (i.e., expression 1a) for the instrument trays and is equal to the cost component f_2 (i.e., expression 1b) for the peel packs, where the container is assumed to be assigned to all procedures (i.e., $y_{tk} = 1$, $\forall\, t \in \{1, \ldots, T\}$ and $k \in \{1, \ldots, K\}$). Therefore, the contribution of a tray t, denoted as O_t, can be calculated as follows:

$$O_t = C_1 \left[\sum_{k=1}^{K} y_{tk} F_k \left(\sum_{i=1}^{I} \sum_{j=1}^{N_i} z_{i^j t} \right) \left(1 - \prod_{i=1}^{I} \prod_{j=1}^{N_i} (1 - z_{i^j t} P_{i^j k}) \right) \right], \; \forall\, t \in \{1, \ldots, T\} |\; t \text{ is a tray}, \tag{12}$$

$$O_t = C_2 \sum_{k=1}^{K} F_k \sum_{i=1}^{I} \sum_{j=1}^{N_i} z_{i^j t} P_{i^j k}, \; \forall\, t \in \{1, \ldots, T\} |\; t \text{ is a peel pack}. \tag{13}$$

In the next step, three walk points are considered in the search scheme as follows. *Walk 1*: combining the two containers with the lowest O_t; *Walk 2*: combining the two containers with the highest O_t; *Walk 3*: combining the container with the lowest O_t and the container with the highest O_t. The repairing mechanism can also be applied when these explorations yield a tray that violates the maximum weight of a tray. Among the visited solutions, the best one in terms of the objective function's value can be added to the current population. This selected solution cab also be considered as the starting point for the next walk. To further explore the solution space and escape from the local optima, the CLS is enabled for random walks in a feasible solution space with the probability α. These steps are successively performed until the number of containers is reduced by γ percent. Algorithm A2 of Appendix A presents the CLS pseudo-code.

For example, it can be assumed that a solution [4,4,10,3,2,1,6,2,4,1,7,4,3] is selected for application to the CLS. This solution represents seven container types, which are indexed as 4, 10, 3, 2, 1, 6 and 7. Given the probabilities of instrument usage in Table 3, $C_1 = 3$, $C_2 = 2$, and $F_{k \in \{1,\ldots,\,6\}} = 10$, the following table shows the instruments in each container and the contribution of each container to the objective function (Table 4).

Table 4. An example of calculating contribution of each container to the objective function.

Container Type	Included Instruments in the Container *	Container Type	Container's Contribution (O_t)
1	$3^1, 4^2$	Tray	155.4
2	$2^3, 3^3$	Tray	7.8
3	$2^2, 5^2$	Tray	99.4
4	$1^1, 1^2$, 4^1, 5^1	Tray	667.1
6	3^2	Peel pack	13.8
7	4^3	Peel pack	3.6
10	2^1	Peel pack	55.2

* i^j indicates the jth copy of instrument i

Now it can be assumed that *walk 1* is intended to be explored. Since containers 7 and 2 contribute the lowest costs to the objective function, they are combined to reduce the number of containers. In this case, all instruments in container 7 can be moved to container 2, which results in a new solution $\mathcal{S}_1$ as [4,4,10,3,2,1,6,2,4,1,2,4,3]. This new solution no longer includes container 7.

5.5. Decomposing Local Search (DLS)

In contrast with CLS, the decomposing local search (DLS) explores the solution space by creating new containers. Similar to the steps described for performing CLS, the DLS also consists of two steps. In the first step, the contribution of containers to the objective function can be calculated according to expressions (12) and expressions (13). The containers with the lowest and the highest contributions are the candidates to be decomposed. If the candidate container is a peel pack, then it can be excluded from the decomposition process.

In the next step, given a container t, the contribution of each instrument to the objective function is calculated according to the expression (14).

$$O_i' = C_1 \sum_{k=1}^{K} F_k P_{ijk}, \ \ \forall\, i \in \{1, \ldots, I\} \tag{14}$$

Finally, the instruments with the lowest and the highest O_i' are removed from their current tray, and each is placed in a new container by itself (i.e., a peel pack). For the DLS algorithm, the same random walk strategy as described for the CLS algorithm can be implemented. The pseudo-code for the DLS algorithm is presented in Algorithm A3 of Appendix A. Since both CLS and DLS algorithms take the contributions of the trays and instruments into account and have random components, they are expected to exploit prior knowledge while exploring the solution space.

6. Experimental Design

6.1. Benchmark Problems

The performance of the proposed algorithms can be evaluated using three datasets introduced by Ahmadi et al. [2], as well as a new *VLD* dataset introduced in this paper for validation purposes. Each dataset contains five instances with the same number of surgeons and procedures. The usage probabilities of the instruments are randomly generated from a uniform distribution [0, 1]. The specifications of the datasets are presented in Table 5.

Table 5. Specifications of the datasets.

Dataset Name	Number of Instances	Number of Surgeons	Number of Procedures	Number of Unique Instruments	Total Number of Instruments
VLD	5	2	3	5	13
1S-7P	5	1	7	76	136
2S-7P	5	2	7	76	136
5S-7P	5	5	7	76	250

The small size instances in the *VLD* dataset are five variations of the example depicted in Table 1, which were constructed upon two surgeons, three procedures, five unique instruments, and thirteen copies of instruments. The weight of each instrument for this *VLD* dataset was assumed to be one pound with a tray capacity of 5 pounds. Additionally, the frequency of each procedure can be assumed to be one time per year. The unit cost of reprocessing an instrument in a tray (i.e., C_1) and the unit cost of reprocessing an instrument in a peel pack (i.e., C_2) were retrieved from Mhlaba et al. [7] at $0.40 and $0.80, respectively. The costs associated with the administration and handling of a tray type (i.e., C_3) and a new peel pack (i.e., C_4) were estimated as follows. Handling a tray was assumed to take 200 s, which included the time needed for picking the tray to build the case cart by logistical staff, the handling of the tray in the OR by clinical staff, and the handling of the tray by SPD staff for re-sterilization. Likewise, the time needed to perform these activities was assumed to be 120 s for peel packs. Considering $18 and $45 per hour as the labor costs for logistical and clinical staff [5], respectively, the average labor cost for handling a container would be $31.50 per hour. With this consideration, C_3 and C_4 were estimated to be $1.75 and $1.05, respectively. The PTOP mathematical model was implemented in GAMS 28.2.0 and ran using the BONMIN branch-and-bound (B-BB) algorithm. All other algorithms were coded and executed in MATLAB R2020a on a personal Intel® Core™ i7 10th GEN CPU @1.10 GHz with 16 GB RAM. The number of generations to terminate the GA for the *VLD* dataset was fixed at 50 generations, and for all other datasets was fixed at 500. The reason for this difference in the number of generations was that the VLD dataset was relatively simple and required fewer computational resources for convergence. However, the other datasets were more complex and required more time to reach convergence. Therefore, a higher number of generations was necessary to ensure that the GA could adequately explore the solution space. Additionally, a time limit of one hour was considered to be a stopping criterion for the BONMIN solver.

6.2. Parameter Settings

In order to tune the parameters of the developed GA, CLS, and DLS algorithms, the Taguchi method was used. Three parameters of $nPop$, μ_c, and μ_m were pertinent to the GA, and two parameters of α and γ belonged to both CLS and DLS algorithms. In the GA, $nPop$ is the population size, μ_c is the crossover rate, and μ_m is the mutation rate. For each parameter, four possible levels were considered, as reported in Table 6. Thus, an orthogonal array of $L_{16}(4^5)$ was designed to perform 16 experiments for the calibration of each parameter. Each experiment is run ten times over the *VLD* dataset independently.

Table 6. The values of the parameters corresponding to each level.

Level	$nPop$	μ_c	μ_m	α	γ
1	30	0.40	0.50	0.20	0.20
2	50	0.50	0.60	0.40	0.40
3	70	0.60	0.70	0.60	0.60
4	90	0.70	0.80	0.80	0.80

The Taguchi method optimizes the value of each parameter by expressing the variability of the response factor as a signal-to-noise (S/N) ratio [39]. Since the goal of tuning the parameters is concerned with obtaining both the optimized computational time and solution quality, the *response* factor is defined as the sum of the normalized execution time (i.e., $Ntime$) and normalized solution cost (i.e., $Ncost$). The Taguchi design for the considered parameters is presented in Table A2 of Appendix A. The Taguchi analysis is performed on MINITAB 18. According to the main effects plot for S/N ratios depicted in Figure A1 of Appendix A, the selected values of the parameters are $nPop = 70$, $\mu_c = 0.6$, $\mu_m = 0.8$, $\alpha = 0.6$, and $\gamma = 0.8$.

6.3. Computational Results

To evaluate the performance of the proposed methodology for solving the PTOP, the results of the developed algorithms were compared with that of the *B-BB* algorithm. Four approaches for solving the PTOP were considered. In the first approach, the classical crossover and mutation operators of the GA described in Section 5 were utilized. The second approach, called *H-GA*, incorporated the p-median heuristic in the initialization process by generating half of the population using the p-median heuristic. For this purpose, the p-median heuristic was successively applied to all feasible numbers of containers, and then the best $\frac{nPop}{2}$ solutions were selected to be entered into the initial population. In the third approach, denoted as *GA-CD*, the GA enabled us to use two local search algorithms of CLS and DLS. Finally, in the fourth approach, denoted as *H-GA-CD*, the CLS and the DLS algorithms were used along with the p-median heuristic.

Solving the PTOP mathematical model, which belongs to the nonlinear mixed integer programming classes, using the *B-BB* algorithm reached an "out of memory" status without finding a feasible solution to the instances of 1S-7P, 2S-7P, and 5S-7P datasets. Thus, the performance of the developed H-GA-CD algorithm against the B-BB algorithm was reported only over the VLD dataset. Given that these algorithms were stochastic in nature, ten independent runs were performed, and the results are reported in Table 7. This table reports the average, standard deviation, computational time in seconds, and the best cost of solutions obtained over ten replications for each instance.

Table 7. Validation of the proposed solution algorithms.

Dataset	Instance #	*B-BB*				*H-GA-CD*			
		Average	S.D.	Best	Time	Average	S.D.	Best	Time
VLD	1	46.7	4.3	44.7	2064.8	40.0	0.2	39.9	24.3
	2	58.4	6.8	46.6	915.10	37.4	0.1	37.3	23.0
	3	43.9	2.4	42.8	2095.9	31.1	0.4	30.9	26.7
	4	40.4	8.9	34.0	1773.6	35.0	0.5	34.7	24.8
	5	43.4	5.2	37.4	1240.0	32.9	0.0	32.9	28.4

Considering the average and standard deviation, the *H-GA-CD* outperforms the *B-BB* algorithms in all instances. The *H-GA-CD* algorithm is shown to be highly robust as it yielded very small solution variation over multiple runs. The *H-GA-CD* algorithm could generate better solutions in considerably less computational time compared to the *B-BB* algorithm. The average computational time over five instances of this validation dataset was 1618 s and 25 s for *B-BB* and *H-GA-CD* algorithms, respectively. Given the computational resources that the commercial *B-BB* algorithm needs for such small-size instances and its failure to find even a feasible solution to larger instances, incorporating the designed metaheuristic algorithm was justified. Next, four solution approaches, including *GA*, *H-GA*, *GA-CD* and *H-GA-CD,* were employed to solve larger instances of the PTOP. The overall results of the five instances in each dataset are presented in Table 8. The computational time is reported in seconds.

Table 8. Computational results of the solution approaches.

Dataset	Instance #	*GA*				*H-GA*				*GA-CD*				*H-GA-CD*			
		Ave.	S.D.	Best	Time	Ave.	S.D.	Best	Time	Ave.	S.D.	Best	Time	Ave.	S.D.	Best	Time
1S-7P	1	10,057	466	9560	1897	**8739**	33	8716	2093	8744	195	8520	1772	8757	189	8538	2147
	2	9889	364	9341	1685	8973	223	8765	2236	8781	139	8573	1763	**8720**	78	8582	1621
	3	9717	357	9131	1712	8813	245	8509	2058	**8776**	172	8489	1721	8835	232	8629	1682
	4	8341	330	7855	1723	7514	284	7229	2051	7446	152	7260	1994	**7316**	151	7168	2134
	5	8370	255	7966	1711	7849	486	7500	2443	**7425**	122	7221	2206	7448	102	7310	1981
2S-7P	1	19,951	449	19,505	5072	18,984	125	18,841	5256	**18,046**	252	17,769	7871	18,864	114	18,786	7649
	2	20,190	345	19,861	5095	19,420	256	19,105	4945	**17,309**	366	16,875	8966	19,285	272	19,048	8218
	3	19,921	381	19,380	4918	18,357	221	18,093	4865	**17,502**	309	17,225	7940	18,439	143	18,223	7956
	4	20,475	391	19,869	5057	19,878	600	19,348	4816	**17,893**	336	17,506	8031	19,502	147	19,332	7824
	5	20,198	376	19,620	4927	18,617	145	18,485	4592	**17,619**	245	17,443	7753	19,351	142	19,188	7302
5S-7P	1	84,102	1068	82,810	79,024	90,673	4165	86,756	81,111	**82,950**	4161	78,972	165,620	83,409	4269	77,557	166,985
	2	85,551	1243	84,536	78,901	90,216	1796	88,398	84,093	82,792	2326	80,335	172,940	**82,432**	2153	79,260	165,187
	3	85,042	1895	82,728	78,869	89,550	1744	87,570	82,359	82,269	3698	78,203	169,844	**80,998**	2800	76,270	167,017
	4	85,270	1848	83,249	77,985	91,259	4093	86,618	80,321	82,731	2868	78,724	171,444	**79,654**	1596	78,274	165,616
	5	85,411	1052	84,432	77,893	88,867	3434	85,064	81,974	83,674	2607	79,609	168,058	**83,248**	2527	80,420	163,162

The results in Table 8 show that incorporating the proposed CLS and DLS algorithms into the GA (i.e., *GA-CD* approach) resulted in solutions with, on average, 11.2%, 12.3%, and 2.6% lower costs than the traditional *GA* in the 1S-7P, 2S-7P, and 5S-7P datasets, respectively. The *H-GA-CD* approach also showed a similar trend as it yielded 11.4%, 5.3%, and 3.7% better solution quality than the *GA* approach in the studied datasets. The *H-GA* approach, however, only showed better performances in the 1S-7P and 2S-7P datasets, with a 9.7% and 5.4% improvement, respectively, compared to the *GA* approach. In the 5S-7P dataset, which is a large-size dataset and the traditional *GA* algorithm performs 5.9% better than *H-GA*. This is likely due to its becoming trapped at the local optima generated by the p-median heuristic, from which classic genetic operators could not assist with escaping from these local optima. It is worth noting that while the computational time required for larger instances is lengthy, once the trays are configured, they would not need frequent updates. Therefore, this is a long-term planning problem where solution quality is prioritized over computational time.

While the CLS and DLS algorithms require longer computational times, the higher-quality solutions they provide justify the increased time. In order to compare the results of these algorithms from a statistical viewpoint, non-parametric Wilcoxon rank-sum tests were examined with a significance level of 0.05. The non-parametric Wilcoxon rank-sum test was selected because it is unlikely that the distribution of the results generated by the algorithms follows the normal distribution. The p-value of the statistical test, along with the superior algorithm in terms of the solution quality, is reported in Table 9.

In order to have an insight into how these four approaches performed in each generation, the average of convergence plots over ten replications; for instance, #1 in the 2S-7P dataset, is illustrated in Figure A2 of Appendix A. This figure proves that using the CLS and the DLS algorithms, along with GA, can significantly improve the quality of the solutions. Figure A2 also demonstrates that incorporating the p-median heuristic into the initial population and utilizing the CLS and the DLS methods can make the GA consistently perform better than the other three approaches. The detailed results of the best solution obtained from the *H-GA-CD* method for the PTCP are presented in Table A3 of Appendix A. It shows how many of each instrument are placed in 14 configured containers, of which 13 containers are instrument trays, and one container is a peel pack. As mentioned earlier, given a solution to the PTCP, the PTAP can easily be solved. The results of the PTAP, along with the likelihood of each container to be used for a surgeon and procedure, are presented in Table 10.

Table 9. Pairwise statistical results of the Wilcoxon rank-sum test for the average cost.

Dataset	GA	H-GA	GA-CD	H-GA-CD
GA	-	-	-	-
H-GA	0.585 (no significant difference)	-	-	-
GA-CD	0.013 (GA-CD performs better)	0.021 (GA-CD performs better)	-	-
H-GA-CD	0.018 (H-GA-CD performs better)	0.252 (no significant difference)	0.358 (no significant difference)	-

Table 10. A solution to the PTAP and the probability of containers to be used during the procedure.

Surgeon	Procedure	Containers													
		1	2	3	4	5	6	7	8	9	10	11	12	13	14
Surgeon 1	Mediport insertion	100%	100%	53%	19%	99%	9%	77%	25%				51%		82%
	Excision of small lesion	100%	100%										76%		
	Lap appendectomy	100%	100%	100%	32%	95%	92%	99%	2%			72%			
	Lap cholecystectomy	100%	100%	67%	99%	50%									
	Lap ventral hernia repair	100%	100%	99%	49%	67%	60%	97%	75%	12%	39%		11%		
	Open hernia repair	100%	100%	100%		99%	100%	100%							
	Bowel resection	100%	100%	100%	86%	100%	96%	100%	48%	35%		56%	20%	55%	4%
Surgeon 2	Mediport insertion	100%	100%	41%	26%	69%	6%	98%						39%	
	Excision of small lesion		100%	100%											
	Lap appendectomy	97%	100%	100%	16%			11%	84%						
	Lap cholecystectomy		100%					100%					2%		
	Lap ventral hernia repair	100%	100%	59%	33%	33%	95%	75%				55%			
	Open hernia repair	100%	100%	99%		100%		68%	99%						
	Bowel resection	100%	100%	100%	37%	98%	100%	98%		21%	74%	98%	9%		
Number of instruments		27	23	13	11	11	9	9	8	7	6	5	3	3	1
Weight (lb.)		14.17	11.56	8.06	5.67	6.6	3.16	5.43	3.62	3.7	2.52	1.4	1.6	0.89	0.56
Resterilization cost per procedure if the container is opened		$10.80	$9.20	$5.20	$4.40	$4.40	$3.60	$3.60	$3.20	$2.80	$2.40	$2.00	$1.20	$1.20	$0.80

As can be seen in Table 10, container 2, which is a tray, includes 23 instruments that are required for all procedures that are performed by both surgeon 1 and surgeon 2. It is expected that instruments within this tray are used during all procedures. Therefore, this tray can be opened before the procedures. There are some trays, however, that are unlikely to be used during certain procedures. For example, given the *lap cholecystectomy* procedure, surgeon 1 would use instruments within tray 5 only 50% of the time. Every time this tray is opened, it would cost $4.40 for re-sterilization. Since this procedure is performed 70 times a year, not opening the tray before the procedure could extrapolate to a yearly cost savings of $154.

7. Managerial Insights

The number of containers is one of the crucial factors for surgeons, clinical, and operational staff [22]. The results reported in Table 10 show that some trays (e.g., container 12 and container 13) include only a few instruments. From a practical point of view, it might not be efficient to configure such trays due to limited physical space. In this case, the number of containers to be created can be restricted by adding a new constraint $\sum_{t=1}^{T} x_t \leq R$, where R is the maximum allowed number of containers. In Table 11, we conducted a sensitivity analysis on R to find how changes in the number of containers affected the expected cost of reprocessing instruments and handling containers.

Table 11. Results of the sensitivity analysis on the number of containers for instance #1 in the 2S-7P dataset.

Value of R	3	4	5	6	7	8	9	10	11	12	13	14	15
Number of trays	3	4	5	6	7	8	8	9	9	11	12	13	13
Number of peel packs	0	0	0	0	0	0	1	1	2	1	1	1	1
f_1	$20,383	$18,393	$17,009	$15,997	$15,326	$14,836	$14,594	$14,027	$13,842	$13,712	$13,292	$13,120	$13,120
f_2	$0	$0	$0	$0	$0	$0	$1	$16	$60	$1	$3	$1	$1
f_3	$2132	$2256	$2849	$3509	$3948	$3976	$3982	$4006	$4067	$4179	$4552	$4641	$4641
f_4	$0	$0	$0	$0	$0	$0	$18	$118	$79	$17	$7	$7	$7
Total Cost	$22,514	$20,649	$19,858	$19,506	$19,274	$18,812	$18,595	$18,167	$18,048	$17,909	$17,853	$17,769	$17,769
Cost Savings/		$1866	$790	$353	$232	$462	$218	$428	$118	$139	$56	$84	$0

Table 11 shows how a minimum of three containers was required and a configuration of 14 containers, 13 of which were trays and one of which was a peel pack, resulted in the lowest total cost. The details of this configuration are presented in Tables 11 and A3 in Appendix A. By configuring fewer tray types the surgeons were exposed to more unrequested instruments, which resulted in higher re-sterilization costs. In contrast, configuring fewer tray types means less effort involved in handling them, resulting in a lower administrative and handling cost. Such a trade-off is depicted in Figure 10. In Table 11, the last row reports on the cost savings resulting from increasing the containers by one unit. Configuring four containers instead of three and five containers instead of four reduced the total costs by $1866 and $790, respectively.

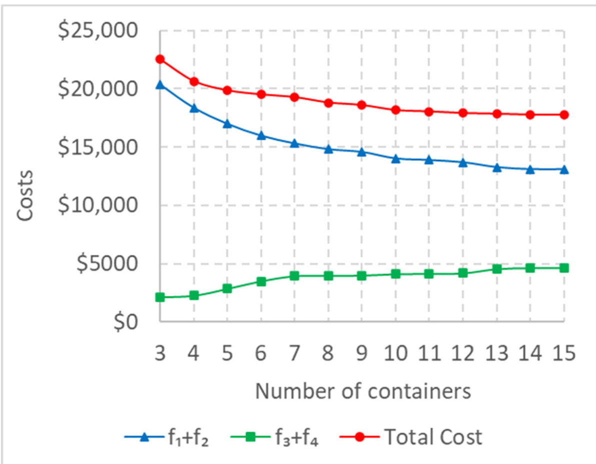

Figure 10. The impact of number of containers on the cost components.

Further cost savings can be made by providing surgeons with information about the re-sterilization costs of instruments and the potential annual savings. This will could them to better decide whether to open a tray with a low likelihood of usage before the procedure or to only open it during the procedure. Within our model, surgeons and inventory managers can estimate the potential cost savings associated with not opening trays before procedures. Figure 11 correlates the probability of containers being used and the potential cost savings if these containers are not opened prior to the procedures. The figure shows that if instruments are optimally grouped into four containers and surgeons choose not to open trays and peel packs that have less than a 50% likelihood of being used before their procedures, this results in a 3% annual cost savings in the reprocessing of instruments. Such cost savings can be increased to 10% and 16% if the instruments are configured into 5 and 10 containers, respectively. An analysis of this kind can identify surgeons, procedures, and containers that could be targeted to be a part of a pilot implementation of this study.

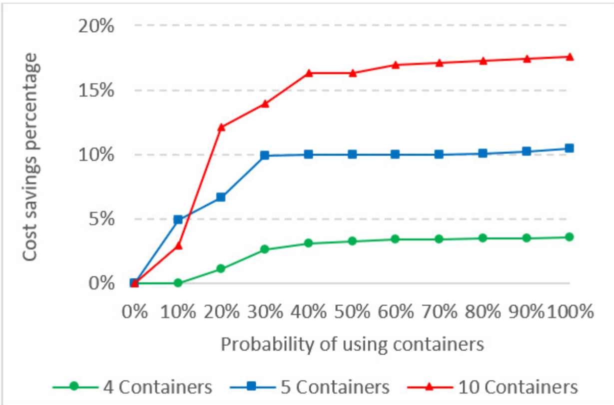

Figure 11. Percentage of cost savings in the re-sterilization costs (i.e., $f_1 + f_2$) due to not opening the trays before procedures.

To examine the impact of uncertainty in a patient's surgical instrument needs on the cost estimation of a prescribed tray configuration during a procedure, a Monte Carlo simulation was conducted. In this simulation, instance #1 from the 2S-7P dataset was selected with four containers configured, and the instrument used for each procedure was modeled using experimental probability distributions. This simulation also accounted for the fact that if the first copy of an instrument was not used, the other copies of the same instrument would not be used either. Therefore, if $P_{ijk} = 0$, then $P_{ij'k} = 0$ for $j' > j$. The results of the simulation are presented in Figure 12, which shows the distribution of the total realized cost over 5000 simulation runs. The data indicates that there is a 23% chance that the actual costs exceed the estimated cost of \$20,649 generated by the PTOP model, as reported in Table 11.

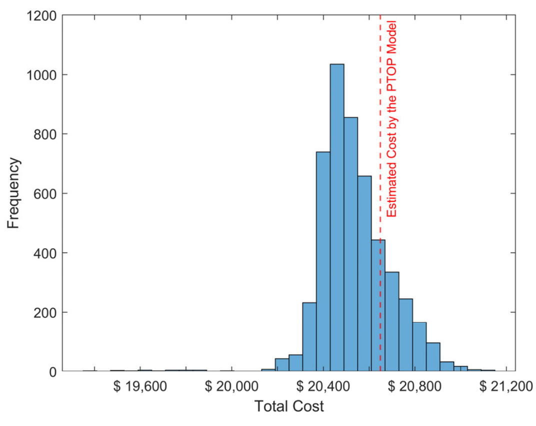

Figure 12. Simulated solution for instance #1 in the 2S-7P dataset with $R = 4$.

8. Conclusions and Discussion

This study dealt with the problem of configuring surgical trays based on the probabilities of instrument usage. This problem is called the probabilistic tray optimization problem (PTOP). The PTOP is formulated as an integer non-linear programming model. Since this problem is in the class of *NP*-hard problems, it is decomposed into two subproblems of the probabilistic tray configuration problem (PTCP) and the probabilistic tray assignment problem (PTAP). Given a solution to the PTCP, the PTAP becomes a trivial problem of an integer linear programming model, which can be easily solved. A heuristic and a metaheuristic were developed to solve the PTCP. The heuristic algorithm provides an approximate solution to the PTCP in a short computational time by formulating the PTCP as a well-known p-median model. However, this method may result in a low-quality solution. Therefore, a genetic algorithm (GA) was also designed to improve the quality of solutions obtained by the p-median heuristic. Moreover, in order to enable the GA to better explore the solution space, two local search algorithms—combining local search (CLS) and decomposing local search (DLS)—were invented and embedded in the GA. The CLS and DLS algorithms attempted to decrease and increase the number of containers, respectively, in a given solution. The applicability of the model is demonstrated through the historical data available in the literature.

Close collaboration with surgeons to improve their conventional tray configurations is key for a successful implementation. The PTOP model can facilitate this collaboration, as the potential cost savings derived from the reconfiguration of trays and not opening trays with a low probability of usage become readily apparent through executing the PTOP model. Given the required data, the PTOP model can be applied in any hospital to reveal how much they can benefit from the optimization of the instrument trays.

Our approach provides the *minimum* number of trays and instruments that need to be stocked for performing procedures that are not scheduled for the same day. However, since, in practice, the re-sterilization process usually takes one day to be completed, the trays undergoing re-sterilization would not be available for use until the next day [17,19,22,25,40]. Therefore, multiple copies of a tray are needed when multiple procedures requiring the same tray type are scheduled to be performed in a day. Such an approach provides a *maximum* number of trays and instruments that need to be stocked for performing procedures. However, the optimal number of instruments and trays highly depends on the OR schedule. For example, if two procedures are scheduled on the same day only a few times a year, keeping two copies of a tray would not be optimal. Instead, by modifying the schedule of those procedures not to take place concurrently, the stocked instruments could be reduced.

It should be noted that our model does not eliminate any instruments that may be used rarely, as we understand their importance in specific procedures. Our model only rearranges all instruments that surgeons request into different tray types by separating frequently used instruments from rarely used ones. This model ensures that the surgeon's preferred instruments are readily available in the operating room. By optimally configuring the instrument trays, the time it takes for surgeons to find the instruments they need during surgery can also be reduced. In this research, the cost savings resulting from our model are associated only with avoiding unnecessary labor-intensive re-sterilization processes rather than potential savings on capital and holding costs. To estimate capital savings, a standardization project, such as the work of Koyle et al. [8], which resulted in a reduction in surgical instruments, needs to be conducted. It is important to note that removing a rarely used instrument tray from stock may compromise patient safety, as the tray may be needed in rare occurrences. Therefore, in such a standardization project, safety stock for these trays should be considered to prevent the risk of tray non-availability.

Since many hospitals currently do not record the use of instruments, one of the considerations toward implementing the findings of this model is that direct observations are required to collect accurate instrument usage data. These observations could be performed after a procedure in the sterile processing department or in the operating rooms. Some surgical tool companies offer RFID-tagged instruments, which facilitate data collection. Since collecting accurate usage data, particularly for instruments without RFID tags, can be difficult, an alternative would be to have surgeons label instruments as "always needed", "sometimes needed", or "rarely needed" and then estimate how likely each label is to be used. Additionally, a time and motion study could help with a more accurate estimation of the labor costs associated with the sterilization process and handling of trays. One may benefit from the works of John-Baptiste et al. [41], and Mhlaba et al. [7] in estimating these labor costs, but analysts should be conscious that the sterilization process in hospitals may be different from each other. Another limitation of this study is that it assumes the probabilities of instrument usage to remain constant over time. However, in reality, these probabilities may change due to variations in surgical techniques or patient demographics. As a result, it may be necessary to periodically update the PTOP model to account for such changes.

Future studies could explore how instrument usages are interdependent and develop a model that captures these relationships. Another interesting future research direction is to incorporate patient demographic variables such as gender, race, age and patient clinical variables such as Body Mass Index (BMI), past surgical history, and past medical history to predict the necessity of an instrument for a given case. Furthermore, studying other heuristics and metaheuristics and evaluating their performance against our solution algorithms would provide another interesting future study.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Algorithm A1: *p*-median based heuristic.

Inputs: A set of vertexes V. A set of edge E.
The distance matrix corresponding to the $d_{ij_m n}$
Set $P = \sum_{i=1}^{I} \max_k \{A_{ik}\}$
While there exist feasible solutions **Do**
    Solve the p-median model
    Solve the PTAP
    $P \leftarrow P - 1$
End While
Output: The solution corresponding to the P that resulted in the minimum objective function value in the PTAP

Algorithm A2: Combining Local Search (CLS).

Extract the initial number of containers, $IniNumCon$, for a given solution $\mathcal{S}$
$NumCon \leftarrow IniNumCon$
While $NumCon > IniNumCon\,(1-\gamma)$
    For $t = 1$ **To** $NumCon$ **Do**
        Calculate O_t using Equations (12) and (13)
    End For
    For $w = 1$ **To** 3 **Do**
    If $Rand() \leq \alpha$ **Then**
        Perform random walk on $\mathcal{S}$ and obtain local optimum $\mathcal{S}_w$
    Else If $w = 1$
        Walk 1: combine the two containers with the lowest O_t and obtain local optimum $\mathcal{S}_1$
    Else If $w = 2$
        Walk 2: combine the two containers with the highest O_t and obtain local optimum $\mathcal{S}_2$
    Else If $w = 3$
        Walk 3: combine the containers with the lowest and the highest O_t and obtain local optimum $\mathcal{S}_3$
    End If
    If $the\ weight\ of\ the\ combined\ containers > L$ **Then**
        Perform the repairing mechanism
        End If
    End For
    Add the best solution among $\mathcal{S}_1$, $\mathcal{S}_2$, and $\mathcal{S}_3$ to the current population
    $NumCon \leftarrow NumCon - 1$
End While

Algorithm A3: Decomposing Local Search (DLS).

Extract the initial number of containers $IniNumCon$ for a given solution $\mathcal{S}$
$NumCon = IniNumCon$
While $NumCon < IniNumCon\ (1+\gamma)$
  For $t = 1$ **To** $NumCon$ except peel packs **Do**
    Calculate O_t using Equation (12)
  End For
  Select the container t with the lowest O_t
  For all instruments in tray t
    Calculate O_i' using Equation (14)
  End For
  For $w = 1$ **To** 2 **Do**
  If $Rand() \leq \alpha$ **Then**
    Random walk: Generate a new solution $\mathcal{S}_w$ by randomly selecting an instrument and putting it in a peel pack
  Else If $w = 1$
    Walk 1: Generate a new solution $\mathcal{S}_1$ by putting the instrument with the lowest O_i' in a new container as a peel pack
  Else If $w = 2$
    Walk 2: Generate a new solution $\mathcal{S}_2$ by putting the instrument with the highest O_i' in a new container as a peel pack
  End If
  End For
  Select the container t with the highest O_t
  For all instruments in tray t
    Calculate O_i' using Equation (14)
  End For
  For $w = 3$ **To** 4 **Do**
  If $Rand() \leq \alpha$ **Then**
    Random walk: Generate a new solution $\mathcal{S}_w$ by randomly selecting an instrument and putting it in a peel pack
  Else If $w = 1$
    Walk 1: Generate a new solution $\mathcal{S}_3$ by putting the instrument with the lowest O_i' in a new container as a peel pack
  Else If $w = 2$
    Walk 2: Generate a new solution $\mathcal{S}_4$ by putting the instrument with the highest O_i' in a new container as a peel pack
  End If
  End For
  Add the best solution among $\mathcal{S}_1$, $\mathcal{S}_2$, $\mathcal{S}_3$, and $\mathcal{S}_4$ to the current population
  $NumCon \leftarrow NumCon + 1$
End While

Table A1. The values of $d_{i^j m^n}$ corresponding to the PTOP example presented in Table 1.

	Instrument												
Instrument	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
1	3.00	6.29	9.55	7.67	6.00	7.66	6.67	6.24	7.93	6.50	6.36	10.69	6.30
2	6.29	0.50	6.27	3.39	1.02	5.29	2.23	1.24	4.53	1.50	1.36	8.58	1.82
3	9.55	6.27	2.76	5.99	5.53	8.22	6.36	5.63	7.43	5.55	5.54	8.89	6.09
4	7.67	3.39	5.99	1.28	2.57	6.59	3.75	2.80	5.00	2.71	2.67	8.37	3.31
5	6.00	1.02	5.53	2.57	0.01	4.69	1.40	0.26	3.99	0.52	0.38	8.01	0.94
6	7.66	5.29	8.22	6.59	4.69	2.34	5.40	4.80	7.51	5.18	5.04	9.61	5.19
7	6.67	2.23	6.36	3.75	1.40	5.40	0.69	1.56	4.81	1.88	1.74	8.69	2.25
8	6.24	1.24	5.63	2.80	0.26	4.80	1.56	0.12	4.22	0.74	0.60	8.05	1.16
9	7.93	4.53	7.43	5.00	3.99	7.51	4.81	4.22	1.99	4.10	4.07	9.86	4.77
10	6.50	1.50	5.55	2.71	0.52	5.18	1.88	0.74	4.10	0.25	0.77	8.03	1.42
11	6.36	1.36	5.54	2.67	0.38	5.04	1.74	0.60	4.07	0.77	0.18	8.02	1.28
12	10.69	8.58	8.89	8.37	8.01	9.61	8.69	8.05	9.86	8.03	8.02	4.00	8.25
13	6.30	1.82	6.09	3.31	0.94	5.19	2.25	1.16	4.77	1.42	1.28	8.25	0.46

Table A2. Taguchi analysis for tuning parameters of the GA, CLS, and DLS algorithms.

Experiment	Parameter's Level					Cost ($)	Time (s)	Ncost	Ntime	Response
	nPop	μ_c	μ_m	α	γ					
1	1	1	1	1	1	40.24	12.86	1.00	0.00	1.00
2	1	2	2	2	2	40.19	21.60	0.80	0.32	1.12
3	1	3	3	3	3	40.04	16.03	0.25	0.12	0.36
4	1	4	4	4	4	40.01	18.19	0.15	0.19	0.35
5	2	1	2	3	4	40.12	20.21	0.54	0.27	0.80
6	2	2	1	4	3	40.04	25.84	0.25	0.47	0.73
7	2	3	4	1	2	40.09	17.04	0.44	0.15	0.60
8	2	4	3	2	1	40.09	16.24	0.44	0.12	0.56
9	3	1	3	4	2	40.06	24.11	0.35	0.41	0.76
10	3	2	4	3	1	40.00	28.37	0.09	0.57	0.65
11	3	3	1	2	4	39.99	21.55	0.05	0.32	0.37
12	3	4	2	1	3	39.97	25.00	0.00	0.44	0.44
13	4	1	4	2	3	39.99	40.25	0.05	1.00	1.05
14	4	2	3	1	4	40.13	27.20	0.58	0.52	1.10
15	4	3	2	4	1	40.06	26.97	0.35	0.52	0.86
16	4	4	1	3	2	40.05	27.70	0.29	0.54	0.84

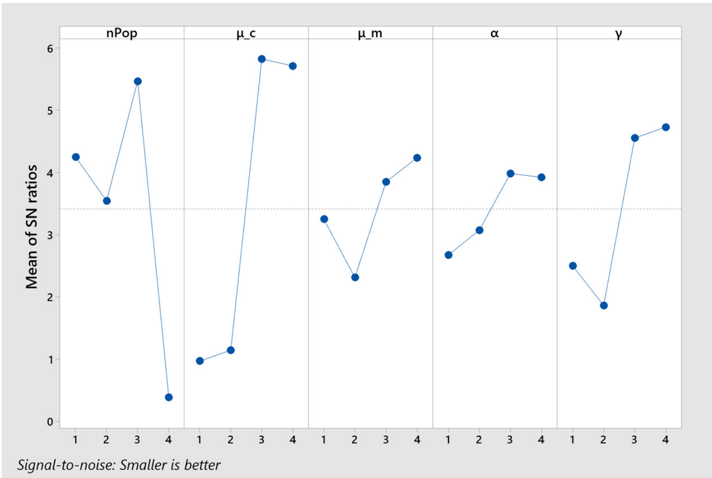

Figure A1. Main effects plot for S/N ratios.

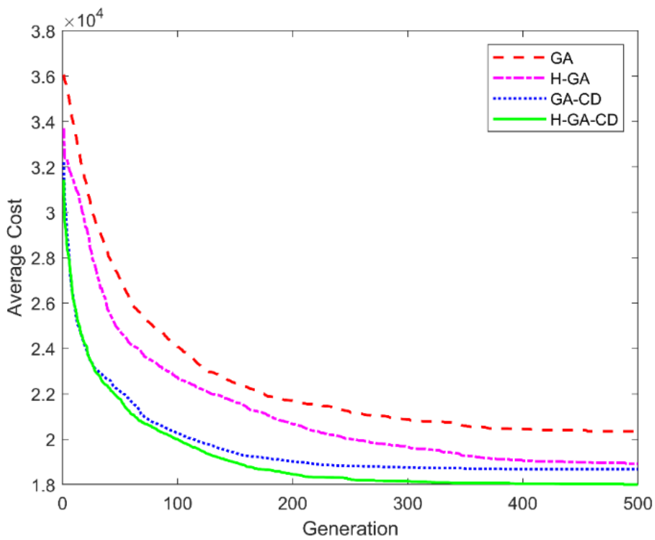

Figure A2. Convergence plot of the four approaches to solve the PTOP (instance #1 in the 2S-7P dataset).

Table A3. A solution to the PTCP.

Instruments	**Containers**													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
1		1												
2	1													
3	1													
4		1												
5	1													
6		1												
7	1													
8			1											
9		1												
10		1												
11	1													
12	1													
13	1													
14	1													
15		1	1											
16					1	1								
17	1			1										
18		1					1							
19							1		1					
20	1	1												
21	1													
22					1			1						
23						1			1					
24	1											1		
25									1			1		
26		1										1		
27	1			1										
28	1									1				
29	1			1										
30		1	1											
31	1									1				
32							1						1	
33	1							1						
34			1								1			
35					1									1
36				2										
37	1			1										
38		1		1										
39							2							
40						1				1				
41		1				1								
42	1				1									
43			1							1				
44			1								1			
45		1						1						
46			1										1	
47						1	1							
48		1							1					
49				1	1									
50		1	1											
51										1	1			
52			1		1									
53	1			1										
54	2													
55			1							1				
56						2								

Table A3. *Cont.*

Instruments	**Containers**													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
57	1								1					
58	1					1								
59								2						
60			1		1									
61	1			1										
62							1	1						
63						1			1					
64	1			1										
65					2									
66		1												
67		1							1					
68	1										1			
69		1					1							
70		1			1									
71		1									1			
72							1	1						
73		1	1											
74					1			1						
75		1	1											
76		1											1	

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