Peel Pack Planning Using Clustering and Decomposition Approach

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Abstract

Peel Pack Planning Using Clustering and Decomposition Approach

Yixuan Wang

In order to improve the operational efficiency in the Operating Room, hospitals customize surgical trays for each surgical procedure. Since, surgical procedures involve a variety of patients and surgeons, the usage of surgical instruments (in terms of quantity) differs from case to case. This poses a significant challenge as the variability in instrument usage makes it difficult to determine the optimal quantity for each instrument for each procedure. In this study, we address the issue of excessive waste in surgical trays by proposing the implementation of custom peel packs. These peel packs could be used (in place of a new surgical tray) if the surgical tray ran out of the instruments. Our objective is to reduce waste by designing custom peel packs associated with multiple surgical procedures while ensuring that all the necessary instruments are available during the procedure without opening a new main tray. We present one decomposition approach to finding the exact solution and a simplified fast approach based on clustering and mathematical programming to find the near-optimal solution in a fractional time compared to the exact approach. Numerical experiments demonstrate the performance of the presented approaches. The findings indicate that the proposed K-means-based clustering method is very effective in configuring peel packs.

Keywords: Surgical tray; clustering algorithm; Linear programming; Optimization; Decomposition; Column generation approach.

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Chapter 1

Introduction

1.1 Healthcare Operations

Rising treatment costs of healthcare systems and intensified demand pose a large challenge to the healthcare industry due to resource shortages, aging population, and epidemiological transitions. In 2020, total healthcare spending in the United States reached $4.1 trillion, representing 19.7% of the gross domestic product, with hospitals accounting for 31% of that spending. Similarly, Canada is projected to spend over $300 billion, 12.2% of gross domestic product (GDP) on healthcare in 2022 Figure 1.1, with hospitals being the largest contributor (Al Hasan, Guéret, Lemoine, & Rivreau, 2019). Healthcare systems are confronted with critical dilemmas including increasing costs, decreasing profitability, inadequate access and resources, and low service level. In order to get out of the way, healthcare organizations should not limit themselves to providing a safe, effective, patient-centered, timely, efficient, and equitable service to patients (McLaughlin, 2008). Consequently, potential improvement in the healthcare area proposes a high requirement for the healthcare's whole operation process. Managerial research has focused on ways to control rising hospital costs, including Operating Room (OR) scheduling, healthcare processes, nurse scheduling, and surgical tray management. Redesigning processes between two surgical procedures decreases nonoperative time and reduces nonclinical disruption (Harders, Malangoni, Weight, & Sidhu, 2006). Fong, Smith, and Langerman (2016) propose that workflow standardization is one potential solution to improve the efficiency of OR and foster closer and more transparent relationships within the procedure team. Mathematical modeling-based methods are very common in healthcare planning and scheduling. Ghazalbash, Sepehri, Shadpour, and Atighehchian (2012) present a mixed integer programming model to meet patients' demands while minimizing OR idle times. J. Wang, Guo, and Tsui (2021) discusses the scheduling of surgeons and the collaboration between the main surgeon and assistant and uses the column-and-constraint generation algorithm to solve a two-stage robust model and seek surgeon assignment and surgery scheduling. The sensitivity analysis indicates that the assistant decision would influence the total cost of OR. Balcik et al. (2022) balance between the central vaccine allocation problem and the equitable problem and propose new linear models which can be solved quickly and get insights into how to allocate the limited number of vaccines equitably and effectively. Cost, dissatisfaction, nurse idle time, and job satisfaction of nurses are included in the multi-objective model to resolve nurse scheduling problems Mobasher (2011). The arrangement of the nurse roster and operating room (OR) scheduling is interactive and integrated to optimize the workflow of operating room (OR)(Xiang, Yin, & Lim, 2015).

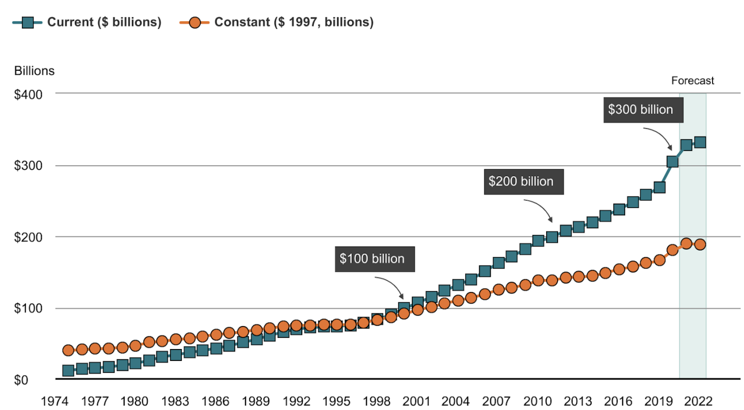

Figure 1.1: Canada Spend on Health

Refer to Canadian Institute for Health Information website https://www.cihi.ca/en/topics/health-spending

1.2 Surgical Tray Management

Providing high-quality and safe service and treatment is a basic requirement for healthcare operations. Medical errors, infections, resource shortages, and other safety risks should be avoided during the healthcare process. Ensuring that surgeons have the correct and adequate tools is an important element of infrastructure(McLaughlin, 2008). Surgical trays (STs) contribute a significant portion of hospitals' revenues & waste and are used in healthcare organizations to provide a centralized material for surgical procedures. Some previous studies propose that surgical trays are often poorly configured, and only 13-25% of the instruments on trays were used in the surgery (Fu et al., 2021). This results in wasted resources, assembly errors, delayed surgeries, and even threats to hospital operations. Standardization of surgical trays is considered as an opportunity to decrease OR cost and human error (Smith et al., 2018). According to the main approaches of surgery tray rationalization, the article can be classified as (i) expert analysis (EA), (ii) lean practices (LP), and (iii) mathematical programming (MP) (dos Santos, Fogliatto, Zani, & Peres, 2021). Classification of expert analysis (EA) and lean practices (LP) are based on authors' declarations. The expert analysis uses types of techniques to improve initiatives, including interviews, observation, checklists, and standardization. The lean practice (LP) applies lean principle techniques to expert analysis (EA). Otherwise, the approach would be perceived as an expert analysis. In the EA category, many surgery tray studies used interviews (ITV) to offer valuable insights that help to observe the surgical tray efficiency and safety problem. (Kroes, 2009; Tibesku, Hofer, Portegies, Ruys, & Fennema, 2013). Checking list (CL) and Focus group (FG) are two of the widely used techniques in surgery tray expert studies (Holland, Kong, Buchanan, & Patten, 2022; Stockert & Langerman, 2014). Lean management is a critical category for tray optimization. The lean healthcare-oriented method generally included the following three main phases: (i) prioritize, (ii) rationalize, and (iii) validation. Clustering procedures algorithms containing a close neighbor algorithm (CAN) and K-means algorithm based on the Hamming Distance (HD) were used to revise surgery trays and analyze the outcome. In the final phase, adjusted surgery trays are put to test in operation rooms (Fogliatto, Anzanello, Tonetto, Schneider, & Muller Magalhães, 2020). Lean techniques on the instrument process workflow are identified as a method to reduce instrument redundancy and improve instrument utilization (Lunardini et al., 2014). However, EA and LP have some limitations, such as human bias because of subjective and substantial variability between different users and the non-optimal result of cost saving. Hence, mathematical programming, specifically linear programming, is proposed as a technique to address these issues by removing unnecessary instruments and reconfiguring new

STs. Linear programming is viewed as a widely proposed technique. The type of trays, the number of trays of each type, and the way that different types of trays are assigned to surgeries are the three main questions to be answered by using Linear programming (Dollevoet, van Essen, & Glorie, 2018). Linear programming models and algorithms are mainly introduced to remove useless instruments and reconfigure new STs.

1.3 Research Questions

In the hospital, nurses are responsible for ensuring that the operating room is equipped with all the necessary instruments and equipment and that everything is sterile and ready for use. Before a surgical procedure, nurses collaborate with the central sterile supply department to assemble the surgical tray based on the surgeon's preference card. The surgeon's preference card is typically created taking into account the surgeon's individual preferences and historical surgical data, such as the usage of specific items in previous procedures. Nurses transport the required surgical tray to the operating room and work with the surgical team to set up the sterile field before the surgery begins. However, surgical procedures involve different patients and surgeons, leading to variations in the number of surgical instruments used for each case. This presents a significant challenge as the variability in instrument usage makes it difficult to determine the optimal quantity of each instrument for every procedure. As a result, surgeons may require additional instruments that are not initially included in the tray. In such cases, nurses have to leave the procedure room and return to the sterile processing department to retrieve a new tray (Figure 1.2), resulting in both time and item wastage.

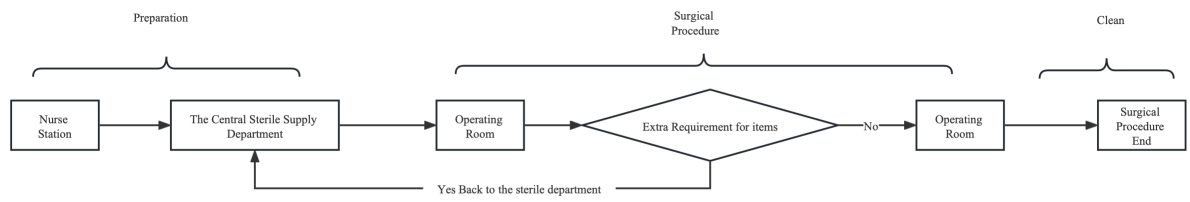

Figure 1.2: Surgical Tray Preparation during Surgical Procedure Process

Toor et al. (2022) define that less frequently used items or items required to satisfy additional uncertain demand are aggregated as peel-packs, which are distinguished from STs. However, the study does not address the issue of tray assignment. In our study, we consider peel packs as replenishment packages or trays for one surgical procedure, or a group of similar surgical procedures. We assume that a surgical tray (i.e. main tray) (Figure 1.3) is designed according to the surgeon's preference card. There are two categories of peel-packs: basic peel-packs, which are designed for each procedure based on service level and main trays; and custom peel-packs (CPPs) (Figure 1.4), which can contain items prepared for specific surgeries or several types of surgeries. Given the uncertainty of demand, it is possible to use the main tray when the CPPs cannot satisfy the demand. The study deals with three questions: (1) Does a surgery qualify for a custom peel pack (CPP)? (2) how to configure different types of CPP in order to minimize overall surgical tray-related costs? and (3) how to assign each CPP to known types of surgical procedures?

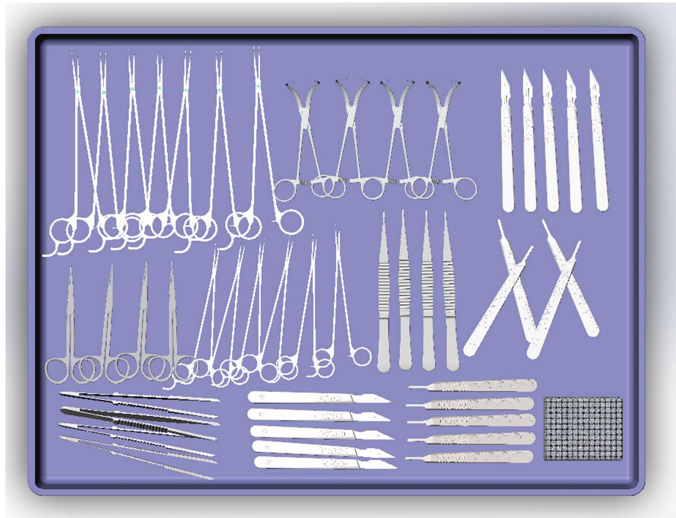

Figure 1.3: Surgical Tray Diagram

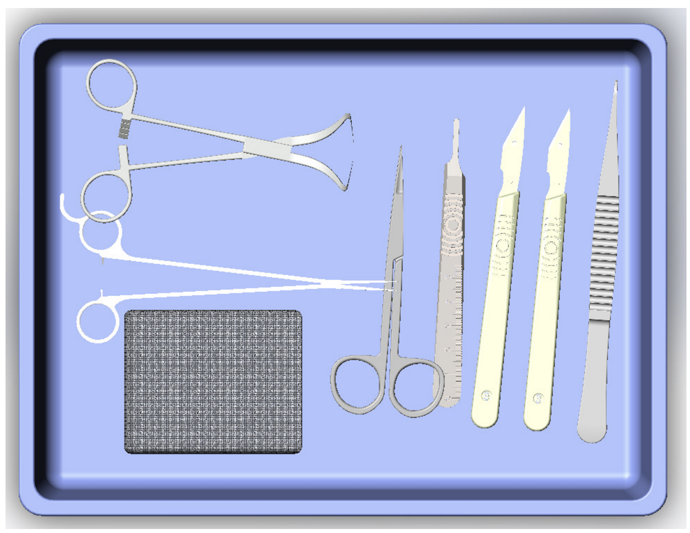

Figure 1.4: Peel Packs Diagram

The rest of the paper is organized into four sections. In Chapter 2, we formally provide a literature review of surgical trays and related methodologies. In section 3, we propose the problems and further describe several variables of the mathematical formulation, along with the solution approaches. We then evaluate these approaches using randomly generated data sets from various scenarios and analyze the computational results in Section 4. Section 5 concludes the paper by summarizing the work, identifying research deficiencies, and suggesting areas of future research.

Chapter 2

Literature Review

2.1 Tray Optimization

Surgical tray optimization to minimize operational costs while ensuring instrument availability for surgeries gains attention in healthcare research. Some articles have proposed sharing surgery trays to reduce instrument redundancy. For instance, more recent research has focused on creating surgical trays that can be used for multiple procedures. Cardoen, Beliën, and Vanhoucke (2015) work on custom packs that are referred for several procedures. Trays are configured to decrease the touch point for non-operative time saving and reducing cost. The view is also supported by Dollevoet et al. (2018) who claim that a tray is potentially required for several types of surgery, while surgery would need multiple types of trays as well. Meanwhile, some articles mention the risk of trays that are served for several surgical procedures. Huynh et al. (2019) develop Just in Time (JIT) to manage instrumentation flow, noting that the use of instruments in multiple types of procedures increases the risk of shortages. However, the discussion on the function of which a tray is shared among different surgeries is mixed.

Several studies have reported experiments on the different specific procedures to realize tray standardization, rationalization, and optimization. Holland et al. (2022) remove the underutilized instruments of breast procedure by observation of tray usage and cost data. Removing unused instruments is demonstrated to decrease waste costs and processing time. Rationalization, in this context, is seen as a measure of cost savings rather than a simple reduction. Malone et al. (2019)

redesign specific, lighter breast lumpectomy tray based on recommendations from breast surgeons This resulted in reduced processing costs and setup time for surgery by reducing physical strain. Right-sizing surgical tray maximizes operating room efficiency. A similar method is used by Wood et al. (2021), who conducted a comprehensive review of the general plastics trays and breast reconstruction trays with surgeons' evaluation and analyzed instrument utilization to configure new trays. Lonner et al. (2021) propose using a lean technique to optimize the tray for knee arthroplasty. Surgeons identified underutilized instruments and reviewed the demand for each tray, instrument utilization rates, and processing time. After several rounds of review and modifications, they provided recommendations for configuring surgical trays. A data-driven approach is used to optimize instrument trays for vascular procedures. Six surgeons evaluated data from 168 procedures and removed underutilized instruments from trays (Knowles et al., 2021). The literature on tray standardization emphasizes the role of operating suite staff to eliminate redundant instruments (Byrnes, Schmitt, Tommaso, & Occhino, 2017). Quality improvement initiatives have been used to optimize trays for otolaryngology procedures by considering instrument usage, process setup time, and tray rebuilding time (Fu et al., 2021). New technologies are important to improve surgery tray assembly efficiency. To rationalize tray configuration and customization, expert analysis, and lean practice are widely applied to different concrete surgical procedure research and waste reduction.Olivere, Hill, Thomas, Codd, and Rosenberger (2021) use Radio Frequency Identification (RFID) technology to track instruments during 15 breast operations and observe the utilization of surgical oncology instruments. They analyzed experimental data and eliminated the unused items in trays. Logistic regression was used to test the feasibility of RFID. The results report no instruments that have been eliminated were asked to be put back during the validation process and RFID in tracking instruments was proven feasibility. Given the complexity of the procedure process and the variance of the procedure, these articles proposed a surgeon-led review by using surgeons' professional knowledge and clinical experience to reduce the underutilized instruments in the tray and save cost.

The deficiency of expert analysis occurs because of its potential surgeon bias and uncertainty surrounding the surgical procedure. Previous research has explored using lean techniques to improve surgical workflow and combat human error (Amati et al., 2022; Fogliatto et al., 2018; Lonner et al., 2021; Smith et al., 2018), but these methods primarily focus on cost savings (Toor et al., 2022).

Consequently, some researchers turn to mathematical methods. Fogliatto et al. (2020) studied instrument reconfiguration. A lean healthcare-oriented method was applied in the sterilization plant to reduce costs. There are three main phases of this method: prioritize, rationalize, and validate. In the second phase, the authors used cluster procedures, Close Neighbor Algorithm (CAN), to identify required instruments. Schneider et al. (2020) also studied CAN for tray optimization problems in the quantitative stage. Lavado (2019) shows deep learning to sort and locate surgical items. This technique helps identify which instrument should be removed first in a surgical kit. The other areas of the study propose various clustering algorithms to improve performance. These studies give us the idea that we can use the clustering algorithm, which figures out the minimum distance between each basic peel pack point, to find the cluster, and then generate our CPPs.

2.2 Mathematical Programming and Data-Oriented Approaches

K-means (Cam & Neyman, 1967) is one popular clustering algorithm to partition the data sets (Shrifan, Akbar, & Isa, 2022). Kodinariya and Makwana (2013) examines six different approaches to cluster number selection problems, including the rule of thumb, Elbow method, Information Criterion Approach, An Information Theoretic Approach, Silhouette, and Cross-validation. Zhu, Li, Zhang, Xu, and Zhang (2022) improve K-means clustering method and determine the optimal cluster number by validity index ICS-VAR. Via the Chebyshev-type inequalities rule, Olukanmi, Nelwamondo, Marwala, and Twala (2022) establish lower and upper bounds for k estimation. These studies inspire further research on selecting the best CPPs' number. Mao et al. (2022) focus on iteratively optimizing of K-means algorithm and propose a parallel clustering algorithm based on the grid density strategy (GDS) to select relatively reasonable initial clustering centers. However, the limitation of this study is the local optimal problem in the initialization of the centroid. Sieranoja and Fränti (2022) apply a density-based initialization method to generate reasonable initial clustering centers as well and repeat this algorithm to update the result of the cluster. However, K-means would generate a poor solution and local optimum due to the initial center selection and the presence of an outlier in real data, which we should take into consideration in our model.

Linear programming is a commonly proposed technique for operation room management. Dollevoet et al. (2018) conduct three new methods: delayed row & column generation, a greedy heuristic, and a genetic algorithm to address three questions: the tray types, the number of trays of each type, and the assignment of tray types to surgeries. A highly scalable advanced greedy algorithm is viewed as an easy method to be applied by hospitals in long-term operation room schedules. The author presents a multi-objective binary integer programming model that considers both patient workload variability and nurse preferences and develops a two-stage non-weighted goal programming solution approach to solve this multi-objective problem (Mobasher, 2011). Ghazalbash et al. (2012) face a similar problem with multi-objectives. They introduce the Lexicography method to solve the mixed integer programming model with two objectives, minimizing Cmax (the completion time of the latest patient's surgery in the operating room) and operating room idle times. Al Hasan et al. (2019) consider uncertainties in surgery duration for operation room scheduling and kit allocation scheduling simultaneously. They study a deterministic model with robust optimization to decrease the OR cost. However, their research does not focus on the configuration of kits. In our model, we focus on multiple objectives for mixed programming as well. For the surgical tray optimization problem, Dobson, Seidmann, Tilson, and Froix (2015) consider surgeons' preferences and surgical schedules and proposed modified integer linear programming and heuristic method to configure an optimal tray. Their assumption mentions the probability of using an instrument during a procedure because the patient's anatomy influences the instrument's demand. However, Dobson et al. (2015) do not consider the probability of instrument usage effects on tray utilization, which we will discuss in our model. Harris and Claudio (2021) come up with expected non-usage rates of instruments as an independent factor of the tray optimization model (TOM). The model develops expected instrument utilization rates and decreases the number of redundant instruments in trays. Cardoen et al. (2015) study non-linear integer programming to develop and configure surgery trays. They mention that the performance of custom tray improvement is not ideal and propose to exploit sharing surgery tray to reduce waste when limited custom packs are used with unequal waste cost. Schneider et al. (2020) analyze the use of ophthalmic instruments by a mixed method. To optimize the number of trays, linear programming is proposed based on the CAN application and takes sharing trays and time of processing as a restriction to generate results like our first model, while their matrix was collected from experts with a bias to some extent. The surgical tray optimization problem normally involves non-linear programming when multiple targets are present. The decomposition approach is presented as a technique to resolve linear and integer programming optimization problems. The basic logic of this approach is to find an optimal solution by adding new variables for the master problem. Column generation decomposes one problem into subproblems (pricing problem) and then can be solved respectively, which is tractable by reducing the size of the problem and addressing the most important variables. Ford Jr and Fulkerson (1958) propose the theory of column generation. This theory is applied to many optimization problems, especially operation room (OR) scheduling and surgery scheduling problems (Fei, Chu, & Meskens, 2009; Ghandehari & Kianfar, 2022; Hashemi Doulabi, Rousseau, & Pesant, 2014; Kamran, Karimi, & Dellaert, 2020; Lamiri, Xie, & Zhang, 2008; Range, Kozlowski, & Petersen, 2019; Y. Wang, Tang, & Fung, 2014; Zhang, Dridi, & El Moudni, 2020). For tray configuration problems, Dollevoet et al. (2018) employ delayed row & column generation for tray types.

Cardoen et al. (2015) define the conception of custom packs as single and customized packs that meet the demand of a particular surgical. To achieve standardization of instruments and reduce redundancy, we customize peel packs for different types of surgeries and consider two specific scenarios. First, we determine the expected number of custom peel packs (CPPs) and use the clustering method to group them into target clusters. A linear programming model is then used to optimize the instrument quantity based on factors such as the demand for the surgery and other clustering information. Second, we construct a linear programming model with a four-dimensional variable to select the number of trays and instrument quantity simultaneously. We formulated our objectives, including the probability of main tray utilization, instrument quantity in each CPP, and the targeted number of peel packs. Our model totally depends on the actual usage data sets.

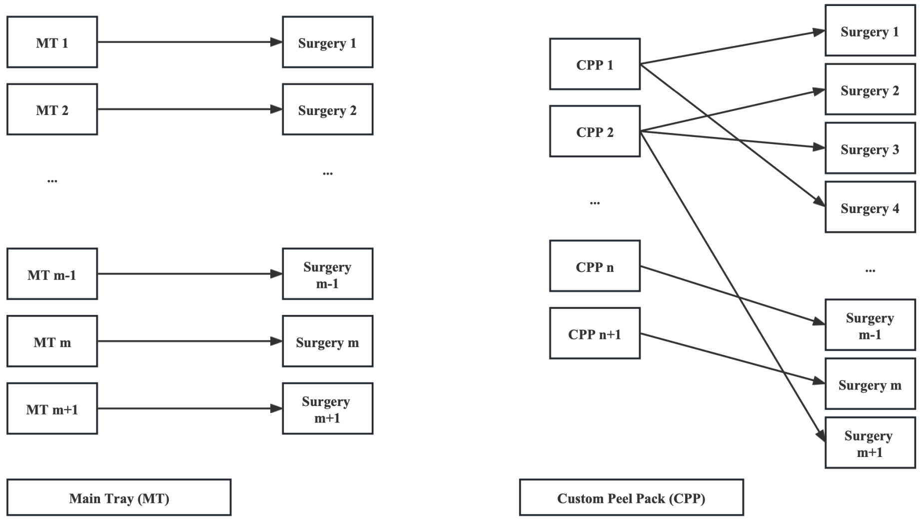

Figure 2.1: Relationship Between the Surgical Trays and Surgeries

Chapter 3

Methodology

Our primary goal is to design a set number of peel packs for surgeries in order to improve the overall utilization of surgical instruments. In the proposed model, we design the peel packs and assign these peel packs to surgeries with the aim of minimizing the surgical trays' related costs. We assume that the surgical main trays (MTs) are already designed according to the specific requirements of the procedure. These trays are custom-designed surgical instrument trays, which are associated with only one surgery. Under normal conditions, instruments available in the main tray (MT) should be sufficient for the successful completion of the surgical procedure. However, as we mentioned before, during the surgical procedure the usage for a particular instrument could be higher than anticipated and the missing number of instruments should be filled by opening a new MT and thus reducing the utilization of MTs or increasing the overall cost. In order to reduce the waste of several unused instruments from the new main tray, we design a custom peel pack based on the historical usage of the instruments in the surgery. The custom peel pack (CPP) which is in place of the main tray should demand an instrument that the actual requirement is above the normal (more than what is available in the main tray). The decision to open either the main tray or the peel pack in response to uncertain instrument demand is left to the discretion of the surgeon.

The following sequence of events will take place in the operating room. (i) The staff will open an appropriate main tray for the surgery, which is assumed to be used for sure. (ii) We assume only one peel pack will be used and only one main tray will be opened after the peel pack. If the procedure requires an extra quantity of one or more instruments, then the staff will open a custom peel pack(CPP) associated with the surgery. (iii) If the custom peel pack also is not able to meet the demand, then the staff will open another main tray. While it is possible to use a custom peel pack, there is also a chance that another main tray may need to be opened. In other words, our objective is to minimize the cost of the peel pack and the expected cost of opening a main tray, ensuring efficient instrument utilization during the surgical procedure.

The decision relies on the cost and if CPPs can meet the demand or not. Based on our previous assumption, the total MTs cost is higher than CPPs. Since multiple surgeries have many similarities (in terms of surgical instrument requirements), our goal is to design peel packs that can serve multiple surgeries and hence reduce the inventory and logistical-related costs. A procedure schedule is known for each scheduling period such as a day or week. Let S be the set of surgeries, I be the set of CPPs, J be the of instruments and K be the set of quantities.

Based on this information, we define the assumption, variable, and parameter as follows:

Table 3.1: Notations used in the complete mathematical model

Index	Explanation
$s \in S$	set of procedures or surgeries
$i \in I$	set of custom peel packs (or cluster)
$j \in J$	set of surgical instruments
$k \in K$	set of quantity (0,1,2,..). Used for deciding the number of instruments in a peel pack.
Decision Variables	
PM_s	The probability of opening the main tray for surgery s. $PM_s = MAX_{j \in J}\{P_{s,j}\}$ i.e. one of the instruments in the associated peel pack is not available in the right quantity. (Complete model)
Ps, j	The probability that the demand of instrument j, for surgery s, is more than the available quantity (main tray).
$t_{s,i}$	Cost of configuring Peel Pack i (associated with surgery s).
$Z_{i,j,k}$	Binary decision variable, instrument j quantity k is allocated to CPP i.
$Z_{s,i,j,k}$	Binary decision variable, instrument j in quantity k for surgery s is allocated to CPP i ($Z_{s,i,j,k}$ is equal to 1.
$X_{s,i}$	Binary decision variable, surgery s is assigned to cluster i, when $X_{s,i}$ is equal to 1.
$Q_{j,k,i}$	Binary decision variable, instrument j quantity k is allocated to CPP i when $Q_{j,k,i}$ is equal to 1.
Parameters	
$p_{s,j,k}$	Probability (based on instrument usage for surgery s) that the demand for instrument j is more than k.
C_s	The cost of main tray.
M	Appropriate Big number.
PC_i	The cost of peel packs i.
cm_j	Cost of instrument j in main tray s.
cp_j	Unit cost of instrument j if used in a CPP.
$m_{j,s}$	Mean usage of instrument j in procedure s.
$SD_{j,s}$	Standard deviation of the mean usage of instrument j in procedure s.
N_i	cardinality of set R_i. $N_i = \|R_i\|$. r surgeries that are associated with peel packs i when N_i =r.

3.1 The Formulation

This section provides the complete formulation to design the required CPPs based on historical instrument usage. We use the binary variable $Z_{s,i,j,k}$ to decide the number (quantity $k \in K$) of instruments $j \in J$ assigned to CPP $i \in I$. We use the same variable to decide whether the procedure $s \in S$ belongs to CPP $i \in I$. In the model, we assume that for surgery, say s, we will use a peel pack associated with the surgery. If the peel pack doesn't contain enough quantity for each required instrument. then the staff will open the main tray (in addition to the peel pack). So, the objective is to minimize the total cost of peel packs (used in all surgeries) and the expected cost of using the main trays (for all surgeries).

To be specific, the probability of using the main tray depends upon the peel pack configuration. For instance, if the peel pack contains huge quantities of each instrument and the surgical procedure only required a few extra instruments, then the surgeon will never run out of any instrument and thus the probability of using the main tray will be zero. Let PM_s be the probability of using the main tray. Now the total expected cost of using the main trays would be:

$$\sum_{s \in S} PM_s.C_s \tag{1}$$

where C_s is cost of the main tray s i.e. $C_s = \sum_{j \in J} q_{s,j}.cm_j$

The cost of the peel pack depends upon the peel pack configuration. Since we are deciding the peel pack configuration, peel pack cost is our decision variable that depends upon the instrument quantity associated with the peel pack. The cost of instrument j is cp_j. The quantity of instrument j is a decision variable. Since we want to keep the overall program as a linear integer program, we decided to model it by the binary variable $Z_{s,i,j,k}$. The variable takes the value 1 if surgery s is associated with peel pack i and quantity for instrument j in this peel pack is equal to k. $k \in \{0, 1, 2, ..., \}$.

$$P1 \;\; Min \sum_{s \in S} \sum_{j \in J} PM_s.C_s + \sum_{i \in I} \sum_{s \in S} t_{s,i}$$

S.T.

$$\sum_{k\in K} Z_{s,i,j,k} \leq X_{s,i}.M \qquad \forall\, j \in J, i \in I, s \in S \tag{2}$$

$$X_{s,i} - \sum_{k\in K} Z_{s,i,j,k} = 0 \qquad \forall\, s \in S, j \in J, i \in I \tag{3}$$

$$\sum_{i\in I} X_{s,i} = 1 \qquad \forall\, s \in S \tag{4}$$

$$\sum_{k=0}^{K} Q_{j,k,i} = 1 \qquad \forall\, j \in J, i \in I \tag{5}$$

$$P_{s,j} = \sum_{i\in I}\sum_{k\in K} Z_{sijk}.p_{s,j,k} \qquad \forall\, j \in J,\ s \in S \tag{6}$$

$$PM_s \geq P_{s,j} \qquad \forall\, j \in J, s \in S \tag{7}$$

$$PC_i = \sum_{j\in J}\sum_{k\in K} Q_{j,k,i} * cp_j * k \qquad \forall\, i \in I \tag{8}$$

$$t_{s,i} \leq PC_i \qquad \forall\, i \in I,\ s \in S \tag{9}$$

$$t_{s,i} \geq PC_i - M + M.X_{s,i} \qquad \forall\, i \in I,\ s \in S \tag{10}$$

$$Q_{j,k,i} \in 0,1,\ X_{s,i} \in 0,1,\ Z_{sijk} \in 0,1 \forall\, i \in I, j \in J, k \in K, s \in S \tag{11}$$

The objective is to minimize the expected cost of using the main tray for each surgery and the total cost of using the peel packs (for each surgery). We can see, the total cost associated with a particular type of peel pack depends upon the number of surgery associated with it. In the formulation, $X_{s,i}$ is introduced for better readability and for linearizing the peel pack cost expression. Constraints (3) simply connect $X_{s,i}$ to $Z_{s,i,j,k}$. Constraints (4) make sure surgery s must be part of only one peel pack. Constraints (5) ensures that every peel pack only picks one of the quantities from $\{0, 1, 2, ...K\}$ for each instrument j. Constraints (7) compute the probability of using main tray s. Constraints (8) compute the cost of each peel pack and constraints (9) and (10) are used to introduce (through linearization) peel pack cost associated with each surgery.

In constraints (6) and (7), in order to determine the probability $P_{s,j}$ (for surgery s, the demand for instrument j is more than the available quantity), we first compute the probability $p_{s,j,k} = Prob(d_{j,s} > k) = 1 - Prob(d_{j,s} \leq k) = 1 - \Phi(Z = \frac{k - m_{j,s}}{SD_{j,s}})$. We assume, the demand for surgical instruments in OR follows the normal distribution. Among the formula, $d_{j,s}$ is the additional demand for instrument j in surgery s, $m_{j,s}$ represents the mean value of additional instrument usage during surgery s, $SD_{j,s}$ denote the standard deviation of instrument j's additional usage in surgery s. We utilize the formula $\frac{k - m_{j,s}}{SD_{j,s}}$ to calculate the corresponding Z value that serves as a measure to find out $P_{s,j}$.

3.2 Clustering Approaches with Linear Programming (LP)

Our goal is to configure the given number of peel packs (CPP) by assigning the surgeries and placing the right number of instruments in each CPP in order to reduce the expected cost of opening the main tray after opening the CPP. The overall problem is computationally very challenging due to many integer variables (See problem $P1$). In order to develop a simplified approach to this problem, we decompose the problem and solve it in two phases. In the first phase, we solve the assortment problem i.e. associating similar surgeries, based on the historical usage of the instruments. And in the second phase, we configure CPP for each assortment. Since the assortment in the first phase will be developed based on the similarities of instrument usage/patterns, we develop an approach based on clustering.

The K-means-based clustering approach is an unsupervised machine learning algorithm for identifying the similarity between points (i.e., instrument j's quantity k). The method randomly selects initial centroids from the data set, groups points of the data set into these centroids based on their minimum distance, and forms clusters. The centroids are then recalculated as the mean of the data points in each cluster, and the process is repeated until the centroids do not change any further.

In order to use the clustering approach, we first compute a basic peel pack (BPP) for each surgery. The BPP contains a sufficient number of instruments to reduce the probability of opening the main tray after a BPP is opened. In order to develop basic peel packs (temporary peel packs) for each surgery, we look at the mean and variability of each instrument usage and decide the right quantity for a given service level using the newsvendor approach (assuming normal distribution). The service level either can be decided based on the costs or based on the management practices. These basic peel packs (BPP) serve as one data point. We consider $|J|$ dimensional space (one axis for each instrument type). In each axis, instrument quantity represents coordinates i.e. for example, if we have only two types of instruments, (say x and y), and a basic peel pack contains 2 units of x and 5 units of y then (2,5) will be the coordinate for this basic peel pack. All such packs together form a matrix $A_{s,j}$that showcases the required instrument quantities for each surgical procedure $s \in S$ and instrument $j \in J$. We adopt the K-means clustering approach to cluster surgeries based on characteristics such as item quantities, instrument cost, and surgical demand. We use the following three different approaches to define the location of each basic peel pack and evaluate its closeness to the current clusters.

3.3 Classical Clustering

In this approach, each instrument quantity (in the basic peel pack) defines the position of a peel-pack point in the n-dimensional Euclidean space. Our objective is to identify several basic peel packs that contain analogous numbers of surgical instruments. We randomly select $|I|$ peel packs and set their coordinates as initial centroids (to obtain —I— clusters). We evaluate the Euclidean distance between each BPP and each centroid (clusters). We select the minimum distance and associate this BPP with the corresponding cluster. Once all the BPP are associated with one of the clusters, we re-evaluate each centroid by taking the mean of the data points (BPP coordinates). We repeat the process by reevaluating the distance of each basic peel pack from each centroid, assigning the basic peel pack to the nearest centroid until no more changes are possible.

3.4 Cost-weighted Clustering

We intend to take instrument cost into consideration. In this approach, we use the cost of the instrument associated with instrument quantity to define BPP coordinate, $A_{s,j}$. To find the best result of clusters, we run a K-means algorithm based on Euclidean Distance (ED). Centroid c_{ij} of cluster i is selected from the matrix $A_{s,j}$ in the first step. Calculate the distance between the $A_{s,j}$ and the centroids, say $d_{A,c_{ij}}$; a smaller distance indicates that basic peel pack s is assigned to cluster i; compute coordinates of $|I|$ new centroids by using mean; repeat previous steps until centroids remain unchanged.

3.5 Demand-weighted Clustering

In the previous approach, all the BPPs are given equal weight. In the demand-weighted approach, the weights are proportional to the demand d_s of surgery s. Let R_i be the set of surgeries associated with cluster i. Needless to say $R_i \subseteq S$ and $R_{i_1} \cap R_{i_2} = \emptyset,\ where\ i_1, i_2 \in I,\ i_1 \neq i_2$. Let $r\ th$ data point (BPP coordinate) is represented by n-tuple $(u_{r,1}, u_{r,2}, ..., u_{r,n})$ where $u_{r,j}$ represents the quantity of instrument j in BPP r, where $r \in R_i,\ j \in J$.

Let $(U_{i,1}, U_{i,2}, ..., U_{i,n})$ be the centriod of ith cluster. In the demand-weighted mean approach, jth coordinate of centroid i (for cluster i) will be calculated using the following expression:

$$U_{i,j} = \frac{\sum_{r \in R_i} u_{r,j}.d_r}{\sum_{r \in R_i} d_r} \tag{12}$$

We change the way to calculate the centroid of clusters in the demand-weighted clustering and the rest calculation steps are the same as the classical clustering.

Once the cluster assignment is completed, our next step is to configure a custom peel pack for each cluster. Since custom peel pack cost computation requires the probability of opening the main trays, we propose the following linear programming approach:

3.6 Custom Peel Pack Configuration

Different from the integrated model where cluster and peel packs are computed jointly, this approach decomposes the problem - first we create clusters based on BPP and then create a custom peel pack for each cluster using linear programming. As a result, a smaller dimension mathematical model is used to solve the overall problem. In the mathematical model, most of the variables and parameters are similar to previous complete models. Binary variable $z_{i,j,k} = 1$ indicates k units of instruments $j \in J$ are assigned to CPP i. PM_s denotes the probability that at least one of the instruments is not available in enough quantity in an associated CPP to perform procedure s. Thus, a main tray associated with surgery s may be used in addition to the CPP.

As defined earlier, R_i is set of surgeries assign to cluster i. Let N_i be the cardinality of set R_i. We assumed CPP will always be used and the main tray will be used only if CPP doesn't contain enough instruments. Our goal is to minimize the expected cost of opening the main trays and the total cost of the peel packs. In the following objective function, the first term computed the expected cost of the main trays and the second term compute the total cost of the peel packs (based on the number of surgeries in each cluster).

$$P2 \quad Min \sum_{s \in S} PM_s.C_s + \sum_{i \in I} PC_i.N_i$$

S.T.

$$P_{s,j} = \sum_{i \in I} \sum_{k \in K} Z_{i,j,k}.p_{s,j,k} \qquad \forall\, s \in S, j \in J \tag{13}$$

$$PM_s \geq P_{s,j} \qquad \forall\, j \in J, s \in S \tag{14}$$

$$\sum_{k \in K} Z_{i,j,k} = 1 \qquad \forall\, i \in I, j \in J \tag{15}$$

$$PC_i = \sum_{j \in J} \sum_{k \in K} Z_{i,j,k}.cp_j.k \qquad \forall\, i \in I \tag{16}$$

$$Z_{i,j,k} \in \{0,1\}, P_{s,j} \geq 0,\ PM_s \geq 0$$

Constraints (13) indicates the probability $P_{s,j}$ that instrument j in CPP i cannot meet instrument demand in procedure s, is written as a sum of $(Z_{i,j,k}.p_{s,j,k})$, where the index s ranges over cluster

i. In order to determine $P_{s,j}$, we define parameter p_{sjk} as instrument j unsatisfied probability for different quantity k in procedure s, and binary variable $Z_{i,j,k}$ for probability selection. Constraints (14) ensure the required demand of each instrument in procedure s can be met. Constraints (15) impose restrictions that only one quantity value k will be assigned to CPP i instrument j. Constraints (16) present the cost of peel packs PC_i based on the clustering result, and constraints (**??**) compute the overall cost t_s of using peel packs for each surgery.

3.7 Decomposition

The integrated model $P2$ is a huge integer program and it is very challenging to obtain a quality solution within a reasonable time (5-10 hours). This motivates us to consider the problem decomposition approach. This is why we proposed a clustering-based approach. We develop a decomposition approach, column generation, to solve $P2$. This approach divided the problem into two parts: a subproblem that generates a cluster as well as creates an optimal custom peel pack for the generated cluster; the master problem evaluates the set of available clusters and picks the right number of clusters to obtain the minimum cost. Although the decomposition approach uses roughly the same sets of constraints as $P2$, in this approach, we work only with one cluster in each iteration (while in $P2$ all the clusters are considered simultaneously) and the problem is solved over several iterations - each iteration for one cluster. Such an approach supposedly should take less time than the integrated approach. 3.2 presents decision variables and parameters used in the decomposition approach. The master problem includes one decision variable, z_i, for cluster i (we call it by column). V_i is the cost of each column. In the pricing problem, we maintain the same set of constraints as in the complete model. The decomposition approach necessitates the updating of the dual values μ_s and ν of the master problem constraints in order to determine the new surgical assignment and peel pack configuration. To achieve this, a new objective function is established to generate new columns for the master problem, which is formulated with the aim of maximizing.

Table 3.2: Notations of Decomposition method

Variable	Explanation
z_i	Binary decision variable. If pack i is selected for one of the surgeries (z_i is equal to 1).
$P_{s,j}$	The probability that instrument j cannot satisfy the instrument's (j) demand in the procedure s.
PM_s	The probability that a procedure s demand cannot be fully met.
$Z_{s,j,k}$	Binary decision variable, instrument j quantity k for surgery s is allocated to the new column when Z_{sjk} is equal to 1.
$QC_{j,k}$	Binary decision variable, instrument j quantity k is allocated to the new column when $QC_{j,k}$ is equal to 1.
y_s	Binary decision variable, surgery s is assigned to the new column when X_s is equal to 1.
t_s	Pack cost for each surgery s assigned to this peel pack.
Parameter	
V_i	Column Cost of column i.
μ_s	Linear Programming relaxations of master problem constraint 17.
ν	Relaxations of master problem constraint (18).
M	Appropriate Big number.
$y_{i,s}$	The coefficient of element s in column i.
yc_i	The coefficient to indicate the feasible column.
C_s	The cost of main tray s.
cp_j	The cost of instrument j in peel packs.
MC	The number of expected clusters.
PC	The cost of a new custom peel pack.

Let Y_i is $|S| + 1$ elements column vector of binary elements (0 and 1) where $|S|$ denotes the cardinality of set S (total number of surgeries). Let $y_{i,s}$, $s \in S$, represents the sth element of ith column. Similarly, we represent the last element of ith column's $(|S| + 1)th$ member by yc_i. Each feasible column represents one cluster (hence a peel pack) and our goal is to create a limited number of clusters. In order to control the number of clusters, we set $yc_i = 1$ for every feasible column. Let V_i be the cost corresponding to column Y_i. We use z_i, a binary variable, to denote if Y_i forms the basis i.e ($z_i = 1$). Let G be the set of all feasible columns, the master problem can be formulated as follows:

$$M1 \quad Min \sum_{i \in G} V_i.z_i$$

S.T.

$$\sum_{i \in G} y_{i,s}.z_i = 1 \qquad \forall s \in S \tag{17}$$

$$\sum_{i \in G} yc_i.z_i <= MC \tag{18}$$

$$z_i \in 0, 1 \; \forall \; i \in G \tag{19}$$

Our goal is to minimize the total expected cost associated with peel packs and main trays. Constraints (17) make sure that each surgery must be part of at most one peel pack or cluster. The maximum number of clusters is limited by (18). MC is a parameter and represents the maximum number of clusters. In the problem $M1$, we assumed the set G contains all the feasible column vectors. This set could be very huge and may not be easily available. Dantizig-Wolfe decomposition (Barnhart, Johnson, Nemhauser, Savelsbergh, and Vance (1998)) does not require all the columns apriori and we can generate the required missing columns as we need and add dynamically in set G. In order to generate a new column that could price out available columns (in G), we need to solve a pricing problem. Let μ_s, where $s \in S$, be dual values associated with constraints (17) and ν be a dual value associated with constraint (18). Since our column also represents a cluster, the cost associated with the column includes both the costs (peel packs and the expected cost of using main trays). The pricing problem can be formulated as follows:

Objective function:

$$PP1 \quad Max \sum_{s \in S} y_s.\mu_s + \nu - \sum_{s \in S} PM_s.C_s - \sum_{s \in S} t_s$$

S.T.

$$\sum_{k=0}^{K} Q_{j,k} = 1 \qquad \forall\, j \in J, \tag{20}$$

$$PM_s \geq P_{s,j} \qquad \forall\, j \in J, s \in S \tag{21}$$

$$PC = \sum_{j \in J} \sum_{k \in K} Q_{j,k}.cp_j.k \tag{22}$$

$$\sum_{s \in S} Z_{s,j,k} \leq Q_{j,k}.|S| \qquad \forall\, j \in J, k \in K \tag{23}$$

$$\sum_{k \in K} Q_{j,k} = 1 \qquad \forall\, j \in J \tag{24}$$

$$PM_s \leq y_s \qquad \forall\, s \in S \tag{25}$$

$$y_s \leq \sum_{k \in K} Z_{s,j,k} \qquad \forall\, j \in J, s \in S \tag{26}$$

$$t_s \leq PC \qquad \forall\, s \in S \tag{27}$$

$$t_s \geq PC - M + y_s.M \qquad \forall\, s \in S \tag{28}$$

$$Z_{s,j,k} \in \{0,1\},\ Q_{j,k} \in \{0,1\},\ y_s \in \{0,1\}$$

The goal is to maximize the reduced cost. The first term, in the objective function, includes the dual cost for each surgery, included in the column, and the second term is the dual cost associated with constraints (18). The cost of the column (last two terms) includes the expected cost of using the associated main tray and the total cost of the peel pack (for each included surgery). The last two terms are V associated with this column (cost of the column). All the constraints are similar to the original problem except (27) and (28). We introduce these two constraints to include the cost of the peel pack (PC) for each surgery associated with this column. $t_s = PC$ if surgery is part of this column i.e. $y_s = 1$, otherwise zero. M is a big number used to implement these two constraints.

In order to start the algorithm, we add $|S|$ initial columns (one for each surgery). In the column, all the elements are zero except $y_{s,i}$, which is 1 for the sth column. The cost of the column is the cost of the associated main tray C_s. These columns, although costly, provide a feasible solution to the master problem $M1$. The solution to $M1$, in each iteration, provides the dual costs ($\mu_s,\ \nu$). We use dual cost to solve the pricing problem ($PP1$). If the reduced cost is positive and bigger than a predefined positive constant (say 0.001), we add the column in $M1$. We follow this procedure till we reach the time limit or the algorithm failed to obtain a new column with a positive reduced cost. the reduced cost.

Given the decomposition approach is able to compute non-binary results, we set an additional procedure. After generating all-new columns and calculating the final column-selection result (i.e., z_i), we recalculate the z_i as the binary variable based on the final column results if z_i is not 1 or 0.

Chapter 4

Numerical Experimentation

In order to evaluate the performance of the proposed approaches, we have conducted numerical experimentation. All the algorithms are implemented using IBM-CPLEX with C++ as well as PyCharm. As mentioned in the previous section, the overall problem is a big assortment problem and we segregate similar surgeries (based on the use of instruments and quantity) using clustering approaches. We develop three clustering criteria and hence three clustering algorithms. In order to pick the right clustering algorithm for our overall problem, we numerically tested these algorithms using randomly generated data sets.

4.1 Performance of Clustering Approaches

To perform three different clustering-based approaches with linear programming, we set various scenarios with different numbers of surgeries, instruments, and clusters performed during a period and calculated the cost and computational time by using Python. For each simulation, we conduct 20 iterations.

First, we defined the service level as 90% which means designed trays will meet 90% of every instrument demand in each procedure. We assume that the number of surgery types which will happen per day ranges from 25-510. The number of surgeries performed in one hospital depends on many factors like the size of the hospital, the number of operating rooms, the types of patients treated, and so on. Different hospitals may have different specialties and scales which can result in differences in the type of surgeries number performed. Otherwise, the number of instrument types varies in each tray between 5-100. The type of surgery being performed is one of the factors that influence the surgical instrument used for each surgery. Some instruments are commonly used in various surgeries, such as scalpels, scissors, clamps, and needle holders. However, some unique or special instruments are required for one surgery. Therefore, we try to examine our three clustering-based approaches under different scenarios (different scales of hospital and different types of surgery). Moreover, we randomly generate the cost of the instrument. The cost of each instrument in the main tray ranges from \$0.19 to \$0.43, while the cost of instruments in the peel packs varies between \$0.99 and \$1.24. We refer to the instrument cost in the article, Toor et al. (2022). Furthermore, We simulated various factors including quantity in main trays with the constraint of maximum quantity, mean usage of instruments(0.3-1.5 of instrument demand), and the standard division of instrument usage(0.2-0.8 of instrument mean usage).

All three algorithms were tested on these generated data sets. We first generated the clusters of surgeries using each clustering algorithm then we use linear programming to configure a peel pack associated with each cluster. The LP provided the total expected cost of using the peel packs and opening the main tray if the peel pack cannot meet additional demand.

Table 4.1: Performance of three clustering approaches

Problem Size			Demand weighted		Classical		Cost weighted	
No. of Surgeries	No. of Instruments	Clusters	Cost	Time(second)	Cost	Time(second)	Cost	Time(second)
25	10	5	1	0.6473	0.9961	0.601	0.9907	0.6043
25	10	10	1	0.7239	0.9935	0.6655	0.9927	0.6781
		Avg:	1	0.6856	0.9949	0.6333	0.9927	0.6412
25	25	5	1	4.034	1.0044	4.3483	0.9915	0.9721
25	25	10	1	4.2182	1.0016	4.2842	1.0012	4.2419
		Avg:	1	4.1261	1.0031	4.3161	0.9961	4.0817
25	50	5	1	11.6639	0.9994	12.6837	0.9959	14.161
25	50	10	1	11.8474	0.9939	12.2412	0.9967	12.9016
		Avg:	1	11.7557	0.9967	12.4625	0.9963	13.5309
150	10	20	1	4.8369	1.0041	5.4712	1.0009	5.1868
150	10	50	1	7.5816	1.0022	7.7950	1.0004	7.5473
		Avg:	1	6.2093	1.0032	6.6331	1.0007	6.3671
150	25	20	1	33.186	1.0013	34.3866	1.0002	34.8923
150	25	50	1	33.6483	1.0021	31.7993	1.0000	1.6174
		Avg:	1	33.41715	1.0017	33.0930	1.0001	33.2549
150	50	20	1	125.1713	1.0008	97.5847	0.9996	99.7093
150	50	50	1	97.132	1.0013	97.6216	1.0031	101.4326
		Avg:	1	111.1517	1.0010	97.6032	1.0035	100.5710
510	10	50	1	21.7908	1.0010	21.9304	1.0009	21.7838
510	10	100	1	25.7372	1.1084	26.5031	1.1078	26.0733
		Avg:	1	23.764	1.0496	24.2168	1.0492	23.9286
510	10	50	1	35.7134	1.0014	34.9204	1.0000	34.8666
510	10	100	1	41.4057	1.0012	43.3003	1.0003	43.3298
		Avg:	1	38.5596	1.0013	39.1104	1.0002	39.0982
510	50	50	1	96.6455	1.0024	99.7324	1.0011	97.7207
510	50	100	1	114.6675	1.0009	119.9811	1.0000	120.4464
		Avg:	1	105.6565	1.0016	109.8568	1.0006	109.0836
		Total Average:	**1**	37.2583	1.0047	**36.4361**	1.0036	36.7285

In table 4.1, the first three columns define the problem size followed by the performance of three clustering algorithms. For each algorithm, we present the cost and computation time in seconds. We normalize the cost with respect to the demand-weighted clustering (the first clustering algorithm in the table). For instance, in the first row, the cost related to the classical clustering approach is

0.9961 - which simply means classical clustering reported a 0.39% (1-0.9961) better solution than the demand-weighted clustering approach. Each problem (with respect to the number of surgeries and instruments) is solved for two cluster sizes (small and big). We report the average cost and time too. Based on the overall experiment and based on the average cost, we can see that weighted algorithms perform better than classical clustering and among the two weighted algorithms, the performance of the demand-weighted algorithm is better than the cost-weighted algorithm.

4.2 Performance of Decomposition and K-means Algorithm

In this section, we aim to present a comprehensive evaluation of the solution methods discussed in the previous section. The parameters that were considered during this evaluation include the number of instruments required for surgical procedures and the number of clusters to be formed. In order to thoroughly assess the performance of these methods, we have generated instances that take into account the aforementioned parameters. Our evaluation focuses on two key methods, namely the decomposition approach and the clustering-based approach (Surgery-weighted K-means clustering). The decomposition approach seeks to optimize tray assignment and configuration by generating new columns. This is achieved through the use of mathematical programming and optimization algorithms that consider the constraints and limitations of the problem. On the other hand, the clustering-based approach leverages the benefits of mathematical programming and clustering algorithms to find the tray assignment solution and obtain the integer solution for tray configuration. It's noteworthy that both methods adhere to similar constraints and limitations in their mathematical programming, thereby ensuring a fair comparison between the two. The results of our evaluation will be presented in terms of both model solution and computational time, providing a comprehensive overview of the performance of each method.

4.2.1 Results Analysis without Time Restriction

In order to demonstrate the performance of the decomposition approach and clustering approach, we set 27 small-size problems and compute 20 instances for each problem size [7-15 surgeries, 3 different cluster sizes (2 clusters, 3 clusters, and 4 clusters), and different instrument number ranges(instrument number: 1-3, 2-6, 3-9, 4-12, ..., 10-30)].

Figure 4.1 visualizes the mean cost gap of different expected peel packs number for each value of surgery number (from 7 to 15). In Figure 4.1, the X axis represents the surgery number s, and Y axis means the cost gap value for various problem sizes. The results show that the mean cost gap increases by increasing the number of surgery types. For example, when we expect to calculate 2 peel packs, the cost gap between the proposed cluster algorithm and decomposition algorithm increases when the surgery number is from 7 to 15. The changes in surgery numbers can be viewed to reflect the size of the hospital to some extent.

From this figure, we can see that the number of peel packs is not the absolute factor to influence the cost gap between those two algorithms, especially when the surgery number is not large. One of the reasons is that the instrument number is not fixed. The instrument number would influence the resulting gap between the two different algorithms.

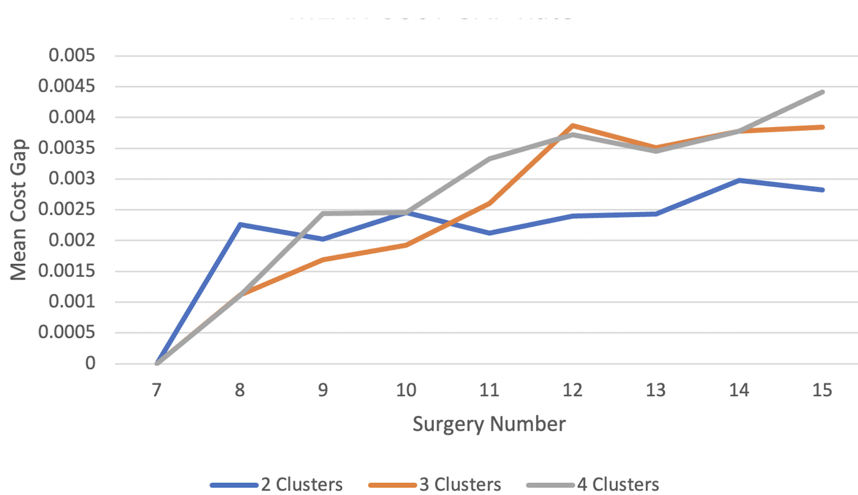

Figure 4.1: Comparition of Mean Cost

In Figure 4.2, we present the standard deviation of cost gap for each value of the surgery number.

We notice that the standard deviation of cost is relatively stable. We can also observe that the standard deviation of cost is larger when the peel packs (cluster) number is bigger. When we expect to configure more peel packs, the process of calculation is more complex.

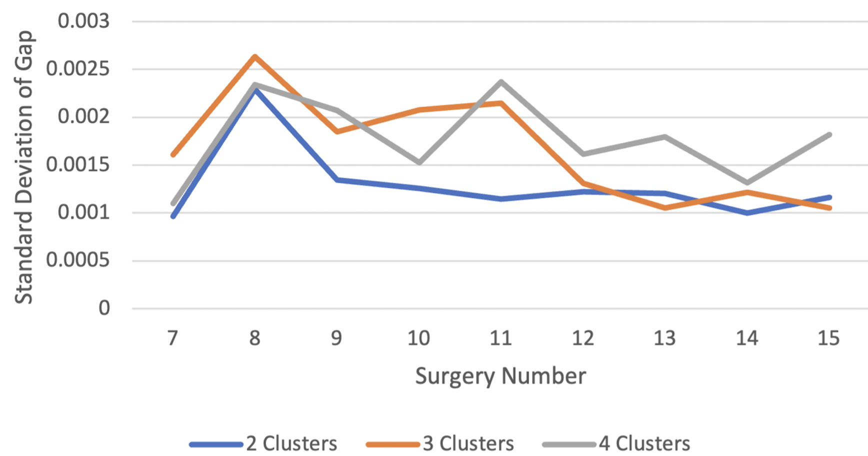

Figure 4.2: Standard Deviation of Gap

Figure 4.3 indicates that the mean time decreases which means the computational time gap between two different algorithms increases with the growth of surgery number. In this figure, the mean computational time gradually gets close to zero when the surgery number is from 11.

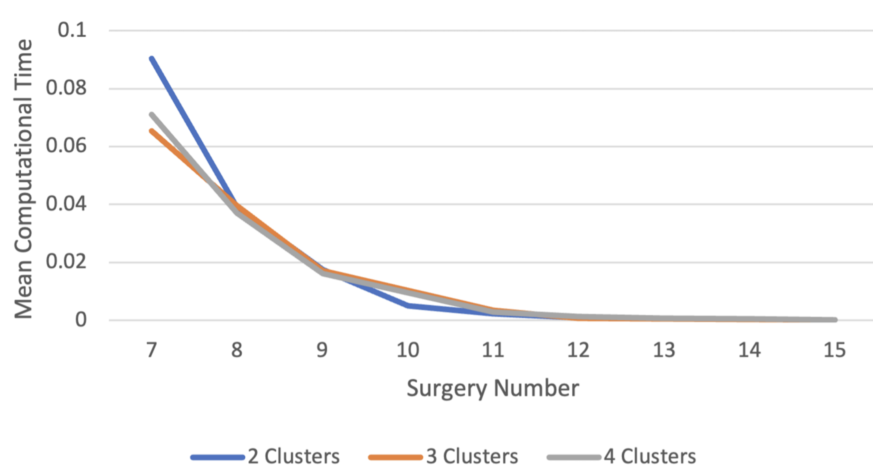

Figure 4.3: Mean Computational Time

Figure 4.4 shows that the standard division time decreases which means the growth rate of the decomposition algorithm is faster than the proposed clustering's. This discrepancy is influenced by the stochastically generated instrument numbers, signifying that the effect of instrument number variations diminishes with a rise in the number of surgeries.

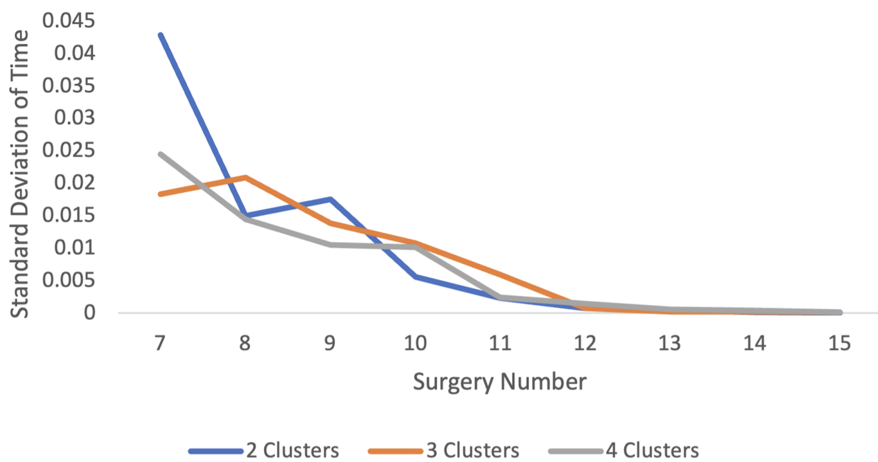

Figure 4.4: Standard Deviation of Computational Time

By analyzing how surgery number (surgery type) influences the final result, we find that a large surgery number increases the difficulty of calculation of the decomposition approach. In other words, the more types of surgery, the more mean cost gap rate, and less mean computational time rate. Simultaneously, we also observe that the instrument number would make an effect on the mean cost gap rate, but not computational time.

4.2.2 Results Analysis with Time Restriction

For each problem category, we tested the approach for a varied number of clusters. We randomly generate 10 instances for every defined cluster (e.g., 3, 5, 10, 20) within the limited range of surgeries (e.g., Surgery: 10-25, Number of surgeries are generated randomly between 10-25), and instruments (e.g., Instrument 5-25, the instrument number randomly generated from 5 to 25).In order to assess the performance of the solution methods, we have calculated several key metrics. These include the mean percentage error, the standard deviation of the percentage error, the mean generation time percentage, the standard deviation of the generation time, and the expected time of the decomposition. The percentage error can be found using the formula $\frac{Sol\_Cluster - Sol\_Decomposition}{Sol\_Decomposition}$, and the percentage of generation time can be indicated by formula $\frac{Time\_Cluster}{Time\_Decomposition}$.

Table 4.2: Comparison Performance of Decomposition and Demand-weighted Algorithm

Problem Size	No. of Clusters	Mean Percentage Error(%)	Std of Percentage Error(%)	Mean Percentage of Generation time(%)	Std Percentage of generation time(%)	Mean Time of Decomposition(Millisecond)
Surgery: 10-25 Instrument:5-25	3	0.93	1.47	2.29	2.62	14538.5
	5	0.14	0.26	4.06	4.78	18828.12
	10	0.35	0.25	3.06	3.06	20462.3
Surgery: 20-50 Instrument:10-50	3	0.02	0.07	0.16	0.15	444558.7
	5	0.05	0.11	0.27	0.34	557715
	6	0.08	0.08	0.08	0.08	868923.6
	10	0.04	0.04	0.06	0.09	1315637.6

Table 4.2 presents the performance of the two solution methods with two decimal places, providing a clear comparison of their performance. In the first experiment, the demand-weighted algorithm's results were close to optimal results according to the mean percentage error. On the other hand, the decomposition algorithm provided the optimal solution but require a significant amount of computational time. As problem sizes increase, the computation time increases significantly and exponentially. The results suggest that the demand-weighted algorithm is a very effective solution method. In order to test the performance of the clustering approach on the bigger size problem, we limited the maximum computation time to 30 mins (1800 seconds)for the decomposition algorithm. This allows us to evaluate the performance of each method within an appropriate time and gain a comprehensive understanding of its capabilities. Since the decomposition approach uses the master problem and pricing problem, we set the maximum time for each instance of the pricing algorithm to 5 mins (300 seconds). We found, multiple times, pricing problems failed to find a feasible solution within the prescribed time, so in our experimentation, we allow CPLEX to polish the solution (heuristic to improve the current solution or find a feasible solution after 100 seconds).

We conducted a new experiment with a new data set and determined that the range of instrument mean usage and standard deviation required adjustments to obtain more findings. Thus, we repeated the experiment, with modifications made to these parameters. Additionally, we kept the surgery and cluster numbers consistent at 5, 10, and 15 to ensure uniformity across all tests and eliminate the effort that the surgery number is close to the cluster number. The new results have been included in the updated Table 4.3 for further analysis and comparison with the previous experiment's findings. Overall, these adjustments have allowed us to obtain a more comprehensive understanding of the effects of both the instrument mean usage and standard deviation on our study's outcomes.

Table 4.3: Performance of Two Approaches with Time Limits 1

Problem Size	No. of Clusters	Mean Percentage Gap(%)	Std of Percentage Gap(%)	Mean Percentage of Generation time(%)	Std Percentage of generation time(%)
	5	-0.11*	0.16	0.021	0.01
Surgery: 25	10	-0.34*	0.28	0.04	0.02
Instrument:5-25	15	-0.65*	0.14	0.07	0.03
	5	-0.14*	0.04	0.04	0.01
Surgery: 50	10	-0.32*	0.10	0.11	0.02
Instrument:10-50	15	-0.54*	0.19	0.13	0.05
	5	-0.07*	0.05	0.05	0.01
Surgery: 75	10	-0.32*	0.12	0.10	0.02
Instrument:15-75	15	-0.48*	0.15	0.13	0.03
	5 (7)	-0.11*	0.05	0.05	0.01
Surgery: 100	10 (6)	-0.31*	0.11	0.07	0.01
Instrument:20-100	15(7)	-0.48*	0.06	0.10	0.02
	5(4)	-0.11*	0.04	0.06	0.01
Surgery: 125	10(3)	-0.32*	0.07	0.06	0.006
Instrument:25-125	15(3)	-0.38*	0.09	0.10	0.007

∗ optimal solution was not available and in nearly all the cases, the clustering approach provided a better solution.

Table 4.4: Performance of Two Approaches with Time Limits 2

Problem Size	No. of Clusters	Mean Percentage Gap(%)	Std of Percentage Gap(%)	Mean Percentage of Generation time(%)	Std Percentage of generation time(%)
	5(0)	-	-	-	-
Surgery: 150	10(3)	-0.19*	0.03	0.11	0.01
Instrument:30-150	15(0)	-	-	-	-
	5(0)	-	-	-	-
Surgery: 175	10(1)	-0.16*	-	0.08	-
Instrument:35-175	15(0)	-	-	-	-
	5(0)	-	-	-	-
Surgery: 200	10(0)	-	-		-
Instrument:40-200	15(0)	-	-	-	-
	5(0)	-	-	-	-
Surgery: 225	10(0)	-	-		-
Instrument:45-225	15(0)	-	-	-	-
	5(0)	-	-	-	-
Surgery: 250	10(0)	-	-		-
Instrument:50-250	15(0)	-	-	-	-

∗ optimal solution was not available and in nearly all the cases, the clustering approach provided a better solution.

In most iterations, our proposed clustering approach yielded smaller solutions than the best decomposition result. This suggests that the decomposition approach was unable to achieve the optimal results within the maximum defined time of 1800 seconds. Therefore, the mean percentage error, in all of these cases is negative. We called it as mean percentage gap in this new table.

For surgery 25-100, the decomposition approach is capable of obtaining feasible solutions within the time limit of 1800 seconds. However, for bigger problem sizes (No. of surgeries 125 and above), the decomposition approach was not able to propose even a feasible solution. This is why we did not report the gap. This is also due to the time limitation we set for heuristic in the pricing problem. It is worth noting that the table only considers all feasible solutions and calculates the expected value and standard deviation of gap and time. We take some examples to explain several special results in the table. For instance, when the number of surgeries is set to 125, and the number of instruments varies from 25 to 125, with max clusters set to 10, we obtain feasible solutions only for 7 (out of 10) instances. The number in brackets (beside no. of clusters) simply shows the gap is based on less than 10 instances. The mean percentage gap indicates the cost of the proposed clustering approach is 0.11% lower than that of the solution proposed by the decomposition algorithm (within 30 mins), while the mean time taken by the clustering approach (demand-weighted algorithm) is 0.06 % of the decomposition approach. In the first instance of the next problem size (surgery: 150, instrument: 30-150, and cluster: 5), there is no feasible solution, so no results are presented in the table. Then, the instance where the surgery number is 175 and the cluster is set to 10 only contains one feasible solution, which suggests that we do not have adequate data to calculate the standard deviation. As a consequence, we solely calculate the expected value of the result gap and time. Moreover, when the number of surgeries exceeds 200, even when the hospital only demands 5 clusters, the decomposition is unable to compute the optimal solution. As a result, we omit the remaining result in Table 4.4

Furthermore, the cost gap and mean generation time for this method increase as the cluster number increases. These findings suggest that the decomposition approach may not be suitable for larger cluster sizes, and alternative methods should be considered for such scenarios. Additionally, it was observed that increasing the range of mean instrument usage resulted in a longer computational time for the decomposition method. This information can be valuable in showing the proposed clustering approach of computational efficiency as well.

Chapter 5

Conclusion

Our study on the surgical tray assortment problem provides a comprehensive overview of the proposed approaches, solutions, and their evaluation. We first proposed a formulation of the surgical tray problem which consists of the total tray cost objective function with a set of relevant constraints. This model highlights the challenges and pathways for the following two models. Subsequently, three clustering-based approaches were proposed to address the peel packs' assignment problem, utilizing linear programming with basic peel packs of each surgery to design custom peel packs. These three different clustering algorithms were tested with various problem sizes to compare the performance. The findings indicated that the performances of the two weighted algorithms were superior to the classical clustering algorithm in general. Typically, the demand-weighted algorithm was found to be the relatively superior approach based on the overall experiment and total average cost. To further investigate this assortment problem, a decomposition approach based on the column generation method was proposed, which found the optimal solution. Numerical experiments were conducted to compare the proposed clustering approach (Demand-weighted) and the decomposition approach. In the first small experiment, we examined two approaches simultaneously without any time limitation. We observed that the result of the demand-weighted clustering algorithm is close to the decomposition, which indicates the accuracy of the proposed clustering algorithm. Nevertheless, it was noted that the computational time required for the decomposition approach was considerably higher, thereby impeding the ability to obtain the result for each instance. Consequently, a time limit of 1800 seconds was set in the second experiment. The decomposition approach could not obtain the actual optimal solution within the limiting time, and the bigger problem size, which was over a particular threshold, resulted in an infeasible solution as well. Overall, the findings from both experiments indicated that the clustering approach with LP was efficient, providing results close to the optimal solution within a reasonable time.

In summary, our study provides a valuable contribution to the surgical tray assortment problem, offering practical and efficient solutions for optimizing the assortment of surgical trays. The demand-weighted clustering approaches with linear programming balance the cost and efficiency, making it a useful tool for practitioners in the medical field.

Some limitations exist in our study, so we plan to indicate some possible directions for future research. Firstly, Assortment problems are a ubiquitous challenge in supply chain management. These issues arise in different contexts. Our study's objective is to address such assortment problems in the context of healthcare by allocating surgical basic peel packs in a manner that meets the desired service level for multiple surgeries. The proposed methods are demonstrated to be effective in resolving these types of problems, but it is important to note that when applying these methods to other contexts, it may be necessary to consider additional inventory factors, such as holding costs, safety stock levels, and inventory costs. Then, the determination of the optimal number of peel packs is a crucial objective in our future study. In this paper, we first assume that the hospital has already known how many peel packs they expect. Based on this assumption, we determine the optimal allocation of peel packs by a pre-determined number of clusters. However, in real-world scenarios, hospitals may not have this prior knowledge to decide the optimal number of peel packs based on available usage data. This presents a significant challenge. More specifically, the optimal number of peel packs should balance the trade-offs between service level, inventory costs, and other factors and satisfy all constraints without peel pack number limitation. Moreover, our study assumes that the main trays have already been decided, and the peel packs are designed accordingly. Besides, there is scope for further exploration in this area, particularly in terms of considering both the reconfiguration of main trays and the design of peel packs in a more comprehensive manner. This would involve incorporating the interdependence of these factors, which would make the model more complex. The inclusion of this interdependence would provide a more comprehensive solution that takes into account the overall cost, service level, and inventory levels, as well as the feasibility of the reconfiguration and design processes. The aim of future research in this area would be to develop a more sophisticated model that balances the trade-offs between these factors, resulting in an optimized solution.

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