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COVID Response: Iterative Model Development in the Deployment of Hand Sanitation Stations at a Large Public University

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COVID RESPONSE: ITERATIVE MODEL DEVELOPMENT IN THE DEPLOYMENT OF HAND SANITATION STATIONS AT A LARGE PUBLIC UNIVERSITY

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ABSTRACT

This study illustrates the significance of iterative model development using the deployment of hand sanitizer stations in buildings at Clemson University as a case study. The COVID-19 problem affected Clemson University, a major institution, in several ways requiring adaptations to existing policies and procedures to take place. Following guidelines provided by the Centers for Disease and Control (CDC), the university implemented several new strategies including placing hand sanitizer stations in several buildings on campus in order to try and mitigate the transmission of the virus. This study focuses on learning how the initial decision-making took place to then design a representative model that can provide future recommendations. We first use semi-structured interviews to understand the historical decisions behind the placement of these dispensers. We then come up with an initial model design strategy to capture what was done by the university. Finally, through ongoing interviews with key stakeholders we use an iterative modeling process to eliminate discordance between the model and the actual decision-making strategies to design a representative model. The thesis will first outline the strategies and techniques that were used to gather qualitative information. It will also present some of the quantitative data that was gathered. Next, the iterative modeling development process will be provided in detail. After this, the models are formally outlined and described. The subsequent results are then presented. Finally, the thesis discusses the takeaways from the iterative modeling process as well as the future plans with regards to implementation of the model. The value of this research study is to show how qualitative research methods like semi-structured interviews with key stakeholders

can aid the iterative development of optimization models that lead to an ideal representative model to be implemented in the future.

DEDICATION

I would like to dedicate this manuscript to my family including my Mom, Dad, and younger sister. They have always been there for me through thick and thin. They always offer me such great advice and support me in all of my decisions. I love them so much and can’t thank them enough for everything that they have done for me.

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TABLE OF CONTENTS

Table of Contents (Continued)

Page

LIST OF TABLES

Table Page

LIST OF FIGURES

List of Figures (Continued)

Figure | Page

CHAPTER 1: INTRODUCTION

Overview of COVID-19 Problem at Clemson University

The COVID-19 pandemic massively impacted universities across the nation. This forced them to find different alternatives and strategies to reduce the spread amongst their student bodies, as well as the surrounding communities. In the Spring of 2020, the COVID-19 pandemic forced Clemson University (CU), like other colleges, to shut down its campus and proceed with online instructional methods [4]. CU officials decided to use Zoom as an online video conferencing platform so professors could hold virtual meetings with their students and teach their courses [2]. Throughout the Spring and during the Summer of 2020, CU enhanced its COVID-19 testing procedures to accurately monitor the number of positive cases in the community. Using this enhanced testing method allowed CU officials to recognize a decreasing trend in the number of positive cases. Therefore, they decided that it was safe enough for CU to change its instructional methods to a hybrid/blended approach for the Fall of 2020, and bring more students back to campus. This hybrid/blended approach would allow some CU students to attend their classes in-person during certain days of the week while other students would continue to attend class virtually. An algorithm was developed by the university to help decide which days of the week certain students would attend in-person lectures.

CU began preparing for students to return to campus in the Fall of 2020. Early on in the pandemic, CU formed an organization known as the Emergency Operation Center (EOC). The EOC would hold weekly meetings where several representatives from different departments would attend. **Table 1** shows a list of some of the departments involved with the EOC.

Table 1: List of Interview Participant's Department Affiliations

Department Name	Department Name
Members of Facilities Management	Members of Environmental Health and Safety
Members of Department of Procurement	Members of Student Health Services
Building Security Coordinators	Clemson TigerOne Department
Members of Housing and Dining	

The EOC was put in charge of coming up with ways to fix several of the COVID-19 related problems. At the start of the pandemic, members of the EOC made several quick decisions at the policy and operational levels in anticipation of forthcoming challenges. Due to the uncertain and dynamic course of the pandemic, the university had to constantly monitor and revise these policies. When CU planned its return to campus in the Fall of 2020, they implemented several strategies to do so safely, including: a hybrid instructional method (i.e., having students attend in-person on alternating days), removing seats in classrooms to encourage social distancing, requiring masks in buildings on campus, marketing healthy COVID-19 guidelines across campus, and weekly COVID-19 testing. CU also placed several hand sanitizer stations in buildings on campus (which is the main focus of this study). A vast majority of the policies implemented by the university were discussed during the EOC meetings. Several of the decision that the university made to protect the students were impacted by recommendations from CU's Health and Safety Services as well as the suggestions that came from the Centers for Disease and Control (CDC). The decision to place hand sanitizer stations in buildings was in response to the CDC suggesting individuals partake in frequent hand washing. The university viewed this decision as a way to help mitigate the transmission of the virus amongst the students and faculty, limit potential outbreaks, and support everyone in following the CDC's health guidelines. In an initial interview, we were told that CU was following the CDC guidelines that suggested providing adequate amounts of hand sanitizer and frequent hand washing would offer an advantage to reducing the transmission of the virus, which was ultimately one of the main goals to be able to return to normalcy as seen by the university.

Members of multiple departments were present for these EOC meetings, including the members of the Department of Facilities Management (CU Facilities); who are in charge of cleaning and disinfecting the buildings on CU's campus. In response to the pandemic, they were also tasked with deploying the hand sanitizer stations within the buildings. During the EOC meetings CU Facilities spoke with the other departments about the availability of hand sanitizer supplies and equipment. They started working with the Department of Procurement (purchasing) to start securing supplies as early as February of 2020. Their main focus for acquiring supplies was to get as much supply of hand sanitizer product as possible. In order to determine initial locations for the hand sanitizer stations, CU Facilities spoke with the Building Security Coordinators (BSCs) about ideal locations for the stations. They spoke with the BSCs because they had the best knowledge about the buildings. The current study focuses on the hand sanitizer station deployment and uses semi-structured interviews in order to understand how the initial location decisions were made, and then to be able to create an ideal, representative optimization model in order to determine optimal locations for hand sanitizer station dispensers in campus buildings. We have partnered with CU Facilities and will use the model to recommend new stations locations for the upcoming semesters based on population data. The next section will discuss some of the usefulness related to alcohol-based hand sanitizer.

Usefulness of Alcohol-Based Hand Sanitizer

One of the main reasons that the current study is significant is because of how important hand sanitizer usage is in terms of mitigating the spread of the virus. With limited information on how to remain safe at the beginning of the pandemic, people turned their attention to the CDC and the World Health Organization (WHO) for effective, preventive measures. Several people used their guidelines to learn how to protect themselves and the people around them. Even though handwashing, and using soap and water is preferred over using hand sanitizer, the CDC still suggests that using alcohol-based hand sanitizer is an effective method of cleansing your body of bacteria and germs [9]. The WHO mentions that whenever hand-washing with soap and water is not feasible, using alcohol-based hand sanitizer that is greater than 60% alcohol is still beneficial [12]. They have even provided some references about specific types of hand sanitizer to use [12].

The CDC reports that “Sanitizers can quickly reduce the number of germs on hands in many situations” and applying sanitizer aids in preventing individuals from spreading germs to those around them [11]. Therefore, as an alternative to hand washing, frequently using alcohol-based sanitizer has become an important tactic to hand cleansing during the pandemic. Also, in an article related to hand sanitizer, the company PURELL® separates several of the myths from the truths about using hand sanitizer. It is reported by PURELL® that their product of "Advanced Hand Sanitizer destroys the cell walls, killing bacteria quickly and evaporating before germs have a chance to develop a resistance" [10].

Since CU was following the guidelines of the CDC, they believed it was necessary to provide the students with adequate sanitation supplies (i.e., not only regular hand soap). Supplies were limited, however, and the storage of alcohol based sanitizer on campus became a fire risk issue. CU decided to adapt to these challenges and relied on existing vendor contracts to leverage suppliers out of bidding-wars. They also carefully registered all spaces on campus where sanitizer could be stored safely. They then began acquiring as much supply of alcohol-based sanitizer materials as possible. Ordering stands for the stations was difficult so CU's carpentry shop built stands for CU Facilities so the alcohol-based sanitizer stations could be placed in other locations around campus. An example of one of the stands that was designed by the carpentry shop is shown in **Figure 1** below.

Figure 1: Alcohol-Based Sanitizer Stand Built by CU Carpentry Shop

CU Facilities soon recognized the importance of these stations shortly after the initial deployment. In an interview, an interviewee mentioned that "…the first day we put them out (the sanitizer stations) in the library, I think we, [CU Facilities], had to refill them twice… in normal [situations] one of those containers lasts several weeks, even into a month. [However], we were going through multiple per day so people were, while they were still on campus…[and]…going to the Library, …hitting (using) those stations and I thought that was unique".

The importance of alcohol-based hand sanitizer was prevalent to CU. With that being said, we felt that there was a possibility to work collaboratively with CU Facilities. We believed that an optimization model would provide them with an optimal solution for locations around campus knowing (from the interviews) that initially one of the "hard decisions" that CU Facilities had to make was finding the "most impactful" locations for the placement of these dispensers.

It is also worth mentioning that proper hand washing has been studied in several different healthcare settings, for multiple reasons, because adequate hand hygiene and compliance with hand washing policies has been an issue that many healthcare facilities have attempted to address and improve in order to reduce “healthcare-associated infections” [17]. An article by Allegranzi and Pittet (2009) cites some of the findings from other studies that have analyzed how compliance has resulted in a significant reduction in healthcare-associated infections being transmitted between the patient and the provider [18], [19]. The outcome associated with these results is that the overall compliance with proper hand hygiene improved. This gives light to the current study because it proves that hand hygiene can impact several things. Additionally, other observational studies in healthcare settings have been performed to investigate visitor characteristics to understand just how well visitors participate in frequent handwashing when entering a healthcare facility [15], [16]. Some research has provided evidence to show that alcohol-based gel sanitizer reduces the spread of pathogens from the provider to the patient [13]. Researchers are also looking into finding enhanced ways to monitor healthcare provider hand hygiene in healthcare facilities [24].

Even more so, studies at other college universities analyzed the connection between proper hand hygiene and access to hand sanitizer and how that affects certain illnesses among college students [20], [21]. This proves that studying hand sanitizer usage at college universities has been seen as something of importance for quite some time. Studies like such have been able to show that there is an overall positive impact when students have access to hand sanitizer and engage in frequent hand washing.

Surveys have also been sent out by college universities to get a perspective on hand hygiene amongst students and the results indicate the need to improve hand hygiene education amongst students [25]. The impacts of the COVID-19 pandemic have shown that these types of improvements are necessary. The current study differs from these observational studies, however, because the current study does not study the actual usage of the stations. The current study is focused on building a model to find an optimal solution for where the stations should be placed in university buildings. The effectiveness of the placement of sanitizer stations has been studied using a location model and through surveys in a hospital setting [22], [23]. However, these types of models have not been used to address placement of the sanitizer stations in multiple buildings on a university's campus. All in all, this helps to understand why proper hand hygiene and adequate hand sanitation is a problem that many individuals are trying to improve in order to better protect everyone. This study doesn't focus primarily on increasing hand sanitizer usage but it does develop a model to offer locations for these stations where the foot traffic is the largest and could potentially increase usage. The next section will provide an overview of the modeling related to the current study. Mainly, why the modeling problem is interesting and the iterative modeling process.

Overview of Modeling

The modeling problem itself is interesting because a majority of optimization models incorporate uncertainty within the model to model different scenarios. There are several ways to do this (e.g., stochastic programming, robust optimization, distributionally robust optimization, etc.). On the other hand, in the current study the models that are developed are incorporated within uncertainty. The models mirror real-world decision-making and real-world uncertainty. The strategies and policies implemented by CU were always changing under the uncertainty of the pandemic. Each day the pandemic presented new challenges. Therefore, university policies had to adapt. The current study models that decision-making under uncertainty by creating models informed by qualitative (semi-structured interviews) and quantitative data. These models reflect the policy changes and shifts in operations through an iterative modeling process. As the situation evolved, the models are refined to reflect what is happening to consistently provide a representation of the decisions being made. Using this iterative process, we are able to build an ideal, representative model that can then be implemented by the university in order to make tactical updates to the sanitizer station deployment.

To continue, the modeling problem is interesting because it is related directly to several of the changes that had to happen at the university once the pandemic started. Placing these stations in buildings around campus was a direct result of the pandemic. This makes the model more interesting because it reflects the actual situation but then provides an optimal solution for the locations of the stations around campus to improve the overall effectiveness of their placement. To continue, the modeling problem is also interesting because the current study incorporates the use of qualitative research methods (i.e., semi-structured interviews) which help us better understand how CU adapted to the challenges of the COVID-19 pandemic; focusing primarily on hand sanitation placement. This strategy allowed us to develop a model of the identified decision-making process. All in all, the study uses what we are deeming a “blended approach” to study the situation at CU. This blended approach integrates the actual decision considerations, retrospectively, in the current scenario, and prospectively with the model's optimal solution to evaluate the relative efficacy of those decisions and provide insights to decision-makers to improve their overall understanding of the problem.

Lastly, the iterative modeling process that was used it this study is another reason why the study is interesting. The model was refined coincidently with the input that was gathered during the interview process and ongoing CU Facilities meetings. This created a model that could be implemented by CU Facilities in future situations because it reflected their behavior so they had a better understanding of how it operated and what it was trying to solve. This then lets them have a representative model that reflects their policy and decision-making.

Overview of Current Study

The current study is attempting to show how using an iterative modeling process can improve the overall model and make it more representative of decision-making. The iterative process identifies several limitations related to each model iteration, that can then be modified to develop a representative model which could replace identical decision-making in the future. The iterative modeling process also enables us to evaluate each model iteration against the real-world response. The current study also shows how integrating Operations Research (OR) optimization models with Human Factors (HF) research methods (i.e., semi-structured interviews) provides a better opportunity to understand the initial location decision problem and how it was attempted to be solved. It provides a way to incorporate sources of uncertainty (i.e., decision-making processes and understanding of system) into the design of a model. Furthermore, blending the research techniques enables the model to gain qualitative insight such that the constraints and the model objective show a linkage between those initial decision-making strategies. The model then offers an optimal solution that mathematically solves the deployment of the hand sanitizer dispenser stations.

CHAPTER 2: LITERATURE REVIEW

This next section will discuss the literature that is related to the current study. There were several key references that influenced the development of the study. Several themes needed to be researched in order to understand more about what has been done in the past with respect to the current study. A few of the things that were reviewed were other universities responses to the COVID-19 pandemic, HF and resilience engineering (RE) research techniques, OR and modeling techniques (as they relate to this study), mixed-method research techniques, and interdisciplinary research in academia. The purposes of performing this literature review is to figure out what types of gaps are present in the current literature related to this study and how this current study could contribute to each overarching stream of research. The next few sections will go through the different streams of research that were analyzed and explain how this study contributes to each of those individual streams. The first stream will begin with universities responses to COVID-19.

To begin, when the COVID-19 pandemic hit, several college universities asked for their students to be sent home and not return until further notice. Most universities made these decisions in order to protect their health and safety. Once students returned home, a majority of the universities began planning ways to respond to the virus and restructure their standard policies such that the students could be brought back to campus safely. Several studies have reviewed universities responses to the COVID-19 pandemic. For instance, an overarching blueprint is available to help campuses safely reopen [28], and surveys have been used to understand students' views of campus pandemic responses, including class modality changes [31].

Agent-based and mathematical models have been developed to monitor the spread of the virus on campus and provide universities with intervention strategies [26], [27]. Wi-Fi infrastructures have been used to generate contact networks and to support agent-based simulations to identify potential transmission risk [30]. Even more so, a tool is available to optimally distribute classroom seating to maximize occupancy while following social distancing [30]. The current study demonstrates CU's responses to the pandemic and their adaptation to its challenges using semi-structured interviews with key stakeholders in the decision making process; specifically related to hand sanitizer station placement in buildings on campus. The current study then designs a representative model of the decision-makers' initial deployment method in order to offer an optimal solution to the problem. We provide them with feedback to evaluate the relative efficacy of their decisions and improve their understanding of the problem. The next section will describe the literature related to (HF).

HF or human factors engineering (HFE) is a discipline in which individuals try to better understand how humans interact with the different components of a system [80]. The goal is to improve the design of these system to increase performance, reduce error, and increase safety. Data collection methods within HFE are important because they create a more accurate representation of a system which is a prerequisite to performing further analysis [79]. There are several types of research methods used within HFE to help better understand human decision-making. One of those methods is to use semi-structured interviews. These interviews have some pre-determined questions, however, they allow for flexibility, and some of the further questions asked are sometimes not part of the original interview [79].

Resilience engineering (RE) is a field that focuses on learning and enhancing the resilience of systems by identifying and supporting emergent adaptive capabilities [70]. Enhancing these systems through resiliency work provides the opportunity for them to return to normalcy [70]. These capabilities include monitoring, anticipation, coordination, maintaining readiness to respond, and proactive learning from variability in everyday work processes [71]. RE-based studies have often adapted HFE methods to elicit domain knowledge and patterns of interactions within a system. These methods, which include surveys, semi-structured interviews and observations, generate qualitative insights on how decisions are made by actors in the domain in focus. Research has identified several of the key advantages of using semi-structured interviews to collect data and studies have used these techniques in the context of RE [75]-[78].

One of the research areas within RE is disaster relief. RE studies focus on how a system can become resilient to future challenges presented by disasters. Resilience involves "…anticipating, planning and reducing disaster risk to effectively protect persons, communities and countries, their livelihoods, health, cultural heritage, socio-economic assets and ecosystems" [69]. Several recent studies have explored adaptations in organizations during the COVID-19 pandemic in various domains, including healthcare and education [72]-[74]. However, there is scarce research focusing on understanding adaptations, particularly from an RE lens, of universities as organizations.

The current study hopes to demonstrate the resiliency efforts of a major university (like CU) through semi-structured interviews, and evaluate the efficacy of their efforts by designing a related optimization model. The model itself is representative of their hand sanitizer station deployment strategy which is formulated by qualitative inputs coming from the analysis of the semi-structured interviews. The next section will go over research related to OR.

OR is a scientific approach to decision making that allows individuals to better understand a system and how it operates. More formally, it is defined as "…the scientific process of transforming data into insights to making better decisions" [32]. OR allows individuals to create mathematical models of a system that model human behavior and decisions in order to find ways to make the system perform more efficiently. OR aids in solving very complex problems that may arise in a system [33]. A goal of OR is to identify problems within a system and find ways to improve them so that the operations of the system go smoother and the entities within that system function correctly. There are several examples of areas in which OR can help solve problems, for example "…in the operations of industrial firms, financial institutions, health care organizations, transportation systems, energy and resources, and government" [34].

Optimization models create a representation of a system and provide an optimal solution to a problem within that system. There are several things that can be addressed using optimization models, however, this study focuses primarily on versions of discrete facility location models. Within OR, discrete facility location models are often used to optimize deployment decisions [3]. Coverage location models seek to maximize the number of individuals who are within a certain distance of selected locations. Location models have been used in a broad set of applications, including waste management systems, automation, and disaster relief [39], [40], [42], [35], [36].

Additionally, facility location models are useful when companies are trying to restructure portions of their supply chain network. Studies have shown the effects of using models that consider qualitative and quantitative factors in order to optimally chose a set of suppliers, customers, and distribution centers [43]. Also, facility location models have assisted healthcare systems in developing nations [45]. Some types of facility location models even consider multiple objectives and budget constraints [44]. These types of models also provide a way to design certain distribution systems for most companies [38]. Some facility location models are even being developed in response to the COVID-19 pandemic in order to aid resource allocation [37]. The current study uses versions of a facility location model in order to address cross campus allocation and placement of the hand sanitizer stations in multiple buildings at a major university.

There are many ways to apply facility location models. One of them is known as the maximum covering location model. These models attempt to optimally locate facilities to maximize the coverage of demand nodes. Balcik et al. (2008) define the maximal covering location problem (MCLP) in their research and say these problems attempt to maximize "…the total number of people served within a maximal service distance, given a fixed number of facilities or budget limitations" [51]. The budget limitations, or costs, associated with locating facilities in a MCLP is not always the only factor considered. Other versions of the MCLP have used "timeliness of response to the demands" as key factor to determine where facilities should be located in a MCLP [52]. MCLP problems have been studied extensively in the literature and there are several algorithms that have been developed to solve these problems [49]-[51].

Some have even compared the MCLP to the p-median problem (*p*-MP) to understand how the two methods behave [53]. The *p*-MP problem only allows the model to locate *p* number of facilities, or entities, as opposed to the MCLP which does not restrict the number of facilities. The *p*-MP has been used for several applications; for example, versions of the model have been developed to optimize locating public education facilities, while restricting the number of facilities that can be located [41], [46]. Others have studied the *p*-MP in order to minimize setup and transportation costs [48]. The *p*-MP problem has also been used to solve problems related to distances between suburban homes and a limited number of located schools [54]. Versions of the *p*-MP have been modified to make them more robust when subjected to disruptions [47]. The current study tries to apply both a version of the MCLP and the *p*-MP to maximize the coverage of classrooms in a single academic building while limiting the number of dispensers that can be located in that building. The next section will describe mixed-methods and how it relates to the current study.

The current study relies heavily on using both qualitative (i.e., semi-structured interviews) and quantitative (optimization models) research methods; we have deemed this strategy a blended approach. This blended approach is separated from mixed-methods, which is still an alternative to combining qualitative and quantitative research methods. We focus on improving decisions with mathematical models which is in contrast to standard mixed-methods which is focused on solely understanding a system. Mixed-method studies seek to integrate qualitative and quantitative data to offer a more complete and synergistic utilization of the data [55]. There are several advantages to mixed-method studies (e.g., they offer the opportunity to gather much more rich, comprehensive data, they offer more flexibility, and they better reflect the decision-makers perspective) [55]. Mixed-method studies have been widely used in healthcare settings and primary care [56], [57], [60], [61]. In their article, Creswell et al. (2004) offer several models that have been designed in order to apply a mixed-method strategy. A major focus is to gather qualitative data in order strengthen the design of data collection instruments [62]. Two of the models that are quite similar to the design of the blended approach are the Instrument Design Model and the Triangulation Design Model [56]. The Instrument Design Model begins with qualitative data collection and that data collection leads to the design of a more improved quantitative instrument for data collection that is representative of the decision-makers' views [56]. This type of model has created more structured data collection instruments especially in healthcare facilities [58]. Nutting et al. (2002) used interviews with physicians to design a checklist for barriers to depression care which was then used by physicians to reanalyze these barriers and weight their relevant importance [59]. The current study relates to this model because we seek to design an instrument (an optimization model) that can help key decision-makers make quick, effective decisions surrounding the deployment of hand sanitizer stations on CU's campus. The study involves gathering qualitative data that describes the historical decision-making process, and then this qualitative data feeds into the design of the optimization model.

The other model proposed by Creswell et al. (2004) is the Triangulation Design Model. Creswell et al. (2004) describe the model as gathering qualitative and quantitative data at the same time and then integrating both forms of data in some way to be able to better understand a research problem [56]. Within this model, the data (qualitative and quantitative) is collected simultaneously, and then is integrated in the results or analysis [56]. Creswell et al. (2004) cite a few studies in their article ([60],[61]), surrounding primary care, that applied the Triangulation Design Model. This study also involves simultaneously collecting qualitative and quantitative data and integrating them to produce a representative optimization model. Despite this study using some form of a mixed-method approach (gathering both qualitative and quantitative data and integrating them), rarely has this been done to ultimately create a representative optimization model an implement the model in some real world context at a major university. We have decided to call the approach used in the current study a blended approach.

It is also worth mentioning, that discrete facility location models are nearly always based on quantitative metrics, and even in other types of optimization, very few studies integrate perspectives of real-world actors gathered through HF methods (semi-structured interviews). Elbert et al. (2017) augmented their simulation model on optimal routing policy based on actual human behavioral data on deviations from the optimal route [64]. Others have incorporated qualitative criteria, identified based on surveys, in a manufacturing plant layout design problem [63]. In general, however, there is a lack of integration in these approaches so as to complement their unique advantages. Likewise, the blended approach is a fundamentally different approach that focuses on decision making.

The blended approach combines the two methods to understand historical decision-making strategies as related to hand sanitizer placement. Then it uses the qualitative inputs in order to identify necessary quantitative data to develop several potential representative models of the situation. The models then go through refinement and analysis with key decision-makers until they believe that they can apply the model in their own work to make updates to their deployment. The refinement process, or iterative modeling design, (which included explaining each model version to the key stakeholders) is imperative to the study because it allowed us to identify model limitations that restricted the model's capabilities. Each stage, or iteration, allowed us to redesign the model. Once we were able to create the ideal version, the model is then applied in real context at CU by the decision-makers and aid in future decision-making strategies while also evaluating their initial decisions.

The blended approach of using qualitative, HR methods (semi-structured interviews) and quantitative OR modeling is aimed at developing a deeper understanding of campus adaptation decisions than either could accomplish as stand-alone approaches. We then analyze these themes to come up with constraints and objectives in order to design a representative optimization model. The approach used in the current study is distinguished from more common mixed-methods studies. Mixed-methods are often used to combine qualitative methods with statistical studies to better understand a system and decisions. In the blended approach, qualitative methods are combined with mathematical optimization not only to evaluate past decisions but to support and improve decisions in the future. Such an approach is unique in that it allows us to understand implemented adaptation strategies and to inform future adaptation. Finally, the main focus of this thesis is the iterative model development process and not the blended approach, but it needs to be mentioned since the study itself applied the blended approach to design the resulting optimization models.

Another application of this study is that it incorporates interdisciplinary research in academia. Interdisciplinary research is when "…each team member…build on each other's expertise to achieve common, shared goals" [65]. Interdisciplinary is different from multidisciplinary because in multidisciplinary researchers from different disciplines work together, but each works in their own domain [66]. In interdisciplinary work, the researchers contribute both in their own domain and to others. For example, in this study, the individuals from OR (which designed the optimization models) also helped handle some of the semi-structured interviews (which is the HF component of this study). The individuals from OR and HF did not solely design the models or conduct the interviews, respectively. The researchers from both domains handled multiple portions of the study (e.g., conducting semi-structured interviews, collecting and analyzing data, sharing data, and developing an optimization model). The research was interconnected. Interdisciplinary approaches have been assessed and even applied to research in healthcare [67], [68]. The final section will describe research related to building several optimization models.

Research shows how to formulate several model variants that correspond to different scenarios in order to demonstrate their applicability [81], [84]. Likewise, other studies have developed multiple models to find the best optimal solution and generate different outcomes [82], [83]. Even further, there have been studies that have modeled iterative processes [85]. The current study differs from the previous research because they have not attempted to use an iterative modeling development process that integrates qualitative input into the creation of the models to represent human decision-making strategies. The framework that is presented in this study can be applied to other areas that might want to blend qualitative research studies in order to create a representative optimization model.

CHAPTER 3: DATA COLLECTION AND ANALYSIS

This section describes the data collection and analysis that took place during this study. Throughout the iterative model development process (**Figure 5**), several types of data had to be collected and analyzed. As part of a blended approach, we collected both qualitative (through semi-structured interviews) and quantitative data. The next subsections will describe the different types of data collected. This section will also discuss the analysis of the qualitative data which uses codes to identify and link several key themes. These results will help understand how the qualitative data impacted the subsequent model designs. Some of the key results from the semi-structured interviews will also be provided.

Qualitative Data Collection (Semi-Structured Interviews Process/Protocol)

In order to obtain information, we used a HFE approach and scheduled semi-structured interviews with key figures and stakeholders at CU who were involved in the decision-making process with regards to COVID-19 policies and procedures. The first step to be able to conduct the semi-structured interviews was to receive IRB exemption. The current study was reviewed by CU's IRB and approved under the 'exempt' category. Therefore, we were able to proceed with the semi-structured interviews. The Sanitizer Deployment Semi-Structured Interview Protocol script and questions are shown in Appendix A.

The interviews were a key component to qualitative data collection. We made an effort to interview several participants who were affiliated with the departments involved in the EOC meetings. The interviews were conducted on Zoom and each participant granted us permission to record them. The purpose of recording these interviews was so that they could be reanalyzed for analysis purposes (which will be described later on in this thesis). The interview process in this study gave us a better understanding about how the safety-related decisions with regards to hand sanitation policies were made at CU. There were five major categories of questions in the interview process. The first set of questions was related to the participant's role, specifically at the beginning of the pandemic and how it related to the university's sanitizer deployment. They also described the difficulties that they and their related department/team faced at the start of the pandemic in the Spring of 2020. The next set was related to sanitizer station placement considerations. For example, they were questioned about the information they gathered from different external sources like the CDC and internal sources at CU who advocated for proper hand sanitation policies. These types of interview questions served as a strategy to find out more about ways that these departments shared information (interdepartmental communication).

Thirdly, the participants were questioned about their placement strategies. For example, they were asked about some of the goals and metrics they tried to set for placement totals. In addition, we wanted to know if they used any types of specific data or if they applied modeling techniques when coming up with a solution for where to locate the stations. We also tried to find out what their considerations were for the ideal or optimal deployment. After this, the fourth set of interview questions looked into how they monitored the situation once class modality changed from online to a hybrid model. These questions also asked about monitoring student and faculty usage at the stations.

Along with this, the participants were asked if any adjustments to their initial policies were made. Lastly, the participants detailed directions for the future, and how policies may or may not change. Because these were semi-structured interviews, several probes were included which allowed us to dive deeper into a question and gain more insight.

Qualitative Data Analysis

This section will provide insight into how the qualitative analysis directly influenced the design of each model that was created in this study. As it has been mentioned, this study used semi-structured interviews to be able to understand how CU Facilities shaped their initial deployment strategy. With these interviews, we were able to gather an abundance of information which in turn was used to create a single heuristic and representative models. This was done to show the benefit of blending (HF) and (OR) research methods in order to create models that more accurately depict a situation like the deployment of sanitizer stations. In order to get the qualitative insights that were related to each model, we used a software known as MAXQDA [86]. This software allows one to code segments of an interview transcript with themes such that they can be referenced later on. For the purpose of this study, we labeled the responses from the interviewees with codes related to different types of possible model designs. These responses and suggestions were how the design of each model was generated. The first types of qualitative influences that will be provided are related to the initial heuristic that was created.

Qualitative Influences on Initial Heuristic

The design of the heuristic was generated from the qualitative input of the semi-structured interviews with members of CU Facilities. They stated the following:

> "…the initial deployment [of the hand sanitizer stations] was certainly based on building usage or potential usage. Again, you may have buildings like the new business school (College of Business), for instance, that saw a lot of usage, so we had more stations in that building than maybe we would have had in Harden Hall, or a smaller deal (building)…"

We decided that a heuristic based on proportional allocation would provide a good starting point to begin to access the solution methods that CU Facilities used in their deployment. The next section will describe the qualitative influences that shaped the single building model that was developed.

Qualitative Influences on Single Building Model

Some of the qualitative aspects of the study that influenced the single building model (which will be described more thoroughly in the modeling section) were the preliminary discussions with the primary stakeholders who told us that some of the initial goals were to base their location decisions on classroom usage in buildings. For example, one representative from CU Facilities told us in an interview that "… for the Fall [of 2020], we, [CU Facilities], still left some [of the dispensers] at the entry ways in the larger buildings, but in some cases we just targeted the classrooms". Another interviewee spoke about how the "…classroom buildings and office buildings that had the greatest occupancy throughout the days were the driver [of placement]". Even more so, one interviewee said "…just the buildings where you had the most amount of classroom spaces" is where they tried to get the most sanitizers placed. Additionally, in early discussions with stakeholders, a lot of their focus was on the classrooms because CU was trying to bring students back to campus. The representatives were planning for students to be back in the classrooms. One individual described how they wanted to "…target the rooms that should be high usage" for cleaning and sanitization purposes. They had a good understanding of what this usage would look like. A member of CU Facilities said "…they created what was just a huge spreadsheet… [and] could go in and look at a particular classroom and what that classroom was scheduled for and how many people should be in [that classroom] on that particular day…". With all of this, classroom coverage seemed to play a role in some of the strategies employed by CU Facilities and that is why a single building optimization model was created.

The model idea generation for the single building model also came from interviewees who spoke about how in buildings they wanted to try and cover the most used paths by students. One interviewee from CU Facilities said "As far as putting all those stations that we put in the classrooms they may go away, but I think [we might put them] in the hallways and then the main intersections [of buildings]". Many of these same individuals also mentioned in the interviews that they wanted to minimize transmission rates by positioning stations along high-traffic paths. We were told by an individual who works closely alongside CU Facilities that they tried working with the BCSs to identify the high-traffic areas in buildings. For these reasons, we felt that the single building model was an appropriate modeling framework and would serve as a depiction of these decision-making strategies.

Qualitative Influences on Location Covering Model

There were several ways that we incorporated the qualitative aspect of the study from the semi-structured interviews into the design of the location covering model. Several coded segments suggested how the focus was to get the stands into the busiest buildings, but it did not specifically describe where within those buildings the stations should be placed. For example, an interviewee said "…we built some stands to be able to put them out in our primarily used buildings" or "…We know from a planning standpoint, what the busiest buildings are…" and "…Well, I think you immediately want to put sanitizer stations everywhere you have people". Each of these quotes describes the initial solution strategy. That was to get the stations in the most used buildings. Likewise, other quotes had direct references to the busiest buildings. For example, another interviewee said "On the second hand because they knew that the library was the busiest building on campus". This quote again shows that there was some interest in focusing on the most occupied buildings on campus.

Even more so, members of CU Facilities informed us that the initial goal was to cover the buildings where people were the most. Moreover, they wanted to get the hand sanitizer stations in the buildings that had the most people in them. They were able to work alongside BSCs to determine this information (e.g., word of mouth). Members of CU Facilities also analyzed CU's door access data. We took this information and used the data to determine what buildings people were going into the most. This model applies this data.

Furthermore, some of the members of CU Facilities that we spoke with reported that they worked with BSCs to locate dispensers at one main entry/exit point of each building. Therefore, we filtered some of the data by exterior doors of buildings only. We did not include the data for interior doors. There were estimates for the supply of each dispenser given to us by the members of the CU Facilities. This information was used as a coverage metric for one the model. We estimated each dispenser to supply about 500 pumps of sanitizer fluid (which would mean each station could "cover" about 500 people) before having to be replaced/refilled.

Qualitative Influences on Max Coverage Model (A) and Max Coverage Model (B) with Allocation Across Campus by Door

This section will go through the qualitative influences for both max coverage models by door. These models are grouped together because the influences for them were quite similar. In general, the responses seemed to show that there was a major emphasis on targeting the entrances into buildings because these were the high traffic areas. The flow of students in and out of buildings captured the largest portion of the population which made it seem like a reasonable location for hand sanitizer stations. Since the pandemic had created a modified way of learning (i.e., students not going into classrooms) it was initially difficult to be able to identify high traffic areas in buildings so the best option was to place the stations at the entrances because in terms of "travel paths" for students and staff they would, for the most part, have to come in through one of the main entrances of a building and leave through one of the main exits. If the stations were placed at these locations, CU Facilities felt that it would ultimately capture the majority of the campus population. An interviewee spoke about how the placement was designed to decrease the transmission of the virus. They then said that in terms of decent locations, "…we, [CU Facilities], started looking at the main entrances to the buildings".

Additionally, in the interviews there seemed to be a big emphasis on placing dispensers at the entrances of buildings. In one interview, we were told "The first thing [CU Facilities focused on] was that main entrance [to a building]. We then in our follow ups we're adding those extra stations at those other entrances of buildings]. In another example, an interviewee was speaking about strategic changes and said "One was to cut off the water fountains…so we were recommending not to use the water fountains and then we also recommended that we have hand sanitizers at all the building entrances". Likewise, another interviewee mentioned "…we tried to target the main entry points for those particular locations" which was in reference to the buildings where most of the classes were being held during the time of the pandemic (several buildings were not in use during the pandemic since not as many students were on campus but this has since changed now that CU has returned to normal operations).

To continue, we would question interviewees about how they monitored usage of the stations throughout the semester. With this information, CU Facilities was able to make a determination about appropriate locations for the stations. They said "As the pandemic moved on, we, [CU Facilities], started using the usage. The custodians would check the stations each day and as we saw how much usage was happening, we [decided] this is a good location [for a station], [or] let's try a different entry point. It's just trying to identify where the most people will pass the station". Another interviewee made reference to the door access data and how it influenced some of their decisions. They said "We also had a tool through TigerOne to where we had access to who was using the building…and could see who was using what doors; you can even tell what doors they were accessing".

Some other factors that influenced the first maximum coverage model that focused on allocation of stations at specific doors in buildings were, first, CU Facilities telling us that some buildings (e.g. Cooper Library) have one main entryway into them and the majority of the traffic flows through that one entryway. Therefore, it would be more effective to allocate multiple dispensers to that single entryway instead of at another entryway that is rarely used. Putting multiple dispensers at a single door would actually end up covering more of the population since most of the traffic flows through that one entryway. Therefore, we decided to have a model that would allow some of the doors in buildings to receive more than one dispenser. The next section will discuss some of the key results from the semi-structured interviews.

Results from Semi-Structured Interviews

There were several key takeaways from the semi-structured interviews that helped us understand more about initial decision-making related to hand sanitation deployment. First, the university's primary focus, and the focus of each department was to protect the health and well-being of everyone who would be returning to campus including students, staff, and faculty members (i.e., professors). The departments and the university took necessary measures to ensure everyone's safety which included the hand sanitizer station deployment within buildings to encourage more hand sanitizer use.

We also got a better understanding about information that was communicated between CU Facilities and other departments. During the interviews, members of CU Facilities said that they worked alongside the BSCs to decide on specific locations within each building for the hand sanitizer stations. In the past the BSCs had monitored the flow of students entering and exiting the buildings so they had a good understanding about which entrances and exits were used most frequently. They shared this information with CU Facilities so that they could come up with an initial plan. CU Facilities had an initial deployment goal to cover at least one primary access point to each building and sometimes two. These primary access points were given to CU Facilities by the BSCs. They deployed the initial amount they had on hand given a limited supply.

Interviewees also talked about how the strategy for station deployment aligned with guidelines from the CDC (e.g., maintaining six-feet of safe distance from each other, eliminating two-way traffic patterns in and out of buildings, and preventing individual from having to come into contact with each other). Additionally, following the return of students to campus, CU Facilities realized that there was a surplus of hand sanitation supplies. This was the result of three primary things: (1) students, staff, and faculty members continuing to work remote during the Fall 2020 semester, (2) an overestimation of the number of students returning to campus in the Fall, and (3) behavioral changes related to CDC guideline changes and updated information related to the spread of the virus. These results created several types of parameters for our model.

Quantitative Data Analysis

The quantitative data that was collected throughout the iterative model development process also had a major impact. CU Facilities provided a table that outlined how many stations were in each building and where within each building the stations were located. The building names and quantities per building are shown in **Table 2**.

Table 2: Number of Sanitizer Stations Per Building

Building Name	Quantity	Building Name	Quantity	Building Name	Quantity
Academic Success Center	2	Godley Snell	1	P&A Building	4
Alumni Center	1	Hardin Hall	3	Parking Services	1
Administrative Services Building	1	Harris Smith	1	Police Station	1
Barre Hall	4	Hendrix Student Center	4	Rhodes Hall/Annex	2
Bowling Alley	1	Holtzendorf Hall	1	Riggs	2
Brackett Hall	2	Hunter Hall	1	ROTC Building	1
BioSystems Research Center	4	Jordan Hall	2	School of Computing	1
Brooks Center	2	Kinard Hall	4	Sikes Hall	3
Calhoun/ Forthill	1	Lee Hall 1	1	Sirrine Hall	4
Campbell Museum	1	Lee Hall 2	4	Strode Tower	1
Cook Laboratory	1	Lee Hall 3	1	Strom Thurmond	1
Cooper Library	4	Lehotsky Hall	2	Student Government Senate	1
Daniel Hall	1	Life Science	2	Student Post Office	1
Development Office	1	LittleJohn House	1	Student Union	1
Dillard Building	2	Long Hall	1	Tillman Hall	6
Earle Hall	1	Lowry Hall	1	Trustee House	1
Edwards Hall	2	Martin Hall E Section	1	Vickery Hall	1
Facilities Building	2	Martin Hall M Section	4	Watt Innovation	1
Fluor Daniel	1	Martin Hall O Section	1	College of Business Building	20
Freeman Hall	3	McAdams Hall	2	Gas Turbine Lab (Hugo St)	1
Gentry Hall	1	Newman Hall	1	Clemson Center - Downtown	5
Godfrey Hall	1	Olin Hall	1	Sullivan Clinic Walhalla	16

The first column of **Table 2** is the building name and the second column is the number of sanitizer stations in that building. For the purposes of this thesis, the locations of the actual stations in each building have been excluded. Using this information, we were able to calculate the total number of stations that had been deployed on campus. Representatives at CU also provided PDF versions of building maps which were used to pinpoint the current locations of the stations in each of the buildings. CU Facilities also shared relevant costs pertaining to the stations and sent us the supply of sanitizer materials on hand. The supply data is displayed in **Figure 2**.

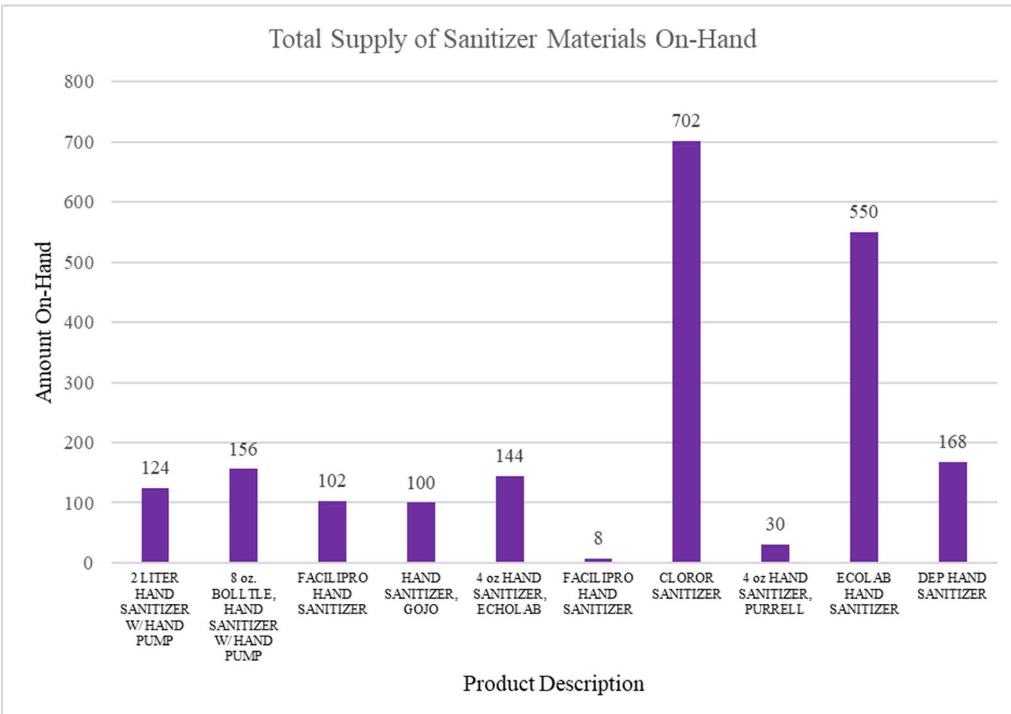

Figure 2: Supply of Sanitizer Materials

During this study data was obtained to make sense of the number of people going into each of the buildings during the Spring 2021 semester. This information, known as Door Access Control Data (DACD), came from CU's TigerOne department. The next few paragraphs will describe the TigerOne department and the DACD.

CU's TigerOne department handles TigerOne card services. TigerOne cards are CU's identification (ID) cards. These cards serve many purposes; one of them being how people affiliated with CU scan into different buildings to gain entry. Prior to COVID, the exterior doors to most of the buildings remained unlocked throughout the course of the day. This allowed anyone to enter the buildings free-willingly. However, the COVID-19 pandemic forced the university to make changes to this policy. CU decided it was necessary to require everyone to scan into the buildings using their IDs. This was done to prohibit anyone who had tested positive for the virus or anyone who was not cleared to return to campus from entering any campus buildings.

Since people had to scan into each building, the TigerOne department was able to keep track of how many times each door was opened. This information, which is the DACD, is what was used in this study to get a sense of where the majority of the population was concentrated on campus. The DACD helped calculate how many people had entered and exited a building on a particular day. This data provided this study with information about standard student movement at the university during the Spring 2021 semester. This type of information was useful for this study because we wanted to focus on building models that could optimally place dispenser stations in locations where the majority of people were situated.

For this study the DACD was used to specifically analyze 36 of the buildings out of the 66 buildings listed in **Table 2**. This accounts for roughly 55% of the high-traffic areas on campus that CU Facilities focused on in their initial deployment. It should be noted that the data can be shown for interior doors in buildings as well. However, the focus of this study was limited to the exterior doors of buildings. Initial data was gathered for one week in Feb. of 2021. **Table 3** shows the data for the one week in February.

Table 3: DACD for One Week in February of 2021

Building Names	DACD Totals	Building Names	DACD Totals	Building Names	DACD Totals
Academic Success Center	1047	Fluor Daniel	1946	Martin Hall (Includes 3 buildings)	2729
Administrative Services Building	726	Freeman Hall	3194	McAdams Hall	2034
Barre Hall	1833	Godfrey Hall	1926	Olin Hall	436
BioSystems Research Center	4272	Hardin Hall	1332	P&A Building	3357
Brackett Hall	3913	Harris Smith	450	Rhodes Hall/Annex	2709
Brooks Center	3794	Holtzendorff Hall	2174	Cooper Library	8428
Campbell Museum	49	Hunter Hall	2065	Sikes Hall	2436
College of Business Building	14335	Jordan Hall	1823	Sirrine Hall	4177
Cook Laboratory	402	Kinard Hall	1676	Strode Tower	1317
Dillard Building	781	Lee Hall (Includes 3 Buildings)	3632	Tillman Hall	4035
Earle Hall	1538	Long Hall	1678	Vickery Hall	1682
Edwards Hall	3608	Lowry Hall	1943	Watt Innovation	7444

The first column of **Table 3** lists the building name and the second column represents the total number of times an exterior door in that building was opened during that one week in Feb. of 2021. The data does not include Saturday nor Sunday since students and staff are not expected to be on campus as much on those days. In order to perform some sensitivity analysis for some of the models developed during this study, data was also collected for three separate weeks in Apr. of 2021. This was done to see if the one week in Feb. was representative of standard student movement during the Spring semester.

The DACD was not only used in some of the models that were developed but it was also was used to create a heat map. Heat maps serve as a useful tool to help visually show where the majority of a population is concentrated like on a college campus such as CU. Heat maps have been used to analyze population densities in urban cities and differentiation in population aggregation related to COVID-19 [6], [7]. The heat map is relevant to this study because this study focuses on gathering information related to population concentration across campus to figure out what might be the most optimal locations to place hand sanitizer dispenser stations. The heat map was created using a software package known as *Mapline* [1]. The heat map is shown in **Figure 3**.

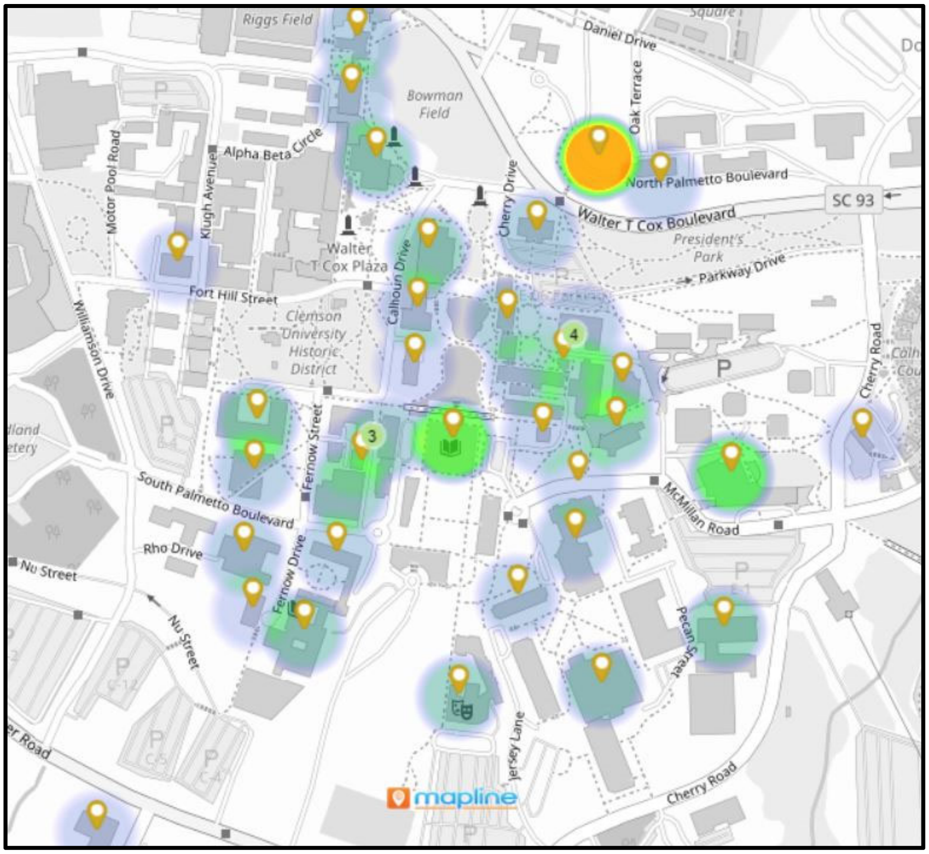

Figure 3: *Mapline* Heat Map Using DACD with February Data

The key for the heat map that was created is shown in **Figure 4**.

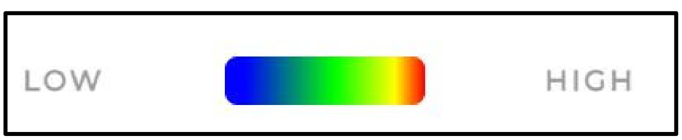

Figure 4: *Mapline* Heat Map Intensity Level Key

Based on the heat map the high levels of intensity are at the College of Business Building while middle to lower intensities are elsewhere. A reason behind this is that the College of Business building is one of the larger buildings on campus (176,000 sq. ft.) and there are approximately 5,000 students (both graduate and undergraduate) enrolled in CU's business school [8]. With this in mind, during the pandemic when CU decided to limit classroom usage in the Fall of 2020 and Spring of 2021, several of the classrooms that were still being used were in the College of Business building.

This concludes the data collection and analysis chapter. The following chapter will outline the iterative model development process and the different model versions.

CHAPTER 4: MODELING

This chapter will detail the framework of the iterative model development process, as well as the models themselves that were created during this study; pertaining to the deployment of hand sanitizer stations at CU. First off, **Table 4** lists the name of each model version.

Table 4: Model Version Numbers and Model Types

Model Version	Model Type	Model Focus
I	*p*-Median Max-Coverage Model	Single Academic Building
II	Target Location-Covering Model	Sanitizer Station Allocation Across Campus – By Building
III	Max Coverage Model (A)	Sanitizer Station Allocation Across Campus – By Door with Building's Limited to Current Capacity of Stations
IV	Max Coverage Model (B)	Sanitizer Station Allocation Across Campus – By Door

The version numbers in the first column of **Table 4** will be used to easily distinguish between the different model types (which are listed in the second column of

Table 4) in this thesis. The thesis will use the model version subscripts strictly for naming purposes. The third column of **Table 4** identifies the focus of each of the model versions. The first model focuses on locating stations in a single academic building. The second model deals with station allocation across CU's campus, specifically by building. The third model focuses on sanitizer station allocation across campus, but now by buildings' doors. In the third version, the buildings are limited to their current capacity of stations, which is provided in **Table 2**. The fourth, and final model design focuses, once again, on station allocation across campus and by the buildings' doors. However, the final model version does not restrict the buildings to their current station capacity. The next section will discuss the framework of the iterative model development process and provide some context about how the framework was applied in the current study which focuses primarily on the deployment of hand sanitizer station dispensers.

Iterative Model Development Process

The framework for the iterative model development process is shown in **Figure 5**. The next few subsections will detail the iterative modeling process, which is a subset of the larger blended approach, and each step in the process that are shown in the figure.

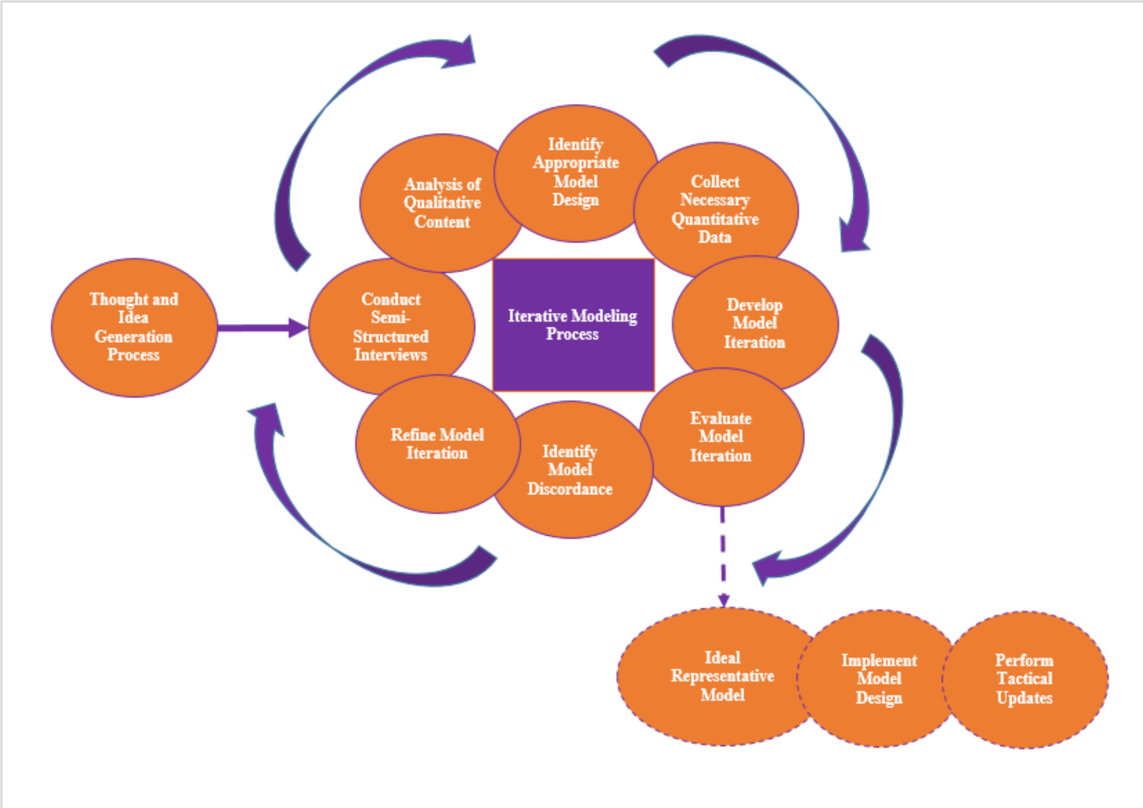

Figure 5: Iterative Model Development Process

Thought and Idea Generation Process

The process begins with the thought and idea generation. This step in the process takes place prior to the semi-structured interviews. This step is essential to the entire framework because it sets up the focus of the model development. The purpose of this step is to come up with questions and identify a problem that can be solved with an optimization model. The generation of the questions is what will fuel the semi-structured interviews. The questions that are asked during the semi-structured interviews will help provide answers and will become the driving force behind the types of models that are created. Individuals must ask questions related to decision-making and modeling techniques in order to take the qualitative data and then create an optimization model. We didn't ask model specific questions (i.e., questions about decision variables, constraints, parameters, etc.). Without related OR questions, it may be difficult to develop a representative model. In the case of the current study, during the thought and idea generation step, we first identified a problem. The COVID-19 pandemic was a major issue, and CU was trying to find ways to adapt to the challenges brought on by the pandemic. One of the strategies CU instituted was to deploy the hand sanitizer stations in campus buildings. There were open questions about how the decisions were made and if they were placed optimally.

At the start of the study, there were introductory meetings with CU Facilities where we got a general idea about the station deployment at CU. We then had an open discussion about ways to possibly model the station deployment around campus to represent the initial decisions made by CU Facilities. We first considered network flow-type models or flow-based models (e.g., flow-capture, path based, located based, etc.). However, these models could not answer the core questions CU Facilities was interested in, and there did not seem like enough data to produce a representative optimization model. Following these discussions, we concluded that the basis of the model should be a discrete facility location model. The next step was then to develop some of the research questions related to a discrete facility location model and resource allocation. These questions, in the case of the current study, would be related to the hand sanitation deployment at CU.

We came up with related questions pertaining to discrete facility location models because it best represented the situation at CU. The hope was then to use semi-structured interviews to get answers to these questions. **Table 5** lists some of the initial questions pertaining to the current study.

Table 5: Questions Related to Initial Model Generation

Questions	Questions (Cont.)
❖ Who are the decision-makers in this process? ❖ From which standpoint should the model be considered from? ❖ How many users should be considered in the model? ❖ Are there any related costs and if so what are they and how do they affect the deployment process? ❖ Is there any limit to how many dispensers can be placed in each building? ❖ Are there any restrictions on dispenser locations?	❖ What data was available that helped in the deployment? ❖ Who else was involved in the process? ❖ What type of information was communicated between groups? ❖ Which locations were considered the "best"? ❖ What was the goal of the deployment? ❖ What strategies were involved in the initial deployment? ❖ Are there any affiliated capacity constraints?

It is important to note that future studies that attempt to apply this framework might generate different types of questions because the initial model generation might be different from a discrete facility location model. The questions that are developed should pertain to the focus of the studies optimization model. At the conclusion, of the thought and idea generation procedure, the process proceeds into the semi-structured interviews.

Conducting Semi-Structured Interviews

The next step in the iterative modeling process is to conduct semi-structured interviews with key stakeholders and decision-makers. In the case of the current study, this involved interviewing members from the departments and groups listed in **Table 1**. Conducting these interviews allows us to gain qualitative insight into the decision-makers methodologies. The semi-structured interviews helped us better understand the situation at CU related to the deployment of the hand sanitizer stations. We became more familiar with the strategies and techniques that were implemented during the initial deployment. The semi-structured interviews that were performed during this study also helped us discover different types of quantitative data that was available to the decision-makers during the process (e.g., the DACD). In general, the interview process is where we gain the qualitative insight that can the facilitate the model development. It will provide a better understanding about the decision-makers techniques and strategies, as well as their goals in the process.

Analysis of Qualitative Content

The next step in the process is for us to analyze the qualitative content, which is the interviews themselves. This portion requires the interviews to be transcribed such that they can later be reanalyzed. Within this section we look for certain codes and themes that are related to model development. The goal is to understand what was done and in terms of the problem. In the current study, we used a software that enabled us to code the interview transcripts with themes related to different model types or model versions. These themes then influenced the types of model that were created. In future studies that apply this framework, there may be variation in the types of codes that are used.

The goal in the analysis of the qualitative content is to find connections and identify valuable information within the interview transcripts that can later be used in the model development. This portion of the process allows us to identify other sources of data that we may have missed during the initial interview. Even more so, the qualitative analysis will identify the initial decision-makers' heuristics. The goal then will be to take these decisions and have them inform the model development. For the current study, it was during the qualitative analysis that we picked up on the idea of using discrete facility location models to model the hand sanitizer station deployment situation at CU. We felt that these models best represented what was actually done by CU Facilities and other decision-makers at CU. Following the analysis, the process proceeds into the next stage which is to identify an appropriate model design.

Identify Appropriate Model Design

Once the qualitative data has been analyzed, the process then moves into the stage of identifying an appropriate model design. In this stage, individuals come together and brainstorm model designs that they think would best depict the problem they are trying to solve. For the current study, we understood that a type of discrete facility location model would be of good use for the sanitizer deployment situation. With this in mind, the next step in this stage was to identify a specific type of discrete facility location model. Reviewing the qualitative information that was gathered during the interviews, the model design will embody that data and reflect what happened. The qualitative input signifies the techniques and strategies used by the decision-makers; integrating this into a model design will better model the decision-maker's behavior. Modeling the situation using an optimization model will provide an optimal solution to the problem.

For this study, we first came up with the single building *p*-Median Max-Coverage Model. At the time of the first model design generation step, the amount of quantitative data was limited. So, we wanted to be able to find a way to make some sort of initial comparison to the original deployment strategy. The *p*-Median Max Coverage Model is representative of the initial decision-makers' strategies because, as it is seen in the qualitative analysis, their (CU Facilities) initial focus, in the deployment, was to make sure classrooms were covered, or stations were placed in such a way that students using the classrooms would come across a station. Likewise, they located stations along paths that saw a high amount of foot traffic. Using this model type, we knew we would be able to collect the quantitative data and build the optimization model to compare the current locations in a single building to the model's optimal solution. Once the design was finalized, the process moved into the next stage, which was to gather the necessary quantitative data.

Collect Necessary Quantitative Data

The next step, which is to collect the quantitative data, highlights where the research method integration begins to happen. After the qualitative data has been analyzed, and a model design has been approved, individuals must determine the types of quantitative data that is necessary to build the optimization model. For the current study, after we initially chose to build a *p*-Median Max-Coverage Model, we started to gather the quantitative data that we needed. For the purposes of this model version, that included the demand locations (classrooms in a single academic building), candidate hand sanitizer station locations, and the coverage times between classrooms and those candidate station locations (shown in **Figure 9** and **Figure 10**). In the other model versions, we relied heavily on the DACD. This step in the process is important because without any quantitative data then it might be difficult to develop the model.

Develop Model Iteration

Once the quantitative data has been collected, the next step is to create the actual model iteration. This means developing the model notation which includes describing the sets, parameters, and decision variables. Each model might have different types of sets and parameters so throughout this process it's important to distinguish between those differences and even highlight if any of the sets, parameters, or decision variables are the same as another model iteration. After developing the model notation, the model framework is built. This means writing out the model objective function and any necessary model constraints. The model objective and the constraints will reflect the decision-makers' strategies and techniques. Then using the quantitative data as input, the model will solve the problem and provide an optimal solution.

Evaluate Model Iteration

Once the model framework is finished, the next step is to solve the model to find the optimal solution. For the current study, the models were coded in Python using the Pyomo package [5] and solved with the Gurobi optimizer. Using this process gave an optimal solution for each of the models. However, it is important to evaluate the solution itself to see if what the model is showing really corresponds to how the original problem was solved. Evaluation also ensures that the results themselves are appropriate within the context of the problem. This may require performing some sensitivity analysis with each model iteration, if possible, to be able to determine that the model is behaving correctly. In the current study, the overall goal of each model was to determine locations for the hand sanitizer stations on campus so once a model was solved for, we checked to make sure the model was doing this.

Identify Model Discordance

The next step is to identify the model discordances with decisions in practice. In some instances, individuals who are involved in the model design are able to identify the model limitations on their own. This is because they are able to refer back to the qualitative input that has been gathered previously. Using that data allows them to determine if the model results match up with the historical decision-making strategies. In other cases, they need to reconvene with the key decision-makers to get their interpretation of the model results. For the current study, we rescheduled meetings with members of CU Facilities and walked them through what the model iteration's capabilities were at the time.

In this process, individuals will share the results with the decision-makers. The goal is to present the results to the decision-makers in a such a way that they can easily interpret their meaning. Once the results are shared, discussions between the two groups progress. It is essential for the individuals to create transparency for the decision-makers during these discussions. This allows the decision-makers to better comprehend the model's functionality and how implementing it would help them solve problems more efficiently. Creating transparency helps the decision-makers identify the discordance between the model and what their initial solution methods were. This is an important step in the process because if there is discordance, then both groups must engage in conversation about what can be added or changed in the model. The primary objective during these follow up meetings is to gain even more qualitative insight into the decision-makers strategies with respect to any policy changes that may have been made since the previous discussions.

Furthering the discussions with the key decision-makers also illustrates the benefits of the iterative process and the value of a blended approach. That is, it enables us to not only retroactively model historical decision-making strategies, but also prospectively model any adjustments that have been made to those historical decisions. Therefore, the model will consistently be designed to represent what is happening. In the current study, the models went through 4 iterations. In each there were long discussions between us and CU Facilities about model changes to represent shifts in their procedures. At the conclusion of the each of the follow-up conversations, if there were any discordances identified, it was our job to then refine the model.

Refine Model Iteration

After the model discordances have been identified, the next step is to refine the model based on the qualitative input that was received in the follow up meetings. Refinement can include a various number of things. There are certain degree levels to model adaptation. For example, in the current study, some changes to the models included changing or adding parameters. In other models, this included adjusting constraints to account for new decisions, or, altering the objective function. In other iterations the design, or focus, of the model was completely changed.

Once the process reaches the refinement stage, the iterative process starts to begin, meaning the process goes back through the previous steps, or repeats. Individuals can conduct more semi-structured interviews to acquire more qualitative data (if needed). This will require further qualitative data analysis. The goal here, again, is to find ways for it to enhance the next appropriate model design. Once a new appropriate design is identified, individuals are then able to determines if they need to collect any new quantitative data to be able to run the model. Or, they may be able to use the quantitative data that has already been gathered and run it with the new model iteration. Once this is finalized they can develop the new model and evaluate the model results. The results are then discussed with the decision-makers. If more refinement is needed, the process repeats. At some point during the iterative modeling process an ideal representative model will be developed. This is indicated by the dashed arrow in the figure that is drawn out of the evaluation stage.

Ideal Representative Model

Once a representative model is designed, the model can then be implemented by the decision-makers. The ideal representative model in the current study was identified after the fourth iteration. For the current study, the model is implemented to offer new recommended locations for the stations in buildings at exterior doors. The model will also provide the decision-makers with the ability to make tactical updates to their decisions. For the current study, this will include looking at shifts in the results using new data from previous months or semesters. CU Facilities has agreed to implement the model but there is still some discussion on how often they plan to do this. There are two ideas and they are to do this on an annual or biannual level. Based on their decision, CU Facilities would implement the new recommendations either once a year or once every semester. In discussions, the goal is to also monitor the data to observe any trends or shifts in it. Doing this might indicate more immediate changes are necessary. Likewise, if the results of the model exceed some set boundary, then it might be necessary to make some adjustments to the policy.

The iterative modeling framework that is shown in **Figure 5** can be applied to several areas and is not limited to the deployment of hand sanitizer stations. We use the deployment of the hand sanitizer stations as a case study to highlight the effectiveness of the framework. Applying the framework in other areas will influence the development of optimization models to solve problems. The overarching goal of the framework is to blend research methods. Using qualitative and quantitative tactics offers a more effective approach to creating ideal representative optimization models. The model can then be used to help further analyze a situation and provide whoever it may be with an optimal solution to that problem. Using the iterative modeling approach will allow the model to adapt concurrently with the alterations that are happening in the actual environment. This is important because if the model does not reflect those changes then there will be discordance. This framework eliminates that discordance and reduces some of the model limitations when it is implemented. Likewise, blending OR with HF through this iterative process will enhance the overall design of the models so that they reflect the actual decisions being made. Even more so, the model can then be implemented by the decision-makers themselves.

In summary, the iterative model development process (**Figure 5**) uses a blended approach to integrate qualitative input and recommendations from key stakeholders and decision-makers involved in the initial deployment process to develop representative models and continuously improve, refine and redesign them. The framework itself guides the data collection process. The process begun with gathering historical stakeholder data to understand what took place during the initial deployment. The purpose of these meetings was to find out what went on during the initial placement of the dispensers. Following these discussions, the meetings were then used as an opportunity for us to ask CU Facilities about what types of data they had and the type of results they would want from an optimization model. Using this information, we generated several versions of discrete facility location models that we believed could accurately represent the tactics used by CU Facilities, as well as others involved in the process. Once a model was finished and the results were gathered, we would share them with CU Facilities.

In these follow-up meetings, we talked about the objective of each model and some of the constraints. We kept these discussions at a very high-level and did not try to get into the specifics of each model. We presented the constraints and objective function in such a way that could be easily interpreted by CU Facilities. This gave them a better understanding of what was trying to be accomplished with this study and how the research could potentially benefit them. We allowed CU Facilities to critique the models because they were the ones who had the best knowledge about what needed to happen with the placement of the dispensers. Following this, the process repeated because we were made aware of changes to the process (e.g., more dispenser stations being added to a single building, removing stations from a building, changes in supply, etc.). Strategies and interventions to prevent the spread of the virus were consistently altered which also meant that the university had to make necessary changes to their policies. Therefore, since the policies were changing, there seemed to not be one single model that could represent the entire situation. After each of these meetings we would have more information and data to work with to continue to iterate from each of our previous models. Likewise, after sharing some initial results with CU Facilities, we asked if certain things about the model could be done differently or changed. Taking their recommendations, we would redesign the model to accommodate the needs of CU Facilities. The recurring meetings led to the iterative model development and this is how we generated different modeling designs. This was done because in the end the goal of this study was to be able to provide significant recommendations to CU Facilities about where stations should be located and provide them with a model and algorithm to optimally place the stations across campus. Without their input, then the models would not satisfy their preferences and serve them no purpose, which was not the aim of this study or the framework. The study addresses a real-world issue and not a hypothetical situation meaning providing them something that was not representative would not benefit the decision-makers and the university as a whole.

As well as being a key component of the actual study, the iterative model development process is also a major contribution of this study because it highlights ways in which a single process or situation such as the deployment of hand sanitation stations across campus can be modeled in multiple ways. This study illustrates how adaptive modeling is quite beneficial. Modeling a situation with multiple iterations, as is the case in this study, allows the process to be analyzed in several ways and from different perspectives. It also provides the opportunity to model human behavior more accurately and creates a much clearer representation of real world complexity. The study also proves that performing multiple model iterations creates more flexibility to adjust the model based on new data.

The iterative model development was essential to this study because it gave us different strategies to assist CU Facilities. Each model that was created, in their own respect, can help determine the most optimal locations for hand sanitizer stations. Some from a campus-wide perspective and others from a building-specific perspective. The results of each model could serve some purpose based on the type of information that CU Facilities needed. Each model has its own way of evaluating the effectiveness of the initial deployment. This evaluation allows the model to be compared with historical decisions to offer recommendations about potential policy changes. This concludes the description on the iterative model development process. The next section will describe the model versions that were created in this research study to aid in the deployment of hand sanitizer stations at CU.

Modeling

Using the iterative modeling development process detailed in **Figure 5**, and applying it to the current situation (the deployment of hand sanitizer stations at CU), we went through multiple iterations of model development and produced multiple model versions. This section will introduce each model version. The current study includes 4 optimization models and one heuristic. For each model version, this section will provide: (1) an overview of the model, (2) the model formulation (which includes the solution methods or how the model was solved), (3) the model assumptions, (4) the model limitations, and (5) why another iteration was performed. The section will first begin with discussing the initial heuristic (which was separate from the optimization models developed in this study but still a part of the iterative process to analyze the decision-making strategies). The section will conclude with the final model version that was developed during this study and explain how the research determined this model to be a representative model of the current situation.

Heuristic: Proportional Allocation to Buildings

Overview

To investigate the overall effectiveness of the initial deployment of the hand sanitation stations, one of the first things that was done in this study was to develop a heuristic. The goal of this heuristic is to determine how many sanitizer stations to put in each campus building. The heuristic proportionally allocates stations to buildings based on DACD totals. The data that was used for calculations to solve the heuristic was from the week in Feb. of 2021 (see **Table 3**).

Heuristic Formulation

The heuristic equation (**Equation 1**) is shown below:

Equation 1: Initial Heuristic

$$\frac{d_a}{\sum_{a' \in A} d_{a'}} * N \qquad \forall\, a \in A$$

The d_a in the numerator stands for the DACD per building, or population data, as seen in **Table 3**. For example, when solving the equation for the Academic Success Center the numerator would be 1047 events (i.e., the number of times an exterior door was opened). The denominator sums the DACD across all buildings in the set A, the 36 campus buildings seen in **Table 3**. N is the total number of available dispensers across all of the dispensers distributed amongst the 36 buildings included in set A. We solved **Equation 1** for each building in the set A.

Heuristic Assumptions

One assumption for the heuristic is that d_a represent the foot traffic through 36 campus buildings. We used this to identify where people are concentrated across campus. Another assumption of the heuristic is that placing more dispensers in buildings with larger DACD totals will ultimately result in the dispensers being used more often/frequently because they have been placed in locations where students are the most. Therefore, by placing the dispensers in these locations, we have essentially covered a larger portion of the campus population. Additionally, no building could receive a percentage of a dispenser so the number of dispensers for each building were rounded up. This would also ensure that no building in the set A would receive zero dispensers. Thus, the total number of dispensers needed to be located is greater than the total number available (*N*).

Heuristic Limitations

A limitation of the heuristic is it does not provide specific locations (e.g., doors) for stations to be placed in buildings. Additionally, because the proportions were rounded up, the total number of dispensers that are located amongst the 36 campus buildings based on the results is greater than the current amount of 102 stations that was available. This is a limitation because ideally it would be more optimal to maintain the current total.

Iteration Purposes

The first iteration took place following the creation of the heuristic because it did not provide an optimal solution. We wanted to design an optimization model to help solve the problem and create a better representation of the initial deployment. Although the heuristic provided an initial comparison to analyze how CU Facilities deployed the stations in buildings, it is not an optimization model and therefore does not fully capture one of the purposes of this study. That is to iteratively develop a representative optimization model of ideal decision-making and provide this model to key stakeholders such as CU Facilities. Despite the heuristic being a quantitative solution method, it does not utilize the key functions of OR which is to develop models that capture human behavior.

Even further, iterating from the heuristic to an optimization model would give us an opportunity to deliver results related to an actual optimization model that uses methods of OR. Finding a way to explain these results and the functions of the model to

CU Facilities would be a challenge in itself however it gives us a chance to show non-engineering personnel the benefits of these types of research methods. That in itself is another focus of this study. Being able to find a way to convey the results of an optimization model and the themes related to OR in such a way that it can be interpreted and understood from a non-engineering perspective. This needs to be done so stakeholders can see how engineering functions (specifically OR) are applicable to real-world situations and can help solve many non-hypothetical related problems. All in all, we knew that a heuristic would not answer all of the questions nor be the perfect representation of the situation at CU but was the base to developing an appropriate modeling framework.

Model Version I: p-Median Max-Coverage Model

Model Overview

The first optimization model developed (**Model Version I**) addressed location decisions within a single building. A type of max coverage facility location model, specifically the *p*-Median Max-Coverage Model, was developed to determine the optimal locations for dispensers within Freeman Hall, an academic building at CU. As it was discussed prior, CU Facilities provided us with an Excel Spreadsheet that showed us the number of stations within each building as well as where each station was located. We also had access to the building maps. The first floor of Freeman Hall can be seen in **Figure 6**.

Figure 6: Freeman Hall 1F Floor Layout

The *p*-Median Max-Coverage Model was created to analyze maximum coverage time in Freeman Hall. During the Spring of 2021 there was three classrooms in use and their locations are shown in **Figure 7.**

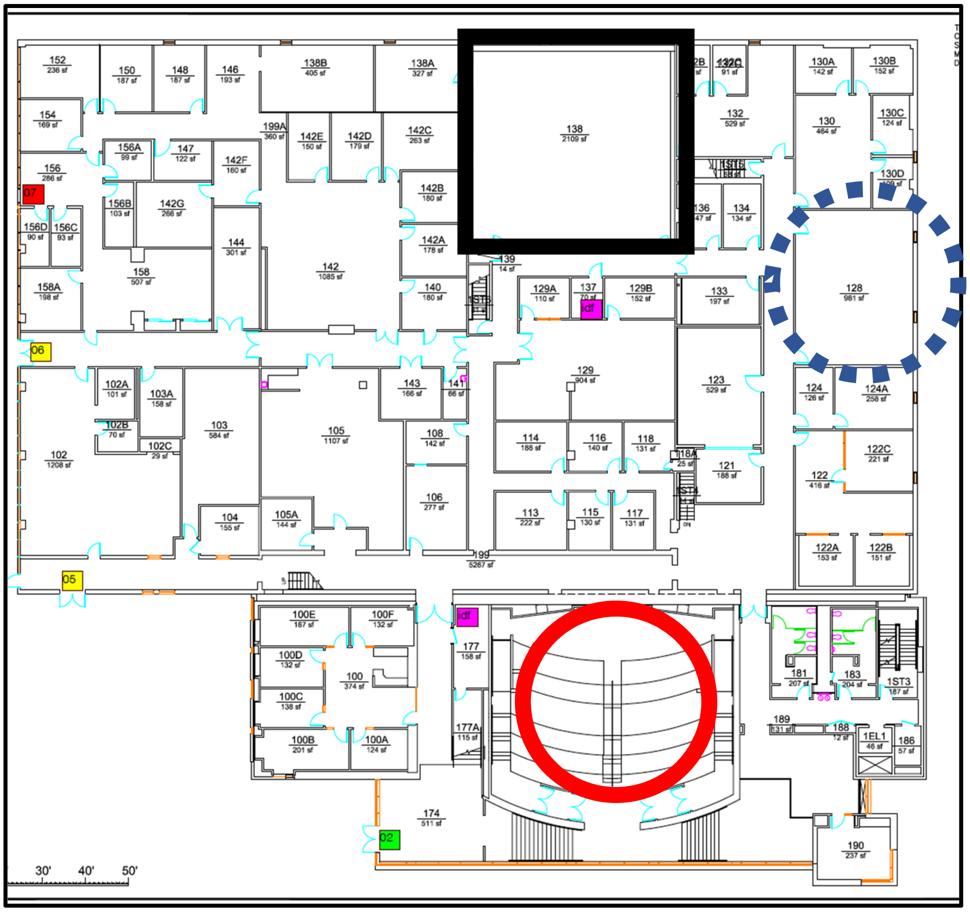

Figure 7: Freeman 1F Floor Layout with Classroom Locations

The solid, red circle is Freeman 078, the blue, dashed circle is Freeman 128 and the solid, black square is Freeman 138.

In **Model Version I,** we considered 10 candidate locations for stations. These locations were based on our experience with traffic flow through Freeman Hall and the most used paths in the building. The 10 candidate locations also included the current station locations. The candidate locations can be seen in **Figure 8**. The three current station locations are numbers **3**, **6**, and **7**.

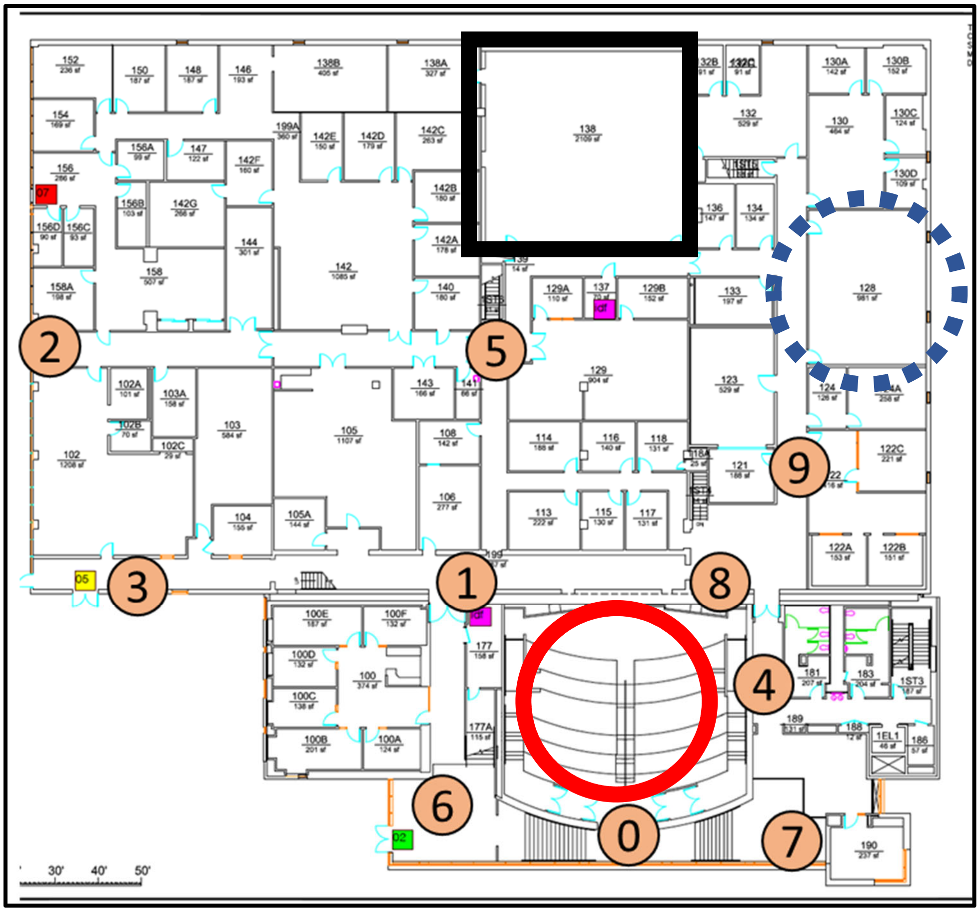

Figure 8: Freeman 1F with Candidate Station Locations

Before proceeding to the model formulation, this paragraph will define maximum coverage time (denoted as parameter T in **Model Version I** notation) which was the quantitative input needed for this model. The coverage metric in **Model Version I** was time. Time was defined as how long it took to get from one of the three classrooms to one of the located stations. In order to get the times for each location, we measured these times by actually walking from each classroom to a hypothetical location of the station. The time to walk started once the door of a classroom was opened and ended as soon as the subject arrived at the location. In order for a classroom to be considered covered, the time it takes someone to walk from a classroom to one of the located dispensers cannot exceed the maximum coverage time. If the time exceeds the maximum coverage time, then that classroom will not be considered covered for that location.

Each classroom has two main entry and exit points (with exception to Freeman 078 that has a third entry point which was not considered). **Figure 9** shows the times for each classroom and each dispenser location for the first door to each classroom. **Figure 10** shows the times for the second door.

Candidate Station Location	Freeman 078	Freeman 128	Freeman 138
1	29.24	25.05	17.73
2	63.86	45.19	27.38
3	41.24	39.97	33.92
4	16.62	60.79	49.13
5	41.34	23.26	6.95
6	46.47	36.17	29.00
7	12.65	56.60	46.73
8	40.80	14.37	27.43
9	46.47	7.05	25.80
10	2.76	44.93	38.47

Figure 9: Times (in seconds) to Walk from Each Classroom to Each Candidate Station Location (Door 1)

Candidate Station Location	Freeman 078	Freeman 128	Freeman 138
1	28.28	31.82	24.8
2	62.11	41.85	33.84
3	41.8	46.22	40.63
4	16.75	69.79	61.39
5	40.54	21.51	13.11
6	17.75	41.21	37.1
7	11.94	64.56	57.54
8	40.9	20.02	25.58
9	48.56	13.51	18.15
10	2.82	55.37	49.07

Figure 10: Times (in seconds) to Walk from Each Classroom to Each Candidate Station Location (Door 2)

Model Formulation

The model notation for **Model Version I** is shown here:

Set(s):

I: Set of classrooms, indexed by *i*

J: Set of candidate hand sanitizer station locations, indexed by *j*

Parameter(s):

$p := number\ of\ hand\ sanitizer\ stations\ to\ be\ located$

$T := critical\ coverage\ time$

$t_{ij} := time\ to\ walk\ from\ classroom\ i \in I\ to\ station\ j \in J$

$$a_{ij} := \begin{cases} 1\ if\ t_{ij} < T \\ otherwise\ 0 \end{cases}$$

Decision Variables:

$$m_j := \begin{cases} 1\ if\ locate\ station\ at\ location\ j \in J \\ \quad 0\ otherwise \end{cases}$$

$$z_i := \begin{cases} 1\ if\ cover\ classroom\ i \in I \\ \quad 0\ otherwise \end{cases}$$

The set J consists of the 10 station locations in Freeman Hall that were determined ourselves. The set I consists of the three classrooms in Freeman Hall. This model is a type of p-Median Max-Coverage Model. A p-Median Max-Coverage Model has a parameter that denotes the number of sites that can be located. This is done such that when the model is solved it limits the number of sites that are chosen so the optimal locations are picked and the model does not locate an infinite number of stations. For **Model Version I**, this parameter is denoted as p and it represents the number of stations that can be located in Freeman Hall. The parameter T represents the critical coverage time, or maximum coverage time that was discussed in the model overview section for **Model Version I**. The parameter t_{ij} is the time, in seconds, it takes to walk from a classroom i in I to each station location j in J. Once again, these times are shown in **Figure 9** and **Figure 10**. We ran the model using times from both doors. The parameter a_{ij} checks that the times to walk from a classroom i in I to each station location j in J are less than the critical coverage time T (which is set by us). There are two decision variables for **Model Version I**. The first decision variable, m_j, is a binary decision variable that tells us if a station is located at location j in J or not. The decision variable z_i evaluates whether or not classroom i in I is covered or not based on the candidate station locations j in J that are chosen.

The model formulation for **Model Version I** is as follows:

$$\max \sum_{i \in I} z_i \qquad (1)$$

s.t.

$$\sum_{j \in J} a_{ij} m_j \geq z_i, \forall i \in I \qquad (2)$$

$\sum_{j \in J} m_j = p$ (3)

$m_j \in \{0,1\}, \forall j \in J$ (4)

$z_i \in \{0,1\}, \forall i \in I$ (5)

The objective function (1) maximizes the number of classrooms in the set *I* that are covered. Constraint (2) is the coverage definition constraint. It ensures that classrooms in the set *I* are only considered covered by chosen sanitizer station locations [3]. Constraint (3) allows the model to only choose *p* locations for stations. Constraints (4) and (5) set the decision variables to binary. We coded the model in Python using the Pyomo package [5] and it was solved with the Gurobi optimizer. The model was run for four values of *p* (the number of sanitizer stations to be located) and those values were 1 – 4. This meant that if we chose *p* to be two then the model would find the two most optimal locations. The model was run for each of these *p* values and the value of *T* was adjusted in the model to ensure that all three classrooms would remain covered. For example, when trying to find the two most optimal locations ($p = 2$), if after the model was run with some set value for *T* and not all three classrooms were considered covered (the objective function value, *Z*, was less than three) then the value of *T* would be increased until the objective function was three, which meant that all three classrooms were covered. These operations were performed in order to determine the maximum coverage time for each value of *p*.

Model Assumptions

There were a few assumptions that had to be made when developing **Model Version I.** First off, the times shown in **Figure 9** and **Figure 10** are measured by us.

When finding the times to go from a classroom to a location of one of the stations we used routes that we considered the most logical based on personal knowledge and experience. The time to use the dispenser was not considered in the travel time because we did not have a station at every single candidate location. Additionally, we cannot know with exact certainty that if the dispensers are placed at new locations based on the model results that it will result in them being used more often. However, we assume covering a classroom with high usage potentially increases the probability of station usage, or provides a better opportunity to use one.

Model Limitations

Model Version I does not account for individuals actually using the dispensers. The results of the model do not suggest that the stations will be used more frequently. This model focuses specifically on coverage and maximizing the coverage of the three classrooms in Freeman Hall. This focus is achievable with **Model Version I**. Future work that uses this model could test to see if relocating the stations based off of the results would increase usage of the stations.

Another limitation of this model is that it focuses on the coverage of classrooms within Freeman Hall and not the coverage of the exterior doors of Freeman Hall. We believe that, for this model, classroom coverage is more important because individuals do not all use the same doors when entering and exiting the building. However, all of the individuals (i.e., faculty, staff, and students) in Freeman Hall have to be within one of the classrooms that are in use. So if the classrooms are all considered covered, then it is guaranteed that the individuals in those classrooms can also be considered covered by the locations of the dispenser stations. An additional limitation is that similar to the model not focusing on the exterior doors of Freeman Hall, the model also does not consider building offices. Future work with this model could include the times to travel from each of the offices to a candidate location of one of the stations. The results of the model would then show the optimal locations for the stations such that the coverage of all rooms in Freeman Hall, and not just the classrooms, is maximized.

Lastly, some people might take routes through Freeman Hall that don't match the routes that were used to determine the times to travel from each classroom to a candidate location of a station. This model does not account for those routes, however we used logic and experience when we chose the routes. We determined these routes to be representative of standard movement in Freeman Hall.

Model Iteration Purposes

Model Version I was successful in providing results for one individual building on campus but it was limited in capacity because the times that were used in the model were estimated by us. In order to get data for other buildings on campus a similar process would have to be performed and this is time consuming. This model only focused on one building on campus which limited the overall scope of the study. We needed another way to allocate the stations campus-wide. Therefore, we iterated from **Model Version I** and created a model to optimally allocate stations to multiple buildings on campus.

Model Version II: Target Location-Covering Model

Model Overview

Iterating from the single building model (**Model Version I)**, we wanted to focus on campus wide allocation of stations (like what was done with the initial heuristic). However, it was crucial to develop an optimization model instead of a heuristic. Therefore, we created a target location-covering model, which is **Model Version II**. The data used in the model is the same DACD that was used for the heuristic calculations from the month of Feb. of 2021. The overall goal of **Model Version II** is to determine how many hand sanitizer stations to locate in each building that is given in the DACD based upon results of an optimization model. The hope for this model is to then illustrate to CU Facilities how their deployment compares to the results of an optimization model. Also, this model would provide a clearer picture for members of CU Facilities to see how much their initial deployment would have to be adjusted if they chose to redeploy the stations around campus.

Model Formulation

The model notation for **Model Version II** is as follows:

Set(s):

A: Set of buildings, indexed by a

Parameter(s):

$d_a \coloneqq population\ data\ for\ each\ building\ a,\ \forall\ a \in\ A$

$N \coloneqq total\ number\ of\ dispensers\ available$

$u \coloneqq number\ of\ available\ pumps\ per\ station$

Decision Variable(s):

$x_a \coloneqq number\ of\ dispensers\ located\ in\ building\ a, \forall\ a \in\ A$

The set A consists of the 36 campus buildings listed in **Table 3** that were provided in the DACD from the week in Feb. of 2021. For the purposes of this model these buildings are where the stations will be located. The parameter d_a represents the population data, or demand (DACD), for building $a \in A$. The parameter N represents the total number of dispensers available to be located, and u is the number of people each station can serve. The decision variable, x_a, determines the total number of dispensers that are to be located in each building within the set A.

The model formulation is as follows:

$\min \sum_{a \in A} (d_a - u x_a)^2$ (1)

s.t.

$x_a \geq 1, \quad \forall a \in A$ (2)

$\sum_{a \in A} x_a \leq N$ (3)

$x_a \geq 0$, integer, $\forall a \in A$ (4)

The objective function (1) minimizes the number of people uncovered by a hand sanitizer station in each building. Constraint (2) ensures that each building receives at least one hand sanitizing station. Constraint (3) limits the total number of located stations across all buildings in the set A to the total number of stations available amongst the 36 buildings in set A. Constraint (4) requires the number of dispensers assigned to be non-negative and integer. The model was coded in Python using the Pyomo package [5] and solved with Gurobi optimizer.

Model Assumptions

The supply of sanitizer for each dispenser, u, was estimated by CU Facilities. The total number of sanitizers available to pool from is (parameter N) the sum of all stations in buildings in the set A. Likewise, the DACD was combined for the three sections of Lee Hall and Martin Hall, instead of looking at each section of each building separately since the sections are connected. The population data (DACD) used represents a weeks' worth of data from Feb. of 2021 (initial model). This data was cross-checked with DACD from the past 45 days to assure credibility. Finally, we do not account for station usage in the model.

Model Limitations

One of the limitations related to **Model Version II** is that it does not provide specific locations within buildings for dispensers. The model itself only provides information about how many dispensers a building should get. An iteration from **Model Version II** was necessary to be able to offer a more accurate depiction of locations around campus for the stations. This was achieved with the final two model versions.

Model Iteration Purposes

Despite successfully being able to optimally redeploy sanitizers across campus buildings in the set A using **Model Version II,** we, following a meeting with CU Facilities, decided another iteration was necessary. This is because **Model Version II** does not tell us where within each building, or at what door, the dispensers should be located at. The model does not give priority to high volume doors but instead to high volume buildings. CU Facilities felt that it would be beneficial for them to have a model that shows specifically at what door the stations should be placed. The DACD does show data by door so we knew it was possible to come up with a similar model to the location covering model that focuses on locating the stations at specific doors of buildings.

Likewise, the model does not consider building layouts and where main entry points are located. For example, Cooper Library has two main entry points into the building. These doors are the ones used most often (this info was gathered from a meeting with CU Facilities following us sharing the model results). Even though the building has other exterior doors they are not used as frequently. After running the model, the results (see **Table 8**) had Cooper Library receiving a large portion of the stations because of the high volume through those two main entry points. CU Facilities felt that it would be much more optimal to place possibly only two or three dispensers at the main entry points instead of multiple stations throughout the building. Therefore, we adapted to the recommendations provided by CU Facilities. The attention was now focused on designing a model that that would find locations for stations based on doors of buildings coming from the buildings given in the DACD.

Model Version III: Max-Coverage Model (A)

Model Overview

Iterating from **Model Version II**, we had to build another optimization model that could provide exact locations for the stations within buildings. These locations would be the exterior doors. Exterior doors are the entry and exits to each building. The DACD that we had access to provides the counts by door for each of the buildings. Therefore, we had the necessary data we needed to build the model. The model itself would behave differently than **Model Version II** because instead of trying to minimize the population that is uncovered, the current model would try to maximize the coverage of population across campus. The model also compares to **Model Version I** because it focuses on locating stations within a building. However, it is not focused on classroom coverage like **Model Version I** was. The DACD from the three weeks in Apr. was used for this model because it was with that data that we were able to see the counts individually by door. Some other purposes for creating this model, besides determining if the current locations match the model results, is to see if the current deployment will match the model results without varying the amount that each building can get. This model was also developed such that if the results were shared with the members of CU Facilities then they wouldn't have to change the number of dispensers that are in each building but instead would just have to change their current locations. Another reason that this model was developed is because we wanted to test to see how the results would look if some doors could receive more than just one station. This again comes from the qualitative input where CU Facilities mentioned how they sometimes placed more than one dispenser at each door since the majority of the traffic came through that one entry point.

Model Formulation

The model notation for **Model Version III** is shown here:

Set(s):

$\hat{A}$: Set of buildings, indexed by $\hat{a}$

B: Set of door numbers, indexed by b

Parameter(s):

$\hat{d}_{b\hat{a}} \coloneqq population\ data\ for\ door\ b \in B\ in\ building\ \hat{a} \in \hat{A}$

$s_{\hat{a}} \coloneqq number\ of\ sanitizer\ tations\ in\ building\ \hat{a}\ \in \hat{A}$

$$y_{b\hat{a}} \coloneqq \begin{cases} 1\ if\ door\ b \in B\ is\ in\ building\ \hat{a} \in \hat{A} \\ \quad 0\ otherwise \end{cases}$$

Decision Variable(s):

$\hat{x}_{b\hat{a}} \coloneqq number\ of\ stations\ located\ at\ door\ b\ \in B\ in\ building\ \hat{a} \in \hat{A}$

The set $\hat{A}$ is the set of buildings, which is the 36 campus buildings included in the DACD for the three weeks in the month of Apr. of 2021. The set B is a set of door numbers ranging from 0-28. The range begins with zero for indexing purposes. The set B goes to 28 because 28 is the maximum number of doors in one building across all 36 buildings. The parameter $\hat{d}_{b\hat{a}}$ is the new population parameter and it is now a matrix that stores the population data (DACD) for each door b in B in building $\hat{a}$ in $\hat{A}$. The parameter $s_{\hat{a}}$ represents the number of stations in each building $\hat{a}$ in the set $\hat{A}$. This information was again provided by CU Facilities and is shown in **Table 2**. The parameter $y_{b\hat{a}}$ is used to check if door b in B is in building $\hat{a}$ in $\hat{A}$. For example, if a building has two doors then the parameter will have values of one for the first two doors (represented by 0 and 1) and then zero for the other doors. The decision variable $\hat{x}_{b\hat{a}}$ determines the number of stations that are located at door b in B in building $\hat{a}$ in $\hat{A}$.

The model formulation for **Model Version III** is as follows:

$$max\ \sum_{b \in B} \sum_{\hat{a} \in \hat{A}} y_{b\hat{a}} \hat{x}_{b\hat{a}} \hat{d}_{b\hat{a}} \qquad (1)$$

s.t.

$$\sum_{b \in B} \hat{x}_{b\hat{a}} = s_{\hat{a}} \qquad \forall\ \hat{a} \in \hat{A} \qquad (2)$$

$$\hat{x}_{b\hat{a}} \leq 2 \qquad \forall\, b \in B, \hat{a} \in \hat{A} \qquad (3)$$

$$\hat{x}_{b\hat{a}} \geq 0, \forall\, b \in B, \hat{a} \in \hat{A} \qquad (4)$$

The objective function (1) maximizes the coverage of the population in the 36 buildings included in the DACD. Constraint (2) ensures that the number of stations for each building equals the number of stations that each building currently has or their current capacity. Constraint (2) also ensures that the total number of stations that are located does not exceed the total number of dispensers available to place in buildings. Constraint (3) enables some doors to have up to two dispensers, but not more. Constraint (4) sets the decision variable $\hat{x}_{b\hat{a}}$ to binary. The model was coded in Python using the Pyomo package [17] and solved with Gurobi optimizer.

Model Assumptions

One of the assumptions of this model is that it assumes the stations will be located at exterior doors only. The model assumes that stations cannot be located within a building. The model is also assuming that doors can have up to two dispensers but no more. Another assumption for this model is that the data from Feb. is no longer suitable for this model because it does not show the counts by door by building. Therefore, we assume that the DACD for the three weeks in Apr. of 2021 is representative of standard foot traffic into buildings on campus. Likewise, we decided to sum the counts by door for the three weeks instead of running the model for each separate week. This was done purposely because we felt that using a wider range of data would allow them to make more tactical decisions if necessary since in the future, and moving forward, we hope to be able to provide tactical recommendations to CU facilities instead of operational. These updates on the model results seemed more appropriate to be offered as short-term improvement [14] instead of day by day or week by week updates [14]. Furthermore, we assume that the number of stations that can be located cannot exceed the number of stations that are available to locate amongst the 36 buildings included in the set $\hat{A}$. Lastly, we assume that placing stations in these locations will increase usage.

Model Limitations

A limitation of **Model Version III** is that each building is restricted to its current capacity meaning that the model does not address cross-campus allocation. If future DACD was used and a building had different results then it would make sense to add another dispenser to that building, however this model does not allow that. It restricts the buildings to the current amount of dispensers. Another limitation of this model is that because the model is trying to maximize population coverage and some doors can get more than one station, the model automatically allocates the maximum amount of dispensers it can to the door with the largest counts of DACD. This is reasonable in some cases however in others there may be a door that has similar door data but not exactly the same and it might not be getting a station in this model because the dispensers were allocated to the door with the larger counts of door data.

Model Iteration Purposes

Iterating from **Model Version III** to **Model Version IV** occurred because despite successfully determining locations for stations within buildings, the model itself restricted the number of stations that a building gets to its current capacity. However, it might be necessary to put more dispensers in a building because the total number of people going into that building could increase or change overtime. The model was run with the DACD from Apr. of 2021, however these numbers might be different in future months and because of this we wanted a model that no longer restricted the buildings to their current capacity. We wanted a model that could be used for tactical updates such that if a range of DACD was used the model could provide updates to CU Facilities. Another reason that we iterated from this model to the next is because the model was more building specific in terms of coverage because the buildings were limited to their current capacity. We felt that the model could be adjusted, and using the same principle would now provide campus wide allocation.

Model Version IV: Max-Coverage (B)

Model Overview

The fourth and final model version that was designed in this study (**Model Version IV**) built on the ideas that were first introduced in **Model Version III**. To reiterate, we took the qualitative information gathered from the semi-structured interviews that identified doors (exterior doors – entrances and exits) as some of the most important locations chosen for the stations around campus. Then using the DACD and filtering it by door and by building, we developed a model that was able to identify locations for dispensers in buildings. Those locations being near the most appropriate doors suggested by the model results. In **Model Version III**, we first started off by allowing some doors to receive more than one station because in the interviews with CU Facilities, we were told that certain building layouts, and the way that students enter those buildings make it more impactful to place more than one dispenser at that single entryway, as opposed to locating it at a less used exterior door. However, in **Model Version III**, the buildings themselves were limited to their current capacity, and therefore the model itself became more of a "building specific" model. It did not allow us to focus on cross campus allocation, which in this study was one of the more important issues that we wanted to be address. Being able to focus on the entire campus, and covering more areas of the campus (covering meaning placing stations in locations where populations are congregated the most) was a top priority for us.

The next step in the iteration process was to design a similar model that behaved like **Model Version III** but no longer restricted the buildings to their current capacity of hand sanitizer stations. The model that we came up with achieved just that. Again, we applied the data from the three weeks in Apr. of 2021. This would, again, be the population data to help identify where the foot traffic into the buildings was the highest. Then the model would optimally choose exterior door locations for the dispensers. We first wanted to test the model with only allowing doors to receive one station instead of multiple to see how the results would compare with the heuristic results and **Model Version II**. Future sensitivity analysis will be performed, however, to see how the model will behave when allowing some doors to receive multiple dispenser stations (i.e., 2). To summarize, **Model Version IV** will provide an optimal solution that gives locations for dispenser stations by exterior doors.

Model Formulation

The model notation for **Model Version IV** is as follows:

Sets(s):

$\hat{A}$: Set of buildings, indexed by $\hat{a}$

B: Set of door numbers, indexed by b

Parameter(s):

$\hat{d}_{b\hat{a}} \coloneqq population\ data\ for\ door\ b \in B\ in\ building\ \hat{a} \in \hat{A}$

$N\ \coloneqq\ total\ number\ of\ dispensers\ available$

$y_{b\hat{a}} \coloneqq \begin{cases} 1\ if\ door\ b \in B\ is\ in\ building\ \hat{a} \in \hat{A} \\ \quad\quad 0\ otherwise \end{cases}$

Decision Variable(s):

$\hat{x}_{ba} \coloneqq \begin{cases} 1\ if\ we\ locate\ a\ dispenser\ near\ door\ b \in B\ in\ building\ a \in A \\ \quad\quad 0\ otherwise \end{cases}$

An explanation of the model notation is as follows. The set $\hat{A}$, which is the same as it was in **Model Version III**, consists of the 36 buildings included in the DACD for the three weeks in Apr. of 2021. The set B is the same as it was in **Model Version III**. This set consist of door numbers, again, ranging from 0-28 because the maximum number of doors that one of the buildings has is 28. The reason this is done will be reiterated shortly. The parameter, $\hat{d}_{b\hat{a}}$, is the population data for each door b in B in building $\hat{a}$ in $\hat{A}$. More specifically, the data for p_{00} would represent the counts on the door opened data for the first door in the first building included in the set $\hat{A}$. Again, this data was summed across the three weeks included in the DACD for the month of Apr. in 2021. The parameter, N, unlike the parameter, $s_{\hat{a}}$, that was used in **Model Version III**, is the total number of dispensers that are available amongst the 36 buildings included in the set $\hat{A}$. This parameter has to be included in this version of the model because the buildings will no longer be limited to their current capacity (the number of stations that are currently located in each building).

Moving on, the parameter, $y_{b\hat{a}}$, performs a check to evaluate if door *b* in *B* is in building $\hat{a}$ in $\hat{A}$. The parameter performs this operation for all the doors in each building. If the building has "X" amount of doors then that parameter will take on a value of one, and for the rest of the numbers up to 28, the parameter will take on a value of zero. Finally, the decision variable being solved for by the model is represented as $\hat{x}_{b\hat{a}}$. The decision variable determines if a station is located at door *b* in *B* in building $\hat{a}$ in $\hat{A}$.

The formulation for **Model Version IV** is as follows:

Model Version IV Formulation:

$$max \ \sum_{b \in B} \sum_{\hat{a} \in \hat{A}} y_{b\hat{a}} \hat{x}_{b\hat{a}} \hat{d}_{b\hat{a}} \qquad (1)$$

s.t.

$$\sum_{b \in B} \hat{x}_{b\hat{a}} \geq 1 \ \ \forall \hat{a} \in \hat{A} \qquad (2)$$

$$\hat{x}_{b\hat{a}} \leq 1 \qquad \forall \ b \in B, \hat{a} \in \hat{A} \qquad (3)$$

$$\sum_{b \in B} \sum_{\hat{a} \in \hat{A}} \hat{x}_{b\hat{a}} = N \qquad (4)$$

$$\hat{x}_{b\hat{a}} \in \{0,1\}, \forall \ b \in B, \hat{a} \in \hat{A} \qquad (5)$$

The objective function (1) is to maximize the coverage of the population using the DACD. Constraint (2) ensures that each building has at least one hand sanitizing dispenser. Constraint (3) makes sure that a door can only receive, at most, one dispenser. Constraint (4) ensures that the number of dispensers that are located does not exceed the number available (*N*). Constraint (5) sets the decision variable $\hat{x}_{b\hat{a}}$ to binary. The model was once again coded in Python using the Pyomo package [17] and solved with Gurobi optimizer.

Model Assumptions

Several of the assumptions related to **Model Version IV** are similar to the assumptions that had to be made for **Model Version II** and **Model Version III**. First off, the buildings included in the set $\hat{A}$ are assumed to represent 55% of the high foot traffic areas on campus. Additionally, the parameter *N* is equal to the total number of dispensers available amongst the buildings included in the set $\hat{A}$. Likewise, the data that is being used in this model to provide numerical values for the $\hat{d}_{b\hat{a}}$ parameter comes from the DACD collected from the three weeks in Apr. of 2021. The data is summed together for the three weeks for each door (*d* in *D*) in each building ($\hat{a}$ in $\hat{A}$). Through evaluation we felt that the data was representative of standard student movement during that time. To continue, the model accounts for exterior doors only (the model will provide locations for stations at these exterior doors). The exterior doors, as it has been mentioned, include the entrances and exits into each of the buildings in the set $\hat{A}$. Finally, we assume putting doors at these locations will increase usage.

Model Limitations

A limitation of **Model Version IV** is that even though the results show the doors where stations should be located, we currently do not have access to maps that show building door names related to the names shown in the DACD. In future work, we hope to collaborate with CU Facilities and members of CU's TigerOne department to determine what these locations are in order to make updates, if necessary, to the current plan. We have the ability to find the optimal solution, however, it is a matter of being able to identify which door in a building is represented by which name in the DACD.

Once this is completed, we will be able to provide CU Facilities with even more detailed results such that they can compare the effectiveness of their deployment. Likewise, another limitation of this model is that the model needs more representative DACD for a full in-person semester (like Fall 2021). Once data like this is acquired we will be able to rerun the model and provide more accurate feedback to CU Facilities.

Model Iteration Purposes

The results of the current model (**Model Version IV**) were provided to CU Facilities and with their approval it was concluded that this model was an ideal representation of their decision-making and would provide valuable insights to decisions moving forward. Therefore, an agreement was made to create an algorithm for CU Facilities such that they could use the current model to improve their overall understanding of the problem and make tactical updates. The algorithm described will be discussed further in the future work section of this thesis. All in all, this concludes the final iteration of this case study. Referring back to the iterative modeling process framework shown in **Figure 5**, **Model Version IV** is the ideal, representative model that will be implemented by CU Facilities to perform future tactical updates.

It is important to note that even though CU Facilities agreed to implement this version of the model, there are still possibilities of discordance in the model, and future iterations are still possible. Even though we are able to provide CU Facilities with a usable model, that was representative of the situation, we know that the iterative process can push forward. This will only continue to refine the model and consider alternate situations. Through discussions, we hope in future model iterations, to consider diminishing returns in the objective function. Specifically, we would use such a consideration when loosening the one-dispenser-per-door constraint and instead allowing some doors in buildings to receive more than two stations but not limited to their current capacity. This is an important consideration that needs to be considered in future iterations because if the current model, as is, was run and doors were allowed to receive more than one dispenser, then the model would allocate two stations to doors with the largest amounts of counts.

However, this may not be the ideal situation or even accurate because those doors, despite receiving a lot of traffic, may not be the only entryway into the building and could possibly be taking a station away from another door that should still be getting a station. The model is providing an optimal solution, however that optimal solution may not actually be representative of what is actually going on in terms of foot traffic and covering those main areas. In order to account for this in the next iteration of the model we can apply a certain percentage to a door that sees a majority of the traffic. Then running the model, if other doors in the building do not surpass a certain threshold, the model will locate more than one dispenser at the other door. Such a model iteration will also require us to study the building layouts. We may also have to consider adding constraints for certain buildings where one main entry way is more applicable. Not all of the buildings might follow the idea where individuals enter through a single exterior door. Therefore, building constraints can be added to the model that consider buildings with multiple floors, their actual layouts and how students enter them, and the building’s square footage. The iterative modeling process can continue to move forward because policies are always changing. Continuing to gather qualitative input introduces new ideas and constraints that can be brought into the model. This once again illustrates just how effective the iterative process can be. In certain situations, we would conduct the interviews, and then move forward with one model version that we believe best fits the data gathered. On the contrary, this study continuously gathered qualitative information and proactively refined the model and its constraints in order to build upon the decisions being made by the decision-makers involved in the process of deployment.

CHAPTER 5: RESULTS

Heuristic: Proportional Allocation to Buildings

The figure shown below (**Figure 11**) is a histogram meant to compare the results of the heuristic to the current deployment. The histogram is meant to be interpreted as follows: the x-axis are bins which represent the difference in number of stations between the heuristic results and the current deployment. For example, the bin (0,1] will count the number of times the heuristic showed a building needing one more dispenser than the building currently has. The y-axis is the number of buildings that fall into each bin. The data labels show the counts on the number of buildings that fall into each bin (category). The distribution of the histogram shown in **Figure 11** is right skewed, which indicates that CU Facilities might've over-covered some of the campus buildings. This directly relates to some of the input that was received from the qualitative analysis where members of CU Facilities mentioned how they wanted to almost “smother” campus with sanitation supplies.

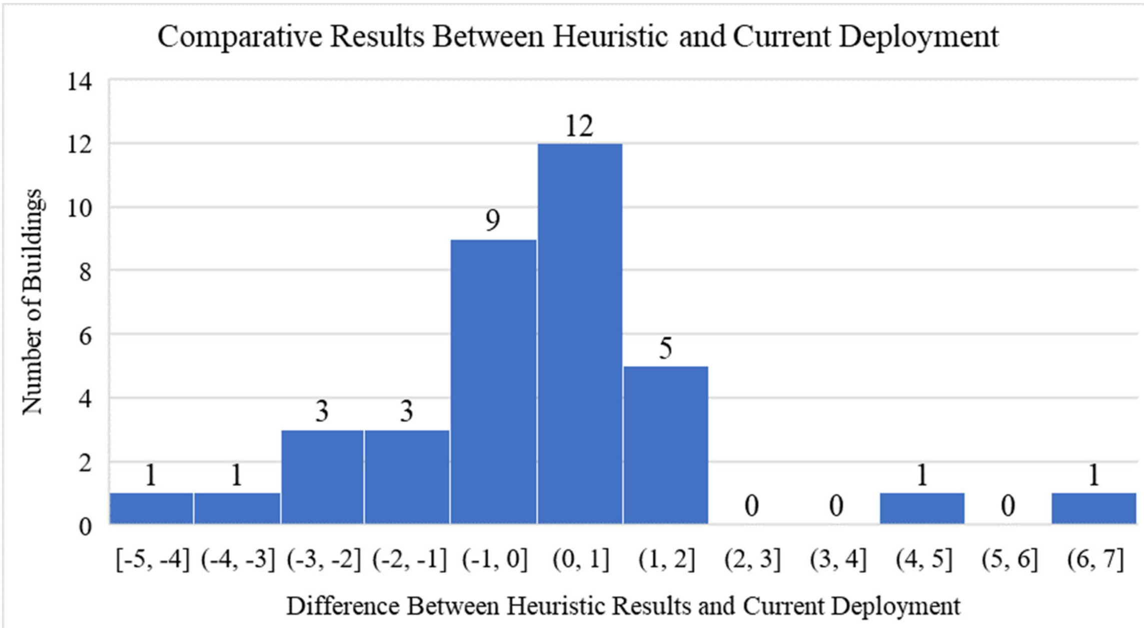

Figure 11: Histogram to Compare Heuristic Results with Current Deployment

After creating the histogram, nine of the buildings have results in the heuristic that are the same as the current deployment. For example, the Academic Success Center is shown to maintain the two stations that it currently has. There are nineteen buildings that are shown to need more dispensers than they currently have. For example, Fluor Daniel currently has one dispenser but based on the heuristic results it should be receiving 2 dispensers. This would mean it needs one more dispenser than it currently has, which would fall into the (0,1] bin as seen in **Figure 11**. Finally, eight of the buildings had heuristic results which were less than the current amount of stations that they currently have. The heuristic suggests then that eight out of the 36 buildings need less dispensers than they currently have. One example is Barre Hall which currently has four stations but the heuristic suggest that it should get just two dispensers. This means it needs two less dispenser than it currently has. The entire table of results are shown in **Table 6**. It should be mentioned again that the sum of all the dispensers located in buildings for the heuristic is greater than the current amount of dispensers, *N*, and that is because the proportions were rounded up so that a building would not receive a fraction of a dispenser.

Table 6: Current Deployment and Heuristic Results

Building Name	Current Deployment	Heuristic Results
Academic Success Center	2	2
Administrative Services Building	1	1
Barre Hall	4	2
BioSystems Research Center	4	5
Brackett Hall	2	4
Brooks Center	2	4
Campbell Museum	1	1
College of Business Building	20	15
Cook Laboratory	1	1
Dillard Building	2	1
Earle Hall	1	2
Edwards Hall	2	4
Fluor Daniel	1	2
Freeman Hall	3	4
Godfrey Hall	1	2
Hardin Hall	3	2
Harris Smith	1	1
Holtzendorff Hall	1	3
Hunter Hall	1	3
Jordan Hall	2	2
Kinard Hall	4	2
Lee Hall (Includes 3 Buildings)	6	4
Long Hall	1	2
Lowry Hall	1	2
Martin Hall (Includes 3 Buildings)	6	3
McAdams Hall	2	3
Olin Hall	1	1
P&A Building	4	4
Rhodes Hall/Annex	2	3
Cooper Library	4	9

Sikes Hall	3	3
Sirrine Hall	4	5
Strode Tower	1	2
Tillman Hall	6	5
Vickery Hall	1	2
Watt Innovation	1	8

Sensitivity Analysis: Heuristic

After calculating the results using the heuristic with the DACD from the week of Feb. of 2021, we decided to perform some sensitivity analysis with the heuristic and used DACD from three separate weeks in Apr. of 2021. The set of buildings remained the same. **Figure 12** shows the results for the first week in Apr.

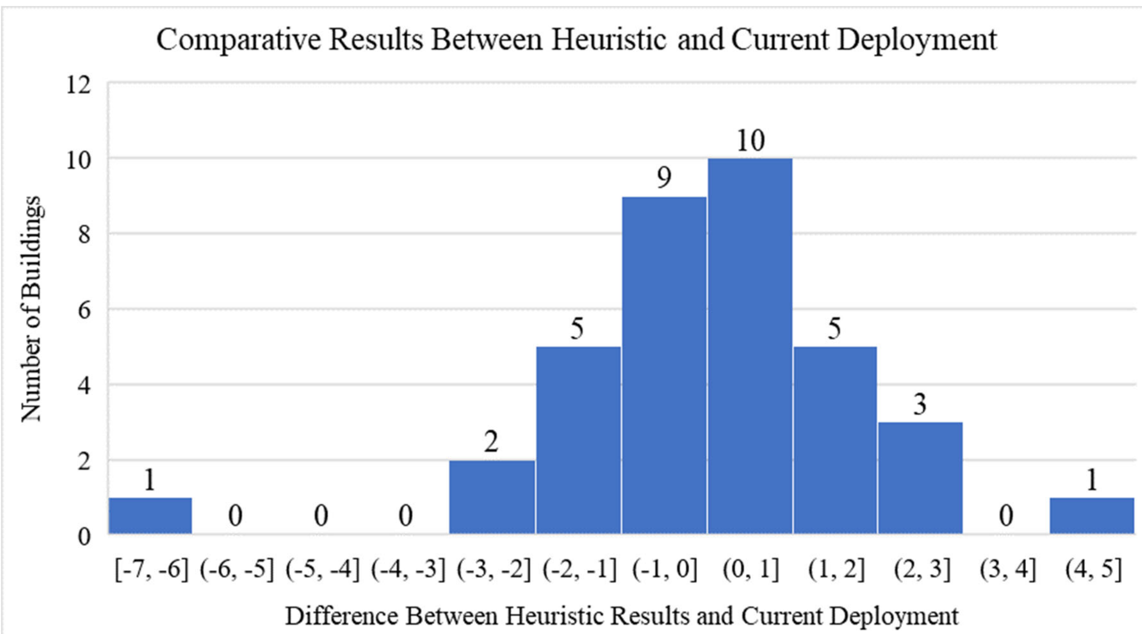

Figure 12: Comparative Results Using DACD from Apr. Week 1

Based on the results shown, it is evident that nine of the results matched the current deployment, 19 of the results suggested that buildings need to receive more stations, and eight of the buildings had results that suggested they receive less stations.

Figure 13 shows the results for the second week in Apr.

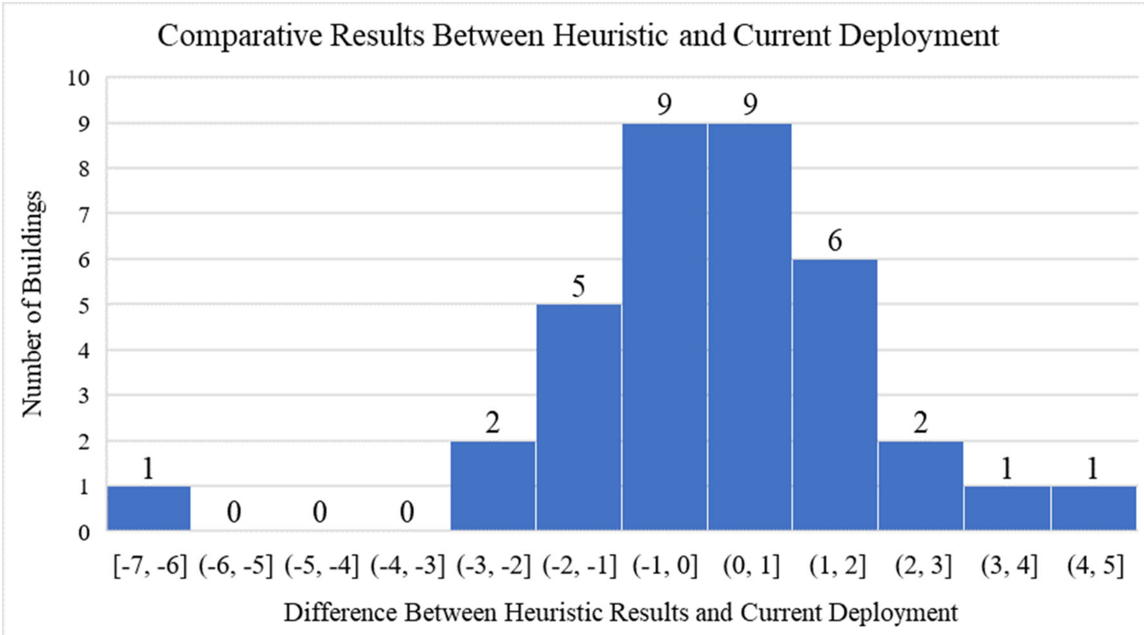

Figure 13: Comparative Results Using DACD from Apr. Week 2

The results indicate that nine of the buildings had results that matched the current deployment, 19 of the buildings had result that suggested that buildings needed more dispensers, and eight of the buildings had results that showed that they need less dispensers.

Figure 14 shows the results for the third week in Apr.

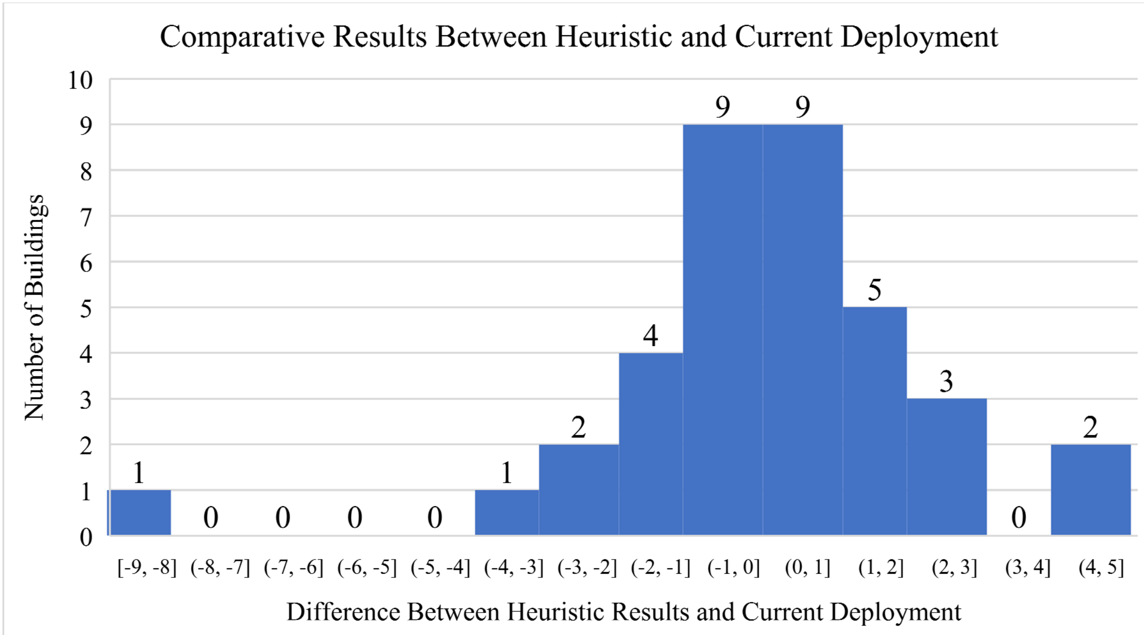

Figure 14: Comparative Results Using DACD from Apr. Week 3

The results indicate that nine of the buildings had results that matched the current deployment, 19 of the buildings had result that suggested that buildings needed more dispensers, and eight of the buildings had results that showed that they need less dispensers.

In general, after performing sensitivity analysis using DACD for three separate weeks in the month of Apr. of 2021, it is clearly evident that the results were very similar to the results when we used the DACD from the week in Feb. Each of the weeks had results that showed 9 of the buildings having the same amount of stations that they currently have, 19 of the buildings needing more stations, and 8 of the buildings needing less. The buildings themselves varied from week to week, as well as the exact difference in dispensers but nonetheless the results in general were similar. With this we are then able to confirm that the heuristic proves to be a good predictor for possible future redeployment strategies solely based on proportions related to the DACD and number of dispensers available. It also showed that the DACD is quite consistent and valid even for weeks that are separated by almost 2 months. The DACD is a good predictor of student movement in and out of buildings.

Model Version I: p-Median Max Coverage Model

Model Version I was run for each of the four *p* values (i.e., 1-4) and we are able to identify the optimal locations for the stations within Freeman Hall based on the coverage time metric. **Table 7** summarizes the results of **Model Version I**.

Table 7: Results for **Model Version I**

Value of *p*	**Optimal Dispenser Locations**	**Maximum Coverage Time**
$p = 4$	0, 1, 5, 9	$T = 8$ sec
$p = 3$	0, 5, 9	$T = 8$ sec
$p = 2$	0, 5	$T = 24$ sec
$p = 1$	1	$T = 30$ sec

The first column shows the value of *p*, the middle column shows the optimal station locations for each of those *p* values (the numbers refer to the numbers that are shown in **Figure 8**), and the last column is the maximum coverage time that enables all three classrooms to be considered covered. Based on these results it is clear to see that it is possible to relocate the three current hand sanitizer stations in Freeman Hall to cover all three classrooms and ensure the time to get from a classroom to a station is minimized. The results also indicate that the optimal deployment based on **Model Version I** differs from the current deployment of the hand sanitizer dispensers (which is based on locating $p = 3$ stations). The current locations are **3**, **6**, **7** in **Figure 8** and the locations based on **Model Version I** are **0**, **5**, and **9** in **Figure 8**.

Model Version II: Target Location-Covering Model

After running **Model Version II**, the results were compared with the historical data from CU Facilities (i.e., the current deployment in each building). A histogram (**Figure 15**) was designed to visually represent the similarities and differences between the current deployment and the results of **Model Version II**. The bins (located on the x-axis) of the histogram represent the difference amounts (these amounts were found by subtracting the current deployment from the location covering model results). Zero indicates no change in the number of sanitizers in a building. The histogram has a total of 15 bins each with a bin width of one. Five of the bin widths had totals of zero. The y-axis shows the number of buildings that fall into each bin, or category. The numbers above each bar indicate the number of buildings that fall into that category. The bins that lie to the right of the bin (-1,0] represent the amounts for buildings that need more dispensers and the bins that lie to the left of this represent the amounts for buildings that need less dispensers. In general, the distribution in the difference in model-recommended vs. historical implementation is right-skewed; this indicates that decision-makers may have over, rather than under-covered campus.

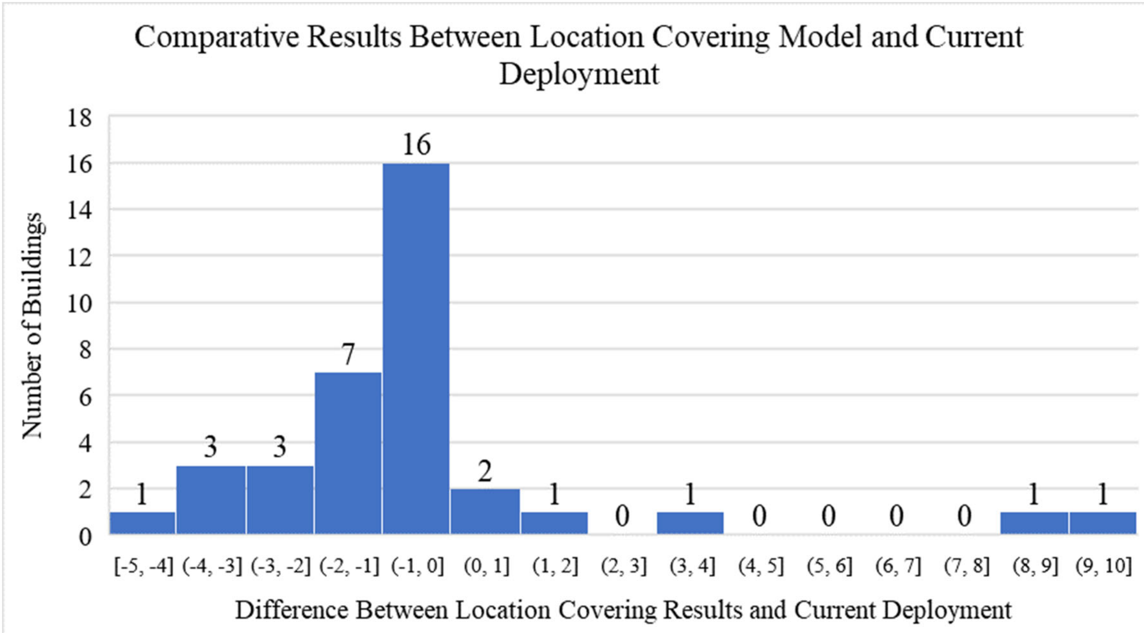

Figure 15: Comparative Results Between Model Version II and Current Deployment Using Feb. DACD

Sixteen buildings have a current deployment that matches the recommended amount from **Model Version II** (e.g., the Administrative Services Building is recommended to maintain its one station). Fourteen buildings may have too many dispensers (e.g., Sikes Hall currently has three stations, but the model recommends fewer, with one). Finally, six buildings may have too few (e.g., Brackett Hall currently has 2 but is recommended to have 4). A table of comparative results is shown below (**Table 8**).

Table 8: **Model Version II** Results Compared to Current Deployment of Dispenser Stations

Building Name	Current Deployment	Week of February
Academic Success Center	2	1
Administrative Services Building	1	1
Barre Hall	4	1
BioSystems Research Center	4	4
Brackett Hall	2	4
Brooks Center	2	3
Campbell Museum	1	1
College of Business Building	20	24
Cook Laboratory	1	1
Dillard Building	2	1
Earle Hall	1	1
Edwards Hall	2	3
Fluor Daniel	1	1
Freeman Hall	3	2
Godfrey Hall	1	1
Hardin Hall	3	1
Harris Smith	1	1
Holtzendorff Hall	1	1
Hunter Hall	1	1
Jordan Hall	2	1
Kinard Hall	4	1
Lee Hall (Includes 3 Buildings)	6	3
Long Hall	1	1
Lowry Hall	1	1
Martin Hall (Includes 3 Buildings)	6	1
McAdams Hall	2	1
Olin Hall	1	1
P&A Building	4	3
Rhodes Hall/Annex	2	1
Cooper Library	4	13
Sikes Hall	3	1
Sirrine Hall	4	4
Strode Tower	1	1
Tillman Hall	6	4
Vickery Hall	1	1
Watt Innovation	1	11

Sensitivity Analysis: Model Version II

We decided to perform some sensitivity analysis with **Model Version II** using the DACD from three separate weeks in Apr. of 2021. The model was run with this data and the results of the Apr. data model are compared to the current deployment. This helps to see how the Apr. data compares to the Feb. data. **Figure 16** shows the results of Model Version II using Apr. week 1 DACD.

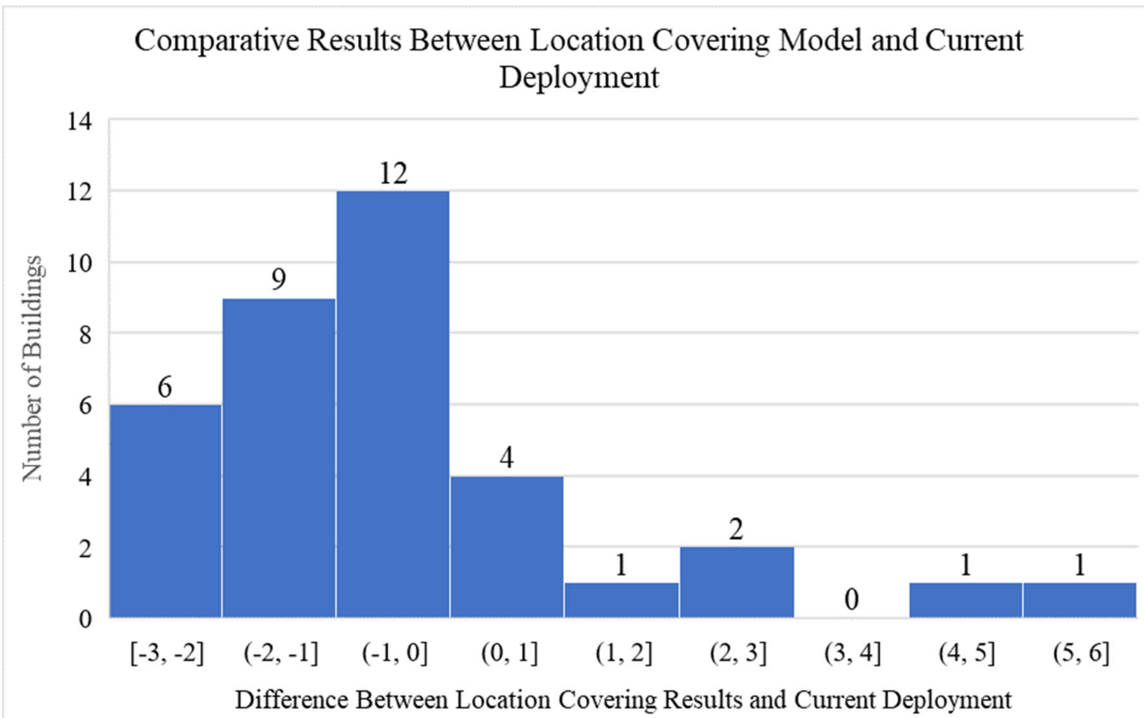

Figure 16: Comparative Results Between Model Version II and Current Deployment Using Apr. Week 1

Based on the results that are shown in **Figure 16**, it is evident that 12 of the buildings had results that were the same as the current deployment. Nine of the buildings had results that suggested that they need more dispensers than they are currently getting, and 15 of the buildings had results that suggested that they should be getting less dispensers than they currently have. The next figure (**Figure 17**) shows the comparative results using the Apr. week 2 DACD.

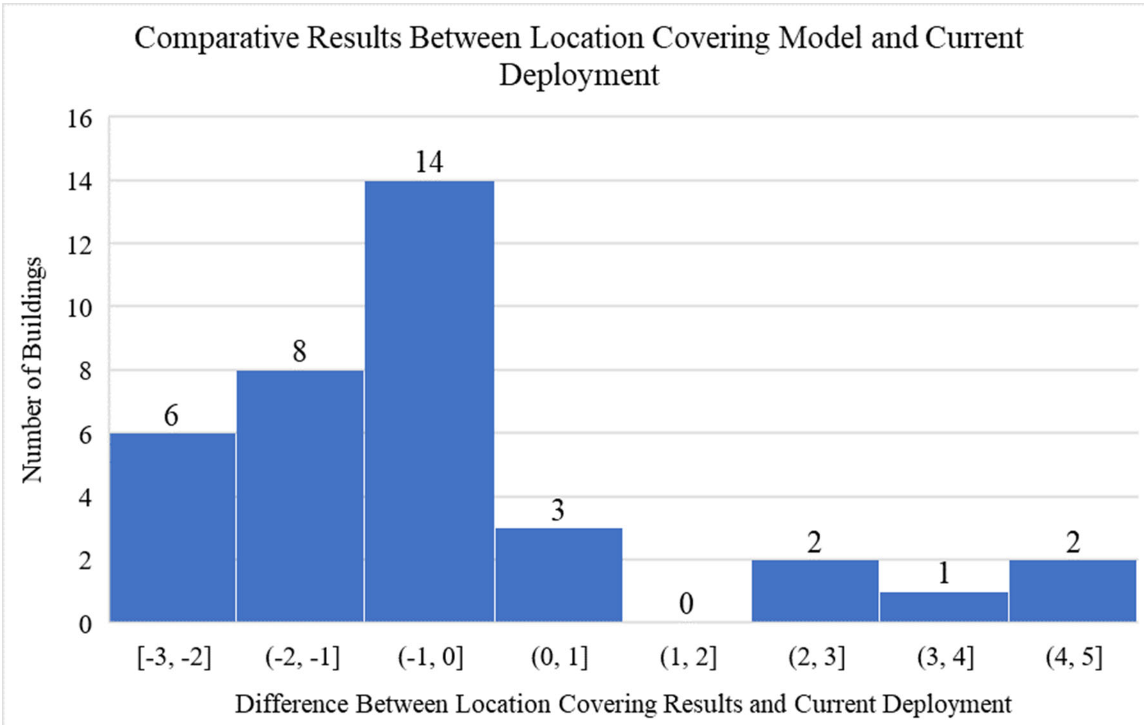

Figure 17: Comparative Results Between Model Version II and Current Deployment Using Apr. Week 2

Based on the results that are shown in **Figure 17**, it is evident that 14 of the buildings had results that were the same as the current deployment. Eight of the buildings had results that suggested that they need more dispensers than they are currently getting, and 14 of the buildings had results that suggested that they should be getting less dispensers than they currently have. The last figure that was created during the sensitivity analysis (**Figure 18**) shows the results of Model Version II for the third week of DACD in Apr.

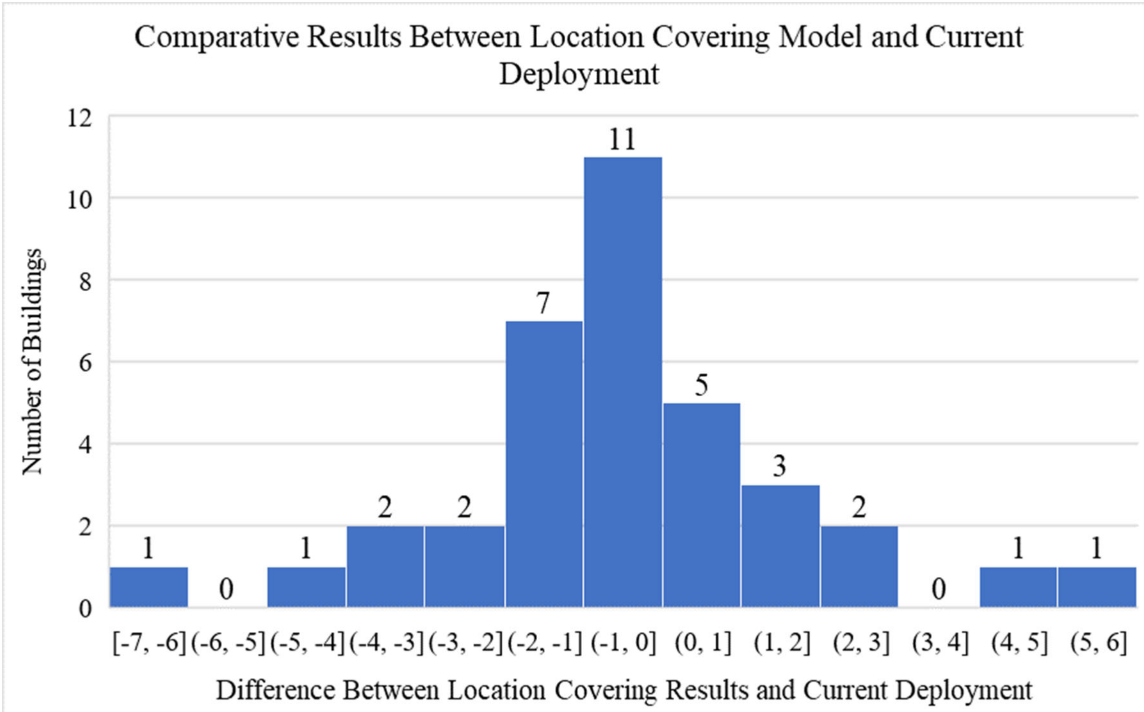

Figure 18: Comparative Results Between Model Version II and Current Deployment Using Apr. Week 3

Based on the results that are shown in **Figure 18** it is evident that 11 of the buildings had results that were the same as the current deployment, 12 of the buildings had results that suggested that they need more dispensers than they are currently getting, and six of the buildings had results that suggested that they should be getting less dispensers than they currently have.

After comparing the **Model Version II** results for the three weeks of Apr. DACD, we then compared these results with the results of the model using the Feb. DACD. Ultimately, the results for the weeks of Apr. were relatively the same as the results for the week in Feb. For the first two weeks in Apr., 18 of the buildings had the same results as the week in Feb. (50%), while 18 of the results were different. For the third week in Feb., 15 of the buildings (42%) had results that match the results for the week in February.

Therefore, it was concluded that the data from the week in February is representative of standard student movement across the 36 buildings given in the door access control data.

Model Version III: Max-Coverage Model (A)

After the model was run, the results for each building were determined. Because in this model the buildings were limited to their current capacity there was no difference in the amount that each building was getting so a histogram for a comparison to the current deployment across campus was irrelevant. However, with this model, we are able to view which doors in each building were getting a station, or two, or none at all. Some examples are shown here. **Table 9** shows the results for Barre Hall. The last column shows the number of stations at each door. In this case, two of the doors got two dispensers and the rest had none.

Table 9: **Model Version III** Results for Barre Hall

Building Name	Door Name	Station Count
Barre Hall	Door 0	0
	Door 1	0
	Door 2	0
	Door 3	2
	Door 4	0
	Door 5	2
	Door 6	0
	Door 7	0

Table 10 shows the results for the College of Business.

Table 10: **Model Version III** Results for College of Business

Building Name	Door Name	Station Count
College of Business Building	Door 0	2
	Door 1	0
	Door 2	2
	Door 3	0
	Door 4	0
	Door 5	0
	Door 6	0
	Door 7	0
	Door 8	2
	Door 9	0
	Door 10	0
	Door 11	2
	Door 12	2
	Door 13	2
	Door 14	2
	Door 15	2
	Door 16	2
	Door 17	2

The results for the College Business have ten of the doors receiving two stations (20 total stations currently deployed in the College of Business Building) and none of the doors receiving only one station.

Finally, the results for Freeman Hall are shown in **Table 11**.

Table 11: **Model Version III** Results for Freeman Hall

Building Name	Door Name	Station Count
Freeman Hall	Door 0	2
	Door 1	0
	Door 2	0
	Door 3	0
	Door 4	0
	Door 5	0
	Door 6	0
	Door 7	1
	Door 8	0
	Door 9	0

The results in the table above show that one of the doors is receiving two stations while one of the doors is receiving one station. This is interesting because currently, as it is in Freeman Hall, three of the exterior doors have one station only. However, based on the model results, it might be more effective to place two stations at one of the doors that is receiving more of the traffic.

Model Version IV: Max-Coverage Model (B)

The model results for **Model Version IV** are represented in the histogram shown in the **Figure 19** below. A comparison was performed to understand how the model's optimal solution compares to the current deployment. The comparison was best represented by a histogram. The histogram shows the difference in the number of stations in each building between the model results and the current deployment. When looking at the histogram, the bins, or the x-axis, represent the difference itself. These bins have a width of one. The y-axis of the histogram shows the number of buildings that fall into each bin. The distribution of the histogram was also evaluated to get a better understanding of the decision-making strategies of CU Facilities. The figure is shown here.

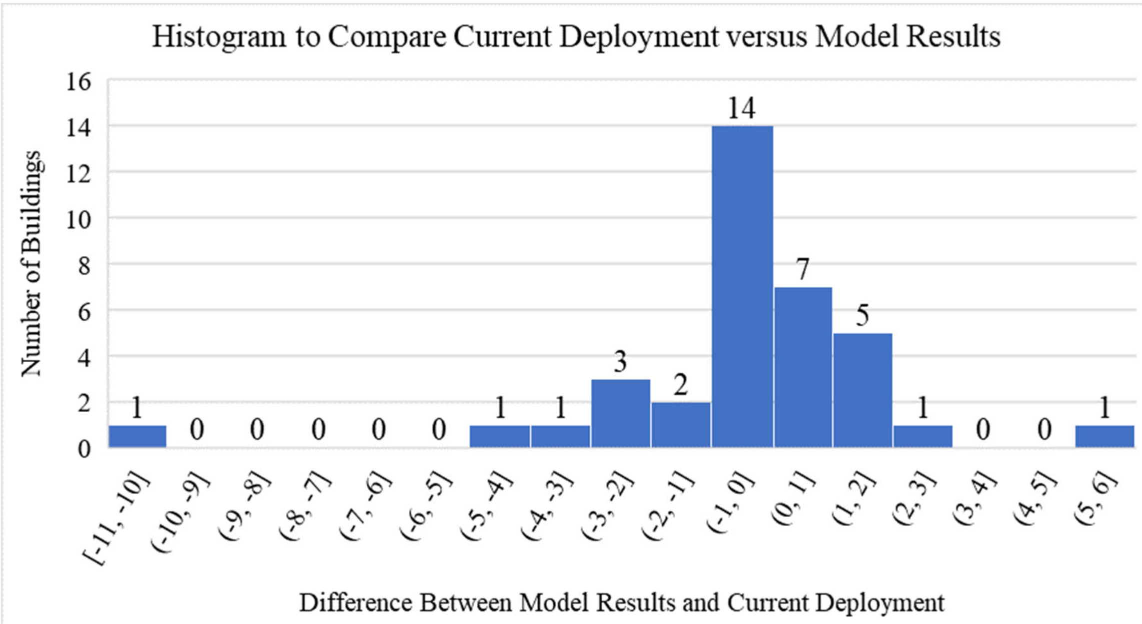

Figure 19: Histogram to Compare Model Version IV Results to Current Deployment

As seen in the figure above, 14 of the buildings had results that matched the current deployment. For example, the Academic Success Center currently has two dispensers and the model results suggest it should maintain those two dispensers. Similarly, 14 of the buildings in the optimal solution had results that suggested they need more dispensers then they currently have. For example, the Administrative Services Building currently has one dispenser but the model suggests that it should be receiving seven stations. The difference then between these results is six stations. An important note relates to the data being used for this model (the Apr. DACD). During the time when the data was acquired, the majority of the population on campus was faculty and staff. The Administrative Services Building is one of the buildings with offices dedicated to these employees. Students, during this time, were wrapping up the semester and preparing for finals, therefore not as many students were going into campus buildings. With this being said, the Administrative Services Building saw more foot traffic during this time period and that is why the model indicates it should be getting more dispensers.

One of the benefits of results like this is it shows how the model could be used for tactical updates to the deployment plan. Running the model at different points in the semester could provide CU Facilities with an alternative strategy to redeploy the stations around campus based on trends in foot traffic. These trends are associated with university breaks, finals week, and much more. Running the model during these associated time periods would allow CU Facilities to adapt to the changes in foot traffic around campus and give them the opportunity to consistently maintain coverage over the high foot traffic areas. Now, to move forward, the model suggests that eight of the buildings need a lesser amount of stations than they currently have. For example, Hardin Hall has three stations but the model results suggest it should only be receiving one station. That results in a difference of 2 stations. More specifically, Hardin Hall, as suggested by the model, should be getting two less stations then it currently has.

Analyzing the distribution of the histogram, it would appear that it is left-skewed. This would suggest that the current deployment of the stations in buildings undercovers campus as opposed to over covers. With respect to this, it is worth mentioning that the initial comparison used DACD from Feb. of 2021. The current model, however, uses data from Apr. of 2021. There was a shift in foot traffic during these time periods which again shows the model's success at providing tactical updates to the deployment strategy. CU

Facilities could use the model with up-to-date DACD to analyze if the deployment is sufficient, or if changes need to be made to their current plan.

To continue, the current model addresses one of the key components of this study and that is finding specific locations to place stations. The model provides locations at exterior doors of buildings for locations for stations. It should be reiterated that these locations seemed reasonable based on the qualitative input that was gathered during the qualitative analyses. The model provides locations based on the doors that were provided in the DACD. A few examples will be provided to illustrate how we are able to view these results by door. **Table 12** presents the results for two of the campus buildings. These are Freeman Hall and Cooper Library. The table displays the building name, the door name (the exact naming has been disclosed for privacy reasons), and the station count at each of those doors.

Table 12: Examples of Individual Building Results for **Model Version IV**

Building Name	Door Name	**Station Count**
Freeman Hall	Door 0	1
	Door 1	0
	Door 2	1
	Door 3	0
	Door 4	1
	Door 5	0
	Door 6	0
	Door 7	1
	Door 8	0
	Door 9	0
Cooper Library	Door 0	0
	Door 1	1
	Door 2	0
	Door 3	1
	Door 4	1
	Door 5	0
	Door 6	0
	Door 7	0
	Door 8	0
	Door 9	1

Based on the results shown above it, it is evident that both of the buildings are receiving a total of four stations. These results are interesting, for one, because the square footage (ft^2) of Cooper Library is much greater than Freeman Hall. Cooper Library is 200,134 ft^2 while Freeman Hall is only 71,132 ft^2. That is a difference of about 129,002 ft^2 which is impressive. Despite Cooper Library being larger than Freeman Hall, the results in terms of the number of stations are the same. This displays the effectiveness of a model that is run by door because if the deployment was based on building square footage (on its own) then the deployment might not be adequate because it does not really capture the foot traffic into the buildings. Thus a deployment of such might not be as effective. Another reason that, despite Cooper Library being a much larger building, the results are the same is that Cooper Library is one of the buildings where the flow of traffic into, and out of the building, goes primarily through one main entrance and one main exit. This goes back to CU Facilities providing us with information during the interview process about how one of the changes that the university made to their existing policies was to eliminate two-way traffic patterns in buildings to try a minimize the number of times that individuals crossed paths when entering and exiting buildings. (A side note with regards to this is that it again illustrates the benefits of incorporating the input of the key decision-makers into the model design because it allowed us to produce results that accurately align with the procedures that were implemented at the university). Therefore, it is appropriate to place stations at these points and as the results show, some of the other doors might not get stations because the foot traffic through them is not as large, despite this being a larger building.

It is worth mentioning that these results were also shared with members of CU Facilities so that they could get a better understanding of the model and its functionality. Upon review, CU Facilities indicated that these results, and a model like would help them with their problem solving with respect to station placement around campus. We also plan to perform sensitivity analysis with this model using DACD from more recent months. Once this data is acquired we can run the model with the new data and again share the results with CU Facilities so they can make a decision if a change to the current deployment is necessary. They have indicated though that they would be willing to make changes to the deployment if the model suggests so.

CHAPTER 6: DISCUSSIONS/CONCLUSIONS

This study used an iterative model development process (**Figure 5**) to develop and refine one heuristic and several optimization models that provide an optimal solution for the deployment of the hand sanitizer stations in buildings near exterior doors across CU's campus. The iterative modeling approach incorporated qualitative research methods (e.g., semi-structured interviews) into the model development to gain qualitative insight into what actually happened at CU so we can present a much more representative model. The hope was to make these models intuitive for the decision-makers but also add transparency for the original decision-makers. Through semi-structured interviews, we are able to understand more about the decision-making process and how CU Facilities and others came up with an initial solution. Using this input, we were able to design models that replicated their decision making. Ultimately, we designed an ideal model that provides locations for stations by exterior doors of buildings on CU's campus. In general, the results of several of the models prove that the initial station deployment across campus that CU Facilities and the other key stakeholders used was very effective in covering several percentages of the campus population. However, the initial deployment was implemented under extreme time and resource pressure. Using the qualitative input to shape the model objective and constraints thus provides an opportunity to perform tactical updates to the current deployment to better meet the goal of consistently covering the campus population.

Furthermore, this study is also unique because it finds an alternate way to implement a max coverage model for location based decisions using CU's DACD that provides information on how many times exterior doors are being opened which directly relates to the foot traffic through campus buildings. The data could be gathered for multiple buildings and multiple doors on campus to give a better idea of where the foot traffic through buildings is the greatest. With this information it seemed reasonable to incorporate it into the model and cover these areas to potentially provide the campus population with better access to hand sanitizer station supplies. The DACD is also interesting because it was used more consistently once the pandemic started which again demonstrates CU’s adaptation to the challenges that the pandemic presented.

In addition, this work shows how an optimization model would provide an optimal solution to the scenario as well as an alternate perspective and strategy to address the problem of location decisions in buildings on CU’s campus. The model does indicate that an improved distribution of coverage is possible; including areas which may need more stations for upcoming semesters. The supply of sanitizer stations is less constrained than in the initial decision process (because of wider availability), and there is the opportunity to add more to areas that are currently under-covered. Likewise, the model gives CU Facilities a way to handle the deployment and check for ways to track the traffic flow in and out of buildings. In the event that another pandemic ever happened again this work would help CU Facilities to act on the situation.

Several of the models offered a way to address the location decisions at CU. The initial heuristic offered a basic depiction of the current deployment and provided the opportunity to make an initial comparison. Iterating from the heuristic to the first optimization model, **Model Version** I, helped to address the issue and provide suggestions for locations within a specific building (e.g., Freeman Hall). The model provided results that would maximize the coverage of classrooms in use during a typical semester. With this model, we are also able to identify the maximum coverage times when choosing values of p (the number of stations to be located) between one and four. The optimal station locations for each p value (middle column of **Table 7**) differs from the current station locations in Freeman Hall. For example, when **Model Version I** was run with p equal to three (meaning that the model would choose three optimal locations for stations), which matches the current number of stations in Freeman Hall, neither station **3**, **6**, or **7** (the numbers refer to the labels in **Figure 8**) was chosen. Instead, locations **0**, **5,** and **9** were determined to be the most optimal when p is three.

Even more so, when p is equal to three and p is equal to four, the maximum coverage time remains at eight seconds (see the third column of **Table 7**). This means that if p is equal to four or p is equal to three, the maximum amount of time it will take someone to get to the nearest dispenser station from any of the three classrooms remains at eight seconds. This provides more evidence to suggest that that CU Facilities' initial deployment of three stations in Freeman Hall was efficient. The individual building model focused on coverage time proves that it would not be better to locate four stations as opposed to only three. However, the contributions of this model prove that even though the current number of stations in Freeman Hall can remain the same (three stations in total), the specific locations of these dispensers could be adjusted to reduce the amount of time it takes someone to travel from one of the three classrooms to a location of one of the stations. In general, the results of **Model Version I** help to understand more about how using a *p*-median Max-Coverage Model can help find optimal locations for hand sanitizing stations within a single academic building such that the coverage of the classrooms in that building in use is maximized. The contributions of this model could be extended to other buildings on CU's campus. Then the coverage of the classrooms within each of those buildings could also be maximized. Even more so, the coverage parameter, which in the case of this model was time, could be changed to distances. Then running the model this way could determine the number of stations that would maximize coverage of classrooms based on the distances between a classroom and a location of a dispenser. All in all, the results of this model can certainly be used in practice to effectively help CU Facilities determine locations for stations based on some coverage metric.

Moving on from **Model Version I**, we wanted to design a model that addressed campus wide allocation. The location covering model (**Model Version II**) did just this. **Model Version II** recommended locations for stations in buildings where the foot traffic through those buildings was the highest. The model-recommended locations differ from the initial deployment (shown in **Figure 15**); the recommendations tend to be to reduce the number of located stations. This indicates that campus is largely over-rather than under-covered. Once again, this relates to how CU Facilities suggested they preferred to distribute more supplies than less. The model itself gave a better comparison than did the heuristic for locations around campus, however these locations weren't building specific (i.e., the model only suggested how many stations each building should be getting based on foot traffic). Then we reconvened and came up with another iteration of the location covering model that would offer specific locations for stations within buildings.

Model Version III was the first optimization model that offered locations (exterior doors) for station dispensers. The optimization model itself used the DACD by door as opposed to by building and the model optimally located stations at the doors that saw the most foot traffic. This model was also the first of its kind during this study that allowed some doors to receive more than one station. The model was shown to be effective in its allocation but the results for each building were limited in that the buildings were restricted to their current capacity of dispensers. With that being said we knew that it was imperative to make a change since the model was not relocating across campus by door. In the end, removing the capacity constraint from **Model Version III** led to the design of the last model version (**Model Version IV**).

Model Version IV provided us with suggested locations by door across campus. This model was seen as the ideal representation of the initial decision-making strategy. It fundamentally incorporated several of the decision-maker's deployment approaches. It would also enable CU Facilities to make tactical updates to their policies based on up-to-date DACD. After discussions with CU Facilities, their hope is to use the model and run it once, and potentially twice a year, to see if they need to make any necessary changes to the deployment in order to maintain their goal of campus coverage. We hope we can continue to work with CU Facilities and provide them with a better understanding of how to run the model on their own and interpret the model results.

Limitations

There are some limitations associated with the framework outlined in **Figure 5**. For one, the process can be very time consuming. Therefore, it might be difficult to use the model to make quick decisions. Moreover, each of the model iterations do not consider human behavior. That is, the current study does not focus on the station's usage. This study is focused primarily on population coverage, or coverage of the high foot traffic areas through buildings using different versions of discrete facility location models. We believe that placing stations in these locations may present the opportunity for usage as opposed to actually predicting exact usage. Additionally, the models do not consider any of the financial aspects associated with placing the sanitizer stations in the buildings. This is assumed because CU Facilities reported that finances were not a concern when trying to acquire sanitizer materials. The goal at the time was to acquire as much as possible and as soon as possible such that they could "smother campus" with sanitation supplies. Future modeling work could consider coverage and expenses. Such a model could accurately determine the optimal number of stations to place while also minimizing the total cost to CU.

Future Work

As it has been mentioned, once we are provided with an accurate data set of DACD for a more recent semester (e.g., Fall 2021), we will rerun the ideal representative model (**Model Version IV**) with this data. We will then analyze the data and provide recommendations to CU Facilities in the hope of a planned redeployment of hand sanitizer stations in preparation for the next upcoming semester (e.g., Spring 2022). We have spoken with CU Facilities and the plan is to get accurate DACD to be able to use the ideal representative model in a tactical style. This will allow CU Facilities to monitor the effects of changing demand (i.e., foot traffic through campus buildings) and determine thresholds for demand spikes that would trigger recommendations for additional sanitizer stations to be located in under-covered areas. Additionally, the model results may suggest stations ought to be removed from buildings if there is a significant decline in foot traffic in that area. Even more so, the results might show that a station at a door in a building might need to be moved to another door in that building. Again, these types of tactical updates to the current deployment are all possible and achievable with the current model version (**Model Version IV**).

Other work involving the model would include increasing the number of buildings in the DACD. Increasing the set of buildings would, theoretically, increase the number of stations that are available to locate which will modify the results. Another area of interest for us to consider is coverage and expenses in the objective function of the model. It was mentioned in the limitations of this study that the model, in its current form, does not account for financial expenses. This is something that could be addressed in future modeling work. Additionally, with the current model (**Model Version IV**) we could see if there is any correlation between the results signifying a building is under-covered (meaning the building currently does not have enough stations) and positive COVID-19 cases.

Moreover, we have generated ideas about other ways to blend the two research methods (i.e., OR and HFE). One of the possibilities is to pair the optimization model results with an observational study. This study would involve measuring the usage of the stations in their current locations for a semester (e.g., Spring 2022). In order to measure usage, we have discussed working with CU Facilities and having them keep track of how many times a station has to be refilled throughout the semester. Then we will rerun the model with updated DACD from the semester (Spring 2022) and redeploy the stations in conjunction with the model results for the next upcoming semester (Fall 2022). We would again monitor the usage of the station, and following the conclusion of the next semester (Fall 2022) the research could see if the usage increased or decreased from one semester (Spring 2022) to the next (Fall 2022) based on redeployment.

Observational studies involving the usage of hand sanitizer stations have been performed in the past, however, it would be motivating to see if the usage increases after a redeployment of the stations based on results supplied by an optimization model. This would demonstrate the effect of blending research methods. Equally, we also plan to continue to meet with CU Facilities to address any changes in CU's policies to see if the model can be further refined or modified to accommodate those changes. Further qualitative analysis of these meetings using the MAXQDA software might result in additional iterations upon the current ideal representative model. Likewise, we believe it is worth considering the students who use the campus buildings as one of the stakeholders. Through semi-structured interviews, these students could evaluate the approach and provide feedback on the deployment.

Moving forward, we hope to be able to build an algorithm for CU Facilities that utilizes **Model Version IV**. The algorithm would enable them to add more campus building and doors so that they can test the model and analyze the results with other buildings and doors. It would also allow them to be able to run the model with different timeframes of DACD. Providing them with this type of deliverable would allow them to make their own tactical changes to the station deployment and track demand spikes of DACD in additional buildings. Furthermore, we hope to work with CU Facilities to determine the doors that currently have stations and see how the model results compare with that current deployment. This would then provide a comparison to the initial deployment but also allow CU Facilities to make any changes or improvements they deem necessary.

Besides other academic buildings being added, the model could also include residence halls (i.e., on-campus student living) and dining halls as possible locations. These types of buildings also account for a lot of the foot traffic on campus as well. Several of the interviewees during the interview process talked about how they knew that residence halls were where the majority of the students would be located upon returning back to campus, so it would be beneficial to consider these locations in the model as well. The model could also allow some doors to have more than one dispenser like what was done with **Model Version III**. It makes more sense and is more effective to place multiple dispensers at one door instead of multiple throughout based on the layout of the certain buildings.

Additionally, an algorithm like this could have other applications at different universities across the nation. Many universities may also use key card scanners like CU's TigerOne cards to gain access into buildings. If they have the ability to collect data on this information, then they too would find a model and algorithm such as this one useful. Likewise, at CU specifically, providing CU Facilities with an algorithm would allow them to monitor traffic flow in and out of buildings. With this information available, they could make other placement decisions for things like garbage cans, marketing techniques related to healthy COVID-19 guidelines, mask placement, etc. The model would not have to be used solely for sanitizer station placement. Similarly, we understand that the application of this type of integrated methodology is not limited to hand sanitation decisions or university COVID-19 responses. By identifying stakeholder adaptations through qualitative analysis, modeling can be better informed and more accurately represent other real-world systems.

Another area of interest that could be addressed with this study would be to use the representative model to consider locations within the interior of several buildings. From the interviews, the research identified several other potential locations that were considered by CU Facilities and other stakeholders. For example, an interviewee said that they looked at areas "…near the main elevator banks" because large portions of the campus population would congregate at these locations. Especially, for buildings with multiple levels, one of the considerations to CU Facilities when deciding on placement "…was always the main way for folks getting up to the other levels" besides the elevators. With this, it might be worth using the model to analyze main stairwells in buildings with multiple levels as possible locations. Another point of interest is that several of the buildings on-campus have meeting areas where portions of the population will gather. For example, some of the buildings have a Starbucks, markets, dining areas, etc. It would be reasonable to consider these locations in the model because they are high volume areas. Even more so, the interviewees identified interior locations that were "high-touch points" (i.e., elevator buttons, door handles, etc.). The representative model could incorporate these locations into the model and apply a certain percentage to these locations that would suggest if the other entry points do not exceed some threshold then the station should instead be placed at that interior location. All in all, while this study is in-part retroactive in evaluating historical allocation decisions through models created with hindsight, it may be possible to use models concurrently with decision-makers during reactive situations. Similarly, if decision-makers and stakeholders are able to predict necessary adaptations, modeling could be utilized to successfully present optimal solutions to problems that do not yet exist.

APPENDICES

Appendix A

Qualitative Data Collection

COVID Response: Sanitizer Deployment Semi-Structured Interview Protocol

Brief introduction about the study and purpose of the interview. *"The purpose of this study is to understand how Clemson University adapted to the COVID-19 pandemic. We are particularly interested in understanding how decisions were made relating to hand sanitation strategies on campus and how these strategies have been implemented. During this interview, we will ask you to describe your role in Clemson's response and hand sanitation policies, and seek your perspectives on what worked and what didn't. We seek your permission to continue recording this interview for the purpose of transcription and analysis. Do you have any questions or concerns before we begin?"*

Note to interviewer: The questions listed below represent important themes or categories of information to be obtained from the participant. The order of questions can be adjusted according to the flow of the interview and topics emerging from the participant's responses. 'Probes' listed alongside some of the questions indicate items or themes that the interviewer should look out for in the responses and ensure are covered during the interview. They may be used as follow up questions to guide the response of the participant or to have them elaborate on a response.

Questions

Your role / beginning of the pandemic

- Briefly describe your role at Clemson University and your general responsibilities.
  - How does your role relate to the University's hand sanitation policies?
- What were the main challenges you and your team faced at the start of the pandemic (around March 2020) in terms of decisions around facilities / hand sanitation?
- Was there a contingency plan already in-place available for the pandemic response or a similar crisis (either provided by the university or some other organization?

Sanitizer Placement Considerations

- What were your main goals in terms of hand sanitation on campus?
  - Probes: Infection control; graduation times; student stress; resources for remote classes
- How did students' and their families' perspectives factor in to your decision making process?

- What were some of the student-specific considerations that emerged?
- Probes: Safety; flexibility; accommodation (esp. for those coming from outside of Clemson);

- What types of information were needed or sought regarding hand sanitation? Were these available?
  - Probes: Categories and sources of information
- How was this information shared?
  - Probes: Media of communication – emails, dashboards, databases, messaging systems
- How were hand sanitation information and decisions communicated across institutional layers – President and Provost's offices; college-level leadership; departmental leadership; other administrative offices?
  - Probes: Emails, town halls, dashboards, meetings/taskforce
- How did you know what information to look at and when?
  - Probes: Government and external reports and guidelines (e.g. CDC, WHO, Federal, SC State)
- How were decisions and implementation actions coordinated across various bodies? Who were the facilitators?

Sanitizer Placement Strategies

- What are the current benchmark goals or metrics for right now and future semesters concerning hand sanitizers on campus?
- Did you use any data analytics or modeling in the station placement? Please describe this process.
  - Did you use any "rule of thumb" style decision processes early on?
- How did you decide what might be an 'optimum,' or *ideal* number of stations for individual buildings and the entire campus?
  - Was the strategy to cover (reaching the ideal number of sanitizers) individual buildings one-at-a-time or all of campus?
  - How did you balance allocating sanitizers between large buildings with significant square footage and busy buildings with heavy traffic?
  - Probes: no. of classrooms or spaces; classroom size; no. of students who wanted to be on campus vs. remote; other
- How did variability and uncertainty influence your decisions?
  - Probes: changes in advisories/guidelines; infection rates; student attendance; other
- Was there any simulation or testing involved to better understand student behavior with the hand sanitizers?

Course Corrections

- Once classes resumed (hybrid / full in-person), how did you monitor how things were going with hand sanitizers?

- Probes: attendance; infection rates; testing protocols; compliance; other

- How have hand sanitation plans/strategies been adjusted based on the actual dynamics of classes and student-presence on campus? What have some of these changes looked like?

Future Direction

- Looking back, what types of information/data have been most important or useful in this process?
  - Is there any additional data or information that would have also been useful?
- What directions are being looked at for the future? Will hand sanitation strategies drastically change moving into the fall?
  - Is there any plan to reduce the number of hand sanitizers on campus in the future?
- If COVID-25 were to happen in a few years, how has this experience working with hand sanitizers prepared you for a similar crisis such as that?

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