Drive-Through Vaccination Clinic Modelling Using VBA

by

Sherline Ravisha Jayamaha

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Dalhousie University is located in Mi'kma'ki, the
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We are all Treaty people.

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Abstract

With the strain placed on healthcare systems due to the COVID-19 pandemic, the Canadian healthcare system needed to adopt creative ways to immunize communities. Adopting models from drive-through vaccination clinics in other jurisdictions, providers in Canada adapted to deliver vaccines in drive-through clinic settings. However, the novelty of this delivery mechanism made planning for an efficient drive-through clinic challenging. Planning and organizing a drive-through vaccination clinic is an intricate process involving thoughtful assessment of various factors. This includes the availability of space and infrastructure, staffing requirements, vaccine supply, and communication strategies, all of which must be planned and executed to ensure a successful and efficient vaccination process.

The presented model is a valuable tool for healthcare providers to streamline the design and planning process of drive-through vaccination clinics. Its user-friendly interface, built on the widely used Microsoft Excel program, requires no additional software or specialized simulation skills, making it accessible to a wide range of users.

The model creates a generic clinic layout while adhering to bottleneck limitations using an M/M/s/K (limited/finite capacity) queuing network model. This method provides a picture of how the clinic runs, allowing for efficient clinic performance adjustments.

A feasibility study was carried out to validate the model, showing its practicality and giving decision-makers the assurance to design and operate an effective clinic. The feasibility check determined if the horizontal and vertical space available in the clinic's layout was sufficient to accommodate the minimum number of stations required for efficient operation and an adequate queue to reduce patient wait times.

This model is an important addition to the planning and design tools used by the healthcare industry due to its usability, which ultimately raises the standard of care provided to patients.

List of Abbreviations and Symbols Used

DES	**D**iscrete **E**vent **S**imulation
DSS	**D**ecision **S**upport **S**ystem
FCFS	**F**irst **C**ome, **F**irst **S**erved
K	Capacity of the lane
L	Expected number of vehicles in queuing system = $\sum_{n=0}^{\infty} nP_n$
L_q	Expected queue length (excludes customers being served)
n	Number of vehicles
P_0	Probability of zero vehicles in the queuing system
P_n	Probability of exactly n vehicles in the queuing system
POD	**P**oints **O**f **D**ispensing
PPE	**P**ersonal **P**rotective **E**quipment
R	Service time at each station/server
RealOpt	**Re**source **al**location **Opt**imization
s	Number of servers/stations (parallel service channels) in the queuing system
SARS	**S**evere **A**cute **R**espiratory **S**yndrome
t	Operation time (time the clinic is open per day)
W	Waiting time in the system (including service time) for each vehicle
W_q	Waiting time in queue (excludes service time) for each vehicle
WHO	**W**orld **H**ealth **O**rganization
λ	Mean arrival rate (constant for all n)
μ	Mean service rate for the overall system when n number of vehicles are in the system
ρ	Utilization factor

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Chapter 1: Background

The COVID-19 pandemic had a significant impact on the global economy and caused widespread illness and death worldwide. This global crisis was caused by SARS-CoV-2, a large family of viruses categorized as a type of coronavirus, a contagious respiratory illness like influenza (Variants of the Virus that Causes COVID-19, 2021). The name SARS-CoV-2 was given to the COVID-19 virus as it mirrors the genetic relationship of the Coronavirus SARS, which broke out in 2003 (Kost, 2020). Although the coronavirus and the seasonal flu have similar symptoms like cough, fever, and body aches, the virus differentiates itself by spreading more rapidly than the regular flu and has a higher fatality rate, especially among older adults and those with underlying health conditions.

The outbreak appears to have started in Wuhan, China, in mid-November 2019, with its first cases identifying as a strange new flu (60 Minutes Australia, 2020) (CBC News: The National, 2020). By early December, Chinese authorities declared that the new virus was nothing like the 2003 version of SARS (Severe Acute Respiratory Syndrome). On December 31st, 2019, China reported twenty-seven cases of a type of new pneumonia from an unknown cause to the WHO (World Health Organization), with speculation that the spread might have come via a live fish and animal market (wet market) (Bryner, 2020) (Davidson, 2020). The source of the virus is yet to be disclosed, but speculations are that the virus was carried via animals in the wet market, and people were infected by handling these animals (CBC News: The National, 2020). The official announcement from China in late December 2019 stated that there was no evidence of human-to-human spread. However, on January 20th, 2020, China officially declared that the virus could be spread from person to person as health workers in Wuhan were starting to get sick (CBC News: The National, 2020), with over 400 cases a day of this new virus were identified (60 Minutes Australia, 2020). By mid to late January 2020, other Asian countries like Thailand, Japan, and South Korea started reporting cases of this new coronavirus, confirming that the virus can spread from person to person (Channel 4 News, 2020). Canada established its first coronavirus case on January 25th, 2020, after a man travelling from Wuhan, China, tested positive for the virus. By 30th January 2020, WHO declared the outbreak a global public health emergency as over 9,000 cases were reported within 18 countries beyond China (CBC News: The National, 2020). By March 11th, 2020, the outbreak in China was declared a global pandemic by WHO. By then, the virus had already started to spread globally via people who initially travelled in and out of Wuhan before the lockdown in China (60 Minutes Australia, 2020) (Channel 4 News, 2020).

Like any other virus, the novel coronavirus changes through mutation, resulting in new variants of the virus (Variants of the Virus that Causes COVID-19, 2021). In the fall of 2020, the United Kingdom (UK) identified the first variant called B.1.1.7 (Variants of the Virus that Causes COVID-19, 2021) (CBC News, 2021) with a large number of mutations, that quickly spread if they came into contact with a person. Different variants were later discovered in other parts of the world. The SARS-CoV-2 virus could efficiently spread more than the influenza virus, but less efficiently than measles, which still categorizes the SARS-CoV-2 virus as one of the most contagious viruses known (Variants of the Virus that Causes COVID-19, 2021).

Towards the end of March 2020, restrictions were enforced globally to slow the spread of the virus. In Nova Scotia, Canada, masks became mandatory in any public setting to reduce transmission through breathing, public gatherings were prohibited to minimize public exposure to people that might be unknowingly carrying the virus, provincial lockdowns were enforced to isolate the spread of the virus, a social distancing of at least six-feet apart was implemented at public locations (like grocery stores, hospitals, etc.) to slow the spread of the virus from person to person, a two-week quarantining period became mandatory for travellers (Channel 4 News, 2020) (Prevent Getting Sick, 2021). Provinces like Nova Scotia that strictly enforced these restrictions were able to reduce the spread of the virus within their communities.

In the latter part of 2020, COVID-19 still lacked a definitive cure and restrictions were still in place to control the spread of the virus. However, by December of 2020, vaccines were available in Nova Scotia to limit the impact of the disease. Therefore, communities had to find alternative methods of safely delivering vaccines for the seasonal flu and COVID-19. Since keeping a safe distance between people (i.e., social distancing) was essential, health systems adapted alternative methods to deliver seasonal flu shots and COVID vaccines to communities. One such method was the drive-through vaccination clinic, which is perceived as a safer and less contagious mode of vaccinating recipients. Drive-through vaccination clinics had been utilized in the past, especially in North America, to mass vaccinate during public emergencies (Asgary et al., 2020). During the

COVID-19 pandemic, many countries adapted to vaccinating via drive-through clinics, and past research and clinic models were revised and incorporated into clinic modelling.

To vaccinate the community against the seasonal flu, a local health clinic in Halifax, Nova Scotia, Canada, wanted help to deliver seasonal flu shots more safely to the families in its practice. Since Halifax already had a COVID testing drive-through clinic, it was decided to incorporate a similar drive-through clinic model to deliver the seasonal flu shots to families in their vehicles over two separate days during the months of September and October of 2020.

1.1 Introduction

In response to the ongoing COVID-19 pandemic, many countries like South Korea, Canada, and the United States adopted drive-through COVID testing centers (Kim, 2020) since they reduce the amount of direct contact between people and thus reduce transmission of the virus (Prevent Getting Sick, 2021). In Nova Scotia, Canada, drive-through COVID testing centers became popular, mainly due to the regulations of social distancing and the fear of contracting the virus due to exposure to other people. In Dartmouth, Nova Scotia, the Nova Scotia Health Authority operated a drive-through COVID testing clinic on an appointment basis, which allowed Nova Scotians displaying symptoms to get a swab test done. Not only were these drive-through testing clinics faster than a traditional setting, they also allowed more residents to get tested with a degree of certainty of not contracting the virus in these testing sites, as there was no exposure to other patients (Al-Hakim, 2020). Similarly, regions in Canada, like Ontario, Saskatchewan, Edmonton, and British Columbia also deployed drive-through testing sites to accommodate more people in their respective communities (Al-Hakim, 2020).

Adopting and repurposing drive-through testing center models and infrastructure, potential mass vaccination strategies can be leveraged to vaccinate communities against both the seasonal flu and the COVID vaccine. Vaccines are an effective way to stop disease spread, as vaccination is the primary strategy for deterring and controlling seasonal and pandemic influenza (Osterholm, 2012). A vaccine protects the people vaccinated and others around them by building immunity to the disease, making it difficult to spread (Reasons to vaccinate, 2020). The more people in a community are vaccinated, the harder it becomes for a disease to spread. In the case of COVID-

19, where the SARS-Cov-2 coronavirus infected the airways and lungs, it was essential to take measures that prevented the spread of the virus. One such measure was the COVID-19 vaccine, which reduced the risk of getting sick and hospitalization (COVID-19 Vaccines, 2022).

Drive-through vaccination clinics not only increase efficiency by increasing the number of patients treated per unit time, reduce space allocated for administration and waiting areas, but also reduce personal protective equipment (PPE) wastage when compared to a traditional clinical setting, as medical professionals do not come into contact with individuals as much (Kim, 2020, Al-Hakim, 2020). Nova Scotia's first-ever drive-through vaccination clinic was operated by the Dartmouth General Hospital on the 10th of May 2021, after adapting their COVID-19 drive-through testing clinic model. This drive-through vaccination clinic provided an initial vaccine rollout of approximately 160 vaccines per day (Nova Scotia's first drive-thru COVID-19 vaccine clinic opens, 2021).

Mass vaccination clinics administer immunizations (vaccinations) to many people in a short period of time. Due to the lower virus transmission possibility in drive-through clinics, it has proven to be effective for vaccinating communities during public emergencies like the H1N1 and COVID-19 pandemic. Drive-through facilities for mass vaccinations must be executed in open areas, like a parking lot, as they allow ample space to accommodate many vehicles to move about in their respective lanes (Asgari, Valtchev, & Chen, 2020). This allows for a more efficient and organized flow of traffic, which is vital for ensuring that the vaccination process runs smoothly and safely. By setting up the vaccination site in an open area, such as a parking lot, the clinic organizers can easily create a layout with multiple lanes or a specific traffic flow pattern to ensure that vehicles move quickly and efficiently through the site.

Additionally, an open space allows for many vehicles to be accommodated, which is important for mass vaccination campaigns, where a large number of people need to be vaccinated quickly and efficiently. Moreover, open areas, like parking lots, typically have easy access and egress, which facilitates traffic management and helps to prevent congestion. This allows recipients to get in and out of the vaccination site quickly, reducing wait times and improving the overall vaccination experience.

If the drive-through clinic for mass vaccinations is large, support from local emergency services like the police, fire department, and paramedics should be acquired in case of emergencies (Asgari, Valtchev, & Chen, 2020). This is because emergencies can still occur even with careful planning and implementation, and having trained professionals available can help ensure a timely and appropriate response. Local emergency services can help manage traffic and aid in the event of a collision or other emergency that may occur in or around the vaccination site. In addition, they can provide medical support and care for individuals who may experience adverse reactions or other medical emergencies after receiving the vaccine.

The typical layout for a drive-through vaccination clinic involves at least a registration operation, a screening operation, a vaccination operation, and a post-vaccination hold area. The registration operation is the first operation in the drive-through vaccination clinic, where workers greet the patient, check to determine if the patient(s) is (are) eligible for the vaccine, verify the patient's identity, and distribute any paperwork (registration forms, consent forms, etc.) that must be completed.

The standard second operation at the drive-through vaccination clinic is the screening operation. Workers check the patients' registration forms, provide information about the immunization procedure, and direct them to the vaccination stations. During the screening process, workers may also ask patients about their medical history and current health status to identify potential risk factors or contraindications for vaccination. The screening process is essential to ensure that patients are prepared for vaccination and understand the procedure and potential risks. It also helps to ensure the vaccination process runs smoothly and efficiently, with minimal delays or issues.

In the vaccination operation, patients are vaccinated and are then directed to the discharge area to wait for 15 to 30 minutes to be monitored for any reaction from the vaccine (Covid Vaccine Drive Thru Protocol, 2021, Zerwekh, et al., 2007). This is done so that if a patient does experience an adverse reaction to the vaccine, healthcare professionals can attend immediately.

While drive-through vaccination clinics are convenient and efficient, it is vital to store the vaccines adequately. Vaccines should always be stored at temperatures recommended by the manufacturer until it is administered to the recipients. Exposing vaccines to temperatures outside the recommended temperature ranges can reduce the quality and potency of the vaccine (Vaccine

Storage and Handling, 2021). Pharmacies or hospitals running drive-through vaccination clinics must accommodate space for the storage of appropriate freezers, refrigerators, or temporary cold containers (i.e., coolers) to store the immunizations throughout the time the drive-through vaccination clinic is running. The ideal temperature for vaccines storage is between 2˚C and 8˚C (36˚F and 46˚F), although some vaccines require colder temperatures (National Vaccine Storage and Handling Guidelines for Immunization Providers, 2007). The temperature of the storage unit should be monitored and recorded at least twice a day using calibrated thermometers. The vaccines must be kept in a continuous "cold chain" from the manufacturer to the point of administration. This means vaccines must be transported in a properly insulated container protected from temperature extremes during transport. Vaccines should also be stored in a dedicated refrigerator used only for vaccine storage (National Vaccine Storage and Handling Guidelines for Immunization Providers, 2007).

Canada implemented one of its first-ever drive-through COVID-19 mass vaccination clinics for York Region residents in the parking lot of Canada's Wonderland in Vaughan, Ontario, on 30th March 2021 (Drive-through vaccine site opens at Canada's Wonderland, 2021). To have an efficient vaccine delivery system in this drive-through vaccination clinic, multiple vaccines were pre-drawn and set aside in trays before the mass vaccination event, making it easier and faster for immunizers (Swift, Aliyu, & Byrne, 1971). The vaccines were stored in refrigerators placed in busses at each lane, where the nurses could draw and load the vaccines. Simultaneously, the vaccinators retrieved pre-drawn vaccine doses from the designated bus and proceeded to administer them to the recipients (Drive-through vaccine site opens at Canada's Wonderland, 2021).

Drive-through vaccination clinics are favoured in urban and rural areas having lower-than-average population density and wealth (Kim, 2020) for several reasons. First, in areas with lower population densities, drive-through clinics can be more efficient and cost-effective than other methods of vaccine distribution. This is because drive-through clinics can serve a large number of people quickly and efficiently without requiring a significant number of staff or infrastructure. Additionally, drive-through clinics can be set up in open areas, such as parking lots, which are often readily available in less densely populated areas. Second, drive-through clinics are often more accessible for individuals who may not have easy access to healthcare facilities, such as those living in rural areas. Rural areas often need more healthcare facilities and services, making it challenging for individuals to access healthcare, including vaccinations. Drive-through clinics can address this issue by providing a temporary and mobile vaccination site that can be set up in locations that are more accessible to rural communities, such as parking lots or community centers.

This thesis will look at the drive-through vaccination clinics in the Canadian context and the standards that must be maintained to run a drive-through vaccination clinic efficiently and successfully.

1.2 Motivating Example

This thesis is motivated by the mass immunization clinics conducted during the recent pandemic of COVID-19. With the need for social distancing to minimize the spread of the virus, healthcare professionals opted for drive-through clinics to deliver vaccines. The concept of drive-through vaccinations was a novelty at the beginning of the COVID-19 pandemic in Canada, which motivated us to take a deep dive into clinic modelling and functionality in more detail.

To better understand the drive-through clinic's function, we collaborated with a local clinic in Halifax, Canada that was providing vaccinations against the seasonal flu. This clinic was observed in person, and the functions of the clinic were studied in-depth to provide a stepping-stone in creation of the model. By analyzing the clinic's operations, we identified the key factors contributing to an efficient drive-through vaccination clinic's success.

The results generated via the model can guide the design and implementation of drive-through vaccination clinics in the future, particularly in the context of public health emergencies. The research can help healthcare professionals understand the best practices for designing and operating these clinics, optimizing patient flow, and minimizing wait time, while assuring that social distancing and other safety measures are maintained.

Overall, the thesis contributes to the growing body of research on healthcare management and public health emergency response, providing valuable insights into how drive-through vaccination clinics can be modelled and optimized to deliver effective care while minimizing the risk of spreading infectious diseases.

1.3 Objectives

The objective of this thesis was to create a user-friendly desktop application that enables decision-makers at medical facilities to generate a standard layout for drive-through vaccination clinics. The application was developed using Microsoft Excel, a commonly used program accessible to most Canadian health care providers. The primary goal of this application is to facilitate efficient and effective planning of immunization clinics by providing decision-makers with the tools to allocate appropriate resources and ensure a smooth flow of traffic throughout the clinic. By achieving this, the thesis contributes to the ongoing efforts to combat the COVID-19 pandemic and enhance the overall quality of healthcare delivery in Canada.

1.4 Tool Overview

The model is run via Excel VBA (Visual Basic for Applications), enabling the user to generate a model with a simple button push. Queuing theory and feasibility checks have been incorporated into this model to verify a clinic's functionality. Questions like, "how many staff are needed and how many stations are required for a clinic to run smoothly without a bottleneck while efficiently using resources" are easily discernable with this tool.

The model created in this project uses the M/M/s/K queuing model within a user-friendly framework implemented in Microsoft Excel/VBA that achieves the following objectives. It:

1. Develops a model that, with a push of a button on the Excel sheet, will generate a table with metrics and a visual representation of the vaccination clinic.
2. Completes feasibility checks to validate the layout.
3. Determines if the proposed layout is feasible/not feasible.

1.5 Thesis Outline

This thesis identifies the minimum number of stations needed to run a drive-through vaccination clinic effectively. To achieve the proposed objectives in this thesis, an understanding of the need for drive-through vaccination clinics during pandemic situations is needed. This is discussed in Chapter 1.

Chapter 2 discusses other models created by researchers for drive-through mass vaccination clinics. This chapter discusses the various models developed, their primary outcomes, and areas of focus. The chapter also highlights the differences between the model created via this project and the models found in the literature. The chapter also discusses the M/M/s/K queuing model used to develop the tool.

To better understand why this thesis was conducted, a discussion on the motivating example is described in Chapter 3. An analysis of the motivating drive-through vaccination clinic can also be found. This section details how this drive-through clinic was modelled, and the changes needed to ensure the clinic ran smoothly.

The design of the model and the methods used to develop the tool are discussed in depth in Chapter 4. The feasibility and effectiveness of the model created in this thesis are also discussed in this chapter.

Finally, conclusions of the drive-through vaccination clinic and modelling of drive-through vaccination clinics are discussed in Chapter 5, along with limitations of the current model and recommendations for future research.

Chapter 2: Theoretical Background

This chapter explains the concept of a drive-through vaccination clinic and demonstrates the various drive-through vaccination clinic models created by researchers to assist during pandemic situations. The focus areas for each model, including the clinic layout, patient flow, staffing requirements, resource allocation, and other factors that can impact clinic throughput, are discussed in section 2.1.

Section 2.2 delves into the queuing theory used, which is a mathematical model that can be used to analyze and optimize waiting lines. The chapter explains how queuing theory can be applied to drive-through clinics and discusses the specific model used to create the drive-through clinic model for the project.

2.1 Drive-Through Clinic Models Found In The Literature

There is significant literature on drive-through vaccination clinics designed to mass vaccinate people during terrorist attacks, public emergencies, and even against the seasonal flu. Various researchers have created models to simulate effective drive-through vaccination clinics or to suggest resource allocations for the clinic to run smoothly. In this literature review, a search was done for mass vaccination and drive-through clinics to identify the application of a drive-through clinic and how this concept can be applied to a Canadian context.

Rapid vaccination using drive-through clinics requires proper site selection and design, human resource management, and careful attention to operational and logistical details (Asgary et al., 2020). Planning for a drive-through vaccination clinic allows the clinic to disperse vaccines adequately in a given time frame. To prepare for an effective drive-through clinic, the clinic planner must first identify parameters that can help plan for the clinic. These include the number of patients to be vaccinated in a day or a given event (this can correspond to how many vaccines the clinic has on hand), how many hours the clinic should be running across an event, how many operations (e.g., an operation to register patients, an operation that vaccinates patients, etc.) the clinic wants to have (this corresponds to breaking down tasks in the vaccination clinic), and the parameters of the space to host the clinic (i.e. the length and width of the space available), since the scale of the drive-through clinic depends on the location available. Optimization around these parameters leads to efficient drive-through vaccination clinics. Since drive-through vaccination clinics require thorough planning and design, multiple simulation models can be found in the literature.

To better plan for emergencies, multiple studies were conducted, and models were developed to enhance the planning process of a drive-through mass vaccination clinic. Lee et al. developed and used the RealOpt (Resource allocation Optimization) simulation software, a standalone computerized decision-support system (DSS), to facilitate layout and resource allocations for a mass vaccination clinic during public emergencies. The DSS combines mathematical models and computer simulation to support the planning and execution of mass dispensing clinics. This system was created with mathematical models like network modelling, queuing theory, and discrete event simulation to optimize the performances of complex systems (Lee et al., 2006).

The RealOpt simulation software by Lee et al. can identify bottleneck areas, assuming different clinic designs and variations from past data, spatial layout of the area, access population, and demographic density. This system facilitates "what-if" scenarios, which help plan and re-configure emergency strategies ahead of time. One of the key features of RealOpt is its optimizing capabilities. The software can automatically optimize the simulation model based on user-defined objectives and constraints, such as minimizing costs or maximizing throughput. The optimization engine uses heuristics to find the best solution within the model's constraints. It can simulate stochastic inputs, such as arrival and processing times, and generate detailed outputs like queue lengths, waiting times, and resource utilization. RealOpt also can generate charts and graphs to help users identify trends and patterns in the simulation data. It can also generate detailed reports that summarize the key findings of the simulation.

Emergency coordinators have used RealOpt to explore staff allocations, disease propagation analysis, assess the availability of resources, conduct large-scale virtual drills, perform calculations, investigate alternative strategies, and design a variety of dispensing scenarios that include emergency event exercises to train personnel (Lee et al., 2006). According to Lee et al., the type of disaster dictates the design of the clinic layout. During the COVID-19 pandemic, the layouts for drive-through vaccination clinics had to maintain social distancing between all stations, which required ample open space.

According to Asgary et al. (Asgary, Valtchev, & Chen, 2020), drive-through mass vaccination facilities are better served when there is adequate and accessible space to accommodate various lanes and stations and when there is a good percentage of the population in the area that can use drive-through facilities, meaning, access to vehicles to partake in the drive-through clinics. Asgary et al. introduce a meta-model (model of models) created using the simulation tool AnyLogic for a drive-through mass vaccination clinic that can be used to enhance the planning, design, operation, feasibility, and effectiveness of the facility (Asgary, Valtchev, & Chen, 2020) (Asgary et al., 2020). The model integrates discrete event and agent-based modelling techniques to simulate the flow of vehicles through the vaccination clinic. It provides outputs that visually and numerically show the average processing and waiting times and the number of vehicles and people that can be served under different staff and service lanes. This model can identify bottlenecks and inefficiencies in the system and help decision-makers optimize the operations in the drive-through vaccination clinic.

In a drive-through exercise conducted by the Hawaii Department of Health to distribute medical supplies, it was proven that a drive-through clinic model presented by Zerwekh et al. could disperse supplies effectively with minimal bottlenecks (Zerwekh, et al., 2007). The model used in this study predicts the number of different types of staff needed at each station in a drive-through clinic to respond to a disaster. The model considered different factors, such as the number of dispensing lanes, the arrival rate of vehicles, the processing time for each vehicle, and the number of staff available for dispensing medication.

The throughput of a drive-through vaccination clinic correlates to the number of people vaccinated within a specific time frame. This throughput can be improved by increasing the number of dispensing lanes and reducing traffic intensity (Asgary et al., 2020). Likewise, if a particular operation in the drive-through clinic takes significant processing times, it can create a bottleneck in the system. According to Asgary et al., in a mass vaccination setting, the registration operation usually contributes to the formation of bottlenecks due to longer processing times than other stations (Asgary et al., 2020). This was found to be true for the Halifax drive-through clinic.

According to Banks et al., in a drive-through mass vaccination clinic conducted on days with fair weather, it was discovered that the processing time to deliver the influenza vaccine was less per person when there were more people in a single vehicle compared to a single person per vehicle (Banks et al., 2013). They also noticed a trend in the flow of larger groups of people per vehicle towards the early hours of the day amidst a flow pattern of many single persons per vehicle. Further observations by Banks et al. state that there was no negative impact on the processing times when children of ages nine and above were present in the vehicles among adults (Banks et al., 2013). When researching the efficacy of a drive-through clinic, observations from different researchers were identified in the areas of throughput and processing times. While some experimented with potential changes in the processing times in the presence of children, others experimented with the processing times for several heads per vehicle, disregarding any classification of occupant type. Our project ignores the heads per vehicle and considers the average service times per vehicle at each operation. In a queuing system, the service time refers to the amount of time required to complete a single service or task.

Beeler et al. (Beeler et al., 2014) created models to improve human resource management in a mass vaccination clinic. The model developed by Beeler et al. was created using Simul8. Simulations via this model generated results for costs, throughput, and infection risk, which enabled decision-makers to allocate appropriate resources to reduce costs or increase throughput. Another recent simulation model was developed by Van de Kracht et al. using Siemens Plant Simulation. This computer modelling program generates a drive-through clinic layout and offers the staffing necessary to distribute vaccines effectively (Van de Kracht et al., 2020).

The model presented by Gupta et al. presents a simulation and optimization model for drive-through mass vaccination clinics using a generalized approach. The model was created using the Arena simulation software, where the outputs generated from the model were performance measure values, enabling the decision-maker to plan the clinic for mass vaccinations according to the number of people expected to be vaccinated, operational cost, and the area required for the clinic (Gupta et al., 2013). The model uses a metaheuristic algorithm to optimize the operations of the vaccination clinic by finding the optimal number of vaccination lanes, the optimal processing time for each vehicle, and the optimal number of staff required for the clinic. Using this model, the decision-maker can adjust input variables, including the anticipated number of arriving vehicles, number of consent form lanes, number of consent form workers per lane, cost per consent form worker per hour, length of a consent form lane, number of vaccination lanes, number of medical workers per lane, cost per medical worker per hour, and the length of a vaccination lane to distinguish the impact of changes. The output of the model provides the fraction of vehicles arriving but not entering the system, the average number of vehicles in the system, the average number of vehicles waiting in a queue, the average time in the system per vehicle, the average waiting time in line, and the utilization of the workers. Using an Arena built-in tool, called Process Analyzer, the decision maker can compare the impact of different combinations of inputs on the model outputs. The model is customizable and can be used for any community size, whether mass vaccination or a seasonal flu drive-through clinic for a local community.

The model presented in this thesis creates a generic layout, enabling the user to input key performing indices such as parking lot length, width, number of hours intended to operate, the expected number of vehicles in a day, number of operations (e.g., screening operation registration operation, and vaccination operation = 3 operations, i.e., three operation lanes), and maximum percentage of time the system should be full. While models in the published literature focus on simulating drive-through clinics via simulation platforms, the model presented in this thesis uses Microsoft Excel, a platform accessible to everyone.

2.2 Queuing Theory

Queuing theory is a mathematical study identifying wait times and queue lengths in a waiting-in-line situation. A queue is typically formed when there is more demand for service than the capacity available to provide that service at that specific time. A queuing system consists of customers or units that require service. These customers arrive at a service facility where the necessary service is provided. If the service is not immediately available, they join a queue and wait for their turn. Once they receive service, they leave the queuing system. However, in some instances, customers may choose to leave the system without joining the queue or depart without receiving service even after waiting for a certain period (Mehdi, Chapter 2, 2003).

The input pattern of a queuing system plays a critical role in the functioning of the system. The queuing system's performance and the customers' waiting experience are influenced by the arrival or input pattern, which is determined by the time between consecutive customer arrivals, known as the interarrival time. To measure the input pattern in a Poisson arrival process, one can calculate the average span of the interarrival time, or its reciprocal, which is the average number of arrivals per unit time (Mehdi, Chapter 2, 2003). A queue with a high average number of arrivals per unit time and/or a low service rate may experience a high traffic congestion, which can lead to longer waiting times and potential delays. On the other hand, a queue with a low average number of arrivals with a higher service rate may underutilize the system's capacity. This is due to low to no traffic congestion resulting in wasted resources. To address this issue, it is important to analyze the system's peak hours and adjust the number of arrivals accordingly to ensure optimal utilization of resources.

The interarrival time may be deterministic, meaning that the time between arrivals is fixed and known in advance, such as a fixed interval of two minutes between customers. However, in many real-world queuing systems, the interarrival time is stochastic, which means that the time between arrivals varies randomly, and its distribution must be specified (Mehdi, Chapter 2, 2003). In this case, the distribution may follow a particular probability distribution, such as the exponential distribution, gamma, or normal distribution, depending on the system's characteristics.

Other factors that may affect the input pattern of a queuing system include the time of day, day of the week or other forms of seasonality. For example, a retail store may experience higher customer traffic during the holiday season or on weekends, which may result in a different input pattern compared to weekdays during non-holiday periods.

It is crucial to comprehend the input pattern of a queuing system and service capacity to evaluate and enhance its performance. By examining the input pattern, system designers can calculate key performance metrics such as the average number of customers in the queue, the average waiting time, and the utilization of the system. This information can then be used to design and implement strategies to manage the queuing system, such as adjusting the number of servers or service rate. They can also determine the appropriate capacity of the system, design the queuing system to accommodate a given input pattern, and implement effective scheduling policies to manage customer traffic.

In the context of service operations management, the pattern of service refers to the way the service is provided to customers. This is an essential characteristic of a queuing system because of the behaviour of the system and the performance measures associated with it. In a queuing system, customers arrive and wait in line for service, and one or more servers provide the service. The pattern of service determines how quickly each customer can be served and how much variability there is in the service times. The time taken to complete a service can be constant (deterministic) or stochastic (Mehdi, Chapter 2, 2003).

Understanding the service pattern is vital as it helps decision-makers optimize the queuing system's efficiency. If the service time is stochastic, meaning random, decision-makers can use statistical tools to estimate the average service time and the variability of service times and then use this information to make decisions about the number of servers needed, the capacity of the queue, and the expected waiting time for customers.

Each queuing model incorporates a queue discipline to identify the order in which customers are served. The most common queue discipline is "First Come, First Served" (FCFS), which means that the first customer to arrive will be the first to receive service. Other queue disciplines such as "Last Come, First Served," random order service, and priority-based service can also be modelled (Mehdi, Chapter 2, 2003).

Identifying wait times and queue lengths in a queuing system can help decision-makers allocate adequate resources to provide quality services before executing a clinic. For example, in a drive-through vaccination clinic, identifying the average wait time and queue length can help decision-makers understand how long patients must wait before receiving their vaccination and how many people are waiting in the queue at any given time. This information can then be used to allocate resources to reduce bottlenecks in the system, such as adding more staff or vaccination stations, improving the registration process, or streamlining the overall workflow.

There are many queuing models available that are used to analyze and optimize different types of queuing systems. Some of the most common queuing models are:

1. M/M/1 queuing model: This is the simplest queuing model and assumes a single server in the system with a Poisson arrival rate and an exponential service time distribution.
2. M/M/s queuing model: This model assumes a single waiting line, some number of servers (perhaps greater than 1), a Poisson arrival rate, and exponential service time distribution.
3. M/D/1 queuing model: This model assumes a single server with a Poisson arrival rate and a constant service time distribution.
4. M/G/1 queuing model: This model assumes a single server with a Poisson arrival rate and a general service time distribution.
5. M/M/1/K queuing model: This model assumes a finite capacity K in a single-server system with Poisson arrival and exponential service time distribution.
6. M/M/s/K queuing model: This model assumes a single waiting line, with a finite number of servers, and a finite capacity K, with Poisson arrival and exponential service time distributions.
7. M/M/ꝏ queuing model: This model assumes a single waiting line with an infinite number of servers and Poisson arrival and exponential service time distribution.

These models, along with many others, can be used to analyze queuing systems in various real-world applications and optimize their performance by adjusting the number of servers, the waiting line capacity, the service time distribution, and other system parameters and metrics.

2.2.1 The M/M/s/K queuing model

In this thesis, the model created uses the M/M/s/K finite queuing network model to analyze the performance of queuing systems, such as drive-through vaccination clinics. The service facility in the queuing model presented in this study consists of a single waiting line, a finite waiting area, and a constrained number of servers. The M/M/s/K queuing model is commonly used in the analysis of various queuing systems, such as telecommunication networks, healthcare systems, and transportation systems.

The "M" in the M/M/s/K queuing model stands for Markovian, which indicates that the inter-arrival and service times are memoryless and follow an exponential distribution. This means that the probability of a customer arriving or receiving service is not dependent on past experiences or the length of time they have already spent waiting in the queue. The letter “s” represents the number of servers available to server customers, while “K” represents the maximum capacity of that the model can accommodate (Winston, 2004). The M/M/s/K queuing model allows for the analysis of various performance metrics such as average waiting time, queue length, and service rate.

In the case of a drive-through vaccination clinic, arrivals are the vehicles containing persons whom need to receive the vaccine, and the servers are the healthcare workers who administer the vaccines and work the operation stations. The waiting line can be represented by the cars waiting in a line with patients to receive the vaccines.

The M/M/s/K queuing model is widely used in many real-world applications, where customers or items must be processed through a limited number of servers. By using this model, decision-makers can optimize the system’s performance, reduce waiting times, and improve customer or item flow through the system. The model will also help decision-makers identify bottlenecks and inefficiencies in the system and take appropriate actions to improve the system’s performance, such as adjusting the number of servers/stations in each service lane or increasing the capacity of the queues.

The queue discipline used in this queuing model is FCFS, where the customers are served in the order of arrival. Although each operation in the model generated has several service lanes, vehicles will join the queue in a single line. At each operation, the vehicles waiting in line to be served visit the next available station to be served (see Figure 1).

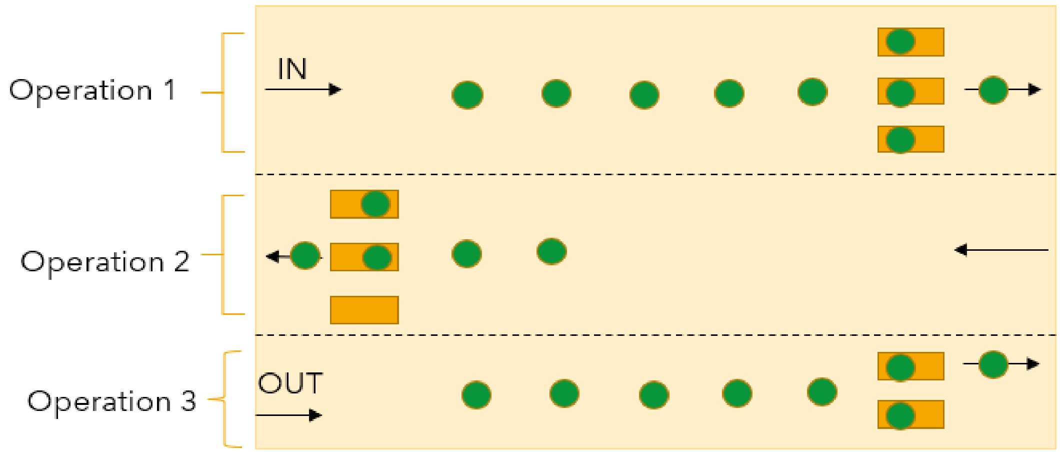
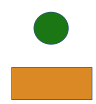


Figure 1: Illustration of Vehicle Queueing and Service Stations for Each Operation at the Drive-Through Vaccination Clinic.



Indicates vehicles

Indicates stations

When modelling the service time in a queuing system, the service times are assumed to follow an exponential density function, with a mean service rate, ‘μ’ can be calculated by taking the reciprocal of the average service time, which is the time it takes for one service to be completed (Winston, 2004). The mean service rate helps determine the overall capacity of the system. The higher the mean service rate, the faster services can be completed, and the more vehicles the system can process in a given period of time.

Utilizing the M/M/s/K queuing model, this thesis offers insights into how queuing systems can be designed to ensure efficiency and minimize customer wait times. This analysis can be useful for healthcare professionals implementing drive-through vaccination clinics.

2.3 Gaps In The Literature

The published literature on drive-through vaccination clinics either focuses on optimizing the clinic’s efficiency through simulation software or discusses strategies to increase the throughput of the clinic model. Literature from Asgary et al. uses AnyLogic simulation software to simulate different scenarios and test the effectiveness of various strategies before implementing them in the real world (Asgary et al., 2021). Similarly, Lee et al. developed the RealOpt simulation software that facilitates resource allocation based on 'what-if' scenarios, enabling decision-makers to model different scenarios and test the effectiveness of various strategies before implementing them in the real world (Lee et al., 2006).

Literature from Zerwekh et al. and Banks et al. focuses on increasing the efficiency in the throughput of the clinic model. This can be achieved by optimizing patient flow, streamlining the registration station and check-in process, and minimizing wait times. These approaches can reduce the time required for each patient and increase the number of patients that can be served in each time period.

In contrast, the tool presented in this thesis does not require any specialized software or fundamental simulation expertise to operate. It is easily accessible to anyone possessing a computer with Microsoft Excel. The model encompasses codes written in VBA that are not visible to the user. Instead, the VBA code is linked to the buttons or other controls on the Excel sheet, providing the user an easy-to-use interface.

This approach aligns with the findings of other literature that emphasized the need for user-friendly tools to enhance productivity, reduce errors, and improve the overall efficiency of drive-through clinic workflows. By using VBA to create this custom tool within Excel, this thesis has provided users with a means to optimize the drive-through clinic model.

Chapter 3: Drive-Through Vaccination Clinic in Halifax, Nova Scotia

This chapter gives insight into the drive-through vaccination clinic conducted in Halifax, Nova Scotia. Detailed analysis of how the clinic was modelled are discussed. The chapter also examines the various changes that had to be made to the clinic's original design to ensure that its goals were met. Overall, this chapter provides insights into the planning, design, and execution of a drive-through vaccination clinic.

3.1 Clinic Analysis

During the COVID-19 pandemic, to reduce exposure to the virus transmission, the Duffus Health Clinic in Halifax, Nova Scotia, Canada, conducted a drive-through seasonal flu vaccination clinic over two separate days in September and October of 2020. The clinic was held for three hours on the first day and six hours on the second day in a parking lot close to the clinic's physical location. Participants were pre-registered days before the clinic, so the provider had information on the number of flu vaccines needed for adults and children.

The clinic was designed firstly through a capacity planning exercise that assigned the number of desired operations (four operations in the Duffus Health drive-through clinic). Then, a layout was proposed based on the area available. The number of stations for each operation was allocated based on the area available while observing COVID-19 safety measures of social distancing. Figure 2 below shows a satellite view of the area available, the route, and the operation stations.

This drive-through vaccination clinic consisted of a total of four primary operations. A greeting operation, a screening operation, a registration operation, and a vaccination operation were the activities of this clinic. Once the final operation was completed, vehicles were directed to the post-vaccination area. Figure 2 below shows the Google satellite map of the Duffus Health drive-through vaccination clinic and visually represents the clinic's location and layout. The map shows the clinic's location, marked with a pin, and the surrounding area, including the parking lot utilized for the drive-through vaccination clinic. The map in Figure 2 also shows the clinic's entrance and exit, and the clinic's route is marked with arrows for a visual representation.

Figure 2: Google Maps. [Google maps satellite view of the Duffus Health drive-through flu vaccination clinic]. Retrieved October 19, 2020, from https://www.google.com/maps/@44.6546434,-63.6266829,409m/data=!3m1!1e3.

Indicates the pathway for vehicles to exit the clinic if they entered the clinic if they entered the parking lot without prior registration

Indicates the pathway of the clinic vehicles should take

1 Greeting operation

2 Screening operation

3 Registration operation

4 Vaccination operation

Indicates the location of the Duffus Health clinic

Figure 3 shows the flow of the drive-through vaccination clinic from the point of entry to the exit. Below is a brief description of the tasks carried out at each of the operations at the drive-through clinic.

1. *Greeting Operation* - A quick screen was conducted to ensure the vehicles entering the lane were vehicles for the drive-through vaccination clinic. Vehicles participating in the drive-through vaccination clinic were then directed to the screening area. If the vehicle was not participating in the vaccination clinic, it was directed to exit safely without entering the drive-through clinic layout.

2. *Screening Operation* - A pre-screening was conducted to check if the personnel in each vehicle were pre-booked and had arrived at the scheduled time slot. If a vehicle arrived early, it was directed to a waiting area and asked to join the lane at the correct time. Once the pre-screening was complete, general COVID questions were asked, followed by a brief explanation of the layout of the clinic. Then vehicles were directed to the registration stations.

3. *Registration Operation* – Medical and consent forms were reviewed at the registration operation. Vehicles with children below 15 were marked with a yellow sticker so the vaccinators could identify the vehicle with children and ensure flu shots for children were on hand. Once the registration of all individuals obtaining the vaccines was verified, the vehicles were directed to the vaccination area.

4. *Vaccination Operation* – Passengers in the vehicles were vaccinated in the vaccination operation area. Once completed, the vehicles were directed to the post-vaccination waiting area.

5. *Post-Vaccination Area* – After receiving the vaccine, the vehicles were directed towards an area to wait for 15 minutes to ensure the passengers in the vehicle did not have any adverse reaction to the vaccine. After 15 minutes, the vehicles could exit the layout if all passengers felt well.

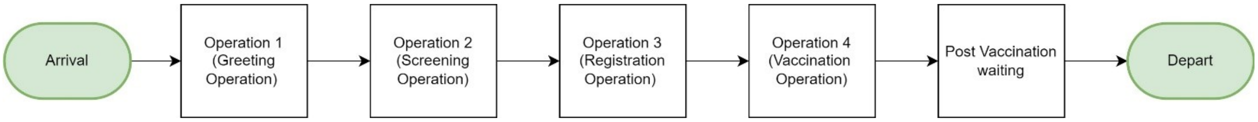


Figure 3: Flow Chart Illustrating the Sequence of Events of the Duffus Health Drive-Through Vaccination Clinic.

To allow for a smooth drive-through vaccination clinic, the syringes used for vaccination were preloaded with the flu shot for both adults and children and stored in a cooler. The clinic was staffed by doctors and nurses from the Duffus Health clinic, who volunteered for both days of the event.

Efficient clinic operations were evaluated through the use of a digital timer and paper records to record data such as time measurements at each station. The identification of potential bottlenecks and delays in the vaccination process led to necessary modifications for enhancing efficiency. For instance, the clinic could investigate methods to simplify check-in and minimize wait times if data indicates that a significant portion of the delay arises during this phase.

3.1.1 Drive-through vaccination clinic on day one

The clinic opened at 9 AM on a Saturday (7th September 2020) and ended at noon, vaccinating approximately 267 patients over three hours. The clinic was opened on a Saturday to make vaccination accessible to individuals who may have difficulty attending clinics during the work week.

The recorded time measurements and person count from the sample of 79 vehicles provided data on the vaccination process. This data was used to improve the organization and planning of future drive-through vaccination clinics by identifying areas where improvements could be made regarding wait times, staffing, and overall patient experience.

On day one of the clinic, it was decided that one staff member was sufficient for the greeting and screening operations. However, two volunteers were stationed at the registration operation to streamline the check-in process and reduce patient wait times. Since the registration operation takes the most amount of time, the vaccine receivers were pre-registered prior to the day of the clinic, which made it easy to streamline the registration and check-in process. This helped enhance the patient experience and ensured smooth operations in a timely manner.

The vaccination operation took place in a covered parking lot with barriers, as shown in Figure 4. To make the best use of the available space, three vaccination stations were arranged in a zigzag order. This layout ensured that each vehicle had enough room to access the vaccination stations without any obstructions, allowing for efficient movement of vehicles and minimizing congestion at the clinic. Additionally, each vaccination station was staffed with two doctors/nurses, expediting the vaccination process, and ensuring accurate administration of vaccinations to patients.

The zigzag order of the vaccination stations, combined with the staffing arrangement, helped optimize the workflow of the clinic, considering the physical constraints of the covered parking lot area. This ensured smooth flow of vehicles during the vaccination operation and maximized the utilization of available space. Figure 4 displays the layout of the covered parking lot utilized for the vaccination operation. Overall, these operational strategies contributed to the successful functioning of the clinic and providing a positive experience for patients while ensuring timely vaccinations.

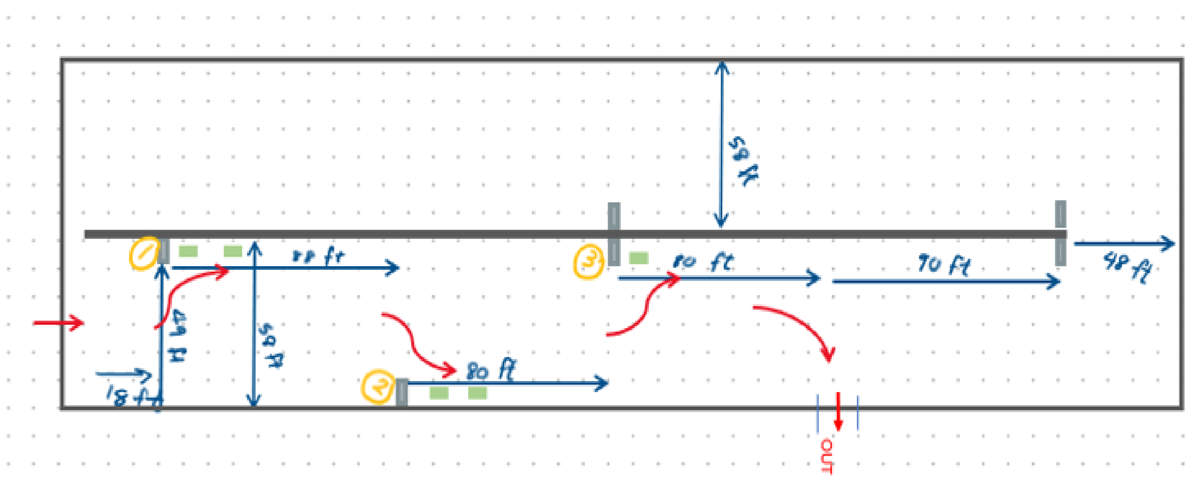


Figure 4: Vaccination Station Layout on Day One of the Drive-Through Vaccination Clinic Organized by the Duffus Health Clinic in Halifax, Canada.

Indicates a vehicle

Indicates barriers that were present in the covered parking lot

1 First vaccination station in the vaccination operation

2 Second vaccination station in the vaccination operation

3 Third vaccination station in the vaccination operation

3.1.2 Drive-through vaccination clinic on day two

On the second day of the vaccination clinic, minor adjustments were made to the layout to improve the visibility and efficiency of the vaccination process. The decision to shift the vaccination crew in stations one and three to the same side of the lane as station one (see Figure 5), where there was more natural light, was made to ensure that the crew could see clearly and administer vaccines accurately. Table 1 summarizes the service times from both day one and day two, providing an overview of the average clinic parameters from both days. The clinic served 406 patients in just six hours on the second day.

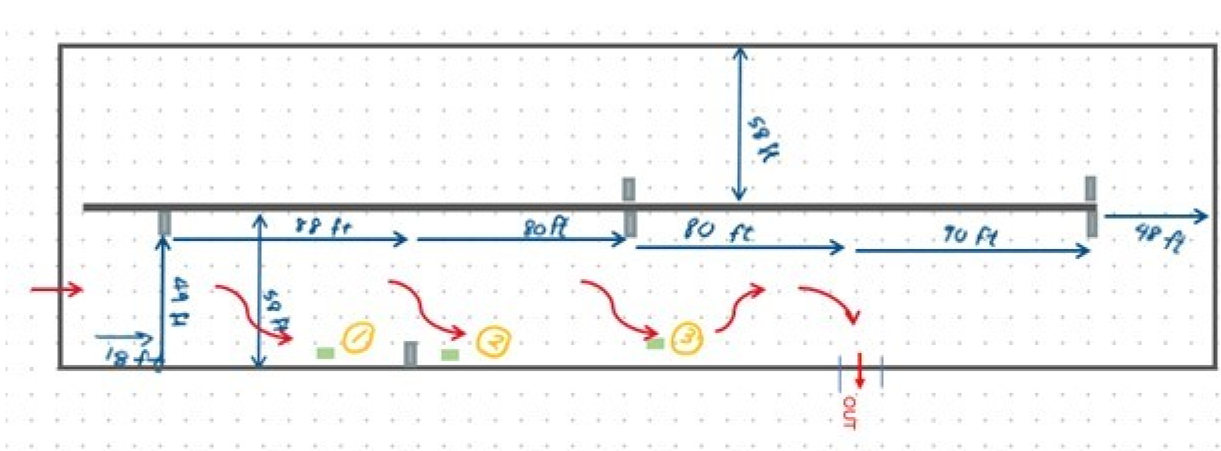


Figure 5: Vaccination Station Layout on Day Two of the Drive-Through Vaccination Clinic organized by the Duffus Health Clinic, with the Stations on the Same Side of the Underground Parking Lot.

Overall, the adjustments made on the second day of the clinic illustrated the flexibility and adaptability of the organizers and staff, as well as their commitment to ensure the safety and well-being of patients. By making changes to the layout in response to the lack of natural light, the organizers were able to improve the flow of the vaccination process, while making sure that patients received the care they needed in a timely and effective manner.

3.2 Clinic Parameters and Metrics

A drive-through vaccination clinic's quality and efficiency can be evaluated using clinic metrics. By following key performance indicators, such as wait times, throughput, and utilization rates, decision-makers can identify areas that require improvement and make informed choices based on data to optimize clinic operations.

In this thesis, we present a set of clinic parameters obtained from the drive-through vaccination clinic conducted by the Duffus Health clinic in Halifax, Canada. Tables 1 and 3 provide the average values of key clinic parameters, including parking lot dimensions, expected number of vehicles, clinic operation time, and average service times for each service area/operation (Greeting operation, Screening operation, Registration operation, and Vaccination operation). The model proposed in this thesis utilizes these clinic parameters to generate relevant metrics, which will be used to generate a generic layout for drive-through vaccination clinics. By leveraging these input parameters, the model provides insights and recommendations for optimizing the layout and operation of drive-through vaccination clinics, with the goal of improving their efficiency and effectiveness.

The clinic scheduled vehicles to arrive at a rate of one vehicle every two minutes prior to the start of the clinic, resulting in a total of 30 vehicles booked per hour. Based on this scheduling, the clinic was expecting 90 vehicles on the first day and 180 vehicles on the second day of operation. Table 3 provides the summarized values for average service time and standard deviation, based on Table 2, which were obtained from the data collected during the Duffus Health drive-through vaccination clinic conducted on both days of operation. This table also provides the number of stations that were allocated to each operation during the clinic. The raw data collected from the clinic can be found in Table 13 and Table 14 in the Appendix.

The average service time is the time it takes a vehicle to complete a particular service. This includes any time spent interacting with staff at the operation station and receiving the service. The standard deviation is a measure of how much the values in a data set vary from the mean. A high standard deviation indicates that the values are spread out over a wider range, while a low standard deviation indicates that the values are closer together around the mean.

Table 1: Clinic parameters for the Duffus Health drive-through vaccination clinic.

Arrival rate (λ)	**Average number of vehicles per day (n)**	**Average operation time (t) (minutes)**	**Length of the parking lot (ft)**	**Width of the parking lot (ft)**
0.5	135	270	406	200

Table 2: Average clinic parameters: Comparison of service times from day one and two of the Duffus Health drive-through vaccination clinic.

	Day 1			**Day 2**		
Operation	Average Service Time (minutes)	Sample Size	Standard Deviation	Average Service Time (minutes)	Sample Size (number of vehicles)	Standard Deviation
Greeting operation (R1)	0.47	5	0.33	0.41	6	0.33
Screening operation (R2)	1.23	5	0.64	1.16	6	0.45
Registration operation (R3)	3.51	21	0.50	3.53	40	0.68
Vaccination operation (R4)	4.35	58	1.83	4.32	59	1.85

Table 3: Summary of average service times by service operation in the Duffus Health drive-through vaccination clinic from day one and two.

Operation	**Sample Size**	**Average Service Time (minutes)**	**Standard Deviation**	**Service Rate (μ)**	**Number of Stations at Each Operation (s)**
Greeting operation (R1)	11	0.44	0.31	2.27	1
Screening operation (R2)	11	1.19	0.51	0.84	1
Registration operation (R3)	61	3.52	0.62	0.28	2
Vaccination operation (R4)	117	4.34	1.83	0.23	3

Building on the results presented in Table 1 and Table 3, we incorporated the same data into our custom-built model to generate comprehensive performance measures for the drive-through vaccination clinic. These measures are tabulated in Table 7 and Table 8, and the values for the service rates, number of stations, and arrival rate at each operation are consistent with those in Table 1 and Table 3. In Chapter 4, we delve deeper into the development of the model and its various features

Chapter 4: Tool Methodology and Design

The purpose of this tool was to enable a decision-maker to calculate the minimum number of stations needed for each operation to function smoothly and identifies wait times for each operation, capacity at each operation, and the likelihood that the operation lane is full. Sections 4.1 and 4.2 discusses the formulation of the model and the computational approach taken to formulate the model in VBA respectively. Section 4.3 discusses the verification of the model through a feasibility study.

4.1 Model Formulation

A lane in a drive-through vaccination clinic refers to a designated area or pathway vehicles drive through to receive a part of the vaccination service. Typically, each lane consists of a series of stations or checkpoints, where different aspects of the vaccination process, such as registration, vaccination, and observation, are carried out by workers. Each lane is usually wide enough to accommodate a line of vehicles and has staff stationed at various points to guide drivers through the process. The number of lanes in a drive-through vaccination clinic can vary depending on the capacity and layout of the site and the expected number of people to be vaccinated.

A lane in a drive-through vaccination clinic is deemed "full" when there are no more openings for vehicles to access that specific lane. This may occur if there is a backlog of vehicles waiting to enter a particular lane. For instance, Figure 6, depicts a scenario where the operation one lane has reached its maximum capacity, hence is deemed full, and further entry of vehicle is not possible due the lack of space available. To maintain a safe and efficient flow of traffic through the drive-through vaccination clinic, it is important to ensure that each lane is not overcrowded or congested.

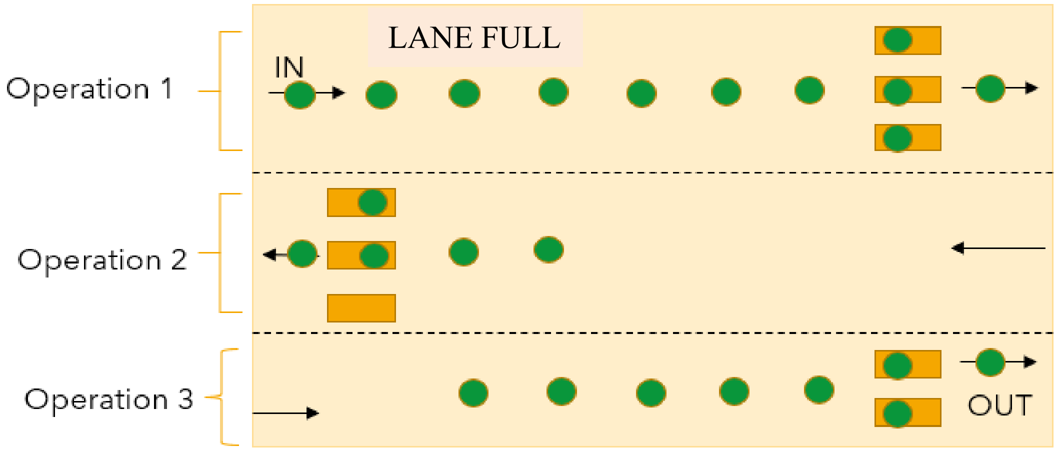
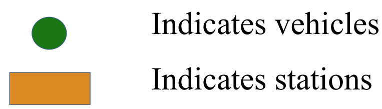


Figure 6: Diagram Illustrating a Drive-Through Vaccination Clinic Layout, Highlighting Operation Lanes.



The model created in this thesis uses the M/M/s/K queuing theory to analyze the behaviour of the queuing system, where 's' stations are available to serve patients that arrive with an arrival rate λ. Each station in the drive-through vaccination clinic takes an exponentially distributed amount of time with a service rate of μ to serve a patient/s in a vehicle. The model uses a finite-capacity queuing system with a maximum number of vehicles, 'K', and the number of stations 's', in that particular lane at any given time.

The tool created offers an optimal layout with the minimum number of stations required to prevent bottlenecks while adhering to the specific layout parameters provided. Each lane in this model is modelled as an M/M/s/K problem. Since the model assumes a single line of cars within a lane, we overestimate a vehicle's average length and width, so that safety concerns for space between lanes can be ignored. This allows for a higher certainty that there is enough space between lanes and avoids the complexity of adding space for the safety barriers between lanes.

The model provides flexibility for decision-makers to adjust parameters to achieve optimal results. Within the model, the decision-maker can

- Enter layout parameters (length and width of parking lot)

- Enter the number of vehicles that are expected to be served.
- Enter the duration of time the clinic should stay open in a day.
- Enter the number of operations the clinic desires to have.
- Enter the threshold percentage that will determine the capacity at which the lane is considered full.

Once the user inputs the parameters, the model will perform a series of calculations for each operation lane to derive crucial metrics. These include the service rate (μ), the minimum number of stations needed (s), the lane capacity (K), utilization rate (ρ) as a measure of system utilization, the average waiting time (W_q) for each operation, and the probability of the operation lane reaching full capacity (P_n). These calculated values are indicated in a table on the Excel sheet, as shown in Table 8 below. Once these metrics are calculated, the model then gives a visual output of the layout, as seen in Figure 7. This visual representation of the clinic, generated via parameters the user inputs, allows the user to get insight into the clinic's design and organization.

4.2 Computational Approach

The model is designed so that each main operation consists of a lane exclusive to a particular operation (see Figure 7). For example, if the decision-maker desires four operations, then the layout generated from the model will have four major lanes. Each lane in the layout will contain 's' number of stations that indicate sub-lanes to a specific operation (refer Figure 7). The 's' number of stations drawn in this layout at each lane corresponds to the minimum number of stations needed for that operation. If the lane space is inadequate, meaning the vertical space available to accommodate the minimum number of stations for that particular operation is insufficient, the model will provide an error message (see Figure 9), which indicates the user must adjust input parameters like parking lot dimensions, number of operations, number of vehicles expected, hours of operation of the clinic, or even service times.

The M/M/s/K queuing theory was selected to estimate the expected queue lengths in the clinic given its fixed capacity and multiple stations/servers. To ascertain the practicality of this approach, a feasibility study was conducted on the proposed model. Further details on the feasibility study carried out can be found in Chapter 4.3.

During the feasibility study conducted on the proposed model, several scenarios were tested to assess the model's performance. One of the scenarios involved revising the parking lot length entered by the clinic planner, which triggered an error message from the model. If the parking lot length entered by the clinic planner is less than the average length of a vehicle, the model will provide an error message to increase the length of the parking lot dimensions. The model will also indicate error messages if the layout's width is not sufficient to accommodate clinic stations with the proposed number of operations.

Assuming that the arrival rate λ and the service rate μ are known, the M/M/s/K queuing model can be used to calculate various performance measures of the drive-through vaccination clinic, such as the minimum number of stations needed (s), the utilization (ρ), the average waiting time (W_q), and the probability of having n vehicles in the system (including those being served) at any given time (P_n) for each operation. P_n is an important metric in analyzing the performance of a queuing system as it can help determine the average waiting times (W_q), average number of vehicles in the system (L), and the average number of vehicles waiting in the queue (L_q).

Let us examine the example of the Duffus Health drive-through vaccination clinic, which had four operations, to demonstrate the application of the queuing model. The clinic operated for 270 minutes and expected to serve 135 vehicles during that timeframe. Table 1 and Table 3 outline the clinic's parameters, which will be used in the subsequent calculations to obtain the performance metrics utilized in this scenario.

The first step is to calculate the arrival rate λ of vehicles at the clinic, which is obtained by dividing the total number of expected vehicles (n) by the total duration of the clinic's operation during the day (t) using Equation 4.1.

$$\lambda = \frac{n}{t} \tag{4.1}$$

$$\lambda = \frac{135\ vehicles}{270\ minutes}$$

$$\lambda = 0.5 \text{ vehicles per minute}$$

To find the number of stations (s) for an operation, the number of vehicles expected (n) is multiplied by the service time at that particular operation (R), and then divided by the operation time of the clinic (t). In this scenario, we will consider the first operation, which is the Greeting operation in the Duffus Health drive-through vaccination clinic. This operation had an average service time of 0.44 minutes. The number of stations needed for the Greeting operation can be calculated via Equation 4.2, which would result in having a minimum of one station in that operation lane.

$$s = \lceil n(R/t) \rceil \tag{4.2}$$

$$s = \left\lceil 135\ vehicles \left(\left(0.44 \frac{minutes}{vehicle} \right) \Big/ (270\ minutes) \right) \right\rceil$$

s = 0.22 stations ~ 1 station

To calculate other important performance measures like the expected wait time, the expected number of vehicles in the system, and the expected utilization of the service facility, the mean service rate (μ) is a crucial metric to be known. In this context, the mean service rate is the expected number of vehicles completing service per unit time. This is calculated by taking the reciprocal of the average service time (Winston, 2004). In this scenario, since the service time for the Greeting operation is 0.44 minutes, μ is (1/0.44), which gives a mean service rate of 2.27 vehicles per minute.

A performance measure, such as the utilization factor (ρ), can be used to evaluate a service system's efficiency. This factor indicates the proportion of time the stations in the clinic are busy serving customers. It is calculated as the product of the arrival rate (λ) and the average service time ($1/\mu$) divided by the number of stations (s), as seen in Equation 4.3 below. According to the scenario mentioned above, the utilization factor can be calculated using Equation 4.3.

$$\rho = \frac{\lambda}{\mu s} \tag{4.3}$$

$$\rho = \frac{0.5}{(2.27)(1)} = 0.22$$

A 0.22 utilization factor can mean that this particular operation has a relatively low usage or activity. If the utilization factor is too high, generally above 0.8, it can lead to long waiting times and potential bottleneck in the system due to high traffic intensity since it is operating close to the system's capacity.

Readers will note the M/M/s/K queuing model differs from the standard M/M/s queuing model; the number of customers in the system is limited to a finite capacity *K,* thus

$$P_0 = 1 \Big/ \left[\sum_{n=0}^{s} \frac{(\lambda/\mu)^n}{n!} + \frac{(\lambda/\mu)^s}{s!} \sum_{n=s+1}^{K} \left(\frac{\lambda}{s\mu}\right)^{n-s} \right] \tag{4.4}$$

$$P_0 = 1 \Big/ \left[\sum_{n=0}^{1} \frac{(0.5/2.27)^n}{n!} + \frac{(0.5/2.27)^1}{1!} \sum_{n=1+1}^{26} \left(\frac{0.5}{1 * 2.27}\right)^{n-1} \right]$$

$$P_0 = 1/[1.22 + 0.22(0.28)]$$

$$P_0 = 0.78$$

This shows that at any given point in time, the Greeting operation has a 78% probability that the station in this operation is idle, meaning zero customers to serve. This implies that station in this operation is occupied about 22% of the time. Using the value of P_0 generated using Equation 4.4, the probability of having *n* number of vehicles in the system can be calculated using Equation 4.5 below (see Table 4 for P_n values).

The probability of precisely '*n*' vehicles in the queuing system is denoted by P_n as shown in Equation 4.5. For the scenario where the clinic is expecting 135 vehicles over the course of a 270-minute operation, if the lane capacity is 26 vehicles (this includes 25 spaces in the queue and one server) and this particular operation lane has a single server, with a service time of 0.44 minutes, we can calculate P_n using the equations below.

$$P_n = \begin{cases} \dfrac{\left(\frac{\lambda}{\mu}\right)^n}{n!} P_0 & for\ n = 1,2,3, \dots\ s \\ \dfrac{(\lambda/\mu)^n}{s!\ s^{n-s}} P_0 & for\ n = s, s+1, \dots K \\ 0 & for\ n > K \end{cases} \tag{4.5}$$

Table 4: Calculated Pn Values for Single Server with 26 Vehicle Capacity.

n	**P_n**
0	0.78
1	0.17
2	0.04
3	0.01
4	0.00
5	0.00
6	0.00
7	0.00
8	0.00
9	0.00
10	0.00
11	0.00
12	0.00
13	0.00
14	0.00
15	0.00
16	0.00
17	0.00
18	0.00
19	0.00
20	0.00
21	0.00
22	0.00
23	0.00
24	0.00
25	0.00
26	0.00

Once P_n is known, we can find the expected number of vehicles in the queuing system (L), and the expected queue length (L_q) as shown via Equations 4.7 and 4.6 below. The expected number of vehicles waiting in queue (excludes the number of vehicles being served), also known as the queue length, is denoted by L_q as shown in Equation 4.6. This measure denotes the length of the queue, which can impact customer satisfaction and the overall efficiency of the clinic. If the L_q value is high in a particular operation compared to the rest, then it can denote that increasing the number of stations can help reduce the length of the line in front of that operation. Continuing with the example from before, the queue length is calculated via Equation 4.6.

$$L_q = \frac{P_0\,(\lambda/\mu)^s\,\rho}{s!\,(1-\rho)^2}\,[1-\rho^{K-s}-(K-s)\rho^{K-s}(1-\rho)] \tag{4.6}$$

$$L_q = \frac{0.78\,(0.5/2.27)^1\,0.5}{1!\,(1-0.5)^2}\,[1-0.5^{26-1} - (26-1)0.5^{26-1}(1-0.5)]$$

$$L_q = 0.062\ vehicles$$

When a queue is congested or when the lane is starting to queue up, L_s is an important performance metric that provides insight into the queuing behavior of the system. L_s represents the average number of vehicles being served, which in this scenario is 0.22.

Similarly, L is an important measure that helps to develop optimum queuing systems that are efficient, cost-effective, and meet desired performance goals. Maintaining the example from above, L for the Greeting operation in the Duffus Health clinic was calculated to be 0.56 vehicles as shown in Equation 4.7.

$$L = \sum_{n=0}^{s-1} nP_n + L_q + s\left(1-\sum_{n=0}^{s-1} P_n\right) \tag{4.7}$$

$$L = \sum_{n=0}^{1-1} nP_n + 0.34 + 1\left(1-\sum_{n=0}^{1-1} P_n\right)$$

$$L = 0.56\ vehicle$$

According to the Little's formulae $L = \lambda W$, typically W is calculated as L/λ. However, in the finite capacity model, a phenomenon known as "balking" occurs when the number of jobs n reaches the systems capacity K. Thus, when $n = K$ the arrival rate λ drops to zero. Therefore, the Little's equation has to use an adjusted arrival rate λ' to account for this limitation in the queue's capacity. Equation 4.8 provides the calculation for λ', ensuring accurate estimations of the average number of vehicles in the system while considering the occurrence of job balk due to capacity constraints.

$$\lambda' = \lambda\,(1 - P_n) \qquad where\ n = K \tag{4.8}$$

$$P_k = \frac{(0.5/2.27)^{26}}{1!\ 1^{26-1}}\ 0.78\ = 6.44 * 10^{-18}\ \sim 0$$

$$\lambda' = 0.5\,(1 - 0) = 0.5 \text{ vehicles per minute}$$

Having calculated λ', now W can be calculated. W is the expected wait time a vehicle spends in the system, which includes both the time spent waiting in line (W_q) and the time spent receiving the service. Both W and W_q are important performance measures for a queuing system, as they help determine the level of service provided to the customers and can help in making decisions regarding the number of stations and the capacity of the system. A shorter waiting time, represented by a smaller W_q, can result in higher customer satisfaction. Equations 4.10 and 4.11 calculate W and W_q, which indicates that this particular operation has an average waiting time of 1.12 minutes in the operation lane, while the average wait time in the queue is 0.12 minutes.

If the predicted values of W and W_q are too high, the decision-maker can adjust the queuing system to reduce queue lengths and wait times. Increasing the number of stations (s) or system capacity (K) may be a potential solution to relieve congestion and enhance throughput. One may also enhance the overall performance of the system by modifying either the arrival rate (λ) or service rate (μ).

$$W = \frac{L}{\lambda'} \tag{4.10}$$

$$W = \frac{0.56\, vehicles}{0.5\,\frac{vehicles}{minute}} = 1.12\, minutes$$

$$W_q = \frac{L_q}{\lambda'} \tag{4.11}$$

$$W_q = \frac{0.062\, vehicles}{0.5\,\frac{vehicles}{minute}} = 0.12\, minutes$$

Based on the calculated waiting time in the queue (W_q) for the Greeting operation at the Duffus Health drive-through clinic, which is 0.12 minutes, it can be concluded that the Greeting Lane is operating efficiently without any queue or backlog of vehicles waiting at the station.

4.1.1 Assumptions

When creating this model, several assumptions were made to simplify the process while incorporating the Markovian assumption. First, we assumed that the system was in a steady state. This meant that the system had reached a state of equilibrium, and the average arrival and departure rates remained constant over time. This assumption aligned with the Markovian property as it allows the model to focus on the long-term behaviour of the system, assuming that the future state depends only on the current state.

Additionally, the model assumed that the mean arrival rate was the same at each operation and did not vary over the course of the day. It also assumed that the mean service time remains the same during the clinic and that each vehicle's service time is independent and identically distributed, aligning with the Markovian assumption.

Another assumption made was that only one vehicle could arrive at any given instant, and there were no bulk arrivals. This assumption associates with the Markovian assumption by considering the current state (arrival process) and assuming the independence of events.

Finally, the model assumed that the safety barriers separating each lane would take up negligible space. In our model, we increased the assumed width of a car to accommodate for extra width space in a lane.

These assumptions collectively streamlined the model, leveraging the Markovian assumption to analyze the system's behavior effectively and make informed decisions based on the simplified representation.

4.2.1 Model verification and usage

Verification of the model is a crucial step to ensure that the model accurately represents the actual clinic operations. In this study, the data obtained from the Duffus Health drive-through vaccination clinic in Halifax were compared with the results generated from the model. The input values used in the model, such as parking lot dimensions, number of vehicles that arrived per day, hours of operation, number of operations, and service times, were considered as input variables to the model.

By comparing the actual data from the clinic with the results generated by the model, we were able to assess the model's accuracy and identify any discrepancies or areas for improvement. This model verification process is important because it ensures that decision-makers can rely on the model to make informed decisions about clinic operations and resource allocation. Despite the limited availability of long-term data from the Duffus Health drive-through vaccination clinic, the comparison of actual data with the model results yielded valuable insights into the model's performance. It helped validate the model's ability to accurately represent the real-world clinic operations and provided confidence in its use for decision-making. The input variables used in the model were carefully considered, and any differences or discrepancies between the actual data and the model results were thoroughly examined to identify areas for improvement.

Let us analyze the data obtained from the Duffus Health drive-through vaccination clinic and compare it with the results generated from the model. Based on the data obtained, the clinic's average service time values for four operations can be found in Table 5. Since the clinic scheduled vehicles to arrive every two minutes, this resulted in an average arrival time of 0.5 vehicles per minute. The clinic expected an average of 135 vehicles (n) during the average operational hours of 270 minutes per day (t), with a parking lot spanning 406 feet in length and 200 feet in width, as per Table 1 and Table 3 which outline the parameters of the Duffus Health drive-through vaccination clinic. Table 5 also presents the average service times and the number of stations at each operation, based on the parameters from Table 1 and Table 3.

Table 5: Overview of Average Service Times and Station Count at Duffus Health Drive-Through Vaccination Clinic.

Operation	**Average Service Time (minutes) (R)**	**Number of stations in each operation (s)**
Greeting operation (R1)	0.44	1
Screening operation (R2)	1.19	1
Registration operation (R3)	3.52	2
Vaccination operation (R4)	4.34	3

Using the parameters obtained from the Duffus Health drive-through vaccination clinic, the metrics were calculated using the equations outlined in section 4.2. the results of these calculations are tabulated in Table 6.

Table 6: Hand-Calculated Clinic Metrics for Duffus Health Drive-Through Vaccination Clinic Parameters.

Operation	Service Rates (μ)	Minimum Number of Stations (s)	Utilization of the Station (ρ)	Waiting time in Queue (W_q)	Probability that there are ‘n’ vehicles (P_n)
Greeting operation (R1)	2.27	0.22 ~ 1	0.22	0.12	0.00
Screening operation (R2)	0.84	0.60 ~ 1	0.60	1.79	0.00
Registration operation (R3)	0.28	1.76 ~ 2	0.89	11.19	0.01
Vaccination operation (R4)	0.23	2.17 ~ 3	0.72	2.67	0.00
Post Vaccination	0.07	7.5 ~ 8	0.89	8.88	0.00

Upon reviewing the hand-calculated results as presented in Table 6, it is evident that the outcomes obtained from the model are consistent with calculations made by hand. This level of consistency instills confidence in the validity of the results generated by the model.

By utilizing the parameters obtained from Table 1 and Table 3, our model generated a visual representation of the drive-through vaccination clinic layout with the minimum number of stations at each operation, as illustrated in Figure 7. This layout serves as a useful tool for optimizing the clinic design and ensuring efficient usage of stations during the vaccination process.

Table 7: Table Generated by Model: Duffus Health Drive-Through Vaccination Clinic Parameters and User Input.

Length of the parking lot (x)	Width of the parking lot (y)	Number of vehicles expected (N)	Hours of operation in mins (T)	Num. of operations desired	Desired threshold % to indicate the lane is full
406	200	135	270	4	90

Table 8: Table of Key Output Metrics Generated via the Model for Input Parameters from the Duffus Health Drive-Through Vaccination Clinic Data.

	Operation Name	Service Time (min) (r)	Service Rates (μ)	Min. # of servers/ stations needed in lane (s)	Capacity (K)	Utilization of the station (ρ)	Waiting Time in Queue (W_q)	Probability that there are 'n' vehicles (P_n)	Avg. # of arrivals per unit time per minute (λ)
1	Greeting	0.44	2.27	1	26	0.22	0.12	0.00	0.5
2	Screening	1.19	0.84	1	26	0.60	1.79	0.00	0.5
3	Registration	3.52	0.28	2	27	0.89	11.17	0.01	0.5
4	Vaccination	4.34	0.23	3	28	0.72	2.69	0.00	0.5
5	Post Vaccination	15.00	0.07	8	33	0.89	9.01	0.00	0.5

In Table 7 and Table 8 above, the green boxes serve as entry points for decision-makers to input values into the queuing model. The model generates a range of metrics, such as service rates, minimum station requirements, capacity limitations, utilization rates, average queue waiting times, the probability of *n* vehicles in the system, and the average arrival time for each operation lane. By leveraging the outputs generated in Table 8, the model determines the minimum number of stations required for each operation lane and creates a layout that visually represents the clinic's layout, as shown in Figure 7. This visual layout allows decision-makers to easily assess the potential for including additional stations in the clinic’s layout, aiding in the optimization of the clinic design and operational efficiency.

Please note that the model incorporates the “Post vaccination” operation as a default process, since it is required in any drive-through vaccination clinic. The inclusion of this operation enables the clinic planner to determine the necessary space required to accommodate the minimum number of vehicles during the post vaccination phase.

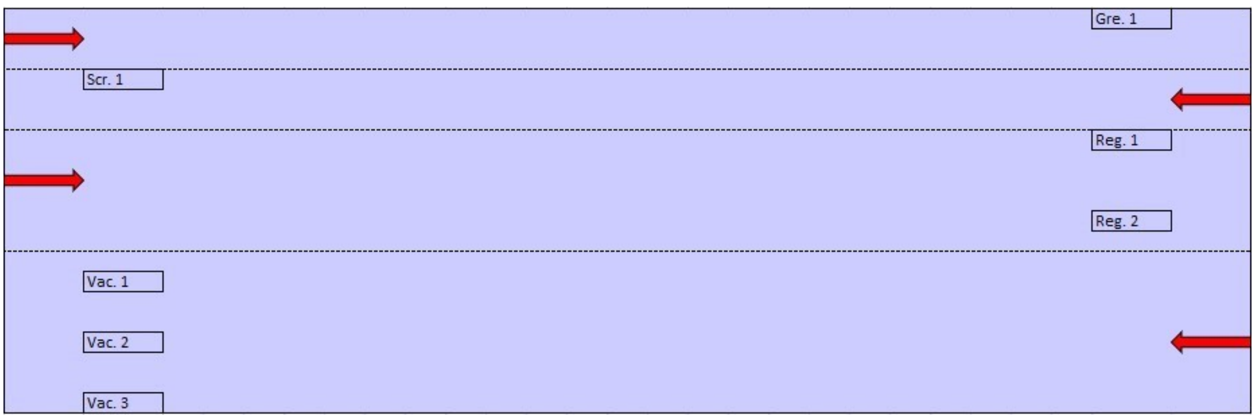


Figure 7: Visual Representation of the Drive-Through Vaccination Clinic Layout Generated via the Model with the Duffus Health Clinic Parameters Collected.

The model possesses the capability to dynamically adapt and update itself to accommodate various scenarios, such as changes in the number of vehicles, adjustments in service times, variations in the number of operations the clinic plans to hold, modifications in the parking lot dimensions, or shifts in the operating hours of the clinic. This flexibility allows the model to provide accurate and relevant layout recommendations based on the specific parameters provided, ensuring its effectiveness in assisting with drive-through vaccination clinic planning and optimization. Figure 8 below is an example of how the model can generate unique layouts by taking into account different user inputs.

Let us now consider a scenario where the Duffus Health clinic intends to reduce the service time at the Registration operation, by introducing two Pre-Registration operations instead of a single registration operation with an average service time of 4.34 minutes. This change increases the total number of operations to six, with corresponding service times of 0.44, 1.19, 1.50, 1.50, 1.80, and 4.34 minutes, while maintaining the same parking lot dimensions of 406 feet in length and 200 feet in width. The expected number of vehicles remains unchanged at 135 vehicles during the operational hours of 270 minutes per day. (Please refer to the green cells in Table 9 and Table 10 for these clinic parameters).

Table 9: Generated User Input Table with Clinic Parameters for Six Operations, Derived from Model Using Mentioned Scenario.

Length of the parking lot (x)	Width of the parking lot (y)	Num. of vehicles expected (N)	Hours of operation in mins (T)	Num. of Operations Desired	Service Level %
406	200	135	270	6	90

Table 10: Table Generated via the Model for the Scenario of the Duffus Health Drive-Through Clinic with Six Operations.

	Operation Name	Service Time (min) (r)	Service Rates (μ)	Min. # of servers/ stations needed in lane (s)	Capacity (K)	Utilization of the station (ρ)	Waiting Time in Queue (W_q)	Probability that there are 'n' vehicles (P_n)	Avg. # of arrivals per unit time per minute (λ)
1	Greeting	0.44	2.27	1	26	0.22	0.12	0	0.5
2	screening	1.19	0.84	1	26	0.6	1.79	0	0.5
3	Pre-Registration	1.50	0.67	1	26	0.75	4.47	0	0.5
4	Scanning Forms	0.80	1.25	1	26	0.40	0.53	0	0.5
5	Registration Completion	1.20	0.83	1	26	0.60	1.80	0	0.5
6	Vaccination	4.34	0.23	3	28	0.72	2.69	0	0.5
7	Post Vaccination	15.0	0.07	8	33	0.89	9.01	0	0.5

Table 10 generates key metrics for the clinic, explicitly tailored to the six operations that were input by the decision-maker. These metrics, based on the provided parameters, form the basis for generating a visual layout as shown in Figure 8. The layout visually represents the potential flow of the clinic, taking into account the specified six operations. Using this layout, the decision-maker can explore the option of incorporating more stations within each of the six operations to enhance overall clinic performance.

Comparing the results from Table 10 and Table 8, breaking down the Registration operation reduced the waiting time in the queue. This also means that since we now have at least three stations, we need at least three staff members to man these stations. Whereas before, when the registration operation had a service time of 3.52 minutes, we needed at least two stations, meaning we needed at least two staff members to man the stations.

Figure 8: Visual Layout Generated via the Model for the Duffus Health Drive-Through Vaccination Clinic, if the Number of Operations Increased to Six.

Gre.1 – Greeting station 1

Scr.1 – Screening station 1

Pre.1 – Pre-Registration station 1

Sca.1 – Scanning forms station 1

Reg.1 – Registration complete station 1

Vac.1 – Vaccination station 1

Vac.2 – Vaccination station 2

Vac.3 – Vaccination station 3

The visual layout provides the decision-maker with opportunities to optimize the clinic design by including additional stations in each operation. For example, one could consider adding one more station to the Registration operation or multiple stations to the Vaccination operation to accommodate more vaccine receivers. This information aids in identifying and leveraging potential enhancements to the clinic layout for improved efficiency and effectiveness.

4.3 Feasibility

A feasibility check is performed when new models are developed to ensure that the model is practical and feasible for real-world implementation. A feasibility check involves assessing whether the model can meet certain criteria or requirements for the system it represents (Bridges, 2021). By conducting a feasibility check, we can determine if the proposed design is practical and feasible, or if changes need to be made to improve its efficiency and effectiveness.

In this study, a feasibility check is conducted to evaluate the vertical and horizontal distances in the layout. The horizontal distance within a lane determines if they are long enough to accommodate an adequate number of vehicles, while the vertical distance ensures there is enough room for the minimum number of stations required for each operation. The feasibility check also considers factors such as space needed to manoeuvre vehicles in and out of the parking lot and the availability of adequate space for staff to perform their duties efficiently.

For example, if the horizontal length of the parking lot is too short, traffic congestion and long wait times could occur. Similarly, if the vertical space is inadequate, there might not be enough space to accommodate the minimum number of stations needed at each operation to reach throughput, which could lead to delays and longer wait times.

4.3.1 Vertical and horizontal feasibility

The feasibility of the layout's vertical spacing is determine by the model, which considers the minimum number of stations required at each operation to ensure efficient function. This is an important consideration, as insufficient vertical spacing can result in overcrowding and delays in the process. Therefore, the model has been designed to provide an error message, as seen in Figure 9, if the vertical space in a particular operation lane is deemed insufficient to accommodate the minimum number of required stations.

The calculation of the minimum number of stations required for an operation is based on the M/M/s/K queuing model, where the minimum number of stations is calculated according to Equation 4.2. However, the minimum number of stations required may not guarantee that the probability of a number of vehicles in the system is less than a certain threshold.

The model ensures that the operation lane has sufficient vertical and horizontal space to accommodate the minimum required number of stations and meet the desired probability threshold for the number of vehicles in the system. This is achieved by checking the calculated probability P_n against the targeted probability specified by the user, and iterating until the calculated P_n is less than or equal to the target probability. This approach enables the model to generate a feasible layout for the drive-through vaccination clinic that meets the operational requirements and desired performance metrics.

Consider the Duffus Health drive-through vaccination clinic scenario. Now, the clinic wants to accommodate 1000 vehicles instead of 135 vehicles, using the same input parameters as showcased in Table 1 and Table 3 (refer to Table 11 and Figure 9). However, due to inadequate parking lot space, the minimum number of stations required for each operation to efficiently handle 1000 vehicles within the operational day cannot be accommodated. As a result, the model will generate an infeasible message, as shown in Figure 9, indicating the vertical infeasibility. This prompts the user to either adjust the parking lot constraints so the clinic can handle 1000 vehicles in a span of a 270-minute operational day or expect a lesser number of vehicles during the operational day to proceed successfully.

Table 11: Table of User Input Parameters for Layout Generation in the Model.

Length of the parking lot (x)	Width of the parking lot (y)	Num. of vehicles expected (N)	Hours of operation in mins (T)	Num. of Operations Desired	Service Level %
406	200	1000	270	6	90

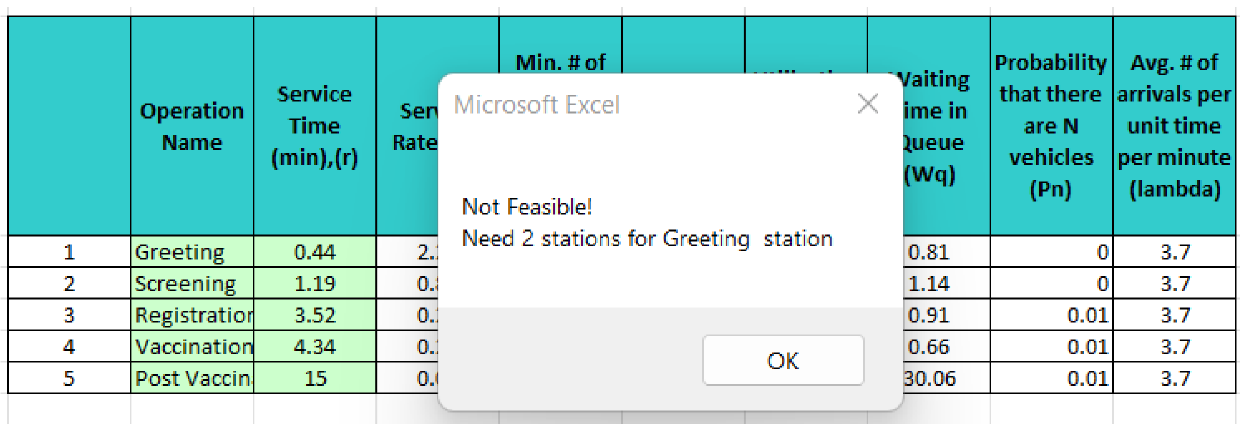


Figure 9: Error Message Generated by the Model for Vertical Infeasibility: Attempting to Accommodate Excessive Number of Vehicles in a Limited Parking Lot Space.

The model created in this thesis has a predefined minimum horizontal length limitation of three cells. Each cell's length is approximated as a vehicle's average length, which is approximately 10 feet long. If a decision-maker attempts to input a value for the length of the parking lot that is less than 30 feet, the model will automatically alert the decision-maker that an increase to the parking lot’s length is required to generate a viable layout. The user of this model has the flexibility to modify the horizontal limitation by changing the minimum number of cells needed horizontally on the design table as outlined in Table 12 below.

The minimum horizontal length limitation is a crucial aspect of the model, as it guarantees that the drive-through vaccination clinic layout is functional and efficient. If the length of the parking lot is too short, it may be challenging to accommodate all the required stations and vehicles, leading to a potential bottleneck and delays in the vaccination process.

Apart from the minimum length limitation of the available space for the clinic, the model also checks the horizontal availability of the lane by calculating the minimum number of stations required. The model calculates the probability of having '*n*' vehicles in the system (P_n) and compares it with the target probability specified by the user (The service level percentage as seen in Figure 10 below is the target probability specified by the user). If P_n is greater than the target probability, the model will add another station to a lane and recalculate P_n. This impacts the vertical feasibility of the solution, but in the case that there is not enough room to place an additional station, the issue could be resolved by increasing the horizontal length of the layout. If the horizonal length of the lane is greater than the horizontal length required as indicated by the probability of having *n* vehicle in the system being less than the target probability indicated by the user, then the layout of the clinic is horizontally feasible. If one of these criteria is not satisfied, then the model will indicate an error message for horizontal infeasibility as seen in Figure 10 below.

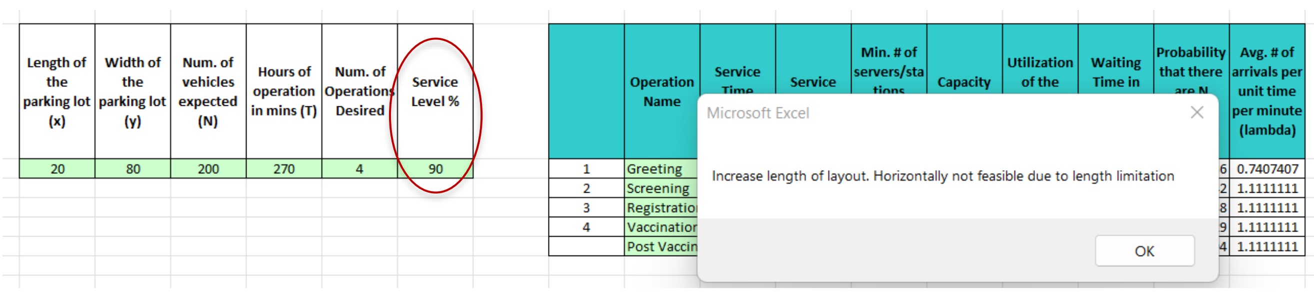


Figure 10: Example of Horizontal Infeasibility Message Box Pop-up.

4.4 Flow Charts Of The Function Of The Model

In this section, we describe the flow charts that represent the model's performance and decision-making processes. These visual aids provide users with a clear understanding of how the model operates. The flow charts shown in Figure 11 and Figure 12 represents detailed flow charts outlining the model's performance and decision-making processes.

4.4.1 Flow chart that indicates the process of the 'Button Click' functionality that generates the clinic layout

The flow chart shown in Figure 11 provides a detailed outline of the process for the "Button Click" functionality that generates the clinic layout. To begin the process, the user must click on the

"Generate Layout" button and input key parameter values such as parking lot dimensions, the expected number of vehicles, intended hours of operation, service level percentage, and service times for each operation. Once the user inputs these data, the model generates the service rates, minimum number of stations required, capacity of the lane, utilization rates, waiting time in queue, and the probability that there are 'n' number of vehicles in the queue at each operation lane.

If there are any vertical or horizontal infeasibility issues with the input data, the model will display an error message, prompting the user to adjust the data and click on the "Generate Layout" button again. If there are no further horizontal and vertical infeasibility issues, the model will proceed to check if the vertical lane space is utilized effectively. This is done by calculating the probability of precisely 'n' vehicles in the queuing system (P_n), against the targeted utilization probability entered by the user. If P_n is greater the target probability, the model will increase s and recalculate P_n until the calculated P_n is less than or equal to the target probability indicated by the user. Once this criterion is satisfied, the model will generate a layout that visually indicates the minimum number of stations required at each operation lane along with the direction of traffic flow. Figure 7 and Figure 8 show examples of the generated layouts via the model with different user inputs. The flow chart in Figure 11 below provides a comprehensive overview of the process that generates a clinic layout and allows the user to follow each step clearly.

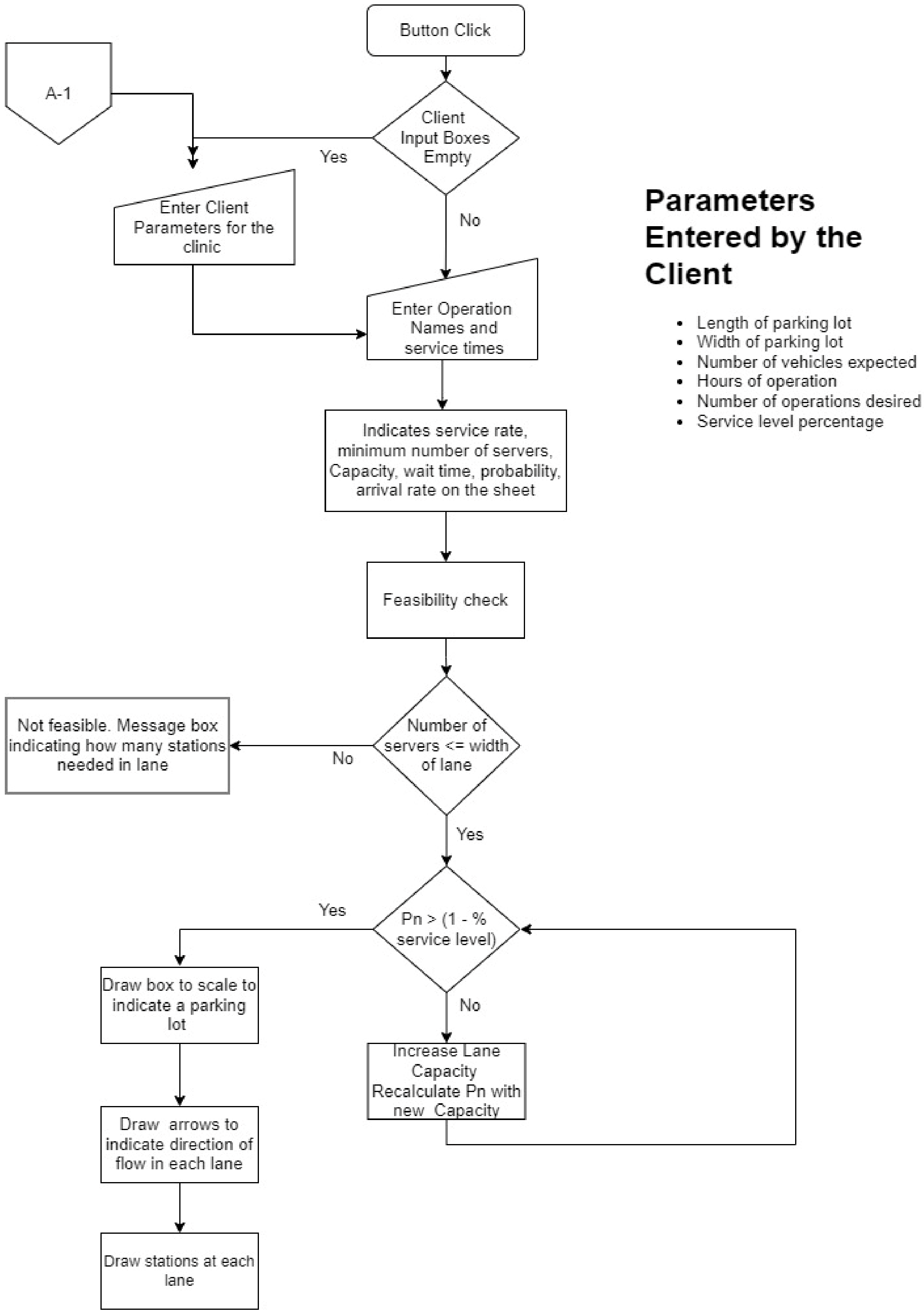


Figure 11: Flow Chart Illustrating the Sequence of Events Triggered by the 'Draw Layout' Button Click in the Model.

4.4.2 Flow chart that indicates the RESET button click process

The "RESET" function is a critical tool for any modelling system as it provides users with the ability to reset the model back to its original state. This feature can be particularly useful in scenarios where multiple modifications and iterations of the model's parameters are required. Figure 12 below displays the flow chart of the “RESET” button function of the model presented in this thesis. When the “RESET” button is clicked, the model resets all default values to the values as shown in Table 12 below. This allows the users to efficiently explore a variety of scenarios without the need to manually reset the model themselves.

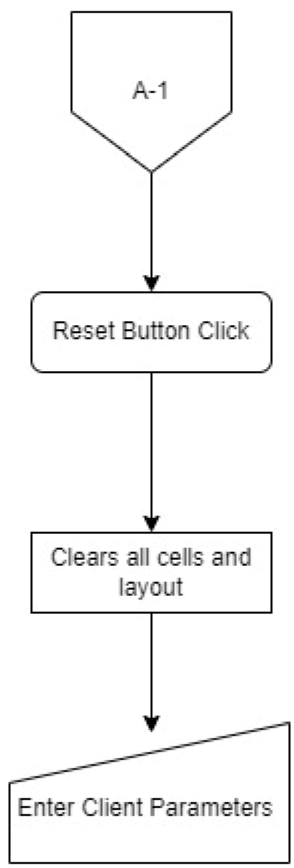


Figure 12: Flow Chart Illustrating the Sequence of Events Triggered by the “RESET’ Button Click in the Model.

Table 12: Table Displaying the Default Values for Layout Generate for a Drive-Through Vaccination Clinic Model upon RESET Button Click.

Average length of a vehicle (ft)	Average vehicle width (ft)	Min. # of Horizontal cells	Color Index for layout	Color Index for Table Header	Color Index for Table Body	Color Index for Set Parameter Table	Color Index for Client Parameters	Starting Cell to Draw
15	10	3	24	42	34	40	35	I13

Users may wish to test a variety of clinic parameter values during the modeling process to see how they affect the model's output. If the user wants to modify the default values provided by the model, they can easily do so by directly changing the values on the corresponding table (Table 12). To accommodate this, the "RESET" function was created to make it simple for the user to alter the parameters' default values in Table 12. Users can create a customized clinic layout by temporarily changing the default values on Table 12, allowing them to input and test new values that align with their desired output. For instance, if the user decides that the minimum horizontal length for the layout is five cells and not three, then the output values and the layout generated by the model will adhere to this new clinic parameter value. However, the user can simply click the "RESET" button if they decide they want to start over with the model's initial values. As a result, the values in Table 12 will revert to the model's initial default settings.

Users who are working on multiple iterations will particularly benefit from this feature of the model. The user can simply click the "RESET" button to begin with the original values instead of manually resetting the values to the default values. By streamlining the modeling process with the "RESET" function, users can save time and increase their overall productivity.

Chapter 5: Discussion

This chapter provides the final thoughts on the model created in this thesis and the limitations of the model, along with recommendations for improvement. The model demonstrated the ability to generate accurate results for several important metrics, including service rates, minimum station requirements, utilization rates, average waiting time in queue, and the probability of vehicles in the system at any given time. These values were cross-checked with hand calculations to ensure accuracy.

Based on the collected from Duffus Health drive-through vaccination clinic, it would take an average of 9.49 minutes for a vehicle to pass through the drive-through clinic from start till the point of receiving a vaccination. However, it is worth noting that the clinic parameters were obtained from a relatively small sample size, as the drive-through vaccination clinic was only conducted for two days. As a result, relying solely on this data may make it challenging to make definitive judgements regarding the clinics overall performance. Additionally, the clinic parameters do not consider factors such as patient satisfaction, which could further influence the clinic's performance. Further research and data collection efforts could provide a more comprehensive understanding of the clinic's operations and performance.

5.1 Limitations Of The Model

While the model created using Excel VBA provides valuable insights into the performance of the drive-through vaccination clinic, there are some limitations to the model that should be noted.

One major limitation of the model is that it assumes all vehicles entering the clinic will successfully complete the vaccination process. This means that the model does not account for emergency exit lanes or vehicles that may need to exit the system without receiving a vaccination. In real-world scenarios, there may be situations where a vehicle needs to exit the clinic without being vaccinated.

Additionally, the model assumes a constant arrival rate and operation time throughout the day, which may not be realistic. In reality, there may be variations in the arrival rate of vehicles, or the time taken for each service depending on factors such as weather conditions, staffing levels, higher number of patients in the vehicle, or unexpected events. These variations could impact the overall efficiency and effectiveness of the clinic, and the model may not capture these nuances accurately.

Another limitation of the model created is that it only generates rectangular layouts for the drive-through vaccination clinic. This means that the model may not be suitable for assessing drive-through vaccination clinics that have irregular layouts. This may not provide an accurate representation of the clinic's performance and impact the accuracy of the model's predictions and decisions made based on the model's results.

To address the limitations of the model, future iterations could include the ability to generate layouts with irregular shapes. Additionally, emergency exit lanes should be incorporated into the model to allow vehicles to exit the system without getting vaccinated. By addressing these limitations, the model can become a more comprehensive tool for decision-makers to optimize the operations of drive-through vaccination clinics.

Despite these limitations, the model created using Excel VBA is a useful tool for assessing the performance of the drive-through vaccination clinic, identifying areas for improvement, and generating a visual layout. It provides valuable insights into the average service times, wait times, and resource utilization rates of each service area, allowing decision-makers to make data-driven decisions to optimize clinic operations.

5.2 Actionable Recommendations Based On Observations

There are several lessons that can be learned from previous drive-through vaccination clinics that could be applied to improve the flow of future clinics. Some of these insights are:

1. *Streamlining operations*- Efficiency in the registration process is crucial, as it can often be time-consuming. To expedite the process, measures should be taken to streamline it. One effective approach is conducting pre-screening and registration prior to the clinic day. This can be done through online or phone pre-registration, as well as conducting health screenings beforehand. The Duffus Health clinic successfully implemented this approach to avoid excessive delays on the day of the clinic. Furthermore, clinic designers can

consider breaking down large operations into smaller, more manageable operations. This was evidenced in Chapter 4.2, where the analysis showcased the positive impact of breaking down the Registration operation into smaller operations. This approach can help reduce waiting times in queues and improve overall operational efficiency.

2. *Designing a clear traffic flow plan* – Optimizing the clinic layout requires careful attention to the traffic flow plan. This can be achieved by strategically placing signs and directions for vehicles. The Duffus Health drive-through clinic implemented such signs to indicate the direction of traffic flow. This included strategically placing signs and directions for vehicles to follow. Parking cones were used to separate lanes and guide drivers along the designated path, while clinic staff were also stationed to direct traffic flow, resulting in minimal issues related to traffic management. Clear indications of traffic flow are crucial for larger-scale drive-through vaccination clinics to significantly improve efficiency, streamline the clinic process, and ensure a seamless experience for staff and patients. A well-designed traffic flow plan is a critical element of an optimized clinic layout. By implementing effective traffic flow management strategies, clinics can optimize their layout as delays, and enhance operational effectiveness.

3. *Adequate staffing* – Having an adequate number of staff on hand at all times is imperative for a drive-through vaccination clinic to run efficiently and effectively. By ensuring the right number of staff on hand, waiting times can be reduced and patients can be seen in a timely manner. Staff training and proper equipment are also essential factors when it comes to ensure that the work they perform is done in a timely manner. It consists of training on the administration of the vaccines, the proper use of personal protective equipment (PPE) and dealing with adverse reactions that may occur. In the case of the Duffus Health clinic, the allocated staffing was adequate, resulting in smooth clinic operations during its operational hours.

4. *Ensuring adequate supplies* - Ensuring that the clinic has sufficient supplies of vaccines, PPE, and other necessary materials is critical for efficient operations. Pre-drawing vaccines before patient arrivals can help minimize wait times at the vaccination stations.

Additionally, having a system in place to monitor and restock supplies as needed can help prevent last-minute shortages and keep the clinic running smoothly throughout the day. The Duffus Health drive-through clinic experienced challenges in maintaining adequate supplies consistently, as observed by instances where staff members had to rush to retrieve additional vaccine doses for the next vehicle. Implementing proactive measures to monitor and manage supply levels can mitigate such issues and ensure a seamless clinic experience for both staff and patients.

5. *Observations after vaccination* – Allocating a specific area for patients to rest and be supervised for a brief period after receiving the vaccine can assist in detecting and controlling any immediate negative responses that may arise due to the vaccine. In case medical intervention is required, healthcare professionals can monitor the patient, thereby diminishing the likelihood of severe health complications and enhancing the general security of the facility. Typically, the post-vaccination observation time is short, typically between 15 and 30 minutes, as most patients will not experience any adverse reactions. However, it is critical to have a specified monitoring area to ensure prompt identification and effective management of any adverse reactions that may occur. This approach also enhances patients' confidence and elevates their overall experience at the vaccination center. In the case of the Duffus Health drive-through vaccination clinic, calculating the space required for the observation area was not necessary since the area that was available was very large. However, in situations where space is limited, it is crucial to carefully plan and ensure there is enough space for an adequate observation area. This ensures that post-vaccination patient monitoring can be conducted effectively, even in constrained spaces.

5.3 Recommendations For Improvements Of The Tool

Based on the limitations identified in the model created via Excel, here are some recommendations for improvement:

1. Consider incorporating emergency exit lanes: The model can be updated to include emergency exit lanes, which would allow vehicles to exit the system without getting

vaccinated. This would allow the decision-makers to identify alternative routes and space needed for the clinic layout without increasing any traffic.

2. Incorporate more complex layouts: To address the limitation of generating only square and rectangular layouts, the model can look for alternative ways to incorporate complex layouts.

3. Using simulation to verify steady-state calculations by replicating a queuing system and simulating customer arrival and service times. By running the simulation for a large number of iterations, the system performance metrics such as the average number of customers in the system, the average waiting time, and the average service time can be calculated and compared with the steady-state calculations made by the queuing model. If the results are consistent, it provides evidence that the model accurately reflects the real-world system. On the other hand, if the results are inconsistent, it may indicate that the assumptions made in the model are not entirely accurate and may need to be revised.

4. The queuing model can be simulated to study system performance under different scenarios, and optimization techniques can be applied to identify strategies that can improve system efficiency and reduce wait times.

5. The incorporation of blocking probabilities in the Markov model can provide a comprehensive view of the queuing system and its performance. A simulation of the model allows for validation of the steady-state calculations and enables queuing analysts to investigate the impact of various factors on the system performance, including the effect of blocking on the overall system efficiency. By modelling blocking in this way, queuing analysts can make more informed decisions about how to optimize the system. For example, if blocking is found to be a significant issue, adjustments to station capacity or resource allocation may be necessary to reduce the likelihood of blocking and improve system efficiency.

5.4 Conclusion

The aim of this thesis was to develop a desktop application that decision-makers at medical facilities could use to quickly build a standard layout for drive-through immunization clinics. A desktop application was created using insight from a local drive-through vaccination clinic in Halifax, Canada. The model was created via Microsoft Excel, a common programme that most Canadians can access. Such a tool allows decision-makers to promptly plan for an efficient clinic with appropriate resources.

The model created via Microsoft Excel/VBA is a user-friendly tool that incorporates the M/M/s/K queuing model to recommend adequate resources in the layout. The model generated a table with parameters and a visual representation of the vaccination clinic layout with a push of a button on the Excel sheet.

The model considers input parameters such as parking lot dimensions, number of operations, number of expected vehicles, and hours of operation of the clinic to provide an optimal layout that can accommodate the proposed number of operations and stations. It also completes feasibility checks to validate the layout and will provide error messages if the input parameters are inadequate or unrealistic.

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Appendix

Appendix: Data obtained from the Duffus Health clinic

Table 13: Service Time Data Collected on Day One of the Duffus Health Drive-Through Vaccination Clinic.

	Greeting Operation	**Screening Operation**	**Registration Operation**	**Vaccination Operation**
Count	**5**	**5**	**21**	**58**
Avg. Time (min)	**0.47**	**1.23**	**3.51**	**4.35**
Standard Deviation (min)	**0.33**	**0.64**	**0.50**	**1.83**
	10	60	162	450
	31	60	147	219
	60	139.2	180	302
	27	40	211	179
	13	70.2	210	540
			223	330
			189	130
			180	256
			184	340
			239	125
			239	283
			249	410
			215	240
			249	360
			232	180
			226	180
			231	120
			220	405
			254	180
			189	135
			190	424
				310
				386
				115
				120
				254

	Greeting Operation	Screening Operation	Registration Operation	Vaccination Operation
Count	**5**	**5**	**21**	**58**
Avg. Time (min)	**0.47**	**1.23**	**3.51**	**4.35**
Standard Deviation (min)	**0.33**	**0.64**	**0.50**	**1.83**
				355
				135
				265
				214
				220
				122
				380
				266
				240
				300
				280
				456
				242
				413
				324
				250
				300
				200
				135
				143
				385
				184
				410
				360
				240
				90
				167
				180
				160
				179
				150
				427

Table 14: Service Time Data Collected on Day Two of the Duffus Health Drive-Through Vaccination Clinic.

	Greeting Operation	**Screening Operation**	**Registration Operation**	**Vaccination Operation**
Count	**6**	**6**	**40**	**59**
Avg. Time (min)	**0.41**	**1.16**	**3.53**	**4.32**
Standard Deviation (min)	**0.33**	**0.45**	**0.68**	**1.85**
	15	62	150	317
	30	70	118	348
	12	122	125	452
	62	48	162	492
	9	55	157	400
	20	60	180	275
			210	213
			182	204
			224	382
			240	404
			275	396
			187	360
			200	474
			245	261
			217	227
			180	301
			231	211
			246	415
			235	450
			225	160
			257	141
			209	329
			222	196
			190	150
			230	320
			204	184
			201	202
			170	337
			274	281
			234	262

	Greeting Operation	Screening Operation	Registration Operation	Vaccination Operation
Count	**6**	**6**	**40**	**59**
Avg. Time (min)	**0.41**	**1.16**	**3.53**	**4.32**
Standard Deviation (min)	**0.33**	**0.45**	**0.68**	**1.85**
			244	330
			122	265
			231	400
			239	205
			248	482
			223	130
			268	260
			246	240
			252	120
			223	98
				173
				169
				300
				214
				189
				269
				139
				378
				239
				130
				95
				153
				80
				137
				288
				198
				96
				250
				117

	Greeting Operation	Screening Operation	Registration Operation	Vaccination Operation
Count	**11**	**11**	**61**	**117**
Avg. Time (min)	**0.44**	**1.19**	**3.52**	**4.34**
Standard Deviation (min)	**0.31**	**0.51**	**0.62**	**1.83**
	10	60	162	450
	31	60	147	219
	60	139.2	180	302
	27	40	211	179
	13	70.2	210	540
	15	62	223	330
	30	70	189	130
	12	122	180	256
	62	48	184	340
	9	55	239	125
	20	60	239	283
			249	410
			215	240
			249	360
			232	180
			226	180
			231	120
			220	405
			254	180
			189	135
			190	424
			150	310
			118	386
			125	115
			162	120
			157	254
			180	355
			210	135
			182	265
			224	214
			240	220
			275	122
			187	380
			200	266
			245	240

	Greeting Operation	Screening Operation	Registration Operation	Vaccination Operation
Count	**11**	**11**	**61**	**117**
Avg. Time (min)	**0.44**	**1.19**	**3.52**	**4.34**
Standard Deviation (min)	**0.31**	**0.51**	**0.62**	**1.83**
			217	300
			180	280
			231	456
			246	242
			235	413
			225	324
			257	250
			209	300
			222	200
			190	135
			230	143
			204	385
			201	184
			170	410
			274	360
			234	240
			244	90
			122	167
			231	180
			239	160
			248	179
			223	150
			268	427
			246	317
			252	348
			223	452
				492
				400
				275
				213
				204
				382
				404
				396
				360

	Greeting Operation	Screening Operation	Registration Operation	Vaccination Operation
Count	**11**	**11**	**61**	**117**
Avg. Time (min)	**0.44**	**1.19**	**3.52**	**4.34**
Standard Deviation (min)	**0.31**	**0.51**	**0.62**	**1.83**
				474
				261
				227
				301
				211
				415
				450
				160
				141
				329
				196
				150
				320
				184
				202
				337
				281
				262
				330
				265
				400
				205
				482
				130
				260
				240
				120
				98
				173
				169
				300
				214
				189
				269
				139

	Greeting Operation	Screening Operation	Registration Operation	Vaccination Operation
Count	**11**	**11**	**61**	**117**
Avg. Time (min)	**0.44**	**1.19**	**3.52**	**4.34**
Standard Deviation (min)	**0.31**	**0.51**	**0.62**	**1.83**
				378
				239
				130
				95
				153
				80
				137
				288
				198
				96
				250
				117