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DISCRETE EVENT SIMULATION FOR COVID-19 DRIVE-THROUGH MASS VACCINE DISTRIBUTION EVENTS

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The key aim of this research is to demonstrate how a discrete-event simulation model and the simulation-based optimization model could help organizers of the mass vaccination distribution site better understand the system dynamics and make effective data-driven decisions. The proposed simulation model was developed based on empirical data collected during the COVID-19 drive-through vaccination events and insights provided by the system experts. Both the simulation and the simulation-based optimization models are found to be effective in helping the COVID-19 drive-through events' decision-makers by providing information on how their system would respond over time under various scenarios leading to more informed and systematic decisions about the process and resource management. The model could easily be extended and reused for any other drive-through mass vaccination facilities in the future.

Keywords: Discrete Event Simulation, COVID-19, Drive-through Site, Mass Vaccination, Simulation Optimization.

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1. INTRODUCTION

The COVID-19 pandemic has adversely affected human life across the globe (Nicola *et al.*, 2020). As of June 3, 2021, over 171.5 million people have tested positive for the SARS-CoV-2 virus, and over 3.5 million people have died due to various virus-related complications (Coronavirus Resource Center, 2021). There was no recent precedent of the COVID-19 pandemic that required the bigger portion of the world population to get immunized at a rapid pace to mitigate the outbreak (Goralnick *et al.*, 2021). On January 30, 2020, the World Health Organization (WHO) declared the novel coronavirus outbreak as a public health emergency of international concern (World Health Organization, 2022). Research communities across the world have worked diligently to develop COVID-19 vaccines to end the pandemic (Asgary *et al.*, 2020). On November 18, 2020, Pfizer and BioNTech announced that their COVID-19 vaccine showed a 90% efficacy rate during the clinical trials (U.S. Food & Drug Administration, (n.d.)a). Shortly afterward, Moderna announced that their COVID-19 vaccine showed 94.5% effectiveness in a large clinical trial (U.S. Food & Drug Administration, (n.d.)b).

In the interim period, when the first cohort of COVID-19 vaccines was undergoing testing and approval processes, the Center for Disease Control and Prevention (CDC) and several other US health authorities planned for rapid distribution of the vaccine. By August 2020, CDC released an interim vaccination plan for the state and local officials and communicated with the state governors to ensure distribution sites were functional by November 1, 2020 (Machaud and Kates, 2020). The US Food and Drug Administration (FDA) agency approved the emergency use authorization (EUA) of the Pfizer and BioNTech vaccines on December 11, 2020 (Garde and Herper, 2020), and the Moderna vaccine on December 18, 2020, respectively (Grady, 2020).

Although US health authorities held some prior knowledge of mass vaccination and pill dispensing, the COVID-19 vaccination plan was designed to be executed at a much greater pace and scale in comparison to the other pandemics, such as the H1N1 influenza outbreak in 2009 (Joi, 2020). The distribution task became more challenging due to the cold supply chain management for the vaccines, multiple-dose requirements, diverse US demographics, and lack of operational preparedness in some jurisdictions (Hosangadi *et al.*, 2020).

The CDC provided general guidelines to the mass vaccination sites to maximize the throughput depending on the capacity (Centers for Disease Control and Prevention, 2021b). Based on the CDC's guidelines, the Department of Health for

the states determined how to govern, operate, and control mass vaccination events depending on the local infrastructure and capabilities. In addition, the US Federal Emergency Management Agency (FEMA) released a comprehensive playbook for community vaccination centers (CVCs) to provide guidelines on facility setup, integral resource management, and other managerial tools (FEMA, 2021). Large venues, including stadiums, convention centers, and parking lots, were converted into large walk-in vaccine clinics and/or drive-through sites.

In comparison to walk-in settings, drive-through mass vaccination events have a lower potential for virus transmission rates, as vaccinees stay inside their cars during the process. Additionally, a study conducted by Reid, D.E. found that the effectiveness of the drive-through and walk-in mass vaccination events were comparable (Reid, 2010). Due to these facts and better access to cars, drive-through facilities played a major role in the US COVID-19 mass vaccination process. To the best of our knowledge, there is no public dataset available specifying the total number of COVID-19 vaccines distributed using the drive-through events. However, based on our observation, it is fair to say that the majority of the vaccines in the earlier stage in the US were dispensed using drive-through facilities. By the end of April 2021, there was a significant decline in COVID-19 vaccination demand in the US. Thus, many of the temporary drive-through mass vaccination sites were closed across the country (Durkee, 2021). However, in the future, these facilities might be required to reopen to provide COVID-19 booster vaccines as the pandemic is yet to be over globally (VOA News, 2021).

Initially, COVID-19 vaccine supplies were distributed to the vulnerable groups first to reduce the mortality and hospitalization rates. During this phase, the vaccination site authorities had the opportunity to gain insights on their system; and to adjust for operational improvements, if necessary. Mass vaccinations for other pandemics were also carried out in a similar phased approach (Hosangadi *et al.,* 2020). However, for future outbreaks, the mass vaccine rollout might be subjected to a tighter schedule to minimize fatality and impacts. In that case, health authorities would have minimal scope to optimize the mass vaccination processes through pilot runs and small-scale prioritized operations as done so far. They would need to rely on digital technologies such as discrete event simulation (DES) modeling to design and test the process configurations virtually. The DES models have been widely used in social sciences (Marlin and Sohn, 2014; Marlin and Sohn, 2016), especially in assessing the healthcare delivery system (Gul and Guneri, 2012; Joshi and Rys, 2011). Recently, some DES models have been developed for various COVID-19-related applications, including mass vaccination services (Asgary *et al.,* 2020; Gupta *et al.,* 2013; Jerbi *et al.,* 2023; Wiggers *et al.,* 2011).

Using the DES models, decision-makers can virtually observe how the system evolves with time, perform "what-if" analyses by altering system configurations, and optimize the operation of the vaccination pathway (Asgary *et al.,* 2020; Gupta *et al.,* 2013; Jerbi *et al.,* 2023;). After the anthrax attack in 2001, the public health authorities of Montgomery County, Maryland, developed a DES model for walk-in clinic settings to plan for emergency mass vaccination events to achieve the Public Health Ready designation defined by the National Association of County and City Health Officials (NACCHO) (Aaby *et al.,* 2006). The DES model was validated using the data from an organized mock smallpox vaccination event conducted in Montgomery County, Maryland. It was also used to perform several what-if analyses to evaluate alternative clinic designs and operational policies.

Using the experience from the H1N1 influenza pandemic, Gupta et al. developed a generic simulation modeling tool to help public health officials in determining important parameters, such as the required number of Point of Dispense (POD) lanes, the capacity of the holding lanes, staff needed at the consent handout stations and PODs, and average user waiting time in the system (Gupta *et al.,* 2013).

Asgary et al. (2020) proposed the first generic DES model for the COVID-19 drive-through mass vaccination event using the AnyLogic software (Asgary *et al.,* 2020). The model was developed with the purpose to serve as a guiding tool for the health authorities in the initial planning phase to determine the required resource capacity based on appointment and space availability. As the study was conducted before mass vaccine distribution started, the model was not validated using data from a specific venue.

Jerbi et al. (2023) developed a DES model of a real COVID-19 mass vaccination walk-in center located in Sfax, Tunisia. The authors coordinated with the public health authority, collected data from the event and validated the DES using several KPIs, including the average waiting of vaccinees in the event and the average total time vaccinees spent in the system. They have proposed a system layout alternative and compared it with the base settings model. They found that the alternative layout moderately increases the average number of on-time vaccinations and provides a better staff utilization rate.

Regardless of the type of pandemic, the main process components involved in mass vaccination services tend to be similar. Thus, generalized DES models are usually useful for designing the mass vaccination sites in the initial phase to understand the system dynamics. However, the decision-makers need to verify and validate the generic DES model before applying it to make operational-level decisions about their sites. This would help them to avoid making Type III errors (Kelton, 2002). For instance, as a precautionary measure, the CDC instructed the sites to observe the COVID-19 vaccinees after inoculation (30 minutes with certain allergies, 15 minutes for others) (FEMA, 2021). There were two options provided to organize this postvaccination observation process. The recommended option was to arrange the vaccination and postvaccination observation process in the same spaces. However, if using the same space as the resource were not viable for

the site, then the process would be organized in a nearby area staffed with adequate medical professionals (Centers for Disease Control and Prevention, 2021a). Depending on the specific site demographics, decision-makers select the appropriate option. So, the DES model representing an individual site needed to have the appropriate logic for the postvaccination observation process that the decision-makers selected, else the result derived from the model would not reflect the real-life situation.

Wood et al. (2021) developed the first validated DES model for the COVID-19 walk-in vaccination facility using data from two regional vaccination centers in South West England. For one of the vaccine centers, they analyzed two alternative scenarios along with the base case by varying the arrival rate and resource capacity. Asgary et al. (2020) also performed a similar 'what-if' analysis using their generic DES model. In both of these studies, only a few scenarios were compared, and the values of the control variables were selected by the researchers based on their expertise due to having limited operational experiences at the time of research. However, in reality, there are too many possibilities and combinations of the control variables value to select and test the model with (Kelton, 2002).

Using expertise from the H1N1 mass vaccination event, Gupta et al. (2013) proposed a DES-based optimization model for drive-through mass vaccination events, whose objective is to minimize the average waiting time of the vaccinees, considering specified limits for space availability and balking of the vehicles. However, staffing optimization was not considered in their model.

In our research, we developed a DES model for the New Mexico State University's (NMSU) drive-through COVID-19 mass vaccination event and conducted simulation optimization. To the best of our knowledge, this is the first simulation optimization model which simultaneously considered multiple objectives including aggregated medical staff hiring cost, vaccination area setup cost, and cost of accumulated excess wait time of vaccinees per event. Along with this, a new system alternative was proposed, which aims to reduce the overall waiting time for the vaccines in the system. Table 1 provides a comparison of our work with other similar studies in which the DES tool was developed for mass drive-through vaccination. The case study site was selected due to our proximity to the university community and ease of access to the event organizers.

Table 1. Comparison table of existing research and this study

Study	Covid-19 Pandemic?	Used Real Data?	Proposed alternative Layout	Simulation optimization model	Objectives		
					Total Wait time	Cost of hiring vaccination staff	Cost of vaccination setup
Asgary *et al.* (2020)	✓				✓		
Gupta *et al.* (2013)		✓		✓	✓		
Wiggers *et al.* (2011)		✓		✓	✓		
Wood *et al.* (2021)	✓				✓		
This Study	✓	✓	✓	✓	✓	✓	✓

2. SYSTEM OVERVIEW

New Mexico was one of the four states chosen by Pfizer and BioNTech for the COVID-19 vaccine delivery pilot program to help address storage and distribution challenges in the earlier stage (Boyd, 2020). On December 14, 2020, the first doses of Pfizer's COVID-19 vaccines were administrated in New Mexico (Rodriguez and Porter, 2020). The NMSU main campus was selected as one of the COVID-19 vaccine distribution sites situated in Doña Ana County, the second-most populated county in New Mexico. Around 9,000 vaccines were dispensed through the site between January – May 2021 (Lopez, 2021). The site was operated by volunteers from various NMSU academic and logistic departments with external support from the Emergency Response Department of Las Cruces City/Dona Ana County and New Mexico's Department of Health [26]. The Deputy Chief of the NMSU Fire Department served as the incident commander of the site and helped as the main system expert in this project.

The NMSU COVID-19 drive-through vaccination event was organized in an outdoor parking lot located within the university premises. The site could hold up to 255 cars in the pre-vaccination holding area and around 60 cars in the vaccination area at a respective time. Between 200 to 600 vaccines were administrated every Friday, mostly during the spring 2021 semester. On a typical day, around 60-100 cars were scheduled to arrive at the beginning of every half-hour slot between 10 am and 12:30 pm (6 slots). To better understand the facility layout, a 2-D schematic diagram is provided in Figure 1. Typically, the car enters through the check-in area (Zone 1), where a safety staff confirms the appointment schedule of the vaccines and directs them to their designated holding area slot (Zone 2). In the case that the vaccinees are unable to prove the appointment, they are requested to leave the event area through the first exit. The slots in the holding area are allocated based on the arrival and appointment times of the vaccinees to prioritize early appointments and avoid unnecessary mixing of different appointment groups. Table 2 outlines the holding area allocation routine for the vaccinees based on appointment

time and arrival time. When the appointment time for a particular time slot begins, the traffic control staff signals a certain proportion of the cars from the holding area (Zone 2) to the vaccination area (Zone 3), depending on the number of spaces available in the vaccination area.

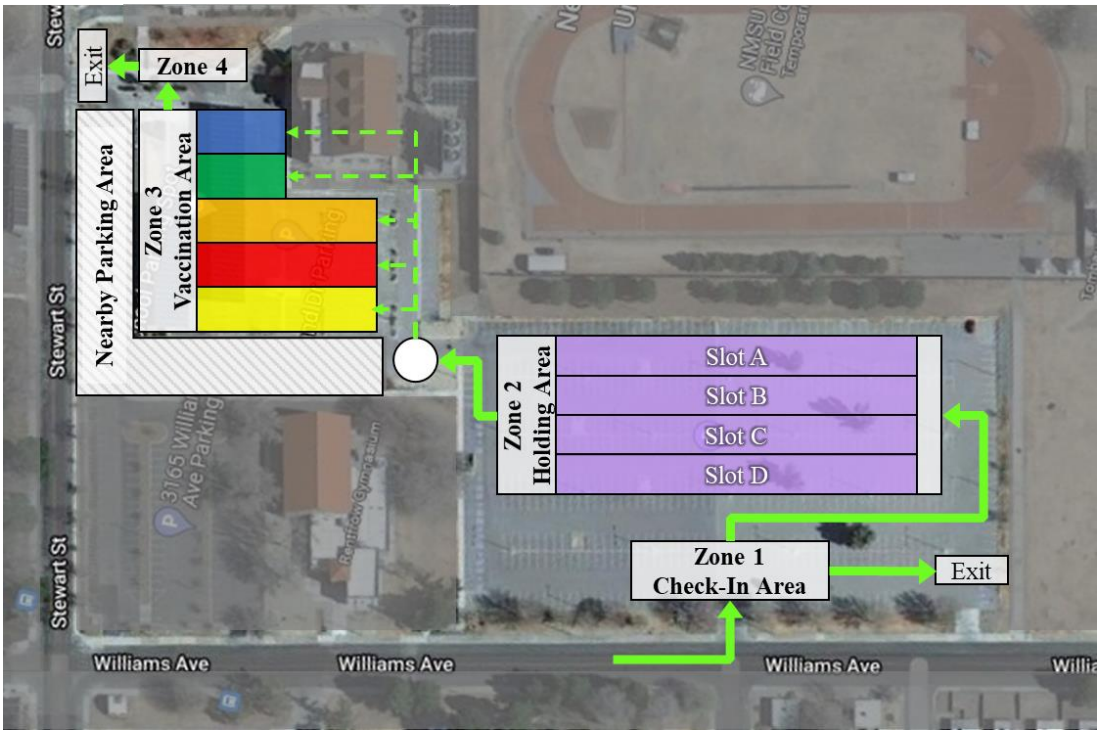


Figure 1. Schematic facility layout diagram of NMSU COVID-19 vaccination drive-through site

The priority to enter the vaccination area is based on appointment time, i.e., an earlier scheduled appointment time, resulting in higher priority. Within each appointment time slot, vaccinees are served on the FIFO ("first-in, first-out) basis. For instance, if there are 2 cars held in Slot B and 6 cars in Slot C at 11 am, the traffic control staff allows the first car waiting in Slot B to enter the vaccination area once space becomes available.

Table 1. Assignment of car entities in Zone #2

Appointment Time	Arrival Time	
	Up to 11:30 am	11:30 am onward
10:00 am	Slot A	Slot C
10:30 am	Slot B	Slot C
11:00 am	Slot C	Slot C
11:30 am	Slot D	Slot D
12:00 pm	Slot D	Slot A
12:30 pm	Slot D	Slot B

The vaccination area consists of 5 divisions (Blue, Green, Orange, Red and Yellow). Vaccinees with known allergies are directed to the dedicated Yellow division if space becomes available. This protocol allows the facility to minimize unnecessary post-vaccination wait time for non-allergic vaccines, as the required observation period for the allergic vaccinees is fifteen minutes longer than the non-allergic vaccinees. Typically, the traffic protocol is to fill the divisions from right to left (Blue to Red). For example, if the Blue and Green divisions each have available space, then traffic staff would signal the car towards the Blue division.

Each vaccination division had an appointment supervisor, medical teams consisting of an inoculator, and a scribe and traffic control personnel. The division supervisor was responsible to monitor the overall vaccination and recovery process for their division. Upon entering the vaccination area, an available medical team greeted the vaccine recipient(s), confirmed the

medical appointment, and then administrated the vaccine. The registration confirmation and vaccination process were combinedly performed during this process. The queue disciple for the process was FIFO.

After getting vaccinated, the vaccine recipients (without allergies) wait in their car for 15 minutes or 30 minutes (with allergies) in the vaccination spot. During this observation period, the division supervisor monitors the vaccinees to ensure they have no symptoms and/or reactions. If any vaccinee had an allergic reaction, the emergency medical team (EMT) intervened to stabilize the vaccine (s). In the case of a severe reaction, the vaccine recipient(s) were required to be transported to a nearby designated healthcare facility. Otherwise, vaccine recipients were allowed to leave the facility through Zone 4 after the observation period was over.

2.1 Data

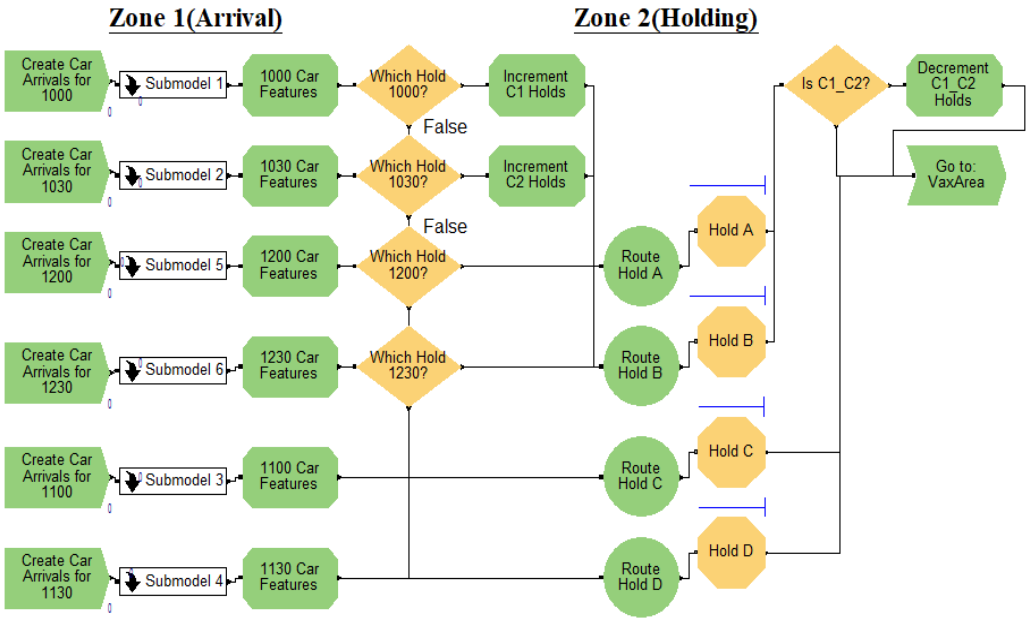
Using an electronic barcode scanning system data was collected from the event. In the check-in area (Zone 1), after confirming the appointment, the security staff explained the purpose of our study to the vaccine recipients and asked whether they would like to be a part of the system improvement study voluntarily. If the vaccinees agreed to participate in the study, a removable label containing a scannable barcode was placed on their windshield.

The barcode on each car was scanned in all four zones labeled in Figure 1 to collect the arrival time (Zone 1), holding area wait time (Zone 2), vaccination time (Zone 3), and departure time (Zone 4). The inoculation timestamps from Zone 3 were collected by the scribes assigned in each division. If there were multiple vaccines in a car, the scribes scanned the barcode after completion of each inoculation. This way, the number of vaccine recipients in each car was tracked.

Six hundred (600) barcode labels were prepared for each event. For ease of distribution and tracking, the labels were organized into 6 different stacks, each stack containing 100 labels dedicated for every half-hour time slot. The barcode number consisted of two pieces of information, the prescheduled appointment time and a unique serial number. For example, the number on the barcode for the first car scheduled for the 10 am slot was "1000-001". The combination of these two pieces of information helped to track the movement and timing of the cars carrying vaccinee(s) in the system. If a car carrying vaccinee(s) arrived before the beginning of their designated appointment time slot, they are directed to the appropriate holding area.

2.2 Modeling details

We developed the COVID-19 drive-through vaccination DES model using the Academic Research version of ARENA 16.1 simulation software. The empirical data was prepared and processed using the Pandas library in the Python programming language. The ARENA's Input Analyzer was used to fit the input probability distribution for processing times. The flowchart view of the simulation model is provided in Figure 2. In the subsequent sub-sections, the details of the modeling process are provided.



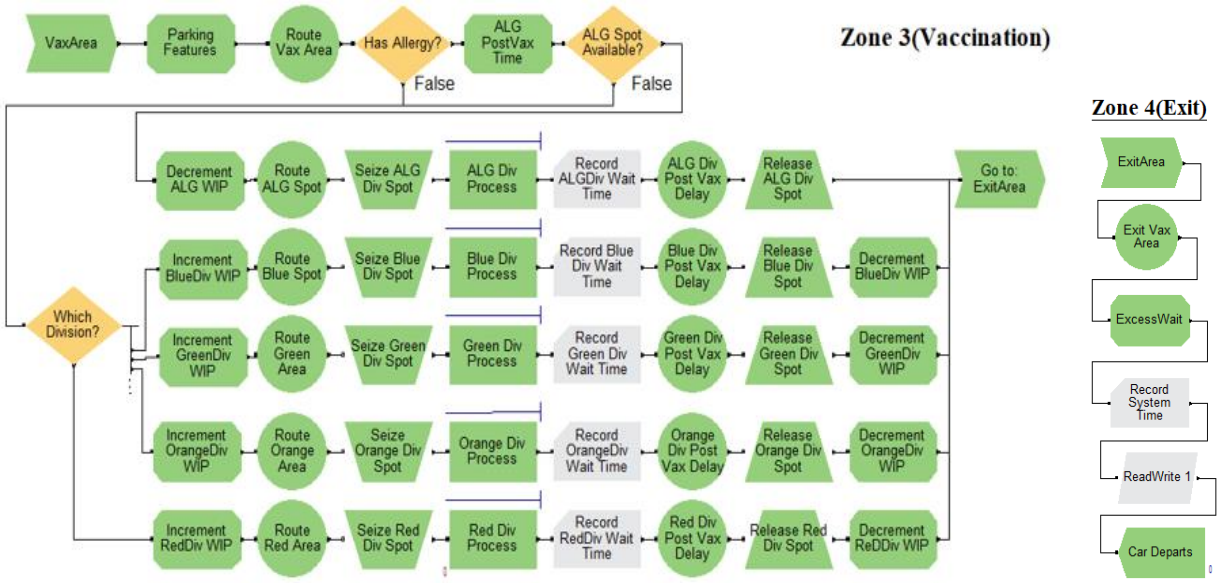


Figure 2. Flowchart View of NMSU COVID-19 Drive-Through Vaccination Simulation;

2.2.1 Check-in Area

Six "create" modules were used to generate the car arrivals in the system for each half-hour time slot between 10:00 am to 12:30 pm. The number of appointments usually varied among the time slots. For instance, on a particular day of the data collection event, 70 vaccinees were scheduled for the 10:00 am slot, 30 for the 10:30 am slot, and so on. In addition to this, as early and late arrivals of vaccinees were allowed into the system, the actual number of car arrivals across different time slots was not always consistent with the scheduled numbers. We performed a single-factor ANOVA test to evaluate whether the mean interarrival times for the six appointment time slots were different or not. The p-value for the test result was 0.0007, which was less than the 5% significance level. Thus, we concluded that the mean interarrival times were different among the appointment time slots. As the arrivals of cars were independent and identically distributed, we assumed the car arrivals followed a non-stationary Poisson process with a piecewise constant rate. Hence, the interarrival time was exponentially distributed.

The "Schedule Data" module in ARENA was used to define the arrival rate of the cars for each of the half-hour-long appointment time slots. These schedules were used inside each individual "Create" modules to generate interarrival times of car entities respectively.

Each "Create" module was attached to a "Submodel" module, inside which the logic was set to check whether the arriving vaccinees were scheduled, using a predefined probability. A delay module, 'Appointment Confirmation Delay'was placed in the submodel, where the appointment checking process time was defined, followed by a decide module, 'Has_Appointment', where based on probability, the car entities may pass forward in the system or get disposed of ."Assign" modules were placed downstream of these "Submodel" modules, where the three attributes' assignments were made to the car entities, namely the number of vaccinees, arrival time, and appointment slot. Additionally, the total number of vaccinees in the system was incremented by the appropriate number, using a variable. The routing delays from the check-in area to the holding area were defined using four "Delay" modules, respectively. As stated in Table 2, the holding area assignment for the first and last two slots was based on the arrival time. Hence, four "Decide" modules were used to check the current simulation time and channel the car entities to the appropriate holding queue using one of the routing "Delay" modules.

2.2.2 Pre-vaccination Holding Area

Four "Hold" modules (Hold A through Hold D) with the FIFO queues were placed to represent the pre-vaccination waiting area logic. For all of the holding queues, two common conditions were set to check before releasing a car entity. The first condition checked whether the simulation time has reached the beginning of the appointment slot. The second condition enabled scanning of the availability of one or more vaccination spots in the vaccination area to accommodate the current car entity. Along with these two conditions, other additional conditions were also checked before releasing a car entity from each queue to ensure the system protocol enlisted in Table 3.

Table 2. Additional release condition for holding area queues

Hold Name	Release Condition(s)
Hold A	If the car's appointment is for 12:00 pm, then the number of cars waiting in the holding queue C and D must be zero.
Hold B	If the car's appointment is 10:30 am, then the number of cars waiting in the holding queue A from 10 am must be zero. If the car's appointment is for 12:30 pm, then the number of cars waiting in the holding queue A, C, and D must be zero.
Hold C	The number of cars waiting in the holding queue A from the 10 am appointment and B from the 10:30 appointment must be zero.
Hold D	The number of cars waiting in the holding queue A from the 10 am appointment and B from the 10:30 appointment must be zero. In addition, the number of cars in the holding queue C must be zero.

Note: The early arrivals from noon or later appointment slots before 11:30 am will join hold queue D and would be released before their appointment time if space becomes available to avoid delaying the release of 11:30 am arrivals.

The number of cars in the holding queue A and B from 10:00 am and 10:30 am appointments were traced using a 1D variable. As shown in Figure 2, two assigned modules were placed downstream of the "Which Hold 1000?" and "Which Hold 1030?" decide modules to increment the 1D variable, respectively. The "Is C1_C2?" decide module checked the releasing entity type from Hold A and Hold B. If the vaccinees were from 10:00 am or 10:30 am appointments, then the entity was passed to "Decrement C1_C2 Holds?", where the 1D variable was decremented. Otherwise, it was directly routed to the "Go to VaxArea" module. From 11:30 am onward, car entities from Hold C & Hold D queues were prioritized over Hold A and Hold B, as the later queues mostly were holding vaccinees scheduled from appointment slots # 5 & 6. However, if vaccinnes from the 10 am and 10:30 am slots were still waiting in the Hold A and B queues, they were prioritized over Hold C and Hold D. This 1D variable tracks the number of vaccinees in Hold A and Hold B from appointment slot #1 and slot #2, and helps to model release condition of the Hold C and Hold D respectively.

2.2.3 Vaccination Area

After the cars were released from one of the holding queues, they entered the "Parking Features (assign)" module through the "VaxArea (label)" module, where the holding area wait time was assigned. Following that the total work in process in the main vaccination area was increased by 1. The routing time for the car from the holding area to the vaccination area's entry point was defined using the "Route Vax Area (delay)" module. Next, the car would pass through the "Has Allergy (decide)" module, where, based on predefined probability, the path of the cars carrying one or more (true end) vaccinee(s) with known allergies were separated from the rest.

The car coming out of the true end of the "Has Allergy" module then would enter the "ALG PostVax Time (assign)" module, where the post observational time was assigned. Next, the car would route to the "ALG Spot Available (decide)" module, where the expression has been set to scan whether the current number of busy spots in the allergy division was less than the scheduled capacity. When the condition was met, the car would pass through the "Decrement Vax_WIP (Assign)" module, where the total work in process in the main vaccination area was decremented by 1; then, the car seized one of the allergy division spots. On the other hand, the false end of the "ALG Spot Available (assign)" module is connected with the "Which Division" decide module, whereas the false end of the "Has Allergy (decide)" module is also connected for selecting the appropriate vaccination division.

The "Which Division (decide)" module contains three different logical expressions, which were checked sequentially by the passing car entity to move forward into the system. When one of the conditions was met, the entity followed the path instantly instead of checking the remaining logic expression(s). The priority order for division selection decreased from Blue to Red division, so the first output of the "Which Division" module is connected to the Blue division, followed by the second output linked to the Green division, third to the Orange division, and the else end to the Red division. Each of the branching conditions contained two logical parts. The first part is set to check the variable value, which specifies whether the division was open or not, followed by the second part, which checks whether the current number of cars in the particular zone was less than the scheduled capacity (of vaccination spots). When both of the conditions were set to true, the current car passed into the respective division. According to the system experts, due to its proximity to the Allergy division, the Red division was always kept open for ease of setup and other functions. Thus, the false end of the "Which Division" is connected to the Red division logic.

The cars passing through all five vaccination divisions were managed similarly. Hence, the model logic was also defined analogously. Thus, the movement of a car through the Blue division is discussed here as an example. Hypothetically, after selecting the Blue division, the car would enter the "Increment BlueDiv WIP (assign)" module, where a variable would get

incremented to keep a count of the total number of cars in the Blue division. Next, the car would move through the "Route Blue Spot (delay)" module, where the routing time between the vaccination area entrance to the Blue division was defined. Then it would pass through the "Seize Blue Div Spot" module and occupy one of the available Blue division vaccination spots and instantly join the "Blue Div Process" queue. When a medical team listed in the "Blue Div Process" module became available, the car seized the resource and underwent the combined registration and vaccination process. After that, the car entity would enter the "Blue Div Post Vax Delay," where post-observational delay would take place. No human resource was listed for this process, as division supervisors were always available to monitor each car/vaccinees undergoing the observational process. After completion of the "Blue Div Post Vax Delay" delay, the car would be released from the Blue division vaccination spot when passing through the "Release Blue Div POD" module. Then, it would pass through the "Decrement BlueDiv WIP" module to decrease the number of cars in the Blue division and the vaccination area by 1, respectively. The routing delay between the vaccination division and the exit area is defined in the "Exit Vax Area" delay module.

Before the car entities got disposed of in the "Car Departs (dispose)" module, various information about the entities was collected. In the "ExcessWait (assign)" module, the excess waiting time of each car in the system beyond 10 minutes was collected using a variable, which was used as a response variable in the optimization model. In the "Record System Time" module, the average holding wait time and vaccination wait time for the cars were recorded.

In each vaccination division, the total number of teams assigned depended on the total number of available parking spots. Hence, the processing time was expected to vary among the divisions with unequal capacity (i.e., Blue and Green: 9 spots each, Red and Orange: 15 spots each, Allergy: 5 spots). Note that a single-factor ANOVA test was performed and concluded that the processing time among the divisions were different, as the p-value was negligibly small. As the number of parking spots and medical teams in the Orange and Red divisions were equal, a two-sample t-test with unequal variance was performed and found the p-value to be approximately 0.22, which was greater than the 0.05 significance level. Thus, it was concluded that the distributions of the processing times for the Red and Orange divisions were the same. On all data collection events, the system expert kept the Blue division closed as the number of appointments was less than a certain threshold and as a result, there was no data to analyze the processing time for the Blue division. However, as the Green and Blue divisions had the same capacity and usually were served by the same number of medical teams, as mentioned by the system experts, it was assumed that the processing time in the Blue and Green zones would be the same. The processing time of the combined registration and vaccination processes in all of the zones was defined as a function of the number of vaccinees in the car. For example, if there were two vaccinees in a car, then the processing time was multiplied by 2. This reflects the fact that the registration and vaccination operations for all vaccinees in a car were carried out by the same medical team in a sequential manner.

2.2.4 Run Length

To avoid congestion on adjacent streets, management allowed the cars to enter the system ten minutes before the start of the event. Overall, the operation of the facility had a definitive start time (09:50 am) and an end state (all the scheduled vaccinees arrived and received the service). Hence, the end of each simulation run was defined using the terminating condition. The no-show behavior was not considered in the model; thus, the terminating condition was set to check whether all the scheduled vaccinees for the day had arrived and got processed in the system or not. Once met the ongoing simulation run ended. System variables and statistics were reinitiated between multiple replications.

2.2.5 Input Parameters

The input parameters associated with the vaccination divisions are provided in Table 4. The best-fitted probability distribution for the processing time in each division was selected based on the Chi-squared and Kolmogorov-Smirnov (K-S) statistical tests, respectively. In total, there were 53 vaccination spots available in the facility, divided among five divisions for ease of supervision. Each of the vaccination divisions was monitored by a division supervisor as stated earlier. On average, a medical team was assigned for every five vaccination spots in each vaccination division to perform the combined registration and vaccination process.

The relevant discrete probability measures used in the base case setting of the simulation model are listed in Table 5. Interestingly, no one arrived in the facility without a confirmed appointment on the days when the system was observed for data collection.

For the base case settings, 300 vaccinees were scheduled for the event. The average routing time of the cars between several zones in the facility is provided in Table 6, assuming the cars were traveling around 10 miles per hour in the system. The facility maintained a unidirectional traffic flow to avoid potential accidents. Hence, only the routing time for permissible paths are provided.

Table 3. Input Parameters for the Vaccination Divisions

Input Parameters	Red & Orange Division	Blue & Green Division	Allergy Division
Processing time Distribution (minutes)	Gamma (α=1.26, β=2.53)	Lognormal (μ=3.64, σ =2.76)	Triangular (min=2, mode=2.5, max=3)
# of Spots per division	15	9	5
# of Medical Teams per division	3	2	1

Note: The p-values for the K-S test for all three subsets of divisions were greater than 0.15. And p-values for the Chi-squared tests were greater than 0.06 for all three subsets of divisions.

Table 4. Values for the discrete probability parameters

Probability Parameter	Value (%)
Number of Cars without a confirmed appointment	0
Number of Cars with at least one vaccinee having known allergy	8
Number of cars with one vaccinee	95
Number of cars with two vaccinees	3
Number of cars with three vaccinees	2

Table 5. The routing time of the cars between different areas within the facility (in seconds)

To / From	001	002	003	004	005	006	007	008	009	010	011	012
001		60	50	30	10							
002						5						
003						5						
004						8						
005						10						
006							5	5	8	12	15	
007												15
008												15
009												10
010												8
011												5

Note: Where the abbreviations are as follows; 001:Zone 1, 002-005: Hold A- Hold D, 006: Zone 3 Entry, 007: Allergy Division, 008: Red Division, 009: Orange Division, 010: Green Division, 011: Blue Division, 012: Zone 4

Table 7 shows the number of vaccinees scheduled for each appointment time slot as well as the actual arrivals of the vaccinees throughout the event. For instance, 20 of 52 vaccinees scheduled for the 11:30 am appointment slot showed up between 11:00 am to 11:30 am. The vaccinees are allowed to join the holding area queues 10 minutes before the event starts (i.e., 9:50 am) to avoid congestion on the adjacent street. However, they were not allowed to enter the vaccination area until 10:00 am. Based on the arrival rate, we have defined the mean interarrival time for vaccinees from different appointment slots at different time blocks. Note that all of the input parameters enlisted in Tables 4 through 7 could be altered while customizing the model for other vaccination facilities.

Table 6. Scheduled vs. Actual arrivals occurred during the event

Appointment Time Slots	Arrival Time Intervals							Total
	09:50-10:00	10:00-10:30	10:30-11:00	11:00-11:30	11:30-12:00	12:00-12:30	12:30-End	
Slot 1-10:00	8	25	8	4	3	2	0	50
Slot 2-10:30	0	20	27	5	0	0	0	52
Slot 3-11:00	0	0	19	22	3	4	5	53

Appointment Time Slots	Arrival Time Intervals							Total
	09:50-10:00	10:00-10:30	10:30-11:00	11:00-11:30	11:30-12:00	12:00-12:30	12:30-End	
Slot 4-11:30	0	0	0	20	24	4	4	52
Slot 5-12:00	0	0	0	0	25	30	5	60
Slot 6-12:30	0	0	0	0	0	13	20	33

2.2.6 Verification and Validation

The DES model was developed and verified using empirical data. Several techniques were adopted for the verification process. During the simulation run, we observed the movement of the entity in slow motion through the system and modified the model logic as needed. To aid this process, unique pictures for cars were assigned to all six-time slots to easily trace how the cars were sent to the holding and vaccination area. We also traced the intermediate variable values using the expression boxes from the animate toolbar. In addition to that, we altered the arrival rate, processing time, and/or priorities of the entities and checked whether the outputs were varying accordingly.

The model validation process was performed using the average total time of cars carrying the vaccinees in the system as a performance measure. The actual average total time of cars spent in the system, $\bar{\mu}_{actual}$, on a particular day, was used as the hypothesized mean. The DES model was replicated 30 times, and the average total time of the cars spent in the system for each replication was recorded. Graphically, we found the sample data collected from the replications on the average total time of cars were normally distributed. Hence, the one-sample t-test was used for model validation purposes. The p-value for the test result was 0.99, which was greater than the 0.05 significance level. Thus, we concluded that there was no statistical evidence to disregard the validity of the proposed simulation model. In addition, according to the system experts, based on their observations, the average total time for the cars would range between [25,40] minutes. The average total time provided by the simulation model was within this range as well. This ensured the face validity of the model.

3. RESULTS AND DISCUSSION

To better understand how the system evolves, three measures of performance were recorded and depicted in Figure 3. These measures are the average time a car entity spent in the system, including the time being served at the vaccination area (W), average time waited in the holding area (W_{q_h}), and average waiting time in the vaccination area (W_{q_v}). The simulation model ran for 30 replications to ensure the validity of the model and account for errors. The system time of 9:50 on the horizontal axis maps to the actual clock time, 9:50 am. This is the time at which cars are allowed to enter the system but must wait in the holding area until the vaccination starts at 10:00 am (i.e., maps to 10:00 forward in the system time axis).

Looking at the first half-hour into service, the car entities started to depart the system around 10:20 am, so the value of W suddenly spiked (total system time gets recorded once the car leaves the system through Zone 4). For the first wave of cars in slot #1, though the W_{q_h} and W_{q_v} were relatively low, due to post-vaccination observation time, 15 or 30 minutes, along with vaccination and routing time, (W) was over 25 minutes. During this period, though the W_{q_h} was decreasing as the cars carrying vaccinees scheduled for the first appointment slot (i.e., 10 am) were entering the vaccination area relatively quickly, W_{q_v} increased as more cars were joining the queue in the vaccination area. Towards the beginning of the slot #2 appointment (i.e., 10:30 am), the value of W sharply dropped. This could be attributed to the fact that for appointment slot #1, the early-arriving vaccinees experienced longer wait times in the system compared to the on-time/late-arriving vaccinees. The latter group didn't have to wait for their appointment to become current to begin processing. Thus (W_{q_h}) also showed a gradual declining trend over time during slot #1, almost becoming 0 towards the end of slot #1. At 10:30 am, most of the early arriving vaccinees from slot #1 completed their service, freeing up the vaccination spots for vaccinees from slot #2. As the first wave of vaccinees from slot#2 entered Zone 3, their holding area wait time was recorded, which contributed to the sudden spike of (W_{q_h}).

As more cars started to join the holding area queues and vaccination area queues during the next 30-minute period (i.e., 10:30 am – 11 am), the W for the cars showed an increasing trend. After that, the W slightly decreased and plateaued for an hour. At around 11:50 am, when the cars with vaccinees from appointment slot #5 started to join the system, the W for the cars slightly increased as the total number of appointments for this slot was a little higher compared to the other five slots.

The W_{q_v} consistently stayed below 4 minutes throughout the event and the average value was around 2.33 minutes, which signifies that once the cars entered the vaccination area queues, the waiting for vaccination was reasonably short. On the other hand, the W_{q_h} varied as time progressed. An interesting characteristic observed in Figure 3 is that, at the beginning of each appointment slot, there was a rise in W_{q_h} since some people tend to arrive a little earlier at the vaccination area before their appointed time slot. Being a tally statistic, W_{q_h} only updated after an entity (car, in this case) departed the queue. In our case, right before an appointment slot began, there were already cars in the holding area queue that were waiting for their

appointment slot to begin. Generally speaking, these cars would have a higher waiting time in the holding area compared to the cars that were scheduled for one of the earlier slots. However, their waiting times are not reflected in the W_{q_h} until they depart the holding area queue. Once the new appointment slot starts, designated cars for that slot start to depart the holding area queue (as per holding area releasing conditions) towards the vaccination area. Since these cars had higher waiting times in the holding area, a spike in the W_{q_h} is observed as soon as they departed the holding area queue. The degree of this phenomenon was dependent on the frequency of cars arrived the system earlier than the riding vaccinees' scheduled time, and how early they arrived.

In addition to the sudden rise during the start of the appointment slots, an overall increasing trend of the W_{q_h} was observed as the event progressed until 12 pm. It is important to understand that the increased W_{q_h} is a domino effect propagated from the downstream events. More specifically, post-vaccination observation for 15 or 30 minutes at the same spot as the vaccination area led to a higher waiting time in the holding area to some extent. In the upcoming discussion, we have proposed and analyzed an alternative system configuration to address this issue.

Figure 4 shows how the total number of cars in the system, L, is varied over time. After the initial peak around 10:50 am, there is a slight dip of the curve attributed to the fact that more vaccinees from appointment slots #1 and #2 were completing the service. Between 11 am and 11:50 am, around 44% of the scheduled vaccinees arrived at the system, indicating an increasing pattern of L. The plot then shows a decreasing pattern with a slight increase noted around 12 pm for 10 minutes due to the vaccinees from appointment slot #6 entering the system. The breakdown of vaccinees' arrivals during each appointment slot is shown in Figure 5.

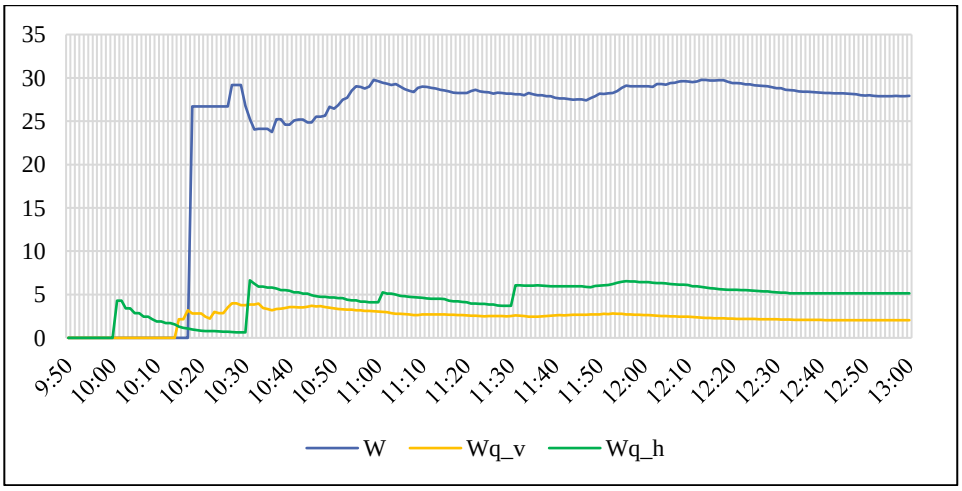


Figure 2. Representative example of system KPIs evolving over time

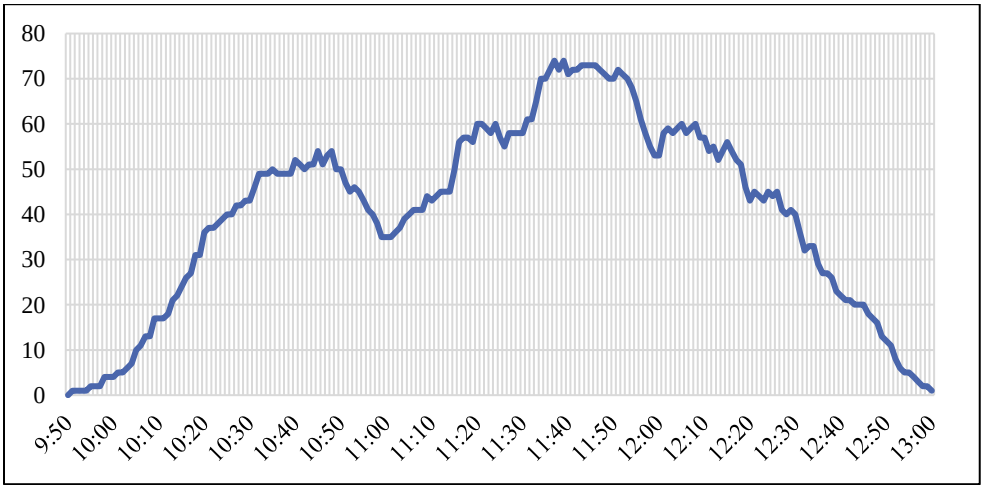
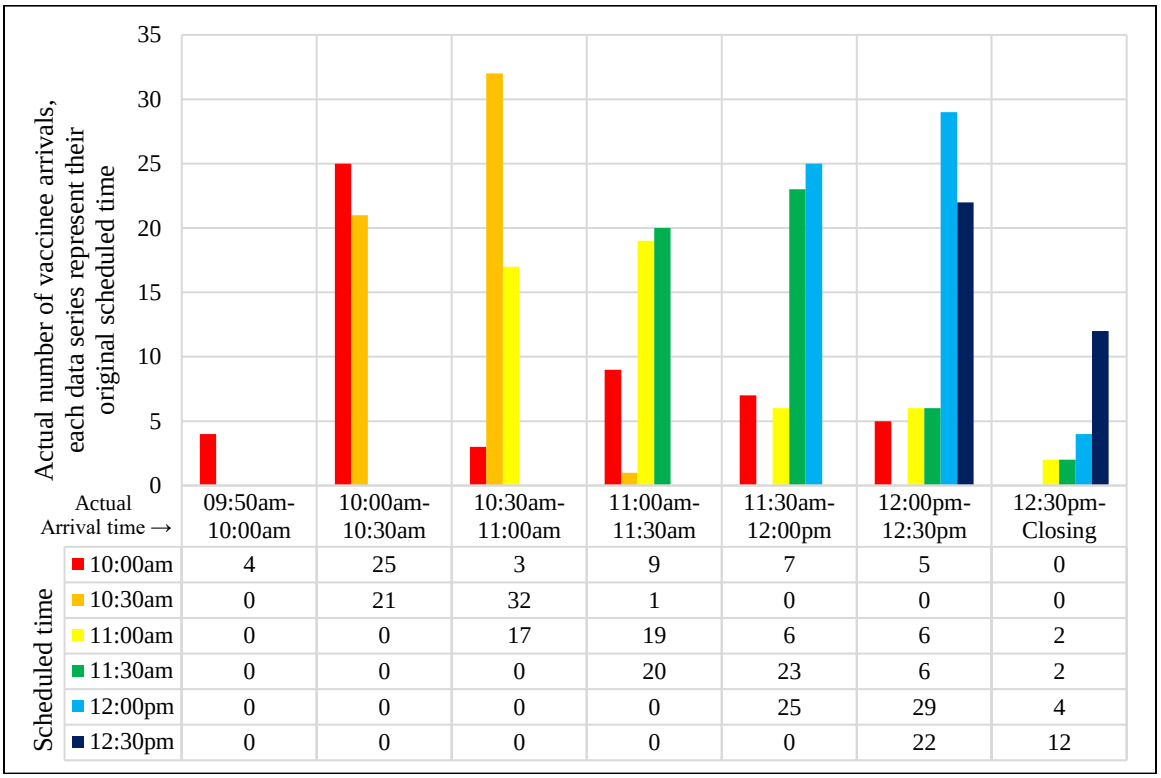


Figure 3. Total number of cars in the system (L)



Scheduled time \ Actual Arrival time →	09:50am-10:00am	10:00am-10:30am	10:30am-11:00am	11:00am-11:30am	11:30am-12:00pm	12:00pm-12:30pm	12:30pm-Closing
10:00am	4	25	3	9	7	5	0
10:30am	0	21	32	1	0	0	0
11:00am	0	0	17	19	6	6	2
11:30am	0	0	0	20	23	6	2
12:00pm	0	0	0	0	25	29	4
12:30pm	0	0	0	0	0	22	12

Figure 4. Arrival frequency of vaccinees across appointment slots

The bottleneck of this distribution system can be identified in Figure 6, which shows the utilization of the resources in the vaccination area: space and medical team. As the vaccination divisions were filled up from right to left (i.e., Blue, Green, Orange, and Red divisions in order), the utilization of both resources is below 40% in the Red (left-most non-allergy) division, less than half of the utilization in the Blue (right-most non-allergy) division. It is also important to note that the utilization of the space is always slightly higher than that of the medical teams since most vaccinees must wait in the vaccination area for 15 minutes after receiving the vaccine. This forces medical teams to simply wait until another space is available for new vaccinees to enter the vaccination area so that medical teams can provide vaccines again.

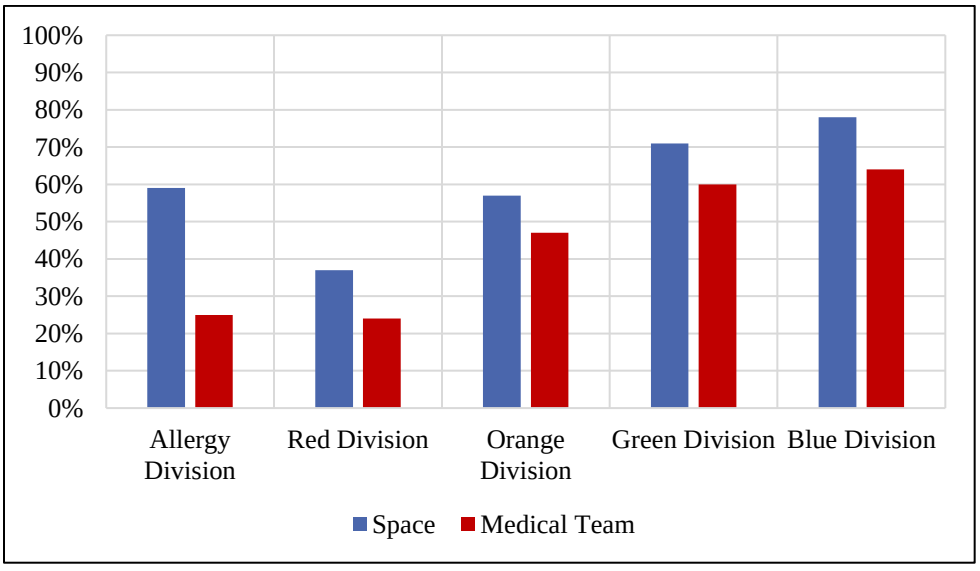
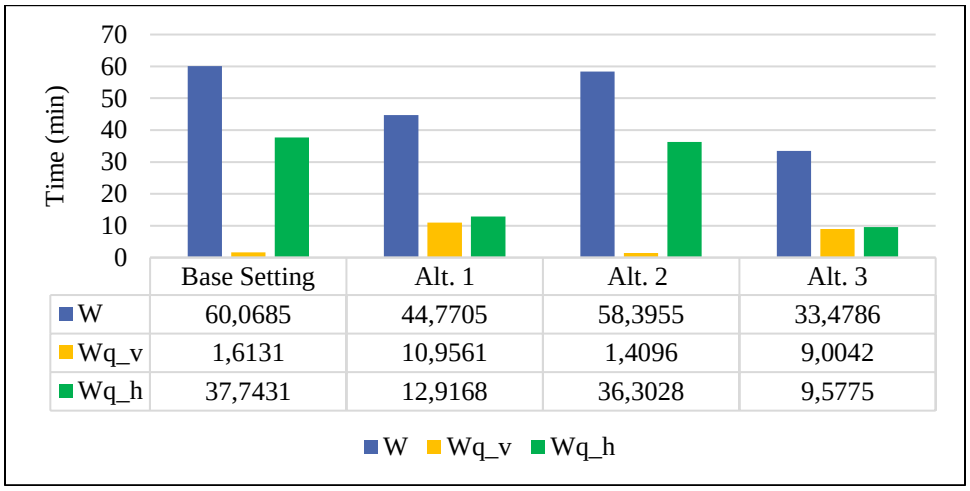


Figure 5. Utilization of vaccination area resources

To resolve this issue, alternative system configurations are analyzed in addition to the base system setting. The first alternative (Alt. #1) proposes that the vaccinees leave the vaccination area immediately after the vaccination and wait in a nearby location during the post-vaccination observation period. Two hundred additional parking spots in the vicinity of the vaccination area were included as new resources for the post-vaccination observation. With this configuration, the average time of cars occupying the vaccination area, as well as the average waiting time of cars in the holding area, would both decrease. Although the selection of vaccination divisions for incoming cars is dependent on the availability of space in each division, the division spaces are always filling up from right to left in the base system. This logic leads to the left-most non-allergy division getting severely under-utilized.

In order to balance the workload among all divisions, the second alternative (Alt. #2) changes the order in which divisions are selected. The substitute selection criteria is set to check the ratio of cars in the division to the number of scheduled medical teams to see if it is lower than other vaccine divisions. It then sends the car to the division with the lowest ratio. If there is a tie for the lowest ratio, the deciding module sends the car to the division closer to the right. The third alternative (Alt. #3) considers both strategies from Alts. #1 and #2. It is important to mention that although both alternative system configurations could be beneficial to improve the performance of the system, the results may not reflect these changes since the system resources, especially the medical teams, were always severely under-utilized, as shown in Figure 6. Therefore, while running the simulation model with the alternative system configurations, the total number of scheduled appointments were increased up to 600. With this change, the system resources could be better utilized. Again, 30 replications were performed for each simulation run, and the results are summarized in Figure 7.



	Base Setting	Alt. 1	Alt. 2	Alt. 3
W	60,0685	44,7705	58,3955	33,4786
Wq_v	1,6131	10,9561	1,4096	9,0042
Wq_h	37,7431	12,9168	36,3028	9,5775

Figure 6. Summary results of the Key Performance Indicators

It is evident that providing extra space in a nearby location for post-vaccination observation improves the system's performance significantly. Alternative system configuration #1 reduces the total time that each car entity spent in the system (i.e., *W*) by more than 25%. Balancing the workload among all divisions using the proposed strategy in Alternative system configuration #2 reduced the (W_{q_h}) by more than 75%, but overall, less than 3% of savings in *W* were achieved. However, by combining both strategies together, the total time spent in the system can be saved by about 45% compared to the base settings.

4. SIMULATION OPTIMIZATION

The goal of this research is not only to develop a DES model for the COVID-19 drive-through mass vaccination event and run/observe system behavior under certain conditions but also to improve system performance by making decisions about system parameters and structure. We used ARENA's optimization tool "OptQuest" (Kleijnen, 2007) to achieve this goal. The OptQuest solver uses metaheuristics, including tabu search, neural networks, and scatter search, into a single search heuristic (Kelton, 2002). A brief explanation of the coordination of these three meta-heuristic algorithms in OptQuest is outlined by Jebri et al. (2019). Using the model inputs that the user provided, OptQuest runs a sequence of simulations to search for a combination of these input parameter values that optimizes the output performance of the model. More precisely, the OptQuest allows users to explicitly define model constraints on the deterministic simulation inputs. The OptQuest also allows

users to specify the selection of the key performance indicator of the model (which is the objective function to be minimized) while, at the same time, satisfying the given constraint requirements. The mathematical model is provided below.

Sets
i : Set of vaccine divisions {Allergy, Red, Orange, Green, Blue}

Decision Variables:
X_i : 1, if vaccine division i is open, otherwise 0 (binary)
Y_i : Total number of medical teams assigned to division i (integer)

Dependent Variable:
T_{wait} : Accumulated excess wait time experienced by all the entities beyond a threshold (positive integer)

Parameters:
$Cost_{medteam}$: Cost of hiring a medical team
$Cost_{div}$: Cost of opening a vaccine division
$Cost_{ewait}$: Cost of excess waiting time per minute for vaccinees beyond 10 minutes

$$\text{Min}\left(\text{Cost}_{\text{medteam}}\left(\sum_{i\epsilon I} Y_i\right) + \text{Cost}_{\text{div}}\left(\sum_{i\epsilon I} X_i\right) + \text{Cost}_{\text{ewait}}(T_{\text{wait}})\right) \quad (1)$$

Set to:

$$Y_i \geq m_i^L . X_i, \qquad \forall\, i\epsilon I \quad (2)$$

$$Y_i \leq m_i^U . X_i, \qquad \forall\, i\epsilon I \quad (3)$$

$$X_i = 1, \quad \forall\, i: \{\text{Allergy}, \text{Red}\} \quad (4)$$

We have selected the daily average total operating costs per event as objective stated in equation 1, which is comprised of three main components: 1) staffing cost of all medical teams for an event; 2) setup cost for each division, including the hiring cost of the division supervisor and traffic staff to keep the division up and running; 3) penalty for the accumulated excess waiting time over the predetermined threshold (e.g., 10 minutes) for cars carrying the vaccinees in the system. The first two constraints (eq. 2 & 3) are set up to ensure that the number of medical teams in any of the open divisions is within the maximum and minimum allowable limits. Based on our system expert, the allergy division and at least one vaccine division need to be opened during the event. Due to the proximity of the red division with the Allergy division, they wanted to ensure these two divisions were always open during an event. Equation 4 ensures this requirement. Note that *X* is a binary integer variable indicating whether a vaccine division is open, which is defined in the model as a user-defined variable.

On the other hand, *Y* is a general integer variable stating the number of medical teams assigned to each division. We have used the built-in Arena variable to track the value of Y for each division. The total number of the medical team(s) that could be assigned to each operating vaccination division is restricted by the physical configuration of the facility. T_{wait}, is used to track the total accumulated excess wait time of vaccinees in the system, which we have collected using a user-defined variable in the model. A user-defined output data object is created to define the objective function using the above-mentioned variables, which is used as the Response variable in OptQuest during optimization. Table 8 provides the upper bound (m^U) and lower bound (m^L) on the assignable number of medical teams for each operating vaccination division during an event.

Table 7. Upper and Lower bounds on the number of medical teams assigned in each vaccination division

	Blue Division	Green Division	Orange Division	Red Division	Allergy Division
(m^L, m^U)	(1,3)	(1,3)	(1,5)	(1,5)	(1,2)

Note that while adopting the proposed model for a different facility, the authorities may customize cost parameters, along with the traffic and system data, to reflect case-specific facts. As the case study site, was operated by volunteers, there is no actual case-specific data available on costs. Thus, the cost parameter values were approximated based on external sources.

Usually, the vaccination event was officially scheduled for eight hours. Thus, it is assumed that $448 per event ($28 per member per hour) is required in order to hire a medical team consisting of an inoculator and a scribe to perform the combined registration and vaccination process (Hrywna, 2021). According to the system experts, a supervisor is required to set up and manage the medical aspects of the division. As no other significant costs were involved for the division setup process, the hiring cost of the division supervisor is considered the division setup cost. In our facility, a registered nurse (RN) serves as the division supervisor and the average salary of an RN is reported as $35 per hour in 2021 (Glassdoor, 2021). Hence, it is also assumed that $280 is considered to hire a division supervisor during the eight-hour event. Additionally, a $1 penalty is imposed for every excess minute of waiting over a predetermined threshold.

The OptQuest automates the simulation runs and 30 replications that were conducted in each simulation. Table 9 summarizes the results from the OptQuest describing the optimal allocation of medical teams for each division under a different number of scheduled appointments (representing a range of system load conditions). When the total number of appointments was set to 600, for example, the average accumulated excess waiting time beyond the threshold for the cars was reported to be around 1349.8 minutes, yielding the penalty of $1,349.8. In this case, 14 medical teams were hired at a total labor cost of $6,272. The setup cost for opening the three divisions was $1,120. Together, the total operating cost came up to $8,741.8. Note that although spreading out the workload evenly between all divisions can also be beneficial, the main goal is to minimize the total operating cost. Therefore, even if the workload is not equal throughout the divisions, the total operating cost can be minimized by using this tactic.

The optimization model would always perform trade-offs between competing objectives. Thus, sometimes, a solution might not be intuitive to understand. For instance, with 400 appointments, instead of operating the red division at full capacity (5 teams), 4 medical teams were allocated. The blue division was opened, and 1 medical team was scheduled to work there. With further investigation, we found that the excess total wait time for having 5 red teams outweighs staffing & setup costs for having 4 red teams & 1 blue team. Hence optimizer selected the solution with 4 red teams and 1 blue team for this scenario.

Table 9. Resource allocation for different numbers of daily vaccine appointments

Total Appointments	Average Total Cost	Blue Team	Green Team	Orange Team	Red Team	Allergy Team	Total # of Team
200	$5,058.8	3	3	0	1	1	8
300	$5,707.6	3	3	0	1	1	8
400	$6,609.8	1	3	0	4	1	9
500	$7,375.5	0	1	5	4	1	11
600	$8,741.8	0	3	5	5	1	14

5. CONCLUSION AND FUTURE WORK

In this research, we developed a DES model for the NMSU COVID-19 drive-through mass vaccination event and conducted simulation optimization. The purpose of this research is to provide the decision-makers with the insights they expect from the analytic mass vaccination event through virtual planning and analyzing the operational alternatives before implementing any changes to the site in real life. Empirical data from the actual vaccination events were used to develop the simulation model. We also provided modeling details of the simulation that are not just important to the modeler but should be explained to the decision-makers, too, as to provide the end user with a true understanding of the simulation's limitations and constraints as well as its potential utility.

Future work requires the integration of subject matter experts, stakeholders, and decision-makers to facilitate potential scenarios that are more detailed, allowing a focused modeling scope. Given the right group of subject matter experts, the potential to increase the accuracy reflecting the real system through the proposed parameters and models will only increase model accuracy. This will facilitate national-level analysis as it pertains to the future of mass vaccination events with the distribution of booster doses. Additionally, using a fundamentally similar simulation to model other regions should demonstrate the model's flexibility, thus proving it is a robust and useful tool. Finally, the DES model with system dynamics or even a mathematical program could provide new insights while developing a new paradigm in mass vaccination distribution modeling.

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