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Abstract

Proper planning and execution of mass vaccination at the onset of a pandemic outbreak is important for local health departments. Mass vaccination clinics are required to be setup and run for naturally occurring pandemic outbreaks or even in response to terrorist attacks, e.g., anthrax attack. Walk-in clinics have often been used to administer vaccines. When a large percentage of a population must be vaccinated to mitigate the ill-effects of an attack or pandemic, drive-through clinics appear to be more effective because a much higher throughput can be achieved when compared to walk-in clinics. There are other benefits as well. For example, the spread of the disease can be minimized because infected patients are not exposed to uninfected patients. This research extends the simulation modeling work that was done for a mass vaccination drive-through clinic in the city of Louisville in November 2009. This clinic is the largest clinic set up in Louisville with more than 19,000 patients served, over two-thirds via ten drive-through lanes. The intent of the model in this paper is to illustrate a general tool that can be customized for a community of any size. The simulation-optimization tool will allow decision makers to investigate several interacting control variables in a simultaneous fashion; any of several criterion models in which various performance measures are either optimized or constrained, can be investigated. The model helps the decision maker determine the required number of Points of Dispense (POD) lanes, number and length of the lanes for consent hand outs and fill in, staff needed at the consent handout stations and PODs, and average user waiting time in the system.

Keywords: *Pandemic, mass vaccination, walk-in clinics, drive-through clinics, discrete event simulation, optimization.*

1. Introduction

Proper planning and execution of mass vaccination at the onset of a pandemic outbreak is important for local health departments. Mass vaccination clinics are required to be setup and run for naturally occurring pandemic outbreaks (e.g., seasonal flu or H1N1 outbreaks) or even in response to terrorist attacks (e.g., anthrax attack). The most recent outbreak of H1N1 in 2009 highlighted the importance for governments to make or update plans for mass vaccination [1, 2]. Though forecasting natural disasters is difficult, data shows that the frequency of these disasters is increasing. According to Michel-Kerjan and Slovic [3], more than half of the earth's costliest catastrophes since 1970 have occurred since 2001. The authors point out the reasons behind this increase is due to the growth of the world's population at a fast rate, larger concentration of assets in high-risk areas, and the increase in social and economic dependencies. They predict that disasters will continue to increase in frequency and intensity. Although not all disasters will require mass dispensing of vaccines and medical supplies, it is clear that the disasters expose our vulnerability and point out the need for detailed planning in order to minimize the impact of a disaster.

To minimize the number of people affected by a disaster, the response by the public health protection agencies must be fast and efficient. As a first line of response during a pandemic influenza outbreak, governments begin vaccinating people with seasonal flu vaccines before the strain specific vaccine is developed. To be able to distribute the medical supplies in a short period of time, a number of national stockpiles (also called Strategic National Stockpiles (SNS)) are located around the country. Each location holds large quantities of medicines including flu vaccines and medical supplies to protect the American public in the event of an emergency. Each state and vendors also carry some inventory in their warehouses in anticipation of an emergency and until national SNS supplies arrive. In the event of emergency, the national supplies can be deployed to any of the states in the United States within a 12-hour time period. It is then the state’s responsibility to ensure distribution of supplies and vaccines to PODs in a 24- to 48-hour time period. The focus of this paper is the design of a drive-through mass vaccination clinic to vaccinate a large number of people in a short period of time.

An estimate of the number of cases and deaths that would result from an influenza attack in a large urban area is presented by Kaplan, Craft, and Wein [4]. They argue that timely mass vaccination results in both far fewer deaths and much faster epidemic eradication for a wide variety of diseases and is an important intervention mechanism. Reid [5] presented a study to compare drive-through and walk-in mass vaccination clinics and concluded that drive-through mass vaccination is an efficient method for delivering vaccinations to the masses safely and quickly. Unfortunately little research has been done in the area of modeling mass vaccination clinics, especially the drive-through mass vaccination clinic.

Zerwekh et al. [6] presented outcomes of a drive-through exercise conducted by the Hawaii Department of Health to distribute SNS supplied medications. The authors conclude that a drive-through clinic model can effectively dispense SNS medications with minimal bottlenecks during public health emergencies. The Bioterrorism and Epidemic Outbreak Response Model (BERM) used in the study predicts the number and type of staff needed to respond to a disaster. The capability at the clinic level has been included in the model presented in this paper as the model predicts the number of different types of workers needed at each station in the drive-through clinic. Carrico [7] discussed the operational aspects of a drive-through vaccination clinic and mentions that the scale of drive-through vaccinations can vary based upon operational scope and the physical locations available for dispensing.

The above studies attest that the research presented in this paper is a valuable contribution. Lee et al. [8-10] have developed a software package called RealOpt which allows users to investigate locations for dispensing-facility setup, clinic and POD layout design, staff allocation, and disease-propagation analysis. Public Health departments in the United States use RealOpt for the above mentioned capabilities. The model presented in this research can be used in conjunction with RealOpt as RealOpt does not have the capability of designing a drive-through clinic as presented in this research. Hupert et al. [11] mention that computer simulation modeling may assist in designing walk-in antibiotic distribution centers. They conclude that discrete event simulation modeling is a useful tool in developing public health infrastructure for bioterrorism response. Aaby et al. [12] presented discrete-event simulation models, capacity planning and queuing system models to improve clinic planning for the Montgomery County (Maryland) Public Health Services. The above two papers describe the simulation models for walk-in clinics and our research will be extended to have a simulation model with both types of clinics as actually done in city of Louisville. Another paper by Aaby et al. [13] presented a spreadsheet based model called Clinic Planning Model

Generator with the similar decision making capabilities including size of the PODs, number of patients vaccinated, number of staff, and process flow in a POD, as in [12] but the model was developed to overcome the need of specialized discrete-event simulation software like, Arena. Washington [14] presented a discrete event simulation to evaluate the capability and cost of a mass influenza and pneumococcal vaccination clinic. Mason [15] used operations research techniques to assist in staffing a smallpox POD site when limited staffing was available.

The University of Louisville hospital has had experience with drive-through vaccination since 1995. Twice a year, a drive-through is implemented to vaccinate students and faculty against seasonal flu. The scale of these drive-through clinics is relatively small. To contain the spread of the H1N1 flu in 2009, a plan had to be developed to vaccinate a large part of the Louisville population. Relatively extensive expertise with the drive-through model was already available and this helped the application of the drive-through concepts on a larger scale. A plan to administer more than 19,000 vaccines (via nasal sprays and syringes) using walk-up tents and ten drive-through PODs with 4 nurses at each POD was developed by the School of Public Health and Information Sciences (SPHIS) at the University of Louisville of Metro Louisville (see van de Kracht et al., 2013). The law enforcement agencies required assurance that the plan would not impact traffic around the Papa John Cardinal stadium where the event was planned and not have unduly long wait times for vehicles , for example, wait times longer than one hour.

The techniques of operations research have been employed in healthcare for over 30 years with varying degrees of success (Rais and Viana [17]). Most of the applications have involved the use of either simulation methodology or optimization methodology alone. In recent years however, these two methodologies have been used in a combined fashion, as is discussed in this paper. For examples, see the applications of Lee et al. [18] in the management of dialysis therapy, Lamiri et al. [19] in the area of operating room planning, and Haijema et al. [20] in the area of blood platelet production.

Seymour [21] observes that many general clinicians have little or no exposure to analytical or simulation modeling techniques. He suggests the introduction of modeling techniques necessary to further develop software which is easy to use and fully compatible with existing data handling and computer systems.

In the published literature, both analytic and simulation models are used for a variety of problems in healthcare. For complex problems, simulation models are much more flexible and versatile compared to queuing analytic models. Also, for making any changes in the model, it is much faster to develop the logic and modify a simulation model than an analytic model.

To estimate important performance measures of the drive-through clinic and help build the confidence of the event planners and law enforcement, the Logistics and Distribution Institute (LoDI) at the University of Louisville partnered with the SPHIS to develop a simulation model for the drive-through lanes. One of the authors in this paper was directly involved in the data gathering process and also for the entire model development phase. In addition to estimating key performance measures, the simulation model also helped the project planners to make changes to important design variables such as the number of PODs, the number of consent form handout lanes and the number of consent form fill-in points. The model also provided an estimate of the staff needs at each of the different parts of the drive-through (see [16]). Since the model was developed specifically for the city of Louisville, the Department of Homeland Security (DHS) officials who funded a larger effort for pandemic response expressed the need to make the model general enough so that it could be applied to any community, large or small. In response, a new simulation model has been developed. It is a generalized version of the original model for Louisville. The model is developed in Arena, v13 software [22]. The input distributions for arrival rates of people and processing rates at different stations used in the model are determined from data gathered during the H1N1 drive-through vaccination clinic held in Louisville, Kentucky in 2009 [23]. The new model has been tested for the number of people vaccinated in the city of Louisville and the results were consistent with those from the original model and the field observations. We have also tested the model for communities of various sizes.

2. Material and Methods

We designed and built a discrete-event simulation model of the drive-through mass vaccination clinic using Arena 13.0 offered by Rockwell Automation [22]. Based on our experiences from an H1N1 and seasonal flu vaccination clinics, we had acquired knowledge of the key operations in a drive-through clinic. For model validation, the data pertains to the input distributions for vehicles arrival and processing times at different points of service were also available from the same. The flow of vehicles – cars, minivans, sport utility vehicles, pickup trucks - is shown in a flow diagram of the system (see Figure 1).

Figure 1: Mass Vaccination Drive-Through Flow Diagram

The various stages in a generic drive-through clinic are listed below.

- *Arrival*

Depending upon the expected number of vehicles (user input) arriving at the clinic during the day and the multiplication factor for each hour (can be default or provided by the user), the model generates the number of arrivals for each hour. After a vehicle arrives, the number and mix (adult and children) of individuals is assigned to each vehicle. After entering the system, the vehicles proceed to a station that hands out consent forms. Vehicles are assigned to consent hand out lanes with the fewest vehicles. If all consent lanes are full when a vehicle arrives, it does not enter the system.

A consent lane is considered to be full if the length of space taken by the vehicles in the lane is greater than or equal to an input control variable for the maximum length allowed for the space. The linear space taken by vehicles in a lane is equal to the number of cars in the lane multiplied by another input variable representing the “vehicle gap length”; this input variable was set to a value of 12 (feet).

Cars are assumed to arrive to the clinic according to a nonstationary Poisson arrival process, in which the rate varies by hour through the day. More specifically, two inputs are used: the number of cars expected to arrive to the clinic throughout the day, and a set of multiplication factors, one for each hour of the day that the clinic is open. For a particular hour of the day, the multiplication factor corresponds to what was observed at the seasonal flu drive-through clinic.

As an example, consider a clinic that is open for 12 hours, from 7AM to 7PM. If the number of cars set to arrive is 10000, and the multiplication factor for the first hour is set to 1.1, then the expected number of cars for the first hour is 917 (= 1.1 * 10000/12).

- *Consent Form Hand Out*

At this point of the drive-through clinic, each individual in the vehicle receives a consent form to be filled out. Each vehicle is assigned one consent form worker who distributes and then receives the filled-out consent forms from the passengers in the vehicle. In this way, multiple vehicles in any specific lane can be processed simultaneously for the consent form hand out and fill in activities, if the lane has more than one consent form worker; the number of consent form workers is another input control variable for the model.

- *Consent Form Fill-in*

After receiving copies of the forms, the people in the vehicle fill them out. The time required for a vehicle to pass this part of the system depends upon the length of the queue (driving time) and the mix of individuals in the vehicle (form fill-in time). It is assumed that adults will fill out their own forms and then fill out the forms for any children in the vehicle.

- *Vaccination at the POD*

The processing time at a POD depends upon the mix of individuals in the vehicle. The model can also be extended for alternate modes of vaccination. During the operation of the H1N1 clinic in Louisville in 2009, intravenous and nasal vaccination options were available. As opposed to the processing for the consent form hand out and fill in, only one vehicle at a time can be processed for vaccination. However the time required to process each vehicle for the vaccination is a function of the number of medical workers in each lane (an input control variable) and the number of passengers in the vehicle. For example, if two medical workers are in a lane, then the length of time required to vaccinate the passengers in a four-passenger vehicle is twice that required for a two-passenger vehicle. As another example, if two medical workers are present in a lane, the length of time required to vaccinate the passengers in a five-passenger vehicle is equal to that required for a six-passenger vehicle.

- *Detour or Depart from the System*

After receiving services at the POD, the vehicles either leave the system right away or take a detour that allows people in the vehicle that may be experiencing some after effects of the vaccination, to stay in the clinic a bit longer. The probability of a vehicle getting detoured has been modeled as a user input.

In summary, the basic flow process for the vehicles is given by the following sequence of activities.

1. A vehicle enters the system if the chosen consent lane is not full; otherwise the vehicle exits system and is counted as a rejected vehicle.

2. A consent lane is chosen for each vehicle based on the queue length in each consent form lane.
3. The vehicle travels to the back of a consent form queue..
4. The vehicle waits in a consent form queue.
5. A consent form worker hands out the consent forms to the driver and the vehicle occupant(s) fill out consent form(s).
6. A vaccination lane is chosen for the vehicle based on the length of queue in each vaccination lane.
7. The vehicle waits for space in vaccination lane (during which time the consent form worker is not allowed to proceed to another vehicle).
8. The vehicle travels to the back of the chosen vaccination lane.
9. The vehicle waits in the vaccination lane.
10. Medical workers administer vaccination to vehicle occupants.
11. The vehicle may or may not go through an extra loop designed to accommodate patients requiring extra time in the system to ensure they do not have any reactions to the vaccine.
12. The vehicle exits the system.

Of course, not all of these activities will occur for each vehicle—for example, if there is space in the chosen vaccination lane, then activity 7 does not occur. In the model, all the stages which the cars pass through follow the first-in-first-out (FIFO) rule. This FIFO rule is recommended during the actual clinic operations also to minimize the probability of accidents and to minimize staff required to regulate the traffic.

For users with little or no background in simulation modeling techniques, inputs required from the user are kept to a minimum with many of the data inputs required for the simulation set at default values. For an experienced user, the input normally set at their default values can also be changed, if needed. A list of model inputs is provided below.

Model Inputs

- Expected 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
- Length of a vaccination lane

The model provides the output in the form of performance measure values that help the decision maker plan the clinic. Based on the number of people vaccinated, operational costs, and the area required for setting up the clinic, the decision maker can accept the results as is or modify the inputs to see the impact of these changes.

Model Outputs

- 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 queue.
- The average time in system for vehicles.
- The average waiting time in queue for vehicles.
- The utilization of the workers.

3. Results

The model was tested for a variety of scenarios. One of scenarios and the inputs used in parts of the model are from the data gathered during the drive-through clinic [22].

3.1 Scenario 1, H1N1 Drive-through clinic, held in Louisville KY in 2009

In the first scenario, we ran the model to compare the results of the model with the actual data gathered during the drive-through clinic. Out of a total of 19,000 vaccinations, 12,613 were administered in the drive-through lanes and the remainder in walk-up PODs in the mass vaccination clinic organized at the Papa John's Cardinal football stadium. Inputs to the simulation model include arrival frequency of number of individuals per vehicle, arrival frequency of type of individuals, service time distribution for each activity, and multiplication factor for arrival rate for each hour of the day. The individuals per vehicle range from one to six and their frequencies are 0.267, 0.405, 0.206, 0.097, 0.021, and 0.004 respectively. The frequency of arrival of baby, child, adult, and pregnant adult are 0.05, 0.12, 0.78, and 0.05 respectively. The gamma distribution is used for each of the activities including service time consent hand-out, service time consent fill-in, service time POD – vehicle with the parameters (alpha, beta) as (4.7, 2.3), (4.3, 28), and (2.4, 70.5) respectively. To obtain the interarrival time for each hour of the 12-hour clinic, the overall interarrival time is multiplied by a multiplication factor. The multiplication factors used are 0.9, 0.8, 1.1, 1.3, 1.1, 0.8, 0.8, 1.1, 1.3, 1.1, 0.8, and 0.9. These multiplication factors correspond to what was observed at the drive-through clinic.

To compare the impact of different combinations of inputs on the model outputs, we used the built-in tool in Arena called Process Analyzer [22]. The three modeling components in the Process Analyzer are as follows:

Controls – The inputs that are considered to affect the operation of the model in a manner that can be monitored/viewed in the output of the model.

Responses – The outputs that represent measures of how the model performed during the run.

Scenario - A collection of controls and responses as applied to a given simulation model.

Specifically a scenario can be defined as an ordered combination of four factor values: 1) length of the consent form lane in feet (500 (coded factor level 1), 900 (coded factor level 2), 950 (coded factor level 3)), 2) length of the vaccination lane in feet (500 (coded factor level 1), 100 (coded factor level 2), 50 (coded factor level 3)), 3) number of medical workers per lane (4 (coded factor level 1), 5 (coded factor level 2), 6 (coded factor level 3)), and 4) number of consent form workers per lane (2 (coded factor level 1), 3 (coded factor level 2), 4 (coded factor level 3)). Hence a scenario defined as 2233 in Table 1 would be the scenario with inputs of a consent form lane length of 900 feet, a vaccination lane length of 100 feet, 6 medical workers per lane, and 4 consent form workers per lane.

The length of a consent form lane combined with a vaccination lane is kept at 1000 feet, so accordingly the length of a vaccination lane ranges between 500 feet and 50 feet. The expected number of vehicles is set as 4,000. The number of consent form lanes and vaccination lanes are set as 2 and 10, respectively – the same as those in the actual drive-through clinic. Different lane lengths are modeled by keeping one lane length (e.g., the consent form lane) type longer than the other (e.g., the vaccination lane) and in some scenarios keeping both lane types of the same length. Each scenario was run for 10 replications. Table 1 shows the 95% confidence intervals for various output measures of the simulation model.

For the H1N1 clinic in Louisville, the values of the control variables for maximum throughput (7,732 people vaccinated in a 12-hour period) were as follows:

- Length of the consent form lane – 950 feet
- Length of the vaccination lane – 50 feet
- Number of medical workers per lane – 6

- Number of consent form workers per lane – 4.

In table 1, the last scenario is a representation of the actual set-up at the H1N1 Clinic. The average time (27.4 +/- 0.8 min) in system is very close to the recorded observations pertaining to the actual time spent by the vehicles on those particular days in November 2009. In other words, the last scenario also helps us validate our generalized model. For a fixed length of vaccination lane and consent form lane, increasing the number of consent form workers per lane has a much larger impact on reducing the average time in system and increasing the total number of people vaccinated than increasing the number of medical workers per lane. This can be seen in the first nine scenarios in Table 1, where the lengths of consent form lane and vaccination lane are kept at 500 feet. For all other controls kept the same, when the number of medical workers are increased from 4 to 6 in the scenarios 1111, 1121, and 1131 respectively, the average time in system and the total number of people vaccinated do not change much. But when the number of consent form workers is increased from 2 to 4 in the scenarios 1111, 1112, and 1113 respectively (keeping other parameters the same), the average time in system and the total number of people vaccinated improve drastically. Another conclusion that can be made pertains to increasing the length of the consent form lane/decreasing the length of the vaccination lane. When the length of consent form lane is increased from 500 feet in first nine scenarios to 900 feet in the next nine scenarios shown in Table 1, the number of people vaccinated improves slightly but the average time in the system worsens with almost twice the amount of time spent in the system in the scenarios with the longer consent form lane. The similar effect can be seen in the last nine scenarios shown in Table 1 where the length of consent form lane is increased from 900 feet to 950 feet.

Table 1: Responses of the scenarios defined in Process Analyzer

Scenario	Average Waiting Time for Vehicles	Average Time in System for Vehicles	Number of Vehicles Processed	Number of People Vaccinated	Number of Vehicles Arriving, but Not Entering System	Number of People Arriving, but Not Entering System	Closing Time of Clinic
1111	32.1+/-.5	36.2+/-.5	1781.3+/-26	3950.9+/-45.3	2198.7+/-65.4	4890.3+/-138.2	761.1+/-2.2
1112	20.8+/-.2	24.8+/-.2	2607.1+/-15.2	5788.+/-30.7	1436.3+/-50.5	3173.5+/-121.5	750.2+/-2.2
1113	11.9+/-.5	16.1+/-.5	3435.8+/-32.8	7623.4+/-65.1	563.+/-54.7	1253.3+/-124.1	740.6+/-4.4
1121	32.1+/-.1	36.+/-.1	1785.5+/-7.2	3961.7+/-36.1	2220.1+/-47.7	4942.1+/-107.9	761.1+/-2.7
1122	20.5+/-.2	24.5+/-.2	2639.5+/-15.7	5821.5+/-44.4	1333.5+/-55.6	2938.6+/-128.5	750.1+/-1.7
1123	11.7+/-.7	15.8+/-.7	3442.7+/-28.8	7667.2+/-47.7	543.+/-65.3	1220.4+/-154.	742.8+/-2.4
1131	32.5+/-.5	36.5+/-.5	1760.3+/-23.7	3934.4+/-33.2	2223.+/-43.3	4937.7+/-98.9	758.9+/-2.3
1132	20.5+/-.2	24.4+/-.2	2636.+/-9.9	5854.9+/-33.7	1355.8+/-34.2	3011.+/-76.3	749.1+/-1.9
1133	11.8+/-.7	15.9+/-.7	3434.2+/-30.8	7613.4+/-59.1	553.+/-48.8	1226.2+/-114.9	741.3+/-3.1
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2211	57.3+/-.5	60.6+/-.5	1861.7+/-16.7	4113.3+/-37.6	2130.3+/-39.1	4732.4+/-102.8	789.4+/-2.4
2212	36.8+/-.8	40.2+/-.8	2696.1+/-23.	5988.2+/-48.5	1296.2+/-22.8	2873.+/-51.3	767.3+/-2.6
2213	22.4+/-.8	26.+/-.8	3495.4+/-12.6	7737.2+/-37.8	478.4+/-53.9	1064.6+/-118.5	752.4+/-3.1
2221	57.4+/-.8	60.8+/-.8	1856.7+/-23.4	4103.7+/-46.6	2100.4+/-26.2	4664.6+/-71.8	789.7+/-3.3
2222	36.6+/-.4	40.0+/-.4	2698.6+/-20.7	5997.6+/-38.6	1298.9+/-52.6	2856.2+/-123.1	768.9+/-4.4
2223	22.+/-1.2	25.6+/-1.2	3503.+/-14.	7731.2+/-46.2	465.7+/-35.1	1031.2+/-86.5	752.4+/-3.3
2231	57.9+/-.5	61.2+/-.5	1841.7+/-13.9	4092.+/-29.1	2167.7+/-30.5	4817.8+/-86.	789.2+/-2.4
2232	36.6+/-.6	40.+/-.6	2701.9+/-21.2	5985.8+/-82.5	1268.2+/-53.2	2803.4+/-128.1	767.7+/-2.2
2233	22.2+/-.8	25.9+/-.7	3499.+/-18.9	7751.5+/-59.8	500.1+/-34.4	1116.5+/-88.3	754.4+/-4.
3311	60.4+/-.5	63.8+/-.5	1858.8+/-14.9	4099.5+/-37.8	2142.1+/-32.7	4751.3+/-78.5	793.9+/-2.5
3312	38.9+/-.5	42.3+/-.5	2701.8+/-21.8	5990.1+/-50.8	1302.3+/-46.	2899.1+/-94.	769.9+/-2.3
3312	23.7+/-1.	27.3+/-1.	3511.+/-25.5	7782.2+/-74.1	488.+/-40.3	1076.5+/-88.7	757.8+/-2.6
3321	60.4+/-.6	63.7+/-.6	1863.4+/-14.9	4120.2+/-36.5	2133.5+/-53.	4726.5+/-118.	793.2+/-3.4
3322	38.4+/-.6	41.7+/-.6	2706.+/-29.1	5986.1+/-44.5	1289.8+/-66.2	2857.8+/-150.5	769.4+/-3.2
3323	23.2+/-1.1	26.8+/-1.	3492.9+/-21.	7763.8+/-44.2	485.4+/-44.	1083.+/-91.8	755.+/-4.9
3331	60.7+/-.5	64.+/-.5	1852.4+/-13.9	4123.+/-38.6	2158.9+/-37.	4768.2+/-99.8	792.8+/-2.5
3332	38.3+/-.5	41.6+/-.5	2714.2+/-24.9	6019.3+/-55.1	1280.5+/-46.	2841.8+/-109.6	771.1+/-1.7
3333	23.9+/-.9	27.4+/-.8	3502.6+/-22.2	7745.1+/-70.5	510.+/-41.1	1146.5+/-100.5	754.5+/-3.2

3.2 Scenario 2, Analysis for communities of different sizes

In the second scenario, we derived the clinic design parameters for different community sizes as defined by the expected number of vehicles arriving to the clinic. We designed the experiments for number of vehicles ranging between 4,000 and 10,000 in a 12-hour day. Using different population sizes allows us to perform sensitivity analysis with a variety of problem sizes and to present this simulation model as an evaluation tool for the decision makers in communities of any size. The decision makers are assumed to be local or state health departments responsible for organizing mass vaccination clinics. To derive the design parameters we used the optimization tool OptQuest [22]. OptQuest is an application that decides how to change model inputs that the user selects and then runs a sequence of simulations to search for a combination of these inputs that optimizes an output performance measure designated by the user. The main algorithms that OptQuest uses are the heuristics known as scatter search and tabu search. OptQuest enhances the analysis capabilities of Arena by allowing the user to search for near-optimal solutions within a simulation model.

This procedure involves following steps:

- The model is run for a set of decision variables.
- The results are analyzed and the values of one or more variables are modified.
- Simulation is rerun and the process is repeated until a satisfactory solution is obtained.

The above process can be time consuming and sometimes it is not clear how the values of which variables should be modified to achieve a better result. OptQuest overcomes that limitation automatically searching within simulation models. The user must define the model in OptQuest by specifying the upper and limits on control variables, the set of constraints, and objective function(s). OptQuest will search for the values of controls that optimize an objective function while satisfying the constraints. The optimization capability is especially important when there are number of different decision variables as in this problem. If a simulation model needs to be run for each combination of values of decision variables, it will be a very time consuming and tedious process. The model that we developed was analyzed is given by:

Min Waiting Time (1)

Subject to:

Fraction of vehicles arriving but not entering the system $\leq X$ (2)

Space available $\leq Y$ (3)

The objective function (1) minimizes the waiting time for a car in the system prior to administration of the vaccine to the occupants. Constraint (2) ensures that the fraction of vehicles not entering the system does not exceed a specified percentage. This constraint can also be an additional objective, but for this study we used it as a constraint. Constraint (3) ensures that the space constraints for the clinic are met. Table 2 shows the results for X=0.10 and Y varying between 17,000 sq. ft. (for 4,000 vehicles) and 97,000 sq. ft. (for 10,000 vehicles).

Table 2: Clinic design parameters for expected number of vehicles varying between 4000 and 10000.

	Cars = 4000	Cars = 5000	Cars = 6000	Cars = 7000	Cars = 8000	Cars = 9000	Cars = 10000
Length of Consent Form Lane (feet)	400	489.5	425.8	407.2	409.1	658	667
Width of Consent Form Lane (feet)	12	12	12	12	12	12	12
Number of Consent Form Lanes	2	5	5	5	5	10	11
Number of Consent Form Workers Per Lane	7	6	6	8	8	5	5
Length of Vaccination Lane (feet)	40.3	31.9	44.3	50	49.6	29	30
Width of Vaccination Lane (feet)	12	12	12	12	12	12	12
Number of Vaccination Lanes	10	14	20	20	20	12	20
Number of Medical Workers Per Lane	4	4	6	7	8	5	5
Waiting Time (min)	0.91	1.52	1.88	5.2	6.02	6.8	6.8
Space Required (Sq. ft.)	14436	34729	36180	36432	36450	83136	95244

To determine a ‘near-optimal’ solution, we used 150 evaluated design points and 10 replications for each experiment, keeping the number of vehicles, value of X, and the lane widths as constants. The upper and lower limits are defined for the length of consent form lanes and vaccination lanes, the number of consent form and vaccination lanes, the number of consent form workers per lane, and the number of vaccination workers per lane.

Using alternate combinations of control variables, OptQuest determines a ‘near-optimal’ solution for a simulation model. As the number of arriving vehicles increases, the number of spaces required does not increase proportionally. For example, the number of spaces required for 5,000 vehicle arrivals is more than double that for 4,000 vehicle arrivals. But there is not much difference in the number of spaces required for 6,000 and 7,000 arrivals. This is because OptQuest analyzes different decision points with different combination of values of decision variables. The average waiting time per vehicle for 7,000 vehicles arriving is however, approximately three times larger than that for 6,000 vehicles. After obtaining a near-optimal solution for a model, users can also perform sensitivity analysis. For example, in the scenario for 6,000 vehicle arrivals, what will be impact on other control variables if the number of medical workers per lane is restricted to 4? This gives the decision maker the ability to run the model in real-time to see the impact on objective(s) and control variables, based on resources available.

To investigate the impact of different values of the parameter "X" on average waiting time for the cars, we conducted a sensitivity analysis as shown in Table 3.

Table 3: Change in Average waiting time for cars for different values of 'X'

X	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09	0.1	0.15	0.2
Av. Waiting Time for Cars	No Feasible Solution	No Feasible Solution	No Feasible Solution	7.7	7.7	7.4	7.1	7.1	6.8	6.8	6.7	5.9

The analysis was done for 10,000 cars. The value of X was varied between 0.01 to 0.2. The analysis shows that there is no feasible solution for 3% or fewer cars rejected from the system. The results are intuitive for values of X between 0.04 and 0.2. As the percentage of cars that can be rejected increases, the average waiting time decreases.

One important aspect for large communities is that it is possible that the space recommended by the model may have to be split among multiple locations due to the non-availability of a large enough field. Traffic management will also be problematic in large cities compared to medium and small cities, though traffic management is outside the scope of this model.

4. Discussion

The model is a useful and user-friendly decision making tool for planning a mass vaccination clinic. The model helps the decision maker determine the required number and length of vaccination and consent form lanes, staff needed at the consent handout stations and vaccination stations, and the average user waiting time in the system. Drive-through clinics have proven to be more promising because of the much higher throughput allowed by these clinics. This was observed during the H1N1 flu clinic organized by the Louisville Metro Public Health & Wellness Department. The walk through clinic and drive-through clinics were organized in the Papa John's stadium. The maximum rates for the drive-through and walk-through clinics were 762 and 424 persons/hour respectively and after the 2 day event, 19,079 vaccines were administered with 12,613 administered via a ten-lane drive-through. Compared to walk-in clinics, drive-through clinics also minimize the spread of the virus and offer the convenience of waiting inside a vehicle. The feature that makes the model unique is that it can be customized and used for communities of any size which may or may not have prior knowledge of simulation modeling. Because the main users of this model will be the public health departments who have the responsibility for organizing these clinics, ease of use is one of the most important aspects of a model.

An extension of this work can be the integration of this model with a layout design tool. Once the user identifies the settings for a clinic, a layout design tool can propose different layout options to choose from and the user can select the option that best fits the available space.

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