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Evaluating a Covid-19 vaccine centre in the UK using a DES model

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Abstract: The efficient utilization and management of a Covid-19 vaccine centre (VC) is critical to the smooth functioning of a mass vaccination programme. This study investigates the impact of a set of operational policies on VC behaviour and performance. Specifically, two key considerations are the capacity of the VC (measured as the number of patients served per hour) and the time (in minutes) spent by patients in the VC (this is known as the time-in-system or flow time or throughput time). In this paper, we introduce a vaccination simulation tool that can be used to enhance the planning, design, operation, and feasibility and effectiveness assessment of such facilities. The simulation tool is a discrete event simulation model. The simulation outputs visually and numerically show the average processing and waiting times that can be served (throughput values) under different numbers of hourly arrivals, walk-ins to drive-in ratios, registration, immunization, and observation capacities.

Keywords: mass vaccination centre; Covid-19 vaccination; discrete event simulation, capacity planning

1. Introduction

The lockdown forced by the outbreak of COVID-19 has reinforced efforts to find effective solutions to counter this worldwide pandemic. Although there are, still lots of unknowns about how the virus may evolve in the future, scientists believe that an effective solution is mass vaccination implemented globally, to end the COVID-19 pandemic [1]. Several institutions and laboratories around the world are working and sponsoring vaccine research and development to potentially help susceptible populations to become immune to infection[2].

To bring the COVID-19 pandemic under control and substantially reduce hospitalization, morbidity, and mortality rates, and in the meantime reopen the economy, a large portion of susceptible people should receive the vaccine to become immune to the virus in a short period of time. Thus, similar to other deadly pandemic cases, rapid mass vaccination should be implemented to minimize further human and economic impacts [1,3–5]. Such a large-scale implementation of the COVID-19 vaccine could be among the most challenging public health actions of the decade. From a preparation and planning point of view, this translates into many local mass vaccination sites in each city and town that offer immunization services.

Since the ultimate goal of the vaccine process is to immunize the population against COVID-19, the success of the vaccine very much depends on timely and efficient dispensing which requires extraordinary advance planning and preparation at different levels [6]. This includes, but is not limited to, vaccination prioritization, vaccination delivery methods, public awareness, and design of immunization and points of dispensing (PODs) facilities. In this context, the development of simulation tools that build capacities and enable such planning and preparation become very essential.

This paper introduces a simulation model developed for the design and operation of a mass vaccination facilities. The model is developed using a discrete event simulation (DES) method. The simulation model enables users to estimate how many people may be vaccinated and how many

resources are needed to run such facilities efficiently under different setups and configurations. The simulation can help public health planners and decision makers to evaluate and understand the repercussions of their mass vaccination plans

The rest of this paper is organized as follows: In Section 2, we present the vaccination centre operations. In Section 3, data collection is described. In Section 4, we discuss data analysis. Section 5 illustrates the model building. Section 6 focuses on model testing. Section 7 shows the results and experimentation. This is followed by discussions and conclusions in Sections 8, which concludes the paper.

The scope of the simulation study was limited to the vaccination centre operations and the key performance measures of capacity and time-in-system. Arrival of patients to the centre is assumed to be by car or walk-ins on the basis of 50:50 ratio. Data collection relied upon observational data of a vaccination centre.

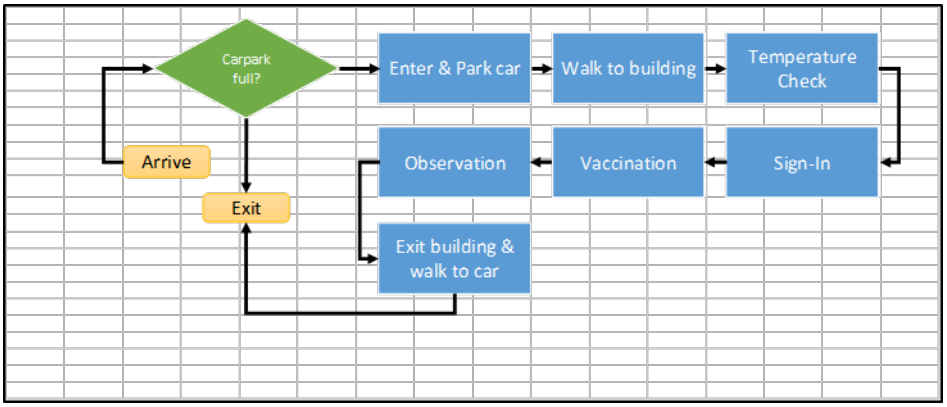
2. Vaccination Centre Operations

Vaccination centres require careful planning and implementation and are governed by National Health Service (NHS) England guidelines [7]. The correct number of staff must be assigned to roles when the centre operates. Two key considerations are the capacity of the centre (measured as the number of patients served per hour) and the time (in minutes) spent by patients in the centre (this is known as the flow time or throughput time). Centre capacity affects the number of centres that must be opened and the total time needed to vaccinate the population. The flow time affects the number of patients who are inside the centre. More patients require more space as they wait to receive treatment. If too many patients are in the centre, they cause congestion, crowding, and confusion. The balance between centre capacity and flow time is very subjective in mass vaccination and regularly tweaked to meet operational targets.

A vaccination centre operates on a pre-booked appointment basis. This means that slots are available on-line for patients to book. The centre receives patients as walk-ins or by car. Either case the patients enters the site via a car park. Cars are directed onto the car park in a controlled manner by marshals (volunteers) who limit car arrivals on to site. Once parked the patient walks to the building and usually joins a patient queue that forms at the entrance. Walk-in patients also join the same entrance queue. The entrance queue moves slowly enabling patients to enter the building containing the centre. Upon building entry, patients have a temperature check done whilst in a moving queue. Patients follow an orderly queue that meanders along the entrance corridor to enter the main hall. Within the main hall, the patient's first stop is Sign-in that involves confirming basic personal details and collecting a personal data sheet. After Sign-in the patient follows the snake like queue and is directed to the next available Vaccination cubicle. Within the Vaccination cubicle, the personal data sheet is collected, information is given, and the vaccine administered. The patient is then directed to take a seat in the Observation area. Volunteers manage the Observation area and allow patients to exit after a 15-minute stay. Patients leave the building through a separate exit and walk through the car park and either drive through or walk through the site gates. A simple flowchart representing the drive-in patient is shown in Fig 1.

For the vast majority of patients, the procedure described earlier reflects their experience. However, some patients are likely to leave the centre with or without vaccination because they have been un-successful at any of the stations. These patients have not been considered in this study because observational evidence suggests the failures are negligible.

Fig 1: Process flowchart for a drive-in patient



3. Data Collection

Operations of the vaccination centre were observed by following the patient flow through the various stations in addition to secondary data [8]. The observations included patient arrivals and mode, queue lengths, walking speeds, distance and capacity of stations, staffing levels, and service times. The various stages involved:

- Arrival (car park – outside the centre)
- Joining the patient queue to enter the centre
- Temperature check whilst in a moving queue line
- Sign-in desk
- Vaccination cubicle
- Observation area
- Exit via the car park

Although the data collection was carefully planned, the data collected was not complete and may have included some inaccuracies due, in part, to the limited number of people, time, and equipment available to conduct the time study. Missing data was estimated from secondary data [8]. Still, the data were sufficient for constructing a valid simulation model.

4. Data Analysis

The raw data collected from the centre was entered into a spreadsheet. This enabled how long a patient spent at each station and ultimately the total time in the centre. It was determined to separate the conveyance timings from station timings. This enabled Table 1 to be devised. It was deemed appropriate to use a triangular distribution for conveyance and station times due to the limited data and wide variability. Table 1 also depicts some key parameters and constraints of the centre.

COVID Vaccine Centre Simulation							
(car & walk-in patients)		Activity Timing Distributions (mins)		Conveyance Timing Distributions (mins)			
Patient Arrivals		1. Temperature Check		1. To Park a Car		2. Walk: Car park to Temp-check	
Number of arrivals expected per hour	100	Minimum	0.3	Minimum	1	Minimum	1
Operational hours per day	12	Mode	0.5	Mode	3	Mode	2
New cars allowed on car park at any one time	5	Maximum	0.8	Maximum	5	Maximum	3
Enter by Car (drive-ins)	50%						
		2. Sign In		3. Walk: Temp-check to Sign-In		4. Walk: Sign-In to Vaccination	
Resources		Minimum	0.3	Minimum	0.5	Minimum	0.5
Temperature-Check	1	Mode	0.5	Mode	0.5	Mode	0.5
Sign-In staff	1	Maximum	1	Maximum	0.5	Maximum	0.5
Vaccinators	8						
Observation spaces	25	3. Administer Vaccine		5. Walk: Vaccination to Observation		6. Walk: Observation to Car	
		Minimum	3	Minimum	1	Minimum	2
Queue Spaces		Mode	5	Mode	1	Mode	5
From Car-park to Temp-Check	50	Maximum	7	Maximum	1	Maximum	7
From Temp-Check to Sign-In	10						
From Sign-In to Vaccination	10	4. Observation		7. Car to Site exit			
From Vaccination to Observation	2	Minimum	15	Minimum	1		
Car park capacity	50	Mode	15	Mode	1		
		Maximum	15	Maximum	1		

Table 1: Operational parameters

5. Simulation Model

Discrete event simulation (DES) is a method of simulating the behaviour and performance of a real-life process, facility or system. DES is being used increasingly in health-care services [9] and the increasing speed and memory of computers has allowed the technique to be applied to problems of increasing size and complexity.

DES models the operation of a system as a (discrete) sequence of events in time. Each event occurs at a particular instant in time and marks a change of state in the system. DES assumes no change in the system between events. DES is used to characterize and analyse queuing processes and networks of queues where there is an emphasis on use of resources. The core elements are:

- Entities: objects that flow through the processes and have work done on them e.g. patients
- Resources: objects that are used in the workflow to process entities e.g. health care services
- Events: important and specific moments in the system's lifetime e.g. vaccination
- Queues: waiting lines.

DES is particularly suitable for models of systems of patient care where the constraints on resource availability are important. This type of study allow patients to have individual attributes and to interact with resource provision.

Due to the superior balance of functionality and ease of use, Witness Horizon software was used to develop a model of the vaccination centre. A table of operational parameters were developed based on a combination of observation data and discussions with management of a vaccination centre. The operational parameters and their values are depicted in Table 1.
A mapping activity produced Table 2, enabling the real world elements to be mapped to Witness Horizon elements.

Table 2: Element mapping

Mapping to Witness Elements	
Description	Witness Element
Patient	Entity
Park car	Activity
Walk to building/Sign-in/Vaccination	Queue
Temperature Check/Sign-in/Vaccinate	Activity
Observation area	Queue
Drive/walk off site	Activity
Patient ID / mode of arrival	Attribute
KPI display	Variable array

A DES model was developed and iteratively refined to credibly represent the operations at the target vaccination centre. Fig 3 displays the vaccination centre after 12 continuous hours of simulation. One of the key drivers was

to establish what level of service is achieved in relation to a patient arrival rate (hourly). An acceptable level of service was defined by three criteria:

- Average patient flow time is about 40 mins
- Maximum patient flow time not to exceed 65 mins
- Total number patients refused entry due to carpark being full should not exceed 25 patients a day.

To ensure variability and realism, the patient arrival rate (hourly) was implemented using an exponential inter-arrival time.

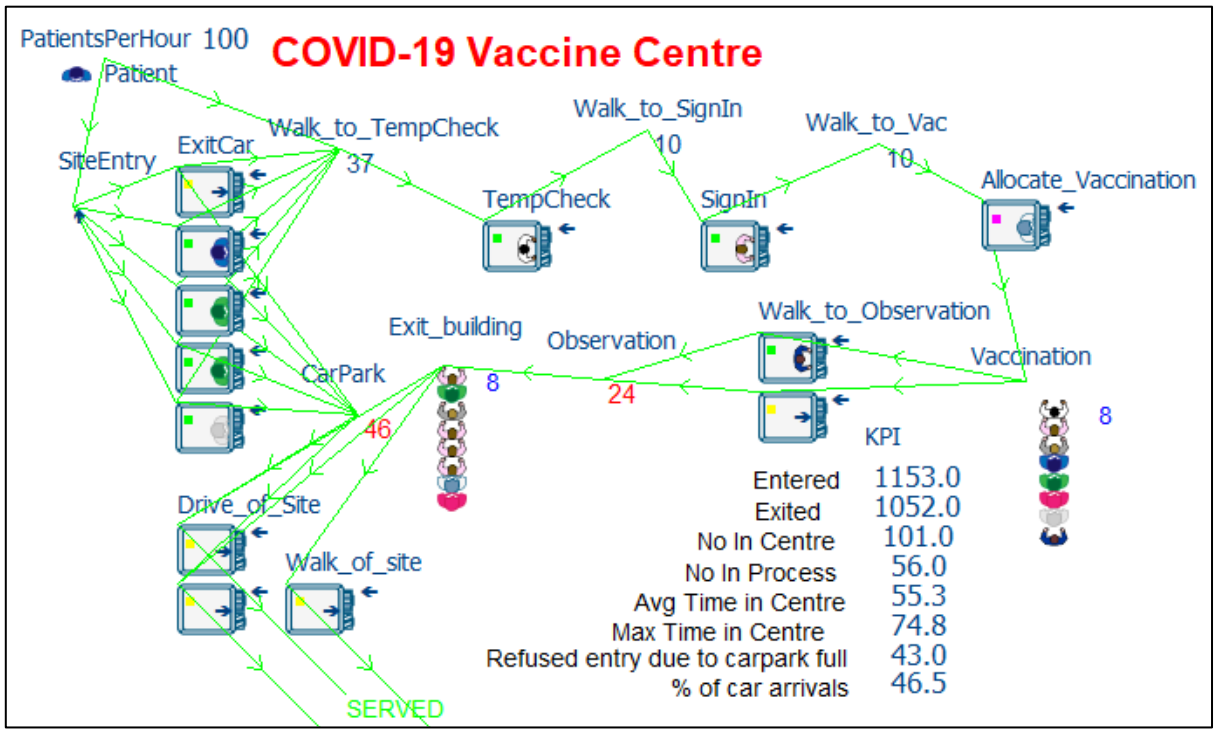


Fig 3: Simulation Model @ 12 hours

6. Model Testing

To be useful, the model must logically represent the process flow observed in the vaccination centre, known as verification. This was accomplished by techniques such as a structured walkthrough of the model code, test runs and checking of the animation display.

Before the model results were recorded model behaviour was checked to ensure the model is providing valid results. Validation is about ensuring that model behaviour is close enough to the real-world system for the purposes of the simulation study. The model validation process consisted of comparing simulation results with actual statistics to determine the correctness was a critical step before performing what-if analysis. To our initial surprise, in many cases, our simulated results did not closely replicate the performance of the vaccination centre. This was largely due to the absence of some data to model accurately the operations. The model was then fine-tuned to adjust some of the model parameters to match closer with the performance of the vaccination centre [8].

Finally, demonstration of the model between interested parties provided a forum for communication of model behaviour and helped identify any anomalies. The credibility of any model is dependent on reliable data, which are not always readily available in the British Health Service. In essence, a three-step approach was utilised for validation comprising of:

- Building a model that has high face validity.
- Validating the model assumptions.
- Comparison of the model input-output transformations with the real system's data.

Once the model had been validated, it was run over a set time period and results collected. At this stage, the model is simply reproducing the behaviour of the current process. This "as-is" model provided a visual representation of the whole process, which was important to provide a consensus that the model provides a convincing representation of the process.

7. Results

In this section we present the results of several experiments including parameter variation and sensitivity analysis of the proposed simulation model. The base experiment is one realization of the Simulation.

7.1 Base Experiment

We ran the simulation with all stations open in full capacity. This runs the model for 12 continuous hours under a fixed rate of 100 patient arrivals per hour. Parameter settings for this experiment are shown in Table 1. All of the parameters are changeable from within the model before or during the simulation at an appropriate stop point.

An arbitrary single simulation run of 12 hours of operations is illustrated in Fig 3.

Fig 3 reveals that most patients spend about 55 minutes in the centre on average. Early users spend less time, however as more patients enter the centre queues are formed and thus the total flow time increases. The maximum time patients spend in the centre, in this simulation run is 74 minutes.

Fig 4 shows the actual number of patients that were in the centre compared to the number of patients being processed. Patients being processed are defined from Temperature Check station to completion of Observation. As illustrated in Fig 4, the number of patients entered but not in the process has steadily grown to around 100 patients. Whilst the number of patients being processed is relatively steady at around 55.

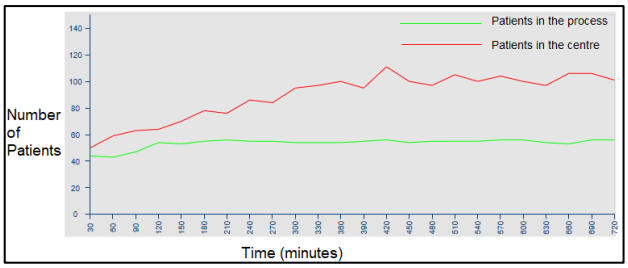


Fig 4: Patients in centre vs. patients in process

The key performance indicators (KPIs) discussed above reveal that acceptable service levels were not achieved in the base experiment replication.

7.2 Parameter Variations

In this section, we present the simulation results by varying different parameters and options including patient arrival rates, drive-in to walk-in ratio, resources.

If we reduce the patient hourly rate to 90 per hour then the results produced are much more favourable (Fig 5) as they achieve the set service levels at the cost of losing 2% output.

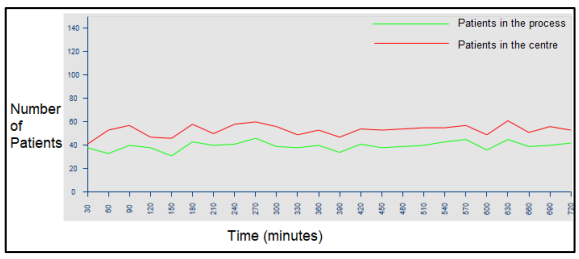


Figure 5: Patients in system with reduced arrivals of 90 per hour.

If we increase the ratio of drive-in patients to walk-ins to 60:40 for the base model, we find the results produced are very promising moving towards desired service levels as shown in Fig 6.

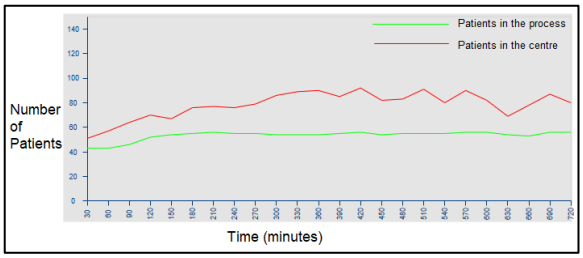


Figure 6: Patients in system with 60% drive-in patients.

If we increase the vaccination cubicles from 8 to 10 to the base model, understandably the patient output increases by 7%. In addition, the desired service levels are achieved as shown in Fig 7.

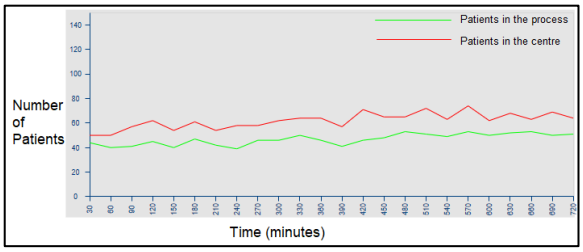


Figure 7: Patients in system with an increase in vaccination cubicles.

Due to stochasticity in the model, the results can be different in each replication. Therefore, some experimentation was deemed necessary. We have ran the base model with the same parameter settings for 100 replications, shown as scenario 1 in Table 3. The results of the base model have shown relatively small variation but still demonstrate that desired service levels were not achieved. To experiment further we arbitrarily selected three controlling parameters: Patients per hour, Vaccination capacity, and Carpark capacity and explored their sensitivity on the patient output. These are detailed as scenarios 2 to 12 in Table 3. The results show that a reduction in arrival rates to 90 patients per hour yield good patient output and achieve the desired service levels with no changes. This is quite important as there is no costs associated with this change. However, for improved patient output, Each scenario was run for 100 replications and average results collated. The results for scenario 4 (Table 3) indicate a 7% improved patient output is possible by increasing the vaccination capacity by an additional 2 staff and achieve a productive level of service.

	Scenario Name	Parameter			Response			
		PatientsPerHour .Value	Vaccination .Capacity	CarPark .Capacity	Avg time in centre	Max time in centre	Refused entry due to carpark full	Patient output
1	Scenario 1	100	8	50	54.092	76.145	46.590	1053.360
2	Scenario 2	90	8	50	35.587	48.728	0.000	1024.860
3	Scenario 3	80	8	50	33.554	46.837	0.000	916.270
4	Scenario 4	100	10	50	40.137	53.571	0.270	1124.030
5	Scenario 5	90	10	50	34.067	46.400	0.000	1028.980
6	Scenario 6	80	10	50	33.216	46.526	0.000	917.620
7	Scenario 7	100	8	60	54.072	76.469	46.700	1053.530
8	Scenario 8	90	8	60	35.587	48.728	0.000	1024.860
9	Scenario 9	80	8	60	33.554	46.837	0.000	916.270
10	Scenario 10	100	10	60	40.137	53.565	0.270	1124.000
11	Scenario 11	90	10	60	34.067	46.400	0.000	1028.980
12	Scenario 12	80	10	60	33.216	46.526	0.000	917.620

Table 3: Experimentation results.

8. Discussions and Conclusions

We introduced a simulation tool for evaluating a Covid-19 vaccination centre. Such tools can help with enhancing the service level and operational performance of such facilities. We used Witness Horizon simulation software to develop the model as it provides opportunities for more effective functionality and visualization (2D and 3D) capability over other available tools.

The results presented in Fig 3 were generated by one realization of the simulation for demonstration purposes. The parameters here have been set using observation data from the vaccination centre. The results of our single simulation produced were rather different to those observed due to stochastic

elements. Some experimentation was conducted with 100 iterations resulting in the identification of the most appropriate patient arrival rate (hourly) that would achieve a satisfactory service level. Table 3, displays a set of average results when a combination of stepped changes are made to three of the critical parameters. The average values for patient flow time, max time-in-centre and number of patient's refused entry (due to carpark capacity) are shown. Our results show that under a reduced hourly arrival rate e.g. 90, patient congestion reduces enabling patient service levels to be achieved.

This simulation model can provide some insights regarding different vaccination centre parameters in terms of patient arrival rate (hourly), staff levels, queue capacities, vaccination cubicles, car park capacity.

Public health agencies can use our simulation model to examine how many people can be vaccinated for a given number of days, shifts, and working hours per shift. Moreover, the model can help decision makers to have an estimate of how many vaccination centres would be needed to achieve a certain number of immunizations in a specific time period.

Another important point is that the patient arrival rates impacts the results significantly [10]. In the reported experiment in this paper (the base run), we used a fixed arrival rate of 100 patients per hour, but this arrival rate does not have to be fixed and can vary during the day depending on demographic and environmental factors. This arrival rate has significant impacts on the number of people being vaccinated. It has been assumed that pre-registration has been done and all patients have pre-booked appoint slots. According to previous studies, the registration stage contributes most to the formation of bottleneck in mass vaccination systems.

The service times used in our model have come from observation data and published data [8}. One limitation of this simulation that demands further work is consideration for additional behavioural and user needs, such as the ability of the simulation to allow people who change their mind after they enter the vaccination line to leave, people who need further recovery time and might even need to be taken care of in a caregiving area, patients need for washrooms, etc.

Although this study is based on observational data, measuring the actual impact of proposed interventions on patient arrival rates and patient flow times requires a real-world implementation. Such efforts, however, require financial support. As such, this is another limitation of the current study.

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