DOI:https://doi.org/10.52756/ijerr.2024.v45spl.020 *Int. J. Exp. Res. Rev.*, Vol. 45: 251-260(2024)

Original Article | Peer Reviewed | Open Access

International Journal of Experimental Research and Review (IJERR)
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ISSN: 2455-4855 (Online)
www.iaph.in

Queuing Theory-Based Model for Optimization of Covid-19 Vaccination and Booster Delivery

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Article History:

Received: 09th Aug., 2024
Accepted: 22nd Nov., 2024
Published: 30th Nov., 2024

Keywords:
Covid-19 vaccination, healthcare, optimization, queuing theory, vaccination efficiency

How to cite this Article:
Kanika Sharma, Shubham Agarwal and B. K. Singh(2024). Queuing Theory-Based Model for Optimization of Covid-19 Vaccination and Booster Delivery. *International Journal of Experimental Research and Review*, *45*, 251-260.
DOI:https://doi.org/10.52756/ijerr.2024.v45spl.020

Abstract: Although queuing theory is commonly utilized in businesses to analyze and model processes involving waiting lines, the healthcare sector sees a difference from other industries when it comes to optimizing fixed resources under alterable demand conditions. To enhance operational effectiveness and cut down on waiting times, hospital operation managers need to be informed on the state of business processes. A scientific method to reduce systemic inefficiencies and raise patient satisfaction is the queuing theory. The objective of this study is to use queuing theory to optimize COVID-19 vaccination and booster delivery. This study discussed two distinct models, one for bigger MV hubs and the other for smaller GP vaccination clinics. The current study demonstrated how these models may be used to anticipate staffing needs to prevent bottlenecks, predict daily throughput given staff capacity limits, and simulate the queuing process. With respectable face validity, we produced accurate estimates of the distributions of given service times and overall processing times. In the future, this may be improved by carrying out a time-use survey to get empirical data on total processing time, which could be compared to the projected processing time of the model and service times for each station, which would help guide the model's inputs.

Introduction

Health care delivery and capacity planning have long benefited from the application of OR techniques (Fetter et al., 1975; Woodside et al., 1977; Hershey et al., 1981; Albin et al., 1990; Pierskalla et al., 1994). The diverse range of healthcare applications is highlighted by Salleh et al. (2017). These applications include community health care (Palmer et al., 2018), emergency departments (Mohiuddin et al., 2017; Gul et al., 2015; Elalouf et al., 2022), obstetrics (Takagi et al., 2017), radiotherapy (Vieira et al., 2016), surgery (Guerriero et al., 2011; M'Hallah et al., 2014; Soh et al., 2017) and distribution of blood products (Belien et al., 2012). These techniques have also been used in the past to address issues that arise during a pandemic. In order to simulate and optimise nurse allocation in a hypothetical influenza outbreak, an emergency department was employed (Rico et al., 2007). In 2009, a drive-through MV clinic effectively immunised nearly 20,000 inhabitants against the H1N1 virus over the course of 1.5 days using similar techniques (Kracht et al., 2021). It is not surprising, given this lengthy history and wide range of uses, that simulation techniques were quickly adopted to inform several facets of the pandemic response at the start of COVID-19.

Using FlexSim Healthcare software, a DES was employed to replicate the COVID-19 screening and testing procedure in India (Gowda et al., 2021). Through simulation, this investigation was able to determine where there was a bottleneck in the patient flow within the testing facility. A model was employed in Canada to simulate the throughput of a mass vaccination facility that operated as a drive-through. This model used a variety of assumptions, such as staffing levels, service hours, car occupancy, and the availability of drive-through lanes, to

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estimate overall throughput as well as average processing and waiting times. The model is web-based and was implemented with AnyLogic simulation software (Asgaryet al., 2022). In India, waiting is a necessary part of providing healthcare services, and long wait times are a major problem for nearly all large hospitals. Extended wait times may indicate inefficiencies in hospital operations.

Sharma et al. (2024) the application of queuing theory to ambulatory waiting times, medical scheduling, and operational facility efficiency improvement were examined in the study, these results will help the government prepare for a similar pandemic in the future. A mechanistic model of the immune response to vaccinations was created by Dogra et al. (2023) as an in silico tool for optimizing dose schedules. Also forecasted customized vaccination dose schedules to reduce breakthrough infections, particularly for immune compromised persons, by assessing population vulnerability to breakthrough infections. In order to support public health planning for vaccination delivery, the objective of this study was to use SQN models to simulate the vaccination process. This paper described two distinct models, one for bigger MV hubs and the other for smaller GPV clinics and also demonstrated how these models may be used to anticipate staffing needs to prevent bottlenecks, predict daily throughput given staff capacity limits, and simulate the queuing process. Two significant additions to the literature are made by our analysis. In order to reconstitute vaccines just prior to administration and usage within a set timeframe, it is crucial to consider these principles when integrating the vaccine preparation process into the queuing network. Secondly, the simulation models are available to everyone via an open-source, free web-based user interface. This eliminates the need for specialised software, installations, or subscriptions and enables anybody to utilise our modelling tool.

Literature review

Hanly et al. (2021) demonstrated how stochastic queuing models may be used to forecast daily throughput based on staff availability, simulate vaccination lines, and provide guidance for service delivery. In order to determine the ideal distance to prevent the spread of viruses from person to person and to evaluate the efficiency of using face masks and eye protection in preventing viral transmission, Chu et al. (2020) conducted a systematic review & meta-analysis. Carrillo et al. (2019) assessed how the triage process can benefit from the application of queuing theory, leading to the development of practical ways to enhance patient care in the emergency room. According to Joseph (2020), queuing equations help to account for the impact of variability on delays and service times by modelling the demand for various ED processes. Utilisation is a rapid way to compare the demand for different resources because it measures a process's throughput in relation to demand. Queuing theory has been applied to EDs with some notable success, but overall, the field is still underutilised in ED operations.

Queuing theory was applied by Cho et al. (2017) to examine how outpatient waiting times changed before to and following the implementation of EMR systems. Pumpo et al. (2022) presented a "queuing theory" based method in which real-life arrival rate variability was determined by studying a COVID-19 immunisation site that targets healthcare professionals based in a teaching hospital. In order to accomplish quick containments and population protection during a pandemic, Lee et al. (2022) developed a system that assists decision makers in real time in determining the MV tactics that make the best use of limited resources. A stochastic queuing model for vaccination procedures are all integrated into a single platform by the general-purpose framework. Various solutions were recommended by Kaushal et al. (2015) to decrease hospital patient waiting times. Previous studies show that in some emergency rooms, up to 50% or more patients can receive treatment in a "fast track" manner as opposed to the usual protocol. Safdar et al. (2016) reported a novel use of DEA to assess wait times in an outpatient department of a hospital without the need for an appointment. Hospital efficiency comparisons have been the primary application of DEA. In their paper, Saxena et al. (2021) offered a fresh perspective on medical consultation and pandemic research in relation to game theory.

Considering the Wood et al. (2021) paper, which employed the M/G/c/∞/FIFO model, the application of queuing theory was adequate to describe the vaccination process in the United Kingdom. The Markov, exponential inter-arrival time distribution is represented by M; the number of servers is represented by G, infinite capacity is indicated by ∞ and the queue discipline is FIFO (first in, first out). The author of this study considered two distinct scenarios by adjusting the arrivals % to the vaccination centre. As a result, the queuing model demonstrates its suitability for improving the operations of the immunisation centres. The trade-offs between work-sampling and time-and-motion models were demonstrated by Finkler et al. (1993). A fake set of work-sampling data points was created using that data

DOI:https://doi.org/10.52756/ijerr.2024.v45spl.020

collection. In an effort to lessen methodological variability within each sub-technique and to make future findings aggregation easier, Lopetegui et al. (2014) proposed a more detailed naming scheme for sub-techniques inside continuous observation time motion investigations.

In order to ensure effective allocation of various COVID-19 vaccines to individuals with varying degrees of vulnerability, Jahani et al. (2022) designed a queuing theory based model for a crisis-induced vaccine supply chain. Alekhya et al. (2022) tracked 196 recipients of the COVID-19 vaccine over the course of a month from the time they arrived at the immunisation facility until they departed. A stopwatch and a data collecting form were used to determine how long it took for each task related to the delivery of the COVID-19 vaccination. The time was reported as mean and median, and the M-W U-test was used to evaluate the times for the first and second dosages.

Materials and methods

Two separate queue networks are presented, one for GPV clinics and one for MV hubs, based on actual cases where COVID-19 vaccines have been administered in Australia using these various delivery methods. 3 baseline models (low, medium, and high staffing availability) for each queuing networks are defined. two possible system pressures. R software V4.0.3 and related packages were used for the analysis (R Core Team, 2020; Wickham et al., 2019). The queue computer software, which performs a computationally efficient technique up to three times quicker than traditional DES methods (Ebert et al., 2020), was used to simulate queuing models.

Suggested queuing networks for the GP vaccination clinic and mass vaccination hub have different station layouts and assign different key responsibilities to different stations. One or more servers, or staff members, handle the responsibilities necessary for each step of the process. First-come, first-served policy dictates that patients are attended to by the next available server, who then moves on to the next station in the network. Figures 1 and 2 give an overview of the two queuing networks, which are explained in greater depth below. The primary distinction is that the GP network assigns the required responsibilities to fewer stations, presumably with less workers and a smaller physical footprint.

Two suggested designs are comparable to the "Separate" & "Combined", investigated by Wood et al. (2021) in this regard, with the combined design combining the vaccination and clinical assessment stations. Patients passed through five stations in the suggested queue network. The first four stations are designed as tandem queuing processes, where newcomers

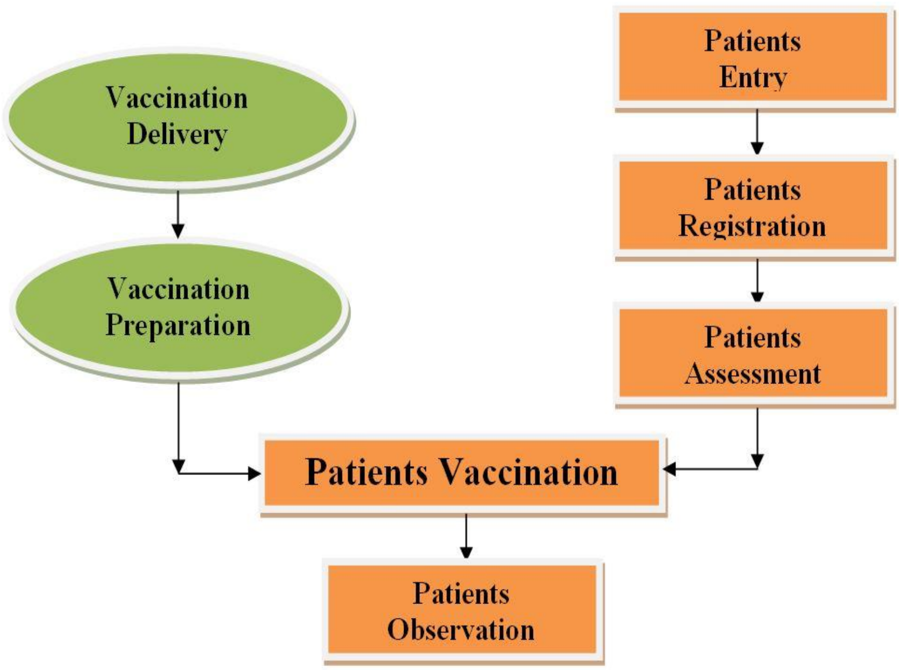

Figure 1. Queue networks for MV hubs.

Baseline daily throughput has been determined for each delivery method by calibrating the rendezvous agenda to maintain staff utilization and service times within acceptable bounds. Also investigated how the various queuing networks and personnel capacities responded to are served on FCFS basis. Patients do not have to wait for a staff member to become available at the observation station; instead, to mimic the capacity constraint of the observation area, patients are "served" by available seats in a queuing procedure. Due to the huge space

DOI:https://doi.org/10.52756/ijerr.2024.v45spl.020

requirements of mass vaccination locations, the queue network also included a little walking distance between stations. It is imperative that vaccine doses be made in close proximity to the administration time, as any delays in this process would inevitably cause delays at the immunization stage. A parallel queue for preparation of vaccine is shown in Figure 1 and connects the patient queuing at the vaccination place. Depending on the vaccine being given, there will be differences in the precise stages involved in getting ready. Figure 2 shows the suggested queuing network for a nearby GP immunization clinic. Patients move through three different stations in this queue network: registration, vaccination, and observation. Patients must wait for the next staff to become available in order to proceed through the Registration and Vaccination places.

As a result, these stations are designed to resemble queuing processes, where patients receiving care from the next staff on a FCFS basis. The observation station, like the mass vaccination concept, is depicted as a queuing procedure where patients are "served" by chairs that become accessible and where a separate queue designated for vaccine preparation merges at the vaccination place. The time required to move between stations in a general practitioner's office is assumed to be insignificant and excluded from the model due to the implicitly reduced venue size.

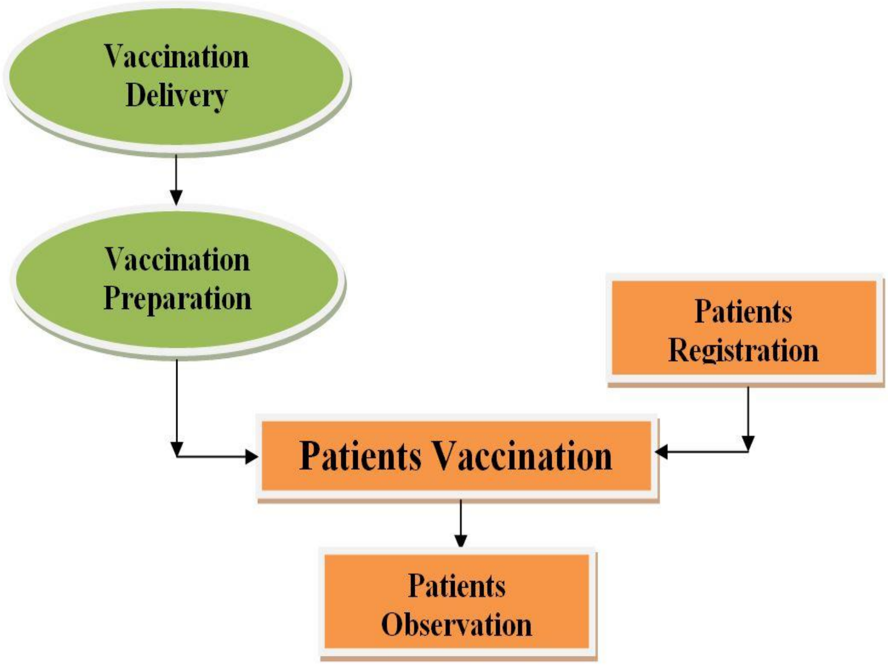

Figure 2. Queue networks for GP vaccination clinics.

Models parameterization

Three inputs are required in order to model queue dynamics based on a specific queue network:

- Accurately calculated service time for every station
- Accurately calculated arrival time for every station
- The quantity of employees, servers, or unfilled lines at each station.

Establishing the service hours at each node was made easier by our experience working at a general practitioner's office and a mass immunization centre. Then arrival frequency will be adjusted to provide baseline models with analogous queue performance for all scenarios based on two criteria: staff utilization and median processing time. The Hospital would serve as a high-capacity MV hub, with observation area seats for up to 175 patients.

Service times

Service time distributions for every station must be specified by the user for both the models. The period of time spent at each node is sampled from the appropriate user-specified dist. for every patient in the simulation. As described in Table 1, the station service periods in the simulations given here were sampled from exponential distributions. The selection of exponential distributions corresponds to the hypothesis that the majority of patients process information reasonably quickly, while a small percentage of patients require more time. The observation station is an exception.

In order to represent a low incidence of bad reactions, it was modelled as a bimodal dist., with normally dist. observation durations for a small random group of patients and normally dist. observation durations for the maximum number of patients who do not have an

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unpleasant response. Set the probability of an unfavorable reaction to 2% in our simulations. Table 1 presents an overview of each station's exponential rate parameters, estimated minimum service times, and resulting service time distribution. Users can set service times using our web-based applet by selecting one of five parametric distributions: gamma, Weibull, normal, log-normal, and exponential.

Table 1. Service time dist. (Assumed) for the MV hub & GP clinic.

Station	Function	Percentiles in Min.				
MV hub		**5%**	**25%**	**50%**	**75%**	**95%**
Vaccination Preparation	$1 + e(\lambda = 3)$	1	1.1	1.2	1.5	2
Patient Entrance	$2 + e(\lambda = 1)$	2	2.3	2.7	3.2	4.8
Patient Registration	$3 + e(\lambda = 0.7)$	3.1	3.4	4	5	7.3
Patient Assessment	$2 + e(\lambda = 1)$	2.1	2.3	2.7	3.4	4.9
Patient Vaccination	$3 + e(\lambda = 1)$	3.1	3.3	3.7	4.3	5.8
Patient Observation	$N(\mu = 20, \sigma = 0.5)$	19.8	19.9	20	20.1	20.2
Adverse reaction	$20 + e(\lambda = 0.1)$	20.4	22.9	26.7	33	46.1
GP Clinic						
Vaccination Preparation	$1 + e(\lambda = 3)$	1	1.1	1.2	1.4	1.9
Patient Registration	$3 + e(\lambda = 1)$	3.1	3.3	3.7	4.3	5.9
Patient Vaccination	$5 + e(\lambda = 0.5)$	5.1	5.6	6.3	7.7	11.2
Patient Observation	$N(\mu = 20, \sigma = 0.5)$	19.2	19.6	20	20.3	20.8
Adverse reaction	$20 + e(\lambda = 0.1)$	20.4	22.6	26.6	33.3	48.7

Table 2. Arrivals (Assumed) for the MV hub and GP clinic.

Size	Appointment interval (hr)	No. of Appointments issued per interval
MV hub		
L	1	60
M	1	120
H	1	180
GP clinic		
L	1/6	2
M	1/6	4
H	1/6	6

Arrival time

Arrivals for an eight-hour clinic were produced using a set appointment mechanism for both queue networks. Appointment spaces for mass vaccination centers would be distributed every hour and anticipated that GP clinics would offer 10-minute appointment windows. Table 2 summarizes the no. of appointments that are issued for each appointment slot in different scenarios. For each of the three different staff capacity scenarios, the no. of available engagements was adjusted so that the queue performance metrics for baseline models remained consistent and within acceptable bound.

Specifically, the number of appointments was reduced to keep the staff utilisation rate below 0.8 at all stations and the median time under 1 hr. Based on the no. of appointments made for each appointment slot and some random noise, stochastic arrival times were produced. These arrival times reflected the hypothesis that most people turn up relatively early, while a smaller percentage arrive on or beyond their scheduled time. A tiny percentage of no-shows were also explained by simulated arrival times, which were set at 2% for both GP offices and mass immunisation sites.

Staffing levels

Models with different staffing availability were identified for each of the suggested queuing networks; the ranges for mass immunization locations were 21-63 healthcare personnel, and for GP vaccination clinics were 4-12 healthcare staff, shown in Table 3. Regardless of the overall staffing capacity, the staffing distribution among the queue network's stations was maintained constant. The related observation area capacity and personnel numbers provided above suggest the approximate sizes of different capacity vaccination centers and general practitioner clinics. For instance, the so-called low capacity hub employs 21 people in total, including five vaccinators and 25 waiting room seats. A high-capacity hub employs sixty-three people, has fifteen vaccinators, and seventy-five chairs for waiting. The former would more closely resemble a neighbourhood community centre, while the latter would suggest a bigger facility with greater room, like a stadium or hospital, even if the model is agnostic regarding the physical environment.

Result and Discussion

According to our baseline models, 95% of patients were processed in the time of 67 min. or less, with an approximate median dispensation time of 52 minutes at MV clinics. 95% of patients visiting GP clinics had their cases completed in less than 37 minutes, with a projected median processing time of 32 minutes, as shown in Figure 3 & 4. Every station's employee's utilization was kept below 80%. For these baseline simulations, it was intended that both queue performance indicators would remain constant throughout all different staffing capacities. For an 8-hour clinic at an MV hub, the corresponding expected daily throughput varied from approximately 500 vaccines for a low-capacity hub to 1400 for a high-capacity hub. The projected daily throughput for general practitioner clinics varied, with low-capacity clinics producing approximately 100 vaccines per day and high-capacity clinics producing

Table 3. No. of Staff (Assumed) at station for different staffing availability.

Capacity	Capacity of Observation area	No. of Staff					
		Vaccination Preparation	Patient Entrance	Patient Registration	Patient Assessment	Patient Vaccination	Total
MV hub							
L	25.0	2.0	4.0	6.0	4.0	5.0	21.0
M	50.0	4.0	8.0	12.0	8.0	10.0	42.0
H	75.0	6.0	12.0	18.0	12.0	15.0	63.0
GP clinic							
L	5.0	1.0	-	1.0	-	2.0	4.0
M	10.0	2.0	-	2.0	-	4.0	8.0
H	15.0	3.0	-	3.0	-	6.0	12.0

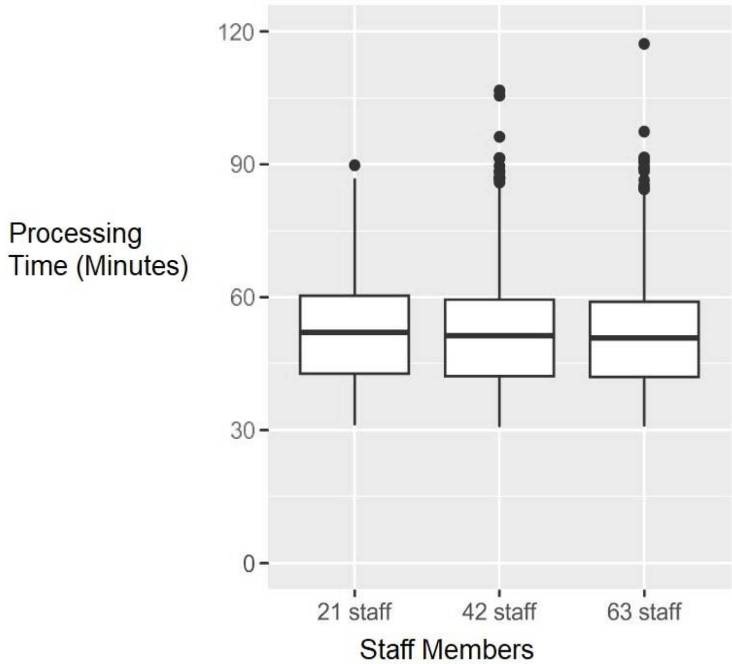

Figure 3. Approximate processing times for MV hubs with different staffing capacity.

Queue performance

To measure staff utilisation, processing time, and queue performance, we employ two measures. The whole time from the beginning to the end of the queue network, or more accurately, the total time from entry to exit, is the processing time, which is expressed in minutes here. The average percentage of employees who are caring for a patient during the simulation run is known as staff utilisation. A well-known characteristic of queuing models is that when worker utilisation rises above 80%, queue performance quickly deteriorates (Little, 1961).

DOI:https://doi.org/10.52756/ijerr.2024.v45spl.020

nearly 300, as shown in Figure 5 & 6. These findings demonstrate that the no. of daily vaccinations scaled linearly with additional healthcare staff, retaining constant queue performance metrics.

responsibilities, which vary throughout the year and significantly rise during the winter, are more likely to affect smaller general practitioner clinics. GP clinics benefit from their current infrastructure and patient

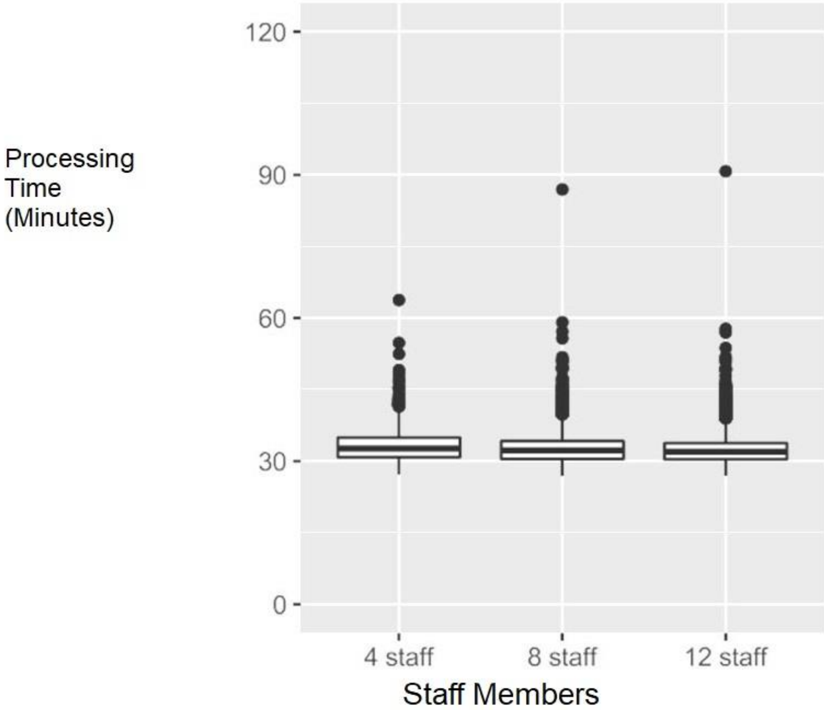

Figure 4. Approximate processing times for GP clinics with different staffing capacity.

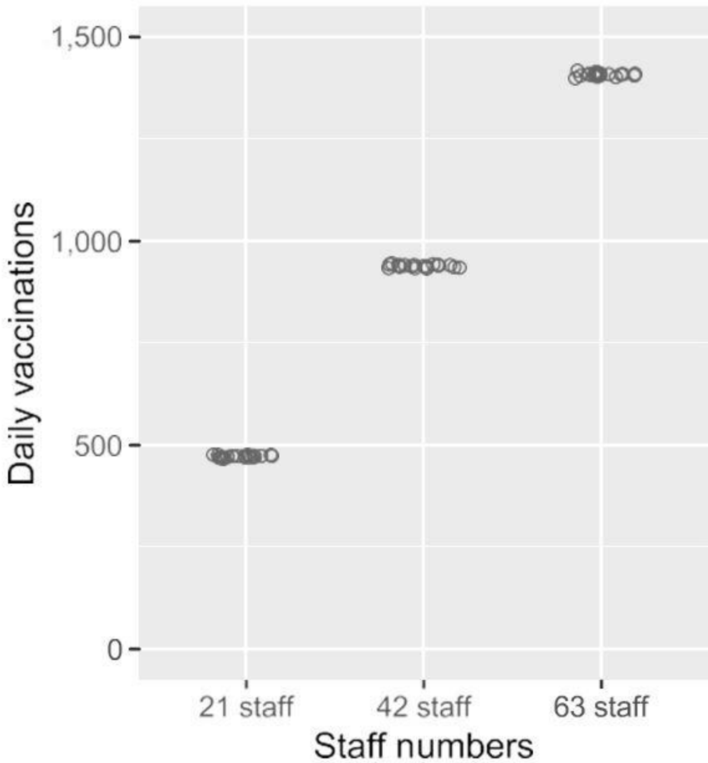

Figure 5. Approximate daily throughput from 20 simulations for MV hubs

There are clear benefits to using GP clinics and mass vaccination hubs as vaccine distribution methods and also demonstrated that mass immunization hubs are extra resilient to systemic stresses such as heightened arrivals and staff shortages. Concurrent, conflicting job relationships. As seen by the carpark drive-through testing stations that numerous practices assisted in setting up during the COVID-19 epidemic, general practitioner clinics are also incredibly adaptable and can change to meet local conditions & unique requirements.

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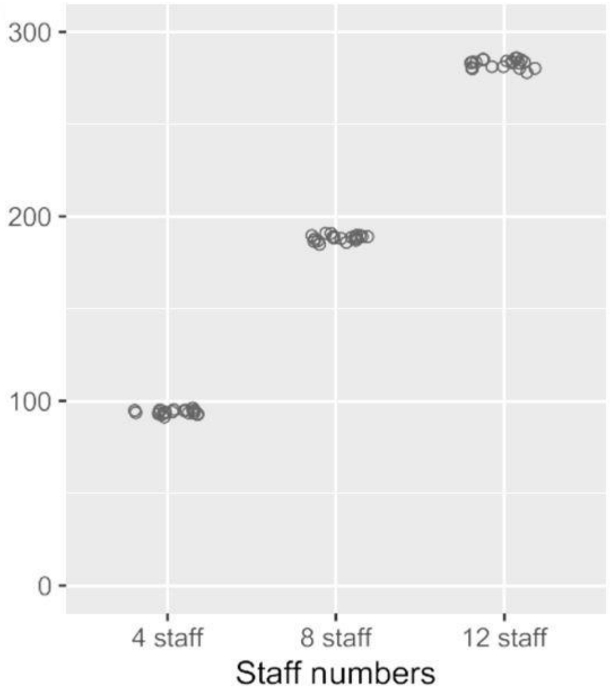

Figure 6. Approximate daily throughput from 20 simulations for GP clinics.

Conclusion

By examining the relationships between staffing levels, arrival frequency, and service times on queue performance, stochastic queue networks (SQN) can be utilize to model immunization procedures and provide guidance for vaccine rollout. Distinct vaccine delivery methods offer varying advantages and difficulties. Although they require larger facilities and more people, mass vaccination centres have a higher daily throughput and are further adaptable to increasing arrivals and reduced staff readiness. Compared to mass vaccination hubs, GP clinics can provide immunizations at a rate per staff person that is comparable, but given current workloads, it could be challenging to maintain a high throughput. Optimizing the delivery of COVID-19 bulk vaccination and booster shots may be aided by a varied profile of vaccination locations that capitalizes on the advantages of both distribution methods. Also the realistic estimations of overall processing times and specified service times distributions with a decent face-validity have been generated. In the future, this could be enhanced by conducting a time-use survey to collect empirical data on service times for each station, which would help inform the model's inputs, and overall processing time, which could be compared to the model's estimated processing time. In light of the urgency of future pandemic, further research utilizing the Queuing Theory paradigm in vaccination and other healthcare settings is desperately needed. For example, the scientific literature might greatly benefit from more intricate analyses that link the results of organizational decisions based on models of human and financial resources that are influenced by queuing theory.

Acknowledgement

The authors owe their indebtedness to all those researchers and writers whose work has been consulted in the present research.

Conflict of Interest

The current study has no conflicts of interest.

References

Albin, S. L., Barrett, J., & Ito, D. (1990). A queuing network analysis of a health center. *Queueing Systems, 7*(1), 51–61. https://doi.org/10.1007/BF01149303

Alekhya, G., Giri, P. P., M. C., A., Behera, B. K., & Subba, S. H. (2022). A time-motion study of the COVID-19 vaccination process in an urban primary health center of Odisha, India. *Human Vaccines & Immunotherapeutics*, *18*, 2073759. https://doi.org/10.1080/21645515.2022.2073759

Asgary, A., & Najafabadi, M. M. (2021). Drive through mass vaccination simulation for COVID-19. Available online: https://cloud.anylogic.com/model/583c2075-6a8b-41be-8a03-d692eba71683?mode=SETTINGS

Belien, J., & Force, H. (2012). Supply chain management of blood products: A literature review. *European Journal of Operational Research*, *217*(1), 1–6. https://doi.org/10.1016/j.ejor.2011.05.026

Cho, K. W., Kim, S. M., Chae, Y. M., & Song, Y. U. (2017). Application of queueing theory to the analysis of changes in outpatients’ waiting times in hospitals introducing EMR. *Healthcare Informatics Research*, *23*(1), 35–42. https://doi.org/10.4258/hir.2017.23.1.35

Chu, D. K., Akl, E. A., Duda, S., Solo, K., Yaacoub, S., & Schünemann, H. J. (2020). Physical distancing, face masks and eye protection to prevent person-to-person transmission of SARS-CoV-2 and COVID-19: A systematic review and meta-analysis. *The Lancet*, *395*(10242), 1973–1987. https://doi.org/10.1016/S0140-6736(20)31142-9

Di Pumpo, M., Ianni, A., Miccoli, G. A., Di Mattia, A., Gualandi, R., Pascucci, D., Ricciardi, W., Damiani, G., Sommella, L., & Laurenti, P. (2022). Queueing theory and COVID-19 prevention: Model proposal to maximize safety and performance of vaccination sites. *Frontiers in Public Health*, *10*, 840677. https://doi.org/10.3389/fpubh.2022.840677

Dogra, P., Arap, P. & Cristini, V. (2023). A modeling-based approach to optimize COVID-19 vaccine dosing schedules for improved protection, *JCI Insight*, *8*(13), 1-20. https://doi.org/10.1172/jci.insight.169860

Ebert, A., Wu, P., Mengersen, K., Stewart, R. J., & Song, Y. (2020). Computationally efficient simulation of queues: The R package queue computer. *Journal of Statistical Software*, *95*(5), 1–29. https://doi.org/10.18637/jss.v095.i05

Elalouf, A., & Wachtel, G. (2022). Queueing problems in emergency departments: A review of practical approaches and research methodologies. *Operations Research Forum*, *3*(1), 1–46. https://doi.org/10.1007/s43069-021-00101-8

Fetter, R. B., & Mills, R. E. (1975). HOSPSIM: A simulation modeling language for health care systems. *Simulation, 24*(3), 73–80. https://doi.org/10.1177/003754977502400305

Finkler, S. A., Knickman, J. R., Hendrickson, G., Lipkin, M., Jr., & Thompson, W. G. (1993). A comparison of work-sampling and time-and-motion techniques for studies in health services research. *Health Services Research*, *28*, 577–597.

Gowda, N. R., Khare, A., Vikas, H., & Bhattacharya, A. (2021). More from less: Study on increasing throughput of COVID-19 screening and testing facility at an apex tertiary care hospital in New Delhi using discrete-event simulation software. *Digital Health*, *7*, 1–8. https://doi.org/10.1177/20552076211044792

Guerriero, F., & Guido, R. (2011). Operational research in the management of the operating theatre: A survey. *Health Care Management Science*, *14*(1), 89–114. https://doi.org/10.1007/s10729-010-9143-6

Gul, M., & Guneri, A. F. (2015). A comprehensive review of emergency department simulation applications for normal and disaster conditions. *Computers & Industrial Engineering*, *83*, 327–344. https://doi.org/10.1016/j.cie.2015.02.018

Hanly, M., Churches, T., Fitzgerald, O., Caterson, I., MacIntyre, C. R., & Jorm, L. (2021). Modelling vaccination capacity at mass vaccination hubs and general practice clinics. *Health Policy*. https://doi.org/10.1016/j.healthpol.2021.07.003

Hershey, J. C., Weiss, E. N., & Cohen, M. A. (1981). A stochastic service network model with application to hospital facilities. *Operations Research*, *29*(1), 1–22. https://doi.org/10.1287/opre.29.1.1

Jahani, H., Chaleshtori, A. E., Khaksar, S. M. S., Aghaie, A., & Sheu, J.-B. (2022). COVID-19 vaccine distribution planning using a congested queuing system—A real case from Australia. *Transportation Research Part E: Logistics and Transportation Review*, *163*, 102749. https://doi.org/10.1016/j.tre.2022.102749

Joseph, J. W. (2020). Queuing theory and modelling emergency department resource utilization. *Emergency Medicine Clinics of North America*, *38*, 563–572. https://doi.org/10.1016/j.emc.2020.04.010

Kaushal, A., Zhao, Y., Peng, Q., Strome, T., Weldon, E., Zhang, M., & Chochinov, A. (2015). Evaluation of fast-track strategies using agent-based simulation modeling to reduce waiting time in a hospital emergency department. *Socio-Economic Planning Sciences*, *50*, 18–31. https://doi.org/10.1016/j.seps.2014.12.002

Kracht, T., & Heragu, S. S. (2021). Lessons from modeling and running the world's largest drive-through mass vaccination clinic. *INFORMS Journal on Applied Analytics*, *51*(2), 91–105. https://doi.org/10.1287/inte.2021.1076

Lee, E. K., Li, Z. L., Liu, Y. K., & LeDuc, J. (2021). Strategies for vaccine prioritization and mass dispensing. *Vaccines*, *9*(5), 506. https://doi.org/10.3390/vaccines9050506

Little, J. D. C. (1961). A proof for the queuing formula: L = λW. *Operations Research*, *9*(3), 383–387. https://doi.org/10.1287/opre.9.3.383

Lopetegui, M., Yen, P. Y., Lai, A., Jeffries, J., Embi, P., & Payne, P. (2014). Time motion studies in healthcare: What are we talking about? *Journal of Biomedical Informatics*, *49*, 292–299. https://doi.org/10.1016/j.jbi.2014.02.017

M'Hallah, R., & Al-Roomi, A. H. (2014). The planning and scheduling of operating rooms: A simulation approach. *Computers & Industrial Engineering*, *78*, 235–246. https://doi.org/10.1016/j.cie.2014.10.004

Mohiuddin, S., Busby, J., & Savović, J. (2017). Patient flow within UK emergency departments: A systematic review of the use of computer simulation modelling methods. *BMJ Open*, *7*(5), e015007. https://doi.org/10.1136/bmjopen-2016-015007

Moreno-Carrillo, A., Arenas, L. M. Á., Fonseca, J. A., Caicedo, C. A., Tovar, S. V., & Muñoz-Velandia, O. M. (2019). Application of queuing theory to optimize the triage process in a tertiary emergency care ("ER") department. *Journal of Emergencies, Trauma, and Shock*, *12*, 268–273. https://doi.org/10.4103/JETS.JETS_50_19

Palmer, R., Fulop, N. J., & Utley, M. (2018). A systematic literature review of operational research methods for modelling patient flow and outcomes within community healthcare and other settings. *Health Systems*, *7*(1), 29–50. https://doi.org/10.1057/s41306-017-0024-9

Pierskalla, W. P., & Brailer, D. J. (1994). Applications of operations research in health care delivery. *Handbooks in Operations Research and Management Science*, *6*, 469–505. https://doi.org/10.1016/S0927-0507(05)80129-4

R Core Team. (2020). *R: A language and environment for statistical computing.* R Foundation for Statistical Computing. https://www.R-project.org/

Rico, F., Salari, E., & Centeno, G. (2007). Emergency departments nurse allocation to face a pandemic influenza outbreak. In *Proceedings of the 2007 Winter Simulation Conference* (pp. 1292–1298). https://doi.org/10.1109/WSC.2007.4419703

Safdar, K. A., Emrouznejad, A., & Dey, P. K. (2016). Assessing the queuing process using data envelopment analysis: An application in health centres. *Journal of Medical Systems*, *40*, 32. https://doi.org/10.1007/s10916-016-0391-1

Salleh, S., Thokala, P., Brennan, A., & Mujica-Mota, R. E. (2017). Simulation modelling in healthcare: An umbrella review of systematic literature reviews. *Pharmaco Economics*, *35*(9), 937–949. https://doi.org/10.1007/s40273-017-0534-6

Saxena, S., Agarwal, S., Kapoor, R., & Singh, B. K. (2021). Medical consultation and pandemic investigation: Pertinence to game theory. *Global and Stochastic Analysis*, *8*(3), 167–185. https://doi.org/10.5281/zenodo.13993353

Sharma, K., Singh, B.K. & Agarwal, S. (2024). An approach of optimization technique through queuing theory on covid-19 vaccination: a study of immunization drive in India. International Conference on *Data Analytics and Management (ICDAM-2024)*, organized by London Metropolitan University, London, UK, 14-15 June, 2024.

Soh, K. W., Walker, C., & O'Sullivan, M. (2017). A literature review on validated simulations of the surgical services. *Journal of Medical Systems*, *41*(4), 1–11. https://doi.org/10.1007/s10916-017-0701-y

Takagi, H., Kanai, Y., & Misue, K. (2017). Queueing network model for obstetric patient flow in a hospital. *Health Care Management Science*, *20*(3), 433–451. https://doi.org/10.1007/s10729-016-9364-4

Vieira, B., Hans, E. W., & Van Vliet-Vroegindeweij, C. (2016). Operations research for resource planning and use in radiotherapy: A literature review. *BMC Medical Informatics and Decision Making*, *16*, 1–11. https://doi.org/10.1186/s12911-016-0286-y

Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L. D., François, R., Grolemund, G., Hayes, A., Henry, L., Hester, J., Kuhn, M., Pedersen, T. L., Miller, E., Bache, S. M., Müller, K., Ooms, J., Robinson, D., Seidel, D. P., Spinu, V., ... Yutani, H. (2019). Welcome to the tidyverse. *Journal of Open Source Software*, *4*(43), 1686. https://doi.org/10.21105/joss.01686

Wood, R. M., Moss, S. J., Murch, B. J., Davies, C., & Vasilakis, C. (2021). Improving COVID-19 vaccination centre operation through computer modelling and simulation. *MedRxiv*, *2021*, 2003. https://doi.org/10.1101/2021.03.22.21254189

Woodside, C. M., & Hunt, R. E. (1977). Medical facilities planning using general queueing network analysis. *IEEE Transactions on Systems, Man and Cybernetics*, *7*(11), 793–799. https://doi.org/10.1109/TSMC.1977.4309815

How to cite this Article:
Kanika Sharma, Shubham Agarwal and B. K. Singh (2024). Queuing Theory-Based Model for Optimization of Covid-19 Vaccination and Booster Delivery. *International Journal of Experimental Research and Review*, *45*, 251-260.
DOI:https://doi.org/10.52756/ijerr.2024.v45spl.020