COVID-19 Drive-Through Mass Booster Vaccination in Quirino Grandstand Simulation

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***Abstract*—During a pandemic, rapid mass vaccination requires the use of both traditional and new temporary vaccination sites. Different mass vaccination options are available to rapidly and safely immunize a large number of people against COVID-19. Among other ways, the use of drive-through has been suggested as one of the possible effective temporary mass vaccination methods. Drive-through clinics were previously employed in vaccination efforts and are currently being more widely implemented for COVID-19 vaccination in different parts of the world due to multiple benefits such as large daily throughput, utilizing existing infrastructure, and enforcing social distance by default. A suitable site, as well as a careful focus on layout and process design, are required for successful, effective, and efficient drive-through facilities. In this paper, the researchers presented a drive-through vaccination simulation tool that may be used to improve the planning, operation, design, and feasibility assessment of such facilities. The simulation tool is a hybrid model that integrates discrete event and agent-based modeling techniques. This model is created by using the AnyLogic (version 8.7.12) simulation software to aid in the operation of a COVID-19 drive-through mass vaccination site operated by Quirino Grandstand in Ermita, Manila. Simulations aided in the optimization of the Quirino Grandstand drive-through mass vaccination site design and operations by highlighting potential bottlenecks, queuing, and overflows, as well as defining the required number of supporting staff. The simulation results illustrate the average processing and waiting times, as well as the number of cars and people that can be handled (throughput values) under different numbers of service lanes, staff, screening, registration, and immunization. The researchers found that current simulation tools with analytical capabilities and advanced visuals are extremely valuable for effective mass vaccination facility planning, design, and operations management.**

***Index Terms*—COVID-19, drive-through vaccination, discrete-event, agent-based, simulation, hybrid simulation model**

I. Introduction

COVID-19 was first discovered in humans in December 2019 in Wuhan, China's capital of Hubei Province [1, 2]. On January 30, 2020, the World Health Organization (WHO) declared this outbreak a Public Health Emergency of International Concern, and on March 11, 2020, it was declared a pandemic. Since the outbreak in China in early December 2019, the number of patients confirmed to have the disease has exceeded 530,000,000 and more than 6,000,000 people have died from COVID-19 infection (up to June 03, 2022, *https://coronavirus.jhu.edu/map.html).*

Since the COVID-19 pandemic began, many countries have started vaccine development and production initiatives. It is believed that the most effective way to terminate the pandemic and lessen its impacts would be to develop an effective vaccination. Once a vaccine is developed, the next challenge will be to vaccinate a large number of individuals in a short period in order to reduce the pandemic's future human and economic repercussions [3, 4]. The development of multiple local immunization clinics is required for rapid mass vaccination. Given that a vaccine will be ready for general public usage in the near future, it is critical to begin planning ahead of time in order to properly and efficiently deploy mass vaccination [5]. As a result, access to mass vaccination modeling and simulation tools has become critical for public health units that will plan, manage, and operate various types of mass vaccination facilities.

The drive-through approach is one of the mass vaccination strategies proposed in the literature and utilized for testing in the past and during the COVID-19 pandemic. Drive-through clinics are particularly useful in infectious disease cases since patients wait in their vehicles, limiting virus transmission as compared to walk-in clinics [6]. According to studies and relevant experiences, drive-through mass vaccination clinics have several advantages and can be an efficient approach for quick and safe vaccinations [7–9]. Rapid mass vaccination via drive-through, on the other hand, requires extensive planning, design, skilled human resources, and sufficient preparedness to improve their efficiency and effectiveness [10].

This study presents a simulation tool developed for the operation and design of drive-through mass vaccination sites. The tool was created utilizing a hybrid approach that combines discrete event and agent-based modeling techniques to simulate ongoing operations in a drive-through mass booster vaccination site. The model can be used to improve the planning, operation, design, effectiveness, and feasibility of such facilities as a significant option for pandemic vaccination treatment. Users can use the simulation tool to evaluate how many people can be vaccinated and how many staff are needed to run such facilities efficiently under various configurations and setups. Furthermore, the simulation tool can assist public health planners and decision-makers evaluate the consequences of their drive-through vaccination strategies using drive-through options.

The efforts of this study are organized as follows: in Section II, the background of the study is presented. Model conceptualization and development, as well as the experimental setup, are included in Section III. This is followed by the demonstration of some of the model results in Section IV. In Section V, the discussion of the results and the limitations of the current study. The current literature on mass vaccination, specifically on drive-through mass vaccination simulation is presented in Section VI. Finally, the conclusion and effectiveness of the model are discussed in Section VII.

II. Background

Coronavirus disease (COVID-19) is an infectious disease caused by the SARS-CoV-2 virus. The seventh human coronavirus, Severe Acute Respiratory Syndrome Coronavirus 2 (SARS CoV-2), was discovered in Wuhan, Hubei Province, China, during the recent pneumonia epidemic in January 2020 [1, 2]. When an infected person coughs, sneezes, speaks, or breathes, the virus can spread in microscopic liquid particles from their mouth or nose. These particles range in size from big respiratory droplets to tiny aerosols [11]. Most patients infected with the virus will have mild to severe respiratory sickness and will recover without the need for any special treatment. Some, though, will become very ill and require medical attention. People over the age of 65, as well as those with underlying medical disorders such as cardiovascular disease, diabetes, chronic respiratory disease, or cancer, are at a higher risk of developing a serious illness. Anyone of any age can become very ill or die as a result of COVID-19 [12].

The global epidemic was prevented to some extent because the COVID-19 vaccine was gradually and widely distributed, but the emergence of SARS-CoV-2 mutations is alarming. Booster shots, according to research, train your body to recognize the virus or bacteria and defend itself. Most people who have received a COVID-19 vaccine are already protected against serious coronavirus diseases. However, even highly effective vaccines often become less effective over time, and coronavirus vaccines are no exception. Initial evidence on mRNA vaccines such as Moderna and Pfizer suggests that their effectiveness against infection and serious disease starts to decrease regardless of virus variant [13].

Staying up to date on vaccinations is more important than ever, and drive-through mass booster vaccination sites are making it easier for patients to receive booster vaccine without leaving their vehicles. As of January 24, 2022, a total of 10,100 vehicles with 26,000 drivers and passengers have been served by the city government of Manila at its COVID-19 drive-through booster vaccination at the Quirino Grandstand grounds [14]. The motivation for developing this model was driven by research and reports that many individuals did not want to step into a brick-and-mortar location during the ongoing COVID-19 pandemic to get vaccinated. With concerns about COVID-19, offering a more convenient option is important.

The use of drive-through vaccination has been tested for rapid testing during previous public health emergencies, including the COVID-19 pandemic, and has shown some promising outcomes [7, 15]. Because patients are isolated in their cars and are not in direct contact with other people, drive-through vaccination sites have a lower virus transmission risk than walk-in clinics [6]. They only interact with immunization staff that is likely vaccinated first and are equipped with personal protection equipment.

However, studies suggest that employing drive-through clinics for rapid vaccination requires good site selection and design, human resource management, and careful attention to operational and logistical aspects [8]. Drive-through facilities have lower disease transmission, low virus exposure, high throughput, improved security, and are more accessible and comfortable, especially for people with mobility problems or who live in remote areas [3, 6, 10]. The drive-through approach has various limitations and weaknesses since its use is influenced by weather conditions, requires sufficient and available spaces, and requires extensive logistical planning. Furthermore, drive-through might generate traffic problems in the surrounding areas and expose employees to carbon monoxide [15]. Despite these, drive-through vaccination facilities are recommended and are carefully examined as part of the COVID-19 immunization process [16].

Despite ongoing research and improvement in this field, there are still gaps in current models that require further study. According to Chiquoine (2019) [17], most existing models do not take into account the effects that arrival patterns have on model outputs, mass vaccination site operations, and transportation-related issues.

Several mathematical models, agent-based, and discrete event simulation systems have been developed and applied in mass vaccination research and practice during the last two decades [3, 10, 18–23]. The main goals of these models and simulation tools site selection, layout optimization, and resource and staff allocation. To guide vaccination site operations, a solution that provides for system performance control while accounting for operational bottlenecks and the system's complex and dynamic nature is sought.

Discrete event simulation (DES) is a method for modeling real-world systems that may be decomposed into a set of logically independent processes that progress through time autonomously. The underlying statistical paradigm that supports DES is based on queuing theory. Discrete-event simulation (DES) has been a popular and effective decision-support tool for the optimal allocation of limited healthcare resources to strike a compromise between boosting patient satisfaction and reducing healthcare delivery costs [24]. [25] provided an overview of how simulation modeling can help lessen the impact of COVID-19. In this work, the regional disease-spread feature and the heterogeneity inpatient pathways were not sufficiently accounted for when modeling the system.

Agent-based modeling (ABM) is also gaining popularity in a variety of fields for developing decision support systems and simulations to assist decision-makers in making better policy and implementation choices [26–30]. ABM is used in public health to visualize, analyze, and inform complex dynamic systems [31]. ABM is another bottom-up computational technique that simulates dynamic and adaptive individual agent behaviors (e.g., individuals, health providers, vehicles, etc.) and their interactions with one another and the environment using established rules [32, 33]. ABM is a suitable modeling method for drive-through simulation that treats distinct sections and lanes of a drive-through as connected agents that change when one influences the behavior of the other.

Furthermore, with recent and ongoing advancements in computer hardware and software, the development of new models and simulations is becoming more feasible and accessible. Finally, new diseases such as COVID-19 provide new challenges that require changes to existing models and simulations.

III. Experiments

The researchers used the AnyLogic (version 8.7.12) simulation software for this study. The simulation tool developed by the researchers employs both agent-based and discrete event modeling techniques. The model consists of a physical layout, several agents that interact with one another according to their predefined logic, and model logic that implements the policies given to the model as user inputs.

A. Dataset

In this experiment, the researchers simulated a data set collected in Quirino Grandstand that illustrates the drive-through vaccination process. The researchers collected data for 24 hours and plotted it by minutes. The data contains four variables: minutes, the car entering the vaccination lanes, the number of passengers in the car, and the duration it took for the passenger to get vaccinated. In the 24-hour cycle, the researchers measured the average of cars, passengers, and vaccination duration. Correspondingly in an hour, the average number of cars in the drive-through is 22, and the average number of passengers is 116. Lastly, the average duration for a passenger to get vaccinated is 3 minutes.

B. Drive-Through Layout

The entire layout is shown in Fig. 1 which comprises five service lanes that the user can toggle on and off at the beginning of the simulation. The area is 200 meters by 30 meters. Cars are admitted to the model at a given rate and must pass through a screening booth that is occupied by a person (a single service station before dispatching the cars into different lanes). At this point, some cars will be rejected and will use the exit point at the Katigbak Parkway. The remaining cars will be distributed to service lanes depending on existing lineups and customer preferences.

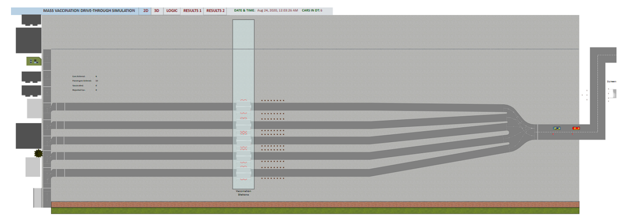

Fig. 1. Physical layout of the drive-through vaccination site

C. Drive-Through Model Agents and Processes

The researchers defined two super-agent types for agents with comparable behaviors in different parts of the model. One super-agent is for staff (human agents), while the other is for different types of service stations. The model contains three subclasses inherited from each of the super-agents mentioned above.

1) ABS_Staff - is a super-agent that represents all staff in the model. Each staff has numerous properties, such as parameters that connect it to PointNodes in the physical layout, variables that let the staff know which car is being served at the time, and resource units that it will need at runtime.
    - Staff_S - represents the staff operating the screening booth. Since there is only one screening booth in the model and each booth can have up to four employees, there could be up to four instances of this agent type.
    - Staff_R - represents the staff who work in the registration booths. The model allows up to five registration booths (one for each service lane), each with up to four employees. As a result, this agent's population may contain up to 20 agents.
    - Staff_V - depicts the staff in the vaccination delivery booths. The model allows up to five vaccination booths (one per service lane), with up to four staff per booth. As a result, this agent's population may contain up to 20 agents.
2) ABS_Station - is a super-agent that represents service stations. Each station has various attributes, including

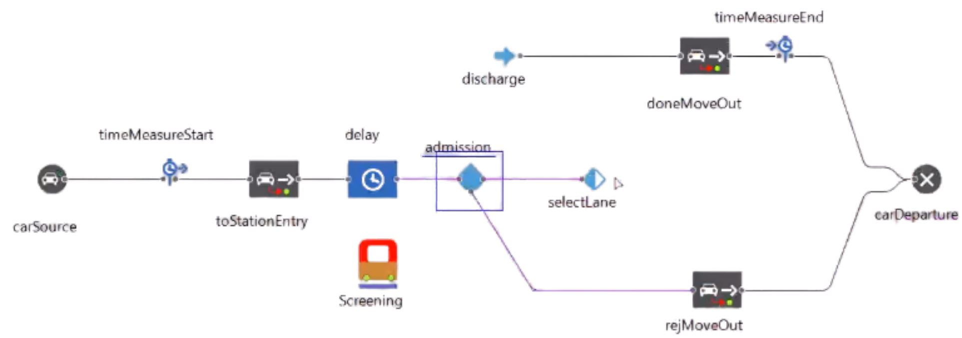

Fig. 2. The car process in the vaccination lane

parameters that connect it to PointNodes in the physical layout, variables that allow the station to know which car is currently being served, and resource units that it will need at runtime. This abstract agent type generates three subagent types, which are as follows:

- St_Screen - represents a screening station, and there is only one instance of it in the model. This agent contains the Staff_S agent population.
- St_Register - represents the registration stations. One registration station instance is created for each active service lane by the model. As a result, the model allows for up to five registration service stations. The St_Register agent class includes a statechart that monitors the state of its instances and switches between "idle" and "serving" modes as needed. This agent also contains the Staff_R agent population.
- St_Vaccine - represents the vaccination stations. One vaccination station instance is generated for each active service lane. As a result, the model may accommodate up to ten vaccination service stations. The St_Vaccine agent type includes a state chart that monitors the status of its instances and switches between "idle" and "serving" modes as needed. This agent also holds the Staff_V agent population.

Other agents are defined in the model in addition to the human and non-human agents mentioned above. ServiceLane is a less physical form of agent. Indeed, the redundant nature of service lanes necessitates building this agent type to enable the replication of a single logic across all service lanes. As previously stated, each service lane has its registration, vaccination, and screening stations. Fig. 2 shows the flowchart of the ServiceLane agent type that defines how an incoming car enters the service lane, moves from one station to the next, and eventually leaves the service lane.

3) Car agent - represent arriving vehicles entering the drive-through site for vaccination services. The arriving cars are generated at a user-defined pace and are eliminated from the model as soon as they leave the recovery area. Separate model variables track the overall number of cars that enter the site. As documented in the Model Logic, the car agent type includes variables for maintaining a computed delay time for each service station based on several specified variables. The car agent has a state chart that he uses to keep track of the car's servicing station. Each instance of the car comprises a unique Passenger agent population.
4) Passenger agent - represents a car passenger. Each car can carry one to five passengers, either an adult or a non-adult. The difference between the two is in the registration process, where the non-adult must give agreement through one of his or her accompanying adults, which is expected to take less time.

D. Simulation Inputs and Outputs

Several parameters are adjusted by user input before the simulation run begins to give the user control over the simulation. The following is a list of all user inputs, their default values, and their acceptable range (if any).

- Open service lanes (minimum: 1; maximum: 5; default: 5).
- Number of staff serving in each open service lane (minimum: 2; maximum: 4; default: 4).
- Average vaccination time per person (default: 3 min).
- Choice to dedicate preferred lanes to vehicles and allocate specific lanes to them or by random.
- Minimum and maximum passengers in a car (default: 1 and 5, respectively).
- Fraction of youth on average (default: 15%).
- Number of incoming cars per minute (default: 5).
- Fraction of cars rejected from the screening booth (default: 1%).
- Number of shifts per day.
- Working hours per shift.
- Number of days (for the whole simulation run).

IV. Results

The researchers simulated with all lanes open at total capacity (four staff in each station). The researchers based all parameter inputs on gathered data from one of the researchers. The researchers execute the model in three shifts over one day at a constant rate of 0.7 arriving cars per minute. Table

1 displays the parameter settings for this experiment. Before starting the simulation, the user can modify every parameter using the control panel.

TABLE I
PARAMETER VALUES FOR THE BASE EXPERIMENT.

Parameters	Value
Screening time per car (minute)	0.05
Average vaccination time (minute) per passenger	3 min
Minimum number of passengers	1
Maximum number of passengers	5
Number of incoming cars per minute	0.7
Fraction of youth, on average	0.2
Fraction of cars rejected, on average	0.01
Number of shifts per day	3
Working hour per shifts	8 hours
Number of days	1
Lanes open	1,2,3,4,5
Staff in each station	4
Preferred Lanes	No

The cumulative and non-cumulative number of cars and passengers that entered and exited the drive-through is presented in Fig. 3 and 4. In the base parameters, a total of 951 cars and 2734 passengers used the drive-through, while around 16 cars and around 30 to 54 passengers were in the drive-through after reaching its highest capacity.

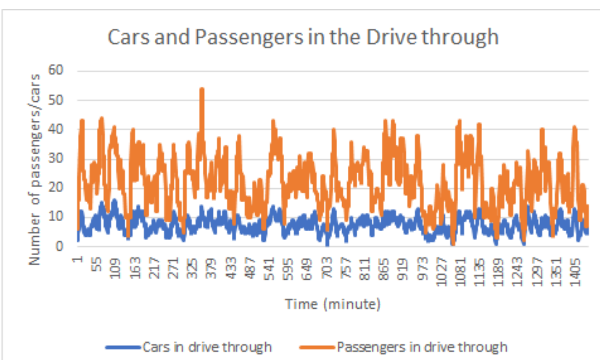

Fig. 3. Cumulative number of cars and passengers using the drive-through facility

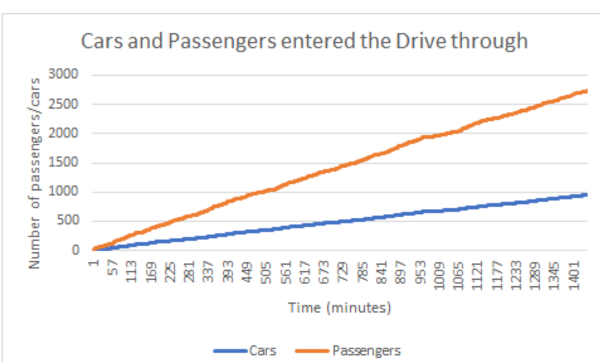

Fig. 4. Non-cumulative number of cars and passengers using the drive-through facility

The total number of people served in each lane is shown in Fig. 5. There are some variations between the total number of cars and passengers for each lane. Fig. 6 shows that most vehicles average between 10 and 12 minutes at the drive-through. Early users of the drive-through spend less time in lanes, but as more cars enter the drive-through and lines form, the waiting time and consequently the overall amount of time spent there rises. The longest period in the drive-through during this run is 12 minutes.

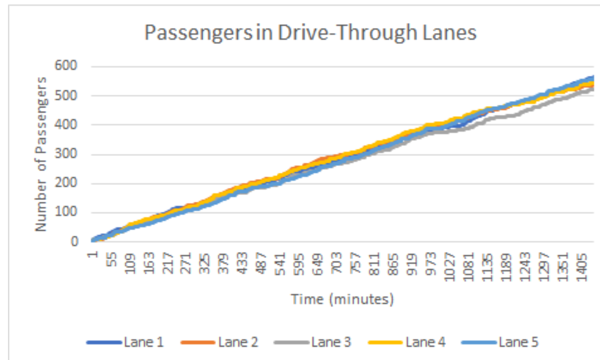

Fig. 5. Number of passengers using the drive-through facility by lanes

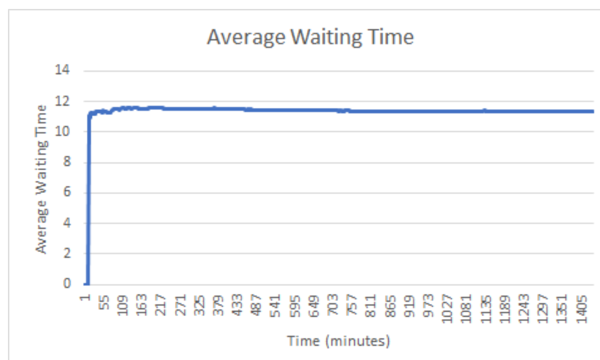

Fig. 6. Average waiting time in the drive-through

A. Parameter Variations and Sensitivity Analysis

In this section, The researchers present the simulation results by varying different parameters and options, including the number of lanes, and arrival rate of cars in service lanes.

B. Number of lanes

The drive-through can be run through the simulation tool with various lane configurations (all first five lanes, alternate lanes, etc.). The simulation results of Fig. 7,8, and 9 represent the result for different numbers of open lanes. In the said experiments, the researchers opened consecutive lanes starting from lane 1 to lane 5. Fig. 7 and 8 illustrates how the number of vehicles and people using the drive-through increases as the number of open lanes increases. Adding more lanes decreases the drive-through facility's average wait time as anticipated. For instance, when only one lane is open, the average time spent by each car in the drive-through is very high and comes close to 297 minutes. On the other hand, As a result in Fig. 9 the average amount of time spent in drive-through drops to about 11 minutes when all five lanes are opened. The number of lanes may also become one factor limiting the number of cars that can access the stations within the specified time; this can only be solved if the number of lanes is increased.

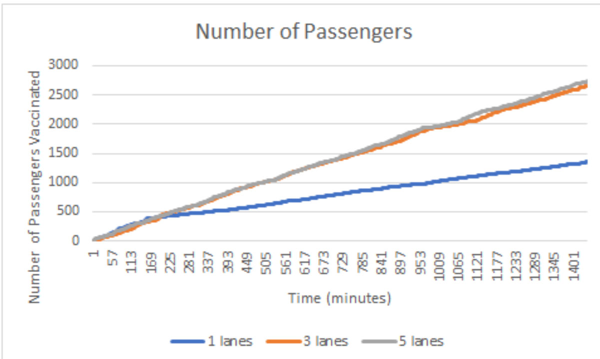

Fig. 7. Number of passengers in all lanes

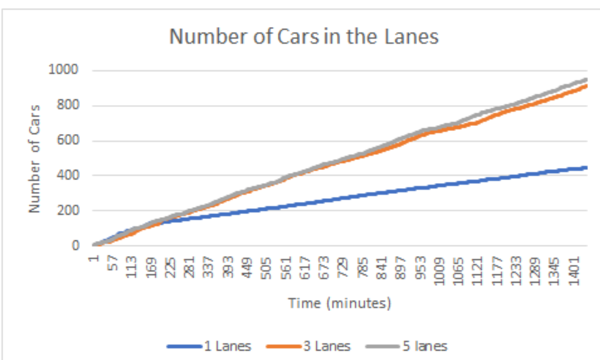

Fig. 8. Number of Cars in all Lanes

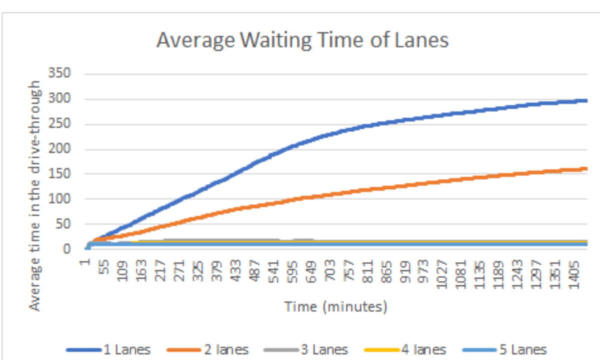

Fig. 9. Average Waiting Time in all lanes

C. Arrival Rate

Arrival rates can be defined in many ways, including fixed rates, arrival schedules, timetables, etc. In this study, The researchers conducted several experiments with varying arrival rates that range from 0.2 to 3 cars per minute (Fig. 10). The findings demonstrate that as the arrival rate rises, more customers are served and spend more time in the drive-through on average. However, these values remain unchanged with higher values of arrival rates due to the unchanged (and limited) capacity of the drive-through facility.

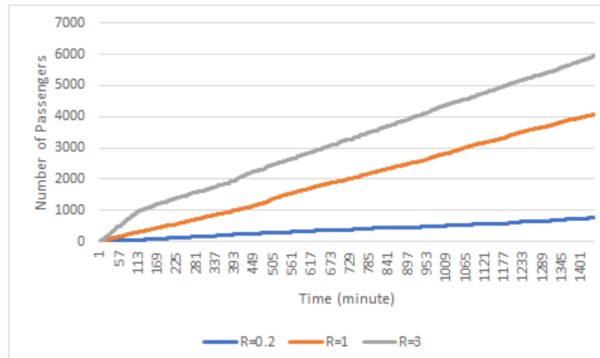

Fig. 10. Arrival Rate of passengers in all 5 Lanes

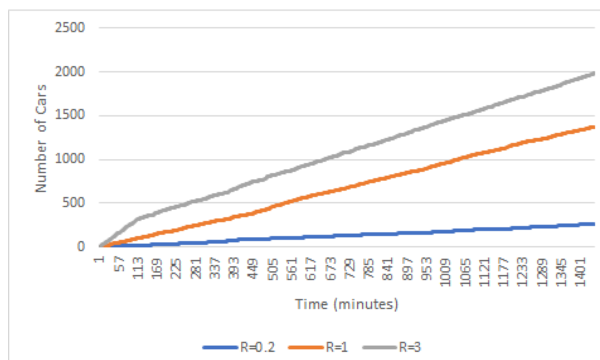

Fig. 11. Arrival Rate of Cars in all 5 Lanes

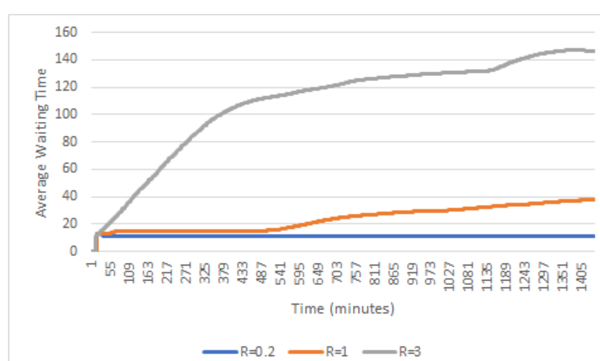

Fig. 12. Average Waiting Time with Different Arrival Rates

D. Validation and Verification Results

The researchers used hypothesis testing to verify and validate the model. The researchers ran the model 20 times and simulated a Monte Carlo simulation with 100 iterations using the same parameter settings. The objective is to get the mean of the two data sets and determine if there is no significant difference between the two means. The Monte Carlo simulation result shows that the average number of vaccinated individuals for 100 iterations is 2962.45, while there is an average of 2972.5 for 20 iterations.

In order to verify the model, the researchers used the independent t-test. The independent t-test is an inferential statistical test determining whether there is a statistically significant difference between the means in two unrelated groups. In order to perform the t-test, the researchers installed the Data Analysis ToolPak in their copy of Excel.

The null hypothesis is "There is no significant difference between the means." The results show that the degree of freedom is 118, and 118 degrees of freedom at an alpha level of 0.05 equals 1.658 for one tail from the t-distribution table. As the p-value is more significant than the alpha level, we cannot conclude that there is a significant difference between the means.

Another way to decide is to compare the t-value with the t-critical value. If the t-critical value is smaller than the t-value, The researchers should reject the null hypothesis. In this particular test, the p-value and the t-critical values are both very large, so there is not enough evidence to reject the null. Therefore, there is no significant difference between the means. Thus, the model is valid.

V. Discussion

The results presented in the results section were generated by one realization of the simulation for demonstration purposes. The screening, registration, vaccination, and recovery rates used in previous cases of mass immunization via drive-through facilities were used to define the criteria. Due to some stochasticity in the model, the results can differ in each run; however, the variations are minor. For example, we ran a Monte Carlo simulation with the same parameter settings with 100 iterations. We found that the difference between our output variables' lower and upper bounds was relatively small. For instance, the number of cars served ranged between 977 to 1008, the number of passengers vaccinated ranged from 2929 to 2990, and the average vaccination processing time changed from 10.4 to 10.21 min.

One of the essential factors in the simulation is the arrival rates of cars. It can greatly affect the result of simulation runs significantly. In the base experiment, the researchers used a fixed arrival rate of 0.7 cars per minute, but this can also be changed depending on the demographic and environmental factors, for instance, on weekends, wheras the people do not have work. Therefore, depending on the drive-through configurations, it is essential to implement strategies to manage the incoming traffic better.

Finally, the model presented in this paper has some limitations that need to be addressed in future versions and as more information about SARS-CoV-2 becomes available. First, the simulation uses only one geometrical layout to analyze different strategies in Quirino Grandstand, Manila. Second, the simulation model demands further work for additional behavioral and user needs, such as the ability of a person to change their mind after they have gone through the screening and potential accidents of vehicles in the vaccination lane. Third, In the simulation, the researchers did not focus on different vehicle types such as motorcycles, bicycles, public transits, etc. The researcher reasoned that it was to prevent infection. Lastly, the limitation of Anylogic in the current version of (8.7.12), mainly the Schedule function, is to allow the user to define how some value changes in time according to the cyclic pattern. In the researcher's simulation model, they have implemented a schedule function that defines the changes in the rate of cars based on the time; the limitation is that it only accepts integer values. For instance, if the user inputs a decimal value, it will not be accepted because the schedule function does not allow decimal values.

VI. Related Works

Several studies have used mathematical models such as discrete event and agent-based modeling techniques to model and evaluate mass vaccination clinics for better layout, efficiency, site selection, resource and staff allocation, and scheduling. Some of these models have been developed into software and tools.

The results of a drive-through exercise done by the Hawaii Department of Health to distribute SNS-supplied drugs were presented by Zerwekh et al. (2007) [34]. The authors argue that during public health emergencies, a drive-through clinic model can successfully deliver SNS medications with minimal bottlenecks. The Bioterrorism and Epidemic Outbreak Response Model (BERM) used in the study predicts the number and type of personnel required to respond to a crisis. Because the model estimates the number of different types of personnel needed at each station in the drive-through clinic, the capability at the clinic level has been included in the model described in this study.

Lee et al., (2009) [35] developed a decision support tool called RealOpt using a combination of mathematical modeling, simulation, and optimization engines, and coupled them with automatic graph-drawing tools and a user-friendly interface. The RealOpt allows users to investigate locations for dispensing-facility setup, clinic and POD layout design, determine staff resources need and their 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.

Aaby et al., (2006) [36] presented discrete-event simulation models, capacity planning, and queuing system models to improve clinic planning for the Montgomery County (Maryland)

Public Health Services. These models were validated by the authors using data obtained during full-scale simulations of disease outbreaks. The authors have created physical design guidelines for clinics based on general queueing principles and personal experiences.

Another paper published by Aaby et al., (2006) [18] presented a spreadsheet-based model called Clinic Planning Model Generator that assists decision-makers in choosing the size of PODs, number of patients vaccinated, number of staff needed, and process flow in a POD, similar to [36], but the model was developed to eliminate the need for specialized discrete-event simulation software such as Arena. The authors calibrated their model using data from a smallpox mass vaccination exercise in Maryland (US) and then applied it to an influenza pandemic scenario.

Washington (2009) [37] demonstrated a discrete event simulation to assess the feasibility and cost of mass influenza and pneumococcal vaccination clinic. The author used a discrete event simulation model to estimate the throughput of the vaccination clinic as the number of clients (arrival intensity) increased and as staff members were reassigned to different workflows. This study depicted processes for three customer types: "Medicare," "Special," and "Cash," with "Special" designating Medicare consumers who required assistance moving through the clinic. The costs of supplies, staff salaries, and client waiting time were included in the model. Furthermore, the author compared the "original" model based on actual clinic staffing and performance to an "optimized" model in which personnel was reassigned to maximize the number of customers vaccinated.

Beeler et al., (2016) [38] developed a discrete event simulation of a mass immunization clinic in order to improve human resource management in mass influenza immunization clinics. The authors built their model using data from Canadian clinics that responded to the H1N1 pandemic. The key attribute of this simulation is the inclusion of flu transmission risk in the simulation. The authors also demonstrated that when waiting costs and infection transmission are not included, the marginal benefit of additional staff in mass vaccination sites is underestimated.

VII. Conclusion

Drive-through clinics may be able to play an essential part in the COVID-19 mass booster vaccination process. Drive-through mass vaccination sites may be the best alternative for reducing contact between healthcare personnel and those seeking vaccine treatment. This is especially useful in communities with limited access to private cars and suitable sites. Drive-throughs offer high throughput and are simple to set up and operate. As such, the drive-through option can supplement other traditional and innovative means of mass immunization. This paper presented a hybrid simulation model that visualized a drive-through mass vaccination site using agent-based and discrete-event techniques. We demonstrated how simulation data might be utilized to create a new and improved predictive machine learning model for drive-through mass vaccination sites. Under various parameter settings, the produced model can be used to obtain rapid forecasts of the number of people vaccinated and the average time it takes for vaccination. The results show promising performance when applied to other parts of pandemic management where vast numbers of simulations are developed for prediction. The model presented can be utilized by healthcare decision-makers to organize their existing drive-through mass vaccination facilities by changing the input variables and obtaining the outcomes.

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