

INSE- 691 Topics in Information Systems Engineering

**Project Report**

On

**Decrease in Wait time for COVID-19 Vaccination using Simulation and Modeling**

Submitted to:

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**Table of Contents**

1. [Introduction 3](#_bookmark0)
2. [Problem Statement 4](#_bookmark1)
3. [Simulation Models 4](#_bookmark2)
   1. [Discrete Event Simulation - Arena 4](#_bookmark3)
   2. [Input Modelling and Data Collection 4](#_bookmark4)
      1. [Assumptions 4](#_bookmark5)
      2. [Parameter’s estimation and Goodness of fit vaccination 5](#_bookmark6)
      3. [Arena Simulation for Arrival Rate 7](#_bookmark7)
      4. [Arena Simulation for Service Rate 8](#_bookmark8)
   3. [Model Design 8](#_bookmark9)
      1. [System with One Counter 8](#_bookmark10)
      2. [Proposed Model – Double Booth 10](#_bookmark11)
   4. [Output Analysis 15](#_bookmark12)
   5. [Verification and Validation of Arena 21](#_bookmark13)
      1. [Verification of Arena 21](#_bookmark14)
      2. [Validation of Arena 21](#_bookmark15)
4. [Monte Carlo Simulation - Microsoft-Excel 22](#_bookmark16)
   1. [Model Description of Monte Carlo 23](#_bookmark17)
   2. [Input Analysis 23](#_bookmark18)
   3. [Current System 24](#_bookmark19)
      1. [Simulation Model – Single Booth 24](#_bookmark20)
   4. [Implemented System 27](#_bookmark21)
      1. [Proposed Simulation Model – Two Booth’s 27](#_bookmark22)
      2. [Proposed Model with Continuous Arrival (Scheduled Arrival) 29](#_bookmark23)
   5. [Output Analysis 31](#_bookmark24)
   6. [Verification and Validation 32](#_bookmark25)
5. [Vensim Simulation 32](#_bookmark26)
   1. [Decrease in wait time suing Vensim Simulation 33](#_bookmark17)
   2. [Casual Loop Diagram 34](#_bookmark18)
   3. [Verification and Validation 35](#_bookmark19)
   4. Verification and Validation 36
6. [Conclusion 37](#_bookmark27)

[7. References 38](#_bookmark28)

# Introduction

COVID-19 an infectious disease that has affected and wiped almost 9.3% of the world and turned everything into a totally new place to live in. people have struggled and are still battling against covid to protect them from this deadly disease. It has been almost 2 years since this all started in the first place. People still need to be very preventive since there is no cure for this disease. The only thing that can help people to withstand these rising cases is take precautions like maintaining social distances, always wearing mask, and sanitizing the hands whenever you get into contact with new people and surfaces. Other than this the next thing that can help us to survive is Vaccine. With wide research and continuous vaccination many countries have found vaccine for Covid but there aren’t many doses that can be sufficient for the whole world. This started panic situation in public and made them rush towards vaccination centers. This increased the number of people at vaccination centers and increased the wait time.



Figure1 People waiting for vaccination at Vaccination center

So, to fix the issue of the waiting time we come up with the simulation-based model that significantly reduces the wait time of the people. We tried making changes to existing models and made tried optimizing the wait times at vaccination centers. We tried to do this by collecting real time data from few of the biggest vaccination centers in Montreal and gathered information to sort out the necessary data which can be useful for simulation and developed a few simulation models using simulation software’s.

# Problem Statement

# Metrics will be determined in the system, such as the number of people visiting the vaccination center, the average time spent per person, the average wait time at each resource, and the average service time required to finish the dose. Person’s arrival time and service time are used as input for the simulation. We will analyze the vaccination process and provide the necessary suggestions based on the simulation results. In addition, we will use different technologies available to simulate the model.

# Simulation Models

We will simulate the model and analyze the results with the help of following simulation models.

* + Arena Simulation Model for Discrete event simulation
  + Vensim Simulation Model
  + Monte Carlo MS-Excel

# Discrete Event Simulation- Arena

Since our model has multiple events, different processes and changes will occur in the system at a specific time, so we chose the discrete event simulation. This is the best because we can observe the system at a micro level. Our model is inherently random, because people arrive at the vaccination center at random.

# Input Modelling and Data Collection

## The input parameters are the person arrival rate and the service rate of the vaccination process. The arrival rate is the number of people who arrive at the vaccination center in one day and the service rate is the time it takes for the hospital administrator to complete the vaccination process.

## 3.2.1 Assumptions

* + - 1. The vaccination center does not operate 24/7.
      2. There can be only 300 to 400 members that can be vaccinated per day.
      3. Some persons may not be allowed into the vaccination center if they have any kind of symptoms.
      4. The person will be standing in the queue for his turn of the dose.
      5. When a person is done with the dose, he/she leave the system.
      6. Same vaccine that he/she took for the first dose are not available.
      7. The minimum service time for a person is 2 mins, and the maximum is 4 mins.

We considered the vaccination center in Montreal, which runs 12 hours a day and collects people’s arrival data by observing the center.

*Figure2* Data representation for Person Arrival Rate

Person Arrival Rate

45

40

35

30

25

20

15

10

5

0

8:00 9:00 10:00 11:00 12:00 1:00 2:00 3:00 4:00 5:00 6:00 7:00

AM AM AM AM PM PM PM PM PM PM PM PM

Time of the Day

Number of People

For service rate at vaccination center, we considered it is the whole time taken by the vaccination center to complete the vaccination process i.e., time taken by receptionist, time taken by the nurse and the time taken for giving the dose and marking the dose number with a proper ID so that it will be used as a proof of vaccination for future purpose.

Service Time in mins

Service Time

4

3.5

3

2.5

2

1.5

1

0.5

0

8:00 9:00 10:00 11:00 12:00 1:00 2:00 3:00 4:00 5:00 6:00 7:00

AM AM AM AM PM PM PM PM PM PM PM PM

Time of the Day

*Figure3 Data representation for Person service Rate*

## 3.2.2 Parameter’s estimation and Goodness of fit vaccination

In this, we use arena software for discrete event simulation. It also suggests the best statistical model to see which fits best with the data obtained. In arena there is an input analyzer which is used to analyze the data and uses its data to estimate the best fit for vaccinations.

In this we are using Chi-square vaccination, Kolmogorov–Smirnov vaccination to evaluate the fitness of the data. For this reason, the raw data values ​​of arrival and service rates (in minutes) are recorded in the vaccination file. For our input data, we recommend using the Beta distribution.

## Chi-Square test:

Here, Chi-square test is used for assessing goodness of fit data. The level of significance is 0.05 . We are considering a sample of 300 people and considering how long will be their wait time till the complete procedure of their vaccination. We divided working hours of the vaccination for every 2 hours is 37, 40, 35 and 36. We are expecting result around 10%, 12%, 9% and 11% respectively.

Null hypothesis: Expected data is true and valid

Alternative hypothesis: Expected numbers of people inflow is false. Pearson’s Chi-square goodness of fit Calculation:

Total number of people observed over a day for vaccination: 300 Ei = Total \* percentage expected

E1= 40

E2= 48

E3= 36

E4 = 44

X2 =∑ [(Oi-Ei)2/Ei]

= ∑ [((37-40)2/40) + ((40-48)2/48) + ((35-36)2/36) + ((36-44)2/44))

= 2.036

From the significance level α =0.05, and Degrees of freedom 3 we get the critical value as X2

= 7.81 from table of X2 Vs p-values.

Since our value of X2 is 2.03 which is less than the critical value of 7.81, our null hypothesis is true and is accepted Since the difference between the expected and the observed value is very small.

## Kolmogorov-Smirnov test:

KS test was used to compare our data with distribution, and it gives us with any significant difference between the distribution and sample data. How good it is, to fit the sample distribution as it follows the theoretical distribution is known by performing the vaccination. Unknown cumulative distribution holds true with theoretical distribution is assumed to be null hypothesis and the opposite is our alternate hypothesis. With 0.05 significance, we do not have sufficient evidence to reject the hypothesis. The difference is calculated using the statistic D with the greatest difference between the Fs(X) and Ft(X). Based on calculations the maximum wait time is found to be 2.39 for the whole observations, which when compared with the p-value- D table from the supreme value for 0.05 significance and a sample of 30, Kolmogorov quartile is 1.69,

lesser than that from the value. Since the assumed sample is to be 30 from t score table, we have value of 1.69, this varies if sample n is greater than 30 as we go for z scores with mean, standard deviation values. So, it is said that the null hypothesis can be accepted as the value is greater than that from quartile.

D statistic = Sup| Fs(X) – FT(X) |

Comparison between the unknown cumulative distribution and theoretical distribution hold true and hence the data is also said to be a good fit as per Kolmogorov-Simonov vaccination.

### **3.2.3 Arena Simulation for Arrival Rate**

![Chart, histogram

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Fig: Data representation for Patient Arrival Rate in Arena

### **3.2.4 Arena Simulation for Service Rate**

![Chart, histogram

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Fig: Data representation for Patient Service Rate in Arena

## 3.3 Model Design

Our model is stochastic because patients arrive at the vaccination center at random. Furthermore, because the state of the system changes in response to events, it is classified as a discrete model. Arena Simulation is being used for discrete occurrences in this case.

**Entities:** Patients

**Queues:** Sanitize hands, Reception Counter, Collect patient details, Vaccination counters.

**Resources:** Receptionist, Health official, Nurse, Sanitizer, Table, Laptop, Printer, Vaccination Kits

**Events:** Arrival, Exit

### **3.3.1 System with One Counter**

We considered the Montreal's busiest vaccination clinics. In the current vaccination method, the patient will arrive and then undergo sanitization to ensure that he is virus-free on the outside. The receptionist will complete the questionnaire with each individual and determine whether they are eligible for vaccination. If the person is not eligible, he will be asked to leave the vaccination center because immunization is not necessary for him, and if he is, he will queue to meet the health official who will collect his insurance and mailing information. After that person will join the queue for the vaccination and the nurse will do the required. In specified intervals of the entire process, the person will go for sanitization multiple times.

Because just one server or resource is used for each event in the existing version, the waiting time in this model will be longer. The patient must spend a significant amount of time in line, and there are little resources available to meet the demand.

### **3.3.1.1 Process Map for Exiting System – Single Counter Waiting time**

![Diagram

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Fig: Process Map for Existing System

*![Diagram

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Fig: Process Map for Existing System in Arena

### **3.3.2 The Proposed model – Double counter**

We have increased the counters at each model queue in the system we propose. When a patient first enters the vaccination center, he or she will be escorted to one of the several reception counters to complete a questionnaire. If he or she is eligible for vaccination, he or she will be referred to the nearest health official counter to provide personal information. Finally, he will be permitted to travel to one of the available vaccine counters, where a Nurse will perform the necessary procedures. The person must leave the immunization center if he is not eligible for vaccination. During the vaccination process, the individual must also sanitize their hands several times.

With the addition of more counters, the wait time in this process model has been considerably reduced. In addition, the service time has been enhanced, and the vaccination process can now accommodate a larger number of patients.

#### **3.3.2.1 Model Setup**

1. Run Setup in Arena

The simulation is performed on a 24-hour clock assuming it runs for 12 hours starting from 8AM –8 PM. Total of 20 days were replicated to measure the accuracy. We have taken the average of 400 patients everyday who visit the vaccination clinics.

Graphical user interface, application

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Fig: Simulation Run setup in Arena

1. Queues in Reception Counter, Consultation, Vaccination.

The time taken at each counter to avail the service is given in the process. A resource such as receptionist, Health official, Nurse has been captured by the patient and is released once he/she avails the service. To achieve this process ‘Seize Delay Release’ was chosen as the action.

Graphical user interface, application

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Fig: Reception Queue setup in Arena

Graphical user interface, application

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Fig: Vaccination Queue setup in Arena

1. Decision making.

The decision process whether a person is eligible for vaccination or not is given as 90% eligible which is a true case. For other decision-making processes at respective counter direction given as 50%.

Graphical user interface, text, application

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Fig: Vaccination eligibility decision setup in Arena

Graphical user interface, text, application

Description automatically generated

Fig: Vaccine collection Counter decision setup in Arena

1. The below Entities were created in the implemented system.

![Calendar

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Fig: Entity table for double counter implementation

![Table

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Fig: Decision making table for double counter implementation

### **3.3.2.2 Process Map for Proposed System – Multiple Counter Waiting time**

![Diagram

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Fig: Process Map for Existing System

![Diagram

Description automatically generated]()

Process map for multiple counters in Arena

## 3.4 Output Analysis

The simulation is done on 24-hour clock starting from 8 AM to 8 PM as the vaccination centre will be opened for 12 hours a day. The model is replicated for 20 days to get the accurate results. The units are considered in hours. Upon running the model simulation, the following results were depicted for both Existing and Implemented model.

The results for the existing system are as follows.

### **3.4.1 Existing System Results – Arena reports**

The reports overview of the existing system is showed below:

![Graphical user interface, text, application, email

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Performance Indicators for Existing System in Arena

![Table

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Results for each entity in Arena reports

![Table

Description automatically generated]()

Results for each Queue in Arena reports

*![Table

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*![Graphical user interface

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![Table

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Averages of the resource Usages in Arena reports

### **3.4.2 Implemented System Results – Arena Models**

Now, these are the results for the proposed model with multiple counters:

![Graphical user interface, application

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Performance Indicators for Implemented system in Arena

*![Table

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Entity performance result for implemented model

*![Table

Description automatically generated]()*

Queue waiting time at each counter for the implemented models in Arena

*![Table

Description automatically generated]()*

*![Table

Description automatically generated]()*

Average Usage of resources for implemented model- Arena

*![A picture containing graphical user interface

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*![A picture containing graphical user interface

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## Observations:

The average customer wait time has decreased from 0.46 to 0.035, and the average total time spent by each patient has decreased from 0.83 to 0.29. The maximum total time spent by each patient is reduced from 2.6 to 0.7, and simulation units are measured in hours. The model that we designed has more resources, and the number of patients served per day appears to have increased in the implemented model.

## 3.5 Verification and Validation:

**3.5.1 Verification**

The model met the system requirements and could operate effectively with better results during the implementation stage; therefore, verification was done using simulation approaches. Static and dynamic testing techniques are the two types of verification techniques.

**Static testing:**

Static testing verifies how well the system would operate with the established technique based just on model specification. We can say that our implemented model of increasing the number of counters in dealing with patients and dedicating a count of patients to treat for each hour would show good results in reducing the waiting time for patients/people who come to be vaccinated, which in either way reduces the exposure and risk. In our situation, additional counters, appointments, and a specific number of testing workers are used to meet the criteria for the model at any moment in all possible conditions.

**Dynamic testing:**

Simulation approaches are used in dynamic testing to verify the model and check behavior in real time. We are confident in declaring that the model is proven for many scenarios because of the advantage of collecting more precise information via simulation techniques. More scenario-based realistic testing was conducted as a single counter and a double counter with various data sets to calculate the average wait time, with good findings. Because our simulation testing is a methodology-based approach to reducing wait time rather than product development, we employed a scenario and model execution to ensure that the system worked as intended. We've gotten outputs in such a manner that the parameters involved have a stronger impact in lowering the waiting or vaccinating time, just like a real-time system, with various values of patients coming in at different hours and varying the counters to manage, just like a real-time system. At the verification step, meeting specifications when dealing with model implementation is desirable, and our model meets the intended specification of vaccinating a given number of people.

**3.5.2 Validation**

Validating our model is to determine that our data which we have provided meets with real world representation and the changes in input have significant bearing over our output. We have used hypothesis testing in determining that our observed data and expected data are good enough in proceeding with the simulation. We also conclude that our model is valid with two other valid vaccination techniques namely degenerate tests and event validity.

**Degenerate test:**

Degeneracy of model behavior is tested with changes in input values and few other modifications in the parameters. There will be decrease in queue, for people to get vaccinated when the service time is less when compared to the longer arrival time. In our case when people visit the vaccination center the arrival times longer than usual then there would be a few people in queue as service time is also reduced than arrival time.

### **Event validity:**

Our model is said to be valid in case of event validity as the event occurrences are way like the real-world scenarios as the events dealing with model are true and valid. Patient arrival times and vaccinating times along with details identification counters and vaccines are all the real-world scenario and as patient wait time reduction simulation model deals with the service times and arrival times.

Along with the above two techniques one strong validation model of hypothesis testing in assessing the data to proceed further was also done in making it to have hypothesis of data and model being used would be true at all possible scenarios.

# Monte Carlo Simulation - MS-Excel

Monte Carlo Simulations are used to model the possibility of different outcomes in a process that cannot be easily predicted due to the presence of random variables. It is also termed as a mathematical technique that is used to calculate the risk of a system by qualitative analysis and decision making. Monte Carlo Simulation is used to analyze systems in various fields like Healthcare, Finance, Engineering and Supply Chain, etc. In the process of simulation for predicting the risk of a system, we face a lot of uncertain variables that make our study difficult to complete. These situations can be addressed by Monte Carlo Simulation modeling by just replacing an uncertainty variable with a single average number, and it is proven that the simulation has yielded better solutions and results.

We decided to choose Monte Carlo simulation to analyze and predict the possible waiting and service times of the patients arriving for a COVID testing center to give their samples. We have considered an existing system with our assumptions by looking at a testing site and come up with a proposed solution to reduce the waiting and service times and provide quick service.

Parameters to be considered for designing a Simulation Model -

Arrival Rate – The number of patients arriving for testing to the COVID testing center in at specified intervals.

Maximum Capacity in Queue – The maximum number of patients can be waiting in the queue.

Arrival Process –Decide the arrival process of the patients, can be at scheduled arrivals or at random times.

Service Pattern – The pattern in which each patient goes through the process and exit the testing center. Based on these patterns, we can derive the Average service time per each patient and the number of patients served every minute or hour.

# Monte Carlo - Model Description

Our Team’s intention is to design a simulation model to determine the waiting time and service times for registered citizens visiting a COVID-19 vaccination center with an existing system(Montreal-based) and then demonstrate a new effective and efficient possible solution after evaluating the outcomes. In the current system, registered people while going to a vaccination center, they go through a set of predefined exercises like exchanging the old mask with a new one, sanitizing their hands and bags, consultation with service desk by providing their identity and then consulting the health department and then finally getting the vaccination shot, wait for 5 minutes, and then exit the vaccination center. At each action, the citizens will spend few minutes of time and then advance to the later stages. The arrival rate and service time at each stage are the demanding specification to be described practically while simulating the model.

Monte Carlo Simulation is an advanced mathematical simulation model, in our case we are considering the distributions that are applicable for arrival rate and service patterns. For arrival rate we are using Poisson Distribution, which is used to describe the distribution of rare events in a large population.

Arrival Rate – Poisson Distribution Service Times – Exponential Distribution Queue Capacity – No Limit

The uniform distribution is a probability distribution model that describes the time between the events that has constant probability. The events occur rate is independent and continuous at a constant rate in this uniform distribution. In Monte Carlo model, the system also has the service pattern at each process is continuous and independent of each other with a consistent service time. So, we are determined to move forward with uniform distribution for service times.

Poisson distribution is a discrete probability distribution that gives the number of registered citizens visiting the COVID-19 vaccination center over a given period, given the average number of citizens visit over that period. Based on the requirement to satisfy the problem statement we must assume that the arrival rate of patients is random, we felt Poisson distribution is the perfect apt for our model.

# Monte Carlo - Input Analysis

Based on our recent research, we are considering that a COVID-19 vaccination center will serve an average of 300 registrations per day and the vaccination center will be open for 8 hours

|  |  |
| --- | --- |
| **Analysis of Arrival rate** | |
| Average number of citizens vaccinated daily | 300 registered citizens |
| No of working hours per day | 08 hours |
| No of registered citizens arrived in an hour | 37.5 per hour |
| Nor of registered citizens arrived in a minute | 0.625 per minute |
| Average minutes per arrival | 1.4 |

|  |  |
| --- | --- |
| **Analysis of Service rate** | |
| Citizens vaccinated per hour | 30 per hour |
| Citizens vaccinated per minute | 0.57 |
| Average minutes per one citizen | 3.8 minutes |

Total Service Time = Sum of Service Times (Sanitization, validity of Identification, Consultation, Vaccination shot)

|  |  |
| --- | --- |
| **Process** | **Service Times** |
| Sanitization | 10 seconds |
| Validity of Identification | 1.5 minutes |
| Consultation | 2 minutes |
| Vaccination Shot | < 1 minute |
| **Total Average** | 4 minutes/patient |

The service waiting times doesn’t include the queue waiting times of each citizen takes to start the process. The output of the Monte Carlo simulation model will demonstrate the Average waiting time of citizens spent in the queue to complete their service.



# Existing System

## Simulation Model – Single Booth

In this model, the vaccination center will only have 1 check-in booth, 1 Identity validation booth, and 1 vaccination booth. The patient arrived at the center will have to go through the entire process sequentially and have exit after getting the vaccination shot by the nurse.

Diagram

Description automatically generated

Fig: Representation of the process using the flow diagram

Registered Citizen vs Total Service Time

The graph below depicts the total service time taken for each registration. Looking at the graph it is clearly demonstrated that service varying at a range of 3 to 7 minutes

Graphical user interface, chart

Description automatically generated

Fig: Citizen Service Rate

Registered Citizen vs Wait Time

The graph below indicates the amount of time each registered citizen must wait to get vaccination shot. From the graph it is demonstrated that the wait time are rising exponentially because of the wait in very long queues.

Chart, line chart

Description automatically generated

Fig: Citizen wait time because of long queues

Replication vs Average Wait Time:

The below graph represents the average wait time taken by all the registered citizens in various replications. The below graph is plotted for 100 replications.

Graphical user interface, chart

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A picture containing timeline

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Fig: Simulation Model for Single counter-Monte Carlo

# Implemented System

## Improvised Simulation Model – Two Booth’s

Registered Citizen vs Total Service Time

The graph below indicates that the total service time taken for each citizen. By viewing at the graph, it is observed that the service fluctuating at a range of 3.5 to 7.0 minutes.

Chart

Description automatically generated

Fig: Citizen Service Rate

Registered Citizen vs Wait time

The graph below indicates the extent number of times each registered citizen must wait to get a vaccination shot. From the below graph it is recognized that the wait time is rising exponentially due to the long waiting queues. However, the wait times has been reduced to 55-60 % when compared to the single booth in the first place.

Chart, line chart, scatter chart

Description automatically generated

Fig: Citizen wait time because of long queues

**Replication vs Average Wait Time**

The below graph shows the average waiting time taken by all the patients in different replications. The graph is plotted for 100 replications. The average waiting time for 100 replications was observed to be 85 minutes.

Chart, line chart

Description automatically generated

*Graphical user interface, application, table, Excel

Description automatically generated*

Fig: Implementation of proposed model with Two Booth’s - Excel

## Improvised Simulation Model with Constant Arrival – Two Booth’s(scheduled Arrival)

Registered Citizen # vs Total Service Time

The graph below depicts the total service time taken for each patient. Looking at the graph it is observed that service varying at a range of 3.5 to 6.5 minutes. Chart, bar chart

Description automatically generated

Fig: Citizen Service Rate

Registered Citizen vs Wait time

The graph below illustrates the amount of time each citizen must wait to get the vaccination shot. From the graph it is demonstrated that the wait time are rising exponentially but the maximum and average waiting times are comparatively very less than the previous versions

Chart, scatter chart

Description automatically generated

Fig: Citizen wait time because of long queues

Replication vs Average Wait Time

The below graph shows the average waiting time taken by all the patients in different replications. The graph is plotted for 100 replications. The average waiting time for 100 replications was observed to be 30 minutes.

*Graphical user interface, text, application

Description automatically generated*

Fig: Citizen average wait times based on number of replications

*Graphical user interface, table, Excel

Description automatically generated*

Fig: Implementation of enhanced and proposed model with Two Booth’s – Uniform Arrival Rate – Excel

# Output Analysis

We have computed the margin of error for confidence interval of 90% and achieved the lower and upper limits of the wait times for every model. Please find the particulars of calculations and observations in the below tables

|  |  |
| --- | --- |
| **Single Booth - 100 Replications** | |
| Mean of the wait times | 169.7 |
| Standard Deviation of wait times | 28.88 |
| No of Count of Replications | 100 |
| Square root of count of replications | 10 |
| T-score scaling factor | 1.98 |
| Margin of Error -  (t-score(standard deviation/square root of count)) | 5.73 |
| Confidence Interval 90% - Lower Limit | 164.00 |
| Confidence Interval 90% -Upper Limit | 175.46 |

|  |  |
| --- | --- |
| **Two Booth’s - 100 Replications** | |
| Mean of the wait times | 87.3 |
| Standard Deviation of wait times | 17.51 |
| No of Count of Replications | 100 |
| Square root of count of replications | 10 |
| T-score scaling factor | 1.98 |
| Margin of Error -  (t-score(standard deviation/square root of count)) | 3.47 |
| Confidence Interval 90% - Lower Limit | 83.79 |
| Confidence Interval 90% -Upper Limit | 90.74 |

|  |  |
| --- | --- |
| **Two Booth’s - Constant Arrival - 100 Replications** | |
| Mean of the wait times | 35.4 |
| Standard Deviation of wait times | 5.46 |
| Count of Replications | 100 |
| Square root of count of replications | 10 |
| T-score scaling factor | 1.98 |
| Margin of Error -  (t-score(standard deviation/square root of count)) | 1.08 |
| Confidence Interval 90% - Lower Limit | 34.32 |
| Confidence Interval 90% -Upper Limit | 36.49 |

Based on the calculations and inspections through this model.

* For single Booth the wait time is in the range of 154 to 185 minutes
* For two Booth’s model the wait time is in the range of 75 to 95 minutes
* For two Booth’s model with constant arrival rate the wait time is in the range of 31 to 39 minutes

# Verification and Validation

## Verification

* In our simulation model, we have taken input parameters as assumptions based on Montreal based vaccination center.
* We have started developing the simulation model with conservative details in the beginning and then we added additional specifics after confirming the model we proposed was accurate.
* We did an analysis by collecting the transitional test results retrieved by the simulation model and compared both the outcomes obtained with real-time handy calculations.
* In our Static Testing, wait time increases with the decrease in staff members or increase in registrations and wait time decreases with decrease in registrations or increase in staff.
* In Dynamic Testing, we have used the Random function in order randomize and vary the input data in real-time. We have verified the relation between input and output validations.
* Simulation model is accomplished with variety of input scenarios and understood if the variation in the output is acceptable.

## Validation

* Sensitivity Analysis was performed on the model by changing and inputs and observed the parameters that are affected because of the input change.
* Followed confidence interval approach and calculated the 90% confidence interval to find the margin of error and obtain the exact outcomes.

All our analysis performed by doing verification and validation are proved to be accurate from the results. By this, we are confident that the model we developed matches with the actual system and any changes suggested to this model to improve the waiting times will also have effect on the actual system

# Vensim – Simulation

# Decrease in wait time using Vensim – Simulation

Vensim is a [simulation software](https://en.wikipedia.org/wiki/Simulation_software) developed by Ventana Systems. It primarily supports [continuous simulation](https://en.wikipedia.org/wiki/Continuous_simulation) ([system dynamics](https://en.wikipedia.org/wiki/System_Dynamics)), with some [discrete event](https://en.wikipedia.org/wiki/Discrete_event_simulation) and [agent-based modeling](https://en.wikipedia.org/wiki/Agent-based_model) capabilities, and also provides a graphical modeling interface with [stock and flow](https://en.wikipedia.org/wiki/Stock_and_flow) and [causal loop diagrams](https://en.wikipedia.org/wiki/Causal_loop_diagram), on top of a text-based system of equations in [a declarative programming](https://en.wikipedia.org/wiki/Declarative_programming) language. Vensim can be used to solve a variety of problems. There are several example applications at our corporate website, in the resources, and of course in the models that come with Vensim. Still, that is only a small sample of things that can be done, and the applications of Vensim are as follows:

* Work education mismatch.
* New C-roads and world climate simulators.
* Integrated sustainable development goals planning model.
* Energy policy simulator.
* Game change Rio.

# Casual Loop diagram

Diagram

Description automatically generated

Fig: causal loop diagram of covid19 wait time

C[ausal diagram](https://en.wikipedia.org/wiki/Causal_diagram) that aids in visualizing how different variables in a system are causally interrelated. The diagram consists of a set of words and arrows. Causal loop diagrams are accompanied by a narrative that describes the causally closed situation the CLD describes. Closed loops, or causal [feedback](https://en.wikipedia.org/wiki/Feedback) loops, in the diagram, are very important features of CLDs.

# Execution of Casual Loop diagram

Diagram

Description automatically generated

Fig: execution of causal loop diagram

In the execution part of reducing the wait time at vaccination center we fixed the error rate as 0.025 according to the normal error rate of Quebec government. and we have used different variables like people arrived, sanitizing level, error rate, details collection point, people with correct information, people with wrong information and exit. In this people information matched refers to the one who have booked a slot for vaccine and arrived the correct place for vaccination and patient information not matched refers to any one of the data is wrong may be arrived to another location for vaccine or not booked the appointment.

# Casual Loop diagram Output

In obtaining output for the above causal loop, we have inserted formulas according to the performance and arrangement of blocks and values are given to the input which will range from 1000 to 20000 per day. Through vaccinating a huge number per day requires many other factors like staff and equipment, here we have just used the value for testing, and we also compared the practical values of vaccinating people with theoretical values which matched exactly. The graphs obtained by performing the operations are below which are with different variables and colors.

Table

Description automatically generated

*Graph: output for specific set of inputs*

# Verification and Validation

Verification which means identifying the truth, correctness and a process if validating the output multiple times to cross check whether we are getting same results after many trails. After multiple performance we can say it is running efficiently and validation is the specific approach of fulfilling requirements of the system by meeting predefined format attributes with other output criteria and evaluating whether the outputs are sufficient with meeting the user expectations by structuring accordingly.

Designing and simulation of reducing waiting of covid19 wait time is a needed thing in this pandemic and the result of the above simulation shows that the error rate is very low and can be vaccinated in great percentage without spreading the infection.

**Trail 1:**

A picture containing table

Description automatically generated

*Graph: out plot of vaccinated people per day trails 1*

**Trail 2:**

Table

Description automatically generated

*Graph: out plot of vaccinated people trails 2*

# Documentation for the executable flow

(01) details collection point=

sanitizing level1-(error rate\*sanitizing level1)

Units: \*\*undefined\*\*

(02) error rate=

0.025

Units: Day

(03) exit=

patients information not matched+vaccination point

Units: Day

(04) FINAL TIME = 100

Units: Day

The final time for the simulation.

(05) INITIAL TIME = 0

Units: Day

The initial time for the simulation.

(06) no of people arrived=

exit

Units: Day

(07) patients information not matched=

details collection point/39

Units: \*\*undefined\*\*

(08) people arrival=

2500

Units: Day

(09) people information matched=

details collection point

Units: \*\*undefined\*\*

(10) sanitizing level 2=

people information matched

Units: \*\*undefined\*\*

(11) sanitizing level1=

people ariival

Units: Day

(12) SAVEPER =

TIME STEP

Units: Day [0,?]

The frequency with which output is stored.

(13) TIME STEP = 0.5

Units: Day [0,?]

The time step for the simulation.

(14) vaccination point=

sanitizing level 2

# Units: \*\*undefined\*\*

# Conclusion

We have successfully implemented the current utilized system of the COVID-19 vaccination center and analyzed the problems in the current system and proposed a new system that rectifies the complication. Two different simulation models were developed and simulated to understand the system, the first one is using Arena Simulation software for discrete event simulation and the other is Monte Carlo Simulation using Microsoft Excel. We have also analyzed the outcomes via Vensim simulation through casual loop diagram and the executable flow. We have evaluated the simulation outcomes achieved from the above models and documented our observations. We have proved that our simulation is realistic through the verification and validation aspects and all the outcomes are practical and credible.

# References

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