SYSC 5001

SIMULATION

PROJECT REPORT

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1.0 PROBLEM FORMULATION

The project's goal is to create a simulation model for the check-in process at Smiths Falls / Montague Airport (SFMA), to reduce passenger wait times and improve operational efficiency. The airport, which is supplied by Air Canada, has two types of flights: regional commuter flights to Ottawa International Airport and provincial flights to Calgary. Commuter flights have 40 coach seats, while provincial flights can accommodate 140 coach and 40 business class passengers. While booking is not required for passengers on provincial flights, it is for those on regional flights, with varying probabilities of securing a seat. The arrival process generates a stochastic passenger inflow by using a Poisson distribution for commuters and a normal distribution for provincials.

When passengers arrive, they go on to the check-in desks, which include up to six stations with different queues for business and coach classes. The service time includes printing boarding passes, checking luggage (with stochastic delays), and resolving any challenges that arise. Passengers then go through security screening, with separate lines for business and coach passengers, with average service times determined by exponential distributions. Finally, travelers reach the gate area, where provincials must be at least 90 minutes before departure to qualify for refunds in the event of missed flights, while commuters wait for the next available aircraft. Simulation time, repetitive trials, and statistical assessments are among experimental design factors for evaluating the project. After the simulation, a report on the design , implementation , output and recommendations for the project.

2.0 OBJECTIVES AND OVERALL PROJECT PLAN

A stochastic discrete-event simulation defines the process involved in handling passengers from flights at Smith Falls airport. Its main objectives are to manage queues for different services such as security screening and check-in, simulate passenger arrivals, and assess how long these procedures take. The simulation evaluates performance metrics including wait times , examines how airport resources are used and calculates profits by comparing operating expenses to revenue. Acquiring expertise on optimizing business processes, improving visitor experiences, and preserving economic stability can aid in the distribution of resources and long-term growth strategy.

2.1 OBJECTIVES

The objective of this project is as follows:

I. Maximize the airline's profit.

II. Reduce the amount of time passengers must wait to check in, particularly in business class.

III. Increase the possibility that travelers from the provinces will make it to their flights.

IV. Reduce commuter passengers' post security screening wait times.

V. Reduce the amount of time agents spend idle.

2.2 THE PROJECT PLAN

The project plan involves:

1. Recognizing how to improve performance of the model.
2. Create my simulation model based on the project requirements.
3. Deploy my simulation model on MATLAB.
4. Carry out replications to ensure my results are accurate.
5. Output statistics of our simulation model that need to be studied.
6. Compose a report outlining every step of the process and the findings.

3. MODEL CONCEPTUALIZATION

In this step I will plan on how I intend to conceptualize the model. I will state the system's attributes, entities, activities, events, and state variables.

ENTITIES	**ATTRIBUTES**	**ACTIVITIES**	**STATE VARIABLES**
PASSENGERS	• **Type of Flight (Regional or Commuter)** • **Arrival Time** • **Ticket Type (business class or coach)** • **No of Bags**	• **Airport Arrival** • **Airport Check in Process** • **Security Screening of Passengers** • **Airport Boarding**	• **Passenger Arrival Queue** • **Passenger Check in Queue** • **Security Screening Queue** • **Passenger Boarding Status**
FLIGHTS	• **Flight Type** • **Departure Time**	• **Departure**	• **Queue at departure** • **Departure Status(has plane departed)**
CHECK IN COUNTERS	• **Counter Number** • **Agent Availability**	• **Check In Process**	• **Counter Queue** • **Agent Status(Availability)**
SECURITY SCREENING	• **Screening Machine Number**	• **Security Screening Process**	• **Screening Queue**

3.1 ENTITIES:

The entities affect how our simulation runs. In this simulation project, the entities are flights, check-in counters, passengers, and security screening.

3.2 ATTRIBUTES:

An attribute is a property of an entity. The attributes include the type of flight, the arrival time, the type of ticket, the number of bags, etc.

3.3 ACTIVITIES:

This is the duration of the event. In our simulation the various activities are Check in Process, Departure, Security Screening Process etc.

3.4 STATE VARIABLES:

These are variables that describe the state of the system. The state variables in our simulation are Arrival Queue, Departure Queue, Screening Queue, Agent Status, Counter Queue.

4.0 DATA COLLECTION AND INPUT MODELLING

Data has been collected for the Commuter Passenger arrival time, Provincial Passenger Arrival Time, Commuter Passenger Bags, Provincial Passenger Bags. Data was also collected for Service Time for the following: Printing Boarding Pass, Checking Bags, Problems and Delays and Screening Machine

Python libraries were used to plot quantile quantile plots. Matplotlib was used for plotting graphs. Scripy.stats helps with statistical models. NumPy was used for an array of numbers. Pandas were used for cleaning and collection of data. Number of Passengers was assumed to be 100.

4.1 Commuter Passengers Poisson Distribution

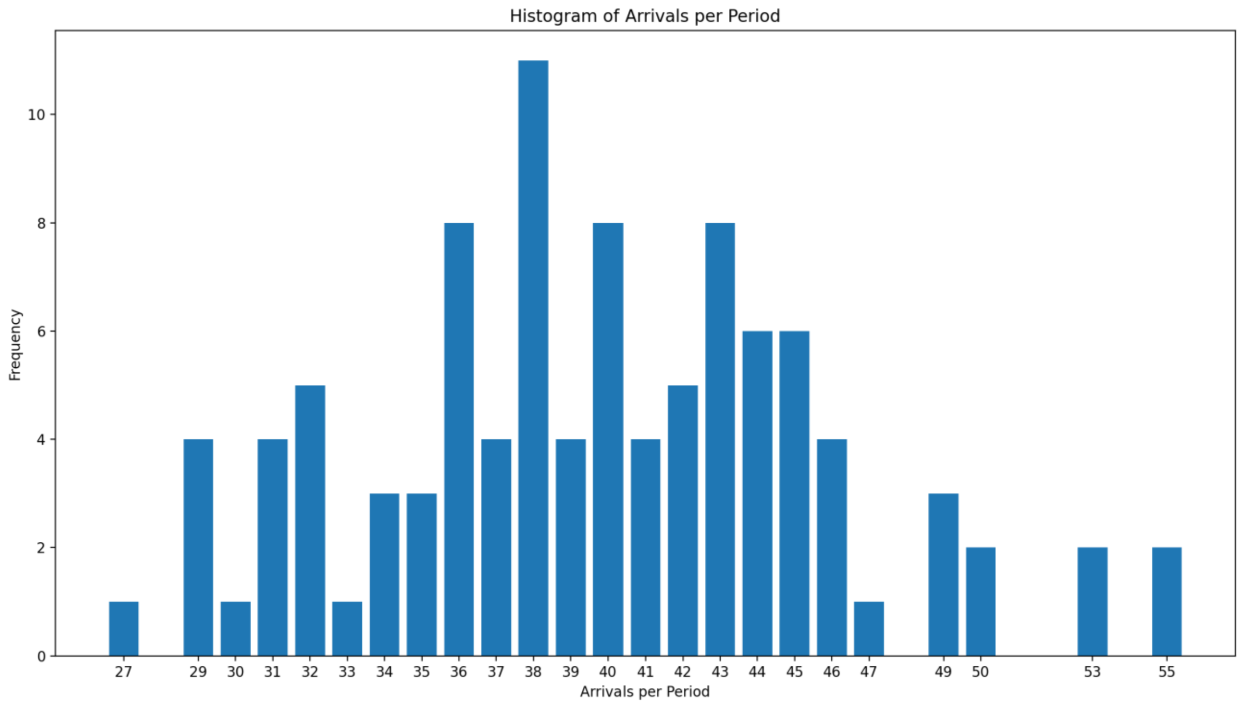
We want to generate a random number for the arrival time of commuter passengers following a poisson distribution.

Inverse-Transform Technique:

For generating random variations, the preferred method is the inverse-transform technique. The inverse-transform technique requires an inversible cumulative distribution function for the distribution to generate from.

To finalize this choice of distribution, a chi-squared test must be performed. This is an appropriate test to use in these circumstances since there are many data points and there are estimated parameters. The estimated parameter follows a Poisson distribution :$\lambda = X = 39.73$

With 10 bins and one variable estimated, the assumed chi-square distribution has **10 − 1 − 1 = 8 degrees of freedom**. Using a significance level of 0.05, the threshold value obtained from tables is **$Zo^2_{0.05,\,8}$= 15.50** By calculating expected frequencies from the hypothesized exponential distribution (see Appendix 1.1), Zo^2 = 6.95. Since this is below the threshold value, the hypothesis can be confidently accepted, and we can say with certainty that the service time for commuters follows a Poisson distribution with λ = 39.73.



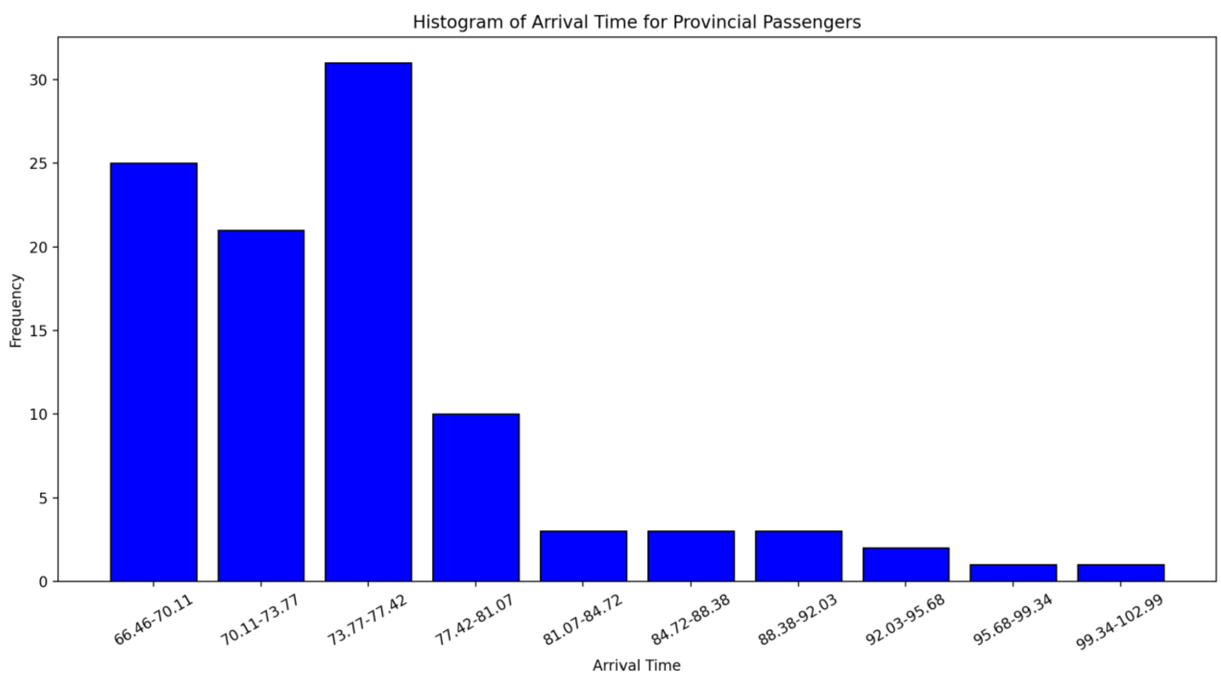
4.2 Provincial Passengers Normal Distribution

We want to generate a random numbers for the arrival time of provincial passengers following a normal distribution. Mean and Variance are specified in the project.

Combined Linear Congruential Generator: This method was used to generate random numbers by combining two multiplicative congruential generators for better statistical periods and longer periods.

Box Muller Transform: The random numbers were converted to normal random numbers using this transform. The Box Muller Transform is a technique for sampling random numbers given a supply of uniformly distributed random numbers, produces pairs of independent, standard, normally distributed random numbers.

Service Time Interval	Frequency
66.76-70.11	25
70.11-73.77	21
73.77-77.42	31
77.42-81.07	10
81.07-84.72	3
84.72-88.38	3
88.38-92.03	3
92.03-95.68	2
95.68-99.34	1
99.34-102.99	1



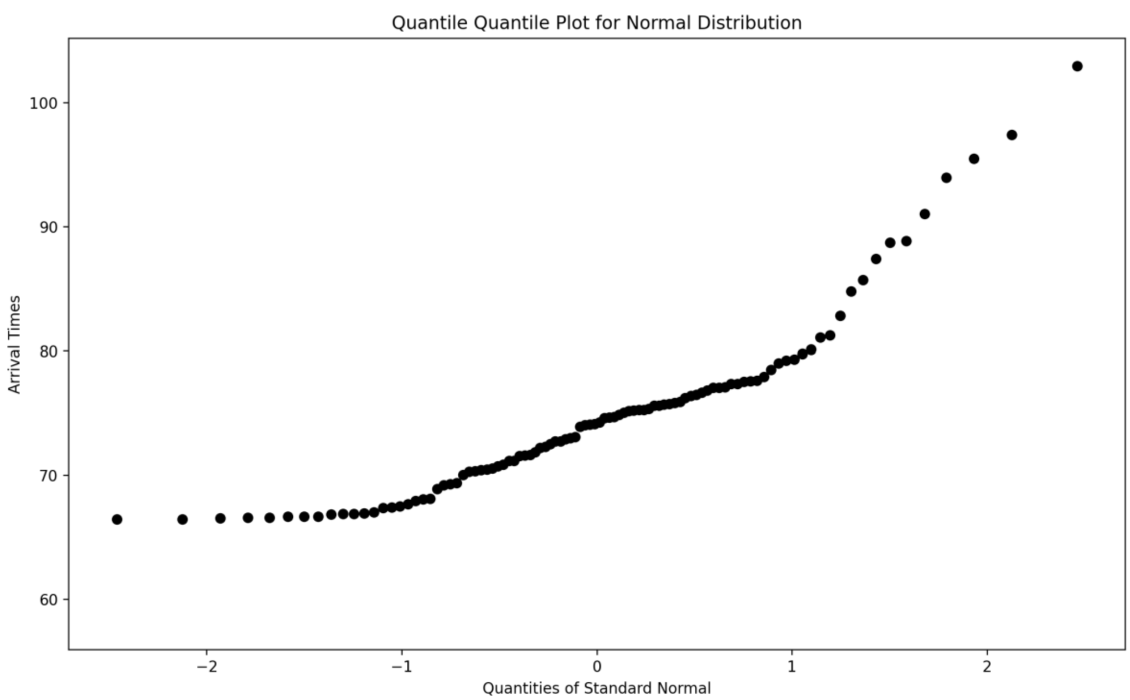
Based on the shape of this plot, the sample data does seem to fit a normal distribution, but quantile-quantile plot and chi-squared test must be used before we can say with certainty that this is the distribution that fits.

These are the suggested estimators for normal distribution.

$$\widehat{\mu} = \bar{X}$$
$$\widehat{\sigma}^2 = S^2 \text{ (unbiased)}$$

The ordered observations are plotted versus $F_p^{-1}\frac{j-\frac{1}{2}}{100}$

The quantile quantile plot is shown below:



To finalize this choice of distribution, a chi-squared test must be performed. This is an appropriate test to use in these circumstances since there are many data points and there are estimated parameters. The arrival time for provincial passengers follows a normal distribution:$\mu = 75.19$ $\sigma = 46.95$

With 10 bins and two variables estimated, the assumed chi-square distribution has **$10 - 1 - 2 = 7$ degrees of freedom**. Using a significance level of 0.05, the threshold value obtained from tables is **$Zo^2_{0.05,\,7} = 14.1$ By** calculating expected frequencies from the hypothesized exponential distribution (see Appendix 1.2), $Zo^2 = 13.1$. Since this is below the threshold value, the hypothesis can be confidently accepted, and we can say with certainty that the arrival time for provincial passengers follows normal distribution with :$\mu = 75.19$ $\sigma = 46.95$

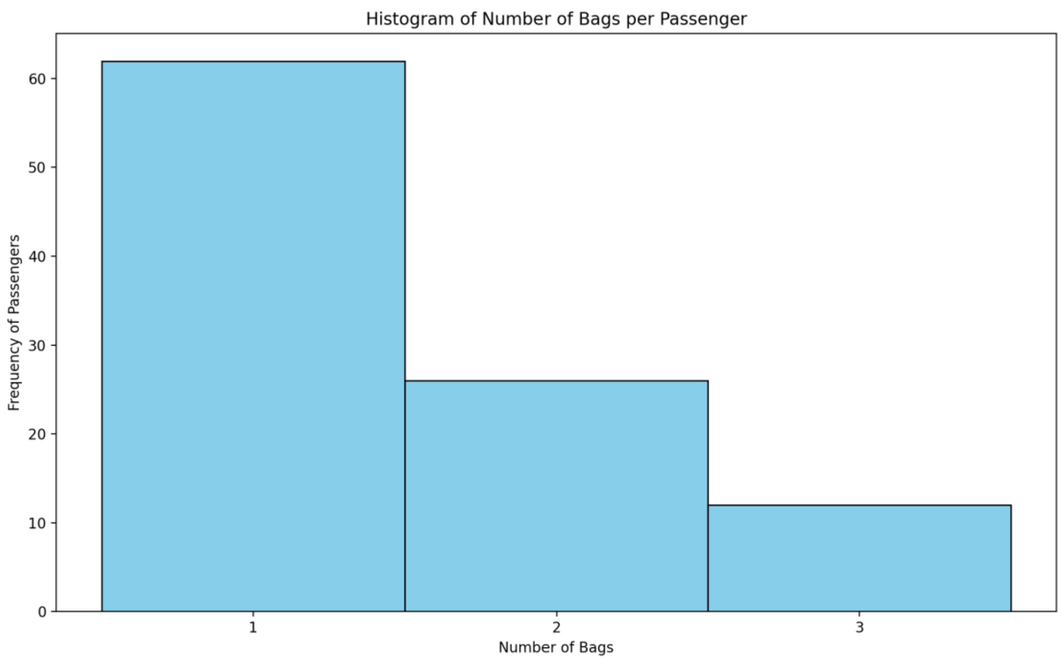
4.3 Commuter Passengers Bags Geometric Distribution

Combined Linear Congruential Generator: This method was used to generate random numbers by combining two multiplicative congruential generators for better statistical periods and longer periods.

Two sets of LCG parameters are defined in this project: m1, a1, seed1 for the first generator, and m2, a2, seed2 for the second. Based on a multiplier (a1 or a2), a modulus (m1 or m2), and the preceding random number (or seed1 or seed2), each generator employs a modulus operation to generate a new random number.
We begin with one bag per person and determine if they will bring extra bags based on a new random number. The passenger stops carrying more bags if the generated uniform random number u (between 0 and 1) is less than the stopping

probability p_stop, until the passenger chooses to stop or the maximum number of bags permitted is reached, this process is repeated.

Number of Bags	1	2	3
Frequency of Passengers	62	26	12



We will proceed to use a goodness of fit test to check if our data fits our distribution.

The probability density function of a geometric distribution is given by:

$$p(x) = \begin{cases} q^{x-1} \cdot p, & x = 0, 1, 2, \ldots \\ 0, & \text{otherwise} \end{cases}$$

The probability that a provincial passenger stops bringing bags is given as follows:

P= $\frac{1}{x} = 0.67$

With 10 bins and one variable estimated, the assumed chi-square distribution has **$3 - 1 - 1 = 1$ degree of freedom**. Using a significance level of 0.05, the threshold value obtained from tables is **$Zo^2_{0.05,\,1} = 3.84$** By calculating expected frequencies from the hypothesized exponential distribution (see Appendix 1.3), $Zo^2 = 3.82$.

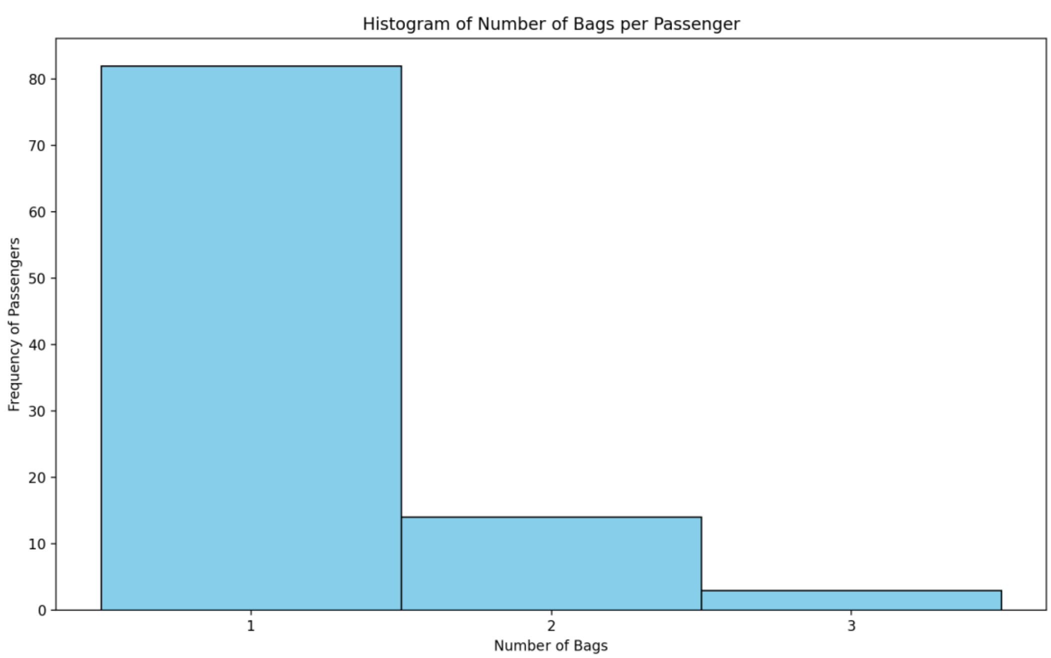
4.4 Provincial Passengers Bags Geometric Distribution

Combined Linear Congruential Generator: This method was used to generate random numbers by combining two multiplicative congruential generators for better statistical periods and longer periods.

Two sets of LCG parameters are defined in this project: m1, a1, seed1 for the first generator, and m2, a2, seed2 for the second. Based on a multiplier (a1 or a2), a modulus (m1 or m2), and the preceding random number (or seed1 or seed2), each generator employs a modulus operation to generate a new random number.

We begin with one bag per person and determine if they will bring extra bags based on a new random number. The passenger stops carrying more bags if the generated uniform random number u (between 0 and 1) is less than the stopping probability p_stop, until the passenger chooses to stop or the maximum number of bags permitted is reached, this process is repeated.

Number of Bags	1	2	3
Frequency of Passengers	83	14	3



We will proceed to use a goodness of fit test to check if our data fits our distribution.

The probability density function of a geometric distribution is given by:

$$p(x) = \begin{cases} q^{x-1} \, . \, p, & x = 0, 1, 2, \ldots \\ 0, & \text{otherwise} \end{cases}$$

The probability that a provincial passenger stops bringing bags is given as follows:

P= $\frac{1}{x} = 0.83$

With 10 bins and one variable estimated, the assumed chi-square distribution has **3− 1 − 1 = 1 degree of freedom**. Using a significance level of 0.05, the threshold value obtained from tables is $\mathbf{Zo^2_{0.05,1} = 3.84}$ By calculating expected frequencies from the hypothesized exponential distribution (see Appendix 1.4), $Zo^2 = 0.15$. Since this is below the threshold value, the hypothesis can be confidently accepted, and we can say with certainty that the fit follows a geometric distribution with

P= 0.83.

4.5 Service Time for Printing Boarding Pass

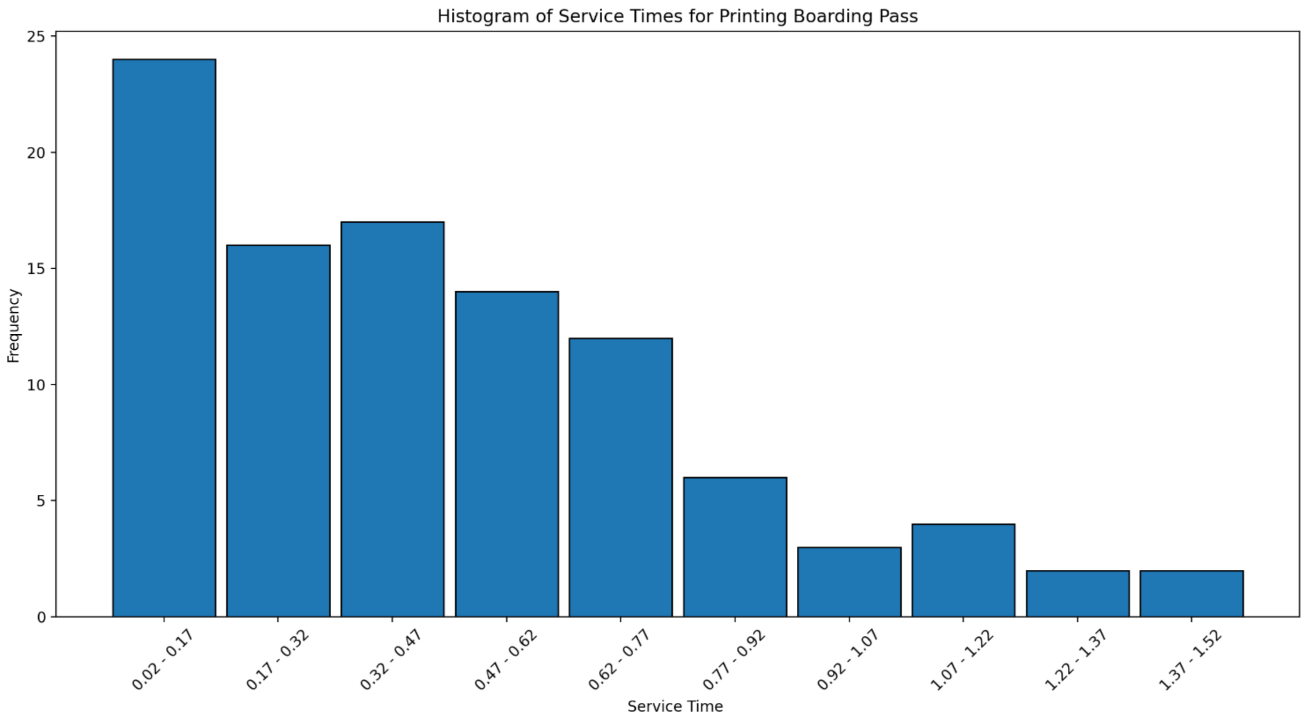
Inverse-Transform Technique:

To get our random variates, I used the inverse-transform technique. The inverse-transform technique requires an inversible cumulative distribution function for the distribution to generate from. Once the inverse of a distribution's cumulative distribution function is determined, then a randomly selected number from a uniform distribution will become the input parameter, and the output of the calculation will be a random variate. This technique will be used for exponential distributions.

Service Time Interval	Frequency
0.02-0.17	24
0.17-0.32	16
0.32-0.47	17

0.47-0.62	14
0.62-0.77	12
0.77-0.92	6
0.92-1.07	3
1.07-1.22	4
1.22-1.37	2
1.37-1.52	2

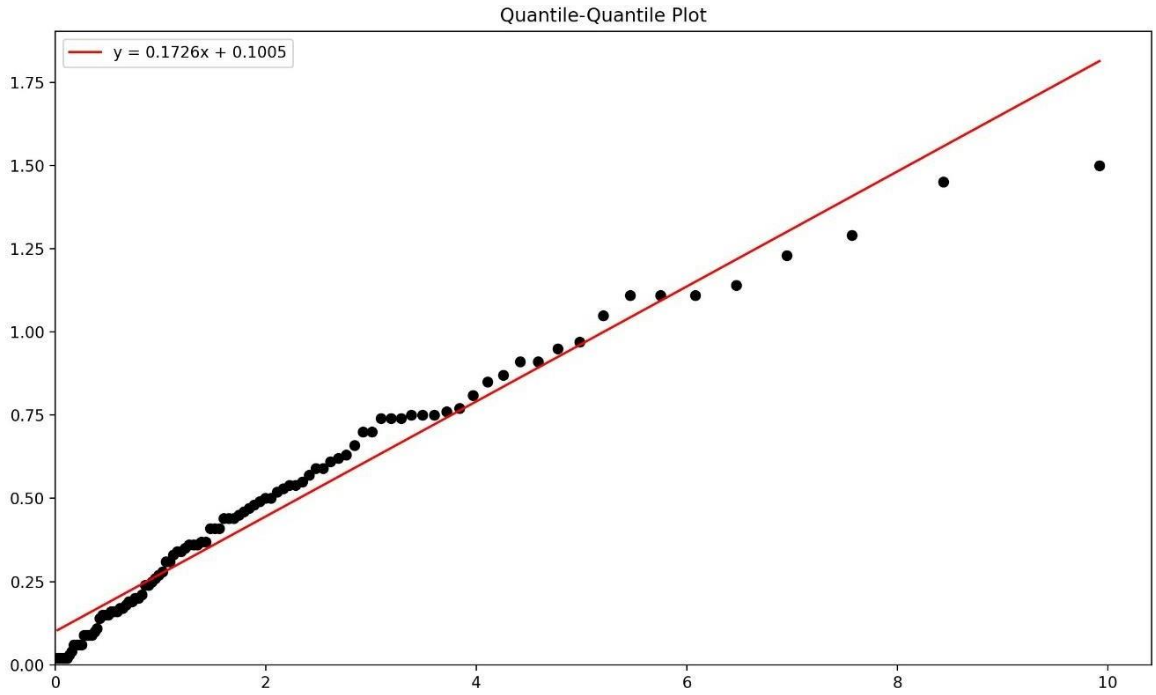
Given that the data represents service times and is a continuous variable and it follows an exponential distribution. As there are 100 data points, $\lceil\sqrt{100}\,\rceil = 10$ bins will be used to produce the histogram below:



Based on the shape of this plot, the sample data does seem to fit an exponential distribution, but quantile-quantile plot and chi-squared test must be used before we can say with certainty that this is the distribution that fits.

Using $\lambda = \frac{1}{\bar{X}}$ the parameter estimation and the quantile function

$F^{-1}(x) = \frac{-\ln(1-x)}{\lambda} = -\bar{X}\ ln(1-x)$ yields the following quantile-quantile plot:



To finalize this choice of distribution, a chi-squared test must be performed. This is an appropriate test to use in these circumstances since there are many data points and there are estimated parameters. The service time for printing a boarding pass follows an exponential distribution: $\lambda = \frac{1}{\bar{X}} = 2.13$

With 10 bins and one variable estimated, the assumed chi-square distribution has **10 − 1 − 1 = 8 degrees of freedom**. Using a significance level of 0.05, the threshold value obtained from tables is $\mathbf{Zo^2_{0.05,\,8} = 15.50}$ By calculating expected frequencies from the hypothesized exponential distribution (see Appendix 1.5), $Zo^2 = 6.95$. Since this is below the threshold , the distribution is accepted, and we can say that the service time for printing boarding pass follows an exponential distribution with λ = 2.13.

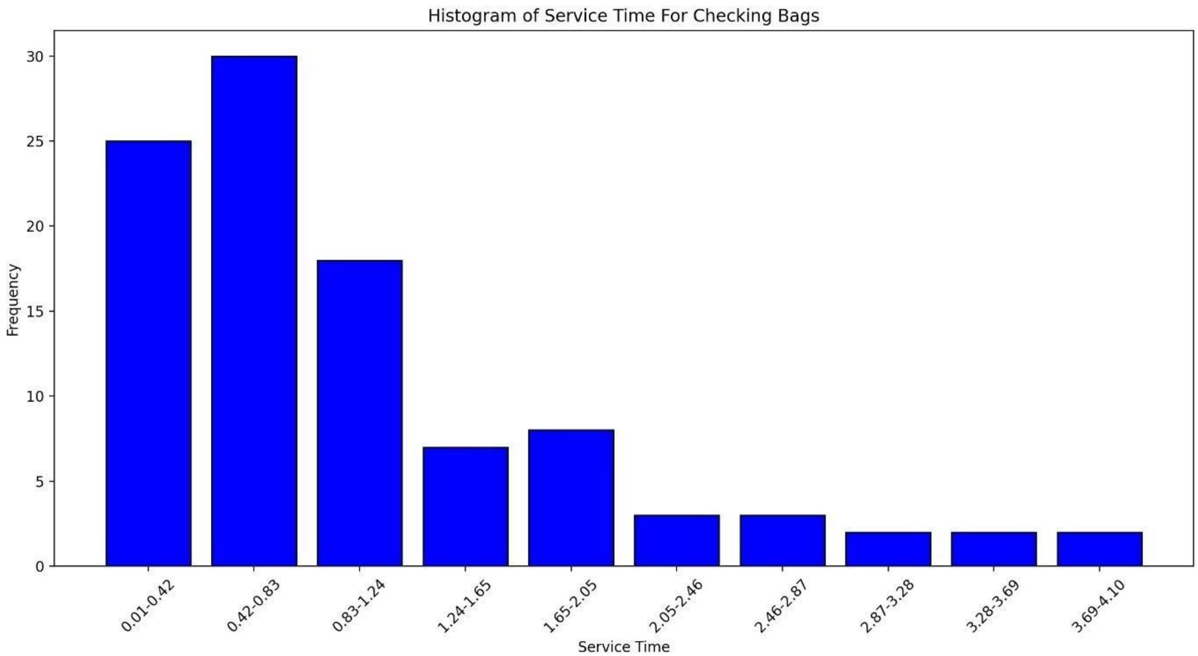
4.6 Service Time for Checking Bags

Inverse-Transform Technique:

The inverse-transform technique requires an inversible cumulative distribution function for the distribution to generate from. Once the inverse of a distribution's cumulative distribution function is determined, then a randomly selected number from a uniform distribution will become the input parameter, and the output of the calculation will be a random variate. This technique will be used for exponential distributions.

Service Time Interval	Frequency
0.01-0.42	25
0.42-0.83	30
0.83-1.24	18
1.24-1.65	7
1.65-2.05	8
2.05-2.46	3
2.46-2.87	3
2.87-3.28	2
3.28-3.69	2
3.69-4.10	2

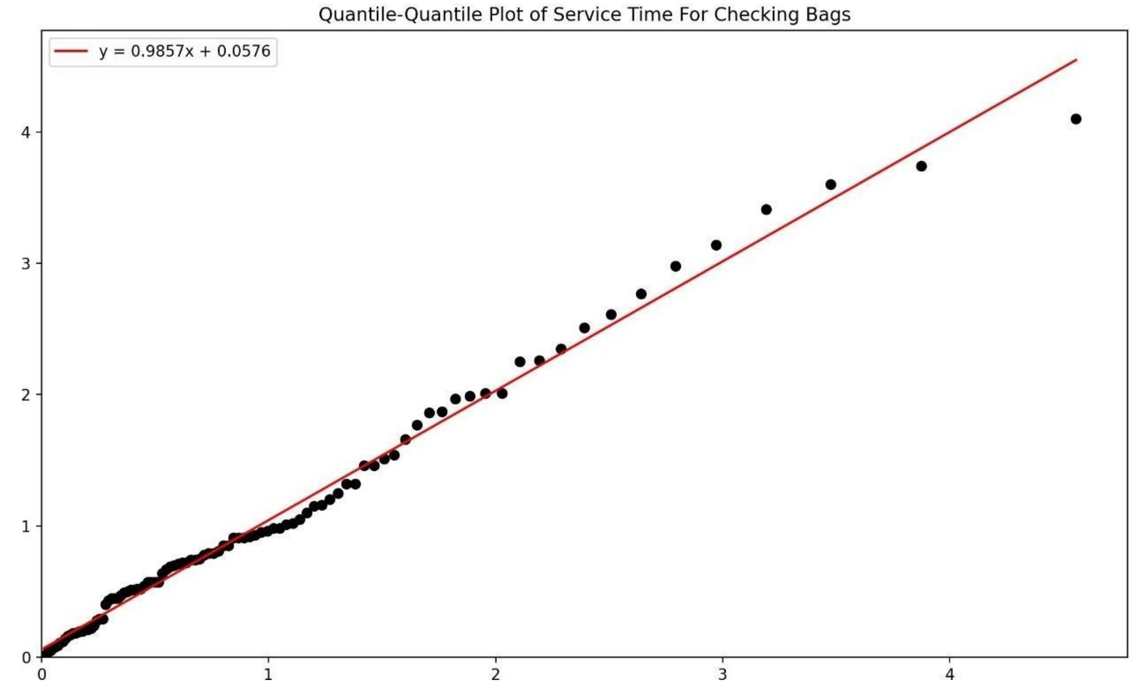
Given that the data represents service times and is a continuous variable and it follows an exponential distribution. As there are 100 data points, $\lceil\sqrt{100}\,\rceil = 10$ bins will be used to produce the histogram below:



Based on the shape of this plot, the sample data does seem to fit an exponential distribution, but quantile-quantile plot and chi-squared test must be used before we can say with certainty that this is the distribution that fits.

Using $\lambda = \frac{1}{\bar{X}}$ the parameter estimation and the quantile function

$F^{-1}(x) = \frac{-\ln(1-x)}{\lambda} = -\bar{X}\ ln(1-x)$ yields the following quantile-quantile plot:



To finalize this choice of distribution, a chi-squared test must be performed. This is an appropriate test to use in these circumstances since there are many data points and there are estimated parameters. The service time for printing a boarding pass follows an exponential distribution:$\lambda = \frac{1}{\bar{X}} = 0.97$

With 18 bins and one variable estimated, the assumed chi-square distribution has **10 − 1 − 1 = 8 degrees of freedom**. Using a significance level of 0.05, the threshold value obtained from tables is $\mathbf{Zo^2_{0.05,\,8} = 15.50}$ By calculating expected frequencies from the hypothesized exponential distribution (see Appendix 1.1), Zo^2 = **8.79**. Since this is below the threshold , the distribution is accepted, and we can say with certainty that the service time for checking bags follows an exponential distribution with $\lambda = 0.97$.

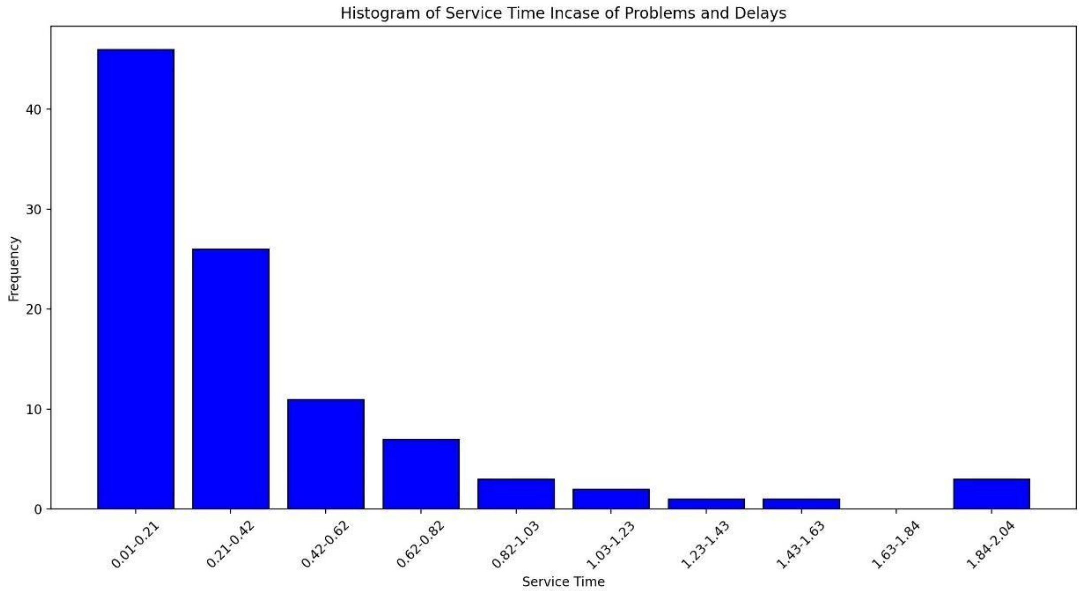
4.7 Service Time In case of Problems and Delays

Inverse-Transform Technique:

The inverse-transform technique requires an inversible cumulative distribution function for the distribution to generate from. Once the inverse of a distribution's cumulative distribution function is determined, then a randomly selected number from a uniform distribution will become the input parameter, and the output of the calculation will be a random variate. This technique will be used for exponential distributions.

Service Time Interval	Frequency
0.01-0.21	46
0.21-0.42	26
0.42-0.62	11
0.62-0.82	7
0.82-1.03	3
1.03-1.23	2
1.23-1.43	1
1.43-1.63	1
1.63-1.84	0
1.84-2.04	3

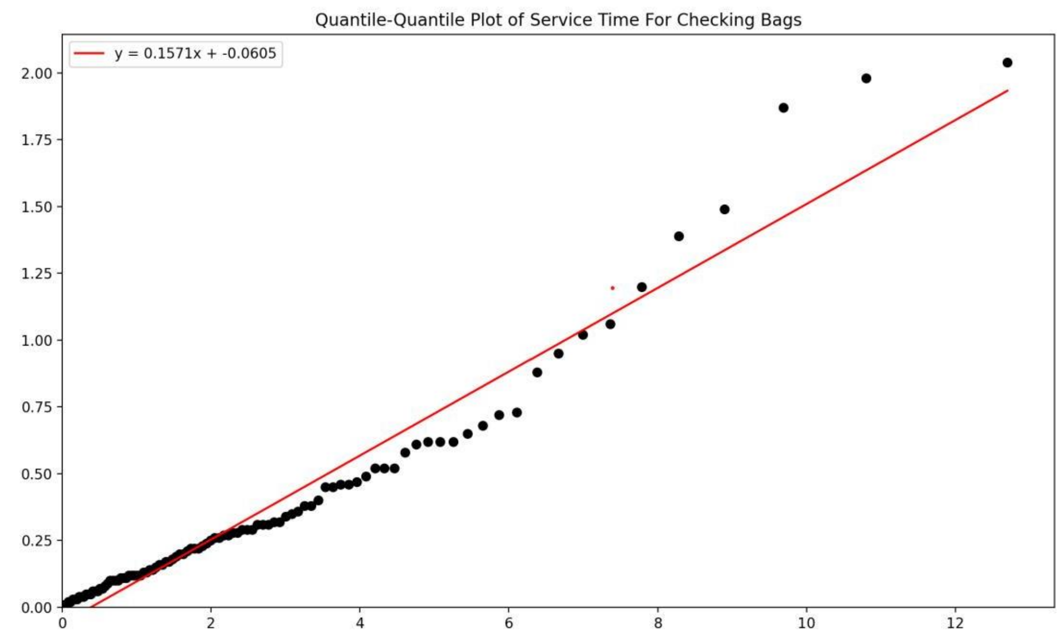
Given that the data represents service times and is a continuous variable and it follows an exponential distribution. As there are 100 data points, $\lceil\sqrt{100}\,\rceil = 10$ bins will be used to produce the histogram below:



Based on the shape of this plot, the sample data does seem to fit an exponential distribution, but quantile-quantile plot and chi-squared test must be used before we can say with certainty that this is the distribution that fits.

Using $\lambda = \frac{1}{\bar{X}}$ the parameter estimation and the quantile function

$F^{-1}(x) = \frac{-\ln(1-x)}{\lambda} = -\bar{X}\ ln(1-x)$ yields the following quantile-quantile plot:



To finalize this choice of distribution, a chi-squared test must be performed. This is an appropriate test to use in these circumstances since there are many data points and there are estimated parameters. The service time for printing a boarding pass follows an exponential distribution: $\lambda = \frac{1}{\bar{X}} = 2.63$

With 18 bins and one variable estimated, the assumed chi-square distribution has **10 − 1 − 1 = 8 degrees of freedom**. Using a significance level of 0.05, the threshold value obtained from tables is $\mathbf{Zo^2_{0.05,8} = 15.50}$ By calculating expected frequencies from the hypothesized exponential distribution (see Appendix 1.7), $Zo^2 = 13.54$. Since this is below the threshold , the distribution is accepted, and we can say with certainty that the service time for checking bags follows an exponential distribution with $\lambda = 2.63$

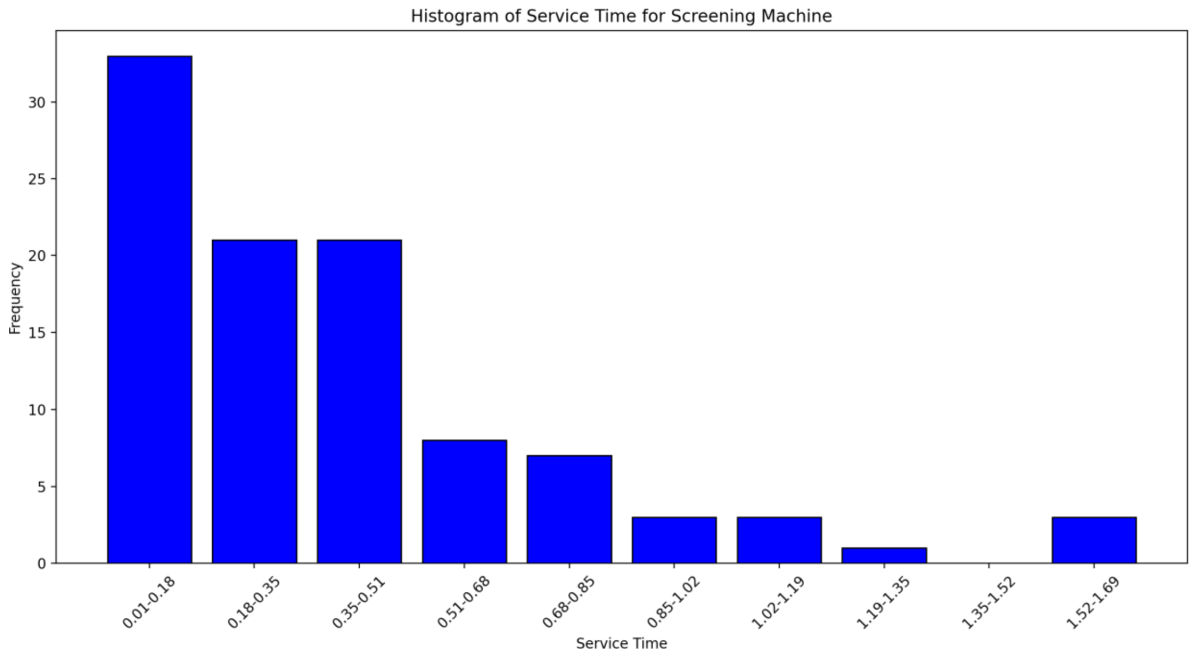
4.8 Service Time for Screening Machine

Inverse-Transform Technique:

For generating random variates, the preferred method is the inverse-transform technique. The inverse-transform technique requires an inversible cumulative distribution function for the distribution to generate from. Once the inverse of a distribution's cumulative distribution function is determined, then a randomly selected number from a uniform distribution will become the input parameter, and the output of the calculation will be a random variate. This technique will be used for exponential distributions.

Service Time Interval	Frequency
0.01-0.18	33
0.18-0.35	21
0.35-0.51	21
0.51-0.68	8
0.68-0.85	7
0.85-1.02	3
1.02-1.19	3
1.19-1.35	1
1.35-1.52	0
1.52-1.69	3

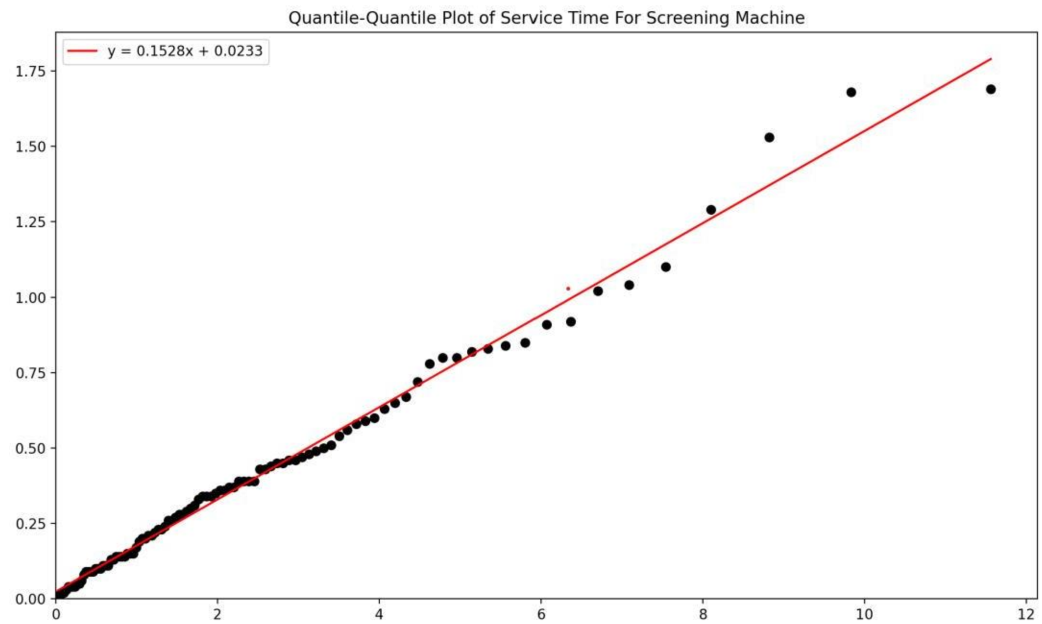
Given that the data represents service times and is a continuous variable and it follows an exponential distribution. As there are 100 data points, $\lceil\sqrt{100}\,\rceil = 10$ bins will be used to produce the histogram below:



Based on the shape of this plot, the sample data does seem to fit an exponential distribution, but quantile-quantile plot and chi-squared test must be used before we can say with certainty that this is the distribution that fits.

Using $\lambda = \frac{1}{\bar{X}}$ the parameter estimation and the quantile function

$F^{-1}(x) = \frac{-\ln(1-x)}{\lambda} = -\bar{X}\ \ln(1-x)$ yields the following quantile-quantile plot:



To finalize this choice of distribution, a chi-squared test must be performed. This is an appropriate test to use in these circumstances since there are many data points and there are estimated parameters. The service time for printing a boarding pass follows an exponential distribution: $\lambda = \frac{1}{\bar{X}} = 2.50$

With 18 bins and one variable estimated, the assumed chi-square distribution has **10 − 1 − 1 = 8 degrees of freedom**. Using a significance level of 0.05, the threshold value obtained from tables is $\mathbf{Zo^2_{0.05,\,8} = 15.50}$ By calculating expected frequencies from the hypothesized exponential distribution (see Appendix 1.8), Zo^2 = 1**4.12**. Since this is below the threshold , the distribution can be accepted, and we can say with certainty that the service time for checking bags follows an exponential distribution with λ = 2.5

5.0 MODEL TRANSLATION

I will explain how the airport simulation runs at a high level, then describe how each activity is carried out and how my design and implementation were carried out.

5.1 WHY MATLAB?

The simulation software I selected was MATLAB because of its numerous advantages over alternative choices. Since MATLAB is easily accessible on university computers and can be downloaded for free using the university license, no specialized software tools will need to be purchased for the simulation. I have used MATLAB before, so much of the time can be dedicated to putting the model into practice rather than picking up the language. Most significantly, MATLAB includes built-in functionality for plotting charts , generating random numbers, building distributions, and sampling from distributions. These are all useful features for the simulation that we would otherwise have to create ourselves.

5.2 HIGH LEVEL DESCRIPTION OF SIMULATION

The results obtained from my input modelling will be used to initialize my model. The first step that was carried out was the development of the Future Event List. This FEL helps us know the order of each event that is carried out in the simulation project. An Event and Event Type was also created to describe the nature of the event. After the simulation has been completed, the FEL is expected to be empty. I will now output the results obtained from the airport simulation. If we are not finished the FEL will keep processing events until all events have been completed. The simulation was carried out to model the airport simulation for two types of flights. Commuter Flights and Provincial Flights. Since the flights have different ways of handling passengers , I decided to carry out two simulations . One for the Commuter Passengers(no business class). Then the provincial passengers (business and coach). In our simulations we initialized some important parameters that need to be defined: Server busy times, Queue Lengths etc. We want to assign the passenger to the server that will be available the soonest. Various events were modelled, and we had to use logic based on our project requirements to properly simulate how each event will be processed. The various events are the Service time to Check Bags, Print Boarding Pass, Screening Machine etc.

After our simulation various performance metrics were printed to see how well our model performed and determine whether I was able to fulfill the project’s objectives. The simulation can be run as a single replication by running the main.simulation file or can be executed several times using the replications.m file. I decided to use the same seed for reproducibility .

5.3 DESIGN CHOICES

5.3.1 FUTURE EVENT LIST IMPLEMENTATION

Although most of the simulation is created in a procedural manner, we alsomade the decision to add custom objects to the events and future event list.

Creating an object for the future event list helped with the program's design because it enables us to encapsulate all the functionalities related to the future event list in one location and create a customized list with capabilities beyond what a standard MATLAB vector could do. Since we made this custom list object, we also had to make an event object so that we could compile and arrange all of the data related to a particular event.

5.3.2 INPUT MODELLING DISTRIBUTIONS

This MATLAB script builds a simulation environment to model the operations of an airport with a commuter and provincial flight focus. The framework of the simulation is established, together with many characteristics like the number of servers, ticket prices, operating expenses, agent reimbursement, and more. For both commuter and provincial arrivals, key variables are initialized to track revenue, processed passengers, and overall wait durations, including arrival and service times. Additionally, a Future Event List (FEL) is initialized to control the events of the simulation. Accurately replicating airport operations depends on this configuration, which enables analysis and optimization of procedures including baggage handling, security screening, and passenger check-in.

5.3.3 QUEUING SYSTEM

For every server, passengers are put into queues. The duration of each line and the amount of time each passenger spends waiting are tracked by the system. The customer at the front of the line receives assistance when a server becomes available, and their wait time is computed and contributed to the overall wait time. With the help of this simulation, which offers a thorough representation of an airport's queuing system, passenger handling-related airport operations can be examined and optimized. It simulates real-world variability in passenger arrivals and service times using stochastic modeling, offering insightful advice on how to effectively manage lines and raise customer satisfaction.

6.0 VERIFICATION

Verification involves ensuring our output results are what is expected in our project requirement and implementation. It basically involves testing whether our system is right.

6.1 CODE ANALYSIS

This verification process involves analyzing the code step by step to ensure that there are no inaccuracies, and everything is done in order. It follows a logical process from start to finish to ensure we are meeting the projects desired requirements.

6.2 INITIALIZATION OF OUR MODEL

When carrying out our simulation initialization.m folder was created where we defined our simulation parameters. Future Event List(FEL) was then created to help keep track of each event and then I used a random number generator with a fixed seed to ensure my simulation starts with a defined state.

6.3 VERIFICATION WITH SIMULATION STATISTICS

This verification process involves take note of key simulation statistics which includes agents idle time, utilization of each server , revenue, cost etc. We can then verify that our simulation model and calculations within the simulation are consistent with expected simulation requirements.

6.4 SIMULATION CLOCK PROGRESSES FORWARD IN TIME

My simulation model requires that we must only advance in clock time. This means we must not try to process an event prior to its scheduled start time.

To confirm this, we ensured, our clock was constantly updated that checks to see if the clock time hasn't passed the event start time. Once this is verified, we adjust the current clock time to match the event's timing to depict the passage of time.

6.5 FLOWCHARTS

The original flowcharts we used to construct our simulation system are included in appendices 2.1 through 2.5. These flow charts now have a second use: they allow us to confirm that our system is correctly running our simulation, even if their original goal was to aid in understanding how our simulation worked. To make sure that every possibility is considered, we can navigate through the flow charts and identify the lines of code that link to each event.

7.0 VALIDATION

Validation basically involves whether we are using the right system. We have to ensure that our project makes sense in the eyes of experts.

7.1 FACE VALIDITY

This can be described as the level in which our simulation appears to calculate the variable that is meant to be calculated. Sensitivity analysis will be used to check the model’s face validity.

7.2 SENSITIVITY ANALYSIS

Sensitivity analysis is not essential for our simulation, nor is it useful for us to test this extensively. In our simulation, only two values—seed and simulation time—are important for sensitivity analysis.

It is completely futile to analyze the seed since, while different seeds produced different random values, all seeds produced random values that were unpredictable.

Depending on the figure we choose for the simulation time, our results can vary somewhat. It is absolutely the case that longer simulation times result in more passengers being processed. This is what we would expect to see. Also, we can therefore see variance in output results if we decide to make changes to input parameters to see how the output parameter will be modified.

7.3 REAL WORLD INPUT DATA

The system output was compared from known input to the system output from random input. Input data was generated using various techniques including Inverse Transform technique, Congruential Methods etc. After analyzing the data we got our estimated service time for various events and we had to access to see if the results made sense .

7.4 REAL WORLD OUTPUT DATA

To ensure our model is accurate, It is best to compare the simulation results with historical data from the real-world systems. Historical data helps us have an idea on how our simulation results should be like regardless of what we get when we carry out our own simulation.

We must explain whether the results make sense as we examine them right now. This approach isn't too bad, but it depends on our ability to predict the final outputs with enough accuracy. We cannot be positive that our system produces the intended or accurate outcomes without access to any real-world output data.

8.0 PRODUCTION RUNS AND ANALYSIS

For our simulation we used a random seed of rng(54321) to carry out an estimated number of 70 replications. The replications.m folder is where our simulation was carried out with a simulation time set as 3000 minutes.

8.1 CONFIDENCE INTERVAL AND NUMBER OF REPLICATIONS

In my simulation model as stated earlier I set a number of 70 replications to get a range of sample marks because the number of replications for the experiment is defines as 70
mean and var functions were used in MATLAB to calculate the mean and variance for each of these measures after I've finished all the replications. The data arrays that contain each parameter's values across all 70 replications are used to build these statistical measures.
The confidence intervals for each statistic are then produced after the mean and variance have been determined.
The most well-defined range of confidence interval is 95%. 95% confidence intervals give a range that is likely to contain the population parameter. The t-distribution serves as the basis for the calculation that determines the half-width of the confidence interval for each statistic.

$$\text{CI Half-Width} = t_{\frac{\alpha}{2},\text{df}} \times \sqrt{\frac{\text{variance}}{\text{numReplications}}}$$

8.2 SIMULATION RESULTS

REPLICATIONS.M SNIPPET

```
% Include your classes and scripts
addpath("C:\Users\hh\Desktop\MODEL TRANSLATION MODULES\");
numReplications = 70;
 initializeSimulation;
rng(54321);
```

The initialize Simulation file contains information simulation time set to 3000 minutes. Output results were collected for the wait time, utilization, service time for various events , profit, revenue and cost for the simulation.

The simulation was carried out for the two types of flights:

Commuter Flights and Provincial Flights .

COMMUTER FLIGHTS RESULTS			
PARAMETER	ESTIMATED MEAN	VARIANCE	95% CONFIDENCE INTERVAL
WAIT TIME	8.6637	2.6708	[8.2740,9.0533]
UTILIZATION	0.946	0.0033	[0.9323,0.9597]
IDLE TIME	2.1783	0.029	[2.1377,2.2188]
REVENUE	38500	0	[38500,38500]
PROFITS	34903.7031	180243.515	[3495.0663,3697.5275]
BOARDING SERVICE TIME	2.142	0.0233	[2.1056,2.1784]
SERVICE TIME TO CHECK BAGS	0.845	0.0037	[0.8306,0.8595]
SERVICE TIME IN CASE OF PROBLEMS	2.0246	0.0297	[1.9835,2.0657]
SCREENING SERVICE TIME	1.705	0.0192	[1.6719,1.7380]

Analysis of Wait Time: From our simulation there is a fairly stable average wait time for commuter flights, which suggests that there may be pressure on the check-in and screening procedures during busy periods. Although the system is generally stable, there are certain times of little deviation which occurs due to high throughput of passengers according to the variance and confidence interval.

Analysis of Utilization and Idle Time: High utilization ratio (95% estimate)indicates efficient use of screening stations and check-in counters. Also, the agent idle time is minimal which can be deduced that the service center is very busy.

Analysis of Income and Profits: While the variance in profits tells us that our costs may be significantly fluctuating, the zero variance in revenue tells us our commuter flight ticket sales are steady in relation to number of passengers and flight types.

PROVINCIAL FLIGHTS RESULTS			
PARAMETER	ESTIMATED MEAN	VARIANCE	95% CONFIDENCE INTERVAL
WAIT TIME	2.6747	0.0002	[2.6713,2.6782]
UTILIZATION	0.6328	0	[0.62,0.64]
IDLE TIME	0.9433	0	[0.9419,0.9447]
COSTS	18911.8496	2582.5133	[18899.7324,18923.9668]
REVENUE	288000	0	[288000,288000]
PROFITS	18911.8496	2582.5133	[269076.0332,269100.2676]
BOARDING SERVICE TIME	269088.1504	25	[2.3035,2.3035]
SERVICE TIME TO CHECK BAGS	0.844	0	[0.8440,0.8840]
SERVICE TIME IN CASE OF PROBLEMS	2.1533	0	[2.1533,2.1533]
SCREENING SERVICE TIME	1.7402	0	[1.7024,1.7024]

Analysis of Provincial Wait Time and Utilization: The Wait times and Utilization are considerably stable in terms of our project requirements, and we can deduce that the passenger boarding process is efficient

Analysis of Provincial Idle Time: While minimal idle time suggests effective agent process , it may also point to the possibility that our agents are working at the peak.

Analysis of Provincial Passengers Revenue and Costs: The statistic in revenue indicates steady earnings from these flights, but the high compensation for missing flights and the stochastic nature of operating costs may affect the variance in costs and profits.

9.0 COMPARING ALTERNATIVE DESIGN TO ORIGINAL DESIGN

To ensure passengers with upcoming departure flights are serviced as soon as possible, this strategy includes protocols that prioritize passengers based on flight scheduling. This technique dynamically adapts to the urgency of passenger needs, as opposed to the main simulation, which handles every passenger event in the same way. The number of replications was then increased to 3 * 70 = 210 replications.

Finally, by including more dynamic, flexible, and passenger-centered operational change, the alternate methodology enhances the foundational simulation. With these changes, we intend to reduce specific errors, better adapt to varying conditions in real time, and eventually deliver a more fluid and effective passenger processing service.

9.1 SIMULATION RESULTS

COMMUTER FLIGHTS RESULTS			
PARAMETER	ESTIMATED MEAN	VARIANCE	95% CONFIDENCE INTERVAL
WAIT TIME	8.8572	3.3736	[8.6073,9.1070]
UTILIZATION	0.938	0.0037	[0.9297,0.9463]
IDLE TIME	2.2035	0.0338	[2.1785,2.2286]
COSTS	3669.8043	267142.8509	3599.4878,3740.1207]
REVENUE	38500	0	[38500,38500]
PROFITS	34830.1957	267172.8509	[34759.4874,3740.1207]
BOARDING SERVICE TIME	2.1372	0.0233	[2.1174,2.1570]
SERVICE TIME TO CHECK BAGS	0.8406	0.8406	[0.8325,0.8488]
SERVICE TIME IN CASE OF PROBLEMS	2.0618	0.0311	[2.0378,2.0857]
SCREENING SERVICE TIME	1.7189	0.0178	[1.7008,1.7370]

PROVINCIAL FLIGHTS RESULTS			
PARAMETER	ESTIMATED MEAN	VARIANCE	95% CONFIDENCE INTERVAL
WAIT TIME	2.662	0.0002	[2.6708,2.6746]
UTILIZATION	0.6393	0	[0.63,0.65]
IDLE TIME	0.9426	0	[0.9417,0.9435]
COSTS	18915.8295	3312.5284	[18899.7324,18923.9668]
REVENUE	288000	0	[288000,288000]
PROFITS	269084.1705	269084.1705	[269076.0332,269092.0001]
BOARDING SERVICE TIME	1.894	0	[1.8940,1.8940]
SERVICE TIME TO CHECK BAGS	0.968	0	[0.9680,0.9680]
SERVICE TIME IN CASE OF PROBLEMS	2.2628	0	[2.2628,2.2628]
SCREENING SERVICE TIME	1.7974	0	[1.7974,1.7974]

9.2 COMPARING ORIGINAL DESIGN TO ALTERNATIVE DESIGN

The alternate plan introduces an elaborate method of controlling airport check-in procedures by prioritizing travelers with earlier departure schedules. The increase in variance for some statistical parameters such as costs suggests that there is a need for a balance between efficiency and the quality of passenger service may be difficult. If implemented properly to reduce effects on wait times and operating costs, this method can improve passenger service and server efficiency. In summary, the alternate strategy proves to provide a reasonable approach for improving airport service delivery by focusing on passenger immediate needs without compromising the performance of our simulation model.

10. CONCLUSION

The simulation model gives details about the operational foundation of commuter and provincial flights. The examination and embrace of an alternative design strategy enabled positive results and viable solutions that can improve the efficiency and financial sustainability of airport operations.

In addition to steady profits from both types of flights, commuter flights have high utilization rates, suggesting substantial demand and a solid basis for growth. One distinctive technique to alleviate bottlenecks and improve passenger service is to use an alternate design strategy that prioritizes people based on their flight trips. Additionally, the difference in revenues and costs, especially with commuter flights, highlights the need for flexible operating scheduling. By changing the amount of check-in agents and expanding the check-in counters, the airline may achieve a balance between maximizing throughput and ensuring customer satisfaction.

There are several benefits to this simulation study:

Enhanced business perspectives: The extensive study supports targeted improvements by providing a deeper awareness of the factors that influence delays, agent idleness periods, and service times.

Economic Efficiency: The revenue consistency in the face of operational adjustments demonstrates that better passenger processing is possible without losing cash flow.

To summarize, our simulation study not only reveals the areas where SFMA's processes now stand out and those that may be improved, but also paves a way for greater modifications and improvements.

APPENDIX 1:1

number of points	100
number of bins	10
max value	102.99
min value	66.46
data range	102.99
bin width	3.65
sample mean	75.19
sample variance	46.95
Standard deviation	6.852007005

	chi square degree of freedom	7
	significance level	0.05
	chi square threshold	14.1
E1<10 Combine values	Yellow means distribution passes	

bin	bin lower range	bin upper range	range	observed frequency(Oi)	MERGED CELLS	expected frequency(Ei)	MERGED CELLS	(Oi-Ei)^2/Ei
1	66.46	70.11	66.46-70.11	25		22.9228922		0.18821259
2	70.11	73.77	70.11-73.77	21		18.8682859		0.24083825
3	73.77	77.42	73.77-77.42	31		20.96687501		4.80107775
4	77.42	81.07	77.42-81.07	10		17.70126416		1.35057582
5	81.07	84.72	81.07-84.72	3		11.32688464		6.1214544
6	84.72	88.38	84.72-88.38	3		5.502226559		
7	88.38	92.03	88.38-92.03	3	10	2.012371415	8.192585035	0.4

8	92.03	95.68	92.03-95.68	2		0.559877798		
9	95.68	99.34	95.68-99.34	1		0.118109262		
10	99.34	102.99	99.34-102.99	1		0		
				100		99.97878694		**13.1021588**

APPENDIX 1:2

number of points	100
number of bins	10
max value	102.99
min value	66.46
data range	102.99
bin width	3.65
sample mean	75.19
sample variance	46.95
Standard deviation	6.852007005

	chi square degree of freedom	7
	significance level	0.05
	chi square threshold	14.1
E1<10 Combine values	Yellow means distribution passes	

bin	bin lower range	bin upper range	range	observed frequency(Oi)	MERGED CELLS	expected frequency(Ei)	MERGED CELLS	(Oi-Ei)^2/Ei
1	66.46	70.11	66.46-70.11	25		22.9228922		0.18821259
2	70.11	73.77	70.11-73.77	21		18.8682859		0.24083825
3	73.77	77.42	73.77-77.42	31		20.96687501		4.80107775
4	77.42	81.07	77.42-81.07	10		17.70126416		1.35057582
5	81.07	84.72	81.07-84.72	3		11.32688464		6.1214544
6	84.72	88.38	84.72-88.38	3		5.502226559		
7	88.38	92.03	88.38-92.03	3	10	2.012371415	8.192585035	0.4

8	92.03	95.68	92.03-95.68	2		0.559877798		
9	95.68	99.34	95.68-99.34	1		0.118109262		
10	99.34	102.99	99.34-102.99	1		0		
				100		99.97878694		**13.1021588**

APPENDIX 1.3

N	100
Mean	1.5
1/X	0.666667
P(1)	0.666667
P(2)	0.222222
P(3)	0.074074
E=N(Pi)	
Variance	0.75

Number of Bags	1	2	3
Frequency	62	26	12

X	Observed(Oi)	Expected(Ei)	(Oi-Ei)^2/Ei
1	62	66.66667	0.326667
2	26	22.22222	0.642222
3	12	7.407407	2.847407

			100		**3.816296**

chi square degree of freedom	1
significance level	0.05
chi square threshold	3.84

APPENDIX 1:4

N	100
Mean	1.2
1/X	0.83
P(1)	0.83
P(2)	0.1411
P(3)	0.023987
E=N(Pi)	
Variance	0.24677

Number of Bags	1	2	3
Frequency	83	14	3

X	Observed(Oi)	Expected(Ei)	(Oi-Ei)^2/Ei
1	83	83	0
2	14	14.11	0.0008575
3	3	2.3987	0.1507324
	100		**0.1515899**

chi square degree of freedom	1
significance level	0.05
chi square threshold	3.84

APPENDIX 1:5

number of points	100
number of bins	10
max value	1.5
min value	0.02
data range	1.52
bin width	0.15
sample mean	0.47
sample variance	0.12

chi square degree of freedom	8
significance level	0.05
chi square threshold	15.5

bin	bin lower range	bin upper range	range	observed frequency(Oi)	expected frequency(Ei)	(Oi-Ei)^2/Ei
1	0.02	0.17	0.02-0.17	24	26.20818882	0.1860525
2	0.17	0.32	0.17-0.32	16	19.04056898	0.4855453
3	0.32	0.47	0.32-0.47	17	13.8332057	0.7249647
4	0.47	0.62	0.47-0.62	14	10.04999274	1.5524944
5	0.62	0.77	0.62-0.77	12	7.30144236	3.023573
6	0.77	0.92	0.77-0.92	6	5.30458697	0.0911662
7	0.92	1.07	0.92-1.07	3	3.853847162	0.1891759
8	1.07	1.22	1.07-1.22	4	2.799866989	0.5144242
9	1.22	1.37	1.22-1.37	2	2.034137533	0.0005729
10	1.37	1.52	1.37-1.52	2	1.477825739	0.1845048
				100		**6.9524739**

APPENDIX 1:6

number of points	100
number of bins	10
max value	4.1
min value	0.01
data range	4.1
bin width	0.41
sample mean	1.03
sample variance	0.77

chi square degree of freedom	8
significance level	0.05
chi square threshold	15.5

bin	bin lower range	bin upper range	range	observed frequency(Oi)	expected frequency(Ei)	(Oi-Ei)^2/Ei
1	0.01	0.42	0.01-0.42	25	32.49689074	1.7294999
2	0.42	0.83	0.42-0.83	30	21.83347659	3.0545802
3	0.83	1.24	0.83-1.24	18	14.66911723	0.7563359
4	1.24	1.65	1.24-1.65	7	9.855645273	0.8274151
5	1.65	2.05	1.65-2.05	8	6.489497253	0.3515863
6	2.05	2.46	2.05-2.46	3	4.492208336	0.4956773
7	2.46	2.87	2.46-2.87	3	3.018151069	0.0001092
8	2.87	3.28	2.87-3.28	2	2.027785711	0.0003807
9	3.28	3.69	3.28-3.69	2	1.36239532	0.2984007
10	3.69	4.1	3.69-4.1	2	0.915343765	1.2852867
				100		**8.7992721**

APPENDIX 1:7

number of points	100
number of bins	10
max value	2.04
min value	0.01
data range	2.04
bin width	0.2
sample mean	0.38
sample variance	0.16

chi square degree of freedom	8
significance level	0.05
chi square threshold	15.5

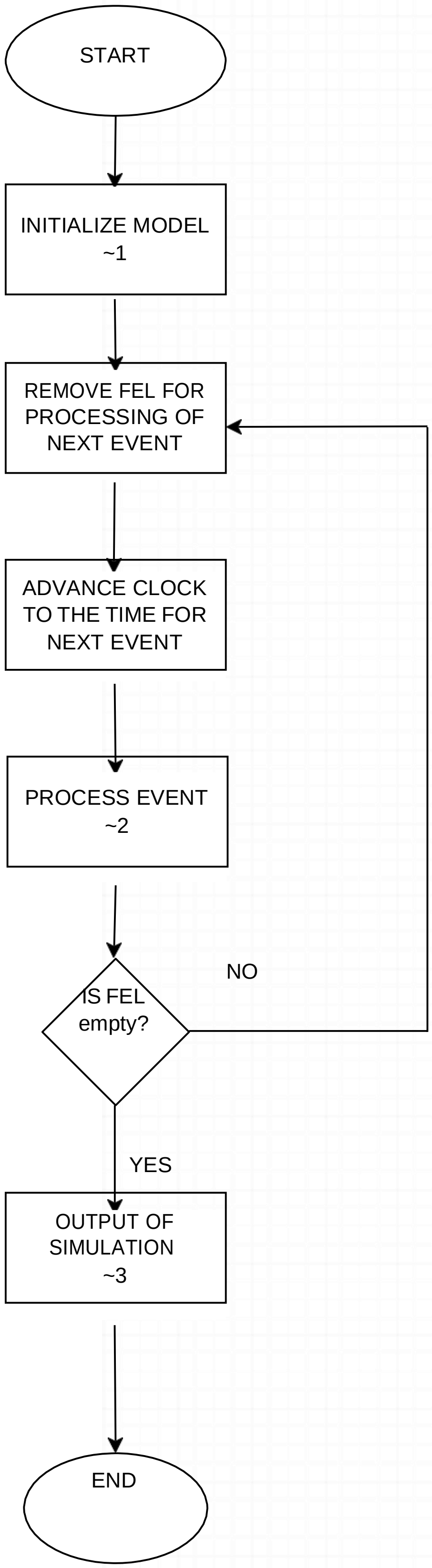
bin	bin lower range	bin upper range	range	observed frequency(Oi)	expected frequency(Ei)	(Oi-Ei)^2/Ei
1	0.01	0.21	0.01-0.21	46	39.84184822	0.9518342
2	0.21	0.42	0.21-0.42	26	24.42809576	0.1011492
3	0.42	0.62	0.42-0.62	11	13.55313415	0.4809584
4	0.62	0.82	0.62-0.82	7	8.009415786	0.1272153
5	0.82	1.03	0.82-1.03	3	4.910785631	0.7434863
6	1.03	1.23	1.03-1.23	2	2.724589631	0.1927006
7	1.23	1.43	1.23-1.43	1	1.610134672	0.2312007
8	1.43	1.63	1.43-1.63	1	0.951531795	0.0024688
9	1.63	1.84	1.63-1.84	0	0.583409426	0.5834094
10	1.84	2.04	1.84-2.04	3	0.323685738	10.12843
				100		**13.542853**

APPENDIX 1:8

number of points	100
number of bins	10
max value	1.69
min value	0.01
data range	1.69
bin width	0.17
sample mean	0.4
sample variance	0.12

chi square degree of freedom	8
significance level	0.05
chi square threshold	15.5

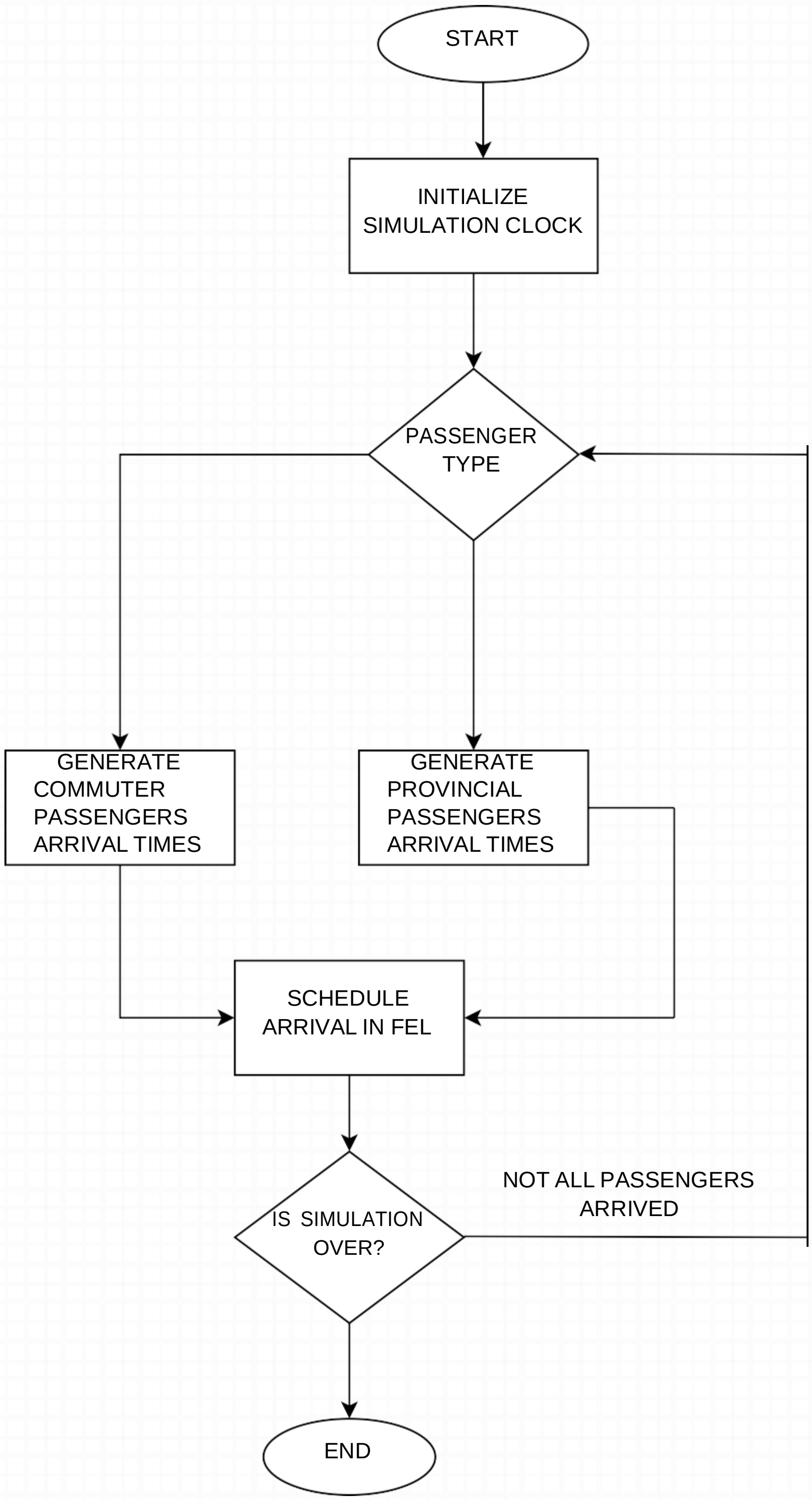
bin	bin lower range	bin upper range	range	observed frequency(Oi)	expected frequency(Ei)	(Oi-Ei)^2/Ei
1	0.01	0.18	0.01-0.18	33	33.76817604	0.01747487
2	0.18	0.35	0.18-0.35	21	22.07661319	0.05250334
3	0.35	0.51	0.35-0.51	21	13.74310515	1.83192316
4	0.51	0.68	0.51-0.68	8	9.674744417	0.28990625
5	0.68	0.85	0.68-0.85	7	6.325055579	0.07202308
6	0.85	1.02	0.85-1.02	3	4.135130227	0.3116034
7	1.02	1.19	1.02-1.19	3	2.7034232	0.03253571
8	1.19	1.35	1.19-1.35	1	1.682931569	0.27713279
9	1.35	1.52	1.35-1.52	0	1.184734646	1.18473465
10	1.52	1.69	1.52-1.69	3	0.774543715	10.12843
				100		**14.1982672**



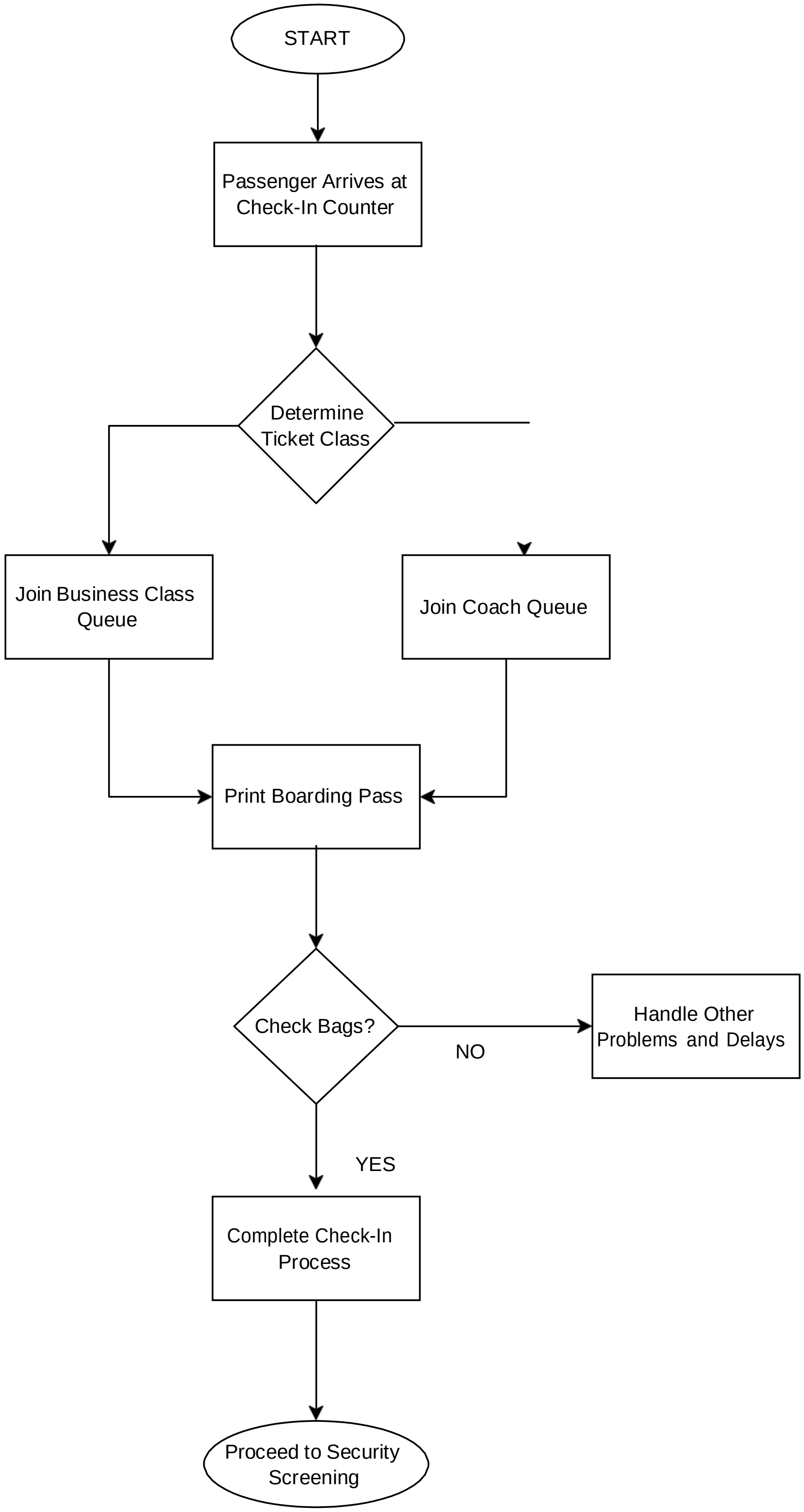
1. INITIALIZE MODEL: This step involves initialization of our simulation model. This involves generating statistical distributions, generating the future event list(FEL) with initial event parameters set.
2. PROCESSING EVENT: This will dive into how each event is handled in our simulation.
3. OUTPUT OF SIMULATION: This is the result we get after we carry out our simulation. It could customers average waiting time, agent idle time etc.

FLOWCHART FOR ONE REPLICATION

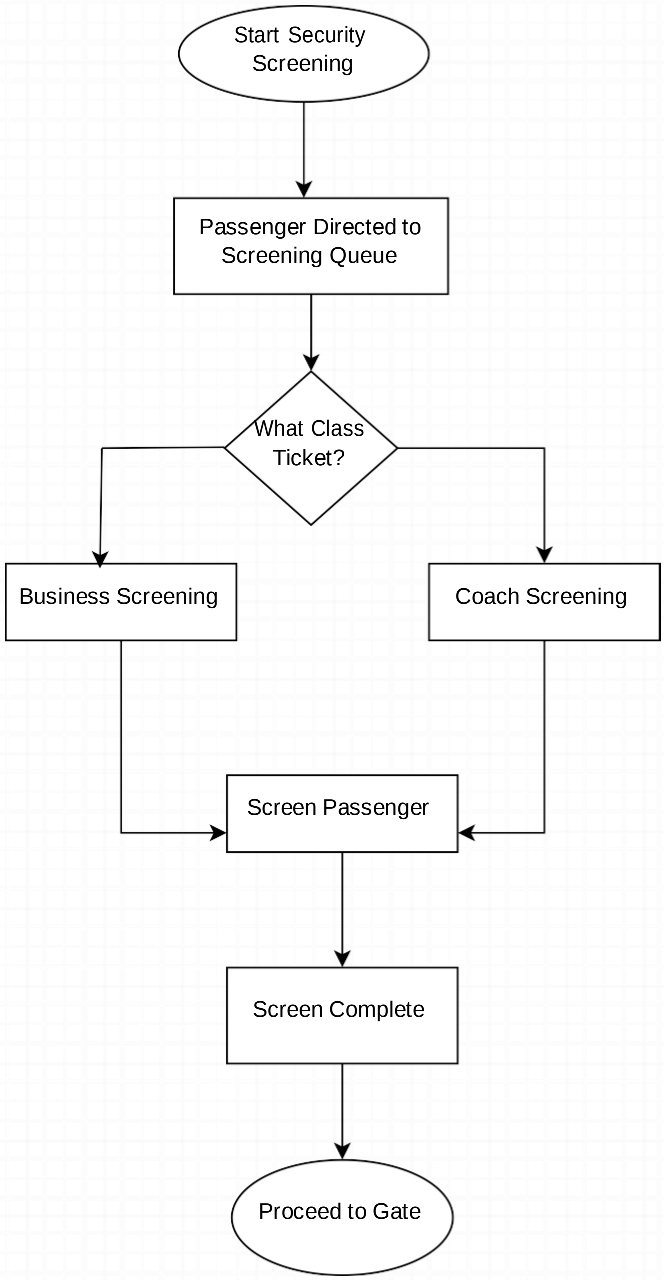
APPENDIX 2.1



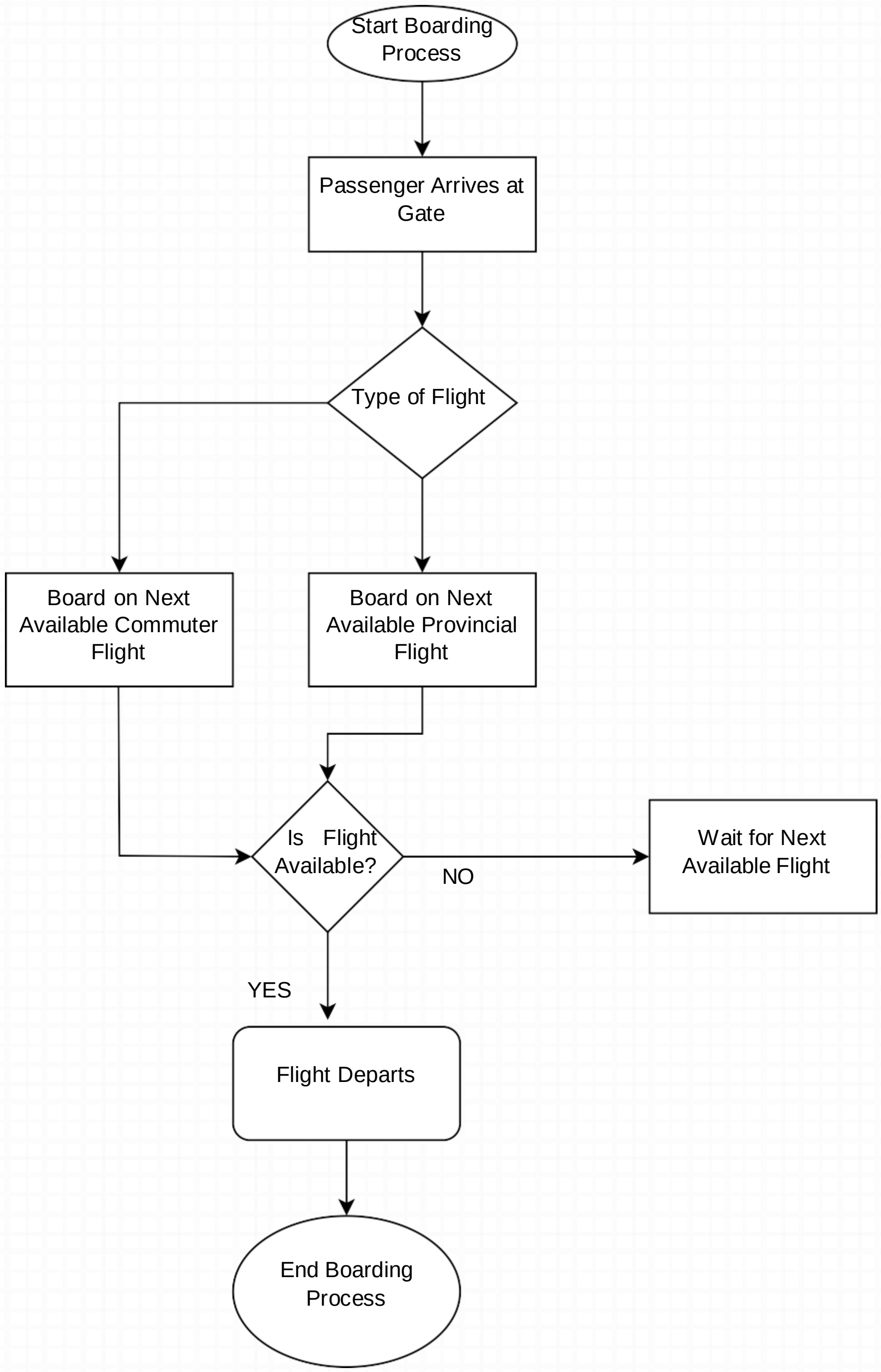
APPENDIX 2.2 : ARRIVAL TIME DIAGRAM



APPENDIX 2.3 CHECK IN PROCESS

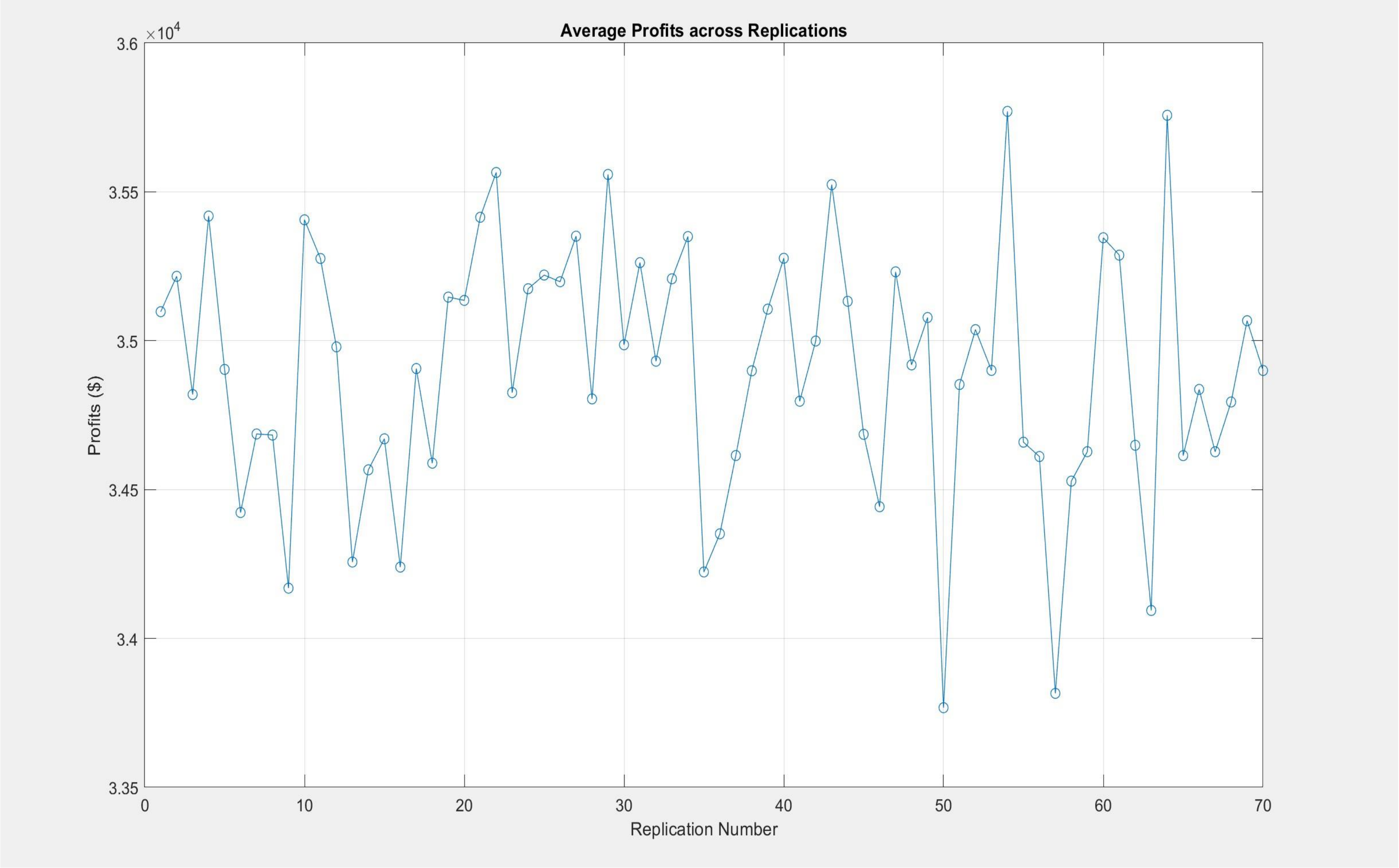


APPENDIX 2.4 : SECURITY

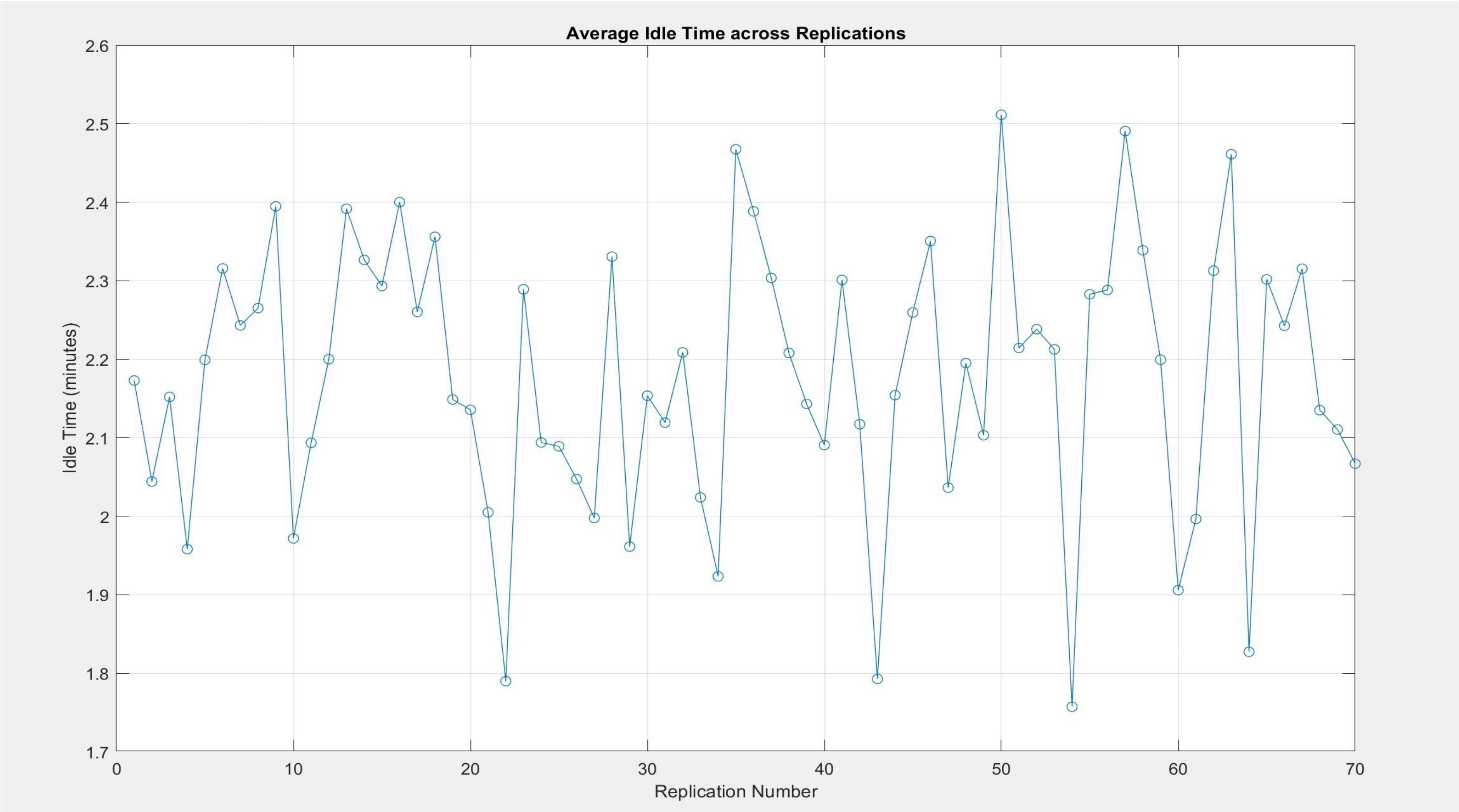


APPENDIX 2.5 : BOARDINGPROCESS

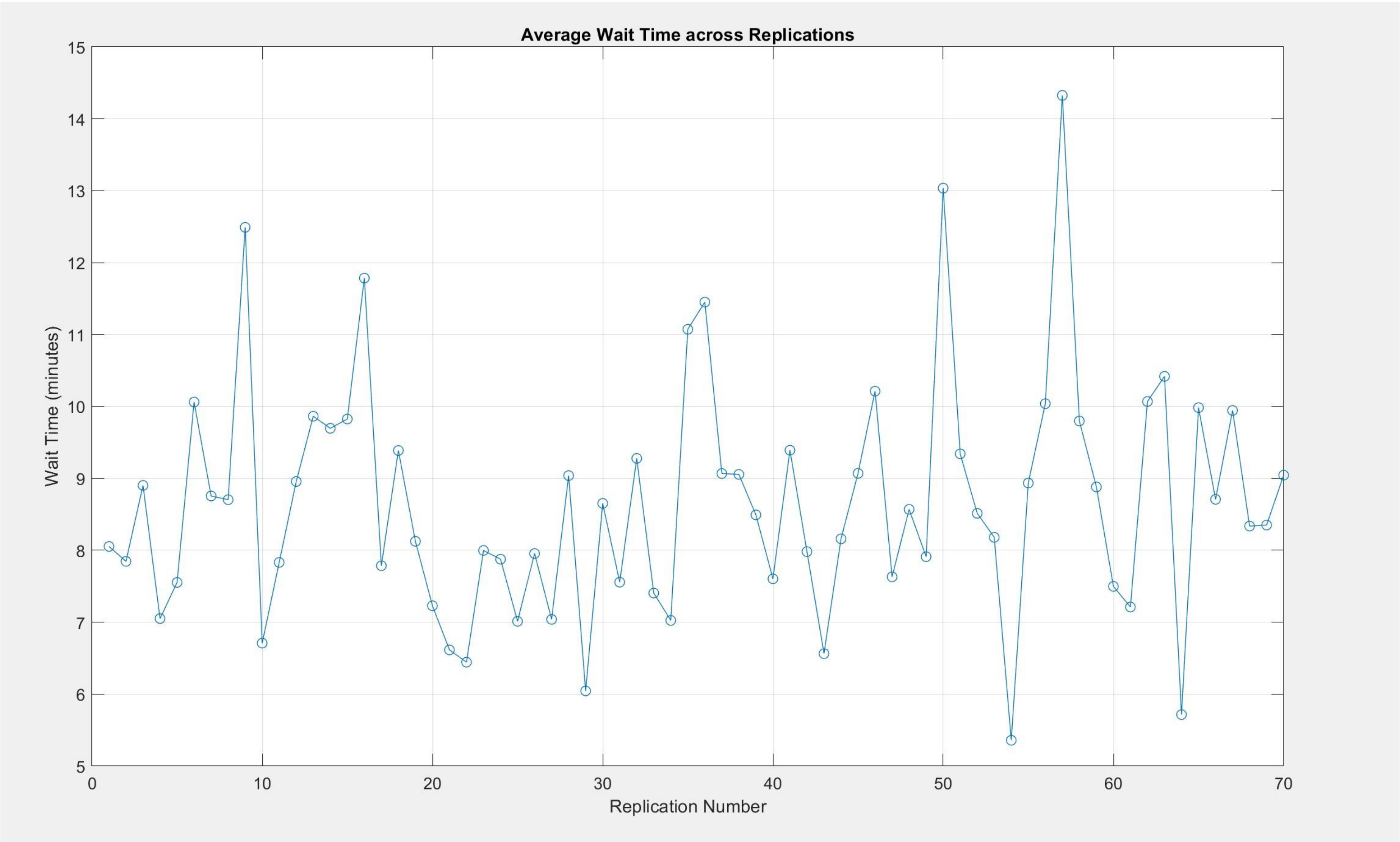
APPENDIX 3.1 AVERAGE PROFITS 70 REPLICATIONS



APPENDIX 3:2 AVERAGE IDLE TIME ACROSS 70 REPLICATIONS



APPENDIX 3:3 AVERAGE WAIT TIME ACROSS REPLICATIONS



APPENDIX 3:4 AVERAGE SERVICE TIME FOR EACH SERVICE ACROSS 70 REPLICATIONS