STRATEGIZING THE M-BUS BURSLEY-BAITS OPERATIONS TO MINIMIZE THE SPREAD OF COMMUNICABLE INFECTIONS AMONG COMMUTERS BASED ON SIMULATIONS PERFORMED IN PROMODEL

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1. ABSTRACT

This paper simulates the M-Bus route between the north and central campus (Looping NC 32 to CCTC - Bursley-Baits), the two main campuses of the University Michigan Ann Arbor. This paper aims to study the spread of contagious infections among commuters and how the spread changes during different scenarios. The simulation model is based on data including bus routes, passenger inter-arrival times, number of commuters etc., received from the Logistics, Transportation & Parking Department at the University of Michigan and in-person observations at various bus stops during peak hours the day. To maximize the output of the paper, the scope of commute is limited between the north and central campus of the University of Michigan.

2. INTRODUCTION

The University of Michigan, Ann Arbor Logistics, Transportation & Parking (LTP) provides free transit service for travel in and around the UofM campuses. U-M campus routes provide frequent service connecting classroom buildings, residence halls and commuter parking lots. The University of Michigan's Logistics, Transportation and Parking department employs more than 100 student and Union drivers who transport over 7 million passengers per year. The enrollment at the University of Michigan for Fall 2021 is ~50,000 students, and as per our calculations, 15000 students commute to and fro between north and central campus each day. With the onset of the pandemic, the bus routes have been modified to minimize the spread of Covid-19. Still, the current schedules aren't the most student-friendly as students have to walk significantly and have high queues at most of the major stations, effectively defeating the purpose of the schedule. Hence, this study was conducted to understand the spread of contagious infections in this setting and find a better way to schedule and operate the M-BUS operations; this simulation would also provide an optimal strategy to curb the spread of any future pandemics/ influenza outbreaks. Bursley-Baits route was studied and optimized in this study. The pictorial representation for the Bursley- Baits route is shown below in Figure 1.

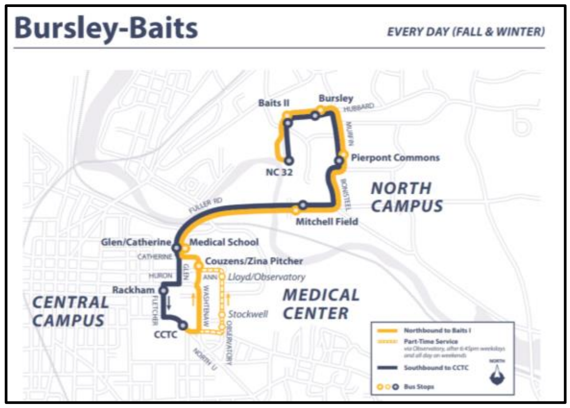


Figure 1: Picture of Bursley-Baits Route

2.1 Literature Review

Bus routes and their lack of optimized scheduling have been an issue for passengers for some time now, especially when the community they're serving is a densely populated city such as Ann Arbor. Current issues regarding the university bus system include the perpetual problems of scheduling routes so students don't struggle for space on the bus. However, new issues involving COVID-19 guidelines introduce a new problem impacting our bus systems. Discrete event modelling and simulations are commonly employed to predict the activity of and within bus systems, as Lindberg et al. (2020) mentioned in their microsimulation study of bus terminals in Stockholm, Sweden. Flittner et al. (2008) analyzed the Bursley-Baits routes operated on the University of Michigan campus and employed discrete event simulation modelling by using Promodel software. They both analyzed the operations of the bus routes and terminals (or stops) and their related capacity issues and how to resolve them. This study focuses on capacity-related issues and the effects of current bus operations on the spread of COVID-19 on campus grounds. Shen et al. (2020) conducted a study observing the transmission rate of COVID-19 on buses where only one bus had a passenger with the virus. As a result of the infected bus, 35.3% of the passengers, including the originally infected, tested positive for covid subsequently. To observe this effect on the campus population, further similar statistics and studies can provide a statistical basis to be applied to discrete event simulations to simulate and predict the spread of COVID-19 through bus operations.

2.2 Problem Description And Importance

The frequency and routes for the M-Bus operations have been changed from what they were during pre-covid times. The core issue that remains is that UofM has seen its highest ever enrollment this fall. Hence, the system needs optimization in terms of bus capacities and masking mandates. There are significantly higher numbers of students on campus. Along with that increase, the risk of infectious diseases is prevalent. We will be simulating a scenario wherein, as per the data collated, we will run simulations to measure the spread of a contagious illness on the Bursley-Baits route system; based on the simulation results, we will try and strategize the bus operation policies at the bus stops and minimize the spread of a communicable disease. This information will help curb the spread of virulent infections and help make public transport a safer way to travel during such pandemics.

2.3 Assumptions

The following assumptions were made for model simplifications

1. The simulation day is considered a typical business day (Monday to Friday).
2. Commuters are static while waiting for the bus at the bus stop and inside the bus. Hence, we will have a fixed Covid-19 transmission rate inside the bus.
3. The simulation runtime is taken as the peak 8 hours (10 AM to 6 PM), and each passenger is assumed

to travel once in the bus, from origin to destination.
4. After completing its journey, the bus would be thoroughly cleaned, and there would be no Covid-19 residues.
5. Passengers waiting to board the bus follow the FIFO rule at the bus stop.
6. Passengers are assumed to be wearing masks in varying percentages in different scenarios on the bus.
7. The bus is supposed to be in perfect condition with no breakdown during the operation.
8. According to data obtained from observations taken manually, the bus runs at an average speed between each stop.
9. Covid-19 is assumed to spread by airborne transmission only inside the bus and not at the bus stops.
10. Surface to the surface transmission of Covid-19 is neglected.
11. Only one bus is assumed in the project and consequently the passenger inter arrival times at each bus stop is scaled down to account for one bus as opposed to multiple buses actually running.

2.4 Questions To Be Answered

We are about to solve the following questions:

- Which bus stops are at high risk for covid infection. This is an important question that needs to be answered to determine what needs to be optimized/changed in the system?
- How can the bus stop capacities and in-bus policies be changed to minimize the covid infection rate? Answering this question is crucial as it explains how to optimize the system to reduce the risk for bus passengers rather than only determining what needs to be changed.
- Can we cap the number of passengers allowed on the bus to minimize the spread?
- Should we have bus stop queue restrictions?

2.5 Flow Chart and Screenshot Of Model Simulation

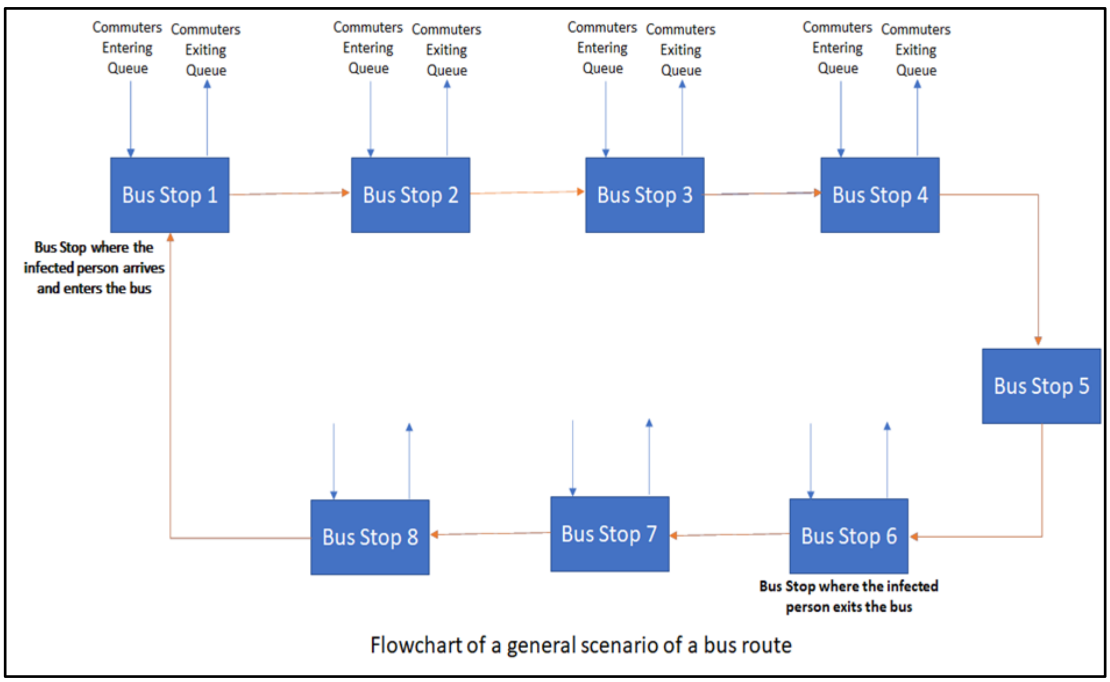


Figure 2: Flow chart of the model

2.6 Novelty in the Paper

The study aims to gather insights into how the spread of infectious disease will happen on the Bursley-Baits route and then provide an optimal strategy to combat the spread of possible future contagious diseases.

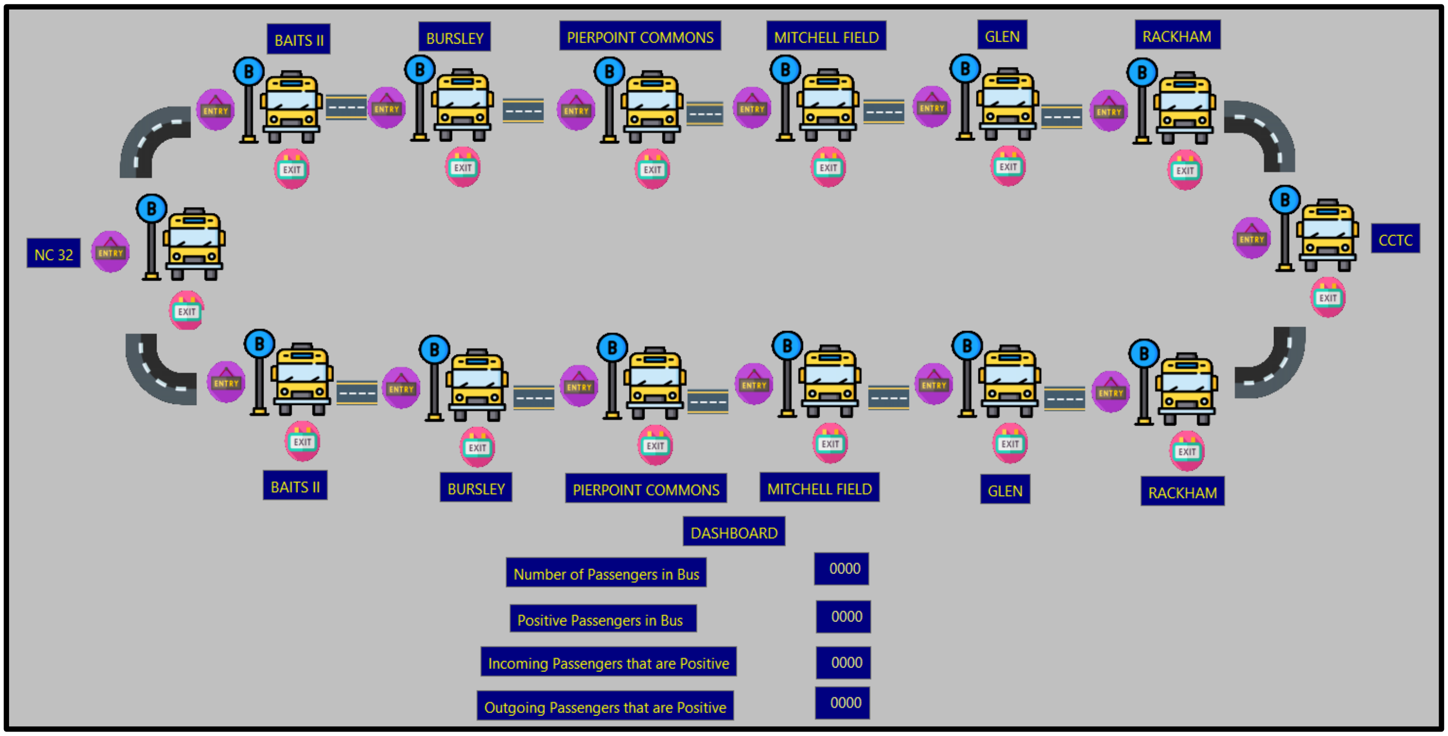


Figure 3: Model simulation

3. SIMULATION METHODOLOGY

3.1 Data Collection

It wasn't easy to collect sufficient and comprehensive data. Hence, we used the following data sources and made assumptions for the rest as mentioned above. Below we list the significant data we collected and give out the method for formulating our input model.

- Bus stops - number of bus stops, the average crowd at the bus stop for different hours. This data has been collected from the website of the Logistics, Transportation & Parking (LTP) department and manual observations.
- Bus capacity - Average bus capacity during peak and non-peak hours, data collected from personal observation made during 10 AM to 6 PM at separate times of the day.
- Bus routes and networks - Arrival and departure times at various bus stops during the day along the Bursley-Baits route and timings have been collected from the Logistics, Transportation & Parking (LTP) department.
- Buses - Type of ventilation used in buses, data collected from the Logistics, Transportation & Parking (LTP) department.
- Communicable Infection data, as a reference for the spread data, we used the Covid-19 infection rate from the UofM Covid Dashboard.
- Transmission rate at different bus stops, in the buses, etc., this data has been extrapolated from the Covid-19 infection spread rate as provided by CDC.
- Mask adherence percentage in UofM, this data has been assumed based on the mask mandate and personal observation.

3.2 Input Modeling

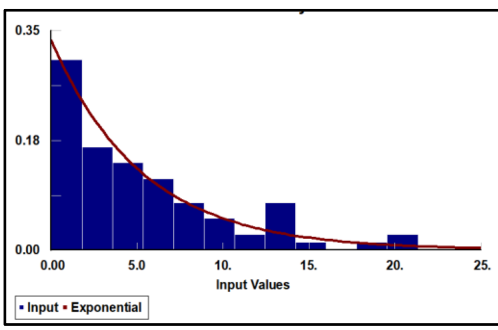
For the simulation, we need to model the following inputs:

1. Bus arrival and departure times at various bus stops
2. Bursley-Baits route
3. Passengers waiting at various bus stops

4. Spread of COVID in bus with mask
5. Spread of COVID in bus without mask
6. Distribution of commuter boarding and deboarding at each bus stop

First, we collected bus arrival times at each bus stop. To get the inter-arrival time of the arrival and departure process, we collected the times from the U-M Logistics, Transportation & Parking website. Since the arrival and departure from 8 pm - 7 am is very few and in stark contrast to the data from 8 am - 8 pm, we divided the process into peak and non-peak hours. And accordingly, we can get the inter arrival times for peak and non-peak hours. Once we got the data, we used Stat fit to fit the data and identified the arrival and departure processes distribution. Next, we modelled the number of passengers waiting at the bus stop. We were not able to get any source for this data. Hence, the team members decided to observe various bus stops (high frequency and low frequency). We then took the mean of our observations and modelled the number of customers waiting at the bus stop. We also used a similar approach to model the distribution of commuters boarding and deboarding at each bus stop. The bus route, length, speed, and bus stop location are available on the U-M Logistics, Transportation & Parking website. In addition to this, we used Google Maps for missing pieces of information in the U-M LTP website to model the bus routes and bus stop locations.

Since this project aims to determine the spread of COVID, we used the case study published by Shen et al. (2020) to model the transmission rate of COVID-19 in buses when a single passenger is infected. We also have neglected to incorporate the transmission rate by vaccination status.



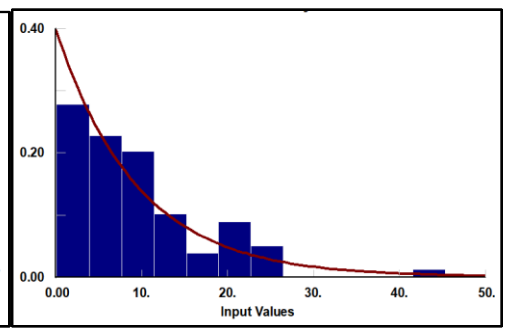
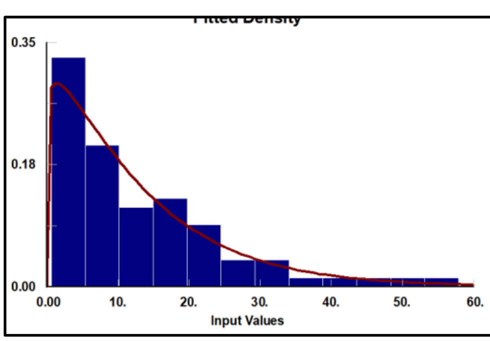


Figure 4: NC32 **Figure 5: Bursley**



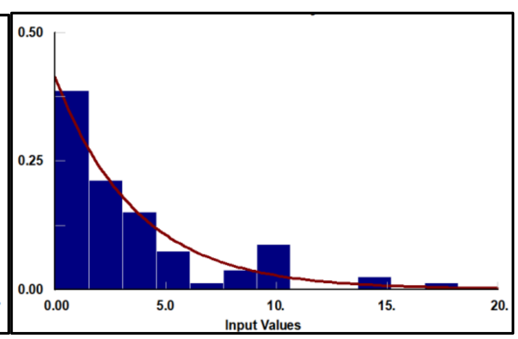


Figure 6: Baits II **Figure 7: Pierpont Commons**

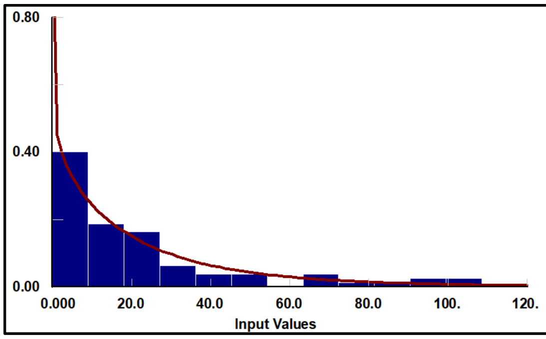


Figure 8: Mitchell Field

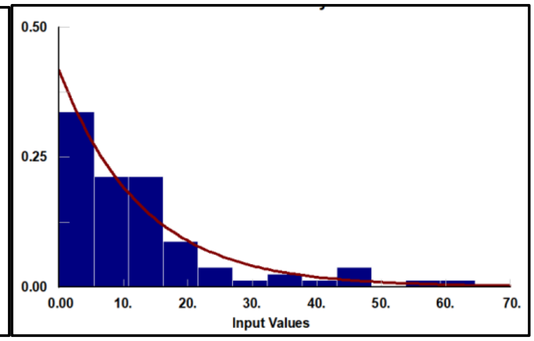


Figure 9: Glen

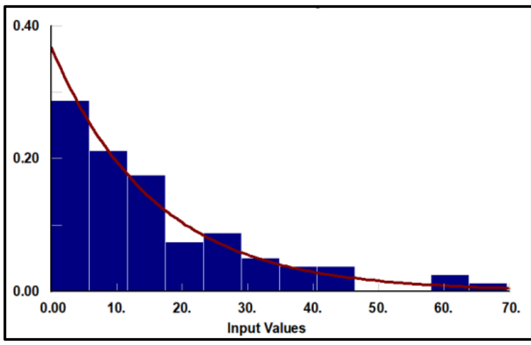


Figure 10: Rakham

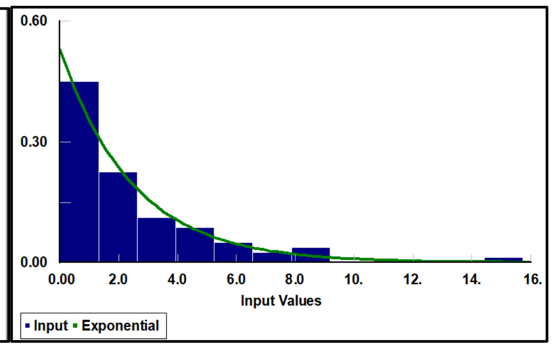


Figure 11: CCTC

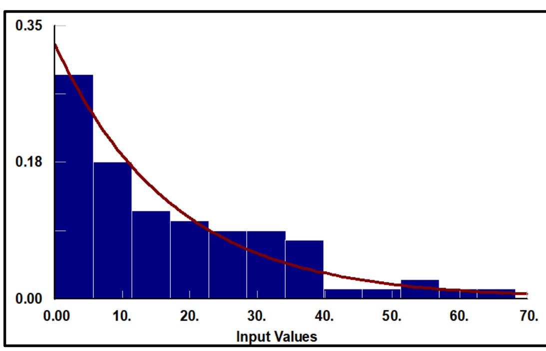


Figure 12: Rackham

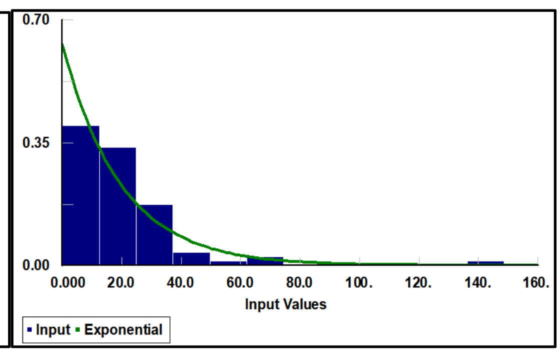


Figure 13: Glen

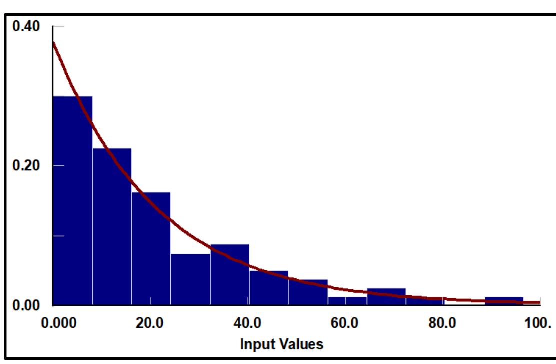


Figure 14: Mitchell Field

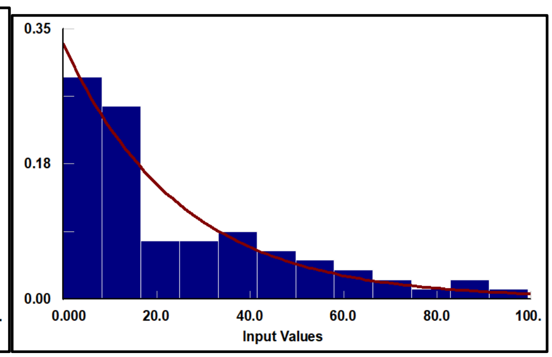


Figure 15: Pierpont Commons

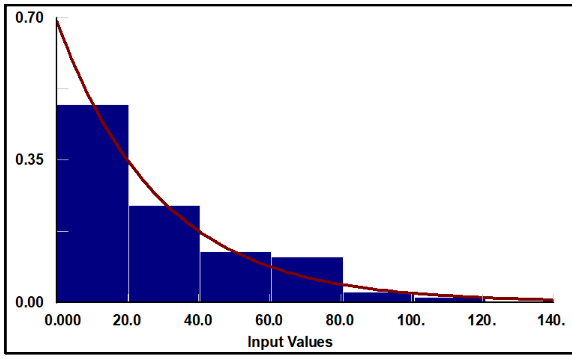


Figure 16: **Bursley**

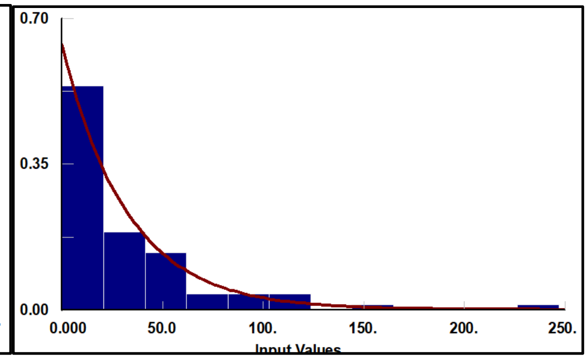


Figure 17: **Baits**

3.3 Model Description

In ProModel, the setting is as follows:

Locations: As we are considering the Bursley-Baits M-Bus route, we took all the bus stops on this route with buses plying on them at their scheduled times. Each bus stop has separate queues for the bus arriving at those stops.

Entities: Commuters are treated as entities and their distribution of onboarding and deboarding a particular bus is taken from data collected manually at different times during the day. Bus is treated as a base entity on which commuter entities get loaded and unloaded.

Events: The events considered in our simulation are:

1. Commuters (including infected passengers) arriving at each bus stop according to inter arrival rates.
2. Commuters standing in queues at the bus stop.
3. Commuters boarding the bus with a set drop off location..
4. Commuters getting infected/ not infected inside the bus based on their masking preference and probability of an infected person being present in the bus.
5. Commuters waiting in the bus to drop off at their desired destination.
6. Commuters deboarding the bus and exiting the system.

Variables:

1. Num_P_x: Number of Passengers waiting at bus stop ‘x’ at current time
2. Num_P_Drop_x: Number of Passengers inside the bus with destination ‘x’
3. P_in_bus: Current number of passengers in bus
4. incoming_positive: Total number of positive passengers entering the bus
5. outgoing_positive: Total number of positive passengers exiting the bus
6. Bus_Capacity: Capacity of the bus (To be changed for different scenarios)

Distributions:

1. positive(): Percentage of positive passengers entering the system
2. covered(): Percentage of masked passengers entering the system
3. Destinationx(): Percentage distribution of destinations for passengers entering the system at stop x
4. spread_dist(): Percentage of spread of covid inside the bus with passenger wearing mask
5. spread_dist_no_mask(): Percentage of spread of covid inside the bus with passenger not wearing mask

Attributes:

1. PassengerType: Defines whether a passenger is covid positive or negative according to positive()
2. Mask: Defines whether a passenger is wearing a mask or not according to covered()
3. Destination: Defines the destination location of a passenger according to destinationx()

4 RESULT

4.1 Model Verification

Model verification was carried out to ensure that the conceptualized system model was an accurate and correct representation of the operational model. The methods used to verify the system were: creating a flowchart of the system and its possible events, having someone who wasn't a developer check the model, confirming system animation accuracy, and testing the model's outputs for validity.

A flow chart, shown in Figure 2, was developed to represent and verify the general system layout for bus systems and their processes and possible events. The flow chart depicted the events of commuters entering and exiting the bus at multiple stops, including the infected passengers. For accuracy, the flow chart's logic was checked against the real-world systems and the operational model.

One of the team members was tasked with performing a check on the model and verifying its code, animation, and outputs. The team member verified the model processing by using the Trace Step function to step through events and verify the process was valid and running correctly. The animation was also viewed for correct process movement to represent the intended bus system accurately.

The last method of verification was testing the model output validity. Passenger exits should be somewhat close to the number of passenger arrivals as, logically, most if not all passengers should be exiting the bus within the simulated time frame. The number of passengers affected by COVID-19 was checked for reasonableness as the rate of spread should not reflect any extreme data given certain model assumptions.

4.2 Model Validation

The simulated model was validated through the use of face and sensitivity validation as well as data validation. Through model building and testing, face and sensitivity analysis was conducted to assess correct event processing and output validity. Data validation was performed to ensure that interarrival times and passenger arrivals/departures were accurately represented.

4.2.1 Face and Sensitivity Validation

The model can be checked and validated through its animation and events list by using face validation. By stepping through the model, both the animation and events list depict the arrival and queueing of passengers at stops, the arrival and movement of the bus, and the exiting of passengers. The animation also shows passengers remaining at stops and waiting for the bus to return when the bus is at capacity. All variables are checked for correct processing to ensure the data collected is valid by stepping through events.

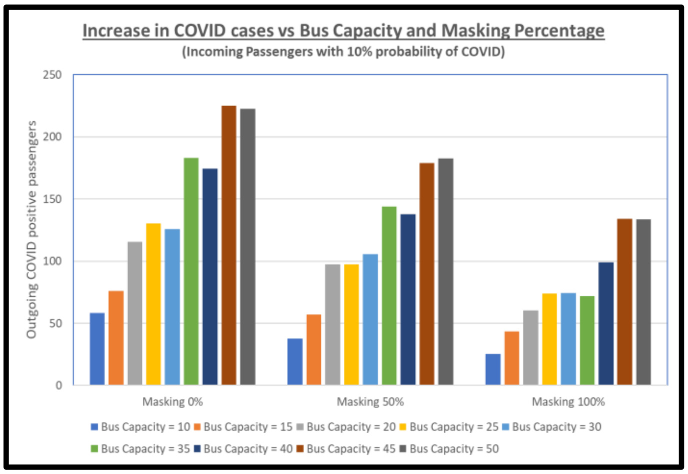
By varying specific parameters of entities and arrivals, the reasonableness of the data and model can be tested by checking the validity of the outputs. Specifically, the interarrival time of passengers, mask rate, bus capacity, and incoming positive case percentage was varied. The interarrival time of passengers was varied by using multipliers of 0.5, 0.8, 1.0, 1.2, and 1.5. Data collected from the varying interarrival time showed that a decrease in IAT increased the number of passengers; however, longer interarrival times did not reflect a large decrease in passengers, which could be due to various factors, including the bus capacity. The mask rate was varied using percentages of 0, 50, and 100, which logically reflected an inverse relationship between infection rates and mask rates as the number of infections decreased due to an increase in mask rate. The bus capacity was varied using increments of 5 from 10 to 50 and reflected an increase in passengers arriving and departing the bus, which logically makes sense. The last parameter changed was incoming positive case percentage which reflected an increase in the number of infected passengers.

4.2.2 Data Validation

Data validation was conducted by using available information and observational data collected from bus routes and stops. Information regarding the bus route, including interarrival time, stop locations, route length, and bus speed, was collected from the U-M Logistics, Transportation & Parking website and confirmed through observation. Passenger interarrival time data and bus capacity limitations were collected through observation, specifically during peak hours for passenger IAT. Data collected from outputs such as passenger exits was checked for reasonableness.

4.3 Output Analysis

The paper aims to analyze scenarios and their outputs to determine the factors relevant to the spread of COVID-19 and their effects on the system. We have created 54 scenarios by varying bus capacity, passenger masking rate, and incoming infected passengers. For analysis, we have grouped various scenarios by the rate of incoming infected passengers into the bus, i.e. incoming infected passengers rate 10% and 20%. These two groups could be assumed to correspond to different phases of COVID-19 over a year. We consider that during the peak phase of COVID - 19, the income-infected passengers are 20%, and 10% is the rate just before or after the peak COVID phase.



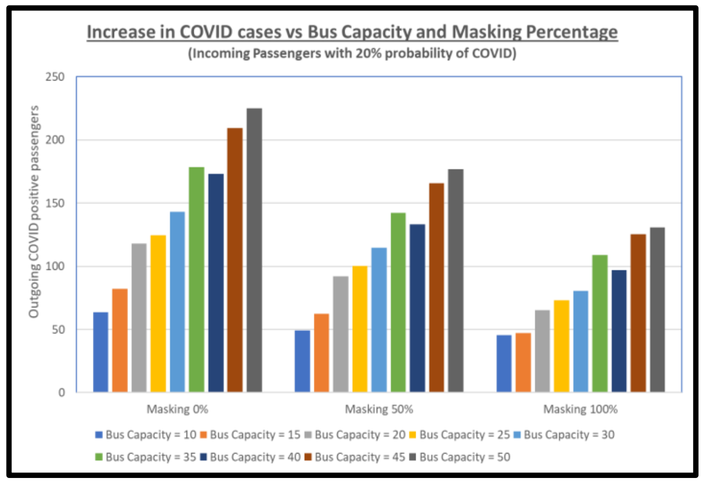


Figure 17 & 18: Scenario Snapshots

4.3.1 Scenario Analyses

On analyzing the model output results in various scenarios, we were able to isolate the effects of an increased infection rate among passengers. We calculated increase in infected patients with varying bus capacities and masking rates and observed the following:

1. An increase in carriers results in a higher number of newly infected passengers
2. Enforcing 100% masking would result in ~ 45% reduction in infected passengers vs no masking regardless of the bus capacity
3. Decreasing the bus capacity would improve the social distancing within the bus and regardless of masking rate we can observe that infected passengers increase with increase in the allowed bus capacity

We further analyzed crowds at various bus stops and observed that with a high average number of passengers at Pierpont Commons and CCTC, they could well be potential hotspots for COVID-19 or any other infectious disease.

We also ran sensitivity analysis on our model to see how the infected passengers increase when the interarrival time of passengers is increased or decreased.

IAT Multiplier	0.5	0.8	1	1.2
Incoming Positive	55.1	50.2	42.3	42.2
Outgoing Positive	269.7	226	168.1	185.7
Infected	214.6	175.8	125.8	143.5

With the increase in IAT of the passengers at bus stops, we observe that the number of infected passengers decreases.

5 DISCUSSION

Bonferoni Analysis - Masking Rates

Replication	0%-50%	0%-100%	50%-100%
1	19	53	34
2	19	36	17
3	37	76	39
4	16	35	19
5	24	52	28
6	39	74	35
7	24	56	32
8	31	63	32
9	35	81	46
10	-41	-12	29
Sample Mean	20.3	51.4	31.1
Sample Std De	23.0	27.2	8.6
Std Error	7.3	8.6	2.7

Bonferoni CI	CI		
0%-50%	20.3	+/-	21.3
0%-100%	51.4	+/-	25.3
50%-100%	31.1	+/-	8.0

	CI Lower	CI Upper	Comments
0%-50%	-1.0	41.6	No difference between 0 and 50
0%-100%	26.1	76.7	0 is Larger
50%-100%	23.1	39.1	50 Larger 100 is the smallest

Bonferoni Analysis - Bus Capacity

Replication	30-15	30-50	15-50
1	23	-73	-96
2	35	-62	-97
3	43	-62	-105
4	-5	-53	-48
5	13	-71	-84
6	44	-95	-139
7	41	-5	-46
8	33	-49	-82
9	4	-66	-70
10	78	-57	-135
Sample Mean	30.9	-59.3	-90.2
Sample Std Dev	23.7	23.0	31.5
Std Error	7.5	7.3	10.0

Bonferroni	CI		
30-15	30.9	+/-	22.0
30-50	-59.3	+/-	21.3
15-50	-90.2	+/-	29.2

	CI Lower	CI Upper	Comments
30-15	8.9	52.9	30 larger
30-50	-80.6	-38.0	50 larger
15-50	-119.4	-61.0	50 larger , 15 is the smallest

To compare the scenario used in the report, we used the Bonferroni approach to compare the output. We compared the effect of mask rates, 0%, 50%, and 100%, while maintaining a bus capacity of 30 to gather data from 10 replications. The average number of newly infected passengers was used as output. We used a paired-t confidence interval of 95% to check which scenario was superior. Based on the analysis results, shown in Table 2, we can see that the confidence intervals indicate that there is no significant difference between 0% masking and 50% masking as it contains 0. The results also suggest that masking 100% is significantly different and the best option out of the mask rates as the outputs are considerably lower than the rest for new infections.

To compare the effect of different bus capacities, we used values 15, 30, and 50. The average number of newly infected passengers was again used as output. Again a paired-t confidence interval of 95% was used to check for the best scenario. Based on the analysis results shown in Table 3, a bus capacity of 15 results in the most improvement for reducing newly infected passengers.

5.1 Conclusion

In this paper, we collected daily arrival and departure time for commuters on the Bursley -Baits route for M-Bus. We modelled a simulation on ProModel to study how the transmission rate varies with varying masking rates and bus capacity. Our results show that the number of people infected in a bus increases with an increase in incoming infected individuals. A 100% masking mandate leads to ~45% reduction in infection spread compared to a situation without that mandate. Also, with the increase in bus capacity, the number of infected passengers increases. Hence, 100% masking and limiting the number of commuters on the bus should be implemented to restrict the spread of infection.

5.2 Scope of Improvement

The current model can be incorporated to further study the following scenarios:

1. Increasing the number of buses on bus routes to accurately model real life scenarios.
2. Replicating the model for other bus routes including Northwood, Diag to Diag Express, Commuter North, Commuter South, etc.
3. Incorporating the vaccination data to improve robustness of the current model.
4. Suggestions including adding or subtracting bus stops on particular M-Bus routes can be made to minimize the risk of disease spread.
5. The current model focused on Covid-19, but can easily be used to model the spread of any other air-borne disease as well.
6. To simulate other modes of public transport such as buses, trains, etc.

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