SIMULATION OF PUBLIC TRANSPORTATION OPERATIONS FOR INFECTIOUS DISEASE SPREADING AMONG PASSENGERS

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ABSTRACT

Public transportation operation strategies' impact on spreading infectious diseases among passengers is critical due to managing diseases like COVID-19. Public transportation can act as significant vectors for transmission due to high passenger densities and close contact. However, few studies have quantitatively compared disease transmission between different operation strategies. In this work, we examine transmission among passengers by considering the number of public vehicles and their travel directions. A novel evaluation method assesses the spread of diseases. Simulation models for eight bus operation strategies indicate that adding more buses decreases passenger close contact on buses and stations. Uniform bus travel direction ensures evenly distributed passengers, lowering close contact compared to varied directions. These findings inform the development of effective strategies to mitigate transmission risks, ensuring public transportation safety and protecting public health during pandemics.

Keywords: public transportation, infectious diseases, transmission, bus operation, passengers

1 INTRODUCTION

The challenges of infectious disease transmission, particularly in the context of COVID-19, pose significant concerns for public transportation arrangements, including trains, airports, and buses. The nature of these transportation systems, which involves the close proximity of passengers in confined spaces, exacerbates the risk of disease spread [1, 2]. Understanding and addressing these challenges is crucial for designing effective public health measures and optimizing transportation arrangements. One of the primary challenges is the high population density within public transportation vehicles, such as buses and trains. Passengers often share limited space, making it challenging to maintain adequate physical distancing [3]. The close proximity of individuals during transit increases the likelihood of respiratory droplets, the primary mode of COVID-19 transmission, being exchanged between passengers [4]. Airports, serving as major hubs for global travel, present additional challenges. The constant influx of travelers from diverse geographical locations contributes to the potential introduction and dissemination of infectious diseases across borders [5]. Moreover, the enclosed spaces within airport terminals and the close interactions during security checks, boarding, and deplaning create environments conducive to disease transmission [6].

Buses, as a common mode of urban transportation, face challenges related to passenger turnover and varying travel duration. Shorter distances between stops and frequent boarding and disembarking increase the chances of individuals with infectious diseases coming into contact with a larger number of passengers [7].

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Additionally, the ventilation systems in buses may not be as effective in mitigating the spread of airborne pathogens [8].

In response to these challenges, there is a need for comprehensive studies to analyze the transmission dynamics of infectious diseases within different modes of public transportation [9, 10]. Improving public transportation routes is crucial in reducing infectious disease spread among passengers [11]. The use of modeling and simulation in research plays a vital role in evaluating the impact of different bus arrangements, schedules, and routes on disease transmission [12]. Modeling and simulation allow researchers to assess the risk of infectious disease transmission within different bus arrangements [5]. By creating realistic scenarios, researchers can predict how variations in bus schedules, seating arrangements, and routes may influence the likelihood of disease spread, providing valuable insights for preventive measures [13]. Simulation models enable the testing of various bus arrangements to identify the configurations that minimize close contacts and reduce transmission risks [14]. This optimization may involve adjusting seating layouts, implementing staggered boarding, or modifying bus schedules to enhance the overall safety of passengers [15].

Simulation tools can be used to conduct scenario analyses, exploring different hypothetical situations and their potential impact on disease transmission [16, 17]. This allows for a comprehensive understanding of the dynamic nature of infectious disease spread within the context of public transportation, helping authorities prepare for and respond to various scenarios [18, 19]. Findings from modeling and simulation studies contribute to the formulation of policies aimed at minimizing infectious disease transmission. Policymakers can use the results to develop guidelines for optimal bus arrangements, schedules, and routes, ensuring a safer and more resilient public transportation system [20].

Modeling and simulation of infectious disease spreading in public transportation provides a proactive approach to public health planning. By understanding how different factors (e.g., public transportation routes and schedules, the number of passengers, and travel directions) influence transmission, authorities can develop long-term strategies and infrastructure improvements to mitigate the impact of future outbreaks.

In this study, we examine the transmission of infectious diseases by considering the quantity of public vehicles and their travel direction within a specific system. Simulation models are developed for encompassing nine scenarios to effectively analyze the aforementioned issue. Our proposed solution introduces the Weighted Cumulative Close Contact (WC3) function for assessing the spread of infectious diseases. The WC3 function takes into account the cumulative number of passengers on each bus throughout its route at any given moment. Implementing cost-effective changes can effectively reduce the spread of infectious diseases within public transportation systems. The main contributions of this paper include:

- Examination of Transmission Factors: The research explores the transmission of infectious diseases within a public transportation system, considering both the quantity of public vehicles and their travel direction. This analysis contributes to a better understanding of the factors influencing disease spread in such environments.
- Development of Simulation Model: The study presents a comprehensive simulation model that encompasses nine scenarios. This model serves as a valuable tool for effectively analyzing the dynamics of infectious disease transmission in public transportation systems, providing a basis for evidence-based decision-making.
- Introduction of WC3 Function: The proposed Weighted Cumulative Close Contact (WC3) function is introduced as a novel solution for assessing the spread of infectious diseases. By considering the cumulative number of passengers on each bus throughout its route, the WC3 function offers a quantitative measure that can guide policymakers and transportation authorities in implementing targeted interventions to reduce disease transmission.

- Important conclusions from simulation results: Increasing the number of buses and having them travel in the same direction both lead to a reduction in the degree of close contact among passengers on the buses.

The findings in this study can inform city planners and policymakers in making informed decisions to reduce the risk of infectious disease transmission. The rest of this paper is organized as follows. In Section 2, we present various simulation models for simulating the public transportation system environment, including bus models, bus station models, and passenger models. In Section 3, we introduce a novel assessment function for the spread of infectious diseases in public transportation, called Weighted Cumulative Close Contact (WC3). In Section 4, we introduce the main simulation experiments, covering aspects such as experimental environment setup, simulation execution, simulation results, and analysis. Section 5 summarizes the entire paper and provides an outlook on potential future research endeavors.

2 SIMULATION MODELS

In this section, we present various simulation models for simulating the public transportation system environment, including bus models, bus station models, and passenger models. Additionally, we introduce a novel assessment function for the spread of infectious diseases in public transportation, called Weighted Cumulative Close Contact (WC3). The created simulation models contain three main types of components: bus route and stops, buses, and passengers. These three types of components are not independent. Instead, there are a lot of interactions between them. We discuss all three types of components in details as follows.

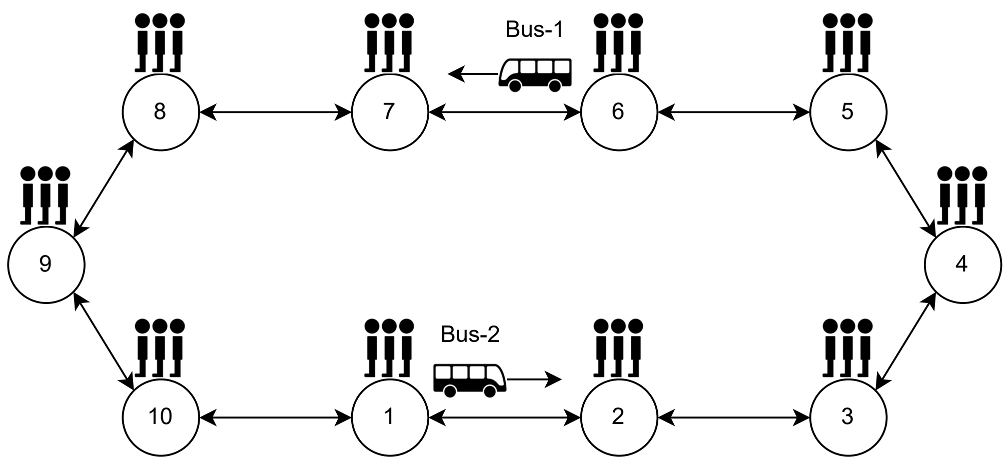


Figure 1: Bus operation loop with ten bus stops.

2.1 Bus Route and Stops

In this paper, we mainly consider a closed-loop bus operation route, as shown in the Figure 1. There are multiple bus stops distributed in the closed-loop bus route. The distance between these bus stops may vary. In the bus route loop, each bus travels in one direction, either clockwise (CW) or counterclockwise (CCW). We assume that passenger arrival rates are the same between all bus stops. It is also assumed that there is no limit on the number of passengers waiting in line at bus stops. This means that the capability of bus stops is unlimited, which is different from the model of buses. The example in Figure 1 contains ten bus stops within the loop.

2.2 Buses

We assume that each bus has only two states: moving and stopping. When the bus travels from one bus station to the next, it is in a moving state. When the bus arrives at a station, it switches from the moving state to the stopping state, until the bus completes unloading and loading passengers and starts off to the next station. We assume that buses in the moving state travel at the same speed. This has two implications: different buses travel at the same speed, and each bus travels at a constant, unchanging speed during its moving state. We consider cases with different numbers of buses such as one, two or three buses operating in the same or different directions in the same loop. The operation directions of buses in the same loop can be different from each other. In the example of Figure 1, as we can see, two buses operate in the same direction which is the counterclockwise direction. All buses have the same capacity , meaning each bus can carry no more than this number of passengers.

2.3 Passengers

When passengers arrive at a bus station, if there is no bus at the station, or even if there is a bus but it is already full (no empty seats), then the passengers will wait at the bus station for the next bus. When a bus arrives at a station, two operations are performed in order: "passengers reaching their destination get off" and "passengers waiting at the station board the bus." The sequence of these two steps cannot be reversed.

First, we scan all the passengers on the bus for their destination stations. If the destination station of a passenger is the current station, we remove that passenger from the bus's passenger list. This means that the passenger has completed his lifecycle in the simulation system. After all passengers are scanned, the operation of "passengers reaching their destination getting off" is concluded.

Then the second step is carried out, namely "passengers waiting at the station board the bus." Passengers waiting at the station board the bus in a "First in, First out" sequence. This means that the passengers at the front of the queue board first, while those at the back of the queue have to wait for those in front to board first. Therefore, it is possible that after some of these passengers board, the bus becomes full. Then, the remaining passengers in the queue will not be able to board and will continue to wait in the queue for the next bus to arrive.

3 WEIGHTED CUMULATIVE CLOSE CONTACT

We have proposed the "Weighted Cumulative Close Contact (WC3)" function to quantitatively assess the degree of close contact among passengers during a given period in the operation of buses. The higher the function value, the more close contact there is among passengers on the bus. We use t to represent time, t_1 to represent the start time of the evaluated period, and t_2 to represent the end time of the evaluated period. N represents the number of buses in the system. We use $n_i(t)$ to represent the number of passengers on the i-th bus at time t. We use $C(N,t_1,t_2)$ to represent the degree of close contact among all passengers on all buses during the time interval $[t_1,t_2]$. The higher the C value, the more close contact there is among passengers.

First, we consider the situation where there is only one bus on a bus route, meaning $N = 1$. In this case, the model is relatively simple, as we can evaluate the degree of close contact among passengers by considering the integral of the number of passengers on this bus with respect to t, which is:

$$C(1,t_1,t_2) = \int_{t_1}^{t_2} n_1(t)dt \tag{1}$$

But we can notice that there is an issue with (1). The C value should be 0 if there is only one passenger on the bus all the time because there is no close contact. But the C value is $(t_2 - t_1) > 0$ if we use (1). So we need to modify (1) to:

$$C(1,t_1,t_2) = \int_{t_1}^{t_2} max(n_1(t)-1,0)dt \tag{2}$$

which means the C value is 0 if there is less than 2 passengers on the bus.

Next, we consider the scenario where there are two buses in the system, meaning $N = 2$. It's important to note that passengers on different buses do not come into contact with each other, so the direction of the buses' travel does not affect the overall close contact situation among passengers in the bus system. For assessing the overall degree of close contact among passengers on two buses, a direct and simple method is to calculate the C value for each bus separately using (2), and then compute the sum of these two C values. That is:

$$C(2,t_1,t_2) = \int_{t_1}^{t_2} max(n_1(t)-1,0)dt + \int_{t_1}^{t_2} max(n_2(t)-1,0)dt \tag{3}$$

Note that (3) can be written in the following form when $n_1(t) >= 1$ and $n_2(t) >= 1$.

$$C(2,t_1,t_2) = \int_{t_1}^{t_2} (n_1(t)+n_2(t))dt \tag{4}$$

This means that the overall degree of close contact for two buses is only related to the total number of passengers on these two buses, and is independent of how many passengers are on each bus separately. This does not quite align with our common sense. Consider these two scenarios: Bus A has 1 passenger and Bus B has 29 passengers; Bus A has 15 passengers and Bus B has 15 passengers. According to (3), two scenarios would have the same C value since the total number of passengers on the two buses is the same. However, it is clear that in the first scenario, there is more close contact among passengers because 29 passengers are all together on the same bus for the entire period. Therefore, we should modify (3) by adding a weight parameter to each item in (3). One way can be:

$$C(2,t_1,t_2) = \alpha \int_{t_1}^{t_2} max(n_1(t)-1,0)dt + \beta \int_{t_1}^{t_2} max(n_2(t)-1,0)dt \tag{5}$$

where

$$\alpha = \frac{2\int_{t_1}^{t_2} max(n_1(t)-1,0)dt}{\int_{t_1}^{t_2} max(n_1(t)-1,0)dt + \int_{t_1}^{t_2} max(n_2(t)-1,0)dt} \tag{6}$$

$$\beta = \frac{2\int_{t_1}^{t_2} max(n_2(t)-1,0)dt}{\int_{t_1}^{t_2} max(n_1(t)-1,0)dt + \int_{t_1}^{t_2} max(n_2(t)-1,0)dt} \tag{7}$$

We actually introduced two weight parameters for the two item in (3). And these two weight parameters α and β satisfy:

$$\alpha + \beta = 2 \tag{8}$$

and

$$\frac{\alpha}{\beta} = \frac{\int_{t_1}^{t_2} max(n_1(t)-1,0)dt}{\int_{t_1}^{t_2} max(n_2(t)-1,0)dt} \tag{9}$$

For general cases when $N >= 1$:

$$C(N,t_1,t_2) = N\frac{\sum_{i=1}^{N}(\int_{t_1}^{t_2} max(n_i(t)-1,0)dt)^2}{\sum_{i=1}^{N}\int_{t_1}^{t_2} max(n_i(t)-1,0)dt} \tag{10}$$

The reason we define the weight coefficients in this way is to consider that the estimate of passenger close contact on buses with more passengers has a greater impact on overall disease transmission than on buses with fewer passengers.

4 SIMULATION

In this section, we introduce the simulation experiments we conducted for different bus operation strategies, covering aspects such as Scenarios, simulations, and results. The code we developed in Matlab for these simulations can be found publicly at https://github.com/Longfei-Zhou/Bus-Simulation.

4.1 Scenarios

To ensure comparability among different bus operation strategies and fairness in comparing different bus operation strategies, we set the same passenger arrival rate, number of bus stops, locations of bus stops, bus travel speed, and maximum passenger capacity for buses for all the different bus operation strategies. The specific numerical settings of these experimental parameters are shown in Table 1. All these parameter values are generated according to a survey of real-world transportation data.

Table 1: Parameters of all eight scenarios held constant.

Parameters	Values
Number of bus stops	10
Location of bus stops	[1.2, 2.4, 3.6, 4.2, 4.8, 6.0, 7.8, 9.0, 10.2, 12.0] km
Average speed of Bus	10 m/s (i.e., 22.4 mph)
Bus capacity	30 passengers
Passengers' arrival interval time	$U(a=1,b=3)$ minutes
Passengers' destination bus stop	$N(\mu=5,\sigma^2=3)$

In the scenario we consider, there are a total of 10 bus stops. The bus route is a closed loop that connects these 10 stops in sequence. This means that the bus starts from the first station and travels in order through different stations until it reaches the last station. Then it returns from the last station back to the first station. To simplify the simulation calculations, we use the travel time of the bus to define the distance between different bus stops. We set the average travel time between the first and last stops to be 20 minutes, passing through eight stations in between.

Since the bus route is a closed loop, the time distance between the first and last stations can be interpreted as the time to complete the loop. After some research, we set the average travel speed of the bus at 10 m/s (approximately 22.4 mph), which is a reasonable speed for buses in busy cities or campuses. The maximum passenger capacity of the bus is set at 30, which is also a reasonable assumption. We use a uniform distribution $U(a=1,b=3)$ to describe the average interval time of passengers arriving at the bus stop. This is a relatively independent variable, depending on the busyness of the city's public transport system.

We use a normal distribution probability function $N(\mu=5,\sigma^2=3)$ to define the number of bus stops between passengers' destination stations and their starting stations. This is based on the following considerations. Generally, most passengers prefer to take the bus to places that are least accessible by walking, i.e., stations that are farthest from the starting station. Usually, fewer passengers choose to take the bus to very close destinations (e.g., a destination at one bus stop away) because waiting for a bus also takes time. For very close destinations, the time it takes to walk there is likely to be less than the time spent both waiting for and riding the bus. Therefore, we use a normal distribution probability function to describe the probability of the number of stations between passengers' destination stations and the starting stations.

4.2 Simulations

The designed simulations examine eight different scenarios with different directions and numbers of buses. Each scenario runs on five different seeds to ensure identical passenger and destination generation. All simulation models created have the aforementioned parameters with a set seed to ensure the same distribution for passenger generation and their destinations.

We modeled and simulated a total of eight different bus operation strategies. These eight strategies differ in terms of the number of buses and the direction of bus operation, with specific differences as shown in Table 2. The "CW" represents the clockwise direction of bus operation, and the "CCW" represents the counterclockwise direction of bus operation. Additionally, to ensure the credibility of simulation results, we ran five independent simulations for each strategy using five different random seeds. Then, we averaged the results of the five simulations to represent the performance of each strategy.

Table 2: Parameters of all tested bus operation strategies.

Operation strategies	Number of buses	Bus operation directions
# 1	1	CW
# 2	1	CCW
# 3	2	CW, CW
# 4	2	CW, CCW
# 5	2	CCW, CCW
# 6	3	CW, CW, CW
# 7	3	CW, CCW, CW
# 8	3	CCW, CCW, CCW

From Table 2 we can see that there are two strategies with one bus, three strategies with two buses, and three strategies with three buses. All these eight strategies are different from each other so that we can indicate how number of buses and bus operating directions impact the spreading of infectious disease among passengers in public transportation systems.

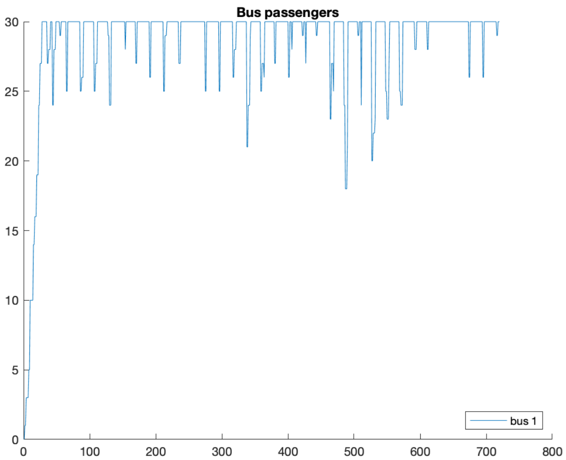
These eight strategies cover all possible scenarios for up to three bus situations. For example, in the strategies with two buses, we considered three situations, namely, both buses are clockwise, both buses are counterclockwise, and one bus is clockwise and the other bus is counterclockwise. Since the strategy of one bus clockwise and one bus counterclockwise is the same as the strategy of one bus counterclockwise and one bus clockwise, we only considered one of them. The same principle applies to the strategies with three buses. That is to say, for all strategies that are functionally the same as each other, we only consider one of them to reduce unnecessary simulation costs.

4.3 Results

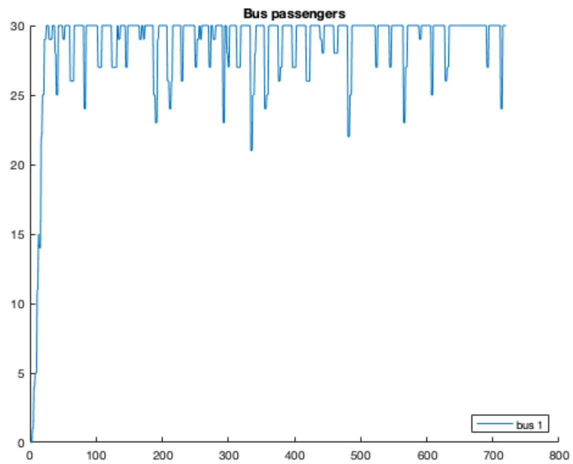
We compare the eight bus operation strategies from different aspects including the number of passengers on each single bus, C values for all buses, and C values for all bus stops.

4.3.1 Number of passengers on each single bus in different strategies

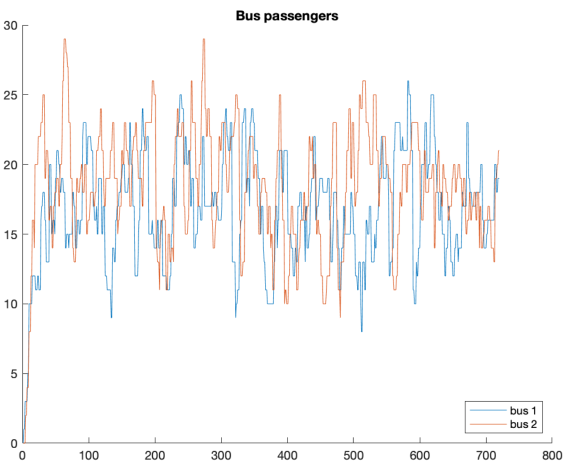
Figure 2 shows the number of passengers on each single bus in different strategies. From the Figure 2, we can observe the following:



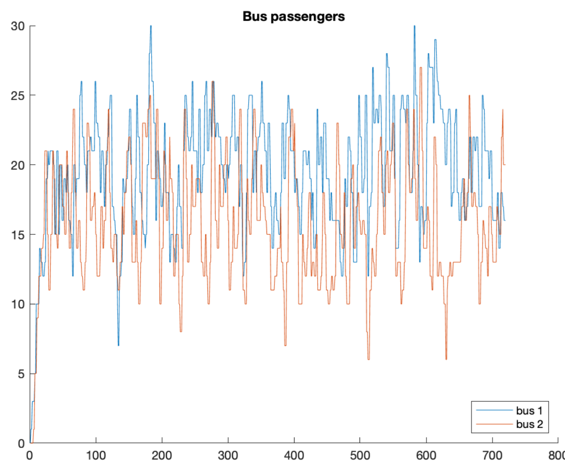
(a) One bus (CW).



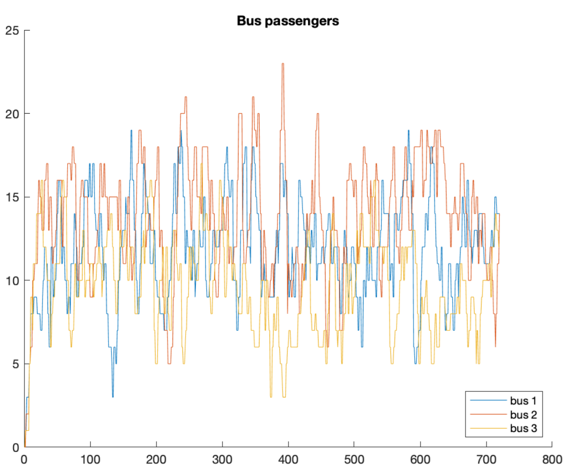
(b) One bus (CCW).



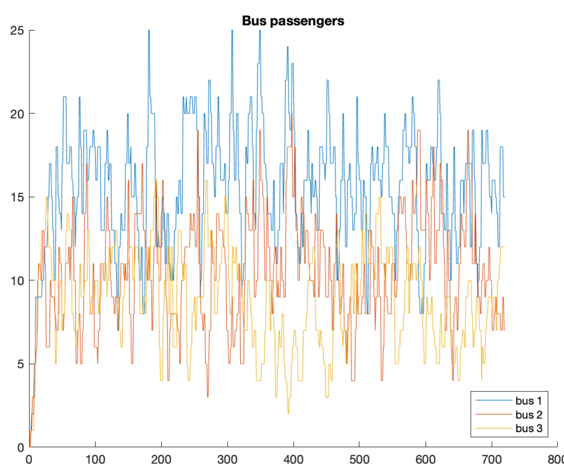
(c) Two buses (CW, CW).



(d) Two buses (CW, CCW).



(e) Three buses (CW, CW, CW).



(f) Three buses (CW, CCW, CW).

Figure 2: Number of passengers on each single bus in different strategies.

- When the number of passengers arriving at the system is the same, the fewer the number of buses in the system, the more passengers there are on each bus. Conversely, the more buses there are in the system, the fewer the number of passengers on each bus. This aligns with our intuitive understanding.
- When there is only one bus in the system, regardless of whether the bus operates in a clockwise or counterclockwise direction, the bus is mostly in a saturated state according to Figure 2a and Figure 2b.
- When there are multiple buses in the system, such as 2 or 3, having all buses travel in the same direction results in a similar number of passengers on all buses. However, if the buses travel in different directions, it leads to variations in the number of passengers on different buses, according to Figure 2c, 2d, 2e and 2f.

4.3.2 The *C* values of all buses in different strategies

We also compare the *C* values over time between different bus operation strategies for passengers in all buses. Figure 3 shows the *C* values of all buses in 8 strategies over time. Observing the simulation results

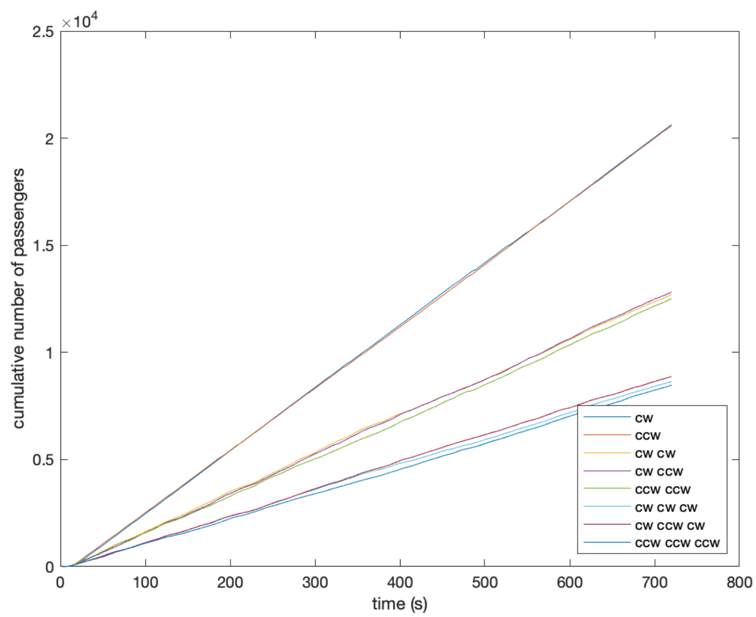


Figure 3: WC3 function values of all buses in 8 strategies over time.

from Figure 3, we can note the following:

- Increasing the number of buses significantly reduces the degree of close contact among passengers, i.e., a lower C value. The strategies of having only one bus result in a C value that is consistently much higher all the time than those with two or three buses. Additionally, the strategies with two buses have significantly higher C values than those with three buses.
- When there are the same number of buses, having all buses travel in the same direction results in a lower degree of close contact among passengers compared to other strategies such as two buses traveling in opposite directions, or one bus traveling in a different direction than the other two.
- When buses travel in the same direction, whether clockwise or counterclockwise, it has little impact on the degree of close contact among passengers.

4.3.3 The *C* values of all bus stops in different strategies

Figure 4 shows the change in the degree of close contact among passengers of all bus stations over time in different bus operation strategies. From the simulation results in Figure 4, we can observe that when there

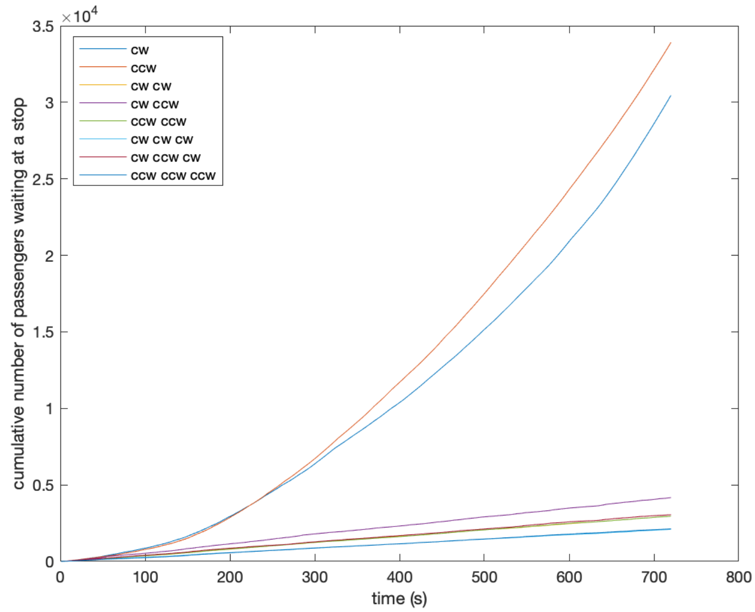


Figure 4: WC3 function values of all bus stations in 8 strategies over time.

is only one bus, regardless of whether the bus is running clockwise or counterclockwise, the *C* value of all bus stations increases significantly over time, almost exponentially. However, with two or three buses, the *C* value of all bus stations increases only gradually. This result is consistent with what is shown in Figure 2. The reason is that when there is only one bus, the bus is almost always at full capacity. This leads to the number of newly arriving passengers at bus stations being higher than the number of passengers boarding the bus. Consequently, the number of passengers waiting at bus stations keeps increasing. When there are two or three buses, the buses are not fully loaded most of the time, so the number of passengers waiting at bus stations does not increase rapidly.

5 CONCLUSIONS

In this study, we examine the transmission of infectious diseases among passengers in public transportation systems by considering the number of public vehicles and their travel directions within a specific system. A novel evaluation method called the Weighted Cumulative Close Contact (WC3) function is introduced to assess the spread of infectious diseases among passengers. Simulation models are developed and simulated for encompassing eight bus operation strategies to effectively analyze the aforementioned issue. Main conclusions that we obtained from the simulation results include:

- Increasing the number of buses significantly reduces the degree of close contact among passengers, i.e., a lower *C* value. More buses can reduce close contact not only among passengers on buses but also among passengers waiting at bus stations as well.
- Having all buses travel in the same direction results in a similar number of passengers on all buses. Having buses traveling in different directions leads to different numbers of passengers on buses.

- When there is the same number of buses, having all buses travel in the same direction results in a lower degree of close contact among passengers compared to strategies with different bus traveling directions.

These conclusions can assist public transportation system designers and decision-makers in formulating reasonable operational strategies for public vehicles. By doing so, while meeting the travel needs of passengers, the degree of close contact among passengers can be minimized, thereby reducing the spread of diseases among passengers within public transportation systems. Future work includes applying the proposed method in real-world public transportation situations to conduct modeling and simulation based on real data. Besides, it would also be beneficial to compare the effectiveness of different passenger close contact functions for different scenarios.

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