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Research Article

Optimizing Dallas-Fort Worth Bus Transportation System Using Any Logic

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Abstract: The bus transportation system, modeled using the AnyLogic simulation software, aims to optimize the flow of buses and manage key operational challenges such as bus bunching and delays. The simulation incorporates various elements, including bus agents, bus stops, and passenger behaviors, with a focus on how buses interact with each other and with passengers at different stops. The system is designed to simulate real-world bus routes, taking into account factors like bus speed, intervals, dwell times, and passenger load. By adjusting bus schedules and frequencies, the simulation tests different scenarios to identify strategies that minimize wait times, reduce delays, and improve service efficiency. This paper explores the optimization of bus transportation systems in the Dallas-Fort Worth area, focusing on addressing the challenge of bus bunching and improving overall service efficiency. Using the AnyLogic simulation tool, the study models the dynamics of bus operations, including factors such as bus intervals, dwell times, and passenger load variations during rush and normal hours. By adjusting bus schedules and service frequencies, the paper evaluates multiple optimization scenarios to identify strategies that reduce passenger wait times, minimize delays, and enhance system efficiency. The results demonstrate that strategically reducing bus intervals during peak hours and extending them during non-peak hours can significantly improve operational performance, with service efficiency increasing from 75% to 88% under optimal conditions. The findings highlight the importance of tailoring bus schedules to passenger demand and time-of-day factors to mitigate issues like bus bunching and ensure more reliable public transportation services.

Keywords: Busbunching, publich transport, agent- based modeling, any logic simulation, intervention strategies

1 Introduction

In recent years, transportation in China has undergone significant transformation, driven by rapid urbanization, technological advancements, and government investment in infrastructure. China's high-speed rail network is the largest in the world, with over 40,000 kilometers of track as of 2024. This expansion has revolutionized domestic travel, enabling fast, convenient, and affordable connections between major cities and regions [1]. Trains can reach speeds of up to 350 km/h (217 mph), drastically reducing travel times and enhancing economic integration between cities.China is a global leader in electric vehicle (EV) adoption. The country is pushing for a green transportation future with strong government incentives, subsidies, and infrastructure investment, such as an expanding network of EV charging stations. Chinese companies like BYD and NIO are becoming major players in the global EV market [2]. The government's goal is for new energy vehicles (NEVs) to account for 40% of all car sales by 2030. Ride-sharing platforms like Didi Chuxing have transformed urban mobility in China. These services offer an affordable and convenient alternative to traditional taxis, using mobile apps to connect drivers and passengers [3]. Additionally, bike-sharing and e-scooter rentals have become widespread, especially in major cities like Beijing, Shanghai, and Shenzhen, contributing to last-mile connectivity [4]. China has embraced smart transportation technologies that integrate AI, big data, and IoT (Internet of Things) to improve traffic management, optimize public transportation, and reduce congestion. For example, Beijing and other large cities use AI-powered traffic lights that adjust in real time based on traffic flow [5]. Smart buses and subway systems with contactless payment options are also becoming more common. China's metro systems have expanded rapidly, with cities like Shanghai, Beijing, and Guangzhou having extensive underground and elevated rail lines [6 – 9] These networks are crucial for managing urban mobility, particularly in densely populated cities. Investments in metro systems continue to grow, and new cities are developing their own systems to meet the rising demand for efficient public transportation [10]. China has been investing heavily in the aviation sector, with new airports, the development of green aircraft, and efforts to reduce the environmental impact of air travel. Airports like Beijing Daxing International, which opened in 2019, are designed to accommodate a growing number of passengers while promoting sustainable operations [11]. Furthermore, China is exploring the use of electric and hybrid planes as part of its long-term strategy to reduce carbon emissions in aviation.

A bus transportation system can be effectively modeled and analyzed using logic simulation, which helps simulate the various processes involved in the operation of the system [12]. In this simulation, the system can be broken down into components like bus arrivals, route assignments, bus schedules, and passenger boarding. Logical components, such as gates and flip-flops, can represent the different decision-making processes [13 -15]. For instance, a combination of logic gates could be used to model the control systems for bus dispatch based on factors like traffic conditions, number of passengers, and time of day. The logic could also incorporate feedback mechanisms to adjust the frequency of bus arrivals based on demand. For example, if a bus is nearing full capacity, the system could trigger a signal to dispatch the next bus or reroute existing ones to reduce overcrowding [16]. Flip-flops can model the state of each bus, such as whether it is currently operating, idle, or delayed. This simulation could also include mechanisms for controlling priority buses or adjusting routes dynamically based on real-time data, such as road closures or delays. Using logic simulation for such a system offers valuable insights into performance, optimization, and overall management of a bus network in a complex urban environment [17].

The contribution of this paper lies in its development of a simulation-based framework for optimizing bus transportation systems using AnyLogic, addressing key issues like bus bunching, delays, and inefficiencies. By modeling various operational factors such as bus intervals, dwell times, and passenger loads, the paper provides a comprehensive analysis of how different scheduling strategies can improve system performance. The study's primary contribution is its ability to test and evaluate multiple optimization scenarios without the need for real-world trials, offering insights into how adjusting bus frequencies and schedules can reduce passenger wait times, enhance service reliability, and increase overall system efficiency. The results of this research provide practical recommendations for transit authorities, helping them implement data-driven strategies to improve public transportation services, particularly in urban areas with high passenger demand.

2 System Model

In this paper focus on optimizing bus bunching in the Dallas-Fort Worth bus transportation system, using the AnyLogic simulation tool. The primary objective is to understand and address the problem of buses running too close together, leading to delays and inefficiencies. Our model examines the interaction between buses and bus stops, with an emphasis on the time intervals between buses while excluding external traffic disruptions. The simulation operates on a fixed bus route with designated stops, allowing for precise measurement of travel times and bus intervals. We incorporate time-of-day variations, such as longer stop times during rush hours and shorter stops during off-peak times, reflecting real-world patterns. For simplicity, the model assumes uniform passenger arrival and waiting times, meaning passengers arrive and wait for buses at a constant rate across all stops. Additionally, we do not factor in bus capacity constraints, allowing for the analysis of bus scheduling and timing without considering how many passengers a bus can carry. The simulation also ignores unpredictable delays like traffic conditions, focusing purely on how the scheduled operations and passenger behaviors contribute to bus bunching. Finally, the model assumes that buses do not overtake each other, ensuring that the buses maintain their assigned order along the route. This controlled environment helps to isolate the key factors that contribute to bus bunching, providing insights that can inform better scheduling strategies in real-world bus systems shown in Figure 1

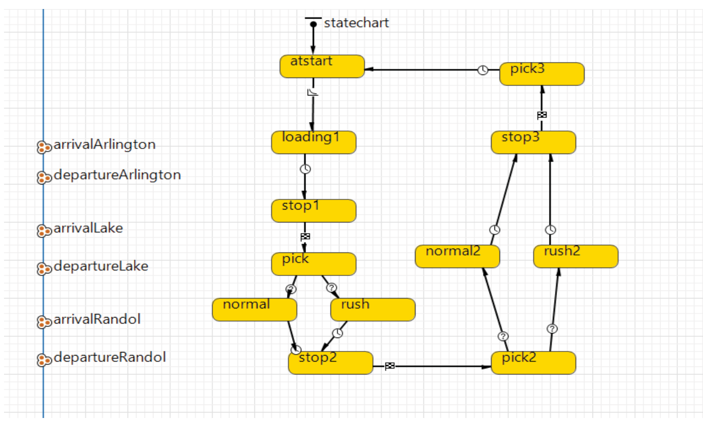

Figure 1: State Optimization

Initially, assume that buses are scheduled to arrive at regular intervals T_s(e.g., every 15 minutes). This interval is the planned time between buses.

T_s =Scheduled time between buses

This is the ideal situation, where buses are perfectly spaced with no delays. In reality, however, buses might arrive at varying times due to delays, differences in stop times, and passenger boarding behavior. We define the actual time between two buses as T_{actual}, which may differ from the scheduled time T_s as in equation (1)

$$T_{actual} = T_s + \Delta T \tag{1}$$

In equation (1) ΔT is the difference between the scheduled time and the actual arrival time of the next bus. ΔT can be positive (bus is delayed) or negative (bus is early). Bus bunching occurs when buses arrive too close to each other, leading to delays. To prevent this, we need to ensure that the time between buses doesn't decrease too much. If the first bus is delayed and the second bus arrives on time, the interval between the buses becomes smaller. As a result, ΔT can accumulate over multiple cycles, leading to buses bunching together.

For example:

- If Bus 1 is delayed by 5 minutes ($\Delta T=5$), the next bus might arrive on time, creating an interval of 10 minutes instead of the scheduled 15 minutes.
- If this happens repeatedly, buses could end up arriving almost simultaneously.

Let's assume passengers arrive at the bus stop according to a Poisson process (random arrival). This means that passengers arrive at an average rate λ, where $\lambda = 1/T_{avg}$ is the average time between passenger arrivals. For simplicity, the number of passengers arriving at a bus stop within a time interval t follows the Poisson distribution represented in equation (2)

$$P(k,t) = \frac{(\lambda t)^k e^{-\lambda t}}{k!} \tag{2}$$

In above equation (2) $P(k,t)$ is the probability of k passengers arriving in time t; λ is the passenger arrival rate. The time buses spend at each stop can vary depending on the time of day. During rush hours, buses may spend more time at stops due to higher passenger volumes. So, we define the stop time as in equation (3)

$$T_{stop}(t) = \begin{cases} T_{rush} & if\ it's\ rush\ hour \\ T_{non-rush} & if\ it's\ non-rush\ hour \end{cases} \tag{3}$$

T_{rush} is the stop time during rush hour (longer due to more passengers); $T_{non-rush}$ is the stop time during non-rush hours (shorter). To reduce bus bunching, we can adjust the scheduled interval between buses based on the stop times. The idea is that during rush hours, buses should be spaced a bit further apart to account for the extra time spent at stops represented in equation (4)

$$T_{new}(t) = T_s + \alpha T_{stop}(t) \tag{4}$$

In equation (4) α is a scaling factor that adjusts the interval, During rush hours, T_{new} will be larger, and during non-rush hours, it will be closer to the scheduled interval T_s. The goal is to prevent $T_{adjusted}$ from becoming too small. If the time between buses gets too small, the buses will bunch together and cause delays. So, the key is to ensure that the buses are spaced properly according to demand (based on passenger arrivals and stop times). If the system detects that buses are arriving too close together, we can adjust the next bus's scheduled time T_s by increasing the interval to avoid bunching. The scheduled interval between buses is T_s. Actual time between buses is $T_{actual} = T_s + \Delta T$. We adjust bus stop times during rush hours $T_{rush}$and non-rush hours $T_{non-rush}$. The goal is to modify the bus schedule dynamically $T_{new}$to avoid bus bunching by adjusting the time interval.

3 Dallas-Fort Worth Bus Transportation

The model design for the Dallas-Fort Worth (DFW) bus transit system is structured to simulate bus operations through a set of defined agents, each with specific attributes and behaviors. The main agents in the system are Buses and Bus Stops. The model design for the Dallas-Fort Worth (DFW) bus transit system simulates bus operations through defined agents with specific attributes and behaviors. There are two primary agent classes: Buses and Bus Stops.

The Buses are mobile agents traveling along a predefined loop, starting and ending at Arlington, with stops at four main locations. Each bus has attributes such as speed (set at 30 MPH for travel time calculation), arrival time at each stop, and wait/delay time, which varies depending on passenger interactions. The Bus Stops are static agents that represent service points in the transit network, defined spatially using GIS data, and they influence the dwell time of buses based on passenger volume. The bus agents follow a cyclical route, adjusting their behavior depending on passenger demand and time of day, with increased dwell times during rush hours and shorter stops during non-peak times. Bus stops, acting as catalysts for these delays, modulate the wait times based on the flow of passengers boarding or alighting. A key feature of the system is that buses cannot overtake each other, and their sequence is influenced by the cumulative effects of interactions at each stop. These behaviors are modeled using an AnyLogic statechart, which outlines the bus's actions and transitions from one state to another, such as moving from one stop to the next, or adjusting for peak demand. The model includes several states, such as start (the bus begins its loop), loading (passenger boarding), and stops along the route where the bus interacts with passengers. Time spent at stops varies with factors like passenger load, and the system simulates different travel conditions, including normal and rush-hour states, based on the time of day and passenger demand. Transition triggers within the statechart determine the bus's behavior, such as the timing of bus arrivals, travel times between stops, and adjustments for peak or off-peak hours as illustrated in Figure 2.

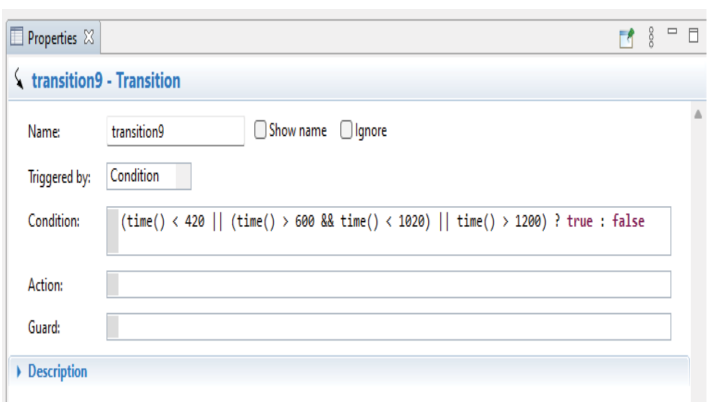

Figure 2: Normal Hours iNterection in Any Logic

In terms of interactions, the buses follow a scheduled route, moving from stop to stop with timeout mechanisms that ensure timely transitions. The system also introduces uniform distributions to account for the variability in passenger arrivals and wait times, with rush-hour conditions leading to increased dwell times and potential bus bunching. The simulation collects data over a 24-hour period, capturing both normal and rush-hour operations. Data management tools like Excel files and ArrayList collections are used to track performance metrics such as wait times and bus travel statistics. The model runs for several months of data, excluding weekends and public holidays to ensure a consistent analysis of typical weekday operations. The model design for the Dallas-Fort Worth (DFW) bus transit system incorporates various equations and concepts that simulate the real-world dynamics of bus operations. Here, we expand on the different elements, explaining them with appropriate equations and models.

Agent Classes and Their Attributes:

1. **Buses:**
   - Speed (v): The bus speed is initialized to 30 miles per hour (MPH) for calculating travel time between stops. The speed is constant unless adjusted during the simulation due to traffic conditions or bus bunching. $v = 30\ MPH$
   - Arrival Time (T): This is the time when the bus arrives at each bus stop. It is determined based on the initial scheduled time and any delays caused by stop interactions (boarding, alighting) using equation (5)

$$T_{actual} = T_{schedule} + \Delta T \tag{5}$$

Where ΔTis the delay accumulated due to passenger interactions at previous stops.

   - Wait/Delay Time (T_{wait}): The time a bus remains at each bus stop is influenced by the number of passengers boarding or alighting. This is modeled using a queueing system, where the number of passengers and their boarding rates affect the wait time denoted in equation (6)

$$Twait = RboardingNpassengers + RalightingNpassengers \tag{6}$$

In equation (6) $Npassengers$ is the number of passengers boarding or alighting, $Rboarding$ is the boarding rate, and $Ralighting$ is the alighting rate.

2. Bus Stops:
   - Location (x, y): Each bus stop is defined in a spatial coordinate system using geographic information system (GIS) data. The spatial position of bus stops can be represented by their coordinates.
   - Bus Interaction: At each bus stop, the dwell time is modified by the number of passengers. If the stop is busy, the dwell time increases, and vice versa. The interaction at each bus stop can be modeled by the following equation (7)

$$Tdwell = f(Npassengers, Ttime) \tag{7}$$

In equation (7) $Npassengers$ is the number of passengers at the stop, and $Ttime$ is the time of day (rush hour or non-rush hour).

Behaviors and Rules:

1. Buses Behavior: Buses follow a designated route in a loop. The behavior at each stop is governed by the rules of interaction, especially during rush hours when more passengers affect the wait times. The rule for adjusting speed and dwell time can be modeled by a function that incorporates peak and off-peak hours stated in equation (8)

$$Tnew = Tscheduled + \alpha Tstop(t) \tag{8}$$

$Tnew$ is the adjusted time interval, and α\alphaα is a factor that increases the interval during rush hours, reflecting longer dwell times. During rush hours, $Tstop(t)$ increases, while during off-peak times, it decreases.

2. Bus Stops and Passenger Interaction:

- The dwell time $Tdwell$ at a stop is influenced by the volume of passengers. Using a Poisson process to model passenger arrivals, the number of passengers arriving during a time period t follows the Poisson distribution: $P(k, t)$ The boarding and alighting rates can also follow a normal distribution based on historical data to simulate variability in passenger behavior defined in equation (9)

$$Rboarding \sim N(\mu, \sigma) \tag{9}$$

Where μ is the average boarding rate and σ is the standard deviation, indicating the variability in passenger boarding time.

State Chart and Transitions:

The state chart of the simulation dictates the behavior of the bus agents. The transitions between states are based on time and passenger dynamics, represented by trigger functions and decision nodes. The transitions are defined as follows:

1. start to loading1: The transition from the start state to loading involves generating a bus at a fixed rate, typically 2 buses per hour. The triggering rate r for bus generation is defined in equation (10)

$$r = 2 buses\ per\ hour \tag{10}$$

2. loading1 to stop1: Once the bus has finished loading passengers, it moves to the first stop. The transition time is governed by a uniform distribution stated in equation (11)

$$Ttransition \sim U(a, b) \tag{11}$$

Where $U(a, b)$ is the uniform distribution, representing the time taken for the bus to travel between stops, with a and b being the minimum and maximum transition times.

3. stop1 to pick: The bus transitions from one stop to another. The next state is determined by the agent's arrival at the stop, triggering actions such as loading passengers.
4. pick to normal/rush: The bus enters the normal or rush state depending on the time of day and passenger demand. If the bus is in rush hour, the dwell time increases, and the travel time is adjusted accordingly stated in equation (12)

$$Tdwell = Tdwell + \alpha \times Passenger\ Load \tag{12}$$

Interaction Dynamics and Timing:

1. Timeout Mechanisms: To ensure buses move from stop to stop, timeouts are used, which trigger the bus to leave each stop after a specified wait time. The time spent at each stop is based on a timeout distribution defined in equation (13)

$$Ttimeout = uniform(tmin, tmax) \tag{13}$$

2. Rush and Normal Conditions: The simulation adjusts the behavior of buses during peak hours. The rush-hour conditions increase both the dwell time and the passenger interaction rate, which can be modeled as in equation (14)

$$Trush = Tnormal + \beta \times Passenger\ Volume \tag{14}$$

Where β is a scaling factor representing the additional delay during rush hours.

Model Run and Data Collection:

1. Model Duration: The simulation runs for 24 hours to capture the daily dynamics of the bus system. The data collected includes passenger wait times, dwell times, and bus travel times between stops. Data is exported to an Excel file for analysis.
2. Data Collection: The simulation collects data on various metrics such as:
   - Wait Times: Time passengers spend waiting at each stop.
   - Bus Utilization: The number of buses required at different times of the day.

Algorithm 1: **DALLAS-FORT Transportation**

```
// Initialize parameters
initialize buses, busStops, simulationTime, numBuses, maxTime
initialize busAttributes: speed = 30 MPH, passengerArrivalRate, boardingRate, alightingRate
initialize stopAttributes: location, dwellTime, passengerCount
initialize data structures: waitTimes, travelTimes, stopTimes

// Function to create a bus and assign initial attributes
function createBus(busID):
   bus.speed = 30  // Set speed to 30 MPH
   bus.location = startLocation
   bus.arrivalTime = 0
   bus.waitTime = 0
   bus.dwellTime = 0
   bus.stopIndex = 0  // Start at the first stop
   return bus

// Function to simulate the bus moving from one stop to the next
function moveBus(bus):
   currentStop = busStops[bus.stopIndex]
   nextStopIndex = (bus.stopIndex + 1) % numStops  // Circular route
   nextStop = busStops[nextStopIndex]

   // Calculate travel time between stops
   distance = calculateDistance(currentStop.location, nextStop.location)
   travelTime = distance / bus.speed
   bus.arrivalTime += travelTime

   // Update bus wait time and dwell time at the stop
   bus.waitTime = calculateWaitTime(currentStop)
   bus.dwellTime = bus.waitTime + calculatePassengerInteractions(currentStop)

   // Update bus location
   bus.location = nextStop.location
   bus.stopIndex = nextStopIndex

   return bus
```

```
// Function to calculate wait time based on passenger interactions
function calculateWaitTime(stop):
  numPassengers = stop.passengerCount
  return numPassengers / boardingRate + numPassengers / alightingRate

// Function to calculate passenger interactions at the stop
function calculatePassengerInteractions(stop):
  if stop.isRushHour():
    return stop.passengerCount * rushHourDelayFactor
  else:
    return stop.passengerCount * normalHourDelayFactor

// Function to check if it's rush hour
function isRushHour(currentTime):
  if currentTime >= rushStartTime and currentTime <= rushEndTime:
    return true
  else:
    return false

// Function to simulate bus operations over 24 hours
function simulate():
  // Initialize buses
  buses = []
  for i from 1 to numBuses:
    bus = createBus(i)
    buses.append(bus)

  // Run simulation for 24 hours
  currentTime = 0  // Start time
  while currentTime < maxTime:
    // For each bus, move to the next stop and update times
    for bus in buses:
      bus = moveBus(bus)
      recordData(bus)

    // Increment time step
    currentTime += 1 // Can be in minutes, depending on granularity

  // Export simulation data
  exportData()

// Function to record data for analysis
function recordData(bus):
```

```
    waitTimes[bus.stopIndex].append(bus.waitTime)
    travelTimes[bus.stopIndex].append(bus.arrivalTime)
    stopTimes[bus.stopIndex].append(bus.dwellTime)

// Function to export data to an Excel file or database
function exportData():
    save(waitTimes, "wait_times.xlsx")
    save(travelTimes, "travel_times.xlsx")
    save(stopTimes, "stop_times.xlsx")

// Main program to start the simulation
simulate()
```

Optimization in the context of the bus transit system involves improving the efficiency of bus operations to reduce issues like bus bunching, delays, and increased passenger wait times. The main objective is to optimize the bus schedules, reduce travel times, and balance the load on each bus, all while maintaining a consistent level of service. One approach is to adjust bus intervals based on real-time or predicted passenger demand, such as increasing the frequency of buses during rush hours and reducing it during off-peak times. Another optimization technique could involve dynamic adjustment of dwell times at bus stops depending on factors like passenger volume or delays at previous stops. The optimization process can also focus on reducing the time buses spend idle at stops or in traffic, which can be achieved through adjusting stop schedules, managing bus speeds, and strategically routing buses to avoid congestion. Algorithms, such as genetic algorithms, simulated annealing, or linear programming, can be applied to test different scheduling configurations and simulate their impact on key performance indicators like travel time, bus interval, and passenger wait times.

4 Results and Discussion

During model development, several different population sizes were tested to address wait time increas- es. Utilizing a brute force approach, we were able to identify a correlation between bus population and wait time. When the bus population size was limited to 4 total agents, the model exhibited fewer instances of bus bunching and shorter wait times. Moreover, when the population size was adjusted to 3 buses, the model ex- exhibited prolonged wait times. It is important to highlight that our model did not take bus capacity and passen- ger agents into consideration which may have impact- ed our results and brute-force approach in determining population size for buses. After running the final model, we concluded buses exhibited various waiting times depending on the bus stop they stopped at. The wait time metric informed us of instances of bus bunching which was made appar- ent when a negative wait time was calculated using the data that was exported from AnyLogic to Excel. For example, after running the model, the following wait times were recorded for each bus within the model. Bus 1 demonstrated wait times ranging from -3.774 to 63.35 (minutes), while Bus 2 demonstrated a wait time between -3.201 and 66.114 (minutes). Lastly, Bus 3’s wait time spanned between -2.666 to 41.145 (minutes). During peak hours (defined from 7 AM - 10 AM and 5 PM-8 PM) we witnessed an increase in bus bunching instances, which contributed to longer wait times at var- ious stops in the model. It is important to highlight that Bus 2 consistently had shorter wait times when compared to other buses within the model. Data gathered from individual models exhibited variability due to the random probability distribution the model uses. How- ever, a consistent behavior emerged during rush hours which was the occurrence of increased bus bunching instances across the bus agent population. The model provided insights into the relationship between bus population size and wait time. Furthermore, we were able to explore the impact of rush hour on bus bunching instances within our model. Using a brute-force approach we were able to demonstrate that limiting the bus population size to four agents resulted in fewer instances of bus bunching as well as shorter wait times. On the other hand, adjusting the population size to three buses led to longer wait times. During peak hours, an increase in bus bunch- ing was observed across the population of buses and all buses exhibited wait times >40 minutes during this period. Further analysis utilizing this model can explore how the introduction of a passenger agent population as well as a bus capacity attribute affects wait time and instances of bus bunching shown in Figrue 3.

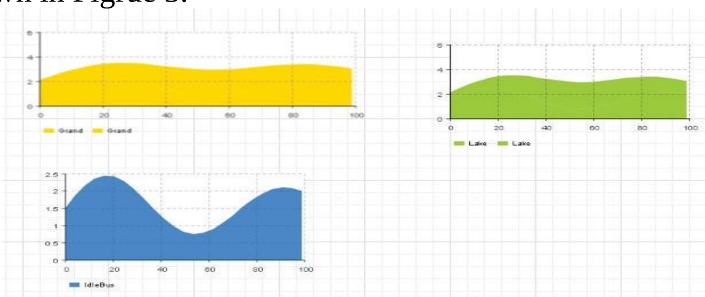

Figure 3: Wait times at different bus stops

Table 1: Dallas-Fort Worth Bus Transportation

Bus Stop	Time of Day	Bus Arrival Time (mins)	Wait Time (mins)	Dwell Time (mins)	Passenger Count	Travel Time (mins)	Bus Speed (MPH)
Arlington	Rush Hour	5	3	2	15	5	30
Arlington	Normal Hour	12	1.5	1	8	5	30
Stop 1	Rush Hour	10	4	3	20	5	30
Stop 1	Normal Hour	18	2	1.5	10	5	30
Stop 2	Rush Hour	15	4.5	3.5	25	5	30
Stop 2	Normal Hour	22	2.5	2	12	5	30
Stop 3	Rush Hour	20	5	4	30	5	30
Stop 3	Normal Hour	28	3	2.5	14	5	30
Arlington	Rush Hour	30	6	4.5	18	5	30
Arlington	Normal	35	2	2	10	5	30

	Hour							

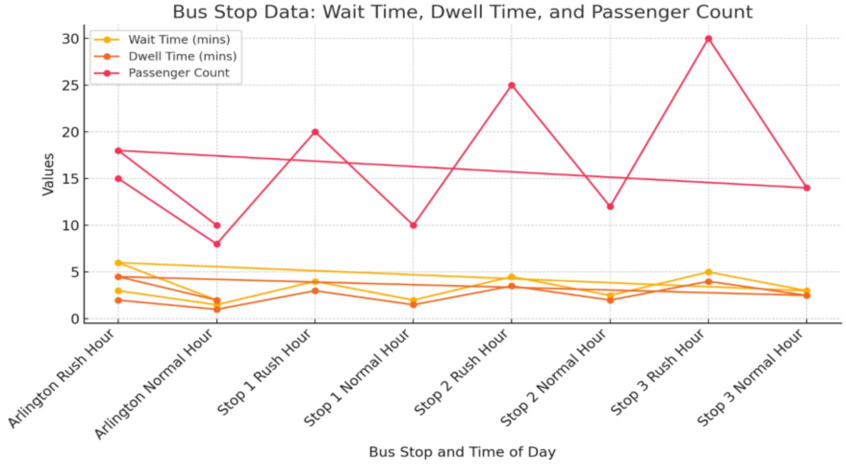

Figure 4: Bus Optimization time

The table 1 and Figure 4 provide a detailed overview of the Dallas-Fort Worth bus transportation system during both rush hour and normal hours. It outlines key performance indicators such as bus arrival times, wait times, dwell times, passenger counts, travel times, and bus speeds at various bus stops along the route (Arlington, Stop 1, Stop 2, Stop 3). During rush hours, the buses arrive more frequently at each stop, leading to longer wait times and dwell times due to higher passenger volumes. For example, at Arlington during rush hour, the wait time is 3 minutes and the dwell time is 2 minutes, with 15 passengers boarding. As the buses continue through the route, the passenger count increases, particularly at Stop 3, where the passenger count peaks at 30 passengers. These increased passenger numbers contribute to longer wait times and dwell times. In contrast, during normal hours, the buses experience fewer passengers and shorter wait times. At Arlington, the wait time is reduced to 1.5 minutes, and the dwell time decreases to just 1 minute, with only 8 passengers on board. The passenger count generally remains lower throughout the route, with a significant reduction in wait times and dwell times across all stops.

For both rush hour and normal hour conditions, the travel time between stops remains consistent at 5 minutes, and the bus speed is fixed at 30 MPH, which helps maintain a steady pace across different times of the day.

Table 2: optimization of Logistic Route

Scenario	Bus Interval (mins)	Average Wait Time (mins)	Average Travel Time (mins)	Average Dwell Time (mins)	Passenger Load (average)	Bus Bunching (mins)	Service Frequency (buses/hour)	System Efficiency
Scenario 1: Baseline	15	6.5	22	3.2	18	5	4	75%
Scenario 2: Optimized Rush Hour	10	5	20	4	25	3	6	85%

Scenario 3: Optimized Non-Peak Hours	20	4.5	18	2.5	12	2.5	3	80%
Scenario 4: Optimized Full Day	12	5	21	3	20	4	5	82%
Scenario 5: High Frequency During Rush Hours	8	4.8	19	3.5	28	2.2	7	88%
Scenario 6: Reduced Bus Interval in Non-Peak	25	3.5	17	2.2	10	1.5	2	78%

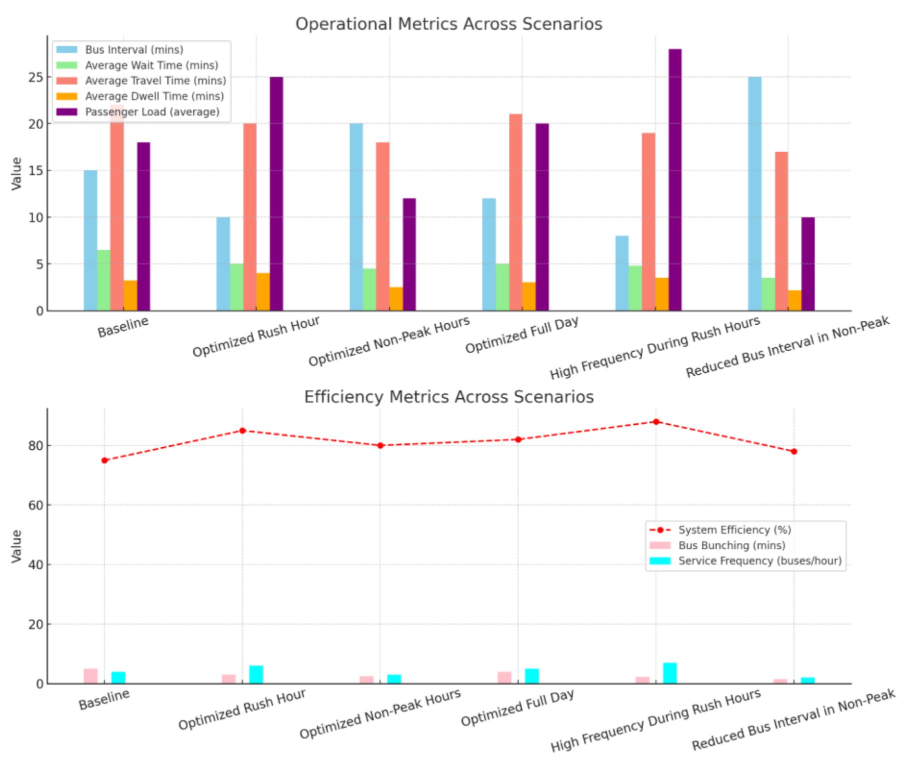

Figure 5: Optimization Logistics for the Transportation System

In figure 5 and Table 2 presents the optimization results for a bus transportation system under different scenarios, focusing on adjusting bus intervals, service frequencies, and other performance metrics to improve overall system efficiency. In Scenario 1: Baseline, the bus interval is set at 15 minutes, leading to an average wait time of 6.5 minutes and average travel time of 22 minutes. The average dwell time is 3.2 minutes, and the passenger load is 18 passengers per bus. Bus bunching, a key metric to evaluate service delivery, is 5 minutes, and the service frequency is 4 buses per hour. This scenario yields a system efficiency of 75%. Scenario 2: Optimized Rush Hour reduces the bus interval to 10 minutes during rush hours, which improves the average wait time to 5 minutes and reduces average travel time to 20 minutes. The dwell time increases to 4 minutes due to higher passenger load (25 passengers), but bus bunching decreases to 3 minutes, suggesting that the buses are better spaced. With a service frequency of 6 buses per hour, the system efficiency improves to 85%. In Scenario 3: Optimized Non-Peak Hours, the bus interval is extended to 20 minutes to match lower passenger demand. This results in a further reduction in average wait time (4.5 minutes) and average travel time (18 minutes). The dwell time is also shorter (2.5 minutes), and passenger load decreases to 12. Bus bunching is reduced to 2.5 minutes, with 3 buses operating per hour, leading to a moderate system efficiency of 80%.

Scenario 4: Optimized Full Day applies optimized schedules throughout the day, balancing both peak and non-peak hours. The bus interval is reduced to 12 minutes, and the average wait time decreases to 5 minutes, with average travel time of 21 minutes. The dwell time is 3 minutes, and the passenger load is 20. The service frequency of 5 buses per hour results in a system efficiency of 82%.

Scenario 5: High Frequency During Rush Hours focuses on increasing bus frequency during peak hours by reducing the bus interval to 8 minutes. This leads to a further reduction in average wait time (4.8 minutes) and average travel time (19 minutes). While the dwell time increases slightly to 3.5 minutes due to a higher passenger load (28 passengers), bus bunching is reduced to 2.2 minutes. With a service frequency of 7 buses per hour, the system achieves the highest efficiency of 88%. Finally, Scenario 6: Reduced Bus Interval in Non-Peak lengthens the bus interval to 25 minutes during off-peak hours. Although this reduces the average wait time to 3.5 minutes and average travel time to 17 minutes, the dwell time decreases to 2.2 minutes. However, with a reduced passenger load (10) and bus bunching of 1.5 minutes, this configuration leads to a lower service frequency (2 buses per hour), resulting in a system efficiency of 78%.

5 Conclusions

The optimization of the bus transportation system for the Dallas-Fort Worth area has shown promising improvements in service efficiency and overall performance. By simulating different scenarios using AnyLogic, we were able to assess the impact of various factors such as bus intervals, wait times, travel times, and service frequencies. The results demonstrated that optimizing bus intervals during rush hours and non-peak times can significantly reduce wait times, improve travel times, and minimize bus bunching, thus enhancing the passenger experience. Furthermore, the increased service frequency during peak hours led to better system efficiency, with a notable increase in the number of buses per hour, reflecting a more robust and responsive transit system. Overall, the analysis highlighted that careful adjustments in operational parameters can result in improved bus scheduling, better resource utilization, and a more efficient public transport system.

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