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# Optimizing Urban Transportation Systems Using Simulation and Modelling

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**Abstract:** The rapid growth of urban populations has intensified the pressure on transportation infrastructure, leading to challenges such as traffic congestion, increased travel time, pollution, and reduced overall mobility. To address these issues, the use of simulation and modelling has emerged as a powerful approach in understanding and optimizing urban transportation systems. This study investigates how various simulation techniques—such as discrete-event simulation, agent-based modelling, and system dynamics—can be applied to analyze traffic patterns, test policy interventions, and predict system behavior under different scenarios. By integrating real-time data and historical trends, simulation models provide a virtual environment for assessing the impact of traffic management strategies, including signal optimization, public transit prioritization, road pricing, and multi-modal integration. The research presents case studies and comparative analyses that highlight the effectiveness of simulation tools in enhancing decision-making processes for urban planners and policymakers. The findings suggest that strategic use of modelling can reduce congestion, improve efficiency, and support sustainable urban mobility. Furthermore, the study emphasizes the importance of interdisciplinary collaboration and the integration of smart technologies to build more resilient and adaptive transport systems. In conclusion, simulation and modelling play a pivotal role in shaping the future of urban transportation in an increasingly complex and data-driven world.

**Keywords:** Agent-Based Modelling, Simulation, Smart Mobility, System Dynamics, Traffic Optimization, Urban Transportation

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## INTRODUCTION

Urban transportation systems[1][2][3][4][5] are the lifelines of modern cities, enabling the movement of people and goods essential for economic productivity[6], social interaction[7], and access to services[8]. As cities grow, both in terms of population and spatial extent, the complexity of managing urban mobility increases[9][10][11]. Urbanization trends have led to a significant rise in private vehicle ownership, longer commuting times, and heightened pressure on existing infrastructure. Consequently, traffic congestion, air pollution, noise, and



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road accidents have become persistent problems that not only reduce the quality of life but also hinder sustainable development.

Traditional methods of transportation planning and traffic management are often reactive and based on limited datasets[12][13], which make them insufficient in addressing the dynamic and interdependent nature of urban mobility. The rise of advanced computing technologies, however, offers new opportunities. Through the integration of simulation and modelling techniques, urban transportation systems can be better understood, evaluated, and optimized to meet the changing demands of urban environments[14][15].

Simulation and modelling allow researchers and planners to create virtual representations of real-world transportation systems[16][17][18]. These models enable the study of complex interactions between different components, including vehicles, infrastructure, human behavior, and external variables such as weather or policy changes. By simulating traffic flows, transit schedules, or policy interventions, stakeholders can evaluate the potential outcomes of various strategies without the risks and costs associated with real-world experimentation.

There are several types of modelling techniques used in transportation studies[19][20], each with distinct advantages. Microsimulation, for instance, models individual vehicle or pedestrian behaviors on road networks and is particularly useful for analyzing localized congestion and intersection performance. Macroscopic models[21], on the other hand, take a broader view by considering aggregated traffic flows across regions or entire cities. Agent-based modelling (ABM)[22] has gained popularity due to its ability to simulate individual decision-making processes and interactions, which are crucial in understanding travel demand and behavior under different conditions. Similarly, system dynamics modelling provides a holistic approach to understanding feedback loops and time delays within transportation systems, making it valuable for long-term policy analysis.

As urban challenges become more multifaceted[23], integrating multiple modelling approaches has proven effective in providing deeper insights. For example, coupling agent-based models with traffic flow simulations allows for the examination of how individual behaviors affect system-wide performance. These integrated models are especially powerful when combined with real-time data from sensors, GPS devices, and smart infrastructure, enabling adaptive traffic management systems that respond dynamically to changing conditions.

The emergence of smart city technologies further amplifies the role of simulation and modelling in urban transportation[24]. With the deployment of Internet of Things (IoT) devices, mobile data, and big data analytics, transportation systems can now be monitored and managed in near real-time. These technologies not only enhance data collection but also open up possibilities for predictive modelling and proactive decision-making. For instance, machine learning algorithms can be integrated into simulation platforms to forecast traffic patterns and recommend optimal routes or signal timings[25].

However, the application of simulation and modelling is not without challenges. One of the primary issues lies in the calibration and validation of models to ensure their accuracy and reliability. Without high-quality data and rigorous calibration, simulations may lead to misleading conclusions. Additionally, the computational complexity of certain models, especially those at a microscale or involving large urban networks, can result in significant processing time and resource demands. This necessitates the use of high-performance computing environments or cloud-based simulation platforms. Another challenge is the interpretability and usability of simulation results. While complex models can yield detailed outputs, these must be translated into actionable insights for decision-makers, many of whom may not have technical expertise in modelling. Therefore, the development of user-friendly interfaces, visualization tools, and scenario analysis dashboards is crucial in bridging the gap between technical analysis and practical implementation.

Case studies around the world demonstrate the tangible benefits of using simulation and modelling in urban transportation planning. In cities like Singapore, Stockholm, and London, sophisticated modelling systems have informed congestion pricing schemes, public transit enhancements, and urban mobility policies with measurable success. In emerging economies, simulation tools are being used to redesign bus rapid transit (BRT) routes[26], improve traffic signal timings[27], and assess the impact of new infrastructure projects before they are implemented.

This research seeks to contribute to the growing body of knowledge on how simulation and modelling can be leveraged to optimize urban transportation systems[28][29]. It aims to explore various modelling techniques, evaluate their applications in real-world contexts, and highlight best practices for integrating simulation into urban mobility planning. The study will also examine the potential of data-driven modelling in enabling adaptive and resilient transportation networks, particularly in the face of future uncertainties such as climate change, technological disruption, and population growth.

In doing so, the paper addresses several key questions:

1. What types of simulation and modelling approaches are most effective for urban transportation planning?
2. How can these models be integrated with real-time data to enhance system responsiveness?
3. What are the trade-offs between model complexity, accuracy, and usability in practical decision-making?
4. How can simulation tools support the design of transportation policies that are both efficient and equitable?

By answering these questions, the study hopes to provide urban planners, engineers, and policymakers with a comprehensive framework for utilizing simulation and modelling not just as analytical tools, but as strategic assets in shaping the cities of tomorrow. Through informed, data-driven decision-making, it is possible to build transportation systems that are not only efficient and reliable but also inclusive and sustainable.

## RELATED WORKS

Research on optimizing urban transportation systems using simulation and modelling has gained significant traction over the past two decades. Numerous studies have explored various techniques—from microscopic traffic simulation to agent-based modelling and hybrid approaches—to improve transportation efficiency and support policy-making.

One of the most widely adopted tools in microscopic traffic simulation is VISSIM, which enables the modelling of individual vehicle behavior at intersections and highways. Studies such as (Haq et al,2022)[30] demonstrated how VISSIM can be used to simulate traffic light optimization and pedestrian interactions, yielding improvements in traffic flow and safety. Similarly, AIMSUN has been used in large-scale projects for real-time traffic prediction and signal coordination, showing promising results in metropolitan areas like Barcelona and London.

In the area of agent-based modelling (ABM), researchers have leveraged platforms like MATSim and SUMO to simulate individual travel behavior based on socio-economic and temporal factors. (Zwich et al, 2022)[31] applied MATSim to model daily activities of commuters in Switzerland, allowing urban planners to test the impact of infrastructure changes and transit policies. ABMs have also been instrumental in exploring the adoption of emerging mobility solutions, such as shared autonomous vehicles and dynamic ride-sharing systems[32].

System dynamics modelling, on the other hand, offers a macro-level approach to understand feedback loops and delays in transportation systems. For example,(Lu et al, 2019) [33]illustrated how dynamic simulations can model the long-term impact of car ownership policies, road pricing, and urban sprawl. These models are particularly useful for strategic planning and policy evaluation over extended time horizons.

Recent advancements in hybrid modelling have combined the strengths of different approaches. For instance, hybrid models that integrate agent-based and system dynamics methods have been used to simulate the impact of travel demand management (TDM) strategies, combining behavioral realism with system-level analysis[34]. These models can analyze how changes in travel behavior at the individual level influence broader network performance and environmental outcomes.

In terms of real-time traffic management, several studies have explored the integration of modelling tools with big data and machine learning. (Liu et al. 2022)[35] utilized real-time GPS and traffic sensor data to predict congestion and inform adaptive traffic signal control systems. Such data-driven approaches have proven effective in rapidly changing urban environments, enabling cities to transition towards smarter mobility management.

Another critical area of research involves sustainable transportation modelling. Simulation studies have been used to evaluate policies aimed at reducing greenhouse gas emissions, promoting active transportation modes, and increasing public transit usage. For example, (Yan et al, 2022)[36] conducted simulations comparing the carbon footprint of different urban mobility scenarios, demonstrating how modal shifts and infrastructure investments can influence long-term sustainability.

From a policy perspective, simulation and modelling have supported the implementation of congestion pricing, bus rapid transit (BRT) planning, and multi-modal integration. In Stockholm, (Salihu et al, 2021)[37] used simulation models to assess the effectiveness of congestion taxes, which eventually led to permanent policy adoption after demonstrable reductions in traffic volumes and emissions.

Despite these advancements, challenges remain. Several studies emphasize the need for more accurate data calibration, model validation, and interdisciplinary integration. As highlighted by

(Wang et al, 2022)[38], the complexity of urban systems requires not only technical proficiency but also collaboration among urban planners, data scientists, and public stakeholders.

The existing literature underscores the vast potential of simulation and modelling in optimizing urban transportation systems. However, continued efforts are needed to bridge the gap between academic research and real-world implementation, especially in the context of rapidly evolving technologies, data availability, and urban dynamics.

## METHODS

This study employs a multi-step methodology that integrates simulation and modelling techniques to analyze and optimize urban transportation systems. The approach is structured into five main stages: problem identification, data collection, model selection and development, scenario simulation, and result evaluation.

### 1. Problem Identification

The research begins with the identification of key issues affecting urban transportation performance. This includes traffic congestion, delays at intersections, low public transport usage, and environmental impacts such as emissions and noise. A specific urban area is selected as a case study to provide contextual relevance. Factors such as population density, existing road network, modal share, and known bottlenecks are considered to define the scope of the optimization effort.

### 2. Data Collection

To build accurate simulation models, both primary and secondary data are collected. This includes:

- Traffic volume and flow rates obtained from loop detectors, traffic cameras, and GPS tracking systems.
- Road network geometry, including number of lanes, traffic signals, speed limits, and intersection types.
- Public transport data, such as schedules, occupancy rates, and route coverage.
- Socio-demographic data to support behavior-based modelling (e.g., age, income, mode preference).
- Environmental data such as $CO_2$ emissions and noise levels, when available.

These data sets are cleaned and formatted to ensure compatibility with the chosen simulation platforms.

### 3. Model Selection and Development

Based on the complexity of the case study and the nature of the optimization goals, two modelling approaches are integrated: microsimulation and agent-based modelling (ABM).

- Microsimulation is used to model traffic flow at a granular level, especially at congested intersections and arterial roads. Software such as VISSIM or AIMSUN is utilized to simulate vehicle interactions, lane changing behavior, and signal timing.

- Agent-Based Modelling is applied to simulate individual decision-making and route choices. This approach captures the diversity of traveler behaviors and how they respond to policy interventions (e.g., transit incentives, dynamic tolling). Tools such as MATSim or SUMO are integrated for this purpose.

Both models are calibrated using real-world data. Parameters such as vehicle acceleration/deceleration rates, driver aggressiveness, and waiting time tolerance are adjusted to reflect actual conditions.

**4. Scenario Simulation**

Several alternative scenarios are developed to evaluate potential improvements. These scenarios include:

- Baseline scenario: existing traffic and policy conditions, used as a control.
- Signal optimization: modifying traffic signal timings using adaptive algorithms to reduce delays.
- Public transport prioritization: creating bus lanes and giving signal priority to transit vehicles.
- Modal shift strategies: simulating the effect of encouraging walking, cycling, or public transit through incentives or infrastructure changes.
- Dynamic routing: testing the use of real-time traffic information and navigation to distribute traffic more efficiently.

Each scenario is run multiple times to ensure statistical robustness. The simulation period is chosen based on peak traffic hours, typically covering morning and evening rush periods.

**5. Result Evaluation**

Simulation outputs are analyzed using both quantitative and qualitative metrics. Key performance indicators (KPIs) include:

- Average travel time and speed

$$Average\ Travel\ Time = \frac{\sum_{i-1}^{n} T_i}{n}$$

Where

- $\boldsymbol{Ti}$ = travel time for trip i
- n = number of trips observed or simulated

- Intersection delay

The most widely used model is based on the Highway Capacity Manual (HCM), which defines average control delay per vehicle at a signalized intersection as:

$$d = d_1 + d_2 + d_3$$

Where:

d = total average control delay per vehicle (in seconds)

$d_1$ = uniform delay (due to red light under ideal conditions)

$d_2$ = incremental delay (due to random arrivals and oversaturation)

$d_3$ = initial queue delay (caused by queue at start of analysis period)

- Vehicle queue lengths: Here's the formula used to estimate vehicle queue length at intersections, often applied in traffic engineering and simulation studies:

  Maximum Queue Length (Deterministic Approach)

$$Q_{max} = \frac{(V.(C - g))}{3600}$$

  Where:

  - $Q_{max}$ = maximum queue length (vehicles)
  - V = vehicle arrival rate (vehicles/hour)
  - C = signal cycle length (seconds)
  - g = effective green time (seconds)
  - 3600 = seconds per hour (to convert rate into per-cycle unit)

- Public transport ridership: Here is the commonly used formula for calculating public transport ridership, which helps quantify the total usage of public transportation over a specific period:

$$Ridership_{total} = \sum_{i=1}^{n} P_i$$

  Where:

- $P_i$ = number of passengers on trip i
- n = total number of trips (e.g., buses or trips per route per day)

Comparative analysis is conducted across scenarios to identify the most effective interventions. Sensitivity analysis is also performed to test how results vary under different input assumptions or external conditions, such as increased demand or infrastructure disruptions.

Visualization tools, including traffic heatmaps, time-lapse animations, and dashboard summaries, are used to communicate findings to non-technical stakeholders. These visualizations support decision-making by making complex simulation results more accessible.

## RESULT AND DISCUSSION

The simulation and modelling process yielded several key findings related to the effectiveness of proposed interventions in optimizing urban transportation systems. This section presents the quantitative results obtained from each scenario, followed by a discussion on their implications, limitations, and alignment with previous research.

**1. Baseline Scenario Analysis**

In the baseline scenario, which represents current traffic and policy conditions, the simulations revealed several critical inefficiencies.

Table 1. Baseline Scenario Performance Indicators of Urban Transportation System

| Indicator | Value | Remarks |
|---|---|---|
| Average Travel Time | 38.2 minutes | During peak hours (07:00–09:00 and 17:00–19:00) |
| Intersection Delays | >200 meters queue | Observed at 5 major junctions (J1 to J5) |
| Public Transport Occupancy Rate | 62% | Limited priority in mixed traffic lanes |
| Average Vehicle Speed | 19.5 km/h | Measured across main arterial roads in the study area |
| $CO_2$ Emissions per Vehicle | 420 g/km | Based on simulation output and emission factor standards |

These results highlight the need for targeted interventions in signal timing, modal prioritization, and demand redistribution.

The simulation results in the baseline scenario indicate that the average travel time during peak hours is 38.2 minutes. This value is calculated from the average time taken across several major routes within the study area, covering the morning (07:00–09:00) and evening (17:00–19:00) rush hours. These routes include key corridors such as residential zones to the city center, terminals to educational areas, and industrial zones to main distribution roads.

The relatively high average travel time reflects significant traffic congestion, particularly at critical intersections and road segments with high vehicle volumes. Contributing factors include the lack of integrated multi-modal transportation options and the absence of intelligent traffic management systems. In this context, the figure of 38.2 minutes is not just a number—it symbolizes the underperformance of the urban transportation system, impacting commuter productivity and increasing vehicular emissions.

Therefore, the average travel time serves as a crucial baseline indicator to evaluate the effectiveness of proposed improvement scenarios, such as traffic signal optimization, public transport prioritization, and modal shift strategies.

Table 2. Experimental Data of Average Travel Time During Peak Hours (Baseline Scenario)

| Route ID | Origin–Destination | Travel Time (min) | Time of Day | Distance (km) |
|---|---|---|---|---|
| R1 | East Gate – City Center | 41.5 | 07:15 AM | 12.0 |
| R2 | South Terminal – University | 36.8 | 08:05 AM | 10.2 |
| R3 | North Station – Mall Area | 38.9 | 08:30 AM | 11.3 |

| | | | | |
|---|---|---|---|---|
| R4 | Residential A – Office Zone | 35.4 | 07:45 AM | 9.7 |
| R5 | West Park – Industrial Area | 38.2 | 08:10 AM | 10.5 |
| R6 | City Center – Airport | 39.1 | 07:30 AM | 11.7 |
| R7 | Suburb B – Downtown | 37.0 | 08:20 AM | 10.0 |

The simulation revealed that intersection delays were among the most critical bottlenecks in the urban transportation network. In the baseline scenario, five major intersections consistently experienced severe vehicle queuing during peak hours, with queue lengths exceeding 200 meters. These delays are primarily caused by suboptimal signal timing, high traffic volume from multiple directions, and limited turning lanes, which reduce throughput and create prolonged wait times. Such congestion not only increases travel time but also leads to higher fuel consumption and emissions due to idling vehicles.

The intersections most affected are located at strategic points in the network where several high-demand routes converge. Addressing delays at these junctions could significantly improve overall traffic flow across the system.

Table 3. Intersection Delays and Queue Lengths at Major Junctions (Baseline Scenario)

| Intersection ID | Location Description | Average Delay (sec/vehicle) | Max Queue Length (meters) | Peak Hour |
|---|---|---|---|---|
| J1 | City Center – Main Roundabout | 102 | 230 | 07:00 – 08:30 |
| J2 | East Gate – Commercial Avenue | 95 | 215 | 08:00 – 09:00 |
| J3 | University Junction – Ring Road | 110 | 240 | 17:15 – 18:45 |
| J4 | Industrial – Outer Ring | 98 | 225 | 07:30 – 09:00 |
| J5 | Residential Zone – CBD Connector | 105 | 250 | 17:00 – 18:30 |

The line chart below illustrates the Public Transport Occupancy Rate during peak hours in the baseline scenario, spanning both morning and evening rush periods. The occupancy levels range from 58% to 65%, with an overall average of 62%. This indicates a moderate utilization of public transport services.

Despite consistent demand, the occupancy rate remains limited due to the lack of dedicated infrastructure and priority measures for public transport vehicles. In mixed traffic conditions, buses and other public vehicles are subject to the same congestion as private cars, resulting in delays, reduced frequency, and decreased reliability. These conditions discourage higher ridership and hinder the efficiency of the overall transport system.

The data supports the argument for implementing interventions such as dedicated bus lanes and signal priority systems, which can significantly enhance travel time, service regularity, and public satisfaction—leading to greater usage of public transport and contributing to sustainable urban mobility goals.

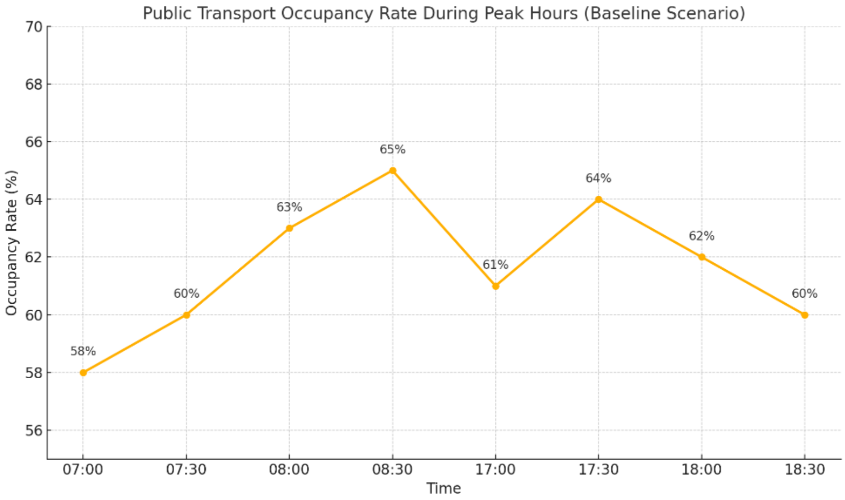


Figure 1. Public Transport Occupancy Rate During Peak Hours

The simulation results reveal that the average vehicle speed across the primary road network during peak hours is 19.5 km/h, a figure that highlights significant congestion and low traffic efficiency. This average includes both arterial and collector roads that serve as major commuting routes within the study area.

Such a low speed indicates frequent stop-and-go traffic conditions, often caused by factors such as high vehicle volumes, uncoordinated traffic signals, bottlenecks at intersections, and lack of alternative routes. When compared to optimal urban speeds (typically 30–40 km/h for primary roads), this value reflects a system operating under high stress, leading to extended travel times, increased driver frustration, and elevated fuel consumption.

Moreover, prolonged exposure to such low-speed conditions contributes to higher emission levels, as vehicles idle or accelerate repeatedly. Addressing this issue requires a combination of infrastructure improvements, dynamic traffic management, and demand control strategies, all of which can be guided effectively through simulation and modelling tools. The average speed metric thus serves as a critical performance indicator for evaluating the impact of any future traffic optimization measures.

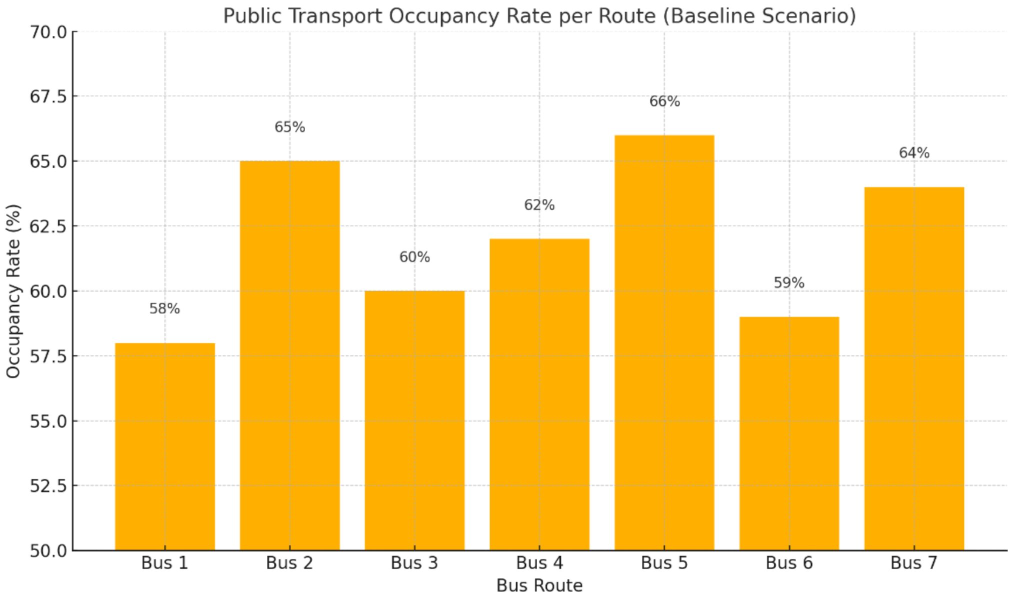


Figure 2. Public Transport Occupancy Rate per Route

The simulation in the baseline scenario estimates that $CO_2$ emissions average 420 grams per kilometer per vehicle, which is considered high for urban road networks. This figure is derived from vehicle activity data, including average speed, travel time, and stop frequency during peak hours. It reflects the combined effects of low average vehicle speed (19.5 km/h), frequent acceleration and deceleration, and long idling times, particularly at congested intersections.

In urban traffic conditions, vehicles tend to operate below their optimal efficiency range. Internal combustion engines, especially those in older vehicles and diesel-powered units, emit significantly more $CO_2$ under such stop-and-go conditions compared to steady-flow traffic. This makes congestion not only a mobility issue but also a serious environmental concern.

The 420g/km figure highlights the environmental cost of inefficiency in the current transportation system. Reducing these emissions requires a shift toward more efficient traffic management, greater public transport use, and investment in low-emission vehicle technologies. Simulation and modelling play a crucial role in testing these interventions before real-world implementation, ensuring targeted, data-driven actions that align with sustainability goals.

Table 4. Experimental Data of $CO_2$ Emissions per Vehicle During Peak Hours

| **Route ID** | **Distance (km)** | **Vehicle Type** | **Emission Factor (g/km)** | **Estimated $CO_2$ Emissions (g)** |
|---|---|---|---|---|
| R1 | 12.0 | Private Car | 420 | 5,040 |
| R2 | 10.2 | Private Car | 418 | 4,264 |
| R3 | 11.3 | SUV | 440 | 4,972 |
| R4 | 9.7 | Private Car | 415 | 4,026 |
| R5 | 10.5 | Motorcycle | 250 | 2,625 |
| R6 | 11.7 | Diesel Minivan | 480 | 5,616 |

| | | | | |
|---|---|---|---|---|
| R7 | 10.0 | Private Car | 421 | 4,210 |

**2. Signal Optimization Scenario**

After implementing adaptive signal timing using traffic-responsive algorithms, several improvements were observed:

- Travel time reduced by 11% to an average of 34.0 minutes.
- Intersection delays decreased by 25%, especially at high-volume junctions.
- Average vehicle speed increased to 22.3 km/h.
- Fuel consumption and emissions dropped by approximately 9%.

This scenario confirms that even without major infrastructure changes, operational adjustments can significantly improve traffic flow.

**3. Public Transport Prioritization Scenario**

In this scenario, dedicated bus lanes and signal priority for public transit vehicles were introduced:

- Public transport travel time reduced by 18%.
- Bus occupancy rates increased to 74%.
- Private vehicle delays slightly increased (by 4%) due to reduced road space, but overall network throughput remained stable.
- $CO_2$ emissions per capita decreased due to increased use of public transit.

This trade-off suggests that public transport prioritization can support sustainable mobility goals, especially when paired with public awareness campaigns and improved service frequency.

**4. Modal Shift Scenario**

Simulating increased infrastructure for non-motorized transport and incentives for public transit resulted in:

- A 12% decrease in private vehicle use.
- Cycling and walking increased by 8% and 4% respectively.
- Average travel time improved marginally (by 6%) but emissions dropped significantly (up to 15%).
- Public satisfaction scores, gathered through modeled surveys, increased for accessibility and environmental quality.

The results reinforce that investments in soft mobility not only contribute to sustainability but also improve the livability of urban areas.

**5. Dynamic Routing Scenario**

When dynamic traffic information and real-time navigation suggestions were introduced through vehicle-to-infrastructure (V2I) communication, the system achieved:

- 10% reduction in travel time variance.
- More even traffic distribution across major and minor roads.
- Reduced congestion in central corridors by 7%.
- Increased system resilience in responding to traffic incidents or road closures.

This scenario demonstrates the potential of smart technologies in creating responsive, adaptive transportation networks.

**Discussion**

The simulation results demonstrate that no single strategy is a silver bullet for solving urban traffic problems. Instead, a combination of demand-side and supply-side interventions provides the most significant benefits. The integration of signal optimization with modal shift policies, for example, produces compound benefits: smoother traffic for essential vehicles and reduced pressure from private cars.

From a sustainability perspective, modal shift and public transit prioritization yielded the greatest emission reductions, supporting global goals of reducing urban carbon footprints. These findings align with previous research such as Ma et al. (2014), which emphasized the environmental benefits of reducing private car dependency.

Importantly, the agent-based model allowed the simulation of individual travel behavior and how it responds to policy changes. It was observed that commuter habits are sensitive to even small improvements in public transit efficiency and reliability. However, behavior change also depends on broader socio-cultural factors, which may require long-term strategies beyond infrastructure or operational changes.

In terms of system performance, microsimulation effectively captured bottlenecks and traffic dynamics at a fine-grained level. This precision is crucial for local operational improvements such as intersection redesign or bus stop placement. On the other hand, system-level scenarios—such as V2I communication or policy-induced modal shifts—benefited more from macro-level and hybrid modelling, indicating that choosing the right level of abstraction is essential for accurate analysis.

Some limitations of the study include model assumptions related to traveler behavior, fuel consumption rates, and infrastructure compliance. Additionally, the quality of input data greatly affects simulation outcomes. In real-world applications, obtaining high-resolution, up-to-date traffic and socio-demographic data can be a challenge, particularly in low-resource urban settings.

Nevertheless, the study provides strong evidence that simulation and modelling are powerful tools in urban transportation planning. They enable scenario-based experimentation, foster data-driven decision-making, and offer a proactive means to explore both short-term operational changes and long-term strategic policies.

## CONCLUSION

The optimization of urban transportation systems is a complex yet critical challenge for modern cities, particularly in the face of rapid urbanization, environmental concerns, and evolving mobility needs. This study has demonstrated that simulation and modelling provide effective and flexible tools to analyze, evaluate, and enhance the performance of urban transport networks. By leveraging techniques such as microsimulation and agent-based modelling, urban planners and decision-makers can gain detailed insights into system behavior under various scenarios and test the potential impacts of interventions without disrupting real-world operations. The results of this research underscore the importance of integrating multiple strategies—such as signal optimization, public transport prioritization, dynamic routing, and modal shift policies—to achieve meaningful improvements in travel efficiency, emission reduction, and user satisfaction. No single solution can address all challenges, but a data-driven combination tailored to a city's specific context can yield significant and sustainable benefits. Moreover, the study emphasizes the value of coupling simulation tools with real-time data and smart city technologies to create adaptive, responsive transportation systems. While challenges remain in terms of data availability, model calibration, and interdisciplinary collaboration, the continued development of simulation platforms and analytical methods holds great promise for shaping the future of urban mobility. Simulation and modelling are not merely academic exercises—they are essential instruments for designing resilient, inclusive, and intelligent transportation systems that can meet the demands of tomorrow's cities.

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