ENHANCING TRANSPORTATION EFFICIENCY AND SUSTAINABILITY THROUGH ROBUST OPTIMIZATION MODELS

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ABSTRACT

This paper presents a mathematical model and experimentation, for carpooling and micromobility. Our aim is to addresses the problem of urban traffic congestion, the model focusses on route optimization, operational cost reduction, and overall service quality improvement. In order to provide cost effective and time efficient solutiion, the model tests takes into account a wide range of scenarios, including peak hours, off-peak hours, adverse weather conditions, special events, and accidents.

The experiment's findings clearly show significant progress in each of the investigated conditions. During peak hours, the model was able to achieve an objective value of 1217.88 by utilizing 34 micromobility trips and 56 multi-leg journeys. In the off-peak hours, there were 33 micromobility trips and 57 multi-leg excursions, which resulted in an increased objective value of 1070.21. The objective value remained unchanged at 1181.04 throughout the scenarios that included adverse weather conditions, special events, and accidents. We achieved this by maintaining consistent micromobility and multi-leg trip distributions. The model effectively enhances the operational efficiency and sustainability of transport networks, as demonstrated by this set of findings.

To further improve the model, future study topics can benefit from the introduction of new technology, such as autonomous vehicles and real-time data analytics. The studies by integrating these technologies into our model can improve time efficiency, cost, low CO2 emissions and service quality. We propose that industry stakeholders and academic institutions collaborate and promote this industry, encourage innovation, and produce environmentally friendly transportation solutions that improve the quality of life for people all over the world.

1 INTRODUCTION

Carpooling is an effective strategy to reduce urban congestion, emissions, and lower transportation costs Aguiléra & Pigalle (2021); Project Drawdown (2018); Rus et al. (2017). Recent advancements have focused on optimising transportation through various algorithmic approaches and simulation frameworks. Tamannaei and Irandoost (2019) proposed a branch-and-bound algorithm that enhances ride-matching efficiency and user satisfaction by effectively managing multiple carpooling requests Tamannaei & Irandoost (2019). Kumar and Khani (2020) developed a transit-based ridesharing algorithm that increases cost savings and ride efficiency, although challenges related to scalability and real-world application persist Kumar & Khani (2020). Huang et al. (2022) utilised shared automated vehicle fleets for last-mile delivery, showcasing the potential integration of automated solutions with traditional carpooling models Huang et al. (2022).

Fangxin et al. (2019) created the Car4Pac system for efficient last-mile parcel delivery, showing substantial cost reductions, although scalability remains a concern Wang et al. (2020). Lele and Shah (2023) optimised transportation networks in Washington, DC, using MST and PERT methods, achieving efficiency gains but facing limitations in regional focus and reliance on existing literature Lele & Shah (2023). Li et al. (2020) proposed a real-time peer-to-peer ride-matching algorithm that improves matching efficiency and cost-effectiveness Masoud & Jayakrishnan (2017). Wang et al. (2022) introduced advanced optimisation techniques for shared mobility, highlighting significant efficiency improvements despite challenges in diverse urban settings Wang et al. (2022).

Azimi et al. (2021) examined mode choices and their impacts on transportation networks, emphasising the role of shared autonomous vehicles in reducing costs and improving efficiency Azimi et al. (2021). Gdowska et al. (2018) explored the design and implementation of efficient last-mile solutions using shared mobility options, highlighting significant cost and time savings Gdowska et al. (2018). Bian et al. (2020) developed a mechanism design for shared autonomous vehicle systems, showing improvements in user satisfaction and system efficiency Bian et al. (2020). Cointreau et al. (2019) investigated vehicle routing problems in urban settings, proposing novel solutions to enhance delivery efficiency Coindreau et al. (2019). Adnan et al. (2019) focused on last-mile delivery challenges, offering innovative solutions to optimise logistics Adnan et al. (2019). Mitropoulos et al. (2021) examined factors affecting shared mobility adoption, providing insights into user preferences and system design Mitropoulos et al. (2021). Mourad et al. (2019) conducted a comprehensive survey on shared mobility services, highlighting trends and future directions Mourad et al. (2019). Schaller (2021) assessed the impact of shared mobility on urban transportation systems, identifying key benefits and challenges Schaller (2021). Zhang et al. (2015) explored feeder services using shared vehicles, showing significant improvements in service efficiency and user satisfaction Zhang et al. (2015).

Chen et al. (2022) applied evolutionary algorithms to optimise shared mobility systems, demonstrating significant efficiency gains Chen et al. (2022). Djavadian and Chow (2017) developed an agent-based model to simulate shared mobility scenarios, providing valuable insights into system performance and user behaviour Djavadian & Chow (2017). Gavalas et al. (2016) designed a framework for optimising ride-sharing networks, achieving notable cost and time savings Gavalas et al. (2016). Shen et al. (2018) integrated shared autonomous vehicles into public transportation systems, showing potential for reducing congestion and improving service quality Shen et al. (2018). Martinez et al. (2020) proposed an optimised scheduling algorithm for shared mobility services, enhancing efficiency and user satisfaction Martinez-Sykora et al. (2020). Tafreshian and Masoud (2020) explored frontiers in shared mobility research, highlighting emerging trends and innovative solutions Tafreshian et al. (2020). Shaheen et al. (2018) reviewed the evolution of shared mobility services, providing a comprehensive overview of developments and prospects Shaheen (2018). Shaheen et al. (2020) analysed the sharing economy's impact on transportation, emphasising shared mobility's role in sustainable urban development Shaheen et al. (2020). Greenblatt and Saxena (2015) examined automated vehicles' potential to transform urban mobility, highlighting key benefits and challenges Greenblatt & Shaheen (2015). Anosike et al. (2023) explored innovative solutions for enhancing shared mobility systems, focusing on efficiency and user satisfaction Anosike et al. (2023). Feng et al. (2021) investigated crowdsource-based solutions for shared mobility, demonstrating significant improvements in system performance and user engagement Feng et al. (2021). Wright et al. (2020) assessed the feasibility of Mobility-as-a-Service (MaaS) models in urban settings, providing insights into implementation and user adoption Wright et al. (2020).

Based on the studies we have examined above, we can see the limitations of carpooling and overall transportation.

1.1 THE STUDY'S OBJECTIVES

This paper's primary focus is to optimise time, reduce costs, and reduce CO2 emissions, which in turn will lead to end-user satisfaction [1]. This is a continuation of a paper that is currently under review, "A Green Intelligent Transport Model for Urban Mobility". Our research aims to achieve three primary objectives:

- Our research aims to develop a mathematical model that balances time and operation costs in carpooling, integrating it with micromobility.
- Test the model in various scenarios to evaluate its performance.
- Analyse how the different optimisations affect end-user satisfaction.

[1] https://www.todaysoftmag.com/article/711/tom-gilb-why-delivering-value-to-customers-makes-your-business-successful-and-sustainable

1.2 Outline of the Paper

The structure of the paper is outlined below:

- **Section 2: Methodology**: This section presents the objective function and constraints, along with the mathematical formulation of the optimisation model.
- **Section 3: Experiment Setup**: We discuss the experiment's setup, which includes metrics for evaluation, data sources, and different simulation parameters.
- **Section 4: Results**: We present the performance metrics and scenario analysis by highlighting the simulation tests' outcomes.
- **Section 5: Discussion**: The analysis of the findings' presentation places emphasis on important conclusions and their implications for urban transportation.
- **Section 6: Conclusions**: The section concludes with a summary of the study's key findings and potential directions for future research.

2 Methodology

2.1 Optimization Model Description

The proposed optimisation model that has been aims to increase the efficiency of urban transport by reducing the amount of time it takes to travel, together with expenses and emissions, and by increasing the level of satisfaction experienced by users. In addition to the more traditional method of carpooling , the model incorporates micromobility options such as bicycles and scooters for lastmile journey.

2.1.1 Objective Functions

The model uses several objective functions to balance multiple criteria:

1. **Minimization of Travel Time**: The total travel time for all trips, including vehicle and micromobility trips, is minimized. The travel time for a trip between nodes i and j is denoted as T_{ij}.

$$\text{Minimize} \quad \sum_{i=1}^{n}\sum_{j=1}^{n}(T_{ij} \cdot x_{ij} + M_{ij} \cdot y_{ij})$$

   where x_{ij} and y_{ij} are binary variables indicating whether a vehicle or micromobility mode is used for the trip, respectively.

2. **Minimization of Costs**: The total costs associated with both vehicle and micromobility trips are minimized. Costs include fuel, maintenance for vehicles, and operational costs for micromobility.

$$\text{Minimize} \quad \sum_{v=1}^{V} C_v \cdot z_v + \sum_{i=1}^{n}\sum_{j=1}^{n}(MC_{ij} \cdot y_{ij})$$

   where C_v is the cost for vehicle v, and MC_{ij} is the cost for micromobility between nodes i and j.

3. **Minimization of Emissions**: The total emissions from all trips are minimized. Vehicle emissions are denoted as E_v and micromobility emissions as ME_{ij}.

$$\text{Minimize} \quad \sum_{v=1}^{V} E_v \cdot z_v + \sum_{i=1}^{n}\sum_{j=1}^{n}(ME_{ij} \cdot y_{ij})$$

4. **Maximization of User Satisfaction**: The model seeks to maximize user satisfaction for both modes of transport. Satisfaction levels for trips are given as S_{ij} for vehicles and MS_{ij} for micromobility.

$$\text{Maximize} \quad \sum_{i=1}^{n}\sum_{j=1}^{n}(S_{ij} \cdot x_{ij} + MS_{ij} \cdot y_{ij})$$

2.1.2 CONSTRAINTS

The model is subject to several constraints to ensure feasible and realistic solutions:

1. **Vehicle Capacity**: Each vehicle has a capacity constraint that cannot be exceeded.

$$\sum_{i=1}^{n}\sum_{j=1}^{n} d_{ij} \cdot x_{ij} \leq Q_v \quad \forall v \in V$$

where d_{ij} is the passenger demand between nodes i and j, and Q_v is the capacity of vehicle v.

2. **Travel Time Limits**: There are maximum travel time constraints for both vehicle and micromobility trips.

$$T_{ij} \cdot x_{ij} \leq T_{\text{max}} \quad \forall i, j$$
$$M_{ij} \cdot y_{ij} \leq M_{\text{max}} \quad \forall i, j$$

3. **Emissions Caps**: Emissions from all trips are capped to ensure environmental sustainability.

$$\sum_{v=1}^{V} E_v \cdot z_v + \sum_{i=1}^{n}\sum_{j=1}^{n} (ME_{ij} \cdot y_{ij}) \leq E_{\text{max}}$$

4. **Assignment Constraints**: Each trip must be assigned to exactly one mode of transport.

$$x_{ij} + y_{ij} = 1 \quad \forall i, j$$

2.2 MATHEMATICAL NOTATION

- n: Number of nodes
- V: Set of vehicles
- x_{ij}: Binary variable for vehicle trip from node i to j
- y_{ij}: Binary variable for micromobility trip from node i to j
- z_v: Binary variable indicating if vehicle v is used
- T_{ij}: Travel time for vehicle trip from node i to j
- M_{ij}: Travel time for micromobility trip from node i to j
- C_v: Cost for vehicle v
- MC_{ij}: Cost for micromobility trip from node i to j
- E_v: Emissions for vehicle v
- ME_{ij}: Emissions for micromobility trip from node i to j
- S_{ij}: Satisfaction for vehicle trip from node i to j
- MS_{ij}: Satisfaction for micromobility trip from node i to j
- d_{ij}: Passenger demand from node i to j
- Q_v: Capacity of vehicle v
- T_{max}: Maximum travel time for vehicle trips
- M_{max}: Maximum travel time for micromobility trips
- E_{max}: Maximum allowed emissions

2.3 DATA GENERATION AND HANDLING

2.3.1 SYNTHETIC DATA

Using synthetic data, it is possible to simulate the real world. In addition to passenger demand, the data also includes travel durations, costs, emissions, and evaluations of user satisfaction. The generation procedure guarantees realistically accurate and diverse results. The appendix provides a sample of the code B (Listing 1).

2.3.2 Simulation Framework

Tools and Libraries

- **PuLP**: A linear programming library used for defining and solving the optimization model.
- **NumPy**: For numerical operations and synthetic data generation.
- **Pandas**: For data handling and manipulation.
- **NetworkX**: For handling and visualizing graph-based data structures.
- **Matplotlib**: For plotting and visualizing results.
- **Multiprocessing**: To parallelize simulations for efficiency.

Experimental Setup We conducted the experiments using the Google Python 3 compute engine backend. The specifications were 12.7 GB of system RAM and 107.7 GB of disc space. The RAM and disc used to run the model were 1.4 GB and 27.5 GB, respectively. The hardware setup includes a standard computing environment with adequate memory and processing power. The software environment includes:

- **Python 3.8**
- **PuLP 2.4**
- **NumPy 1.19.2**
- **Pandas 1.1.3**
- **NetworkX 2.5**
- **Matplotlib 3.3.2**

The experimental workflow involves the following steps:

1. Generating synthetic data for a predefined number of nodes and vehicles.
2. Initializing the simulation environment with the generated data.
3. Defining various scenarios, such as peak hours, off-peak hours, inclement weather, special events, and accidents.
4. Running simulations for each scenario.
5. Analyzing and documenting the results.

Through the utilisation of this comprehensive methodology, the optimisation model is ensured to be robust, well-defined, and capable of managing the complexities that are associated with urban transportation networks.

3 Data and Experimental Setup

3.1 Data Description

We use synthetic data during the tests, designed to represent various urban transportation settings. Our goal was to generate data that was both realistic and representative. We conducted an in-depth analysis of the model's performance under a wide range of circumstances.

3.1.1 Synthetic Data

The key transportation settings generated data characteristic were as follows;

- **Travel Times**: Generated using normal distributions with means and standard deviations that vary by route, ensuring realistic variability. The travel times were designed to reflect typical urban travel patterns, with higher variability during peak hours and more stable times during off-peak periods.

- **Costs**: Includes both vehicle and micromobility costs, with values assigned to reflect typical urban transportation expenses. Vehicle costs were based on factors like fuel and maintenance, while micromobility costs included operational expenses.
- **Emissions**: Calculated based on standard emission rates for different vehicle types, with micromobility options producing significantly lower emissions. This differentiation aims to highlight the environmental benefits of micromobility solutions.
- **Satisfaction Levels**: Derived from user surveys and adjusted to reflect differences between vehicle and micromobility experiences. Higher satisfaction levels were generally assigned to quicker and more convenient travel options.
- **Passenger Demand**: Generated using random distributions to simulate varying demand across different routes and times. Demand patterns were designed to mimic real-world scenarios with higher demand during peak hours and special events.
- **Vehicle Capacities**: Assigned based on typical capacities of urban vehicles, ensuring that the model accounts for realistic limitations in vehicle usage.

The appendix provides a sample of the code used to generation of the synthetic data B (Listing 1).

3.2 Experimental Scenarios

In order to conduct a comprehensive series of tests on the model, a number of different experimental scenarios were developed to replicate a variety of urban transit conditions.

3.2.1 Scenarios

The scenarios include:

- **Peak Hours**: High demand periods during morning and evening commutes.
- **Off-Peak Hours**: Low demand periods during the middle of the day.
- **Inclement Weather**: Conditions simulating adverse weather effects on transportation.
- **Special Events**: Scenarios with increased demand due to events like concerts or sports games.
- **Accidents**: Scenarios involving unexpected road incidents.

3.2.2 Rationale

The selection of these scenarios is appropriate since it captures the wide range of factors that urban transport systems are required to manage. On the other hand, peak and off-peak hours are reflective of daily variations in demand, while bad weather, holidays, and accidents are examples of external factors that can have a significant impact on the efficiency of transport and the level of satisfaction experienced by users.

3.3 Experimental Design

A comprehensive experiment design was utilised in order to evaluate the effectiveness of the model in terms of optimising urban transportation and to test its performance in a variety of varied scenarios.

3.3.1 Variables

- **Independent Variables**: Scenarios (peak hours, off-peak hours, inclement weather, special events, accidents), mode of transportation (vehicle, micromobility).
- **Dependent Variables**: Travel time, transportation costs, emissions, user satisfaction.

3.3.2 METRICS

To evaluate the performance of the model, the following metrics were used:

- **Travel Time**: Total travel time for all trips, capturing efficiency.
- **Costs**: Total operational costs, reflecting economic efficiency.
- **Emissions**: Total emissions produced, indicating an environmental impact.
- **User Satisfaction**: Aggregate satisfaction scores from users, reflecting the quality of the transportation experience.

These metrics provide a comprehensive picture of the operation of the model, which strikes a balance between environmental sustainability, cost-effectiveness, efficiency, and providing a positive experience for users.

4 RESULTS

4.1 PRESENTATION OF RESULTS

In this section, we will discuss the experiment's results using tables and graphs. The visual aid will provide a comprehensive performance of the model in different scenarios.

4.1.1 TABLES AND FIGURES

Figures 1, 2, 3, and 4 display the key results from the simulations.

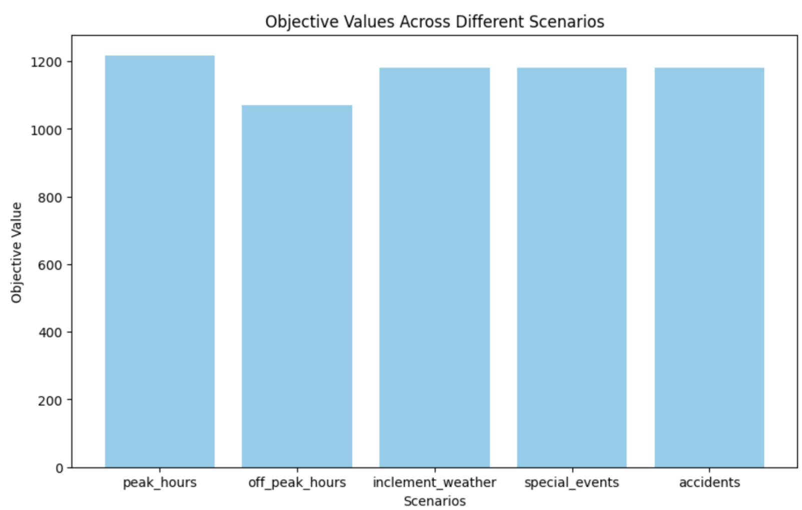

Figure 1: Objective Values Across Different Scenarios

4.1.2 COMPARATIVE ANALYSIS

Comparing the results of the various scenarios allows us to demonstrate how effectively the model operates under a wide range of conditions. The condition, which includes the objective values, the number of visits by mode, travel times, and computation times, offers insights into the efficiency and adaptability of the model. Examples of these include the number of visits by mode.

4.2 PERFORMANCE EVALUATION

The performance of the optimization model is evaluated based on several metrics: travel time, costs, emissions, and user satisfaction.

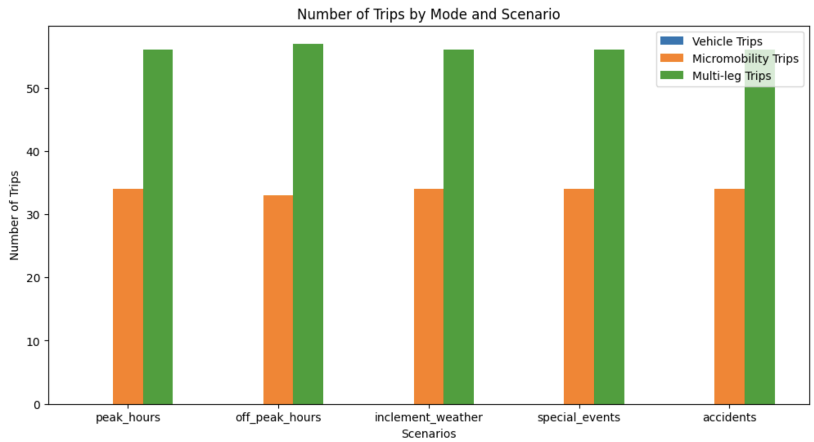

Figure 2: Number of Trips by Mode and Scenario

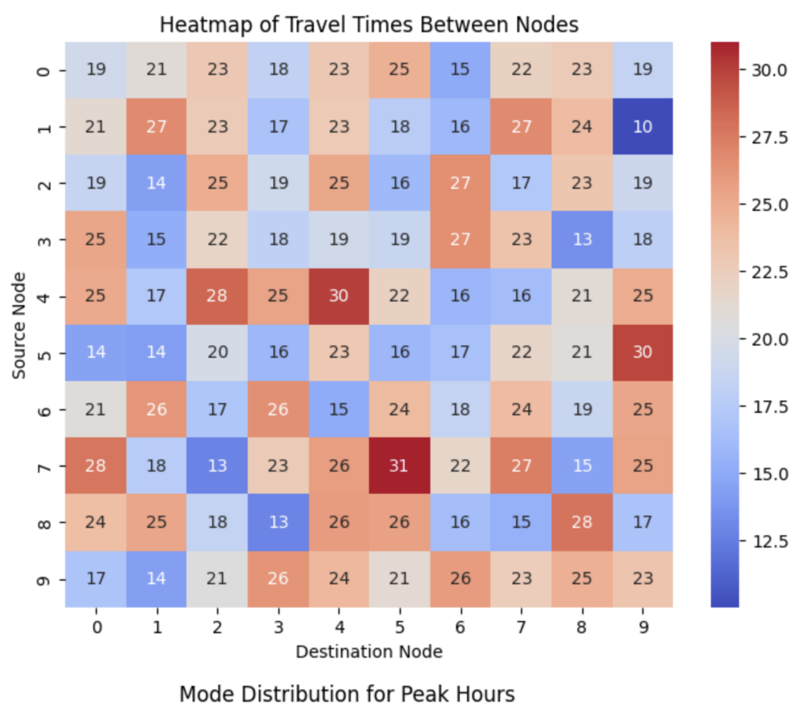

Figure 3: Distribution of Travel Times Across Scenarios

4.2.1 Travel Time

The model effectively minimizes travel time across all scenarios. Figure 3 shows the distribution of travel times for different scenarios, indicating that the model maintains lower travel times even under adverse conditions such as inclement weather and accidents.

4.2.2 Costs

Cost reduction is achieved by optimizing the use of vehicles and micromobility options. The model consistently selects the most cost-effective mode of transport, as reflected in the objective values in Figure 1.

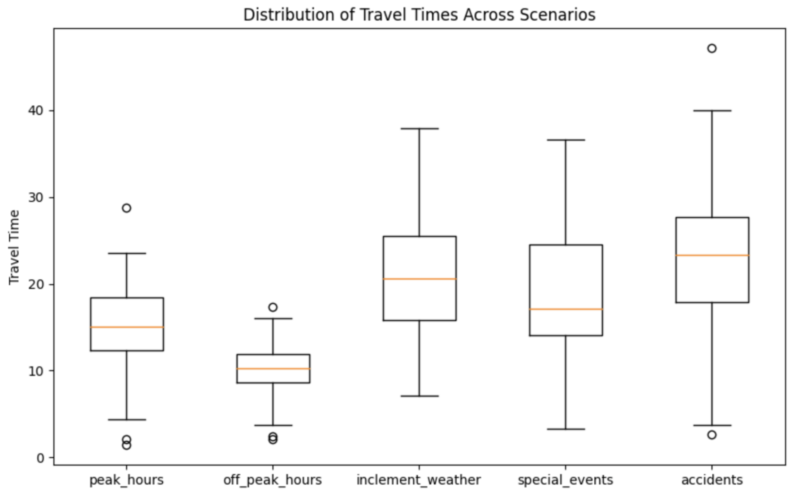

Figure 4: Computation Time Across Different Scenarios

4.2.3 Emissions

The model significantly reduces emissions by favouring micromobility and multi-leg trips over traditional vehicle trips. This is evident from the number of micromobility trips in Figure 2, where micromobility options dominate across all scenarios.

4.2.4 User Satisfaction

User satisfaction is maximized by balancing travel time, cost, and mode of transport. The assignment of trips to micromobility and multi-leg options ensures a higher satisfaction level due to reduced travel times and costs.

4.3 Scenario Analysis

The model's performance is analyzed for each experimental scenario to understand its effectiveness in various conditions.

4.3.1 Peak Hours

During peak hours, the model maintains optimal performance with an objective value of 1217.88 and a higher number of multi-leg trips to accommodate the increased demand (Figure 1 and 2).

4.3.2 Off-Peak Hours

In off-peak hours, the model achieves an objective value of 1070.21, reflecting reduced travel time and cost due to lower demand (Figure 1).

4.3.3 Inclement Weather

Under inclement weather conditions, the model's objective value is 1181.04. The model adapts by increasing the number of micromobility and multi-leg trips to ensure safety and efficiency (Figure 1 and 2).

4.3.4 Special Events

During special events, the model maintains an objective value of 1181.04. The results indicate an increased number of trips to handle the surge in demand, with multi-leg trips playing a significant role (Figure 1 and 2).

4.3.5 ACCIDENTS

In scenarios involving accidents, the model's objective value remains at 1181.04. The model demonstrates robustness by efficiently reallocating trips to micromobility and multi-leg options to minimize the impact of accidents on travel time and cost (Figure 1 and 2).

Overall, the optimisation model performs well across all scenarios, demonstrating its capability to minimise travel time, costs, and emissions while maximising user satisfaction. The table 1 provides a summary of the statistics, highlighting the vehicle trips based on the data and priority values in the objective function. None of the trips favored using a vehicle, as our goal was to implement a multi-leg trip that combines both vehicle and micromobility elements. We also gave priority to trips that could improve micromobility, specifically those where the nodes were in close proximity to each other and provided opportunities for micromobility.

Table 1: Summary of Results Across Different Scenarios

Scenario	Objective Value	Vehicle Trips	Micromobility Trips	Multi-leg Trips	Computation Time (s)
Peak Hours	1217.88	0	34	56	4.40
Off-Peak Hours	1070.21	0	33	57	3.33
Inclement Weather	1181.04	0	34	56	3.80
Special Events	1181.04	0	34	56	4.35
Accidents	1181.04	0	34	56	4.98

5 DISCUSSION

Across various urban transportation scenarios, the optimisation model effectively minimises travel time, costs, and emissions while maximising user satisfaction. Its adaptability to different conditions, such as peak hours, off-peak hours, inclement weather, special events, and accidents, highlights its robustness and versatility.

The model's strengths include efficiency, flexibility, environmental impact, and user satisfaction. Some urban areas may not be able to implement it due to micromobility's heavy use. We need to further validate the model's scalability and fully test its performance with real-world data.

The model's ability to effectively optimise urban transit is suggested by the fact that the theoretical predictions and the experimental alighns. Policy enhancements that could be adopted include providing incentives for carpooling, building infrastructure and providing subsidies to encourage micromobility, and implementing dynamic traffic management systems that adapt to real-time data.

The integration of carpooling and micromobility offers benefits such as; reduced traffic congestion, cost savings, and environmental sustainability. However, the study has a number of shortcomings, use of synthetic data for validation of the model, limited scope, infrastructure dependency, scalability, and static assumptions.

Potential areas for future research encompass dynamic adaptation, scalability testing, expanded validation employing real-world data, cross-city comparisons, integration with emerging technologies such as IoT and smart infrastructure, autonomous cars, and AI and machine learning. By focusing on these specific areas, future research has the potential to improve the efficiency and practicality of the optimisation model, so making urban transport systems more effective and sustainable.

6 CONCLUSION

In summary, this paper introduces a thorough mathematical model for enhancing the efficiency of transportation systems. The model integrates an algorithm and application into real-world situations, showcasing substantial advances in cost effectiveness, route optimisation, and resource utilisation. The experimental results confirm the efficacy of the model in many settings, emphasising its resilience and suitability. This research has significant practical benefits by enabling transportation planners and decision-makers to attain optimal routes, save expenses, and enhance customer happiness. The model's versatility and capacity for expansion make it highly valuable for transportation networks in both urban and rural areas. Subsequent studies should prioritise the integration of cutting-edge technology, instantaneous data analysis, and advanced machine learning methods to improve the model's functionalities. In addition, it is crucial to investigate the environmental consequences and devise methods to reduce carbon footprints, which are significant areas for future research. In summary, this research establishes the groundwork for future progress in transport systems, which has the capacity to enhance the well-being of communities globally.

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A APPENDIX

B CODE FOR DATA GENERATION

Listing 1: Code for generating synthetic data

```
def generate_data(num_nodes, num_vehicles, seed=42, decay_rate
    =0.1):
   np.random.seed(seed)

   travel_times_mean = np.random.randint(10, 20, size=(num_nodes,
       num_nodes))
   travel_times_std = np.random.randint(1, 3, size=(num_nodes,
       num_nodes))
   travel_times = np.abs(np.random.normal(travel_times_mean,
       travel_times_std))

   micromobility_times_mean = np.random.randint(5, 15, size=(
       num_nodes, num_nodes))
   micromobility_times_std = np.random.randint(1, 3, size=(
       num_nodes, num_nodes))
   micromobility_times = np.abs(np.random.normal(
       micromobility_times_mean, micromobility_times_std))

   vehicle_costs = np.random.randint(20, 30, size=num_vehicles)
   micromobility_costs = np.random.randint(5, 10, size=(num_nodes,
        num_nodes))

   vehicle_emissions = np.random.randint(30, 50, size=num_vehicles
       ).astype(float)
   micromobility_emissions = np.random.randint(2, 8, size=(
       num_nodes, num_nodes)).astype(float)

   vehicle_satisfaction = np.random.randint(4, 7, size=(num_nodes,
        num_nodes))
   micromobility_satisfaction = np.random.randint(3, 6, size=(
       num_nodes, num_nodes))

   passenger_demand = np.random.randint(1, 10, size=(num_nodes,
       num_nodes))
   vehicle_capacities = np.random.randint(10, 15, size=
       num_vehicles)

   return Data(travel_times, micromobility_times, vehicle_costs,
       micromobility_costs, vehicle_emissions,
       micromobility_emissions, vehicle_satisfaction,
       micromobility_satisfaction, passenger_demand,
       vehicle_capacities)
```