Al-Kharj Mobility Upgrade

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ABSTRACT

The rapid growth of urban areas necessitates efficient traffic management and road planning, where digital simulation tools play a crucial role. This study employs two widely used traffic simulation programs, SUMO and VISSIM, to model and analyze traffic flow and explore strategies for improving road networks. SUMO, an open-source simulation platform, was first utilized to construct road networks, design intersections, adjust signal timings, and set vehicle speeds. This approach provided valuable insights into traffic dynamics and allowed for the testing of various scenarios to optimize vehicle flow. The use of these tools enabled the development of practical solutions for addressing congestion and improving overall traffic efficiency. Despite challenges encountered during the simulation process, the results were satisfactory and contributed to achieving the research objectives, offering a deeper understanding of traffic management and demonstrating the effectiveness of simulation tools in road planning and optimization.

1. Introduction

With the rapid growth of urban populations and the increasing complexity of road networks, the need for effective traffic management and optimization has become more pressing. Urban transportation systems are essential for maintaining the flow of people and goods, but they often face significant challenges such as congestion, delays, and inefficient routing. To address these challenges, the use of digital simulation tools has become a vital part of urban planning and traffic management. These tools provide a platform for analyzing traffic flow, testing various management strategies, and evaluating the impact of different infrastructural modifications before they are implemented in real-world settings.

In this context, two widely used simulation programs—SUMO (Simulation of Urban MObility) and VISSIM—were employed to model and simulate road traffic, offering robust platforms for understanding traffic dynamics. SUMO is an open-source, highly flexible simulation tool used for modeling traffic, public transport, and infrastructure. It is well-regarded for its ease of use and its ability to simulate large-scale traffic networks efficiently [11]. VISSIM, on the other hand, is a commercial tool that is renowned for its detailed microscopic traffic simulation and is often used in industry for planning and assessing the impact of traffic management measures [5]. Both tools are widely

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utilized in transportation research to simulate complex traffic environments and evaluate different traffic management strategies.

In our study, we initially utilized SUMO for its user-friendly interface and extensive educational resources. This experience allowed us to gain valuable insights into the construction of road networks, the design of intersections, and the optimization of traffic signals. Through iterative simulations, we were able to adjust vehicle speeds, model traffic congestion, and test the effectiveness of different traffic flow strategies. This hands-on approach provided an in-depth understanding of how traffic behaves under various scenarios and how simulation tools can assist in making data-driven decisions for traffic management and infrastructure planning.

By employing these simulation tools, we aimed to analyze traffic flow, identify critical problem areas in road networks, and propose potential solutions for improving traffic efficiency. The ability to simulate various scenarios without the need for physical interventions allows planners to test hypotheses, evaluate the effectiveness of potential solutions, and ultimately make informed decisions that can reduce congestion and improve road safety.

2. Related work

Recent advancements in Large Language Models (LLMs) have transformed various fields, including traffic management. LLMs leverage extensive data processing capabilities and multimodal integration, enhancing the efficiency of transportation systems. In the context of traffic law, the application of LLMs holds potential for improving traffic predictions, reducing congestion, and enhancing road safety through proactive accident prevention. However, the incorporation of LLMs into traffic management systems introduces several legal and ethical challenges, particularly regarding data privacy, liability in automated decision-making, and regulatory compliance. This literature review examines recent studies (2021–2024) that discuss the use of LLMs in traffic management and highlights the implications for traffic (transportation) law.

One of the key benefits of LLMs in traffic management is their ability to analyze large datasets and make accurate predictions. Bilotta et al. [1] demonstrated the utility of convolutional deep learning models in predicting short-term traffic flow in cities. Their study showcased how LLMs could process real-time data, including traffic density, road usage patterns, and external factors such as weather, to deliver highly accurate traffic predictions. These models have the potential to revolutionize traffic management by enabling authorities to make preemptive decisions to prevent congestion. The use of LLMs in traffic prediction can also improve infrastructure planning by identifying high-traffic areas that require intervention [1].

Similarly, Guo et al. [6] developed an optimized graph convolution recurrent neural network (GCRNN) to predict traffic flow, which integrates spatial and temporal data. The combination of graph structures and LLMs allows for more refined predictions that consider the complex interconnections between different nodes in transportation networks.

Such systems are particularly relevant for urban environments where traffic patterns are highly dynamic. From a legal perspective, traffic laws and regulations will need to evolve to accommodate the proactive management of traffic flow through these advanced technologies. Additionally, the integration of LLMs with real-time data sources raises concerns about the legal status of predictive traffic systems, particularly in relation to the accuracy of the predictions and potential liability if accidents occur despite predictions [6].

Furthermore, Chen et al. [2] proposed an edge traffic flow detection scheme based on deep learning in intelligent transportation systems. Their approach utilizes LLMs at the edge of the network to process data locally, reducing latency and bandwidth usage. This is crucial for real-time traffic prediction and management, where delays in data processing can significantly impact system performance. The edge computing paradigm also introduces considerations for data privacy and security, as data is processed closer to its source [2].

Yuan and Li [21] provided a comprehensive survey of traffic prediction methods, highlighting the shift from traditional statistical models to intelligent transportation systems powered by LLMs and deep learning techniques. They emphasized that LLMs can capture complex spatiotemporal patterns in traffic data, leading to more accurate and reliable predictions. The adoption of LLMs in traffic prediction also aligns with the broader trend towards smart cities and intelligent infrastructure [21].

Moreover, Medikonduru et al. [15] explored the use of machine learning for traffic prediction in intelligent transportation systems. Their study underscores the effectiveness of LLMs in handling large-scale traffic data and improving prediction accuracy. They highlighted that machine learning models could adapt to changing traffic patterns, which is essential for managing congestion and improving road safety [15].

Time series models, such as ARIMA, have also been enhanced using hyper-parameter optimization techniques in conjunction with LLMs to improve traffic flow prediction. The 2022 study "Time Series Traffic Flow Prediction with Hyper-Parameter Optimized ARIMA Models for Intelligent Transportation System" demonstrated that integrating LLMs with traditional time series models can lead to significant improvements in prediction performance. This integration bridges the gap between classical statistical methods and modern deep learning approaches, offering a robust framework for traffic prediction.

Accident forecasting using LLMs is an emerging field that promises to significantly improve road safety. Korablev et al. [10] developed a traffic management system architecture model that integrates LLMs for real-time decision making. Their architecture emphasizes the need for scalable and flexible systems capable of handling the complexities of modern traffic networks. The implementation of such systems raises legal considerations regarding the standardization of technologies and compliance with existing traffic laws [10].

Mazurenko et al. [14] discussed the development of an intelligent traffic control system project that utilizes LLMs for adaptive traffic signal control. Their system aims to optimize traffic flow by adjusting signal timings based on real-time traffic conditions. While such systems can reduce congestion and improve efficiency, they also pose legal challenges related to the delegation of control from human operators to autonomous systems [14].

In real-time traffic management, LLMs can also be used to make decisions on adjusting traffic light timings, rerouting vehicles, and deploying resources. Bilotta et al. [1] and Guo et al. [6] highlighted how LLMs could process real-time data streams to optimize traffic flow dynamically. The challenge for traffic law in these cases lies in regulating systems that can autonomously make decisions. Traditional legal frameworks that govern human drivers may not be suitable for managing the complexities of LLM-driven systems that continuously adapt to real-time inputs.

Furthermore, Wang et al. [18] discussed the architecture and development of intelligent traffic signal control platforms. They emphasized the importance of integrating LLMs into these platforms to enhance decision-making capabilities. The use of LLMs in traffic signal control introduces legal considerations regarding system reliability, standardization, and the need for regulatory oversight to ensure safety and compliance with traffic laws [18].

The integration of LLMs into traffic systems brings with it several ethical and legal challenges. Data privacy is a critical concern when using LLMs, as these models often require access to vast amounts of data to function effectively. Hamadeh et al. [7] explored the implications of intelligent transportation systems (ITS) and how the collection of personal and vehicular data for traffic management could infringe on individual privacy rights. LLMs in traffic management often use sensitive data such as vehicle locations, driving habits, and even personal information from connected devices. This creates a need for strong legal frameworks to ensure data protection and compliance with privacy regulations, such as the General Data Protection Regulation (GDPR) in Europe.

Moreover, the issue of accountability in cases of system failure is a significant legal challenge. When LLMs are used to manage traffic signals, predict accidents, or control autonomous vehicles, determining liability becomes more complex. For example, if a traffic signal managed by an LLM malfunctions and causes an accident, it is unclear whether the responsibility lies with the system's developers, operators, or manufacturers. Liu et al. [13] raised concerns about the legal implications of multi-agent attention frameworks used in intelligent traffic light systems, where the automated control of traffic flow could result in accidents if the system behaves unpredictably or fails to adapt to real-time conditions. Therefore, traffic laws must adapt to account for scenarios where autonomous systems, rather than human actors, are responsible for decision-making [13].

Ning et al. [16] discussed the role of blockchain in intelligent transportation systems to address some of these ethical and legal challenges. By providing a decentralized and transparent platform for data management, blockchain can enhance data security and trust in LLM-based traffic systems. However, the integration of blockchain also introduces new legal considerations, such as the need for regulations governing decentralized data storage and the legal status of smart contracts used within these systems [16].

The strength of LLMs lies in their ability to process multimodal data, which includes text, images, sensor readings, and other forms of input. Huang et al. [9] evaluated traffic node importance based on clustering in represented transportation networks. Their study utilized LLMs to analyze complex network structures and identify critical nodes that significantly impact traffic flow. By understanding the importance of different nodes, traffic management systems can prioritize resources and interventions more effectively [9].

Xu et al. [19] developed an interactive web application for traffic simulation data management and visualization. Their platform leverages LLMs to process and visualize large-scale traffic data, facilitating better decision-making for traffic planners and authorities. The integration of LLMs in such applications enhances the ability to interpret multimodal data and provides actionable insights [19].

The use of multimodal data, however, complicates the legal landscape. Laws governing traffic management and data use must address questions about ownership, consent, and data sharing across platforms. Multimodal data is often collected from various sources, including private companies, public infrastructure, and personal devices, which raises concerns about who owns the data and how it can be used legally. Furthermore, the accuracy of LLM-based predictions is only as reliable as the data they process, and inaccuracies could lead to legal disputes if traffic systems fail to perform as expected.

Blockchain and IoT technologies are becoming increasingly important in traffic management systems, especially in ensuring data security and transparency. Ning et al. [16] discussed a blockchain-enabled intelligent transportation system that uses a distributed crowdsensing framework to gather real-time traffic data. By integrating blockchain with LLMs, traffic systems can ensure the integrity of data used for decision-making while maintaining transparency and accountability. This is especially relevant in legal contexts where data authenticity and tamper-proof records are required for traffic law enforcement [16].

Similarly, Rajaguru et al. [17] explored the application of narrow-band IoT in traffic management systems, emphasizing the importance of real-time data collection and low-latency communication for effective traffic control. The combination of LLMs, IoT, and blockchain in traffic systems raises new legal questions about data ownership, cross-border data flows, and the regulatory frameworks that govern interconnected smart cities. The use of IoT and blockchain in traffic management systems is expected to enhance legal accountability by providing a verifiable record of data transactions and system decisions. However, existing traffic laws need to be updated to reflect these technological advancements and the legal complexities they introduce [17].

Given the significant advancements in LLMs for traffic management, several policy recommendations can be made to address the associated legal and ethical challenges. First, there is a pressing need for data protection regulations that govern the collection, storage, and use of data by LLM-based traffic systems. These regulations should ensure that personal and vehicular data is handled securely and in compliance with international privacy laws. Policymakers should also consider the ethical implications of using LLMs to process sensitive data, and safeguards must be put in place to prevent misuse.

Second, liability frameworks must be developed to address the complexities of autonomous decision-making in traffic systems. As traffic control increasingly shifts from human operators to LLMs, laws must clearly define responsibility in the event of system failures, accidents, or data breaches. Policymakers should establish legal standards for the deployment of LLM-based systems, including guidelines for system testing, verification, and compliance with safety regulations.

Third, standardization of technologies and interoperability protocols is essential to ensure that different systems and devices can communicate effectively. This includes developing standards for data formats, communication protocols, and security measures. International bodies and governments should collaborate to develop these standards to facilitate global adoption and integration.

Finally, international cooperation is necessary to ensure that traffic systems powered by LLMs operate seamlessly across borders. Traffic systems, especially in smart cities, are becoming more interconnected, and legal frameworks must be harmonized to address issues of cross-border data sharing, system interoperability, and liability in international contexts.

The integration of Large Language Models into traffic management systems offers significant potential for improving traffic prediction, accident forecasting, and real-time decision making. However, these advancements also introduce complex legal and ethical challenges related to data privacy, liability, and regulatory compliance. The literature indicates that while technological solutions are rapidly evolving, legal frameworks are lagging behind. It is imperative for policymakers, legal experts, and technologists to collaborate in developing comprehensive regulations that address these challenges. By proactively addressing the legal and ethical implications, society can harness the benefits of LLMs in traffic management while safeguarding individual rights and public safety [16, 17].

3. Challenges

In this section, we will summarize the key challenges of our proposed work.

1. **Intersection Design:** Designing intersections that accurately reflected real-world conditions took a considerable amount of time and effort.
2. **Traffic Signal Directions:** Adjusting signal directions to match actual traffic flows required detailed modifications to ensure realism.
3. **Signal Timing Adjustments:** Fine-tuning signal timings to match real-world traffic conditions was a continuous process that required multiple iterations.

Article	Technique			Limitation
	RNN	DL	Other	
Bilotta et al. [1]		✓		Lack of generalization to non-urban scenarios
Chen et al. [2]		✓		Limited scalability for larger traffic networks
Guo et al. [6]		✓		Limited training data may reduce model accuracy
Hamadeh et al. [7]			✓	Not applicable to rural areas
Huang et al. [9]			✓	Limited clustering validation in different scenarios
Korablev et al. [10]			✓	Lack of implementation details
Liu et al. [13]	✓			High computational cost
Mazurenko et al. [14]		✓		Lack of large-scale evaluation
Medikonduru et al. [15]		✓		Lack of comparison with deep learning models
Ning et al. [16]			✓	High resource consumption
Rajaguru et al. [17]			✓	Limited real-world implementation
Kumar et al. [12]		✓		Not applicable for real-time predictions
Wang et al. [18]		✓		Limited scalability analysis
Xu et al. [19]		✓		Limited visualization capabilities for large datasets
Yuan et al. [21]		✓		Lack of experimental results
Yin et al. [20]		✓		Lack of experimental validation
Gao et al. [8]		✓		Challenges in real-time forecasting
Fan et al. [4]		✓		Handling data diversity and complexity
Vlahogianni et al. [3]		✓		Complexity in representation
Yuan et al. [21]		✓		Lack of experimental implementation

Table 1
Limitations of AI, NLP, and DL applications in LegalAI research.

4. **Vehicle Distribution:** Distributing vehicles accurately across the simulation was critical to ensure a realistic flow of traffic.
5. **Lane Modifications:** The initial number of lanes in the imported maps was insufficient, requiring us to expand and modify lanes to accommodate realistic traffic patterns.

4. Main contributions

To address the challenges discussed in 3, the following steps can be taken:

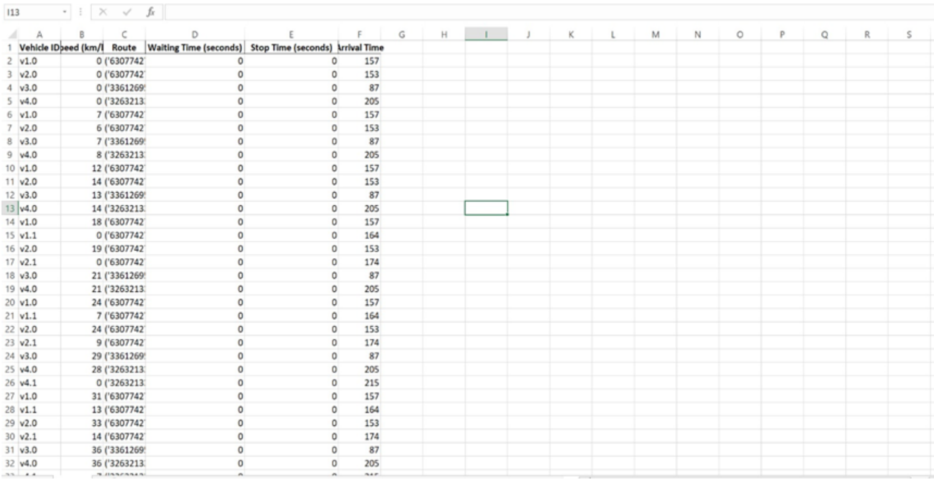
1. **Use data cleaning software:** Tools like Python or Excel can be utilized to remove duplicates and organize the data.
2. **Adjust export settings in SUMO:** Modify the settings to extract only the required details and minimize redundancy.
3. **Focus on key data:** Analyze only the critical data points, such as average speed or the number of stops, instead of every detailed movement.

5. Data Description

The Figure 1 image represents an example of a common issue with the data generated by the SUMO program, where every movement of vehicles is repeatedly recorded. The data includes several fields such as Vehicle ID, Speed,

Street Name	Number of Cars
King Abdullah	1,000
Abdullah bin Amer	500
Riyadh Road	700
Al-Hayatham	200
King Saud	50
Abdullah bin Amer	50

Table 2
Distribution of Cars Across Streets



	Vehicle ID	peed (km/l	Route	Waiting Time (seconds)	Stop Time (seconds)	rrival Time
2	v1.0	0	('6307742	0	0	157
3	v2.0	0	('6307742	0	0	153
4	v3.0	0	('3361269	0	0	87
5	v4.0	0	('3263213	0	0	205
6	v1.0	7	('6307742	0	0	157
7	v2.0	6	('6307742	0	0	153
8	v3.0	7	('3361269	0	0	87
9	v4.0	8	('3263213	0	0	205
10	v1.0	12	('6307742	0	0	157
11	v2.0	14	('6307742	0	0	153
12	v3.0	13	('3361269	0	0	87
13	v4.0	14	('3263213	0	0	205
14	v1.0	18	('6307742	0	0	157
15	v1.1	0	('6307742	0	0	164
16	v2.0	19	('6307742	0	0	153
17	v2.1	0	('6307742	0	0	174
18	v3.0	21	('3361269	0	0	87
19	v4.0	21	('3263213	0	0	205
20	v1.0	24	('6307742	0	0	157
21	v1.1	7	('6307742	0	0	164
22	v2.0	24	('6307742	0	0	153
23	v2.1	9	('6307742	0	0	174
24	v3.0	29	('3361269	0	0	87
25	v4.0	28	('3263213	0	0	205
26	v4.1	0	('3263213	0	0	215
27	v1.0	31	('6307742	0	0	157
28	v1.1	13	('6307742	0	0	164
29	v2.0	33	('6307742	0	0	153
30	v2.1	14	('6307742	0	0	174
31	v3.0	36	('3361269	0	0	87
32	v4.0	36	('3263213	0	0	205

Figure 1: example of a data generated by SUMO

Route, Waiting Time, Stop Time, and Arrival Time. We tested 2,500 cars in a two-hour scenario and distributed the number of cars across these streets, this data distribution is summarized in table 5.

The repetition evident in this data leads to several challenges in analysis, such as:

1. **Excessive redundancy:** Every step of the vehicle is recorded at every time interval, significantly increasing the size of the data.
2. **Processing difficulties:** This large volume of data requires additional time and effort for cleaning and extracting only the necessary information.
3. **Complex analysis:** Repeated data necessitates the use of advanced techniques or algorithms to identify important data points and eliminate unnecessary ones.

6. Adopted simulators

6.1. SUMO

Benefits of Traffic Simulation in Road Planning

1. **Traffic Dynamics Analysis:** Simulation helps understand vehicle movement on roads and accurately identify congestion points.
2. **Testing Solutions Before Implementation:** Various changes, such as adding lanes or adjusting traffic signals, can be tested without the need for costly real-world implementation.
3. **Time and Cost Efficiency:** Simulation reduces the need for extensive field trials, which can be time-consuming and expensive.
4. **Assessing Traffic Policy Impacts:** The effects of policies like speed reduction or changing traffic directions can be studied before they are applied in real life.
5. **Enhancing Traffic Safety:** Simulation can help design safer intersections and assess the impact of signals on accident reduction.

6.1.1. Map Creation

We used Web OSM to import comprehensive maps of the area, including both major and this map was selected from the Web OSM (OpenStreetMap) program to represent the roads and areas that will be simulated in the traffic model. Web OSM is a powerful tool for importing detailed maps, allowing us to design and modify the road network to accurately match the project's requirements.

This image represents the map before the cleaning process, road restructuring, and intersection adjustments. At this stage, the map contained several unnecessary details and errors that needed to be corrected, such as unclear roads and poorly defined intersections. These issues required significant modifications to ensure accuracy for the traffic simulation. After the cleaning and restructuring, the map was optimized to better reflect the real-world road network, with the roads and intersections adjusted for the simulation's requirements. This involved defining accurate traffic flows, correcting road geometries, and ensuring proper connections between key roads for a more realistic traffic model.

minor roads:

- Imported maps required significant cleaning to remove errors and unnecessary details.
- We used NetEdit to reformat and adjust the road network to match real-world conditions.

This image represents the map after the cleaning process and correct road restructuring. At this stage, all the errors present in the previous version of the map, such as unclear roads and poorly defined intersections, have been fixed. The road network has been carefully modified to match the actual infrastructure standards of the area.

Several adjustments were made to enhance the map:

1. **Correcting Routes:** The road paths were modified to align with reality, including adding missing secondary and minor roads.

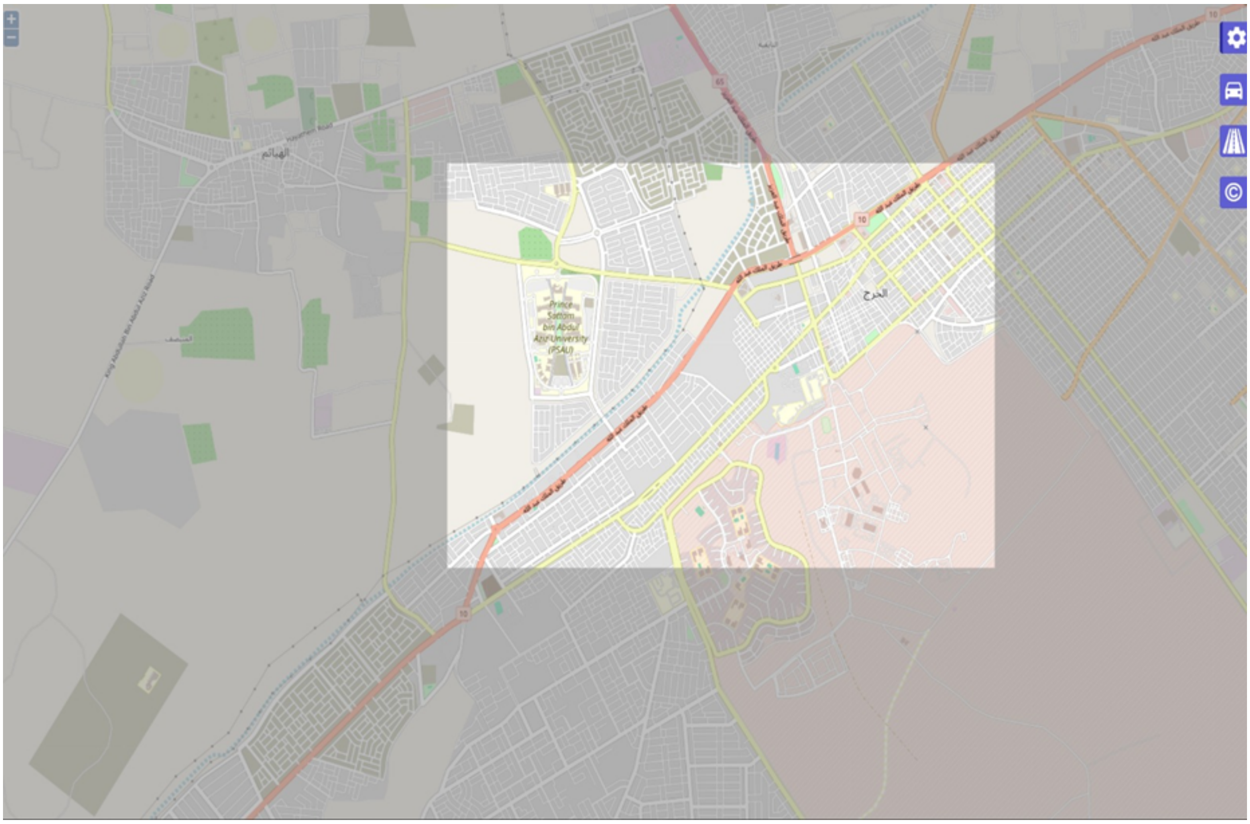


Figure 2: Simulated map.

2. **Improving Intersections:** Intersections were redesigned to reflect real traffic flows and accurately define the required directions.
3. **Removing Unnecessary Elements:** Details irrelevant to the traffic simulation, such as green spaces or unused areas, were removed.
4. **Adjusting Measurements and Dimensions:** Ensuring that each road or intersection reflects the correct dimensions according to real-life standards, making sure the measurements fit the simulation's requirements.
5. **Adding Vital Details:** The details of roads were improved, such as specifying lanes for heavy vehicles or public transportation, and enhancing the representation of highways and internal roads.

With these modifications, the map is now ready to serve as an accurate base for traffic simulation in the area, which will help improve simulation processes and analysis with greater accuracy and realism.

6.1.2. Road Selection

We focused on the main roads leading to the university, as they are the primary traffic routes. Key intersections that directly affect traffic flow were also selected for detailed modeling.

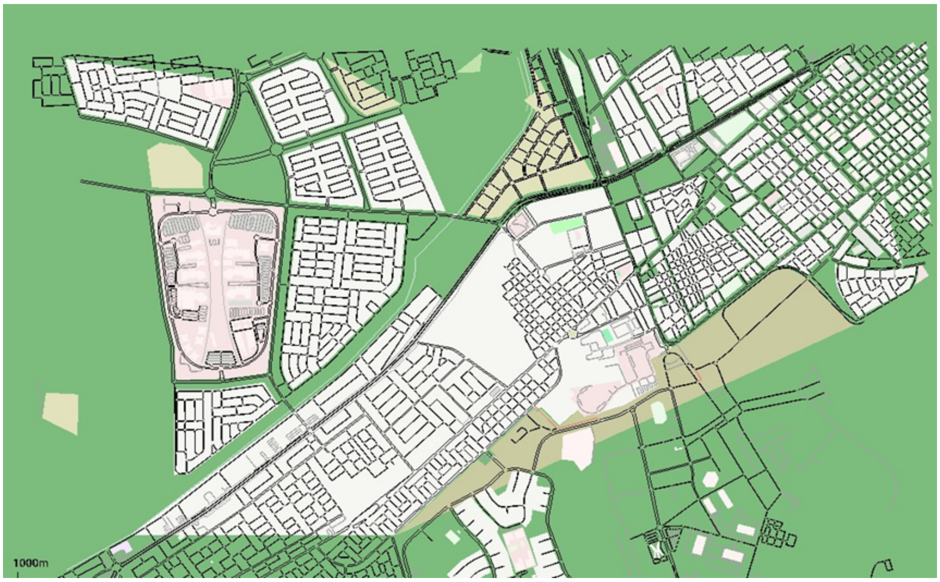


Figure 3: Transformed map using SUMO.

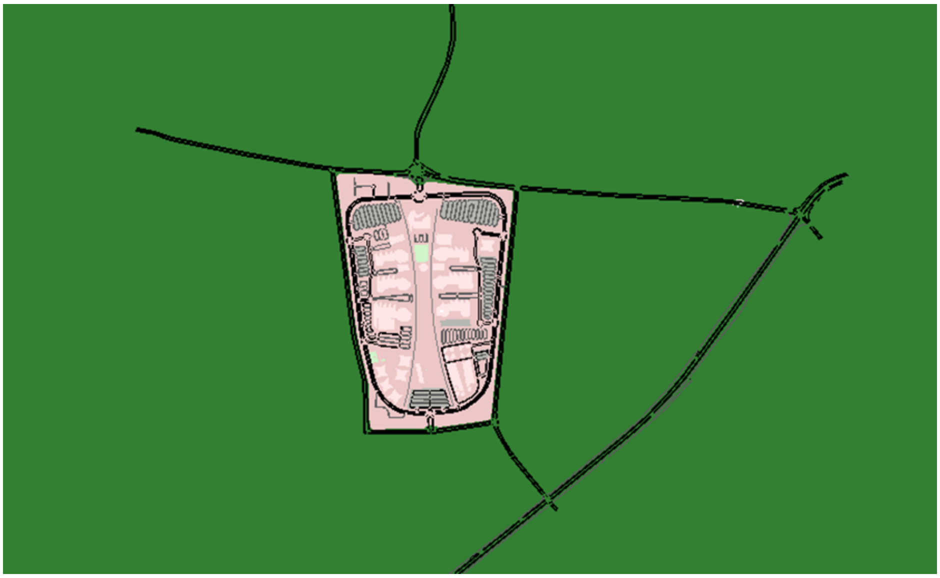


Figure 4: Simulated traffic including PSAU and main roads.

6.1.3. Manually Adding Vehicles

- Vehicles were manually added to the simulation to ensure precise control over their distribution and behavior.

- This customization allowed us to simulate traffic flow more realistically.

6.1.4. Speed Adjustments

- Vehicle speeds were adjusted to match the actual speed limits of the roads to achieve a more realistic simulation.

- Speeds were set based on road types (main or secondary roads) and surrounding area characteristics.

6.1.5. *Traffic Signal Adjustments*

- Traffic signals were adjusted to match real-life conditions, including setting correct directional flow and signal timing. - Accurate timing for traffic signals was established to maintain smooth vehicle flow at intersections.

6.1.6. *Data Extraction and Analysis*

- We utilized a specific library within SUMO to extract various data, such as travel times, vehicle counts, and flow speeds, as shown in figure 5.

- Custom scripts were added to export these data points into Excel files for further analysis.

6.2. VISSIM

VISSIM is a widely used, comprehensive traffic simulation software that excels in providing high-quality visualizations and offering immediate export capabilities for results. Despite its advanced features, the process of recording and analyzing results requires manual intervention. For this project, we utilized the demo version of VISSIM. While the demo provides a valuable insight into the software's potential, it comes with notable limitations, particularly in terms of simulation duration and the availability of advanced features. These constraints hindered our ability to conduct a thorough and extensive traffic analysis.

Nonetheless, the simulation allowed us to:

1. Analyze vehicle flow across major roads and identify key congestion points and bottlenecks.
2. Extract valuable data, which led to recommendations for improvements such as re-adjusting signal timings and adding additional lanes.
3. Test various traffic scenarios, including increased vehicle volumes and changes in traffic directions, all without the need for real-world trials.

6.2.1. *Map Creation*

We initiated our project by capturing screenshots of the university and the surrounding streets. These images were used as the foundation for manually drawing and designing the network. This meticulous process involved detailed mapping and planning to ensure the network was accurately represented. Below is the final result of our map creation.

6.2.2. *Enhancing Visual Representation with 3D Elements*

VISSIM's capability to support 3D visualization allowed us to add cosmetic details that enhance the model's appearance and functionality. We incorporated a 3D model obtained from SketchFab and utilized the 3D elements available in the application to enrich our simulation.

```python
import traci
import pandas as pd

# Define SUMO binary and command
sumoCmd = ["sumo-gui", "-c", "simulation.sumocfg"]

try:
    traci.start(sumoCmd)
    vehicle_data = {}

    for step in range(1000):  # Run simulation for 1000 steps
        traci.simulationStep()  # Advance simulation by one time step
        vehicle_ids = traci.vehicle.getIDList()

        print(f"Step: {step}, Active Vehicles: {len(vehicle_ids)}")

        for vehicle_id in vehicle_ids:
            speed_kmh = traci.vehicle.getSpeed(vehicle_id) * 3.6
            route = traci.vehicle.getRoute(vehicle_id)
            data = vehicle_data.setdefault(vehicle_id, {
                'Vehicle ID': vehicle_id, 'Start Time': step, 'Route': route, 'Stop Count': 0,
                'Speed (km/h)': [], 'Waiting Time (seconds)': [], 'Stop Time (seconds)': [],
                'Fuel Consumption (ml)': [], 'Distance (km)': [], 'Arrival Time': None})

            data['Speed (km/h)'].append(speed_kmh)
            data['Waiting Time (seconds)'].append(traci.vehicle.getWaitingTime(vehicle_id))
            data['Stop Time (seconds)'].append(traci.vehicle.getAccumulatedWaitingTime(vehicle_id))
            data['Fuel Consumption (ml)'].append(traci.vehicle.getFuelConsumption(vehicle_id))
            data['Distance (km)'].append(speed_kmh / 3.6)  # Convert to km per second
            if speed_kmh == 0:
                data['Stop Count'] += 1

        for vehicle_id in traci.simulation.getArrivedIDList():
            vehicle_data[vehicle_id]['Arrival Time'] = step

    # Process data into DataFrame
    processed_data = [{
        'Vehicle ID': vehicle_id, 'Start Time': data['Start Time'],
        'Avg Speed (km/h)': sum(data['Speed (km/h)']) / len(data['Speed (km/h)']),
        'Route': data['Route'], 'Total Waiting Time (s)': sum(data['Waiting Time (seconds)']),
        'Total Stop Time (s)': sum(data['Stop Time (seconds)']), 'Stop Count': data['Stop Count'],
        'Fuel Efficiency (km/L)': sum(data['Distance (km)']) / (sum(data['Fuel Consumption (ml)']) / 1000),
        'Arrival Time': data['Arrival Time']
    } for vehicle_id, data in vehicle_data.items()]

    if processed_data:
        df = pd.DataFrame(processed_data)
        df.to_excel('vehicle_data.xlsx', index=False)
        print("Simulation completed successfully and data saved to vehicle_data.xlsx!")
    else:
        print("No vehicle data collected during the simulation.")

finally:
    traci.close()
```

Figure 5: The SUMO execution code

6.2.3. *Adding a Tram System for Comprehensive Testing*

A tram system was integrated around the university area to explore its impacts in future simulations. This addition aims to test traffic dynamics involving public transportation

Figure 6: The university surroundings street taken from Google Map

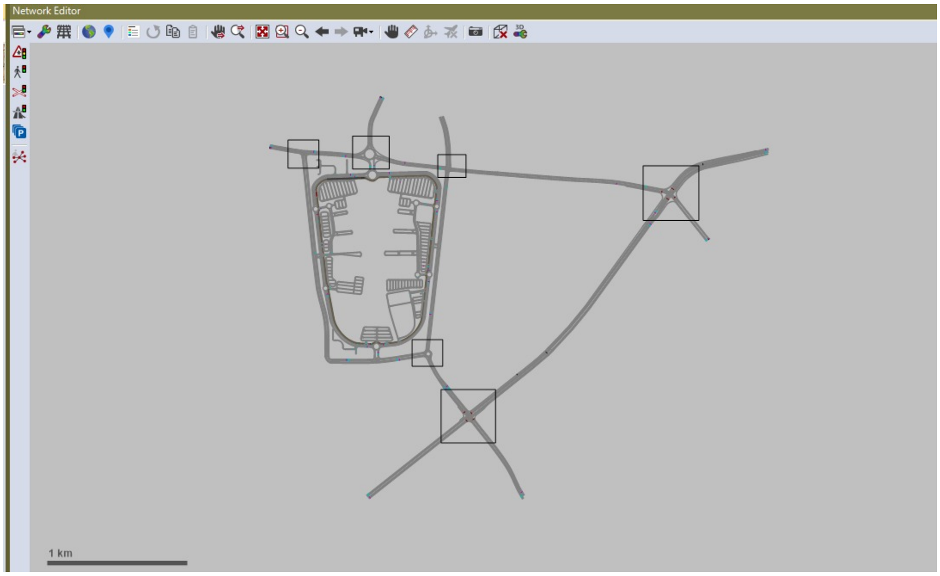


Figure 7: Final result of the map creation

6.2.4. Selection of Roads for Traffic Simulation

We selected five roads for detailed traffic analysis based on their strategic importance and traffic characteristics:

- **Najran Street:** Features almost no stop time and fewer vehicles, ideal for smooth traffic flow studies.
- **King Khaled Street:** Has very low vehicle traffic and minimal stop times, providing a clear picture of traffic under less congested conditions.

Figure 8: Another view for the university surroundings street taken by Google Map

()

Figure 9: The nearest Metro to the university

- **Abdullah Bin Amer:** Observes a higher volume of vehicles with fewer stop times, benefiting from no traffic lights and minimal intersections.
- **Municipality Intersection and Boulevard Street:** Both areas experience significant traffic volumes and stop times, posing challenges in traffic management.
- **King Abdullah Intersection:** The busiest intersection, characterized by the highest vehicle traffic and numerous stop times due to traffic lights and intersections.

Metric	Value
Average of Trip Time in Minutes	2.38
Vehicles Number	2,500
Average of Avg Speed (km/h)	68.35
Average of Stop Count	4.36
Average of Fuel Efficiency (km/L)	11.71

Table 3
Scenario 2022 Analysis

7. Simulated scenarios and results

We prepared a Python script that utilizes the TraCI API to simulate and collect data from SUMO. The script starts the SUMO simulation, simulates for 1000 steps, and collects data such as vehicle speed, route, waiting time, stop time, fuel consumption, and stop count for each active vehicle. It tracks when vehicles arrive at their destination and calculates fuel efficiency based on total distance and fuel consumption. After running the simulation, the collected data is processed and stored in an Excel file for further analysis. This script allows for detailed tracking and analysis of traffic flow and vehicle behavior in a simulated environment.

By using VISSIM, our simulation was limited to one hour. Despite this constraint, we successfully gathered substantial data, allowing for a detailed analysis of traffic patterns across selected roads and intersections. We conducted simulations of three basic scenarios, described in the following sections.

7.1. Scenario 2022

In Scenario 2022, the simulation focused on key metrics such as trip time, average speed, stop count, and fuel efficiency across a set of selected roads and intersections (as illustrated in the figure 10). The map displayed in figure 10 displays the road layout and intersections, which were crucial in understanding how the simulation was set up and how vehicles interacted with the road network.

The data gathered from Scenario 2022 offers insightful results about the performance of the road network under simulated conditions. With a total of 2,500 vehicles and as the results provided in table 7.1, the simulation found that the average trip time of 2.38 minutes suggests a relatively efficient road system, albeit there is room for improvement, especially in terms of reducing the stop count and improving fuel efficiency.

The average speed of 68.35 km/h indicates that, on average, vehicles were able to travel at a reasonable speed, which suggests that traffic congestion was not a major issue during this simulation. However, the average stop count of 4.36 suggests that some degree of congestion or inefficiency in the road layout still occurred. This is further supported by the fuel efficiency of 11.71 km/L, which, while reasonable, could be optimized further through improvements in vehicle flow and signal timing at intersections.

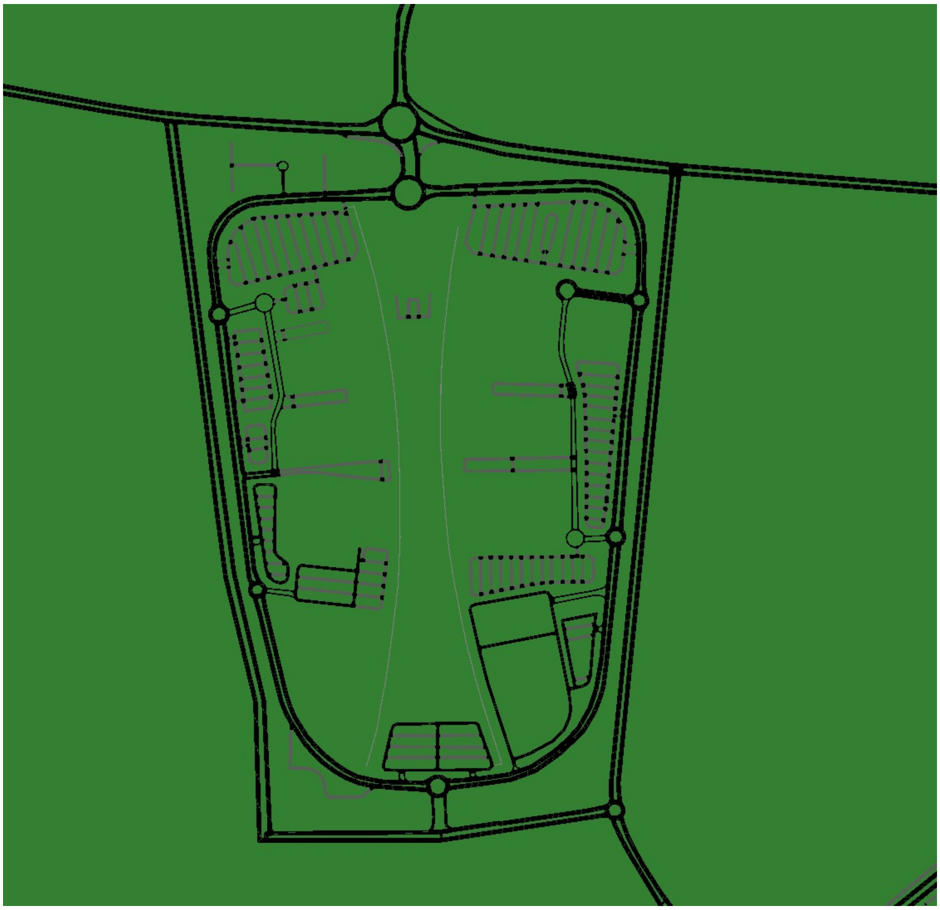


Figure 10: Scenario 2022 with Right Intersection in the Streets

The fuel efficiency metric reveals an important aspect of traffic management: the smoother the traffic flow, the less fuel is consumed. Reducing the number of stops and delays would contribute not only to better vehicle performance but also to reduced environmental impact. This aligns with the goals of the study to propose practical solutions for traffic congestion and optimization.

These results are consistent with our expectations from SUMO's traffic modeling capabilities, providing a foundation for testing various traffic management strategies. Despite the constraint of a one-hour simulation window, the results were valuable in highlighting the importance of adjusting signal timings, optimizing intersections, and redesigning road networks to enhance overall traffic efficiency.

7.2. Scenario 2025

In Scenario 2025, the updated road layout, as shown in the map provided in figure 11, incorporated some modifications to intersections and traffic flow to examine the effect on overall traffic performance.

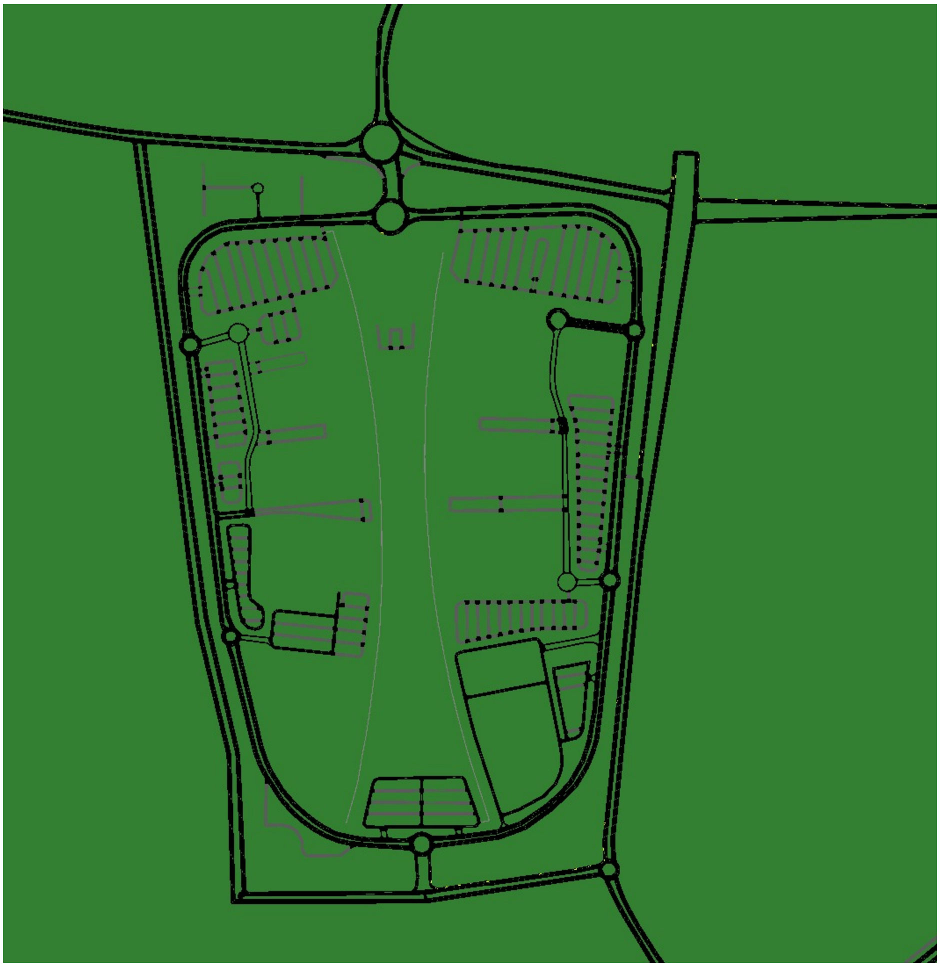


Figure 11: Scenario 2025 with modifying in the Streets and the Gates

Metric	Value
Average of Trip Time (Minutes)	2.77
Count of Vehicle ID	2,500
Average of Avg Speed (km/h)	62.49
Average of Stop Count	4.32
Average of Fuel Efficiency (km/L)	11.51

Table 4
Scenario 2025 Analysis

The results in table 7.2 show the traffic data revealing some important trends. The average trip time increased slightly to 2.77 minutes compared to 2.38 minutes in Scenario 2022. This increase in trip time suggests that the adjustments made to the road layout and intersections, such as new traffic management features or modified routes, might have resulted in some delays, potentially due to increased congestion at key points in the network.

The average speed also saw a decline to 62.49 km/h from 68.35 km/h in Scenario 2022. This drop indicates that the vehicles were, on average, moving slower, likely due to the introduction of traffic control changes that may have caused bottlenecks at specific intersections or areas within the network. Despite the same vehicle count in both scenarios, the road modifications in Scenario 2025 did not appear to facilitate smoother traffic flow.

Furthermore, the average stop count remained relatively consistent, increasing slightly to 4.32 stops per vehicle compared to 4.36 stops in Scenario 2022. This small change indicates that while the adjustments made to the road design may have had some effect on the frequency of stops, the impact was minimal. This could point to the need for further optimization of signal timings and intersection configurations to reduce the number of stops.

In terms of fuel efficiency, the result showed a slight improvement, with an average of 11.51 km/L in Scenario 2025 compared to 11.71 km/L in Scenario 2022. Although the improvement is modest, it suggests that the updated road layout might have contributed to less fuel consumption, possibly due to more efficient vehicle movement in certain parts of the network, despite the slower average speeds.

7.3. Scenario Edited 2025

In the updated version of Scenario 2025, the simulation was run for 2,500 vehicles, and the road layout was adjusted to better optimize traffic flow. The data reveals key improvements and changes from the previous version of Scenario 2025. This version is presented in figure 12. The layout is a design of a road system with intersections and a central roundabout. Key features visible on the map include:

- **Intersection Points:** The map shows several intersections with vehicles entering and exiting different road sections. These intersections play a vital role in controlling traffic flow and were adjusted in the edited scenario to optimize vehicle movements and reduce delays.

- **Roundabout:** Located at the center of the network, the roundabout is a key feature to improve traffic flow by reducing waiting times at traffic signals. The modified design of the roundabout aims to enhance traffic distribution and minimize congestion.

- **Lane Configuration:** The road segments are designed with multiple lanes, providing enough capacity for vehicles to move efficiently. In the edited scenario, the lane configurations were adjusted to allow for smoother transitions between different road sections, optimizing the distribution of vehicles.

- **Parking Areas:** The map also shows parking spaces in various locations, which influence the flow of traffic by providing designated spots for vehicle stops, reducing the chance of stopping along the road.

The results from the updated Scenario 2025 reveal significant improvements compared to the previous scenario. The average trip time increased to 5.51 minutes, suggesting that, while traffic flow was optimized, the larger network or possibly longer distances between some intersections caused a slightly longer average trip time. Despite this, the

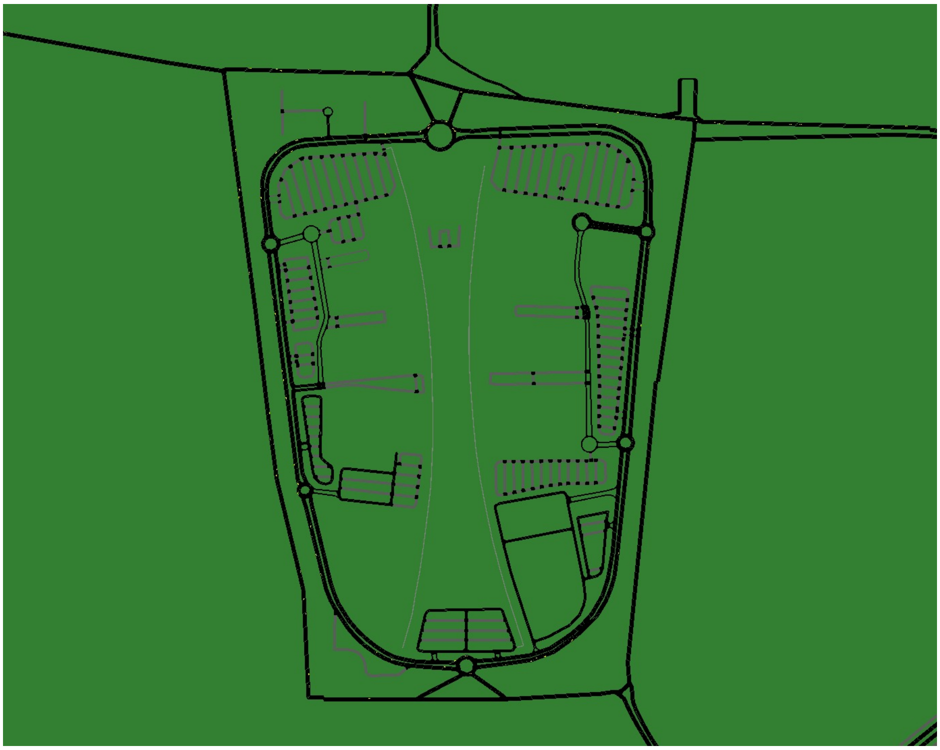


Figure 12: Scenario Edited 2025 with intersections and a central roundabout

Metric	Value
Average of Trip Time (Minutes)	5.51
Count of Vehicle ID	2,500
Average of Avg Speed (km/h)	71.78
Average of Stop Count	2
Average of Fuel Efficiency (km/L)	13.31

Table 5
Scenario Edited 2025 Analysis

average speed rose to 71.78 km/h, an increase from the previous scenario, which indicates that vehicles are traveling faster due to the improved traffic management strategies.

One of the most notable improvements in this scenario is the average stop count, which decreased to 2 stops per vehicle, down from the previous scenario's higher stop frequency. This reduction in stop count can be attributed to the changes made to intersections and the introduction of the roundabout, both of which likely helped maintain smoother traffic flow with fewer interruptions.

Additionally, fuel efficiency saw a considerable improvement, with an average of 13.31 km/L. This increase in fuel efficiency suggests that the optimized traffic flow and reduced stop count allowed vehicles to move more smoothly, consuming less fuel and thereby becoming more environmentally friendly.

Conclusion: Analysis of Traffic Flow Across Three Scenarios

This study evaluates three traffic scenarios, each with distinct road configurations and traffic management strategies, aimed at improving the flow and efficiency of urban roads. The results of these scenarios highlight the impact of different interventions on various performance metrics, such as trip time, speed, stop counts, and fuel efficiency.

Scenario 2022

Scenario 2022 represents the existing traffic conditions before any modifications. Although this scenario demonstrated the **shortest average trip time** of 2.38 minutes, it was characterized by numerous stops, **higher fuel consumption**, and **lower overall traffic efficiency**. The excessive stops and congestion indicated that the existing infrastructure could not efficiently accommodate the volume of traffic, resulting in delays and higher fuel usage.

Scenario 2025

Scenario 2025 introduces a **realistic adjustment before field implementation**, aimed at improving traffic flow. Key changes included modifying the intersection of **Abdullah bin Amer** and **Mohammed bin Salman** to mandate right turns or U-turns heading south. This adjustment resulted in **significant improvements** in **traffic efficiency**, with **reduced stop times** and a smoother flow of vehicles. These modifications provided a more efficient traffic network, albeit without drastically reducing trip times.

Scenario Edited 2025

Scenario 2025 Modified presents a more **innovative and comprehensive vision** for the road network, incorporating several new features to further enhance traffic flow. Notable changes include:

- Transforming the **Abdullah bin Amer** and **Mohammed bin Salman** intersection into three options: north, south, or right toward **Mohammed bin Salman** east.
- **Eliminating the roundabout** at the university's main gate and replacing it with **three direct lanes** leading to **Nasser Road**, **King Khalid Road**, or the **university entrance**.
- Reversing all **entrances and exits** around the university to align with the new road designs and improve traffic flow.
- **Removing the intersection** between **Nasser Road** and the university's back street, converting it into a **two-way street**.
- **Eliminating the roundabout** at **Mohammed bin Salman Street** and creating clearer left and right turn options.

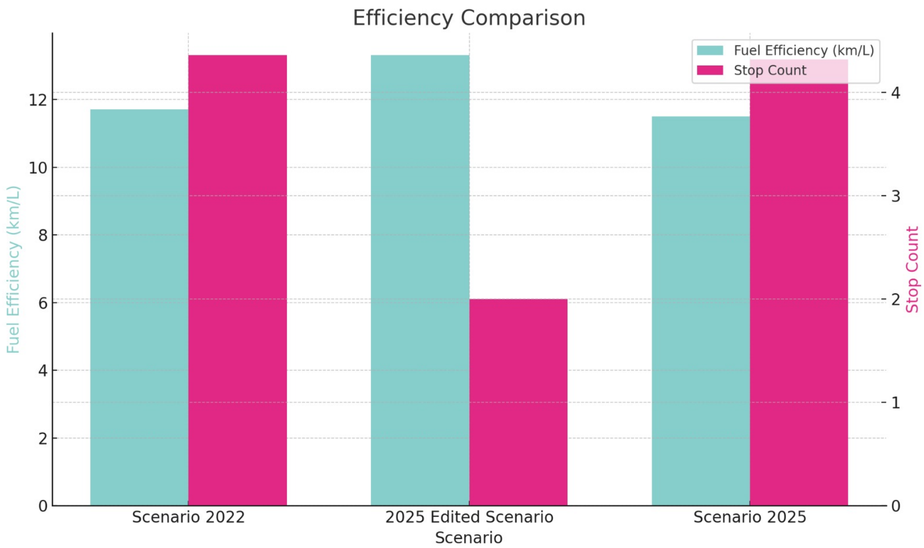


Figure 13: Efficiency comparison across the three scenarios

- Converting all surrounding streets to **one-way** to enhance overall traffic flow and reduce congestion.
- **Removing sidewalks** and transforming the area around the university into a **circular traffic loop**, facilitating smoother movement between the university and nearby neighborhoods.

These adjustments resulted in improved **fuel efficiency** and reduced **stop counts** due to enhanced road network design and signal adjustments. The circular traffic loop around the university further helped reduce congestion, providing a more streamlined and efficient route for both university commuters and local traffic. Figure 13 presents the efficiency comparison across the three scenarios.

Further Enhancements and Data Considerations

1. Traffic Analysis Data: To assess the real impact of these changes, **traffic data analysis** (e.g., average speed, waiting times, and vehicle count) should be included to quantify the improvements observed in each scenario. This data would provide clear evidence of how specific adjustments affect traffic flow in measurable terms.

2. Environmental Impact: A section dedicated to the **environmental impact** of the proposed changes could highlight reductions in fuel consumption, emissions, and overall environmental benefits from improved traffic management. Scenario 2025 and Scenario 2025 Modified, with their focus on smoother traffic flow, are likely to lead to significant reductions in emissions and fuel use.

3. Public Feedback: Incorporating **public feedback** from local residents or commuters can further enhance the evaluation of the proposed changes. Public opinion is critical, especially when large infrastructure changes are involved, to ensure that the solutions meet the needs of the community and are accepted by users.

4. Cost and Feasibility Analysis: A feasibility analysis, including the **cost** of implementing these changes, would be important for assessing whether these solutions can be realistically applied in the future. Scenario 2025 Modified involves substantial road redesigns, and understanding the **financial and logistical** implications of these changes is essential for their practical implementation.

Final Thoughts

The three scenarios demonstrate a gradual progression toward more efficient and sustainable traffic management. While **Scenario 2022** served as the baseline, **Scenario 2025** introduced key adjustments that improved **traffic efficiency** without drastically affecting travel times. **Scenario 2025 Modified** offers the most innovative approach, with extensive changes to road layouts and intersections, resulting in significant improvements in **fuel efficiency**, **stop counts**, and **overall traffic flow**. These findings provide valuable insights into how urban road networks can be optimized for better **traffic performance**, reduced **environmental impact**, and increased **driver satisfaction**. Future research should further explore the integration of **advanced traffic management systems** and **smart infrastructure** to continue improving urban mobility.

8. Conclusion

Simulation tools like SUMO and VISSIM are powerful resources for supporting road planning and improving traffic flow. Through this experience, we gained a deeper understanding of traffic dynamics and presented practical solutions for improving road infrastructure. Despite the challenges faced, the results were satisfactory and contributed to achieving our objectives efficiently.

9. Data availability

Data is available on demand from the corresponding author.

10. Conflict of interest

The author wishes to confirm that there are no known conflicts of interest associated with this work and there has been no significant financial support for this work that could have influenced its outcome.

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