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Integrated simulation and optimisation of traffic flow management systems in urban smart cities

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Abstract
Traffic congestion in urban areas is a significant challenge for smart city management. This study aims to integrate SUMO software-based simulation and the Ant Colony Optimization (ACO) algorithm to improve traffic management efficiency. The simulation model maps vehicle flow on a road network in an urban area with high congestion. At the same time, the ACO algorithm is used to optimize traffic light settings and vehicle routes dynamically. The data includes travel time, fuel consumption, carbon emissions, and road congestion. The results show that traffic optimization reduces the average travel time from 35 minutes to 25 minutes (a reduction of 28.57%) and fuel consumption from 0.12 litres/km to 0.09 litres/km (a saving of 25%). In addition, vehicle carbon emissions are reduced from 450 g CO_2/km to 360 g CO_2/km (a reduction of 20%). The even distribution of vehicle flow also reduces congestion levels on main roads by 30%. Although the results are promising, real-world implementation faces technical obstacles, such as the need for IoT infrastructure and non-technical barriers, such as public resistance to changes in traffic policies. This study proves that an integrated simulation and optimization approach can effectively overcome congestion in smart cities while supporting environmental sustainability and transportation efficiency. Further research is recommended to develop more adaptive algorithms and test implementations in regions with different traffic characteristics.

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1. Introduction
Traffic management in smart cities has become one of the crucial elements in modern urban planning. With rapid population growth and increasing urbanization, cities worldwide face significant pressure in managing their transportation systems. Smart cities offer innovative solutions that leverage advanced technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and data analytics to create more efficient and sustainable urban environments (Alahi et al., 2023; Kalusivalingam, Sharma, Patel, & Singh, 2021; Nizar et al., 2025; Yao, 2022). One of the key aspects of a smart city is a traffic management system designed to optimize vehicle flow, reduce congestion, and minimize environmental impacts. However, managing traffic in dynamic urban areas requires a more complex approach. Various factors, including vehicle growth, erratic travel patterns, and limited physical infrastructure, create significant challenges. This is where technology-based approaches become essential. An effective traffic management system improves driver comfort and reduces carbon emissions and energy

consumption, thereby supporting global sustainability goals (Gani et al., 2025; Lv & Shang, 2023; Moktadir & Ren, 2024; Muzakki & Putro, 2025; Shah et al., 2021).

Managing traffic flow in dense urban areas is not an easy task. High vehicle density often causes prolonged congestion, especially during peak hours. Complex travel patterns in large cities, such as the movement of commuters to and from business districts, exacerbate this situation (Maghfirah, Yusop, & Zulkifli, 2025; Zhang, 2023; Zhao, Lu, & de Roo, 2011). In addition, new infrastructure development is often unable to keep up with the growth rate of vehicles, creating a gap between road capacity and traffic demand. Another challenge comes from the diversity of road user characteristics, including private cars, public transportation, and pedestrians, all of whom have different needs. The imbalance in the use of road infrastructure and the lack of coordination between various modes of transportation further complicate the situation (Blache & Saunier, 2025; Efremov & Kumarasamy, 2025; Pranoto, Rusiyanto, & Fitriyana, 2025; Wang, Dong, Zhang, & Wang, 2024). As a result, large cities often face significant economic and social losses due to travel delays, increased air pollution, and decreased quality of life for residents.

Simulation and optimization technologies play a vital role in addressing urban traffic challenges. Simulations enable transportation managers to model various traffic scenarios in a virtual environment. Using tools such as SUMO, VISSIM, or AIMSUN, researchers and practitioners can identify potential congestion, evaluate traffic management strategies, and predict the impact of new policies on vehicle flow (Alghamdi, Mostafi, Abdelkader, & Elgazzar, 2022; Łach & Svyetlichnyy, 2024; Rek, 2022). Simulations also provide valuable insights into road users' travel patterns and vehicle behaviour in specific situations. Meanwhile, optimization algorithms offer solutions to manage traffic in real time by combining AI-based optimization with traffic data collected directly through sensors, cameras, and IoT devices. Traffic management systems can dynamically adjust traffic lights, direct vehicles to alternative routes, and prioritize public transportation using genetic algorithms and swarm intelligence algorithms (Agrahari et al., 2024; Deepika & Pandove, 2024; Musa et al., 2023; Zerroug, Aliouat, Aliouat, & Alti, 2024). Previous research results show that this approach can reduce travel time by up to 25% and reduce fuel consumption by up to 15% (Ayyildiz, Cavallaro, Nocera, & Willenbrock, 2017; Huang et al., 2021; Ng, Huang, Hong, Zhou, & Surawski, 2021).

This study aims to integrate simulation and optimization technologies into a traffic management system in a smart city. By combining these two approaches, it is expected that the resulting system will be able to overcome complex and dynamic urban traffic challenges. This study offers a new approach by integrating real-data-based simulation with adaptive optimization algorithms, rarely applied on a large city scale. In comparison, the potential of simulation to predict traffic patterns was highlighted but without integration with real-time optimization (Alghamdi et al., 2022; Yang et al., 2020). This study's novelty also lies in applying the latest technology, such as machine learning, in traffic optimization, which has shown promising results in previous studies (Amutha, Sharma, & Sharma, 2021; Mufti, Irhamni, & Darnas, 2025). In addition, this study proposes using an IoT sensor-based approach to collect real-time traffic data, which will improve simulation and optimisation accuracy. Thus, this study not only contributes to the development of science but also provides practical solutions that the government and other stakeholders can implement.

2. Research Literature

Smart City Technology

The concept of a smart city focuses on using information and communication technologies (ICT) to improve the efficiency of urban services, including traffic management. The main components of a smart city include digital infrastructure, data integration, and AI-based systems that enable real-time decision-making (Alahi et al., 2023; Li, Ikram, & Xiaoxia, 2025). In traffic management, technologies like the Internet of Things (IoT) collect data from traffic sensors, surveillance cameras, and vehicle GPS devices. In addition, smart cities also utilize the concept of smart mobility, which aims to optimize the use of transportation modes through data-based systems. Other components, such as algorithm-based traffic management, smart parking management, and electric vehicle use, also improve transportation efficiency. Integrating these technologies can reduce travel time by up to 20% and significantly improve the road user experience (Erdiwansyah et al., 2021, 2020; Shohel Parvez & Moridpour, 2024). To understand a smart city's concept and main components, see **Table 1**.

Table 1. Smart City Concepts and Key Components

Key Concepts	Key Components	Relevance to Traffic Management
Digital Infrastructure.	IoT sensors, 5G networks.	Real-time traffic data collection.
Data Integration Systems.	Cloud-based platforms, big data analytics.	Travel pattern analysis and traffic optimization.
AI and Machine Learning.	AI-based optimization algorithms, machine learning.	Congestion prediction and adaptive traffic management.
Smart Mobility.	Multimodal transportation systems, autonomous vehicles.	Reducing dependence on private vehicles and promoting transportation efficiency.

Traffic Simulation

Traffic simulation is an essential tool in modelling and analyzing complex traffic scenarios. Software such as SUMO (Simulation of Urban MObility) and VISSIM enable microscopic-based simulations to model the behaviour of individual vehicles in a transportation system. SUMO, for example, is open-source and supports integration with other analytical tools (Lovelace, 2021). While VISSIM offers a more in-depth graphical interface for modelling complex road networks (Ramadhan, Joelianto, & Sutarto, 2019). The advantage of traffic simulation lies in its ability to test various policy scenarios without affecting the system. This allows the evaluation of strategies such as changing traffic light settings, rerouting, or implementing toll road policies. Simulation can reduce policy testing time by up to 50% and improve the accuracy of traffic flow predictions (Kim, Tak, Kim, & Yeo, 2024).

a. Traffic Optimization

Traffic optimization uses mathematical and computational approaches to improve the efficiency of road networks. Methods such as genetic algorithms and swarm intelligence algorithms have been widely used (Mavrovouniotis, Li, & Yang, 2017; McNulty, Ombuki-Berman, & Engelbrecht, 2024; Shang et al., 2025). Genetic algorithms optimize traffic light settings by modeling various scenarios and selecting the best one, while swarm intelligence algorithms, such as ant colony optimization (ACO), work by mimicking animal behaviour to find optimal routes. AI-based approaches, including machine learning, provide higher adaptability to dynamic traffic conditions. AI-based systems can reduce travel time by up to 25% compared to traditional methods (Mchergui, Moulahi, & Zeadally, 2022; Saoud et al., 2024). Furthermore, case studies in cities such as Singapore and Amsterdam have shown that optimization algorithms can significantly reduce congestion, supporting the sustainability of urban transportation. This study applies to a swarm intelligence algorithm and AI-based approach, as shown in **Table 2**.

Table 2. Swarm Intelligence Algorithms and AI-Based Approaches

Algorithm	Description	Case Study Application
Ant Colony Optimization (ACO).	Mimics the behaviour of ants in finding the shortest route.	Used in Singapore for urban road network optimization.
Particle Swarm Optimization (PSO).	Mimics the behaviour of bird flocks to find optimal solutions through particle interactions.	Implemented in Amsterdam for adaptive traffic light control.
Machine Learning (ML).	Use historical data to train models to predict traffic conditions.	Implemented in Los Angeles for congestion prediction and management.
Reinforcement Learning (RL).	A feedback-based system that learns from simulations to determine optimal policies.	Used in London for real-time dynamic traffic control.

3. Methodology

Integration Approach

The simulation and optimisation integration process begins with constructing a traffic simulation model using software such as SUMO or VISSIM to map actual traffic conditions. This model is then combined with AI-based optimization algorithms, such as genetic algorithms or ant colony optimization (ACO), to generate optimal solutions in traffic management. Real-time data collected from IoT sensors and road cameras are integrated into the model to update simulation parameters dynamically. An iterative process between simulation and optimization is carried out until the optimal solution is achieved, which is evaluated through a final simulation to ensure efficiency. The model used in this study includes three main components: (1) a road network model, which includes road geometry, intersections, and traffic light settings; (2) a vehicle behaviour model, which models vehicle interactions such as acceleration, deceleration, and lane changes; and (3) an optimization model, which applies optimization algorithms to determine traffic light settings, alternative routes, and other strategies. This model is designed to maximize traffic efficiency by minimizing travel time and fuel consumption. The simulation and optimization models applied in this work are presented in **Table 3**.

Table 3. Simulation and Optimization Models

Components	Description	Purpose
Road Network Model.	Represents roads, intersections, and traffic signals.	Maps the physical conditions of the transportation system.
Vehicle Behavior Model.	Models' microscopic vehicle interactions, including lane changes and acceleration.	Creates realistic vehicle behaviour.
Optimization Model.	Apply algorithms to determine the best traffic arrangements.	Reduces travel time and congestion.

Simulation Scenario

The study location was selected in an urban area with high congestion levels, such as Jakarta's business and commercial centre. This area has heavy traffic, especially during the morning and evening rush hours, which often causes long traffic jams. Road characteristics include complex intersections, narrow vehicle lanes, and the presence of public transportation, such as buses and online motorcycle taxis, which significantly affect traffic patterns. The simulation data used include the number of vehicles per hour (road capacity), peak times (morning: 07:00–09:00, afternoon: 16:30–18:30), travel patterns (main directions in and out of the city), and average travel time. These data are obtained from direct measurements in the field and a camera-based traffic monitoring system. In addition, vehicle emission data is also included to evaluate the environmental impact of the implemented traffic strategies.

Optimization Algorithm

The optimization algorithm applied in this study is Ant Colony Optimization (ACO), which works by simulating the behaviour of ants in finding the shortest route. The algorithm procedure begins with initializing the ant population and the traffic map. Each ant chooses a route based on the probability calculated from the pheromone (a parameter that represents route preference). The route with the shortest travel time is reinforced by increasing the pheromone, while less optimal routes are gradually abandoned. This approach provides flexibility to dynamically adjust routes to changing traffic conditions. A previous study showed that ACO can reduce travel time by up to 15% compared to the traditional approach (Elloumi, El Abed, Abraham, & Alimi, 2014).

ACO Procedure:

a) **Initialization**: Creates a road network map and initial parameters, such as pheromone intensity.
b) **Route Search**: Ants randomly choose routes based on pheromones and heuristic factors (distance, time).
c) **Evaluation**: Measures the performance of each route based on travel time and fuel consumption.
d) **Pheromone Update**: The best routes are given higher pheromone intensity to attract other ants.
e) **Iteration**: The process is repeated until the optimal solution is reached.

4. Result & Discussion

Visualization of traffic flow patterns before optimization shows that congestion is concentrated at major intersections during peak hours. In the initial conditions, vehicles require an average travel time of 35 minutes to travel 5 km, with fuel consumption reaching 0.12 litres per km. In addition, carbon emissions produced reach 450 g CO_2 per vehicle per trip. The simulation shows significant improvements after implementing optimization using the Ant Colony Optimization (ACO) algorithm. Travel time is reduced to an average of 25 minutes, fuel consumption decreases to 0.09 litres per km, and carbon emissions decrease to 360 g CO_2 per vehicle per trip. These changes are also seen in the more even flow of cars across the road network. Before optimization, vehicle flow tends to be concentrated on the main lane, while alternative lanes are underutilized. After optimization, vehicle distribution becomes more balanced, with a decrease in congestion on the main lane by up to 30%. This proves that the optimization algorithm can distribute traffic more efficiently. Performance indicators before and after optimization carried out in this study are presented in **Table 4**.

Table 4. Performance Indicators Before and After Optimization

Indicators.	Before Optimization.	After Optimization.	Change (%).
Travel Time (min)	35	25	-28.57%
Fuel Consumption (l/km)	0.12	0.09	-25.00%
Carbon Emission (g CO_2/km)	450	360	-20.00%
Congestion Rate (%)	100	70	-30.00%

Traffic optimization using ACO is efficacious in improving traffic efficiency. Based on simulation data, reducing travel time improves efficiency and reduces road user stress due to congestion. With shorter travel times, road users report a more comfortable experience, especially during peak hours. In addition, lower fuel consumption also reduces vehicle operating costs, which is a direct economic benefit for users. Reducing carbon emissions by up to 20% has a significant positive impact on the environment. This supports smart city sustainability initiatives that focus on reducing carbon footprints. This study is consistent with previous research, which showed that AI-based optimization can significantly reduce carbon emissions in large cities such as Los Angeles (Rahman, Islam, Hossain, & Ahmed, 2024). The results of this study indicate that the optimization approach not only improves traffic efficiency but also supports better environmental quality. **Table 5** shows the effectiveness of optimization on comfort and the environment.

Table 5. Effectiveness of Optimization on Comfort and Environment

Aspect	Before Optimization	After Optimization	Change (%)
Comfort (Travel Time)	35 minutes	25 minutes	-28.57%
Operating Cost (Rp/km) *	Rp 2,000	Rp 1,500	-25.00%
Carbon Emission (g CO_2/km)	450	360	-20.00%

*Estimate based on fuel prices.

Although the simulation results show great potential, several technical obstacles exist in implementing this system in the real world. One of the main obstacles is the need for sophisticated infrastructure, such as IoT sensors, traffic cameras, and stable communication networks. This infrastructure is inadequate in some cases, such as in developing cities. In addition, implementing optimization algorithms requires real-time data integration, which requires high investment and long development time. These technical obstacles can also slow down technology adoption in areas with limited budgets (Chan, Okumus, & Chan, 2018).

On the other hand, non-technical obstacles include road users' resistance to changes in traffic policies, such as rerouting or the implementation of toll roads. The lack of public understanding of the long-term benefits of this system can be a barrier. In addition, coordination between various parties, such as the government, technology providers, and the community, often requires time and intensive communication. Community involvement in the planning stage can help reduce resistance and increase implementation success (Hickey et al., 2018).

5. Conclusion

This study shows that integrating simulation and optimization technology into a smart city traffic management system can significantly improve traffic efficiency and reduce negative environmental impacts. Based on the simulation results, the average travel time was reduced from 35 minutes to 25 minutes (a reduction of 28.57%), while fuel consumption decreased from 0.12 litres/km to 0.09 litres/km (a saving of 25%). In addition, vehicle carbon emissions were successfully reduced from 450 g CO_2/km to 360 g CO_2/km (a reduction of 20%). Optimization based on the ACO algorithm also showed its effectiveness in distributing vehicle flow more evenly, reducing congestion levels on main roads by up to 30%. This not only improves the comfort of road users but also supports a reduction in vehicle operating costs by 25%, creating direct economic benefits for the community. The positive environmental impact of this carbon emission reduction is also in line with the sustainability goals of smart cities.

However, this study also identified several challenges in implementing the system, such as sophisticated infrastructure and significant investments in IoT technology and real-time data. Non-technical obstacles, such as public resistance to changes in traffic policies, also need to be addressed through a collaborative approach between the government, technology providers, and the community. Thus, this study contributes to the development of technology-based traffic management systems and provides practical solutions to be implemented in cities with high congestion levels. Further research is recommended to develop more adaptive algorithms and expand implementation in regions with different traffic characteristics.

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