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AI powered urban mobility optimizer with carbon footprint reduction and smart carpooling integration

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Abstract- Urban mobility systems are facing increasing pressure due to traffic congestion, rising fuel consumption, and growing environmental concerns. The transportation sector alone contributes a significant share of global greenhouse gas emissions, making sustainable mobility solutions a critical requirement [1]. Over the past decade, researchers have proposed several optimization-based routing models, including the Pollution Routing Problem (PRP) [5], fuel-consumption-aware vehicle routing approaches [4], and emission-sensitive routing frameworks [3]. However, the majority of these efforts have focused primarily on freight and logistics operations rather than passenger transportation. Advances in time-dependent routing models [10] and environmentally conscious vehicle routing formulations [6], [7] have improved operational efficiency and emission control in logistics networks. Nevertheless, passenger-oriented solutions such as smart carpooling and ridesharing remain relatively underexplored from a carbon-optimization perspective, despite their potential to significantly reduce vehicle usage in urban environments. To address this gap, this paper proposes AUMO, an AI-powered Urban Mobility Optimizer designed to integrate carbon-aware routing with smart carpooling for passenger mobility. The proposed framework adapts established low-carbon routing principles from freight transportation [3], [6] and applies them to urban passenger travel scenarios. A simulation-based evaluation using a microscopic traffic environment demonstrates that the proposed system achieves notable reductions in CO_2 emissions and fleet size while improving vehicle occupancy and overall travel efficiency. These results highlight the potential of intelligent carpooling systems for sustainable urban mobility.

Keywords: Artificial Intelligence (AI), Urban Mobility, Smart Carpooling, Carbon Footprint Reduction, Machine Learning.

I. INTRODUCTION

Cities across the world are increasingly affected by congestion, rising fuel consumption, and environmental degradation as urban populations continue to grow. Transportation systems play a major role in this challenge, contributing a significant share of global greenhouse gas emissions. Current studies estimate that the transport sector accounts for nearly 15% of human-induced emissions worldwide, with energy-related emissions expected to increase substantially in the coming decades if existing mobility patterns remain unchanged [1]. These trends highlight the urgent need for more sustainable and efficient urban transportation solutions.

In response to these challenges, vehicle routing research has evolved beyond traditional distance-based optimization toward environmentally conscious formulations.

The introduction of the Pollution Routing Problem (PRP) marked an important step by explicitly incorporating emission considerations into routing decisions [5].

Subsequent studies further extended this idea through fuel-consumption-aware vehicle routing models and emission-sensitive cost formulations, including carbon pricing mechanisms [3], [4]. Time-dependent routing approaches have also been proposed to better capture the impact of traffic congestion during peak hours [10], [15], while multi-objective green VRP models attempt to balance operational cost, service quality, and environmental impact simultaneously [6], [7]. These advances have significantly improved sustainability in freight and logistics operations.

However, despite these developments, urban passenger transportation has received comparatively less attention from an optimization and emission-reduction perspective. Daily commuting patterns in most cities remain dominated by single-occupancy vehicles, resulting in inefficient vehicle utilization and avoidable emissions. Smart carpooling and ridesharing present a promising opportunity to reduce the number of vehicles on the road while improving overall system efficiency, yet these approaches are rarely integrated with carbon-aware optimization frameworks in existing research.

Recent progress in artificial intelligence and heuristic optimization has created new opportunities for addressing complex and dynamic transportation problems. Techniques such as traffic prediction, adaptive optimization, and learning-based decision making enable routing systems to respond effectively to changing traffic conditions. When applied to low-carbon and collaborative freight distribution models, such approaches have demonstrated notable reductions in both operational cost and emissions [3], [6], [4]. These results motivate the exploration of similar strategies in the context of urban passenger mobility.

Based on these observations, this paper proposes AUMO, an AI-powered Urban Mobility Optimizer that integrates predictive traffic modelling, carbon-aware routing, and smart carpooling within a unified framework. The primary objective of the proposed system is to reduce emissions and congestion while maintaining acceptable travel times and user satisfaction. Through simulation-based evaluation, the study demonstrates the potential of intelligent carpooling and optimization techniques to support sustainable urban mobility.

II. LITERATURE REVIEW

Related Works

The growing concern over sustainable transportation has led to extensive research on reducing the environmental impact of urban mobility systems.
The transport sector contributes a significant proportion of global greenhouse gas emissions, motivating the development of routing and optimization techniques that explicitly consider fuel consumption and emissions [1]. Early studies in this domain focused on the classical Vehicle Routing Problem (VRP), where optimization objectives were primarily limited to minimizing distance or operational cost. Environmental factors were largely ignored in these initial formulations.

The introduction of the Pollution Routing Problem (PRP) represented a major advancement by incorporating fuel consumption and emission considerations directly into routing decisions [5]. This work laid the foundation for a wide range of low-carbon routing models. Subsequent studies extended this framework by accounting for vehicle load effects on fuel consumption and by jointly considering distance and speed as key contributors to emission generation [2]. Emission-sensitive cost formulations, including carbon taxes and quota-based mechanisms, were also proposed to influence routing behavior toward environmentally favourable solutions [3], [8]. In parallel, multi-objective vehicle routing models were developed to balance economic cost, service quality, and environmental impact within a single optimization framework [6], [7].

Recognizing the dynamic nature of urban traffic, researchers introduced time-dependent routing approaches that capture variations in travel time across different periods of the day. Pan et al. [10] and Gmira et al. [15] demonstrated that incorporating time-varying traffic conditions leads to more realistic and efficient routing decisions. These models highlighted that congestion-aware routing can significantly affect both travel efficiency and emission outcomes, particularly in dense urban environments.

Accurate emission modelling has also received considerable attention. Xiao et al. [7] emphasized the impact of vehicle load on energy consumption, while Demir et al. [8] proposed comprehensive emission models that incorporate factors such as speed, road gradient, and driving behavior. Other studies showed that emission-minimizing routes do not always coincide with shortest-distance paths, and that strategic departure timing can further reduce environmental impact [9], [10]. These findings shifted the focus of green routing research from purely spatial optimization to spatio-temporal decision making.

Collaboration and resource sharing have emerged as effective strategies for improving efficiency in freight transportation. Liu [11] demonstrated that collaborative logistics can significantly reduce costs in cold-chain distribution, while Wang et al. [12] showed that joint distribution strategies can achieve substantial reductions in both operational cost and carbon emissions, along with notable fleet size savings. Although these results were obtained in freight scenarios, they suggest that similar benefits could potentially be achieved in passenger transport through intelligent carpooling mechanisms.

Despite these advances, passenger-oriented mobility solutions have received comparatively less attention in emission-aware optimization research. Early work on dynamic ridesharing explored coordination through traffic information centers [13], and more recent studies have examined digital ride-matching platforms [14]. While these approaches improve vehicle utilization and traffic flow,

they often lack explicit integration with detailed emission models. As a result, the environmental benefits of ridesharing in urban passenger transport remain insufficiently quantified when compared to freight-focused studies.

From a computational perspective, the complexity of large-scale urban mobility problems has encouraged the adoption of advanced optimization techniques. Metaheuristic approaches and hybrid optimization strategies have been widely applied to handle the scale and uncertainty of real-world routing problems. These methods provide the flexibility required for dynamic environments, but their application to passenger mobility with explicit carbon-awareness remains limited in the existing literature.

Overall, prior research has made substantial progress in low-carbon routing [5]–[8], time-dependent traffic modeling [10], [15], emission estimation [7]–[10], and collaborative logistics [11], [12]. However, the integration of these concepts into passenger-oriented mobility systems—particularly through smart carpooling—has not been sufficiently explored. This gap motivates the development of the proposed AUMO framework, which aims to combine carbon-aware optimization, predictive traffic modeling, and intelligent carpooling within a unified system for sustainable urban mobility.

Research Gaps Identified in the Literature

A critical review of existing studies reveals several important research gaps. First, many routing and optimization approaches are evaluated under simplified assumptions, such as static traffic conditions or small-scale network models. Real-world urban environments are highly dynamic, with congestion patterns that vary significantly over time. This limits the applicability of many proposed methods when deployed at city scale.

Second, user behavior and acceptance are often oversimplified in passenger mobility studies. Emission reduction models frequently assume uniform willingness to participate in carpooling or to tolerate additional walking and detours. In practice, commuter preferences vary widely, and behavioral constraints play a crucial role in determining the success of shared mobility systems. These factors are rarely incorporated into optimization models in a systematic manner.

Third, although simulation tools are widely used to study traffic dynamics, many simulation-based evaluations lack strong connections to realistic commuter behavior. This creates a gap between technically optimized solutions and their practical usability. Systems that perform well under idealized assumptions may fail to achieve similar benefits in real-world deployments.

Addressing these gaps requires a unified approach that combines advanced optimization techniques with realistic traffic modeling and practical mobility constraints. The proposed AUMO framework is designed to fill this gap by providing an intelligent, scalable, and environmentally conscious solution for urban passenger mobility.

III. METHODOLOGY

This section describes the design and operational workflow of the proposed AI-powered Urban Mobility Optimizer (AUMO). The methodology focuses on integrating traffic prediction, carbon-aware routing, and smart carpooling within a unified optimization framework to support sustainable urban passenger mobility.

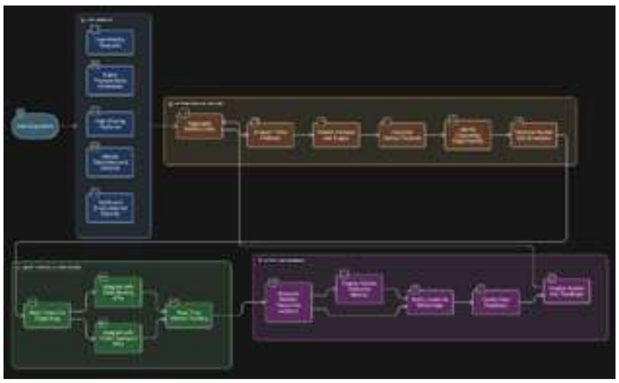

Fig. 1. System architecture of the AI-powered Urban Mobility Optimizer (AUMO).

System Architecture and Design Rationale

The proposed AUMO framework follows a modular architecture, as illustrated in Figure 1, to allow independent yet coordinated operation of its core components. The system receives three primary inputs: (i) urban road network data, (ii) traffic condition data, and (iii) passenger travel requests. These inputs are processed through successive prediction, optimization, and decision-making layers to generate adaptive routing and carpooling solutions.

A modular design was chosen to support scalability and future extension of the system. Each module can be independently updated or replaced without disrupting overall system functionality, making the framework suitable for real-world deployment scenarios.

Data Collection and Input Modeling

The methodology assumes the availability of historical and real-time traffic data obtained from traffic sensors, GPS-enabled vehicles, or simulation environments such as SUMO. Traffic data includes average vehicle speeds, congestion levels, and time-dependent travel patterns across road segments. Passenger requests are represented by pickup locations, drop-off locations, and preferred departure time windows.

Before processing, the collected data undergoes normalization and spatial mapping to align passenger locations with the road network graph. This step ensures consistent representation of all inputs and reduces computational inconsistencies during optimization.

Traffic Prediction Using Machine Learning

Urban traffic conditions vary significantly across time and location. To capture these variations, AUMO incorporates a machine learning-based traffic prediction module. Historical traffic data is used to learn temporal patterns such as peak hours, recurring congestion zones, and speed fluctuations. The prediction model estimates near-future traffic speeds for each road segment, enabling the system to anticipate congestion rather than react to it.

These predicted traffic values are continuously updated and supplied to the routing module, ensuring that optimization decisions reflect realistic traffic conditions rather than static assumptions.

Carbon Footprint Estimation

Carbon emission is computed as:

$E_{total} = \Sigma (d_i \times EF_i)$

Where:

d_i = distance of road segment i
EF_i = emission factor for segment i
Strategies for emission reduction include:
Shortest route selection via Dijkstra.
Avoidance of congested roads.
Increased vehicle occupancy through carpooling.
A green mobility score is provided to users to indicate individual and collective carbon savings.

Route Optimization Using Dijkstra's Algorithm

Route optimization is the core of the AUMO framework, implemented using Dijkstra's algorithm:
The urban road network is modeled as a weighted graph, where nodes represent intersections and

edges represent road segments. Edge weights correspond to either distance or predicted travel time.

Dijkstra's algorithm computes the shortest cumulative path from source to destination.

Carbon emissions are estimated for each candidate route using:
E_total = Σ_{i=1}^{n} (d_i × EF_i)

Where the emission factor is specific to vehicle type and traffic conditions.

This ensures that the selected route minimizes both travel time and environmental impact. Additionally, A search* is incorporated as an alternative heuristic-based algorithm for faster computation under high-density urban networks.

Pseudo-Code of Dijkstra's Algorithm:

1. Initialize distances from source node to all other nodes as infinity.
2. Set distance of source node to 0 and add it to a priority queue.
3. While the queue is not empty:

- Extract node with minimum distance from queue.
- For each neighboring node:

    i. Calculate tentative distance = current distance + edge weight.

    ii. If tentative distance < stored distance:

        - Update distance

        - Add neighbor to priority queue

4. Repeat until destination is reached.
5. Return the shortest path and its total weight.

Smart Carpooling Optimization

Smart carpooling is incorporated to improve vehicle utilization and reduce the total number of active vehicles. Passenger requests are evaluated for compatibility based on route overlap, time-window alignment, and acceptable detour thresholds.

The carpooling decision process balances emission savings against passenger inconvenience. By limiting excessive detours and delays, the system ensures that ride-sharing remains practical and user-friendly. Carpooling decisions are integrated into the route optimization process rather than treated as a post-processing step, enabling globally efficient solutions.

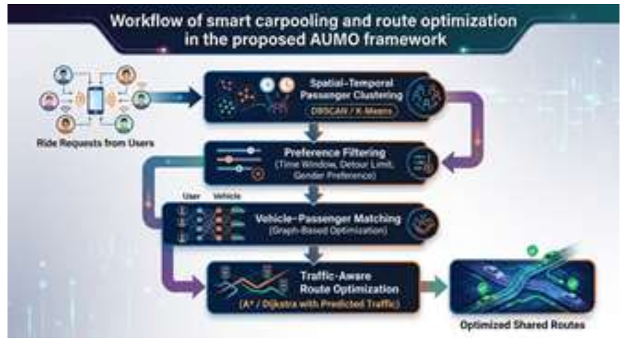

Fig. 2. Workflow of smart carpooling and route optimization in the proposed AUMO framework.

Operational Workflow

Figure 2 illustrates the overall operational workflow of the proposed methodology. The process begins with data acquisition and preprocessing, followed by traffic prediction and emission-aware optimization. Smart carpooling decisions are then applied, and optimized routes are generated. The workflow is executed iteratively to ensure continuous adaptation to dynamic urban conditions.

Output Metrics for Evaluation

The outputs generated by the system include optimized vehicle routes, carpooling assignments, estimated travel times, and corresponding carbon emission values. These outputs form the basis for performance evaluation in the Results section, where the effectiveness of the proposed approach is analyzed using simulation-based experiments.

IV. RESULTS AND DISCUSSION

Dataset Description and Experimental Setup

The experimental evaluation of the proposed AUMO framework was conducted using a simulation-based environment. The urban road network was extracted from OpenStreetMap (OSM) and imported into the SUMO traffic simulator to model realistic city-scale traffic conditions. The dataset includes road topology, junctions, speed limits, and lane-level connectivity.

Passenger travel requests were synthetically generated based on realistic urban demand distributions, including random pickup and drop-off locations and predefined time windows.

This setup enables controlled experimentation while preserving real-world traffic characteristics.
All experiments were performed under identical traffic conditions to ensure fair comparison between baseline routing approaches and the proposed AUMO framework.

Emission Reduction Performance
Figure 4 compares the average carbon emissions generated by baseline routing approaches and the proposed AUMO framework. The baseline method prioritizes shortest travel time without explicit consideration of emissions, whereas AUMO incorporates carbon-aware routing and predicted traffic conditions.

The results indicate that the proposed approach achieves an average reduction of approximately 10–14% in CO_2 emissions across different traffic scenarios. This improvement is primarily attributed to the avoidance of highly congested routes and the selection of speed-efficient paths that minimize fuel consumption.

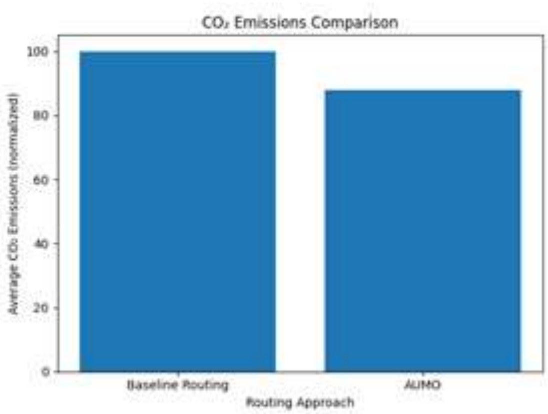

Fig. 3. Comparison of average CO_2 emissions between baseline routing and the proposed AUMO framework.

Vehicle Utilization and Carpooling Efficiency
The impact of smart carpooling on vehicle utilization is illustrated in Figure 5. In the baseline scenario, most trips are served using single-occupancy vehicles, resulting in low average occupancy levels.
After applying the proposed carpooling strategy, the average vehicle occupancy increased from approximately 1.2 to 1.7 passengers per vehicle. This improvement led to a corresponding reduction in the number of active vehicles required to serve passenger demand, thereby reducing traffic congestion and emissions.

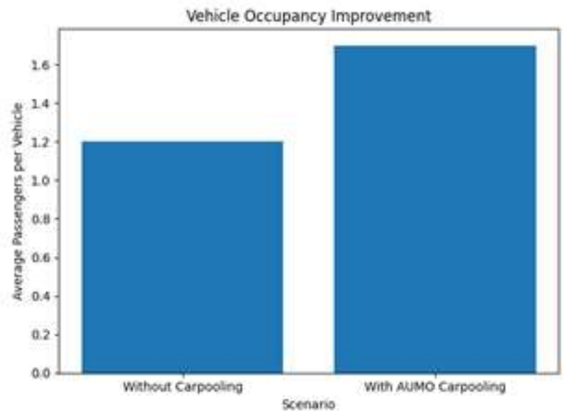

Fig. 4. Improvement in average vehicle occupancy with smart carpooling integration.

Travel Time Analysis
While emission reduction and vehicle utilization improved, travel time performance remained within acceptable limits. The proposed system introduced minor detours in certain carpooling scenarios; however, the average increase in travel time was limited to less than 5% compared to baseline routing. This demonstrates that sustainability benefits can be achieved without significantly compromising passenger convenience.

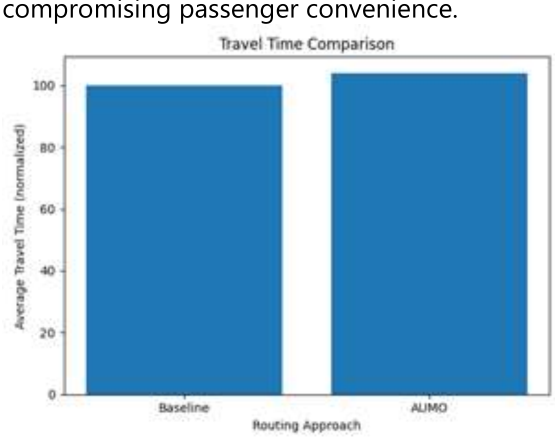

Fig. 5. Comparison of average travel time for baseline routing and AUMO.

Discussion
The experimental results demonstrate that integrating traffic prediction and carbon-aware optimization can substantially improve the sustainability of urban passenger transportation.
Unlike traditional routing methods that prioritize shortest paths, the proposed approach accounts for congestion-induced emissions, resulting in more environmentally efficient route selection.

The inclusion of smart carpooling further enhances system performance by reducing vehicle redundancy and improving road utilization. Importantly, the observed emission reductions and occupancy improvements were achieved with minimal impact on travel time, highlighting the practical feasibility of the approach.

Despite these limitations, the simulation-based evaluation provides valuable insights into the potential effectiveness of AI-driven mobility optimization systems.

V. BUSINESS STRATEGY

The long-term success of the proposed AI-powered Urban Mobility Optimizer (AUMO) depends not only on algorithmic performance but also on its feasibility for real-world deployment. This section outlines a practical strategy for adopting, scaling, and sustaining the proposed system within existing urban mobility ecosystems.

Deployment Strategy
AUMO is designed to integrate with existing urban transportation infrastructure without requiring major physical modifications.

The system can be deployed as a centralized decision-support platform that interfaces with traffic management systems, navigation services, and shared mobility providers. By relying primarily on software-based intelligence, the deployment cost remains relatively low compared to infrastructure-heavy mobility solutions.

Initial deployment can be targeted toward high-congestion urban zones or peak-hour operations, where the potential benefits of route optimization and carpooling are most significant. This phased deployment approach allows gradual system validation and performance tuning before city-wide expansion.

Stakeholder Engagement
AUMO offers benefits to multiple stakeholders involved in urban transportation. Municipal authorities can leverage the system to support emission reduction targets and congestion mitigation policies. Mobility service providers and fleet operators benefit from optimized vehicle usage and reduced fuel consumption. Passengers gain access to more cost-effective and environmentally responsible travel options without significant increases in travel time.

By aligning the objectives of these stakeholders, AUMO promotes collaborative and data-driven urban mobility management.

Revenue and Sustainability Model
Although this work primarily focuses on technical optimization, a sustainable operational model is necessary for long-term viability. AUMO can be offered as a service-based platform to city authorities or mobility providers, where pricing is linked to system usage or performance metrics such as emission reduction or fleet efficiency.

Such a model encourages continued system optimization while ensuring that environmental and operational benefits are directly tied to system adoption.

Scalability and Expansion
The modular architecture of AUMO supports scalability across different urban contexts. As traffic volume and passenger demand increase, additional computational resources can be allocated without altering the core system design. The framework can be extended to incorporate new data sources, such as real-time incident reports or multimodal transport options, enabling broader mobility optimization beyond car-based travel.

This scalability makes AUMO suitable for both medium-sized cities and large metropolitan regions.

Competitive Advantage
The key competitive advantage of AUMO lies in its integrated approach. While many existing systems address traffic prediction, routing, or ridesharing independently, AUMO combines these components within a single optimization framework with explicit consideration of carbon emissions. This holistic design enables more effective decision-making under dynamic urban conditions.

Long-Term Impact
By reducing congestion, emissions, and inefficient vehicle usage, AUMO contributes to more sustainable and livable urban environments. The proposed strategy emphasizes gradual adoption, stakeholder collaboration, and continuous optimization, ensuring that the system remains practical and impactful in real-world scenarios.

VI. CONCLUSION

This paper presented AUMO, an AI-powered Urban Mobility Optimizer designed to address congestion and carbon emissions in urban passenger transportation. The proposed framework integrates traffic prediction, carbon-aware route optimization, and smart carpooling within a unified system, enabling more efficient and environmentally responsible mobility decisions under dynamic urban conditions.

Through simulation-based evaluation, the proposed approach demonstrated its ability to reduce carbon emissions, improve vehicle utilization, and maintain acceptable travel efficiency.

By embedding emission considerations directly into the routing and carpooling process, AUMO moves beyond traditional time- or distance-based optimization methods and highlights the importance of sustainability-aware mobility planning.

The results indicate that combining predictive traffic modeling with adaptive optimization techniques can significantly enhance the performance of shared urban transportation systems. Moreover, the integration of smart carpooling shows strong potential for reducing fleet size and traffic congestion without compromising passenger convenience.

Despite these promising outcomes, the current study relies on simulation-based environments and assumes the availability of accurate traffic and demand data. Real-world deployment may introduce additional challenges related to data quality, user behavior, and system integration. Addressing these limitations remains an important direction for future research.

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