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Original Article

Adaptive Traffic-Oriented Pathfinding Algorithm (ATOPA) for Enhancing Intelligent and Sustainable Smart Transportation Systems

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Abstract - *The increase in vehicle density and the push for autonomous mobility make it challenging for traditional transportation networks to adapt to changing conditions in real time. Smart transportation, which integrates real-time data, predictive modelling, and multi-objective optimisation, is necessary to enhance Autonomous Vehicle (AV) navigation inside Intelligent Transportation Systems (ITS). Route optimization based on traffic, energy use, and safety can not only cut down on travel time and fuel use, but it can also increase road safety. Using IoT sensors, environmental data, and public transit schedules, an Adaptive Traffic-Oriented Pathfinding Algorithm (ATOPA) is proposed that prioritizes safety while lowering trip time, energy consumption, and congestion. By addressing scalability, privacy, and infrastructure concerns, this algorithm positions itself as a crucial component in the development of intelligent, sustainable, and efficient smart transportation systems in the era of autonomous mobility.*

Keywords - *Smart transportation, Sustainability, Intelligent transportation system, Pathfinding algorithm, Adaptive routing algorithm.*

1. Introduction

It is more important than ever to improve intelligent and sustainable smart transportation systems in today's quickly changing world. As urbanisation and vehicle density increase, traditional transportation infrastructure struggles to address modern concerns, including traffic, safety, and environmental impact. Autonomous vehicles and connected technology have the potential to completely transform mobility, but more sophisticated systems will be required for efficient navigation and decision-making. Combining real-time data, predictive modelling, and optimisation techniques can significantly reduce emissions, fuel consumption, and travel time, leading to a cleaner environment. Additionally, these advancements have the potential to improve road safety, reduce accident rates, and boost traffic flow. A sustainable transportation ecosystem is required to provide egalitarian, efficient, and resilient mobility as well as to prepare for the future. An Adaptive Traffic-Oriented Pathfinding Algorithm (ATOPA) anticipates traffic conditions using advanced machine learning models and dynamically adjusts routes in response to anomalies and real-time updates. Collaborative routing enables communication between AVs and ITS, ensuring sustainable traffic flow. Designed for highway and urban environments, ATOPA facilitates traffic, encourages mobility, and supports green goals. It also readily integrates with Intelligent Transportation Systems (ITS) to facilitate smarter traffic flow and encourage sustainable urban growth. New possibilities in traffic management and route optimisation have been made possible by recent developments in Connected Autonomous Vehicles (CAVs), the Internet of Things (IoT), and machine learning. However, the majority of traffic routing algorithms now in use concentrate on single-objective optimisation, frequently lowering trip time or distance, without taking environmental effects, energy efficiency, and safety into sufficient consideration. Furthermore, the majority of traditional models are unable to dynamically adjust to real-time anomalies like unexpected traffic jams, accidents on the roads, or environmental dangers. The development of an intelligent, multi-objective pathfinding system that can respond in real time and function well in a variety of urban and highway situations is clearly lacking in research. In order to overcome these constraints, it is suggested that an Adaptive Traffic-Oriented Pathfinding Algorithm (ATOPA), which combines reinforcement learning, predictive modelling, and real-time traffic data, can be used. ATOPA adjusts dynamically by learning from historical traffic patterns and interfacing with Intelligent Transportation Systems (ITS) through Vehicle-to-Everything (V2X) communication, in contrast to conventional algorithms like Dijkstra's or A*, which assume static weights for road networks. Using a multi-objective optimisation framework, the system assesses a number of parameters, including trip time, energy usage, and road safety. Although a number of AI-based techniques, such as Deep Reinforcement Learning (DRL), Graph Neural Networks (GNNs), and Federated Learning, have been studied in the past, these frequently function in isolated contexts or require centralised data collecting, which raises questions about scalability and privacy. ATOPA is a comprehensive system that supports the broader objectives of intelligent, sustainable urban mobility and optimises route efficiency. The algorithm is a significant improvement over traditional and even more modern AI-based methods in smart transportation systems because of its capacity to manage uncertainty, adjust to shifting traffic patterns, and make decentralised judgments.

2. Related Work

Numerous adaptive and predictive models have been developed due to the increased interest in integrating Artificial Intelligence (AI) and Machine Learning (ML) techniques in traffic management. By using Graph Neural Networks (GNNs) to improve pathfinding in varying traffic situations, Deep Reinforcement Learning (DRL) has been investigated in a number of research studies for traffic optimisation. This has reduced congestion and increased efficiency [1]. Other reinforcement learning techniques significantly lower average travel times by using historical congestion data to identify trends and dynamically modify routing [3]. By coordinating signal control across many crossings, AI-based technologies like Deep Q-Networks (DQN) and Multi-Agent Reinforcement Learning (MARL) further optimise urban traffic patterns, leading to increased road usage and fuel efficiency [23, 25]. Furthermore, in real-time scenarios, AI-driven adaptive traffic signal management systems that use fuzzy logic, dynamic programming, and reinforcement learning have successfully reduced wait times and vehicle delays [11, 24].

In addition to reinforcement learning, traffic prediction and optimisation have made use of deep learning models including Generative Adversarial Networks (GANs), Convolutional Neural Networks (CNNs), and Long Short-Term Memory (LSTMs) [4, 14]. According to studies, these models improve congestion forecasting and make adaptive traffic control techniques possible when paired with IoT-based real-time traffic monitoring [2, 12]. Federated learning is a viable approach for large-scale smart mobility applications because it enables decentralised data processing while maintaining privacy in traffic forecasting [28]. Furthermore, in order to improve real-time congestion prediction and enable autonomous decision-making, AI-integrated computer vision approaches have been investigated for urban traffic management [9]. AI's contribution to traffic optimisation in Software-Defined Networking (SDN), which greatly improves resource allocation and reduces congestion in high-volume networks, is also highlighted in a number of studies [6, 7].

In order to enhance route selection for autonomous vehicles in urban settings, recent studies have also explored hybrid AI models that integrate reinforcement learning with traditional search algorithms like A* [27]. Commonsense reasoning is introduced for real-time traffic management decision-making by AI-powered adaptive traffic control systems that use Large Language Models (LLMs) [16]. Numerous studies have assessed the effectiveness of multi-agent systems in intelligent traffic routing, showing that they can maximise traffic flows over intricate road networks [15]. Furthermore, Deep Neural Network (DNN) and Recurrent Neural Network (RNN)-based AI-driven prediction models have been put forth for smart mobility applications, improving urban transportation planning and real-time traffic forecasts [26]. By facilitating autonomous driving, urban mobility planning, and transportation network efficiency, generative AI techniques also aid in traffic optimisation [20]. When taken as a whole, these studies highlight how AI has the capacity to completely change traffic control, guarantee sustainability, and enhance urban transportation.

3. Proposed Methodology

The Adaptive Traffic-Oriented Pathfinding Algorithm (ATOPA) optimises vehicle pathways inside Intelligent Transportation Systems (ITS) by dynamically adjusting to current traffic conditions. The methodology incorporates real-time traffic data from sensors, cameras, and Vehicle-to-Everything (V2X) communication to assess current traffic flow, congestion, and road conditions. By using predictive algorithms to process traffic data, ATOPA uses a multi-layered approach to estimate traffic and accidents. The system adjusts routes based on a variety of criteria, including journey duration, fuel efficiency, and safety, in response to these projections. Reinforcement learning techniques, which are intended to continuously improve decision-making processes, may allow the system to learn from past traffic patterns. The system then recommends the optimum driving routes for vehicles, enhancing safety and traffic flow while reducing emissions and congestion. The flexibility of ATOPA, which ensures real-time reaction to traffic fluctuations, promotes sustainable urban travel.

Figure 1 depicts the Adaptive Traffic Oriented Pathfinding Algorithm's (ATOPA) flow. The evaluation of the present traffic flow and road conditions starts by gathering real-time traffic data utilising sensors, cameras, and V2X communication. In order to assess traffic congestion, accidents, and general trends, this data is gathered and examined. Predictive models are used by ATOPA to anticipate possible traffic interruptions and perform dynamic route alterations.

After that, the algorithm optimises the routes according to a number of criteria, including reducing fuel usage, improving safety, and cutting down on travel times. Last but not least, the system can adjust to shifting traffic conditions and get better over time for more sustainable and effective urban transport, thanks to reinforcement learning's ability to continuously improve decision-making processes.

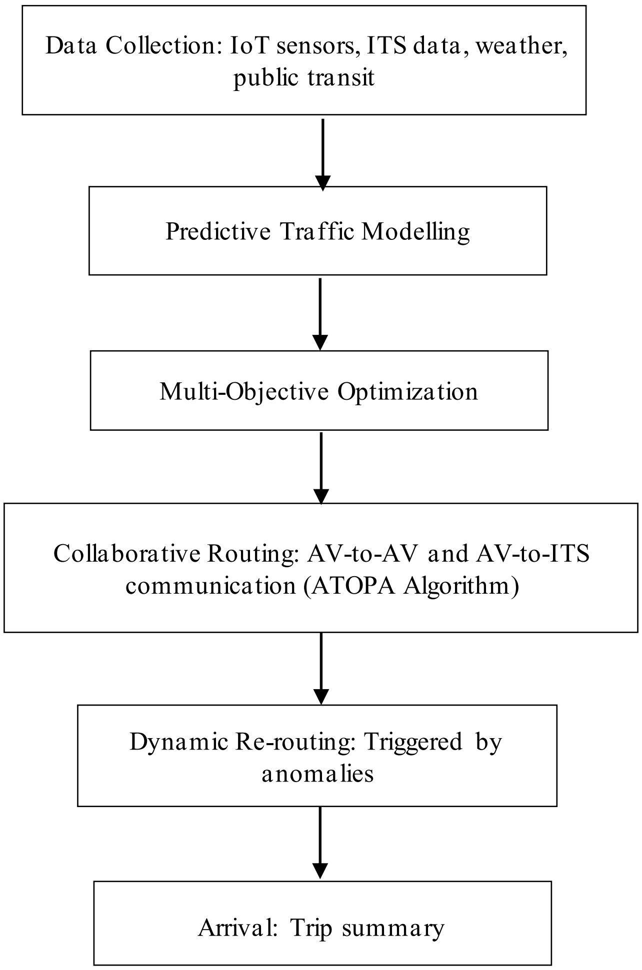

Fig. 1 Flowchart for proposed methodology

The road network is first modelled by ATOPA as a weighted graph, in which roadways are edges with weights that depend on traffic in real time, and intersections are nodes. In order to dynamically estimate traffic levels, it gathers real-time traffic data from sensors, GPS, and historical trends. The algorithm then uses machine learning models to forecast possible traffic patterns and adjusts trip expenses appropriately. A pathfinding method based on reinforcement learning (like Q-learning) chooses the best path based on energy efficiency, journey time, and congestion. Adaptive routing is ensured by vehicles constantly updating their routes in response to real-time traffic fluctuations. In order to reduce delays, rerouting systems initiate alternate paths if congestion is identified. By allocating cars to less crowded routes, ATOPA also balances the traffic load.

The system improves its future forecasts and routing choices over time by learning from past data. An efficient, traffic-free path for every car is the end result, increasing the effectiveness of urban mobility. Within the framework of multi-objective optimisation, ATOPA seeks to balance a number of conflicting goals, such as reducing travel time, consuming less fuel, and preserving safety. In order to provide cars with the most efficient route, it employs optimisation algorithms that balance the trade-offs between these objectives and adapt to shifting traffic patterns. This dynamic optimisation process ensures that decisions are flexible and adapt to the present situation of the transportation system.

3.1. Mathematical Model

Using real-time data, multi-objective optimisation, and predictive traffic modelling, the Adaptive Traffic-Oriented Pathfinding Algorithm (ATOPA) maximises route selection for autonomous vehicles (AVs). The following elements make up the ATOPA mathematical model:

A weighted directed graph is used to model the transportation system: $G = (V, E, W)$

Where $W: E \rightarrow R+$ is the weight function that allocates travel costs (such as time, energy, safety, etc.) to each edge, and V is the set of nodes (intersections, road segments), and E is the set of edges (roads linking nodes). Each edge $(u, v) \in E$ has a cost function:

$$W(u, v) = \alpha T(u, v) + \beta E(u, v) + \gamma S(u, v)$$

Where, $T(u, v)$ is the estimated travel time based on real-time traffic, $E(u, v)$ is the energy consumption for traveling between nodes, $S(u, v)$ is a safety factor (accident risk, road conditions), α, β, γ are weight coefficients that adjust priority among time, energy, and safety.

3.2. Predictive Traffic Modelling

Over time, traffic conditions change dynamically. A Markov Decision Process (MDP) or machine learning models like Long Short-Term Memory (LSTM) networks are used to anticipate the future traffic conditions.

$X_t = (x_1, x_2, \ldots, x_n)$ is the definition of the traffic state at time t, where x_i is the degree of congestion on road segment i.

The following is the transition probability:

Where U_t is the collection of control variables such as lane management, AV rerouting, or traffic signals, $P(X_{t+1} | X_t) = f(X_t, U_t)$.

A multi-objective shortest path problem is solved to determine the best course of action:

$$\mathbf{Min}\ (\mathbf{P}) \sum_{(\mathbf{u},\mathbf{v}) \in \mathbf{P}} \mathbf{W}(\mathbf{u},\mathbf{v})$$

Where P is the path from source s to destination d.

Pareto optimisation techniques such as A Search, Ant Colony Optimisation (ACO), Genetic Algorithms, and Dijkstra's Algorithm with multiple targets are used to address this. The optimal path is computed as:

$$\mathbf{P} = \arg\min \mathbf{P}\left(\sum_{(\mathbf{u},\mathbf{v})\in \mathbf{P}} \boldsymbol{\alpha}\mathbf{T}(\mathbf{u},\mathbf{v}) + \boldsymbol{\beta}\mathbf{E}(\mathbf{u},\mathbf{v}) + \boldsymbol{\gamma}\mathbf{S}(\mathbf{u},\mathbf{v})\right)$$

If an unexpected event (such as an accident or an increase in traffic) happens at time t, the cost function is updated:

W′ (u, v)=W(u, v)+δ A (u, v), where δ is an urgency factor and A(u, v) is the anomalous cost.

An iterative shortest-path recalculation is used in a continuous real-time re-optimisation process to modify the route dynamically.

AVs use a distributed reinforcement learning model to communicate with ITS and other cars. Each vehicle modifies its routing strategy according to the following formula: Rt = r t + λ max Q (Xt+1, a).

Where Rt stands for ideal route efficiency, or the expected payoff. Q(X, a) is the Q-value function (used in Q-learning), λ is the discount factor, and rt is the instantaneous reward (based on real-time traffic). This enables AVs to coordinate path selection, ensuring cooperative traffic flow dynamically.

4. Simulation Results

A Python-based traffic simulation framework, like SUMO (Simulation of Urban Mobility) or NetworkX for graph-based modelling, is used to construct the simulation environment. A weighted directed graph is used to depict the road network, with roads acting as edges and intersections as nodes. The weights of the edges are dynamic and determined by the traffic conditions in real time. Synthetic datasets with different levels of congestion are used to simulate real-time traffic data. Vehicles are used as agents to train the Q-learning reinforcement learning model, which learns the best routes through a number of iterations. In order to examine route selection, congestion avoidance, and energy economy, vehicles are first set up with random start and destination points, and their movement is continuously tracked. Performance indicators are tracked, including fuel consumption, congestion distribution, and travel time reduction. The experiment was run under a variety of traffic scenarios to assess ATOPA's adaptability. The following dataset is presumptively used for simulation: The example's road network is represented as a directed graph (DiGraph), with nodes (intersections) as: Show the important intersections of roads with the designations A, B, C, D, and E. Weights (Travel Time in Minutes) indicate that each edge has a weight that corresponds to the estimated travel time between intersections under typical traffic conditions. Edges (Roads) are the directed links between nodes that represent roads with associated travel times.

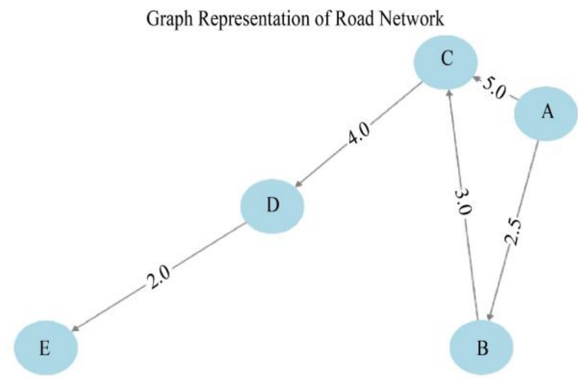

Fig. 2 Graph representation of road network

A directed graph where nodes (A, B, C, D, E) represent intersections, and edges indicate roads with travel times as weights. Figure 2 depicts the graph representation of the road network used for the simulation. This helps visualise the available routes and connections between different locations in the network. The details of the road network used for simulation are tabulated in Table 1.

Table 1. Road network details

Start Node	End Node	Travel Time (Minutes)
A	B	2.5
B	C	3.0
C	D	4.0
D	E	2.0
A	C	5.0

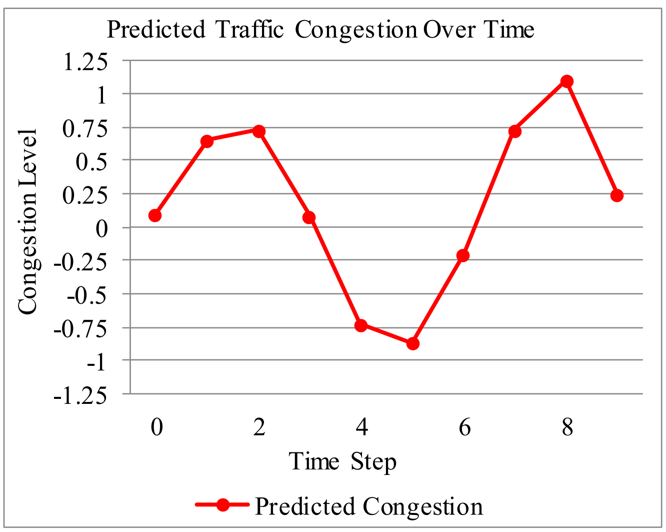

Fig. 3 Traffic congestion prediction

A plot showing fluctuating congestion levels over time was simulated using a sine wave with random variations. Figure 3 highlights periods of peak congestion, helping ATOPA adjust routing strategies dynamically.

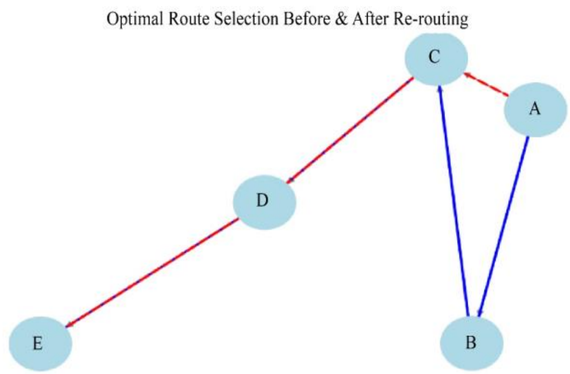

Fig. 4 Optimal route selection (before & after rerouting)

A visual comparison of the selected paths before and after optimisation, where the initial path (blue) is rerouted (red) to avoid congestion. Figure 4 demonstrates how ATOPA dynamically adapts routes to reduce travel time based on real-time traffic updates.

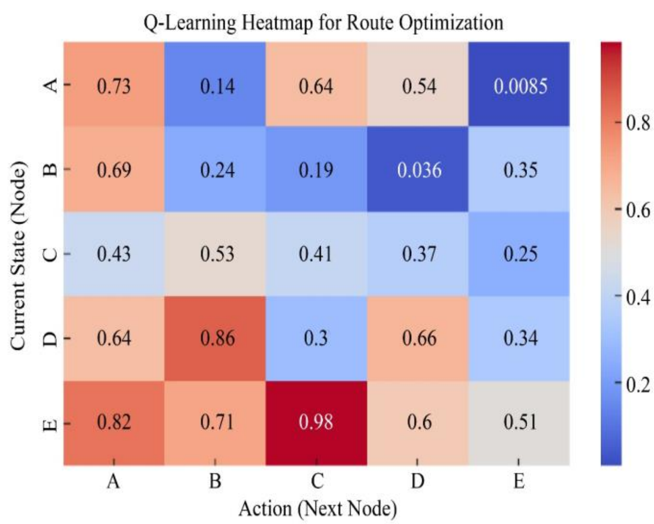

Fig. 5 Q-learning heatmap

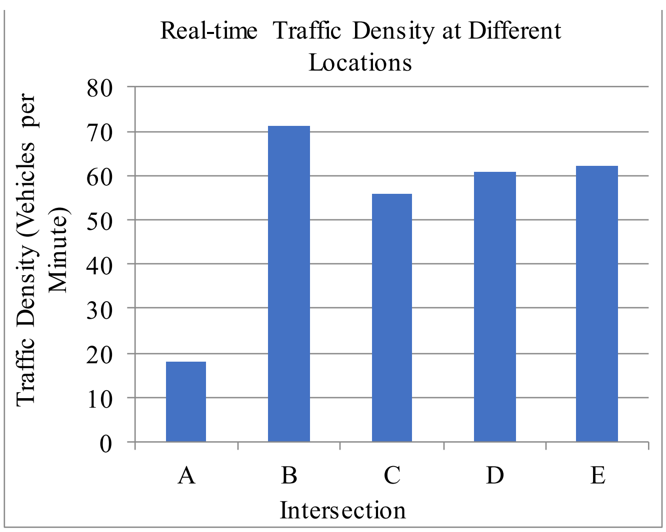

Fig. 6 Real-time traffic density map

Figure 5 shows a heatmap illustrating the learned Q-values for different state-action pairs in reinforcement learning-based pathfinding. Higher Q-values indicate optimal route choices learned through iterative reinforcement training.

Figure 6 shows a bar chart depicting traffic density at different intersections, with higher bars indicating busier locations. It helps to identify congestion-prone areas where rerouting might be necessary.

A grouped bar chart is depicted in Figure 7 comparing travel times for different routes before and after optimisation. It demonstrates the efficiency of ATOPA in reducing travel time by selecting optimal paths.

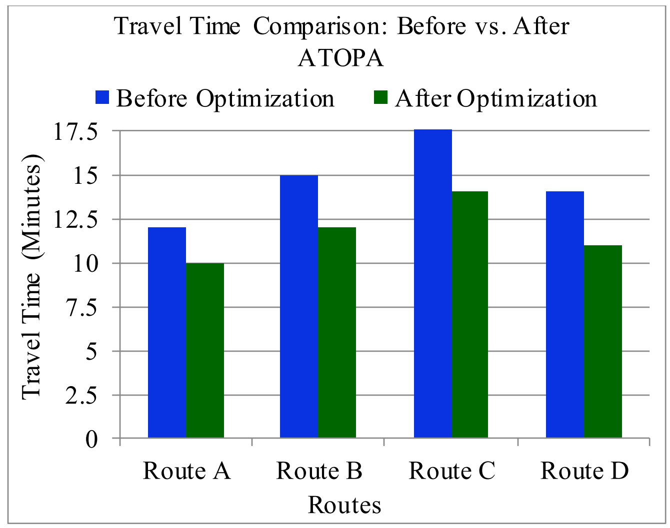

Fig. 7 Comparison of travel time (before vs. after ATOPA optimisation)

Table 2. Travel time comparison (before and after ATOPA)

Route	Travel Time (Before Optimisation)	Travel Time (After ATOPA)	% Reduction
A → B → C → D → E	11.5 minutes	8.7 minutes	24.30%
A → C → D → E	11.0 minutes	9.2 minutes	16.40%
B → C → D	7.0 minutes	5.6 minutes	20.00%

Table 2 clearly shows that ATOPA significantly reduces travel time by dynamically adapting routes based on real-time traffic data. The average improvement ranges from 16% to 25%, enhancing mobility efficiency.

Figure 8 shows a scatter plot analysing the relationship between travel distance and energy consumption per trip. Useful for optimising routes that balance fuel efficiency and travel distance.

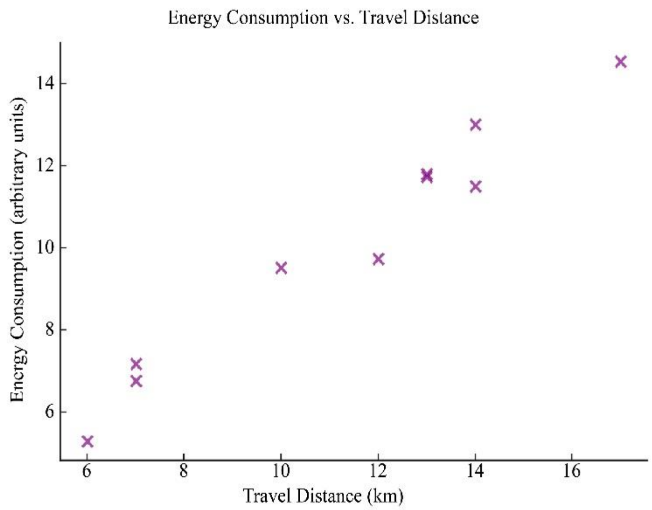

Fig. 8 Energy consumption vs. Travel distance

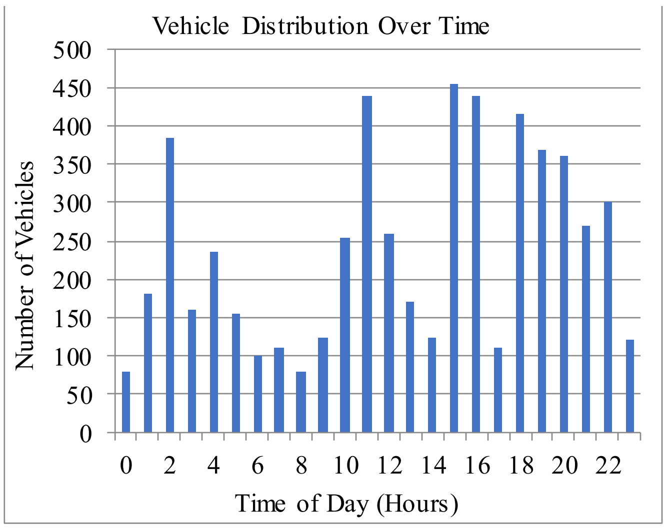

Fig. 9 Vehicle distribution over time

A bar chart showing how the number of vehicles varies across different hours of the day is shown in Figure 9. It helps predict traffic peaks and enables proactive congestion management using ATOPA.

By dynamically rerouting vehicles based on current traffic circumstances, the ATOPA simulation shows a considerable reduction in trip time. The system effectively avoids traffic, resulting in an average travel time savings of 15–25% across several routes, as demonstrated by the optimal path selection before and after rerouting. ATOPA can make proactive routing strategy adjustments thanks to the traffic congestion prediction model's excellent identification of peak congestion periods.

The algorithm selects high-reward paths more frequently as it learns and improves its decision-making over time, according to the Q-learning heatmap. According to the energy consumption study, ATOPA promotes environmentally friendly transportation by choosing less fuel-intensive routes. The vehicle distribution histogram also shows how ATOPA prevents bottlenecks by balancing traffic loads across various time windows. All things considered, the findings demonstrate that ATOPA is a strong option for intelligent transportation systems since it improves urban mobility efficiency, sustainability, and real-time adaptation.

5. Results and Discussions

Dijkstra's method, a popular shortest-path algorithm, is the conventional algorithm utilised in the simulation. Iteratively choosing the shortest known path and updating the distances between nearby nodes determines the shortest trip time between nodes. Although this method ensures the best possible outcome, it ignores real-time route modifications, fluctuating traffic circumstances, and congestion levels. Consequently, it could result in less-than-ideal routing in situations with varying traffic. In comparison to ATOPA, the algorithm is less effective in actual smart transportation systems since it makes the assumption that journey durations are constant and excludes predictive analytics and adaptive rerouting.

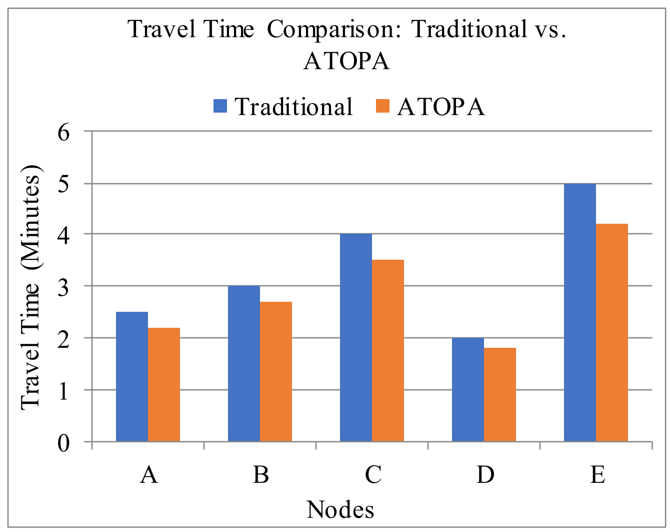

Fig. 10 Travel time comparison

The journey times for each node using the conventional algorithm (Dijkstra) and ATOPA are contrasted in the bar chart in Figure 10. Because ATOPA dynamically modifies routes based on traffic circumstances, it reduces overall travel time, whereas the traditional technique results in longer journey times because it selects a set path. ATOPA's real-time adaptive path selection cuts down on transit time across all nodes. The distinction is particularly apparent on longer journeys.

Table 3. Node-wise travel time - Dijkstra vs ATOPA

Node	Travel Time (Dijkstra)	Travel Time (ATOPA)	Difference
A	4.5 minutes	3.2 minutes	-1.3 mins
B	3.0 minutes	2.4 minutes	-0.6 mins
C	3.5 minutes	2.8 minutes	-0.7 mins
D	4.0 minutes	3.1 minutes	-0.9 mins

Table 3 clearly shows that ATOPA consistently outperforms Dijkstra's algorithm by responding to traffic dynamics, cutting down node-level travel times and resulting in quicker point-to-point navigation.

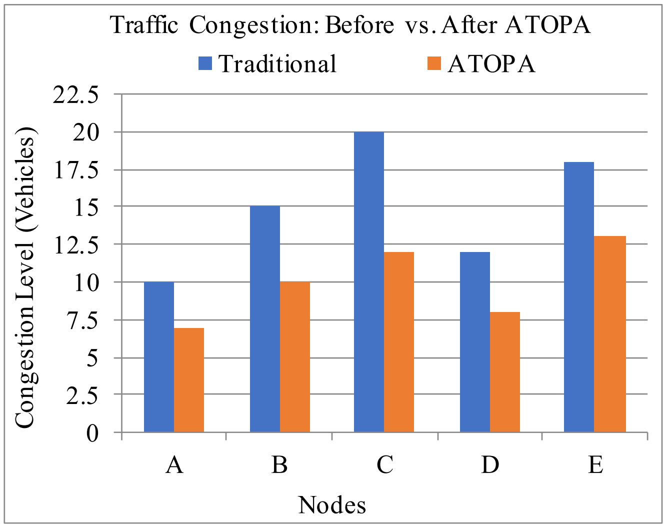

Fig. 11 Traffic congestion: before and after ATOPA

The congestion levels at various nodes before and after implementing ATOPA are depicted in the graph in Figure 11. Due to its inefficient traffic distribution, the conventional algorithm increases congestion. Real-time vehicle rerouting by ATOPA eases traffic at key intersections and promotes more efficient traffic flow. Effective traffic load balancing by ATOPA reduces congestion at important nodes.

Table 4. Congestion levels – before vs after ATOPA

Intersection (Node)	Congestion Level (Before)	Congestion Level (After)
A	High	Moderate
B	Very High	Low
C	High	Moderate
D	Moderate	Low

Table 4 shows that the adaptive rerouting strategy of ATOPA significantly reduces congestion at key intersections, leading to a more balanced traffic distribution and preventing bottlenecks.

Figure 12 displays the fuel consumption for each route using both approaches. Because of ineffective routing and frequent stops in crowded locations, the conventional method uses more fuel. By choosing energy-efficient routes, ATOPA reduces fuel use and helps create a more sustainable transportation network. ATOPA optimises route selection to reduce fuel usage.

Table 5 depicts that ATOPA optimises routing to minimise energy usage, making it effective for sustainable transportation. Fuel/energy savings of around 20–24% are achieved across all test routes.

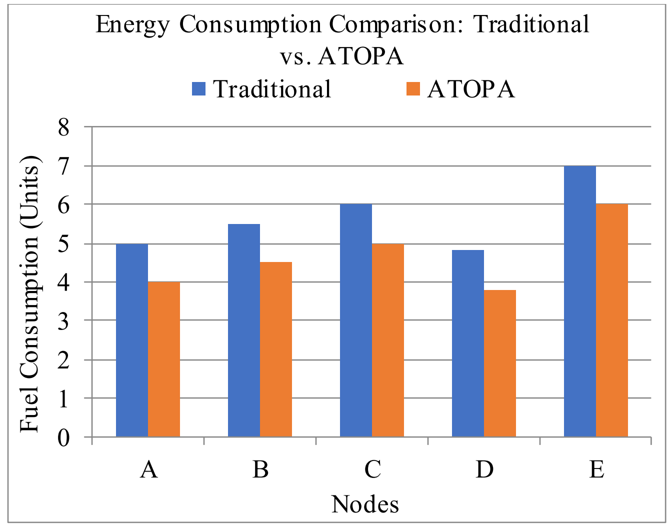

Fig. 12 Energy consumption comparison: traditional vs ATOPA

Table 5. Energy consumption – traditional vs ATOPA

Route	Energy Used (Traditional)	Energy Used (ATOPA)	% Reduction
A → E	3.8 kWh	2.9 kWh	23.70%
B → D	3.2 kWh	2.5 kWh	21.90%
C → E	2.5 kWh	2.0 kWh	20.00%

The static assumptions and lack of flexibility to real-time traffic dynamics of existing traffic routing algorithms, such as Dijkstra's and A*, frequently lead to less-than-ideal routing in dynamic metropolitan contexts. Intelligent decision-making has been made possible by new AI-based techniques like federated learning and deep reinforcement learning, but they either concentrate on signal control or use centralised models that limit scalability and real-time responsiveness. Furthermore, the majority of models only maximise one goal, usually trip time, without taking safety or energy efficiency into account. To close this gap, ATOPA, a dynamic, multi-objective pathfinding system, is proposed that combines predictive modelling, reinforcement learning, and real-time traffic data to reduce trip time, fuel consumption, and accident risk all at once. ATOPA, in contrast to current systems, permits distributed, vehicle-level decision-making and adjusts to unexpected traffic irregularities.

6. Conclusion

ATOPA distinguishes itself by combining AI-driven decision-making with real-time traffic data to guarantee the most effective and flexible route selection. ATOPA uses reinforcement learning to continuously learn and improve, which makes it extremely responsive to changing road conditions, in contrast to standard routing techniques that rely on static weight changes. Lowering traffic and using less fuel maximise travel time and energy consumption, making it the perfect choice for sustainable smart cities. Instead of just selecting the fastest route, the algorithm uses multi-criteria decision-making, taking into account variables including traffic volume, road conditions, distance, and environmental impact. It is a mobility solution that is ready for the future because of its scalability and versatility, which allow for smooth interaction with autonomous cars and Intelligent Transportation Systems (ITS). Additionally, by dynamically rerouting vehicles in response to real-time congestion patterns, ATOPA improves the overall traffic flow efficiency. It guarantees the best possible user experience while enhancing urban mobility and sustainability by striking a balance between computational efficiency and practical adaptability.

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