International Journal of Computer Networks and Applications (IJCNA)
DOI: 10.22247/ijcna/2025/30 Volume 12, Issue 4, July – August (2025)

RESEARCH ARTICLE

Adaptive Network Routing Algorithm for Intelligent and Sustainable Smart Transportation Systems

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Received: 21 April 2025 / Revised: 12 July 2025 / Accepted: 30 July 2025 / Published: 30 August 2025

Abstract – Modern transportation systems face challenges such as traffic congestion excessive carbon emissions and long waiting times because of significant growth in vehicle density and urbanization. The conventional routing algorithms frequently do not work efficiently in this kind of environment because they are mostly rigid and do not consider dynamic elements like congestion, environmental effect and real time traffic density. In this paper, an Adaptive Network routing algorithm (ANRA) is proposed especially designed for intelligent and sustainable smart transportation systems. This algorithm inclines towards overcoming the problems faced by existing systems. The model proposes to minimize the CO2 emissions and round-trip times by intelligently combining the multi-objective optimization and reinforcement learning. This approach utilizes an emission aware reward function which is novel way of improving the ability to explore the best routing policies under different network environments. The proposed algorithm is simulated with grid-based network wherein it has proven to be more efficient and sustainable as compared to traditional approaches such as A*, Dijkstra and random walk approaches. To support intelligent navigation, environment sustainable solutions and dynamic traffic management frameworks, ANRA provides a scalable routing and real time solution that can be integrated with smart city infrastructures. The proposed algorithm- ANRA shows drastic improvement in the performance parameters such as travel time, density, emission and cost. This approach aids to the realization of sustainable, environment friendly and more effective urban mobility systems.

Index Terms – Smart Transportation, Adaptive Routing, Sustainability, Reinforcement Learning, VANET, SUMO.

1. INTRODUCTION

For modern and developing cities the top priority is to have an effective framework for sustainable transportation systems. The significant factors like ever increasing vehicle ownership, rapid urban expansion which leads to growing traffic congestion plays an important role to design efficient frameworks for tackling the issues [1]. There exist effective algorithms for finding optimum routes by conventional approaches like A*, Dijkstra, etc. But these approaches lack in justifying for real time parameters such as congestion patterns, vehicle emissions, traffic density, etc. Due to the static nature of these algorithms, they do not provide effective solution as it doesn’t fit the requirements of environment impacts on complex urban environments. To suffice these requirements, the Intelligent Transportation Systems (ITS) integrate with the data driven and dynamic approaches that utilizes AI to adapt to the real-world conditions [2]. It’s noteworthy to learn to utilize the ability of Reinforcement Learning (RL) to explore the best routing methodologies through communicating with a dynamic environment. To balance the objectives such as reducing carbon emissions, travel time and traffic congestion with multi-objective optimization, reinforcement learning can be explored as a potent tool [3][4].

The suggested algorithm provides a real-time, scalable routing solution that may be integrated into smart city infrastructures to enable adaptive traffic management systems, intelligent navigation, and environmentally friendly logistics. The realization of greener, more effective urban mobility systems is greatly aided by this effort.

The creation of intelligent transportation systems that use data-driven algorithms and adaptive control to overcome these obstacles has received more attention in recent years. Because it may learn optimal techniques through ongoing contact with the environment, reinforcement learning has emerged as a

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promising approach among them [5][6]. With the help of reinforcement learning, agents can adjust to changing circumstances and balance competing goals, including cutting down on travel time while also lessening their influence on the environment.

The main aim of this research is to design an Approach-Adaptive Network Routing Algorithm (ANRA) that integrates the smart and sustainable route optimization in an Intelligent transportation system.

1.1. Objectives

The objective of this work is to:

1. Lower the CO2 emissions, without compromising the efficient travel times.
2. Explore the information about traffic, density, and emission data and find the best possible route at run time
3. For real time urban traffic networks, provide a scalable system which gets adapted as per the requirement at real time.

In this paper, a novel adaptive network routing algorithm with a multi-objective reward function that integrates reinforcement learning is proposed. In contrast to conventional routing techniques, the suggested algorithm takes into account both route mileage and CO2 emissions and traffic congestion, allowing for more ecologically friendly decision-making. To suffice the requirement to dynamically learn routing algorithms that strike a balance between efficiency and sustainability, it is necessary that the updates should be based on feedback from each traversal. This can be accomplished using a Q-learning-based framework [7][8].

Substantial simulations were carried out on hypothetic network representing urban transportation network, the results were compared at varied levels of congestion and emission, to test the performance of proposed strategy. The outcomes are compared with conventional algorithms such as A*, Dijkstra, random walk for the same performance parameters. The effectiveness of the proposed approach in real time dynamic network was validated by the improved performance depicted during the simulation. The major contribution of this paper includes the addressing the vital parameters of modern transportation such as environmental impact and traffic density and incorporating these during the routing decision making process, as well as a unique RL-based routing algorithm [9] [10] integrated with an emission-aware reward function [11]. The efficiency and sustainability for the proposed framework also is found to be elevated due to inclusion of a flexibility and its ability to be used in a wide range of intelligent transportation applications. The approach has proven to be efficient during comparative testing with baseline and classical methodologies.

This research is vital and relevant because of the priority given for sustainable mobility in smart city programs rolled out by Government. Few possible application areas include logistics optimization, adaptive traffic control and eco-routing [12] in GPS systems. The proposed algorithm ANRA will serve as a significant step toward green urban mobility [13] and smart transportation, which aims to bridge the gap between adaptive learning and sustainable routing. The significant contributions are listed as follows:

1. A novel approach to improve traffic efficiency and environment sustainability, based on reinforcement learning with a reward function that is emission aware
2. To provide a framework for multi objective optimization, that makes routing choices based on the real time information on travel time, congestion, emissions, etc.
3. To provide a flexible framework that can be integrated with intelligent city traffic infrastructures, edge computing [14] and VANETs.
4. A simulation-based performance evaluation that exhibits considerable benefits of the proposed methodology in terms of travel time, cost reduction and emission reduction, compared with conventional existing algorithms.

In summary, this approach provides an efficient and smart routing solution for conventional urban environments by bridging the gap between sustainable traffic management and adaptive learning.

1.2. Problem Statement

In order to overcome the drawbacks of conventional static algorithms and guarantee effective, sustainable mobility in smart city settings, urban transportation systems need an intelligent and adaptive routing solution that incorporates real-time traffic, congestion, and emission data through multi-objective optimization and learning.

The forthcoming sections of this paper are organized as follows: The contextual research related to intelligent and sustainable routing algorithms and reinforcement learning is discussed in section 2. The proposed suggested Adaptive Network Routing Algorithm (ANRA) approach and its functional elements are discussed in section 3. The mathematical modelling and optimization methodology is presented in section 4. The simulation environment, performance analysis and comparison table for results is presented in section 5. The conclusions and possible challenges are covered in section 6.

2. RELATED WORK

Intelligent and sustainable routing algorithms designed for smart transportation networks have become more and more popular in recent years. A RL framework was proposed in

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2024 on various aspects of transportation research such as model-free and model-based methods. They also highlight various research gaps such as safety constraints, design of reward function and scalable and responsible RL [1]. A multi objective eco routing framework also dynamically controls connected automated vehicles [2]. Besides this, the usage of context-aware data transfer and other green communication techniques significantly reduce the system energy consumption of the system and it is demonstrated [3]. Altogether, for dynamic traffic control and path planning, the usage of interdisciplinary contributions from networking, environmental sciences and AI are improving intelligent and sustainable routing systems significantly. The ability of reinforcement learning approach to learn from feedback with complex environments has made it a more relevant approach. For instance, promising outcomes are observed by using a deep Q-learning framework for dynamic rerouting specifically in the context of reduction of traffic congestion [4]. Additionally, in order to promote sustainable smart city initiatives, VANET-based routing protocols have been integrated with assessments of air quality and carbon footprint [5]. Friend-DQN promoted agent collaboration to reduce state-action complexity in big crossings in reinforcement learning-driven traffic control [6]. Simulation tools like as SUMO and Veins contribute substantially to validate such frameworks in the actual urban traffic environments [7]. The FedTPS system was created by Orozco et al. and uses generative augmentation techniques to improve trajectory prediction [8]. Others have concentrated on environmentally conscious routing, where the reward function incorporates emission factors such CO_2 levels [9][10]. RL framework is used to optimize the marine routes. It also helps in reducing fuel consumption and CO_2 emission [11]. According to a study, there is a challenge of balancing energy efficiency and travel time [12][13]. To estimate environmental factors along various pathways, such algorithms frequently make use of real-time sensor data [14].

A novel framework is proposed by combining digital twins and Internet of Things (IoT) based analytics for the prediction. In this, the significance of data availability and digitization for deploying green and responsive urban operations [15] is emphasized. Researchers have also utilized Graph Neural Networks (GNNs) to create impact on influence routing decisions dynamically and predict the traffic circumstances. The significant challenges such as interoperability, scalability, dynamic environment are emphasized [16]. Furthermore, to provide a decentralized Vehicle to Everything (V2X) interaction environment and intelligent routing, a cooperative vehicle-infrastructure system is developed [17]. To reduce latency for route adaptations during dynamic routing, the edge AI [18] proves to be significant and its role is emphasized in many studies. By ensuring privacy preserving real time data aggregation over edge nodes, the contribution of strategies such as federated learning and distributed learning models have a major stake in this area [19].

Parallelly, for ad hoc networks of vehicles, a block chain-based privacy preserving framework is researched. The proposed framework elevates message integrity and resilience against malicious nodes as compared to conventional VANET trust systems. [20]. Another approach using a city-scale eco-routing framework is designed by the researchers. They utilize Markov-Chain Monte Carlo technique for pollution aware traffic routing [21]. Furthermore, in another attempt, the authors carried out a study of green communication strategies for Internet of Vehicles in 6G. They highlighted the relevant technologies in their area such as energy harvesting, green resource allocation, edge computing, etc. [22]. In a similar line, to select the routes effectively by coordinating several vehicles, a multi-agent RL system is created [23]. Also, a Spatio temporal graph attention network is proposed to deal with traffic data dependencies for spatial and temporal dimensions [24]. Opportunities to include sustainability criteria into routing policies have been created by these tactics.

Apart from RL-based methods, hybrid models that blend machine learning and classical techniques have also drawn interest. For instance, considerable gains in urban routing efficiency were shown when an A*-based approach was combined with traffic prediction models [25]. In the meantime, efforts have been made to improve routing performance by using energy efficient routing specially for resource constrained IoT environment in smart cities [26]. Although cross layer design and context aware routing are the future improvements for more efficiency in dynamic VANET [27]. All of these studies show how important intelligent, context-aware, and sustainable routing solutions are becoming for contemporary transportation networks.

A distributed neuro-fuzzy hybrid approach-based routing algorithm is also designed to improve energy efficiency in smart cities [28]. An eco-routing framework is used for hybrid electric vehicles considers optimization of fuel consumption and emission also [29]. By merging emission and journey time objectives, hybrid metaheuristic algorithms such as Ant Colony Optimization (ACO) and Genetic Algorithms (GA) have been modified for eco-routing [30].

A number of contributions have concentrated on more extensive system-level improvements in addition to routing. Edge computing-based systems prove to be very effective to decrease reaction latency in dynamic traffic management [31]. For increasing the traffic resilience, the integration of Multi-modal interactions for connected vehicles with routing techniques in the context of vehicle-to-everything (V2X) communication has proved to be working efficiently [32]. For distributed traffic forecasting, the Federated learning is

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explored while balancing the protection of data privacy [33]. Furthermore, the ability of federated learning (FL) to train models cooperatively without disclosing sensitive data has attracted a lot of interest in traffic flow predictions. In order to capture dynamic patterns in urban mobility, Liu et al. presented a spatiotemporal FL framework that makes use of Gated Recurrent Units (GRUs) and Graph Attention Networks (GATs) [34]. This progress demonstrates the effectiveness due to aggregation of multiple technologies such as AI, edge computing, and sustainability to accelerate the functionality and environmental effect of intelligent transportation systems.

For real-time decision-making, Meese et al. presented BFRT integrated edge-based RNNs with block chain and FL [35]. For improved location-specific predictions, Chen et al. created a customized FL technique based on error-driven aggregation. MARVEL used multi-agent learning from observable road data to address changeable speed limits in the real world [36]. To preserve accuracy and cut down on delays, FLAGCN further refined asynchronous training with the use of graph-based learning [37]. By classifying agents according to flow and topology, GPLight enhanced large-scale traffic signal control [38]. Lastly, future research directions in this field are given as comprehensive overview in GNN applications in ITS [39][40].

The literature now in this work identifies a number of urgent issues with smart transportation, such as increased vehicle emissions in urban areas, ineffective route planning, and traffic congestion. Current routing algorithms frequently ignore environmental issues like emissions and sustainability and are unable to dynamically adjust to traffic circumstances in real time. Furthermore, multi-objective optimization and scalability across dense networks are still not well addressed.

By incorporating real-time traffic, density, and emission data into a dynamic, multi-objective model, the Adaptive Network Routing Algorithm (ANRA) directly addresses these problems. It continually improves routing choices by utilizing reinforcement learning, guaranteeing flexibility and environmental effectiveness. Because of this, ANRA is a reliable and expandable option for contemporary intelligent transportation systems that strive for sustainability and peak efficiency. The prominent work reviewed for the literature review is summarized in table 1.

To summarize, current approaches lack an integrated approach which includes the major requirements such as real time adaptability, scalability, multi objective routing, etc. in spite of existing progress has been made using a wide range of AI and optimization techniques. These shortcomings serve as a motivation for the proposed Adaptive Network Routing Algorithm (ANRA), which leverages the strength of reinforcement learning integrated with an emission-aware reward function and dynamic multi-objective optimization which eventually deals with the gaps.

Table 1 Prominent Approaches Reviewed

Reference	Method-ology	Algorithm / Model	Pros	Cons
[1, 10, 14, 21, 24]	Reinforcement Learning (RL)	Single-agent RL, Deep RL	Adaptive signal control, eco-routing, reduced emissions	Requires data training, convergence time
[11, 36, 37, 39]	Multi-Agent RL (MARL)	MARVEL, GPLight, Deep MARL	Efficient in large-scale traffic scenarios	High training complexity, coordination issues
[6, 28, 30–35]	Federated Learning (FL)	FL-GCN, GRU-GAT, Blockchain-FL	Privacy-preserving, distributed forecasting	Device-side load, async updates
[3, 15, 40]	Graph Neural Networks (GNN)	GNN, GAT, STCGAT	Captures spatial-temporal correlations	Training complexity, interpretability
[2, 5, 26]	Edge ML / IoT Systems	Cybernetic IoT, Edge ML	Low-latency, real-time smart city adaptation	Resource intensive edge deployment
[6, 7, 27]	Privacy & Security	FL + Blockchain, Trust Framework	Enhances VANET security, protects privacy	Increased system overhead
[13, 20, 22, 23]	Eco-Routing / Green ITS	MAB, Ant Colony Optimization, Eco-Routing	Reduces emissions and travel time	Complex to calibrate for real-world
[17, 18, 25]	Bio-Inspired / Fuzzy Routing	Neuro-Fuzzy, Hybrid Bio-inspired	Energy-efficient and adaptable	Needs extensive parameter tuning
[1, 4, 16, 19, 27, 40]	Survey / Review	Not applicable	Comprehensive understanding, trend analysis	No original model proposed

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3. PROPOSED MODELLING

The proposed model ANRA aims to dynamically develop an environment friendly and traffic density aware routes by integrating real time traffic information with a reinforcement learning based framework. It considers the influencing parameters such as traffic density, travel time and vehicle emissions all together at the time of deciding over the routes, which is not true in the traditional routing algorithms. The interconnected functional layers as shown in figure 1 that make up the suggested ANRA architecture are intended to combine intelligent route optimization, multi-objective decision-making, and real-time data collection. Because the system is modular, dynamic smart transportation networks can use adaptive routing algorithms.

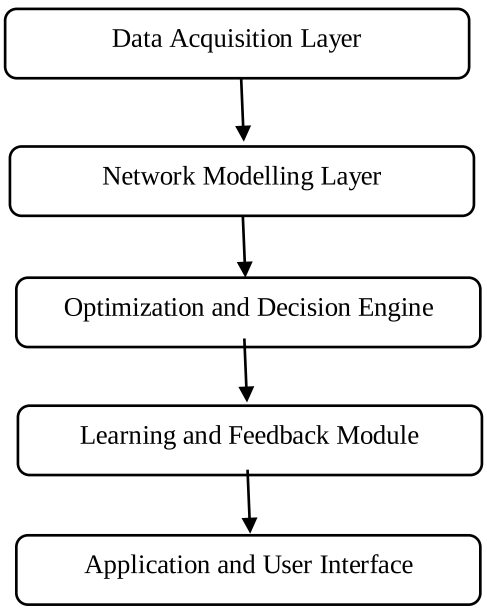

Figure 1 Interconnected Functional Layers of Proposed Model

3.1. Data Acquisition Layer

Distributed sensors, GPS units, vehicular ad hoc networks (VANETs), and traffic monitoring systems make up this layer. It continuously collects crucial parameters, such as real-time vehicle locations, road segment traffic density, average vehicle speeds and environmental data (e.g., CO_2 emissions).

For quick retrieval and algorithmic application, these inputs are processed and stored using edge or cloud infrastructure.

3.2. Network Modelling Layer

The transportation framework can be represented by a directed graph G = (V, E) to mimic the road segments as the edges and the intersections as the nodes. For each edge, the following parameters are dynamically assigned: Travel time (t_e), Traffic density (ρ_e) and Emission rate (ϵ_e).

The graph is regularly updated to show the dynamically changing traffic conditions, in order to provide real-time feedback for routing decisions.

3.3. Optimization and Decision Engine

Fundamentally, a composite cost function is defined for traffic, trip time, emissions, etc. is minimized to formulate an adaptive multi-objective optimization engine. To determine the most efficient route for each vehicle, the algorithm solves the constrained optimization issue using real-time data. Deep Reinforcement Learning (DRL) can be explored in dynamic applications, whereas for smaller, static networks, Mixed-Integer Linear Programming (MILP) can be explored to instantiate the engine. The routing decisions are dependents on the factors which are derived by applying user-defined weights (α, β, γ) in order to customize outputs for various purposes such as reducing emissions in the sensitive zones such as hospitals, schools etc. or increasing throughput during peak hours.

3.4. Learning and Feedback Module

To elevate the decision making, this module recommends the use of real-time performance feedback in reinforcement learning deployments. By virtue of ongoing testing of performance parameters such as fuel consumption, emission levels, and route travel time, the routing policy is updated.

3.5. User Interface and Application Layer

Traffic control centres, smartphone apps, or in-car technologies can be used to update the information of final routing decision to the end user. This layer enables the customizations in the parameters such as route optimization, real-time route guiding, and route comparison and explanation.

When integrated with ITS, ANRA can be effective for traffic signal coordination also. Scalable deployments over suburban and urban road networks are supported by the design.

The design of the Adaptive Network Routing Algorithm for Intelligent and Sustainable Smart Transportation Systems is depicted in the block diagram shown in figure 2. Real-time traffic and environmental data sources, such as GPS units, traffic cameras, Internet of Things sensors, and car emissions monitors, are the first step. These provide information to the Data Collection and Pre-processing Module, which prepares inputs for analysis by filtering, cleaning, and formatting them.

The transportation network is then represented by the Dynamic Network Modeller as a time-varying directed graph with characteristics like emission rates, traffic density, and trip time. The Multi-Objective Optimization Engine receives this model as input and uses the suggested algorithm to find the best routes based on user-specified weights for sustainability, time, and traffic. The Learning and Adaptation

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Module refines the output routes by using machine learning techniques, particularly reinforcement learning, to modify the model in response to system performance and feedback. Through applications and navigation systems, the Decision Dispatcher informs users and traffic controllers of the optimal routes.

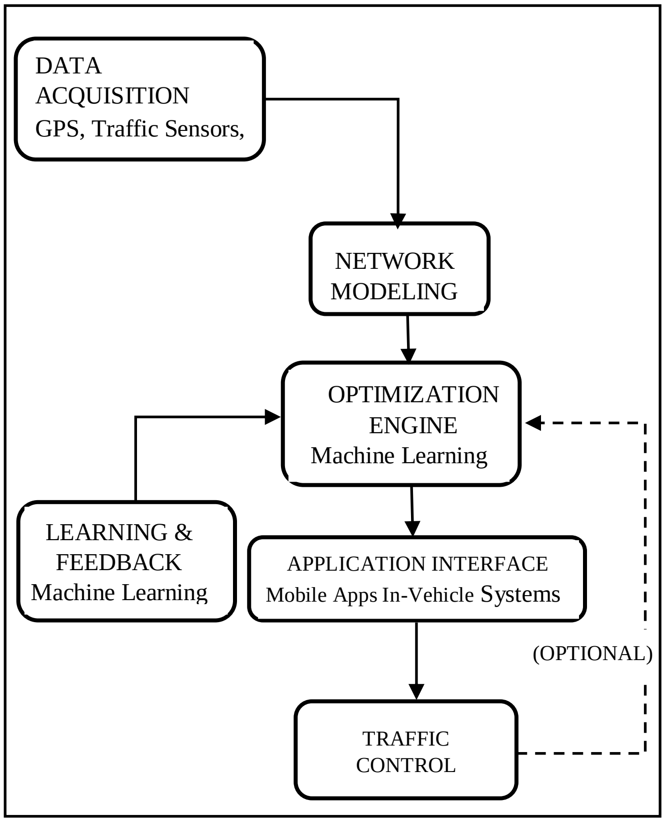

Figure 2 Block Diagram for Adaptive Network Routing Algorithm

The Feedback Loop Module completes the loop by continuously updating the system based on travel outcomes, making sure it adapts to shifting user behaviour and traffic patterns. The Adaptive Network Routing Algorithm for Enhancing Intelligent and Sustainable Smart Transportation Systems (ANRA) functionality is depicted in the flowchart shown in figure 3. The procedure starts with the data collecting module receiving real-time data from emission detectors, traffic sensors, and GPS. The input is pre-processed and transferred to the network modelling layer via this module. There, the transportation infrastructure is depicted as a dynamic graph with variables like emissions, traffic density, and journey time.

The optimization engine then uses a multi-objective cost function with user-defined weights for time, congestion, and environmental effect to assess possible routes. The optimization issue under flow and routing constraints is solved to provide the chosen paths. The learning and feedback loop receives these outputs and uses machine learning, particularly reinforcement learning techniques, to improve future routing decisions by analysing performance indicators.

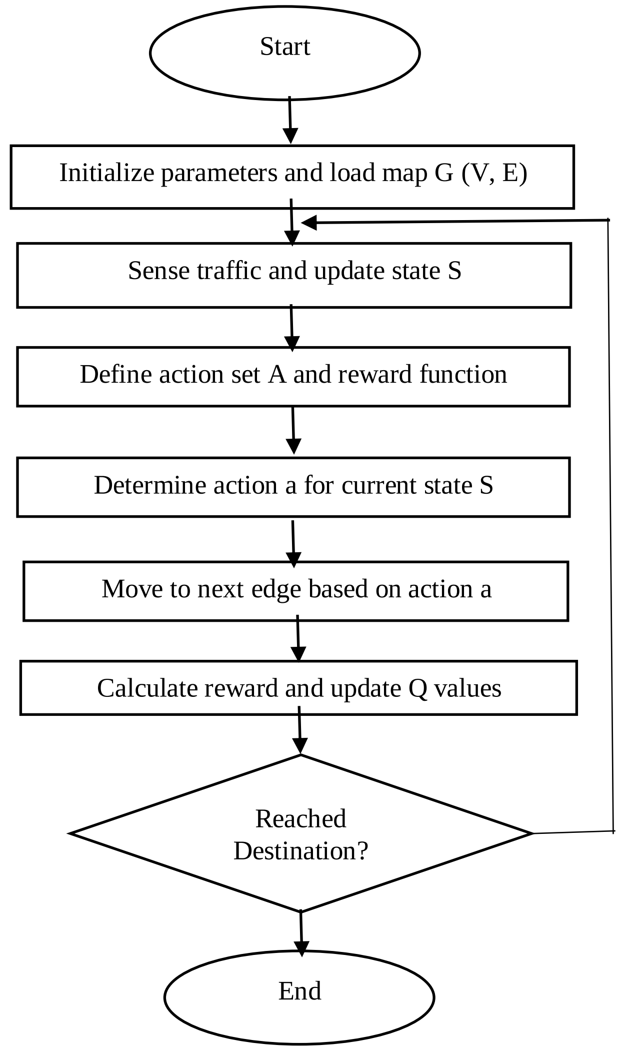

Figure 3 Flowchart for Adaptive Network Routing Algorithm

The best routes are then sent to consumers via the application interface, either through in-car systems or mobile apps. These choices may also optionally influence traffic control systems like adaptive signal timings or toll modifications. As new traffic data enters the system, the loop keeps going, guaranteeing dynamic and sustainable real-time route design.

3.6. ANRA (Adaptive Network Routing Algorithm)

Input: Road network graph G (V, E), where E is a collection of roads with attributes and V is a set of intersections matrix T of traffic conditions (number of vehicles, average speed, and signal condition). Segment-specific emission factors E_f pairs of sources and destinations (s, d). Past profiles of trip time

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and emissions H. α (time), β (congestion), γ (emissions), and time step Δ_t are the reward weights.

Results: R_{opt} is the best path for every car from its starting point to its final destination.

The steps are as follows:

Setting up: Use historical average data to initialize edge weights after loading map G (V, E). Establish the learning rate, reward weights α, β, and γ, and, if using DQN, start the Q-table or deep Q-network.

Update on Sensing and Traffic Conditions:

Update the average speed $\bar{v}_e$ on each edge and the traffic density ρ_e on edge e at each time step Δ_t from vehicular sensors and Emission estimates as shown in equation (1).

$$emission_e = base_{rate} \times (1 + k_1 \times \rho_e - k_2 \times \bar{v}_e) \quad (1)$$

where, state S = [vehicle position, local traffic density, speed, signal status].

Actions A = possible next nodes (turns or moves to connected edges).

Reward Function: For action a taken from state S, the reward function for (S, a) can be depicted as shown in equation (2).

$$Reward(S, a) = -[\alpha \times Travel\ Time + \beta \times Congestion + \gamma \times Emissions] \quad (2)$$

Routing Decision (Learning Loop): Examine each vehicle's current state S, use ε-greedy or a policy generated from the Q-table/DQN to choose action a, proceed to the next edge based on a, gather fresh traffic data, compute reward, and then use the Bellman equation to update Q-values or DQN as shown in equation (3).

$$Q(S, a) \leftarrow Q(S, a) + \eta[Reward + \gamma \max(Q(S', a')) - Q(S, a)] \quad (3)$$

Route Finalization:

Store complete path from s to d as R_{opt} once destination is reached.

Repeat:

Repeat the sensing, learning, and routing steps for each new time step or vehicle entry.

Formally the algorithm is represented in Algorithm 1.

4. MATHEMATICAL MODEL

4.1. Network Representation

Let the transportation network be modelled as a directed graph: G = (V,E), where V is the set of nodes (intersections), and
$E \subseteq V \times V$ is the set of directed edges (road segments).

Three dynamic attributes define each edge $e \in E$, which is a road segment between intersections: the emission rate ϵe, which indicates the amount of emissions in grams per kilometer; the traffic density ρ_e, which indicates the current number of vehicles per kilometer; and the travel time t_e, which indicates the estimated time to traverse the edge.

An urban transportation layout can be seen in a simple but useful way thanks to this abstraction. Each road segment acts as a functional unit, thereby influencing the quality of the route. Along with real-time feedbacks of t_e, ρ_e, and ϵ_e, this approach caters for scalability across substantial road networks parallelly expressing temporal dynamics.

4.2. Variables

Let P_v denote the route depicted for the vehicle, s_v and d_v denote the source and destination of vehicle v, and let $x_{ev} \in \{0,1\}$ denote the binary variable indicating whether the vehicle follows route e.

Following factors determine the vehicle movement in the network: Vehicle v contains the edge in its path if $x_{ev} = 1$; otherwise, it does not. The set P_v is built by testing the network with these decision variables. To ensure legitimate travel throughout the network, each vehicle's path is restricted to starting at its assigned source node S_v and ending at destination d_v. The basis for route optimization and decision-making is this variable configuration.

Objectives:

Define a composite cost function C_v for vehicle v as shown in equation (4) as follows:

$$C_v = \sum_{e \in E} x_e^v \, (\alpha.\ Te + \beta.\ Pe + \gamma.\ \epsilon e) \quad (4)$$

where α, β, and γ > 0 denote the user-defined weights representing the preference levels and te denotes the anticipated travel time on edge e, ρe denotes the congestion level (vehicles per km), ϵe denotes the emissions in grams/km. The objective is to keep the balance between sustainability (low emissions), traffic conditions (low density), and efficiency (quick travel time). By tuning α, β, and γ, the algorithm can prioritize various components of smart transportation. The objective is to minimize C_V for each vehicle, to provide the balanced routing that balances the environmental goals and user preferences.

4.3. Constraints

4.3.1. Flow Conservation

The equation (5) represents the constraints for flow conservation. It represents the difference between the flow of outgoing and incoming edges to the nodes. The constrains are shown for source and destination, represented by s_v and d_v respectively as shown in equation (5).

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$$\sum_{e\in \delta+(v)} x_e^v - \sum_{e\in \delta-(v)} x_e^v = \begin{cases} 1, if\ v = sv \\ -1, if\ v = dv \\ 0\ otherwise \end{cases} \quad (5)$$

Where $\delta^+(v)$ denotes the outgoing edges from node and $\delta^-(v)$ denotes the incoming edges to node. This mechanism ensures the correct entry and exits of a vehicle in the network. The number of outgoing edges must be one additional than the incoming nodes at source node and vice versa at the destination node. Whereas, at all the nodes except the source and destination, the inflow and outflow are equal. This is a common constraint that guarantees route accuracy and continuity in route-finding approaches.

4.3.2. Path validity

The path validity is depicted in equation (6).

$$\sum_{e\in E} x_e^v \geq 1\ \forall v \quad (6)$$

This makes sure that each vehicle is assigned to at least one correct path in the network.

Binary Routing Decision:

$$x_e^v \in \{0,1\},\ \forall e \in E, \forall v \quad (7)$$

The equation (7) is used to ensure the atomicity. This enforces that a vehicle either fully uses an edge or does not use it at all.

4.4. Emission Estimation Model (Dynamic)

$$\in e = \in o.(1 + k1.\rho e - k2.\bar{v}e) \quad (8)$$

Where:

- ϵ_0: base emission rate (vehicle-dependent),
- $\bar{v}_e$: average speed on edge e,
- k1,k2: empirically derived coefficients.

This dynamic model depicted by equation (8) shows the association of emissions, speed, and congestion. If inefficient fuel is used, the emissions usually tend to increase as density or speed decreases. Using this equation, the approach may choose more environmentally friendly paths and adapts to traffic situations in real time.

4.5. Optimization Problem

$$\min_{\{x_e^v\}} \sum_v Cv \quad (9)$$

The equation (9) depicted above represents the optimization problem. It is the central optimization goal of the algorithm. It minimizes the cumulative cost C_v for all vehicles by selecting optimal paths based on the composite metric of time, density, and emissions.

Solving this problem can be approached using mixed-integer linear programming or reinforcement learning, depending on network size and data dynamics. The outcome is a set of efficient, congestion-aware, and eco-friendly routes across the smart transportation network.

Input: Directed road network graph G = (V, E)

1. Initialize the directed road network G=(V,E) where each edge has attributes: travel time t_e, traffic density ρ_e, and average speed $\bar{v}$e.
2. Set initial values for reinforcement learning parameters: learning rate η, discount factor γ, exploration rate ϵ, and reward weights α, β, γ.
3. Calculate emissions for each edge using the dynamic model:

   $\in \mathrm{e} = \in \mathrm{o}.(1 + \mathrm{k1}.\rho\mathrm{e} - \mathrm{k2}.\bar{\mathrm{v}}\mathrm{e})$
4. Initialize Q-table Q (S, A) where S is the current node and A is a possible action (next node).
5. For each vehicle entering the system with source-destination pair (s, d) set initial state S=s.
6. While S ≠ d:
   a. Choose next action A using ε-greedy policy: random (exploration) or best Q-value (exploitation).
   b. Move to new state S′; extract updated metrics t, ρ, ϵ.
   c. Compute reward: R=−(α·t+β·ρ+γ·ϵ)

   d. Update Q-value using Bellman equation:

   Q(S, a) ⟵ Q(S, a)+η[Reward + γ max(Q(S', a'))-Q(S, a)]

   e. Set current state S⟵S′.
7. Once destination d is reached, store optimal path R_{opt} traced by actions with maximum Q-values.
8. Continue learning iteratively for all vehicles; update network state in real-time for continuous adaptation.

Output: Optimal route R_{opt} from source s to destination d.

Algorithm 1 Adaptive Network Routing Algorithm (ANRA)

The algorithm 1 depicts all the major steps involved in the strategy. The distinguishing features of ANRA which makes it special as compared to other existing methodologies are as follows:

1. Emission Awareness: ANRA includes emissions into the learning process directly instead of treating it as an additional metric, as it is existing in the previous works.
2. Adapting reinforcement learning: Unlike other approaches which rely on static routing or heuristic only methodology, ANRA supports dynamic decision making.
3. Real world scalability: ANRA is suitable for VANETs and ITS systems due to its customized design suitable for

International Journal of Computer Networks and Applications (IJCNA)
DOI: 10.22247/ijcna/2025/30 Volume 12, Issue 4, July – August (2025)

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integration with edge computing and intelligent city Infrastructures.

4. Flexible weighting: ANRA allows adaptive system based on policy preferences e.g. lower emissions near healthcare zones.

Table 2 summarizes the aspects in which ANRA outperforms the previous models.

Table 2 Key Innovations Over the Previous Models

Aspect	Previous Models	Proposed ANRA Model
Adaptability	Static or semi-dynamic routing (e.g., Dijkstra, A*)	Fully adaptive using real-time traffic and environmental data
Objective	Single or dual objective (shortest path or minimal delay)	Multi-objective: Minimizes travel time, emissions, and congestion
Learning Framework	Classical RL or heuristic methods	Reinforcement Learning with emission-aware reward function
Environmental Focus	Often overlooked or added as post-processing	Integrated emissions as a core component of route optimization
Scalability	Limited to small or mid-size networks	Scalable to large urban networks using modular architecture
Feedback Mechanism	No or limited learning from outcomes	Real-time feedback loop for continuous route improvement

5. RESULTS AND DISCUSSIONS

The graph nodes and edges represent a hypothetical urban road network as shown in figure 4: A, B, C, D, E represent intersections or locations in the city. Each directed edge between nodes includes the following attributes:

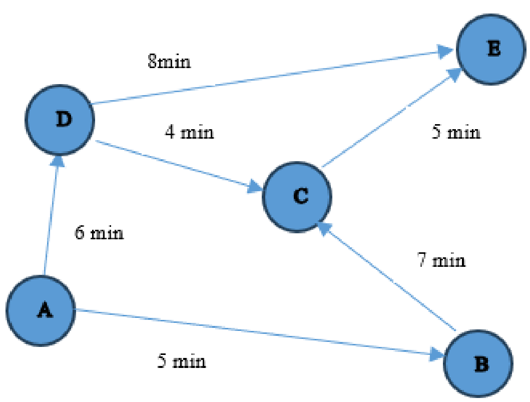

Figure 4 Simulated Urban Traffic Network Graph (Edges Represent the Travel Time)

The table 3 depicts the parameters used for the simulation of ANRA.

From the above table 3, and 4, additional parameters are computed per edge:

Emission (g/km) = $\epsilon_0 \cdot (1+k1 \cdot \rho - k2 \cdot v)$ as depicted in equation (1).

Where, ϵ_0=1.0, k1=0.6 (congestion impact), k2=0.3 (speed reduction impact), ρ is the traffic density, v is the average speed. Composite Cost is given by equation (2) with: α=0.5, β=0.3, γ=0.2.

A controlled simulation setup is designed that mimics a hypothetical model traffic network, to test the performance of the proposed Adaptive Network Routing Algorithm (ANRA). This simulation framework enables comparison of ANRA with traditional routing algorithms under different environment and traffic conditions.

- Network Topology

The simulation network exhibits the nodes as mentioned in table 4 and are labelled A, B, C, D, and E, connected via edges representing the road segments.

Each edge possesses dynamic attributes that influence routing decisions: travel Time (in minutes), traffic Density (vehicles/km) and average Speed (km/h).

- Emission Modelling

For each road segment, emissions are computed using the formula given in equation (1). This model depicts higher congestion and low speed lead to elevated emissions; this reflects the real-world relationship.

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- Composite Cost Calculation

A composite routing cost is computed for each possible path using a weighted formula depicted in equation (2).

The performance of ANRA is tested using a simulation framework for urban traffic network and is tabulated in table 4. It is compared against conventional routing algorithms such as A*, Dijkstra and Random Walk. The parameters considered are: Traffic density, Emission level, travel time and routing cost as shown in table 5.

Table 3 Parameters Used for Simulation

Parameter	Description	Value / Range
Travel Time	Estimated time to traverse each edge	4 – 8 minutes
Traffic Density (ρ_e)	Vehicles per kilometre	20 – 40 veh/km
Average Speed ($\bar{v}_e$)	Speed of vehicles on road segment	10 – 20 km/h
Base Emission Rate (ϵ_0)	Emission rate under ideal conditions	1.0 g/km

Table 4 The Network Details Used for Simulation

From	To	Travel Time (min)	Traffic Density (veh/km)	Average Speed (km/h)
A	B	5	20	10
B	C	7	40	20
A	D	6	25	15
D	C	4	35	10
C	E	5	30	15
D	E	8	20	12

Table 5 Comparison of Performance

Routing Strategy	Travel Time (min)	Traffic Density (veh/km)	Emission (g/km)	Cost
ANRA Algorithm	14.0	27.5	10.2	23.5
Dijkstra	15.0	30.0	11.3	26.4
A*	15.0	30.0	11.3	26.4
Random Walk	19.0	32.5	14.2	32.9

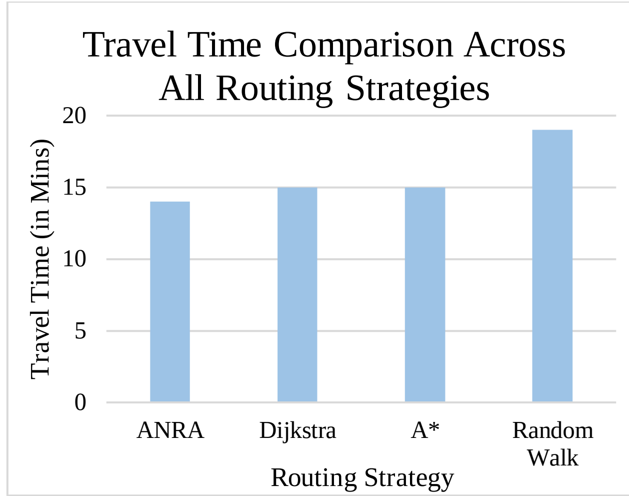

Figure 5 Travel Time Comparison for ANRA, Dijkstra, A* and Random Walk

The average amount of time needed by each algorithm to get to the destination is shown in the journey time graph depicted in figure 5. The suggested ANRA algorithm produces the shortest journey time (14 minutes), surpassing Random Walk by a substantial margin and outperforming Dijkstra and A* (both at 15 minutes). This illustrates how effectively the ANRA chooses quicker routes.

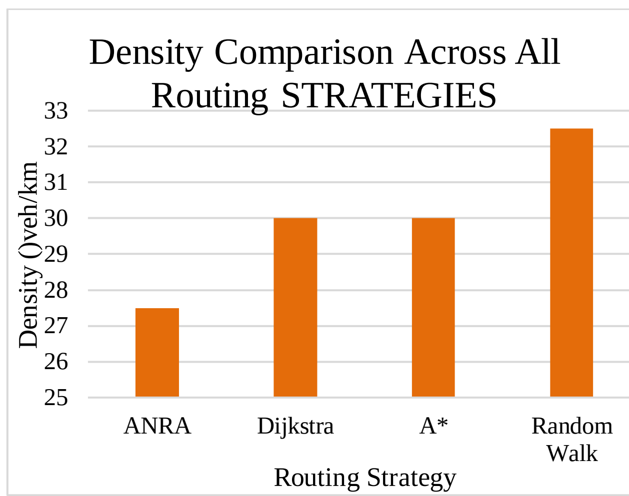

Figure 6 Traffic Density Comparison for ANRA, Dijkstra, A* and Random Walk

The average vehicle density found along the routes chosen by each method is displayed in graph shown in figure 6. With the lowest density (27.5 vehicles/km), ANRA is able to steer clear of crowded roads.

The Random Walk method produces the highest densities (32.5 vehicles/km), whereas more conventional algorithms like Dijkstra and A* display higher densities (30 vehicles/km).

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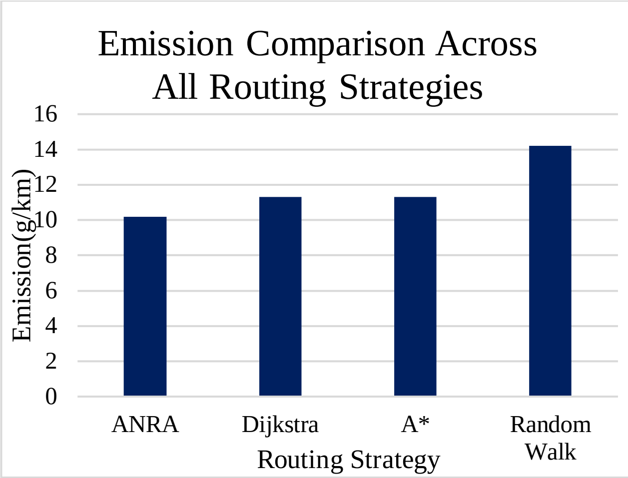

Figure 7 Emission Comparison for ANRA, Dijkstra, A* and Random Walk

The estimated emissions (g/km) generated by each routing method are contrasted in the emission graph shown in figure 7. Because it chooses routes with less traffic and more efficient traffic flow, ANRA once again performs best with the lowest emissions (10.2 g/km). For Dijkstra, A*, and Random Walk, emissions increase gradually before peaking at 14.2 g/km.

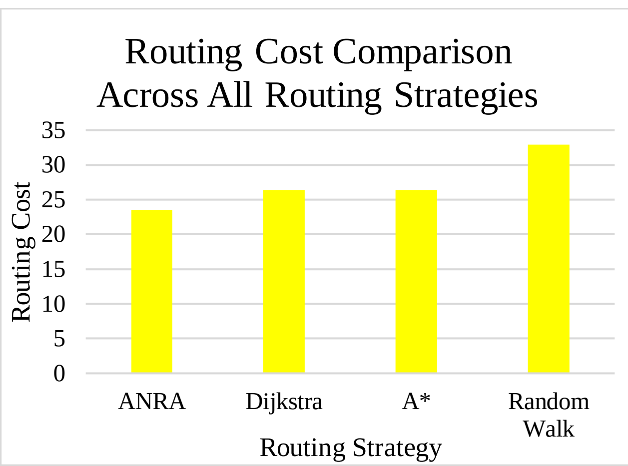

Figure 8 Overall Routing Cost Comparison for ANRA, Dijkstra, A* and Random Walk

The composite cost metric that is generated from emissions, density, and travel time is summarized in graph shown in figure 8. The least expensive method, ANRA, has the lowest cost (23.5), suggesting a more sustainable and well-rounded choice. Random Walk, on the other hand, performs the lowest and has the largest cost (32.9), underscoring its inefficiency, whereas Dijkstra and A* score identically (26.4).

The simulation clearly demonstrates the efficient performance of the proposed system as compared to the conventional routing methods as depicted in table 5. This outperformance is by virtue of adaptation to the emission data and real time density. The simulation exhibits a well-structured cost formulation, dynamic learning loop and realistic emission estimation. This has supported strongly the usage of ANRA in real world environments and urban traffic systems.

The summary of observations is presented below:

1. ANRA consistently performs better than traditional algorithms with respect to all the parameters in reference.
2. The real time environmentally aware routing is enabled by the multi-objective optimization and reinforcement learning based adaptability.
3. For Smart city deployments and eco-routing applications, the improvements in the metrics such as emissions and traffic density are of prime importance.
4. The conventional routing algorithms like those based on Dijkstra and A* are efficient for finding shortest path but they lack the contextual and environmental awareness.
5. Due to the lack of guided decision making in the traffic environment the performance of Random Walk algorithm's gets affected.

The comparison clearly shows the performance of single objective methods are overshadowed by ANRA's multi-parameter routing strategy with respect to efficiency and environmental sustainability. By integrating the environmental considerations with traffic awareness while doing route selections, it ensures an effective and working solution for urban transportation issues. There may be few challenges with practical implementation of ANRA. One major amongst it will be the limitation in capacity to handle the real time data pertaining to traffic density and emission data due to availability concerns of sensors and data latency. Due to large scale networks in the metropolitan cities, large computational complexity may get incurred, which may in long term hamper the communication overhead due to ongoing data interchange. For adapting this approach, it may be required that the traditional infrastructures need to be realigned in order to overcoming the old infrastructure limitations is necessary. The effectiveness of routing may get affected sometimes due to unpredictable occurrences like weather and accidents. The security and privacy issues must be emphasized to preserve data integrity. Lastly, the system performance may get affected due to adoption of routing recommendations and user conduct.

6. CONCLUSION

The proposed Adaptive Network Routing Algorithm (ANRA) performs at par in the environment which needs maximizing intelligent and sustainable smart transportation systems. ANRA outperforms the conventional algorithms like Dijkstra,

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A*, and Random Walk by dynamically adapting routing parameters such as travel time, traffic density, and vehicle emissions. The simulations demonstrate a prominent decrease in emissions and trip time thereby decreasing the composite overall routing cost. The results assure the efficiency and effectiveness of algorithm in adaptive real-time decision-making and its potential for implementation in smart city frameworks and next-generation vehicular networks. The proposed algorithm – ANRA is based on multi-objective optimization strategy and reinforcement learning. It simultaneously considers all the parameters like traffic density, emissions and travel time, hence ANRA provides better results. It integrates the real time traffic data and the environmental data also to make context aware choices. Due to the usage of reinforcement learning systems which provides the learning from the route feedback, ANRA can dynamically adjust to the frequently changing traffic conditions. By utilizing the emission aware reward function, the ANRA approach helps in providing environmentally efficient routes. The modular framework assures responsiveness and scalability which makes it more suitable for smart city Systems. Overall, by combining all the above features, ANRA provides as an efficient and sustainable solution as compared to the conventional algorithms. ANRA can be associated with frameworks like VANETs, GPS navigation and smart traffic control systems. It can be exploited to reduce urban traffic density and carbon emissions. It is robust in dynamic traffic conditions which is a prime requirement for modern urban traffic management systems. The results show that for real time deployment in intelligent transportation systems, ANRA is a strong candidate. There is still a lot of room for further research, though. Incorporating real-time traffic feeds, machine learning-based predictive modeling for projecting congestion, and reinforcement learning to adjust to changing traffic patterns can all improve the program even further. Its suitability for actual smart city settings may also be further demonstrated by scalability experiments on huge metropolitan networks and integration with platforms such as SUMO and VANET simulations.

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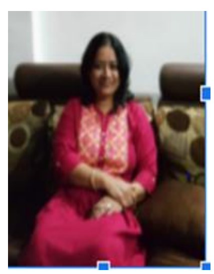

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How to cite this article:

Jyoti Sunil More, Vaishali V. Sarbhukan (Bodade), Reena Lokare, “Adaptive Network Routing Algorithm for Intelligent and Sustainable Smart Transportation Systems”, International Journal of Computer Networks and Applications (IJCNA), 12(4), PP: 487-499, 2025, DOI: 10.22247/ijcna/2025/30.