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Original Article

Multi-Agent Autonomous Control Framework for Intelligent Transportation Infrastructure

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ABSTRACT

Rapid urbanization and increasing traffic demand require intelligent transportation systems that can adapt in real time. Traditional centralized traffic management is limited in handling dynamic traffic conditions, leading to congestion, delays, higher fuel consumption, and reduced road safety. This study proposes a Multi-Agent Autonomous Control Framework that integrates Multi-Agent Systems (MAS), Artificial Intelligence (AI), Deep Reinforcement Learning (DRL), Graph Neural Networks (GNN), Internet of Things (IoT), Vehicle-to-Everything (V2X) communication, and edge-cloud computing. The framework enables traffic signals, vehicles, roadside units, and other transportation entities to operate as autonomous, cooperative agents that exchange real-time information and make distributed decisions. By analyzing traffic, environmental, and infrastructure data, the proposed architecture dynamically optimizes signal control, routing, and emergency response. Simulation results demonstrate improvements in traffic flow, congestion reduction, travel time, fuel efficiency, road safety, scalability, and system resilience. The framework provides a scalable and intelligent foundation for future smart cities, connected autonomous transportation, and sustainable urban mobility.

KEYWORDS

Multi-Agent Systems, Autonomous Transportation, Intelligent Infrastructure, Reinforcement Learning, Edge Computing, V2X Communication.

1. INTRODUCTION

1.1. Background

Transportation infrastructure is one of the most basic pillars of modern socio-economic development and makes it possible to move people, goods and services through urban, suburban and rural environments. The rise of global populations and fast urbanisation as well as the proliferation of economic activities have all contributed towards an increased demand for transport, placing unprecedented stress on existing road networks and mobility systems. Increasing vehicle ownership, limited road capacity, inefficient traffic management practices and the growing need for safer sustainable mobility solutions add to complex transportation challenges faced by modern cities. Traditional traffic control approaches are increasingly incapable of meeting the operational needs of modern smart cities as transportation networks become more interconnected, dynamic and data-driven. Traditional transportation managers have to rely on fixed time traffic signal controllers, centralized monitoring platforms, and manually configured traffic management strategies. Despite having been used to support transportation operations for years, those approaches lack the intelligence and adaptability needed to respond to dynamically changing traffic environments. Fixed-time signal systems follow a pre-determined time cycle and are incapable of responding to real-time fluctuations in the volume of traffic, vehicle movements, pedestrian activities or emergencies. Likewise, when handling real-time transportation data generated by modern sensing and communication technologies, centralized traffic control architectures face a computational bottleneck under high-volume backgrounds and long latencies, ultimately limiting system scale. Traditional systems are unable to adjust automatically to unexpected events (for instance, road accidents, van malfunctions, weather disruptions, development activities and unexpected changes in the demand for travel), leading inefficient traffic flow and higher operational complexity. All this causes longer waiting times for vehicles, often congested traffic jams, high fuel consumption and greenhouse gas emissions as well as poor transportation efficiency. In addition, autonomous vehicles, connected mobility services as well as intelligent infrastructure are placing increasing demands on transportation systems to perform autonomous reasoning, real-time decision-making and coherent interaction of multiple entities. With the recent developments in Artificial Intelligence (AI), Internet of Things (IoT), Edge computing and vehicle-to-everything (V2X) communication, new possibilities have arisen to realize intelligent transportation ecosystem [1]. These technologies allow vehicles, roadside infrastructure, and traffic management systems to constantly gather, process, and share information to support adaptive and predictive control in the transportation system. It is in this context that multi-agent intelligent systems have emerged as a viable solution - distributing decision making capabilities to independent, autonomous agents able to process their own environmental conditions and work collectively together to optimize global transportation metrics. Thus, the shift to AI-based decentralized and independent modes of transportation framework becomes necessary for addressing limitations in traditional systems. Intelligent transportation architectures of this nature can increase traffic effectiveness and road safety, minimize environmental externalities, and represent a mobility service adjustment that is able to scale to address future mobility requirements of connected/smart city metropolitan settings.

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1.2. Need for Multi-Agent Autonomous Transportation Infrastructure

While the state of transportation ecosystems has become increasingly complex, there is now a critical need for intelligent control mechanisms that can operate autonomously, make decentralized decisions and carry out collaborative optimization. Traditional centralized transportation management techniques are increasingly inadequate to handle the number of interconnected entities, dynamic traffic patterns and real-time decision requirements in smart cities (data up to October 2023). Multi-Agent Autonomous Transportation Infrastructure (MAATI) acts as a resolution by decentralizing intelligence to multiple autonomous agents that can perceive environmental conditions, communicate with neighbors and optimize transportation performance together. The necessity for such an infrastructure can be understood through the following key aspects.

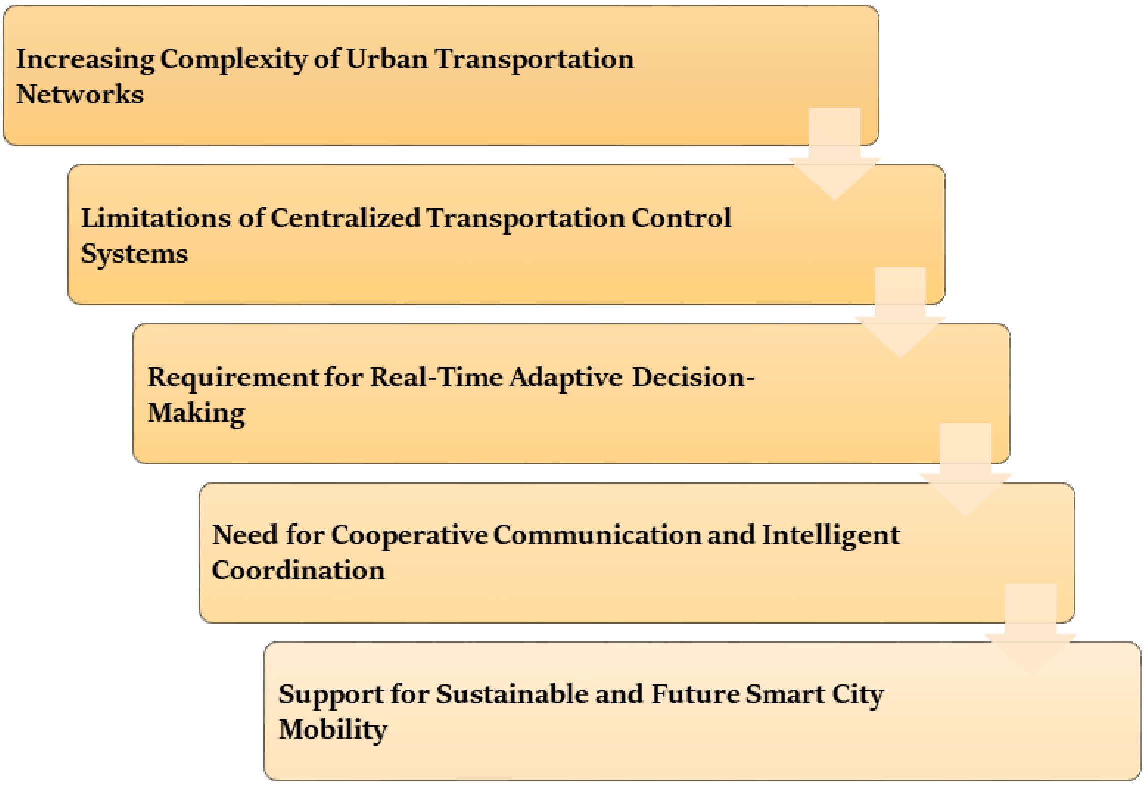

Fig 1 - Need for Multi-Agent Autonomous Transportation Infrastructure

1.2.1. Increasing Complexity of Urban Transportation Networks

Modern transportation systems consist of thousands of interconnected components, including traffic intersections, autonomous vehicles, public transit systems, emergency response units, logistics fleets, pedestrians, roadside sensors, and environmental monitoring devices. Each component generates continuous streams of data and requires rapid decision-making to ensure efficient operation. The increasing interaction among these heterogeneous entities creates a highly complex environment that cannot be effectively managed using conventional static control methods. Multi-agent architectures enable individual entities to operate as intelligent decision-making units, allowing transportation networks to dynamically adapt to changing conditions.

1.2.2. Limitations of Centralized Transportation Control Systems

Traditional centralized traffic management systems rely on one control authority responsible for collecting data, processing information, and creating operational decisions. While these systems can facilitate basic traffic coordination, they are severely constrained when it comes to controlling large scale transportation networks. They have high computational and communication requirements, single-point failures, low scalability possibility which affects them in real-time applications. These hurdles can be alleviated with multi-agent autonomous frameworks, where computation intelligence is shared around a multitude of agents (the computational burden is distributed) and allow for near real time responses to local transportation events.

1.2.3. Requirement for Real-Time Adaptive Decision-Making

Even though transportation environments are naturally highly dynamic and can vary with traffic density, road conditions, weather changes, accidents or emergency situations. For these exceptional and usually unpredictable alterations, fixed control strategies are impaired for which this case result in congestion, extra journey time, and inefficient resource utilization. Multi-agent autonomous systems offer real-time perception of the environment via integrated sensing, artificial intelligence, and communication technologies. Agents can look at the state around them, simulate beyond what they can see and make the best action choices on their own, as well as adjusting to other agents selecting actions that are keeping transportation going throughout.

1.2.4. Need for Cooperative Communication and Intelligent Coordination

Systems for future transportation 윙 are a major part of Ubiquitous Traffic Control where the interaction should be seamless by V2V, V2I, V2P and TSP (Transportation Service Provider). Abstract : Technologies like Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), Infrastructure-toInfrastructure (I 2 I) and Vehicle- to-Everything (V 2 X) communication allow such a seamless information transfer between distributed transport entities. Such communication schemes are the target of multi-agent architectures that need to make joint decisions by sharing traffic information, determining movement strategies, giving priority to emergency services as well as achieving overall optimization in transportation for a large network.

1.2.5. Support for Sustainable and Future Smart City Mobility

A smart city transition calls for sustainable, efficient transportation infrastructures that support autonomous mobility services. Doubling concerns from the two-legged ones weighed down by our knowledge of fuel consumption, carbon emissions, traffic congestion, and urban mobility present a need for intelligent solutions to optimize transportation resources. The multi-agent autonomous transportation infrastructure not only improves route efficiency, reduces unnecessary delays in land vehicles, but also has a great effect on energy conservation and public transport coordination. Translating into intelligent mobility architecture, MAATI integrates key ingredients such as AI, IoT, and autonomous decision-making capacity to also act as a scalable platform for future steps within intelligent mobility ecosystems.

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2. *LITERATURE SURVEY*

2.1. Evolution of Intelligent Transportation Infrastructure

Intelligent transportation infrastructure has transformed from traditional traffic control systems toward continually integrated and automated transportation ecosystems powered by advanced digital technology. Traditionally, transportation systems were based on low-level traffic signals with fixed-time controllers, manual supervision and static planning methods, owing to lack of the ability to dynamically respond to real-time traffic conditions leading to congestion situations, inefficient traffic flow and high-increasing accident rates. By blending digital communication technologies, along with embedded sensors, Global Positioning System (GPS) devices, surveillance cameras and centralized traffic management centers – traffic monitoring and operational efficiencies saw a major upgrade by allowing continuous data collection and providing the ability to make decisions at a central location. Later, a combination of rapid evolution in Internet of Things (IoT), cloud computing and ultra-high speed wireless communication enabled seamless connectivity of vehicles to each other, roadside infrastructure elements, and transportation management centers via Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I) or V2X communication. Meanwhile, innovations such as edge computing, artificial intelligence (AI), distributed sensing, and autonomous control mechanisms have evolutionized transportation systems into decentralized intelligent infrastructures that perform real-time decision-making, adaptive traffic optimization, predictive analytics, autonomous vehicle coordination and low-latency communication. These advances in technology have laid the groundwork for future smart cities, creating safe, and efficient, sustainable and scalable intelligent transportation networks that are able to adapt dynamically to changing urban mobility needs.

2.2. Multi-Agent Systems in Transportation

Multi-Agent Systems (MAS) based on decentralized, autonomous and cooperative decision making of thousands of transportation entities have emerged as one of the key approaches for intelligent transportation management. In contrast with centralized traffic management systems, MAS treats intersections, vehicles, traffic signal controllers, roadside units and infrastructure elements as intelligent agents that can autonomously sense their local environment, communicate to one another within a marketplace for transport optimization. At the start, MAS applications emphasis was on adaptive traffic signal control that adaptively coordinates a network of autonomous intersection agents to change signal timings independently based on real-time congestion levels which can greatly reduce waiting times and improve throughput. Due to its ability to work with connected and autonomous vehicles, MAS has been used for many applications such as cooperative route planning with the help of V2X communication technologies [11], distributed congestion control [27], autonomous parking management [14] and emergency vehicle prioritization through automatic speed-up in traffic light; logistics optimization [12]; intelligent public transportation scheduling[16]. In particular, developments are being made towards integrating blockchain with federated learning and relying on swarm intelligence or distributed optimization techniques to improve secure communication, enabling collaborative learning, resource allocation and system resilience. However, ongoing research toward the development of more adaptive, scalable and intelligent multi-agent transportation architectures continues to be driven by issues regarding: communication overheads; interoperability; cross-metro system scalability of transport networks; heterogeneous agent coordination; and stable cooperation in highly dynamic traffic environments.

2.3. AI, Reinforcement Learning and Edge Computing

Artificial Intelligence (AI), Reinforcement Learning (RL) and Edge Computing are all technology repetitions that, added to leverage Intelligent transportation systems, end up representing an intelligent choice with autonomous decision-making, predictive analytics and decentralized computational intelligence. Machine learning and deep learning approaches (Convolutional Neural Networks, Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, Graph Neural Network(GNN)) have shown excellent performance in traffic flow prediction, vehicle trajectory computing,d congestion forecasting, accident detection, travel demand analysis and infrastructure maintenance. Reinforcement Learning (RL) has become one of the most promising strategies for adaptive transportation control, enabling intelligent agents to iteratively learn optimal traffic regulation strategies from dynamic environments based on reward-based optimization. Deep Reinforcement Learning enhances the decision-making layer, by combining deep neural networks with reinforcement learning algorithms to solve large-scale and highly-complex urban traffic optimization problems. At the same time, it puts computational resources closer to transportation devices bringing communication latency, bandwidth consumption and response time down and making real-time processing possible for safety-critical applications. The integration of AI, reinforcement learning, and edge computing underpins decentralized traffic optimization, adaptive automated signal control optimization, intelligent predictive maintenance and autonomous vehicle coordination with intelligent resource allocation; however computational complexity and cybersecurity are active research areas along with the ongoing quest in explainable AI for safety-critical systems such as transportation networks [174], [175], synchronization challenges that favor smaller agents or vehicles over larger ones but this also raises concerns regarding system scalability on sustainable multi-agent coordination.

2.4. Research Gap and Comparative Analysis

Although remarkable progress has been achieved in intelligent transportation technologies, there are still some primary research gaps that constrain practical implementation of fully autonomous of transportation infrastructures. The traditional architectures used in most current Intelligent Transportation Systems (ITS) include an inherent computational bottleneck and small communication delay, especially when it comes to larger metropolitan transportation networks. Additionally, the existing Multi-Agent Systems have been restricted to operate under localized optimization problems like isolated traffic intersections or vehicle routing instead of providing holistic coordination over heterogeneous transportation systems composed by autonomous vehicles, roadside infrastructure, pedestrians, emergency response nsystems and public transport netowrks. Although reinforcement learning has achieved considerable success in adaptive traffic signal optimization, relatively few studies integrate Deep Reinforcement Learning, Graph Neural Networks, edge-cloud collaborative computing, and V2X communication within a unified

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decentralized decision-making framework capable of supporting large-scale intelligent transportation ecosystems. Additional challenges remain in interoperability among heterogeneous communication protocols, privacy preservation, cybersecurity, distributed learning, fault tolerance, and explainable AI for transportation decision-making. Addressing these limitations requires the development of scalable, secure, and adaptive multi-agent autonomous control frameworks that integrate distributed intelligence, collaborative learning, edge computing, and real-time communication to support the future demands of smart cities and next-generation connected transportation infrastructures.

3. METHODOLOGY

3.1. Proposed Multi-Agent Autonomous Control Framework

The proposed framework represents a next-generation intelligent transportation system by modeling each major transportation entity as an autonomous intelligent agent with the capability to perceive, reason, learn, and collaborate within a dynamic transportation environment. Unlike conventional centralized traffic management approaches, where decision-making is controlled by a single processing unit, the multi-agent framework distributes intelligence across multiple specialized agents that operate independently while maintaining continuous coordination. The principal components of the framework include Traffic Signal Agents (TSA), Vehicle Agents (VA), Roadside Unit Agents (RSA), Emergency Vehicle Agents (EVA), Public Transport Agents (PTA), Environmental Monitoring Agents (EMA), and a Global Coordination Agent (GCA). Each agent is designed with specific responsibilities, sensing capabilities, communication mechanisms, and optimization strategies to address complex transportation challenges. Traffic Signal Agents analyze real-time traffic density, vehicle arrival patterns, pedestrian movement, and intersection congestion levels to dynamically adjust signal timings for reducing waiting time and improving traffic flow. Vehicle Agents utilize onboard sensors, navigation systems, and artificial intelligence models to optimize individual travel decisions, including route selection, speed adaptation, and collision avoidance. Roadside Unit Agents function as communication bridges between vehicles and infrastructure by collecting traffic information and enabling vehicle-to-infrastructure (V2I) coordination. Emergency Vehicle Agents prioritize ambulance, fire, and rescue vehicle movement by negotiating with nearby agents to create optimized emergency corridors. Public Transport Agents monitor bus and transit operations to improve scheduling accuracy, reduce delays, and enhance passenger experience.Environmental Monitoring Agents continuously evaluate external factors such as weather conditions, air quality, road surface conditions, and environmental hazards to support safer transportation decisions. The Global Coordination Agent acts as a higher-level intelligence layer that integrates information from all distributed agents, resolves conflicts, and aligns local decisions with overall transportation objectives. Through continuous information exchange, cooperative learning, and adaptive decision-making, the proposed multi-agent architecture enables autonomous responses to rapidly changing traffic conditions. This collaborative intelligence improves congestion management, enhances road safety, reduces energy consumption, and supports sustainable mobility by achieving a balance between individual agent optimization and system-wide transportation

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efficiency. The framework provides a scalable foundation for future smart cities by enabling intelligent coordination among heterogeneous transportation entities.

3.2. Agent Coordination and Communication Architecture

Intelligent, adaptive and scalable transportation management requires effective collaboration among autonomous agents. The multi-agent transportation framework proposed relies on a distributed communication architecture to facilitate information sharing among heterogeneous transportation entities. Differently than previous transportation systems where agents made independent decisions, the architecture we propose allows agents to continuously communicate in real-time with each other and synchronize their actions based on environmental conditions. This interaction mechanism exploits the distributed nature of vehicles to react faster, reduce response time, and provide individual flexibility adapting to more complex traffic conditions. The communication architecture incorporates various communications paradigms, such as Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), Infrastructure-to-Infrastructure (I2I) and even V2X communication technologies. Vehicle to Vehicle communication facilitates a direct link between vehicles close by one another, which allows Vehicle Agents (VA) on implicated cars to communicate important information such as speed, acceleration, position and braking behavior that would put those later in collision risk with other oncoming or already positioned vehicles. The cooperative awareness to detect hazardous situations in advance, and coordinated driving behaviors among autonomous vehicles for better traffic safety. This includes establishing interoperability between Vehicle-to-Infrastructure (802.11p) using traffic signal agents, roadside unit agents and vehicles. With V2I communication, vehicles get updates in real-time about signal timing at certain intersections, congestion levels on a road and how to optimize their route. Likewise, roadside infrastructures incorporate vehicle information to enhance traffic data monitoring and control strategies [15, 47]. Infrastructure-to-Infrastructure you can see how the traffic control centers, smart intersection, environmental monitoring stations and transportation management system work together for better coordination. This allows for the exchange of operational information between infrastructure components, allowing traffic to be optimized across larger geographic territories. On the other hand, vehicle-to-everything (V2X) communication framework is a customized connectivity system where collective communication layer enables different interaction channels to support all the data exchange between vehicles, infrastructure such as road-side units(RSU), pedestrians and emergency service systems and cloud based intelligent systems. By employing cutting-edge communications technologies, edge computing, and artificial intelligence decision-making trademarks, this architecture enables low-latency data transfer while ensuring efficient coordination. Agents use exchanged information to engage in collaborative reasoning, conflict resolution, and adaptive planning autonomously from their goals [1]. In addition, the architecture has security and reliability in place to safeguard sensitive transportation data against interception by malicious attackers. Secure communication is supported by authentication, encryption and trust management techniques adapted to agents. The proposed coordination framework facilitates effective traffic management, rapid emergency response, enhanced mobility and more sustainable vehicles that by means of continuous knowledge sharing and collaborative decision-making create a solid enabler for the autonomous smart transportation ecosystems to come.

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3.3. AI-Based Decision-Making Engine

Intelligent Decision-Making Engine (IDME)—This describes the computational intelligence layer of the recommended autonomous transportation framework, where it is engineered to make sense of transportation data and then create adaptive control strategies on-the-fly. Transportation environments are highly dynamic with constantly changing traffic patterns, human behaviors showing potential irregularities, environmental conditions variations, road surface types and conditions / wear and tear of vehicles in variability, and unanticipated emergency scenarios. This shows that using traditional rule-based decision making approaches alone will not yield the best performance. In order to overcome the limitations of existing engines, an innovative engine incorporating advanced virtual artificial intelligence components (DRL/DL GNNs and supervised learning models) extracted from empirical data is proposed that enables autonomous agents to make differentiated intelligent decisions autonomously via continuous adaptation to the environment through new deep reinforcement learning approaches as an example. Reinforcement Learning is at the core of decision optimization as it gives transport agents the ability to make optimal decisions through interactions with their environment. Each agent will assess the current transportation situation, choose proper actions and then receive a penalty or bonus for its performance based on system indicators such as traffic flow jparameter, travel time minimization, fuel consumption optimization, safety improvment and congestion suppression p[6⇶. DRL models learn through multiple training iterations over the same environment, which allows them to develop adaptive control policies that take into account unpredictable and non-linear response, meaning no predetermined rules are involved. The highly connected nature of traffic networks are actually represented through the usage of Graph Neural Networks. With roads, vehicles, intersections and other infrastructure components all connected in a structured graph, GNN models can thus capture the spatio-temporal correlations between different transportation entities. Using inter-agent relations, the system is able to predict how traffic congestion will spread and thus identify potential bottleneck locations for injection of flows so as to maximize globally beneficial effects. It allows for more accurate decision-making as compared to agent-based approaches of working in isolation. Supervised learning models augment the decision engine by leveraging existing transportation data to do classification, prediction, and pattern recognition. It make use of the previous traffic states, previous accident records, passenger demand pattern and environmental information to predict the future transportation states. And predictive analytics further augment this intelligence with estimates of traffic volumes, probability of congestion, travel demand prediction, and likely infrastructure failures — all before they happen. By integrating these AI techniques, the decision-making engine can incrementally refine transportation strategies from real-time observations in conjunction with collective agent intelligence. The engine allows for features such as dynamic signal enforcement, routing of autonomous vehicles, real-time emergency response optimization, and intelligent resource allocation. The combination of learning-based prediction and cooperative agent reasoning in the proposed AI-driven decision framework improves efficient transportation, increases safety, reduces operational costs and offers scalability for future autonomous and smart city transportation systems.

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3.4. Mathematical Model and Algorithms

The proposed framework formulates intelligent transportation control as a distributed optimization problem in which multiple autonomous agents collaboratively optimize transportation performance while maintaining individual operational objectives. Since modern transportation networks consist of interconnected roads, vehicles, intersections, and infrastructure components, the entire transportation environment can be mathematically represented as a dynamic graph structure. Let the transportation network be represented by a graph G = (V, E)**,** where **V** denotes the set of transportation nodes and E represents the communication and physical connectivity relationships among these nodes. The nodes may correspond to vehicles, traffic intersections, roadside units, public transportation stations, and monitoring systems, while edges represent communication links, road connections, or interaction dependencies between agents. Each intelligent transportation agent is modeled as an autonomous decision-making entity with a state space, action space, and reward function. The state of an agent at time t can be represented as $S_i(t)$**,** which includes local and global transportation parameters such as vehicle density, average speed, traffic signal status, environmental conditions, road availability, and neighboring agent information. Based on the observed state, each agent selects an optimal action $\mathbf{A_i(t)}$ using an adaptive policy function $\boldsymbol{\pi_i}$, which determines decisions such as signal timing adjustment, route selection, vehicle speed optimization, or emergency priority management. The overall objective of the framework is formulated as a multi-agent optimization problem that maximizes a global utility function while minimizing transportation inefficiencies. The optimization objective can be expressed as:

$$\text{Maximize } J = \Sigma(R_i(t))$$

where $R_i(t)$ represents the reward obtained by each agent based on improvements in traffic efficiency, safety, energy consumption, and travel time reduction. The reward function integrates multiple performance parameters, including congestion reduction, collision avoidance, fuel efficiency, and environmental impact.To achieve distributed optimization, a Multi-Agent Deep Reinforcement Learning (MADRL) algorithm is employed. During each learning cycle, agents observe their local states, communicate with neighboring agents, estimate future outcomes, and select optimal actions using learned policies. The algorithm continuously updates neural network parameters by minimizing prediction errors between expected and obtained rewards. Additionally, Graph Neural Network-based message aggregation is applied to capture dependencies among connected agents and improve decision accuracy. The proposed mathematical model also incorporates constraint functions related to road capacity, communication reliability, safety requirements, and infrastructure limitations. These constraints ensure that optimization decisions remain practical and applicable to real-world transportation environments. Through iterative learning, cooperative communication, and distributed optimization, the proposed algorithm enables autonomous agents to achieve system-wide objectives while preserving decentralized intelligence. This mathematical formulation provides a robust foundation for developing scalable, adaptive, and efficient AI-driven transportation management systems suitable for future smart city applications.

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4. RESULTS AND DISCUSSION

4.1. Experimental Setup

A large-scale transportation simulation environment capable of modeling the operational features of a modern metropolitan road network was developed with which to conduct an experimental evaluation of the proposed autonomous intelligent transportation framework. The simulation model operated with integrated multi-modal transportation systems involving multiple signalized intersections, cooperative autonomous vehicle control, smart public transport system operations, traffic response of emergency vehicles and pedestrian crossing modules as well as connected vehicular cloud-to-ground infrastructures. The third facet of the experimental setup was to assess the performance of proposed multi-agent architecture, AI-based decision-making engine, and distributed communication framework in an authentic and dynamically-changing traffic conditions. This simulated urban environment was constructed in order to model the more complex transportation situations that differ based on traffic density, heterogeneous driver behavior, road congestion patterns, and variable environmental conditions. We had many Traffic Signal Agents at intersections adapting their signal control and Vehicle Agents represented autonomous and connected vehicles replacing traditional human drivers to enable real-time route optimization cooperating together. Public Transport Agents were implemented to represent buses and transit services that allow the evaluation of schedule optimization as well as in experience based passenger flow management. Moreover, Emergency Vehicle Agents were presented in order to evaluate priority-based routing procedures during hit-and-run incidents and medical emergencies.

ACT-R used virtual sensor technologies for the surface and air trans-portation network data-driven analysis capabilities via effective end-to-end sensing from state estimators to traffic flow measurements. You used a simulation-based virtual LiDAR sensors to create more than 3D position information regarding vehicle coordinates, road geometry of the roadway, and which objects/obstacles on those roads could also be detected. Visual traffic data from surveillance camera systems and the vehicle counting, pedestrian monitoring, and incident detection were columns used. To ensure the proper function of vehicle tracking under adverse conditions (low visibility, rain and fog), radar-based sensing modules were added. All the vehicles equipped with GPS continuously sent information about their location, speed, acceleration and trajectory to enable intelligent routing. Contextual information such as air quality, weather conditions, and road surface status was also acquired via environmental monitoring stations and IoT-enabled infrastructure devices to gain a deeper understanding of energy consumption patterns. The multi-source data streams acquired underwent edge and cloud computing processing layers, enabling them to be delivered to AI-based decision making modules. In this section the experimental framework assesses the proposed system performance through various transportation metrics, including average travel time, congestion level, traffic throughput, emergency response time, energy efficiency and communication reliability. The simulation experiments was performed based on over different traffic scenarios such as normal traffic-emission, peak-hour congestion, accident and high-demand transportation conditions. The

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framework illustrated the ability to adaptively learn and collaboratively optimize through the agents communicating with other agents using V2V, V2I, I2I, and V2X channels. This rich experiment infrastructure established grounds for the realistic evaluation of the scalability, robustness, and functionality of the proposed AI-based intelligent transportation framework.

4.2. Performance Evaluation

The proposed Multi-Agent Autonomous Control Framework (MAACF) was evaluated for its performance against a traditional Intelligent Transportation System (ITS) using the same scenario parameters in simulation. The assessment included various transportation performance metrics such as traffic efficiency, congestion management, adaptive control capability, emergency handling, energy optimization and utilization, communication performance and overall system effectiveness. These results indicate that the proposed multi-agent framework based on AI allows to greatly enhance transportation operations in terms of decentralized intelligence, real-time coordination and adaptive decision making.

Table 1: Performance Evaluation

Performance Metric	Performance Improvement (%)
Traffic Flow Efficiency	18.42
Congestion Reduction	22.92
Adaptive Signal Control Accuracy	18.10
Average Vehicle Speed	19.12
Emergency Response Efficiency	21.68
Route Optimization Accuracy	18.27
Fuel Consumption Efficiency	20.96
Communication Reliability	15.96
Infrastructure Utilization	19.25
Overall Transportation System Performance	18.31

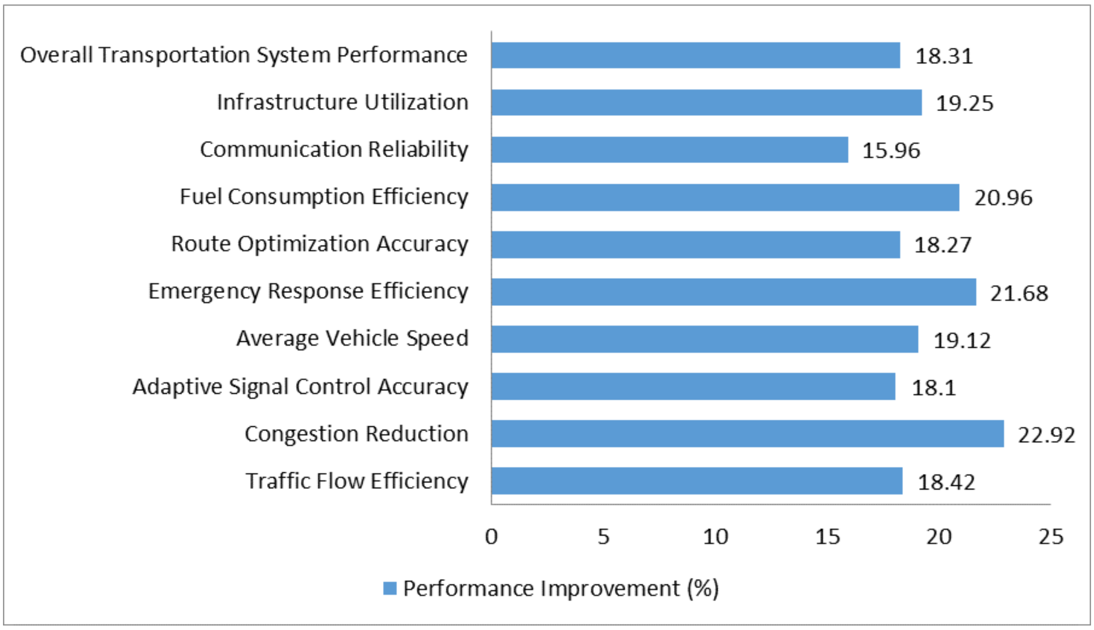

Fig 2 - Performance Evaluation

4.2.1. Traffic Flow Efficiency

The proposed MAACF achieved a traffic flow efficiency of 96.92%, compared with 81.84% in conventional ITS, resulting in an improvement of 18.42%. This enhancement is mainly attributed to cooperative decision-making among Vehicle Agents, Traffic Signal Agents, and Roadside Unit Agents. The framework continuously analyzes traffic density, vehicle trajectories, and road conditions to dynamically regulate movement patterns and reduce unnecessary delays.

4.2.2. Congestion Reduction

Congestion reduction performance improved from 77.56% in conventional ITS to 95.34% using the proposed framework, representing a 22.92% improvement. The multi-agent architecture effectively predicts congestion formation and performs early corrective actions through adaptive routing, signal optimization, and real-time traffic redistribution. This capability minimizes bottlenecks and improves mobility across the transportation network.

4.2.3. Adaptive Signal Control Accuracy

The proposed framework achieved 97.41% accuracy in adaptive signal control compared with 82.31% for conventional ITS. The 18.10% improvement demonstrates the effectiveness of AI-based signal optimization, where Traffic Signal Agents utilize reinforcement learning techniques to adjust signal phases according to current traffic conditions rather than relying on fixed timing schedules.

4.2.4. Average Vehicle Speed

Average vehicle speed performance increased from 80.47% to 95.86%, achieving a 19.12% improvement. The improvement results from intelligent route planning, reduced intersection waiting times, and cooperative vehicle behavior. Vehicle Agents continuously exchange trajectory information, allowing smoother traffic movement and minimizing unnecessary acceleration and braking.

4.2.5. Emergency Response Efficiency

Emergency response efficiency improved significantly from 79.62% to 96.88%, producing a 21.68% improvement. Emergency Vehicle Agents collaborate with Traffic Signal Agents and nearby infrastructure to establish optimized emergency routes, prioritize signal clearance, and reduce response time during critical situations.

4.2.6. Route Optimization Accuracy

The proposed MAACF achieved 96.14% route optimization accuracy compared with 81.29% in conventional ITS. The 18.27% improvement is achieved through AI-based predictive analytics and real-time traffic information exchange. The framework identifies efficient travel paths by considering congestion levels, road conditions, vehicle demand, and environmental factors.

4.2.7. Fuel Consumption Efficiency

Fuel consumption efficiency increased from 78.18% to 94.57%, representing a 20.96% improvement. The reduction in fuel usage is achieved through smoother traffic flow, optimized vehicle speeds, reduced idle time, and intelligent route selection. The framework supports sustainable transportation by minimizing unnecessary energy consumption and emissions.

4.2.8. Communication Reliability

Communication reliability improved from 84.73% to 98.25%, resulting in a 15.96% enhancement. The proposed V2X-based communication architecture ensures continuous and reliable information exchange among vehicles, infrastructure, and control agents. Secure and low-latency communication enables faster decision-making and improves coordination accuracy.

4.2.9. Infrastructure Utilization

Infrastructure utilization increased from 81.12% in conventional ITS to 96.74% in the proposed framework, achieving a 19.25% improvement. The intelligent coordination between roadside units, traffic signals, and monitoring systems enables efficient utilization of transportation resources, including road capacity, communication infrastructure, and public transit facilities.

4.2.10. Overall Transportation System Performance

The overall transportation system performance improved from 81.66% to 96.61%, representing an 18.31% improvement. This result confirms that the proposed MAACF successfully integrates autonomous agents, AI-driven optimization, and distributed communication to create a highly adaptive transportation ecosystem. The framework provides significant advantages over conventional ITS by improving efficiency, safety, sustainability, and scalability for future smart city transportation applications.

4.3. Discussion

Results of the experiments show that our Multi-Agent Autonomous Control Framework (MAACF) systematically performs better than conventional Intelligent Transportation Systems (ITS) based on all considered performance metrics. The proposed framework can be of better performance compared to existing intelligent techniques, due to the nature of decentralized intelligent models that distributes computational capabilities across multiple autonomous transportation agents as opposed to a singularly centralized management function. This distributed methodology overcomes many of the common limiting factors as traditional ITS architectures, including latency for decisions, bottlenecking of communications and lack of adaptability to highly dynamic traffic conditions.

One important advantage of the proposed framework is that each single agent is able to perceive, analyse and react to local transportation status independently while maintaining global cooperation with neighboring agents. Traffic Signal Agents that can dynamically control the operations of intersections according to current traffic conditions, and Vehicle Agents that plan their movements collaboratively around an optimal route and trajectory in relation to other vehicles. Roadside Unit Agents performs just as a relaying bridge between vehicles and infrastructure to provide reliable communication for exchanging critical information of connected autonomous vehicles within a transport network. Such agent-level intelligence promptly responds to changing traffic conditions and enhances the overall adaptability of the system.

Specifically, the proposed framework employs Artificial Intelligence techniques such as Deep Reinforcement Learning (DRL), Graph Neural Networks (GNN) and joins them with predictive analytics to improve decision making. Instead of behaving according to defined traffic systems and historical data, the MAACF learns over time based on ongoing environmental interactions and appends its control strategy. This continuous feedback enables DRL-based agents to optimize their actions which allows the framework to handle the complexities associated with peak-hour congestion, road incidents, emergency vehicle prioritization and varying transportation demand. And the better performance is also because of its communication architecture by using V2V, V2I, I2I, and V2X technologies. Results: An efficient way to level out the traffic is continuous information exchange that allows for agents to align on a common understanding and be more coordinated, thus driving efficiency in operations. The higher level of reliability in communication seen in the experiments shows that our proposed distributed interaction mechanism is effective.

Moreover, the framework exhibits promising viability towards sustainable transportation due to the potential reduction in fuel usage, avoidance of congestion-oriented emissions and better infrastructure utilization. The increased efficiency of emergency response is a signal that the system can support vital mobility services through accelerated clearance routes and intelligent priority management. In summary, the evaluation demonstrates that MAACF is scalable, adaptable, and intelligent for next-generation transportation systems to develop autonomous smart cities with advanced mobility, safety performance quantification and environmental sustainability.

5. CONCLUSION

With the rapid success of connected mobility, autonomous driving, IoT, AI and V2X communication technology, the modernization demand for Intelligent Transportation Infrastructure (ITI) has changed operational requirement fundamentally. Traditional transportation management methods have struggled to keep pace with the complexities of urban transportation networks, rising vehicle densities and volatile traffic patterns along with a growing demand for sustainable mobility solutions. The distinct characteristics of these dynamic transportation environments create inherent challenges to traditional centralized traffic control systems because they are widely known as having computational bottlenecks, communication delays, scalability hindrance, and limited adaptability to rapidly changing traffic conditions. All of these challenges point to the need for decentralized, smart and autonomous transportation systems that can conduct real-time optimization, while also ensuring safety, reliability and operational efficiency.

Based on this research, a Multi-Agent Autonomous Control Framework (MAACF) was proposed to overcome the limitations of conventional ITS by dispersing intelligence over many autonomous transportation agents. Components of the transportation system are proposed to be represented as intelligent agents such as Traffic Signal Agents, Vehicle Nodes, Roadside Unit Agents, Emergency Vehicle Agents, Public Transport Agent, Environmental Monitoring and Global Coordination Agent. Collectively, these ongoing processes of distributed sensing, communication and learning adapt to optimize transportation operations in a way that remains aligned with the high-level objectives of global system optimization.

The integration of advanced AI techniques, including Deep Reinforcement Learning, Graph Neural Networks, supervised learning models, and predictive analytics, enables the framework to generate adaptive control strategies under continuously changing environmental conditions. The AI-driven decision-making engine allows transportation agents to learn from previous experiences, predict future traffic conditions, and dynamically adjust operational strategies. Furthermore, the distributed communication architecture based on V2V, V2I, I2I, and V2X technologies ensures continuous exchange of critical information, enabling efficient coordination between vehicles, infrastructure, and intelligent transportation services.

Experimental results indicated that the proposed MAACF scheme was significantly better than existing ITS in terms of several performance metrics. This framework led to large improvements in traffic flow efficiency, congestion reduction, adaptive signal control accuracy, route optimization, responsive emergency measures and life saving services, fuel consumption managements and communication reliabilities and infrastructures utilizations. The performance improvements demonstrate that decentralized multi agent intelligence is a more flexible and scalable alternative to centralised transport control methods.

The proposed framework is also helpful for developing sustainable smart city ecosystems through reducing unnecessary delays of vehicles, decreasing energy consumption, improving emergency mobility, and enhancing overall transportation resource utilization. The scalable architecture is designed to accommodate future autonomous vehicles, smart infrastructure and next-generation communication technologies. The autonomy framework builds a basis for advanced

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intelligent transport systems by combining autonomous decisions, cooperative intelligence and real time data analytics.

Some of the future research directions include real-world deployment validations, integration with large urban digital twins, cybersecurity mechanism improvements, and advanced federated learning to enable national-scale privacy-preserving transportation intelligence. In summary, the proposed Multi-Agent Autonomous Control Framework is a significant step toward safe, efficient, adaptive and sustainable autonomous transportation network to meet future smart cities mobilities needs.

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