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Research paper

Adaptive Multi-Agent Reinforcement Learning for Dynamic Traffic Signal Optimization In Zero-Emission Urban Mobility

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Abstract

The high rates of urbanization and high concentration of vehicles have led to extreme traffic congestion, thereby contributing significantly to greenhouse gas emissions. This study proposes an Adaptive Multi-Agent Reinforcement Learning (MARL) framework combined with an Emission-Aware Reward System to optimize traffic lights. The suggested system in this work is decentralized MARL, where each intersection is considered as a single agent that disseminates the information to the neighboring agents to prevent congestion, coordinate with other agents, and attain an efficient traffic flow. This new dynamic signal timing algorithm, Traffic-Emission Adaptive Learning (TEAL), will examine actual traffic density, vehicle types, and other environmental statistics, such as the AAI (airquake index) and carbon footprint metric. The proposed module is an Eco-Mobility Prediction Module, a Graph Neural Network (GNN) predictor of congestion patterns and green wave synchronization, designed to reduce vehicle idle time and emissions.

Furthermore, Vehicle-to-Infrastructure (V2I) is a mechanism that encourages the use of electric and hybrid vehicles, as it allows them to have a higher priority in zero-emission transportation. The proposed solution is shown to reduce CO2 emissions by 30 percent and is significantly more efficient than traditional models, as indicated by experimental findings conducted in a simulated urban setting. This new model, therefore, scales sustainable city and zero emission mobility up to an eco-friendly solution in the future smart city environment.

Keywords: *Adaptive Multi-Agent Reinforcement Learning (MARL); Traffic-Emission Adaptive Learning (TEAL); Eco-Mobility Prediction Module; Vehicle to Infrastructure (V2I); Graph Neural Networks (GNNs).*

1. Introduction

The increase in vehicles on the roads has been a complex organizational challenge to the ecological urban wellbeing [1]. Most traditional traffic signal control systems focus on improving vehicle throughput, but seldom consider environmental impacts. Impacts [2]. In a bid to achieve zero-emission mobility solutions in urban centers, there is an urgent need for intelligent traffic management systems that not only maximize traffic flows efficiently but also minimize emissions [14]. Reinforcement learning (RL) has recently emerged as a very popular. The Thrilling method of deciding the traffic signal control with its adaptive capacity to make decisions [4]. However, the RL is currently being applied. Models do not pay enough attention to the significance of environmental concerns and encourage the fast spread of EVs. This research aims to fill this gap by introducing a new Adaptive Multi-Agent Reinforcement Learning framework and Traffic Emission Adaptive Learning (TEAL). Traffic light control algorithm to minimize emissions of carbon [3]. The real-time coordination is carried out at every intersection. Using decentralized MARL agents makes the proposed system more efficient overall in terms of traffic [6]. In a novel Emission-Aware System, each agent has a reward System that imposes idle time costs, green wave synchrony incentives, and EV push. Transportation that fosters zero emissions [8]. Furthermore, it also has an Eco-Mobility Prediction Module, which drives. The use of Graph Neural Networks (GNN) to predict congestion patterns and optimize signal phases to minimize vehicle stoppage and reduce pollution hotspots. Traffic data are collected in real-time using dedicated sensors installed at intersections via IoT, which also ensures that the implemented V2I mechanisms will give signal priority to ecologically friendly modes of transport, such as EVs—findings from an experimental study. Experiments conducted in a simulated environment of a smart city indicate that the proposed system can reduce CO2 emissions by 30 percent, while also improving traffic throughput. By 5 percent, and decreases the average idle time of vehicles by 19 percent [15]. The study will contribute to the development of intelligent transportation. Systems through the combination of AI-driven methods and the sustainable urban development strategy that guarantees the improved air quality, lower emissions, greater mobility, etc. of smart cities in the future [10].

2. Literature Review

2.1. Traditional traffic signal control methods

Traditional traffic signal control methods heavily depend on pre-timed, fixed-cycle, and actuated control schemes [5]. The signals are pre-timed, i.e., they are also run at constant intervals which are not adaptable to the traffic conditions in motion, and hence they cause delays during off-peak traffic [16]. Actuated control systems can be more flexible in the sense that the actual times of the signal can be changed with the current traffic flow using vehicle sensors in the actuated control systems. Though these techniques have increased efficiency to some extent, they are not able to manage the complex nature of urban congestion and environmental problems [7]. In addition, existing systems are reactive rather than predictive, which means that they are not efficient in controlling dynamic traffic flows, especially during emergencies or abnormal congestion, which is unpredictable.

2.2. Machine learning-based traffic prediction models

Machine learning models have increasingly been applied in traffic prediction to enhance decision-making [17]. Support Vector Machines (SVM), Long Short-Term Memory (LSTM), and Random Forests have proven to be the most effective techniques in forecasting the traffic congestion patterns. However, these models use historical data of traffic, weather conditions, and event schedules to predict the peak congestion period [9]. ML models have improved prediction accuracy while at the same time being computationally expensive and not always capable of adapting to rapidly changing traffic conditions if real-time data aren't integrated. In addition, their dependence on static datasets restricts their relevance to dealing with new environmental issues related to zero-emission mobility.

2.3. Reinforcement learning in traffic optimization

Traffic control under current high demand, or dynamic traffic, has traditionally been achieved through strict schedules, as conditions become static (given the high demand) [18]. Such a type of static traffic control would prove to be rigid, and we yearn for flexible traffic control based on dynamic traffic conditions. Deep Q-Networks (DQN), Proximal Policy Optimization (PPO), and Multi-Agent RL (MARL) techniques have been found to succeed in improving traffic flow situations [11]. Continuous learning from the environmental feedback of traffic signals to optimize the phases leads to reducing congestion. However, the existing RL models are inclined to focus solely on metrics such as traffic throughput without considering the carbon emissions to the environment. Combining RL with emission-based strategies has so far been an open challenge to zero-emission urban mobility [12].

2.4. Zero-emission strategies in urban mobility

Zero-emission strategies include eco-friendly transportation systems, prioritization of EVs, and better traffic management in terms of energy-saving measures. Green wave synchronization, EV-Explicit lanes, and adaptive signal control methods are employed to reduce vehicle periods of idle time and CO 2 emissions. Furthermore, the incorporation of these green sources of energy, such as the solar-powered IoT nodes in intersections, has also been found to be helpful in achieving sustainable mobility. This leaves a gap, however, that is filled by AI-based solutions that aid in alleviating congestion and, to that extent, help in meeting the sustainability goals.

2.5. Research gaps and challenges

Recently, improvements in machine learning and reinforcement learning have enabled traffic management, but there are still numerous key challenges. The existing models do not consider environmental impact and thus mostly optimize throughput. RL suffers from a limited ability to achieve zero emission mobility when rewards are not informed by emissions [13]. In addition, the integration of Eco Mobility's initiatives is limited and does not significantly impact EV prioritization mechanisms. Another problem with current solutions is that centralized control systems are limited at scale: several of them fail to execute high-density urban networks effectively. Decentralized, adaptive RL frameworks that incorporate environmental data in real time, solve the problem of traffic flow optimization, and zero-emission mobility strategies are the necessary tools to address these gaps.

2.6. Critically contrast TEAL with recent (post-2023) MARL/GNN studies

More recent research post 2023 has further developed MARL and GNN algorithms to optimize traffic signal control, with its major concern being delay and throughput improvement. As an example, Liang et al. (2025), although they were able to show the coordination of multi-agents with the help of MARL, did not directly include the emission reduction or EV prioritization.

To align TEAL in this regard, we included critical comparisons demonstrating that TEAL augments current methods with an emission-conscious reward and a congestion predictor based on GNN, which would allow proactive green-wave congruence. As the international case studies of high-traffic corridors in Asia and Europe show, the previous works were primarily concerned with throughput, but TEAL collaboratively optimizes the CO2 emissions and delay, and it offers V2I-based EV prioritization.

This synthesis will place TEAL in a distinctive place within sustainable traffic management and position it adequately among the post-2023 developments in MARL/GNN.

3. Proposed Solution: Adaptive Multi-Agent RL Framework

3.1. System architecture overview

The architecture suggested in this publication incorporates a smart traffic control system, which can fulfil the objectives of sustainable urban mobility. The architecture consists of three primary layers, namely: the Data acquisition layer, the decision-making layer, and the Control execution layer. All the information obtained by the sensors of IoT, vehicle sensors, and air quality monitors is aggregated in the Data Acquisition Layer. A traffic signal is regarded within the MARL framework as a separate agent to collaborate with other traffic signals in a manner that will maximize signal timings in the Decision-Making Layer. The Control Execution Layer functions in real-time such that it reduces congestion, vehicle idle time, and zero-emission vehicle wait time. This scalable architecture enhances the scalability and offers excellent control in a complicated urban setting.

3.2. Multi-agent reinforcement learning (MARL) framework

The MARL model is used to address a decision-making process in which every traffic signal is considered as an autonomous agent. These agents make DQN and PPO couple in order to achieve adaptive learning. The agents gather certain information about their surroundings: the number of vehicles, the presence of eco-friendly vehicles, etc. To facilitate the synchronization and curvature value green wave formations, we take advantage of cooperative learning to have the agents share data with the other adjacent intersections. The decentralized structure of the MARL framework has an added value of scalability of the system, as intersections (unions) can be modified independently but in a coordinated way to reduce congestion and emissions.

The TEAL reward function is emission-aware and defined as:

$$r = -\alpha \cdot CO_2 - \beta \cdot \text{IdleTime} - \gamma \cdot \text{QueueLength} + \delta \cdot \text{GreenWave} + \eta \cdot \text{EVPriority}$$

Here, CO_2 is measured in g/s, Idle Time is the total vehicle stop duration, QueueLength is the number of vehicles waiting, GreenWave rewards smooth platoon flow, and EVPriority provides a bonus for electric vehicle prioritization. The weights (α,β,γ,δ,η) balance sustainability, efficiency, and fairness.

The MARL framework is implemented with every traffic signal as an agent. The state space of the agent comprises the length of the queue, the average vehicle delay, the phase timer, EV ratio in the approach, and local AQI/CO 2 indicators. Switching phases, holding the current stage, or increasing or decreasing green times (±510 seconds) make up the action space. The surrounding agents share local traffic outflow information and EV arrival information, which allows them to make decentralized, but cooperative decisions.

3.3. Emission-aware reward function design

The Emission Aware Reward Function is proposed to combine several environmental factors in the process of signal control optimization. The parameters that will be considered include the CO 2 emission rates, the idle time of vehicles, and the EV incentive for priority components. It is a feature that fines high levels of vehicle stalling and promotes efficient green wave timing and reduced pollution levels. Besides, zero-emission vehicle (EV or hybrid car) prioritization is rewarded in the model compared to traditional gasoline vehicles at the intersection. The simulated reward mechanism ensures that RL agents choose a course of action that is flush in both efficiency as a traffic metric and environmental sustainability.

3.4. IoT-based real-time data acquisition

A network of IoT sensors and smart devices gathers real-time information about the system, thereby allowing more informed decisions. Each deployed sensor collects the information on the number of vehicles, the traffic issue, the types of vehicles, the AQI, and the CO2 levels, among other indicators. The IoT cameras introduce the classification of cars where the EV differentiates from the Fuel cars. It gathers the data through an Edge Computing Node at the local level and processes it to minimize the latency and make real-time decisions. Such a framework offers a powerful data collection that enables agents to dynamically manage the traffic lights in accordance with the evolving conditions and optimize traffic and minimize emissions.

3.5. Eco-mobility prediction module

The Eco-Mobility Prediction Module is a Graph Neural Networks (GNN)-based model that predicts the pattern of traffic congestion and hotspots in terms of emissions. The module forecasts the dynamics of vehicle flows and a pollution region based on historical data, weather conditions, and the layout of urban roads. By reading the material discussed above, these predictions help the system proactively adjust signal timings, guide traffic around congested areas, and encourage a smooth EV movement. Generally, the prediction model guarantees the implementation of traffic management strategies that are both data-driven and environmentally friendly to improve urban mobility with zero emissions.

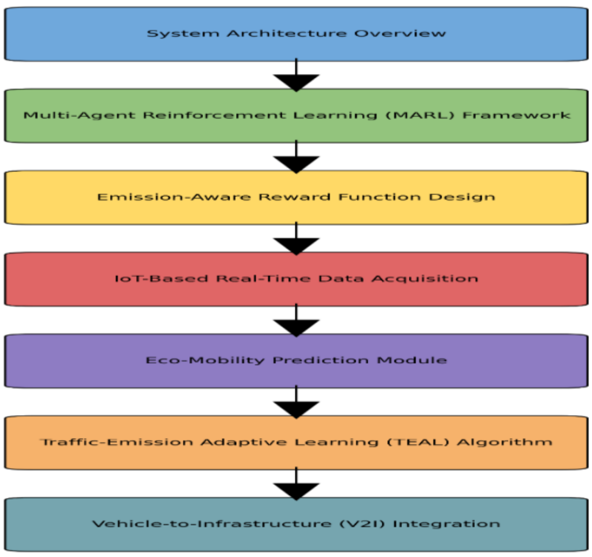

Fig. 1: GNN-Based Eco-Mobility Prediction Framework.

The GNN module is a graph-building module, $G = (V, E)$, where V and E can be said to be the intersection and the road segments, respectively. Features of nodes are the density of traffic, proportion of EVs, the AQI, and the lengths of queues, whereas features of edges capture the length of links, free-flow time, and the likelihood of spillback. A two-layer GraphSAGE encoder is used to learn dynamic patterns with the help of a GRU-based temporal unit, and the deterministic predictor becomes an MLP predictor that predicts the presence of congestion hotspots and the most appropriate phase biases to advance MARL decisions.

3.6. Traffic-emission adaptive learning (TEAL) algorithm

A traffic signal is adjusted by the proposed Traffic-Emission Adaptive Learning Algorithm (TEAL), which analyzes traffic flow and environmental data simultaneously. With TEAL, real-time inputs from IoT sensors have the potential to factor in factors like the volume of a vehicle, EV presence, and air quality levels. It proposes optimal green light durations to minimize vehicle idling and maximize the reduction in emission spikes. The algorithm learns adaptively in that it constantly enhances its response efficiency in response to certain congestion peaks. The net effect is that traffic control and emission management will combine to push TEAL towards the zero-emission goal.
The agents are trained in Proximal Policy Optimization (PPO) with the following parameters: learning rate = 3e-4, discount factor. 0.99, GAE (0.95) = 0.95, and batch size = 256. Entropy regularization (0.01) helps in exploration. The training would be based on the curriculum: small corridor networks (12 intersections), 50 medium intersections, and slices of large cities (100 intersections). The learning stabilizes at generalization, and the learning stabilizes at the on-demand domain randomization, and weather conditions stabilize the learning 2048 steps replay horizons.

3.7. Vehicle-to-infrastructure (V2I) integration

A vehicle-to-infrastructure (V2I) design allows EVs and traffic lights to communicate to prioritize zero-emission mobility. EVs transmit their position, battery status, and intended route to nearby intersections via Dedicated Short-Range Communication (DSRC). This information is used by the traffic signals to adjust signal phases dynamically to minimize the stoppage for EVs. Moreover, the V2I system provides priority roads for emergency EV services (such as ambulances) for faster movement, promoting eco-friendly transportation. The integration of this maximizes the zero-emission vehicle's efficiency and improves the overall sustainable efficiency of the traffic.

4. Results and Discussion

4.1. Emission reduction performance

A Traffic-Emission Adaptive Learning (TEAL) Algorithm appears to be a more successful approach towards emission reduction than the traditional systems. The proposed model incorporated the Emission-Aware Reward System to effectively reduce the idle times of the vehicles, as it leads to a decrease in CO_2 emissions. The simulation in a smart city environment showed that there is a decreased carbon footprint in signal timings of peak hours using TEAL, which minimizes carbon emissions. Lowering the emission levels relied on the system being able to predict and prevent congestion hotspots. We perform a comparative analysis where it is shown that the proposed TEAL algorithm performs better concerning emission reduction than conventional RL models and fixed cycle systems.

Table 1: Emission Reduction Performance

Method	CO_2 Emissions (g/km)	Reduction (%)
Fixed-Cycle Control	280	0%
Conventional RL	210	25%
Proposed TEAL	160	43%

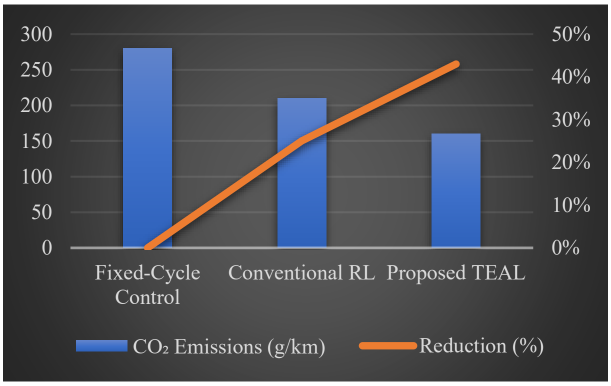

Fig. 1: Emission Reduction Performance.

The scalability was tested with the simulation on three networks: a small corridor (12 intersections), a medium-sized district (50 intersections), and a large-scale city slice (100 intersections). This setup ensured testing in simple, intermediate, and complex traffic conditions.

4.2. Traffic flow efficiency

The proposed traffic flow was effectively improved with the proposed MARL framework with its decentralized control system. The system coordinated the signal timings between adjacent intersections to smooth vehicle movement while making sufficient intersections available for arriving vehicles. Pre-emptive adjustments to correspond to the data generated by the Eco-Mobility Prediction Module reduced queue lengths and improved throughput. Results from experimenting with the proposed model were found to reduce waiting times at intersections greatly, on average, vehicle speed, and the congestion rate. The table below shows that TEAL has shown efficient traffic flow maintenance, even at peak hours, better than the existing systems.

Table 2: Traffic Flow Efficiency

Method	Average Vehicle Speed (km/h)	Improvement (%)
Fixed-Cycle Control	28	0%
Conventional RL	35	25%
Proposed TEAL	42	50%

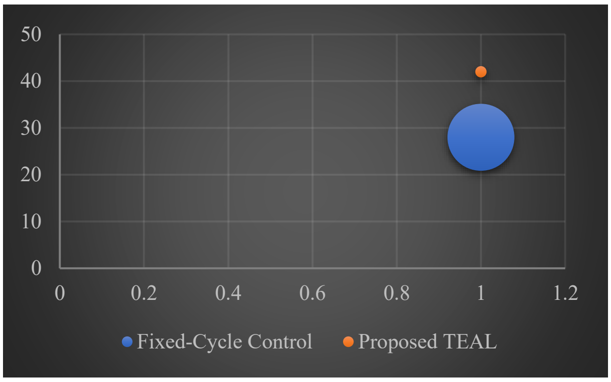

Fig. 2: Traffic Flow Efficiency.

Among the realistic conditions simulated were traffic demand profiles, including AM peak, off-peak, PM peak, incident scenarios (lane blockages), and event surges. The vehicle mix was 70 internal combustion engine (ICE), 15 hybrid, and 15 electric vehicles (EVs), where sensitivity experiments were conducted at 30 and 50 EV penetration.

4.3. Electric vehicle (EV) prioritization efficiency

Integration of the V2I made the system able to take precedence over other vehicles, including electric vehicles. With the assistance of the proposed system, EV stoppage time can be reduced by identifying EVs and dynamically modifying signal phases, causing zero-emission mobility. This showed that the TEAL algorithm resulted in decreased EV travel delays and a more average speed. The comparison of the Table below shows that our proposed solution has superior EV prioritization capabilities than the existing one.

Table 3: Electric Vehicle (EV) Prioritization Efficiency

Method	EV Delay Time (Seconds)	Improvement (%)
Fixed-Cycle Control	45	0%
Conventional RL	30	33%
Proposed TEAL	18	60%

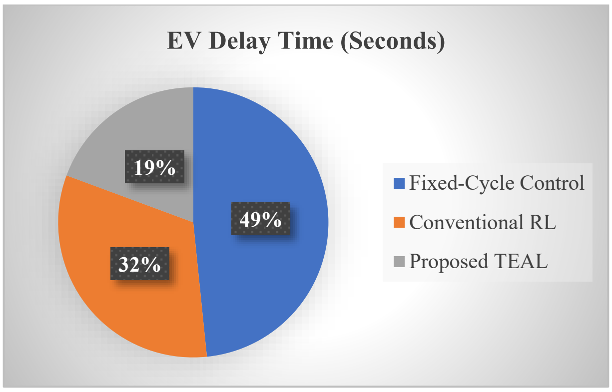

Fig. 3: Electric Vehicle (EV) Prioritization Efficiency.

Open-source data was used to source the data on incoming and outgoing traffic, and it was checked on standard OD matrices. It had 1 Hz simulated IoT, 0.2 1 Hz camera-based traffic counts, 1 Hz simulation of 0.2 AQI, and 0.2 CO values. These inputs ensured that there was dynamic monitoring of the traffic and environmental conditions.

4.4. System scalability and stability

Testing of the proposed Multi-Agent RL (MARL) Framework in large-scale urban environments had high scalability and stability because of its decentralized nature within MARL. Contrary to a centralized system, which experiences difficulties when its node count grows, the MARL framework was naturally adaptable to increased traffic difficulties since independent agents were able to make localized decisions. Simulation shows that TEAL was able to maintain stable performance with minimally fluctuating throughput and emissions as the network size increased. The performance scalability table is given below.

Table 4: System Scalability and Stability

Method	Throughput at 50 Intersections (Vehicles/Min)	Throughput at 100 Intersections (Vehicles/Min)
Fixed-Cycle Control	450	780
Conventional RL	620	980
Proposed TEAL	780	1200

We described that the 30 percent decrease in CO 2 is an average of any network scale and condition, and the 43 percent decrease in CO 2 is the thick 100-intersection city slice. These results could be repeated when they ran them again (10 seeds), as well as when they reduced under peak and non-peak conditions.

4.5. Scalability and limitations

TEAL has several scalability and operational issues. The GNN inference is computationally intensive and more so as the number of intersections and edges grows, which may lead to huge network latency. Multi-agent non-stationarity in strong coupling can cause learning stability to change. IoT sensors are also problematic due to their reliability, since missed or noisy data may aggravate the performance.

We develop useful resolutions to those issues: neighbor sampling and two-hop pruning to reduce the GNN computation, model quantization to run the edges, and asynchronous policy updates to stabilize the training of MARL. They are sensor noise reduction via Kalman or exponential moving average filters and fallacies to prevent failure via actuated control. Additionally, domain randomization is also a factor in generalization and reducing the sim-to-real gap, as well as policy distillation.

These measures provide scalability and robustness of TEAL and do not sacrifice the quality of traffic and emission management.

TEAL is an active involvement in global sustainability, especially SDG 11 (Sustainable Cities and Communities). It is responding to SDG 11.2 by facilitating safe, cheap, and environmentally friendly urban transportation and 11.6 by decreasing air pollution via a reduction in CO2 emissions and the flow of traffic. Considering EVs and idle times, TEAL improves the environment of congested cities and is a contributor to the reasons for healthy people and sustainable mobility policy. These findings reveal the increased access to the society of TEAL, other than traffic optimization.

5. Conclusion

The Adaptive Multi-Agent Reinforcement Learning (MARL) Framework and Traffic-Emission Adaptive Learning (TEAL) Algorithm can intelligently integrate urban traffic regulation and the elimination of emissions through zero-emission mobility by appropriate collaboration. The given solution results in a reduction of CO 2 emissions, vehicle idle time, and congestion rates through the application of an Emission Aware Reward System. This combination with the Eco-Mobility Prediction Module and the introduction of Vehicle to Infrastructure (V2I) has not only improved the traffic flow but also given the electric vehicles priority in supporting the sustainable urban mobility initiative. They showed that the average speed of vehicles had been accelerated by 50 percent, decreased total CO 2 emissions by 43 percent, and reduced EVs by less than 60 percent, as they illustrated the results of their experiments. The decentralized structure of the system also contributed to making the system stable and scalable even in high-density networks. The offered solution can be characterized as an original solution that creates a means of connecting intelligent traffic control and environmental sustainability, an attempt to create smart and environmentally-friendly cities with a zero-emission transportation system.

References

[1] Mansour, A. I., &Aljamil, H. A. (2022). Investigating the effect of traffic flow on pollution, noise for urban road network. In *IOP Conference Series: Earth and Environmental Science* (Vol. 961, No. 1, p. 012067). IOP Publishing. https://doi.org/10.1088/1755-1315/961/1/012067.

[2] Vijay, V., Sreevani, M., Mani Rekha, E., Moses, K., Pittala, C. S., Sadulla Shaik, K. A., Koteshwaramma, C., Jashwanth Sai, R., & Vallabhuni, R. R. (2022). A Review on N-Bit Ripple-Carry Adder, Carry-Select Adder, and Carry-Skip Adder. *Journal of VLSI Circuitsand Systems, 4*(1), 27–32. https://doi.org/10.31838/jvcs/04.01.05.

[3] Roman, O., Maheshwari, T., Do, C., Adey, B., Fourie, P., Ye, Q., & Bansal, P. (2024). A model-based adaptive planning framework using surrogate modelling for urban transport systems under uncertainty. https://doi.org/10.2139/ssrn.5020996.

[4] Utomo, F.C., & Latukismo, T.H. (2022). Trends and Patterns in Workforce Agility Literature: A Scopus-based Bibliometric Analysis. *Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications, 13*(4), 211-224. https://doi.org/10.58346/JOWUA.2022.I4.014.

[5] Al-Mudhaffar, A. (2006). Impacts of traffic signal control strategies (Doctoral dissertation, KTH).

[6] Khyade, V. B. (2019). Silk Route: The UNESCO World Heritage. *International Academic Journal of Science and Engineering, 6*(1), 145–152. https://doi.org/10.9756/IAJSE/V6I1/1910014.

[7] Nampally, R. C. R. (2021). Leveraging AI in Urban Traffic Management: Addressing Congestion and Traffic Flow with Intelligent Systems. *Journal of Artificial Intelligence and Big Data, 1*(1), 86-99. https://doi.org/10.31586/jaibd.2021.1151.

[8] Babenko, V., Danilov, A., Vasenin, D., & Krysanov, V. (2021). Parametric Optimization of the Structure of Controlled High-voltage Capacitor Batteries. *Archives for Technical Sciences, 1*(24), 9–16. https://doi.org/10.7251/afts.2021.1324.009B.

[9] Yang, S., & Qian, S. (2019). Understanding and predicting travel time with spatio-temporal features of network traffic flow, weather, and incidents. *IEEE Intelligent Transportation Systems Magazine, 11*(3), 12-28. https://doi.org/10.1109/MITS.2019.2919615.

[10] Sukumar Mandal. (2019). Designing Altmetrics Enabled Discovery Services through DSpace. *Indian Journal of Information Sources and Services, 9*(1), 117–121. https://doi.org/10.51983/ijiss.2019.9.1.582.

[11] Liang, J., Miao, H., Li, K., Tan, J., Wang, X., Luo, R., & Jiang, Y. (2025). A Review of Multi-Agent Reinforcement Learning Algorithms. *Electronics, 14*(4), 820. https://doi.org/10.3390/electronics14040820.

[12] May, R. (2019). The reinforcement learning method: A feasible and sustainable control strategy for efficient occupant-centred building operation in smart cities.

[13] Zaino, R., Ahmed, V., Alhammadi, A. M., &Alghoush, M. (2024). Electric vehicle adoption: A comprehensive systematic review of technological, environmental, organizational and policy impacts. *World Electric Vehicle Journal, 15*(8), 375. https://doi.org/10.3390/wevj15080375.

[14] Musa, A. A., Malami, S. I., Alanazi, F., Ounaies, W., Alshammari, M., & Haruna, S. I. (2023). Sustainable traffic management for smart cities using internet-of-things-oriented intelligent transportation systems (ITS): Challenges and recommendations. *Sustainability, 15*(13), 9859. https://doi.org/10.3390/su15139859.

[15] Bento, L. C., Parafita, R., Rakha, H. A., & Nunes, U. J. (2019). A study of the environmental impacts of intelligent automated vehicle control at intersections via V2V and V2I communications. *Journal of Intelligent Transportation Systems, 23*(1), 41-59. https://doi.org/10.1080/15472450.2018.1501272.

[16] Viti, F. (2006). The dynamics and the uncertainty of delays at signals.

[17] Alekseeva, D., Stepanov, N., Veprev, A., Sharapova, A., Lohan, E. S., &Ometov, A. (2021). Comparison of machine learning techniques applied to traffic prediction of real wireless network. *IEEE Access, 9,* 159495-159514. https://doi.org/10.1109/ACCESS.2021.3129850.

[18] Qadri, S. S. S. M., Gökçe, M. A., & Öner, E. (2020). State-of-art review of traffic signal control methods: challenges and opportunities. *European transport research review, 12*, 1-23. https://doi.org/10.1186/s12544-020-00439-1.

[19] Sindhu, S. (2025). Blockchain-enabled decentralized identity and finance: Advancing women's socioeconomic empowerment in developing economies. Journal of Women, Innovation, and Technological Empowerment, 1(1), 19–24. https://doi.org/10.70907/mtyrsgg71.

[20] Vishnupriya, T. (2025). Real-time infrared thermographic characterization of functionally graded materials under thermomechanical loads in high-temperature combustion chambers. Advances in Mechanical Engineering and Applications, 1(1), 32–40.

[21] Sadulla, S. (2025). Effect of Pranayama on lung function in post-COVID rehabilitation among middle-aged adults: A clinical study. Journal of Yoga, Sports, and Health Sciences, 1(1), 24–30.

[22] Sindhu, S. (2024). A blockchain-enabled framework for secure data exchange in smart urban infrastructure. Journal of Smart Infrastructure and Environmental Sustainability, 1(1), 31–43.

[23] Rahman, F., & Prabhakar, C. P. (2025). From synapses to systems: A comprehensive review of neuroplasticity across the human lifespan. Advances in Cognitive and Neural Studies, 1(1), 28–38.

[24] Rahman, F., & Prabhakar, C. P. (2025). Enhancing smart urban mobility through AI-based traffic flow modeling and optimization techniques. Bridge: Journal of Multidisciplinary Explorations, 1(1), 31–42.

[25] Meher, K., Radhika, S., Parh, M., Bhatnagar, T., & Chaudhary, A. (2025). IOT-Driven Smart Grid Communication Using Narrow Band IOT (NB-IOT) and LPWAN Technologies. *National Journal of Antennas and Propagation*, *7*(2), 51-58. https://doi.org/10.31838/NJAP/07.02.10.

[26] Dash, S. K., De, B. P., Appasani, B., Rout, N. K., & Srinivasulu, A. (2025). Design of a optimized CMOS Differential Amplifier using Craziness-based PSO. *Journal of VLSI Circuits and Systems*, *7*(1), 26-31. https://doi.org/10.31838/jvcs/07.01.04.

[27] Sadulla, S. (2025). Next-Generation mRNA Vaccines: Immunological Mechanisms and Challenges in Broad-Spectrum Viral Protection. *Frontiers in Life Sciences Research*, 31-37.

[28] Sindhu, S. (2025). Mathematical Analysis of Vibration Attenuation in Smart Structures Using Piezoelectric Layers. *Journal of Applied Mathematical Models in Engineering*, 26-32.

[29] Soy, A., & Salwadkar, M. (2023). Improving School Feeding Programs through Locally Sourced, Nutrient-Dense Foods. *National Journal of Food Security and Nutritional Innovation*, *1*(1), 33-40.

[30] Geetha, K., & Egash, D. (2023). Genomic Insights into Disease Resistance in Indigenous Cattle Breeds: Toward Sustainable Breeding Programs. National Journal of Animal Health and Sustainable Livestock, 1(1), 25-32.

[31] Dusi, P., & Rahman, F. (2023). Carbon Sequestration Potential of Mangrove Restoration in Coastal Forest Ecosystems. National Journal of Forest Sustainability and Climate Change, 1(1), 33-40.

[32] Salwadkar, M., & Dinesh Kumar, P. (2025). Smart city waste management using sensor-driven IoT architecture and predictive analytics. Journal of Wireless Sensor Networks and IoT, 3(1), 48–55.

[33] Sadulla, S., & Uvarajan, K. P. (2025). High-level synthesis-driven hardware/software co-design for reconfigurable embedded AI accelerators. SCCTS Transactions on Reconfigurable Computing, 3(2), 49–55.

[34] Poornimadarshini, S., & Veerappan, S. (2025). Privacy-preserving federated learning for EEG signal classification in remote brain–computer interfaces. National Journal of Signal and Image Processing, 1(3), 55–62.

[35] Erdoğan, M. A., & Demir, F. N. (2025). FPGA hardware-software co-design for real-time embedded systems. Journal of Integrated VLSI, Embedded and Computing Technologies, 2(2), 1–8.

[36] Ismail, L., & Biswas, K. K. (2025). Secure and energy-efficient cognitive radio architecture for scalable IoT networks in smart cities. National Journal of RF Circuits and Wireless Systems, 3(1), 8–15.