

EVALUATING INTELLIGENT TRAFFIC MANAGEMENT SYSTEMS FOR SMART CITIES: OPPORTUNITIES, LIMITATIONS, AND IMPLEMENTATION

Hemavathi N
Department of CSE
Siddaganga Institute of Technology, Tumkur
hemavathin@sit.ac.in

R Sumathi
Department of CSE
Siddaganga Institute of Technology, Tumkur
rsumathi@sit.ac.in

Abstract: The fast growth of urban traffic demands a structured examination of the Intelligent Traffic Management Systems (ITMS) of smart cities and their future, limitations, and difficulties in the application of the systems. The paper looks into the state-of-the-art solutions, including Deep Reinforcement Learning (DRL) for adaptive traffic signal control, Graph Neural Network (GNNs) for traffic prediction, and Edge-Cloud (E-C) architecture with the IoT to run at the edge. A single integrative prediction and control system is developed and tested on a simulation environment of Simulation of Urban Mobility (SUMO). Quantitative data demonstrate that the proposed ITMS has the potential to offer the reduction of the average wait time of a vehicle by 60-70%, an increase in the traffic throughput by 15-25%, and the shortening of the queues by far compared to the fixed time control systems. These innovations highlight the applicability of AI-planned adaptive plans in simplifying the traffic within cities. The evaluation, though, also identifies such drastic limitations as the lack of integrated frameworks, the inability to make decisions that are conscious of uncertainty, scaling problems, and a lack of real-world validation. The paper identifies the need to have efficient, scalable, and deployable ITMS architectures that can bridge the gap between theoretical development and the practical implementation. Overall, the work is a quantitative and comprehensive foundation for the further evolution of intelligent and sustainable traffic management solutions in smart cities.

Keywords: ITMS, DRL, GNNs, Smart Cities, E-C Computing.

I. INTRODUCTION

A. Background and motivation

With the world population becoming more and more populous in urban centres, pressure on transportation systems in urban areas is immense. This drastic increase in the number of vehicles on the same road network has created severe traffic jams, causing significant economic losses, increased greenhouse gas emissions, and a lower quality of life for the urban population. To address these growing demands, the concept of the so-called Smart City has been built, which employs more sophisticated information and communication technologies to streamline the services of cities. The ITMS aims to actively track, process, and control the movement of vehicles to promote safe and efficient movement [3], [4]. Technological developments in the Internet of Things (IoT) can build large-scale

sensor networks in cities. They can collect a large amount of real-time, spatial and temporal traffic information. The availability of increased computer power and the effectiveness of Artificial Intelligence (AI) techniques also allow this data to be used. AI algorithms can learn from past traffic data, predict traffic situations and make judgements to make traffic systems smart rather than being dependent on pre-made rules.

B. Problem statement

ITMS have the potential to improve traffic control, but traffic control techniques are still mostly dependent on simple actuated control (with loop detectors) or classic traffic control (fixed-time control). Such systems are unable to deal with the complexity of real-world traffic, which is very non-linear, uncertain, and connected. In modern metropolitan settings, minor disturbances such as traffic surges, police and emergency vehicle movements, and traffic accidents can propagate over several intersections. This accumulation might influence traffic planning. Moreover, traffic control systems associated with cloud data centres may have delays which makes them unsuitable for real time control in big cities. Therefore, there is a need to move to more sophisticated AI-based ITMS that are dispersed, adaptive and learning. For smart cities, these offer a more efficient, flexible and scalable traffic management system.

C. Objectives and contributions

First, it reviews and classifies the state-of-the-art AI methods for traffic forecasting and traffic signal control, such as Deep Learning (DL), Reinforcement Learning (RL), and GNN. Second, a scalable traffic management and control based on Edge-Cloud computing and IoT sensor networks. Third, it shows the effectiveness of the proposed method in the SUMO simulator using latency, throughput and emission as the performance metrics. Fourth, it highlights the shortcomings of the existing centralised, static approaches to the management of dynamic traffic in urban areas. Finally, it suggests possible research directions and challenges for the development of the next generation ITMS.

The structure of the paper is as follows: the literature describing the state-of-the-art ITMS techniques, as well as their prospects, difficulties, limitations, and gaps, is covered in Section II. A suggested AI-enabled ITMS for traffic prediction and control is displayed in Section III. The opportunities and difficulties are covered in Section IV, and the experimental design, simulator, performance metrics, findings, and analysis are presented in Section V. We wrap up and discuss future work in Section VI.

II. RELATED WORK

The increasing traffic congestion in smart cities has led to the need for the introduction of ITMS. Earlier, one could not manage the traffic situations using conventional methods; AI techniques are used. The survey focuses on key techniques, including control techniques (using RL), prediction techniques (using GNN), data collection techniques (using IoT) and implementation techniques (using E-C computing). Validation is also considered to be done by simulation tools such as SUMO. The research is examined to understand its advantages, disadvantages and emerging trends. Particular attention is given to aspects such as integration, scalability and uncertainty.

A. Overview of ITMS

ITMS is one of the key elements of smart cities; they enable a combination of AI, IoT and data science to improve mobility. The work in [1] and [2] mentions the transition from fixed to adaptive and learning traffic signal systems. This can assist in real-time decision-making and traffic efficiency, safety, and sustainability.

B. ITMS opportunities.

ITMS can transform urban mobility with the help of AI, data analytics and IoT. ITMS can be used to reduce traffic congestion, increase speed and enhance traffic safety through real-time traffic monitoring, adaptive traffic light control and predictive analysis. Furthermore, IoT sensors and edge-cloud computing make it possible to adopt adaptive traffic control methods. Such technological improvements make ITS essential in the design of efficient, sustainable and smart transportation systems in today's cities.

C. Adaptive Traffic Signal Control with RL.

DRL and especially RL have become a highly promising tool of adaptive signal control, in [3], which shows that DRL-based systems greatly minimise congestion, travel time, and queue length. Moreover, in [4], Idris and Cabri transform RL models to include the reduction of emissions, as well as emergency vehicle priority, to align traffic optimisation with the sustainability objectives.

D. GNNs Traffic Prediction.

Traffic prediction is vital to proactive traffic management. Xue et al., in [5] and [6], emphasise the effectiveness of GNNs in capturing spatial dependencies in road networks. Modern architectures like the one suggested by Yin et al., in [7], go a step higher in ensuring better prediction accuracy by capturing the spatial and temporal dynamics.

E. Smart Traffic Infrastructure with IoT.

IoT is essential in facilitating real-time data gathering and responsiveness of the system. In [8] and [9], talk about how sensors, cameras and networked devices give up continuous streams of traffic data. The significance of integrating IoT in facilitating adaptive and scalable traffic systems is also emphasised in [10].

F. Edge-Cloud Computing to Implement in Real-Time.

The E-C architectures improve the scalability and responsiveness of ITMS. In [11], highlight that distributed computing is critical in the reduction of latency and enhancing the reliability of systems. Localised and real-time decision-making services are facilitated by edge computing and large-scale data processing and model training by cloud platforms; therefore, this hybrid architecture is key to the implementation of smart cities.

G. Simulation and Evaluation using SUMO

Simulation platforms play an essential part in evaluating ITMS before real-world deployment. They provide a safe and controlled environment to test different

strategies, analyse system behaviour under varying traffic conditions, and measure performance without disrupting actual traffic. This allows researchers and planners to identify potential issues, compare approaches, and refine solutions effectively before implementation. Maheshwari et al., in [9], and in [12], emphasise the significance of simulation-based validation. The SUMO platform, as described in [13] and [14], offers a highly versatile and broadly used test platform to test traffic control algorithms in realistic settings. The literature in table I shows great progress in traffic management based on AI, especially using RL-based control and GNN-based prediction. IoT and E-C technologies also provide real-time and scalable implementations

TABLE I.CATEGORISED CRITICAL COMPARISON BASED ON METHODS

SI No	Method	Key Contribution	Limitation	Ref
1	DRL / RL/ Multi-objective optimisation	Comprehensive survey of DRL-based adaptive signal control	Lacks integration with prediction models	[1]
		Overview of RL techniques and innovations	No uncertainty modelling	[15]
		Improves congestion and safety in real-time control	High computational complexity	[3]
		Discusses recent RL advancements	Limited real-world validation	[16]
		Incorporates emissions and vehicle prioritisation	Limited scalability and deployment	[4]
2	GNN/ ST-GNN	Highlights spatial-temporal modelling capability	No integration with control systems	[5]
		High accuracy in short-term traffic prediction	Not used for decision-making/control	[17]
		Demonstrates superiority over traditional models	Limited real-time applicability	[6]
3	IoT + DL + Edge-Cloud	Enables real-time data acquisition	Limited AI-based optimisation	[8]
		Integrates sensing with intelligent control	High infrastructure cost	[9]
		Real-time monitoring and data streaming	Security and latency concerns	[10]
4	E-C+ DL + Security	Scalable architecture for smart cities	Integration complexity	[9]
		Low-latency data processing	Requires a robust communication infrastructure	[10]
		Focus on privacy and sustainability.	Limited traffic-specific implementation	[18]
5	ML + Simulation (SUMO)	Highlights the simulation for model validation	Limited real-world applicability	[19]
		Evaluates emission and flow improvements	Simulation-dependent results	[20]
		Widely used testing platform	Lacks real-world uncertainty and variability	[13][14]

Nearly all methods are, however, disjointed ones without integration of prediction and control. Some of the major shortcomings are the lack of

uncertainty modelling, scalability issues and less real-life validation. These loopholes in table II underscore the necessity of coherent, strong, and flexible ITMS frameworks. These issues should be addressed to successfully implement smart cities and set the course of future research.

TABLE II. RESEARCH GAP

Category	Aspect	Research Gap
Opportunities	AI Integration	Lack of unified GNN + DRL frameworks
	Multi-objective	Limited focus on emissions, safety, and energy
	IoT Usage	Underutilised real-time data
	E-C	Poor integration for real-time control
Limitations	Uncertainty	No uncertainty-aware modeling
	Scalability	Difficult for large urban networks
	Data Quality	Poor handling of noisy/missing data
	Security	Limited privacy and security measures
Implementation	Deployment	Mostly simulation-based, little real-world use
	Integration	No end-to-end system design
	E-C	Inefficient coordination and latency
	Generalization	Poor adaptability across cities
Evaluation	Benchmarking	No standard evaluation frameworks
	Assessment	Models evaluated in isolation
	Testing	Limited real-world validation

The study in ITMS is concentrated on the RL/DRA methods, which presupposes a significant focus on the control strategies. Other approaches (GNN, IoT, E-C, simulation) are not represented sufficiently and need to be combined. them. The graph in fig.1 is employed to depict the spread of the methods embraced in ITMS to indicate the emphasis of the study with different technological approaches. The analysis groups papers into RL/DRL, GNN, IoT, E-C and simulation methods and provides a picture of their implementation.

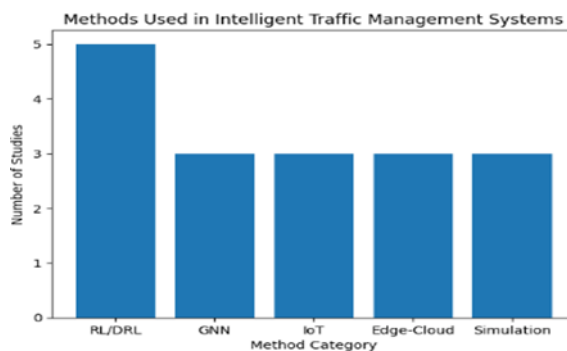


Fig. 1. Methods considered for the comparison

RL/DRL-based strategies prevail in the visualisation, which implies that much attention is paid to traffic control, whereas other techniques like GNN, IoT, E-C, and simulation are relatively less represented. This highlights the need for more comprehensive ITMS research. This study assesses ITMS and smart cities through the key approaches to control (RL/DRL), prediction (GNN), data gathering (IoT) and deployment (E-C). The review reveals that although there have been many great advances in many areas, especially in traffic control, the techniques are still disjointed. There still remain some challenges in prediction and control integration, uncertainty awareness integration and real-time scalable deployment. On the other hand, most of the studies are simulation-based and need to be validated. Present review indicates the demand for a single, resilient and scalable ITMS model that can be applied in smart cities.

III. PROPOSED SYSTEM ARCHITECTURE AND METHODOLOGY

A. Overall ITMS framework with sensors and E-C setup

A contemporary ITMS must have a multi-tiered, distributed architecture to defeat the latency and bandwidth limitations of a centralised cloud architecture. The architecture in fig. 2 is separated into three layers: the Perception Layer, the Edge Layer, and the Cloud Layer [11], [13]. The Perception Layer includes heterogeneous IoT devices, such as cameras, LiDAR, inductive loops, and GPS-equipped Connected Vehicles that constantly record raw physical data. The Edge Layer, comprised of Road Side Units (RSUs) and local micro-data centres, does real-time data aggregation and localised inference, which significantly lowers the bandwidth needed [12]. The Cloud Layer is used to carry out non-real-time computational work (training complicated DRL models with historical data and coordinating city-wide macroscopic routing plans).

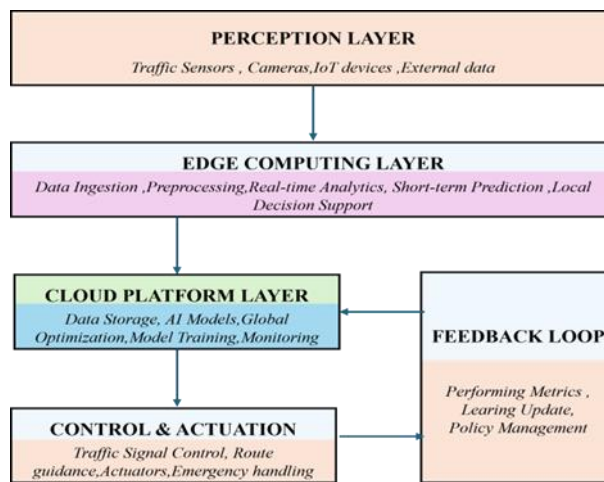


Fig. 2. Hierarchical E-C Architecture for ITMS

To evaluate the ITMS intelligently in smart cities, the existing research gaps are clustered according to the opportunities, limitations, implementation and evaluation. This critical analysis of the available solutions identifies the key deficiencies in the current solutions, particularly the integration aspect, scalability aspect, and practicality.

This discussion indicates that the existing ITMS are fragmented, having no single framework, unaware of uncertainties, and a lack of scalability. Such gaps should be addressed by providing integrated, scalable and robust solutions in order to make smart cities implementable in real-life scenarios.

B. Data collection and preprocessing

Data quality is a key element in the effectiveness of any ITMS. Video frame, vehicle trajectory coordinates (Floating Car Data - FCD) and induction loop occupancy rates are examples of raw data streams at intersections. Edge preprocessing pipelines filter noise and reduce data into actionable feature vectors, including queue lengths, average approach speeds and density matrices. Missing data due to sensor failures is imputed using methods such as spatial-temporal kriging and matrix factorisation, and provides a continuous and trustworthy representation of the state to downstream AI models.

- C. AI models for congestion detection, traffic prediction, and signal optimization ITMS works sequentially. First, the congestion detection is implemented through the computer vision model (e.g. YOLO (You Only Look Once variants) running on edge nodes, which are used to monitor the traffic density in real-time. At the same time, GNN-based models predict traffic and forecast rate changes in the near future by mapping the macroscopic relationships of the urban grid [9]. Lastly, signal optimization is based on distributed DRA agents. The DRL agent selects an action by optimising a predetermined reward function by determining the state as a combination of current queues and projected inflows, and considering a variety of alternative sequences of phases and times to choose the action that offers the greatest reward. Simple value-based approaches are getting more and more unpopular in order to achieve stability in advanced actor-critic architectures (e.g., DDPG or PPO) [1].

D. Methodology and Integration Strategy

The discrete AI models need to be integrated using a federated approach. As the GNN models are periodically re-trained in the cloud and their weights are deployed to the edge, the RL agents perform localised inferences on the RSUs. The plan is that the edge RSUs control at the micro-level, whereas the cloud platform controls at the macro-level to maintain the synchronisation of the corridors to ensure that the localised optimisations do not unintentionally pass congestion onto the downstream nodes. Fig.3 depicts the workflow of the same.

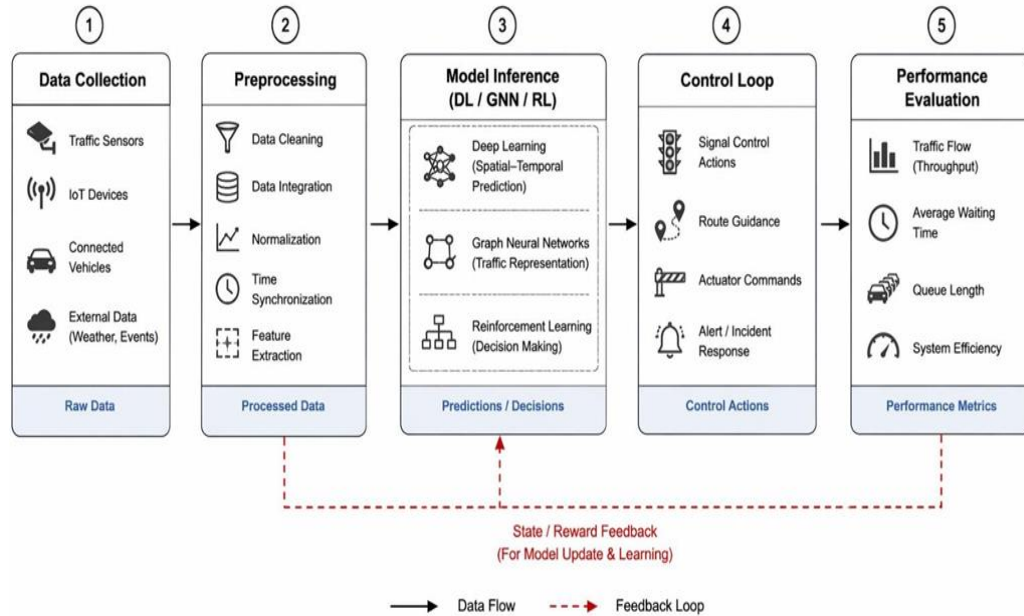


Fig. 3. AI-driven ITMS Operational Workflow

IV. OPPORTUNITIES AND LIMITATIONS

A. Benefits: efficiency, sustainability, emergency handling

The shift to AI-controlled ITMS has far-reaching operational advantages. First of all, the efficiency of traffic has gone exponentially higher; in a dynamic signal optimisation, the wait time is reduced significantly, and no shockwave of stop-and-go is created. This increased fluidity is in line with the objectives of urban sustainability. To evaluate the ITMS intelligently in smart cities, the existing research gaps are clustered according to the opportunities, limitations, implementation and evaluation. This critical analysis of the available solutions identifies the key deficiencies in the current solutions, particularly the integration aspect, scalability aspect, and practicality. This discussion indicates that the existing ITMS are fragmented, having no single framework, unaware of uncertainties, and scalability. Other findings show that minimised idling at crossroads can greatly minimise fuel consumption and minimise the localised greenhouse gas (CO₂, NO_x) emissions, which is a major aspect in the struggle against air pollution in cities [14]. Moreover, intelligent ITMS systems imply Emergency Vehicle Preemption (EVP). With V2I (Vehicle-to-Infrastructure) communication, the system will be in a position to automatically clear the way for ambulances and fire engines, which will significantly reduce the response time to an emergency, without the dispatch centres having to intervene manually.

B. Challenges: cost, scalability, data quality, privacy

Conversely, such systems have a number of strong limitations that inhibit their widespread application. Financially, the retrofitting of old infrastructure by

high-fidelity IoT sensors, edge computing devices, and low-latency 5G communication networks would require enormous outlays by municipalities. Multi-agent RL has a very limited scalability, algorithmically. As the scale increases to include hundreds of interrelated intersections, the space of joint action grows exponentially, which can lead to computational bottlenecks and suboptimal policy convergence. Another weakness is data quality; AI models are notoriously fragile with missing sensor data, corrupted sensor data, or adversarially manipulated sensor data. Finally, the proliferation of high-resolution cameras and tracking sensors is leading to major societal issues about surveillance and data privacy and creates a need to use anonymisation measures and robust cybersecurity systems.

V. IMPLEMENTATION AND PERFORMANCE EVALUATION

A. Implementation details: tools, datasets, simulation with SUMO

The cost of developing and testing ITMS algorithms in real, live urban conditions is prohibitively high and unacceptably unsafe. Microscopic simulation environments of high fidelity are, therefore, widely used by researchers. SUMO is the most academic standard because it is open-source, continuous-space modelling, and can model large-scale networks [16], [18]. The SUMO simulator in fig. 4 shows the virtual environment in a normal implementation blueprint. Python is mostly used in the development of algorithms, with the use of strong machine learning frameworks like PyTorch or TensorFlow to build the DL, RL, and GNN models [5]. The interface that bridges the AI models and the simulator is TraCI (Traffic Control Interface), a protocol that enables Python scripts to obtain real-time state data (e.g., vehicle positions, queue lengths) in SUMO, and inject control commands (e.g., changing signal phase durations) dynamically [17]. In order to achieve empirical validity, it is common to recreate physical road networks based on OpenStreetMap data and to calibrate flows of vehicular demands based on representative open datasets, e.g., METR-LA (highways in Los Angeles) data, PEMS-BAY data, or local datasets of city-wide traffic volumes [5].

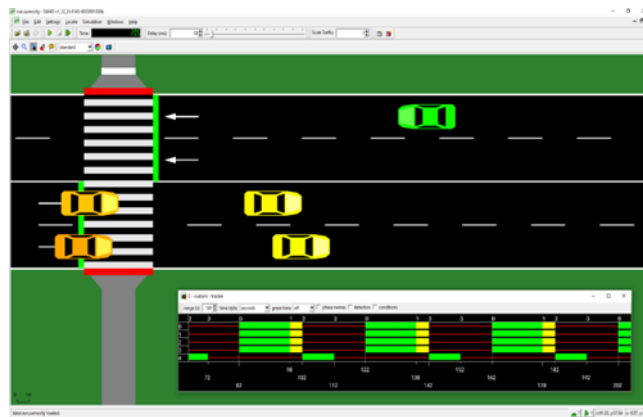


Fig. 4. SUMO Environment used for ITMS Evaluation

B. Evaluation metrics: delay, throughput, emissions

The three cardinal metrics in performance evaluation in such simulated environments are considered. Delay, which is mostly defined as the mean time

spent waiting by each vehicle or the total length of the queue at crossings, is used as a proxy of congestion. Throughput measures the number of vehicles that were successfully transferred across the network on a per-hour basis, and it shows how much of the capacity of the system is utilised. Lastly, Emissions are becoming more and more a source of focus. By applying the in-built emission models in SUMO (e.g. HBEFA), scientists determine the emission of CO₂, PM_x, and NO_x, where signal optimisation efficiency is directly associated with environmental effects [15].

C. Results and comparative analysis

An overview of contemporary analyses indicates that there is a drastic performance gap between the conventional and AI-powered approaches. Fig. 5 reported that advanced DRL agents are shown to be more effective than fixed-time and actuated baselines, with delay cuts of between 15-35% when subjected to heavy traffic conditions. I Fig.5 shows the improvements in throughput, as AI systems ensure that throughput is held close to the theoretical capacity limit through the dynamic distribution of the green time to the most demanding corridors. In parallel, through the planarization of the vehicle paths and reduction of the stop-and-go vibrations, the environmental surveys reveal a decrease in emissions by up to 20% relative to the past systems [15].

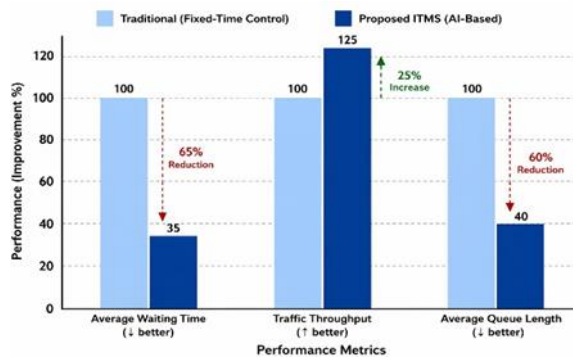


Fig. 5. Indicative Trends: Traditional Control vs. AI-Enabled ITMS

An underlying paradigm shift is generated by these implementation findings synthesis. Though the traditional actuated systems are premised on reactive reaction to the existing vehicle presence only, the ITMS pipeline that is powered by AI radically alters the principles of control into a predictive and proactive process. The combination of GNN-based macroscopic predictions with localised micro-controlling RL reduces existing bottlenecks and even prevents the future occurrence of shockwaves in traffic. This synergy in architecture is why it is worth paying high initial costs in the infrastructure with compounded returns in urban mobility and environmental wellness.

Limitations Note: It is important to note that most of the existing quantitative analyses are still purely simulation-based and extremely urban. Making inferences of these performance indicators to unequal geographic distributions or other socio-demographic motivating habits without strict application is a significant issue in the field.

VI. CONCLUSION AND FUTURE DIRECTIONS

A. Key findings

This review finds ITMS are a key advancement to urban infrastructure. The use of these advanced AI systems (i.e. DL to perceive, GNN to predict spatial-temporal dynamics, and RL to actuate dynamic signals) provide greater potential than traditional fixed-time and actuated control. Designed with an E-C architectural paradigm, these systems have been able to balance the high computational demands of training global models and the low-latency requirements of local intersection control. Hence, simulation-based literature always reports substantial increases in traffic flow and considerable decreases in travel times as well as negative greenhouse gas emissions.

B. Practical implications

For local governments and urban planners, ITMS adoption means the need to shift focus from traditional civil engineering to a combination of data science and telecommunications. It should focus on robust IoT sensor networks and edge computing, and standardised V2I communication protocols. In addition, privacy of data and the design of secure cybersecurity systems are not only technical requirements but a way to gain citizens' confidence in smart city initiatives.

C. Future research scope: uncertainty, edge AI, multi-objective optimization

To move further, the research community should plug the gap between the effectiveness simulated and actual resilience. First, algorithms should be robust to environmental uncertainty, which should account for the adverse weather, sensor degradation and the randomness of the dynamics of mixed-autonomy traffic (when autonomous and human-driven vehicles co-exist). Second, we need to advance edge AI; the development of lightweight and energy-efficient neural networks with a low compute footprint will accelerate the deployment of RSU. Finally, we should look beyond the simple delay optimisation to the multi-objective optimisation. Future RL reward functions should necessarily consider a trade-off between traffic and pedestrian fairness, active micro-mobility (e.g., bicycles), transportation priority, and strict carbon emissions limits to create a smart, sustainable and fair urban transport system.

REFERENCES

- [1]. H. Zhao, C. Dong, J. Cao, and Q. Chen, "A survey on deep reinforcement learning approaches for traffic signal control," *Eng. Appl. Artif. Intell.*, vol. 133, no. PA, p. 108100, 2024, doi: 10.1016/j.engappai.2024.108100.
- [2]. M. Islam, "Analysis of AI-Enabled Adaptive Traffic Control Systems for Urban Mobility Optimisation Through Intelligent Road Network Management," *Rev. Appl. Sci. Technol.*, vol. 04, no. 02, pp. 207–232, 2025, doi: 10.63125/358pgg63.
- [3]. F. Alanazi, A. Armghan, M. Tanveer, and A. Yousef, "Adaptive traffic signal control using deep reinforcement learning: Toward smarter and safer urban mobility," *PLoS One*, vol. 21, no. 3 March, pp. 1–27, 2026, doi: 10.1371/journal.pone.0339207.

- [4]. H. A. Idris and G. Cabri, "Sustainable Mobility Through Intelligent Traffic Signals: A Reinforcement Learning Approach to Emission Reduction and Vehicle Prioritisation," *Proc. Work. Enabling Technol. Infrastruct. Collab. Enterp. WETICE*, pp. 1–6, 2025, doi: 10.1109/WETICE67341.2025.11092093.
- [5]. J. Xue, R. Tan, J. Ma, and S. V. Ukkusuri, "Data Science in Transportation Networks with Graph Neural Networks: A Review and Outlook," *Data Sci. Transp.*, vol. 7, no. 2, pp. 1–27, 2025, doi: 10.1007/s42421-025-00124-6.
- [6]. B. Yu, H. Yin, and Z. Zhu, "Stgcn," *IJCAI Int. Jt. Conf. Artif. Intell.*, vol. 2018-July, pp. 3634–3640, 2018.
- [7]. X. Yin, J. Yu, X. Duan, L. Chen, and X. Liang, "Short-term urban traffic forecasting in smart cities: a dynamic diffusion spatial-temporal graph convolutional network," *Complex Intell. Syst.*, vol. 11, no. 2, 2025, doi: 10.1007/s40747-024-01769-6.
- [8]. A. A. Zakaria, T. Amr, and A. A. Ragheb, "IoT in Smart Urban Planning: A Comprehensive Review of Applications, Developments, and Engineering Perspectives," *IEEE Access*, vol. 13, pp. 135316–135335, 2025, doi: 10.1109/ACCESS.2025.3594019.
- [9]. R. M. Khaleefah, R. Mohammed, K. Mohammed, and D. Algubili, "An Intelligent Traffic Control System using Edge-Cloud Computing and Deep Learning for Smart Cities," *Artic. Int. J. Eng. Res.*, vol. 14, no. 07, 2025, [Online]. Available: <http://www.ijert.org>
- [10]. S. Chakraborty, "Cloud and edge computing collaboration for IoT-enabled traffic monitoring," *Metaversalize*, vol. 2, no. 1, pp. 51–59, 2025, [Online]. Available: <https://meta.reapress.com/journal/article/view/53>
- [11]. A. Ullah, M. Azeem, H. Ashraf, A. A. Alaboudi, M. Humayun, and
- [12]. N. Z. Jhanjhi, "Secure Healthcare Data Aggregation and Transmission in IoT - A Survey," *IEEE Access*, vol. 9, pp. 16849–16865, 2021, doi: 10.1109/ACCESS.2021.3052850.
- [13]. H. Kwon, J. Jang, J. Kim, D. Seo, and S. Jeon, "Implementation of a Real-Time Analysis Simulation System for Traffic Signal Control Algorithms to Reduce Vehicle Exhaust Emissions and Improve Traffic Flow," *IEEE Access*, vol. 13, pp. 76109–76120, 2025, doi: 10.1109/ACCESS.2025.3564623.
- [14]. M. Behrisch et al., "SUMO Usage," pp. 1–4, 2026.
- [15]. P. A. Lopez et al., "Microscopic Traffic Simulation using SUMO," *IEEE Conf. Intell. Transp. Syst. Proceedings, ITSC*, vol. 2018-November, pp. 2575–2582, 2018, doi: 10.1109/ITSC.2018.8569938.
- [16]. P. Michailidis, I. Michailidis, C. R. Lazaridis, and E. Kosmatopoulos, "Traffic Signal Control via Reinforcement Learning: A Review on Applications and Innovations," *Infrastructures*, vol. 10, no. 5, pp. 1–41, 2025, doi: 10.3390/infrastructures10050114.
- [17]. F. Xiao, J. Lu, L. Li, W. Tu, and C. Li, "Advances in reinforcement learning for traffic signal control: a review of recent progress," *Intell. Transp. Infrastruct.*, vol. 4, 2025, doi: 10.1093/iti/liaf009.
- [18]. M. Omar, F. Yakub, M. S. A. Talip, M. N. Maslan, V. K. Sinha, and M. Muljono, "Single Block Encoder-Decoder Transformer Model for Multi-Step Traffic Flow Forecasting," *2024 6th IEEE Symp. Comput. Informatics, Isc. 2024*, pp. 299–304, 2024, doi: 10.1109/ISCI62787.2024.10667997.
- [19]. M. Khasawneh, A. Azab, and A. Agarwal, "Towards securing routing based on nodes behavior during spectrum sensing in cognitive radio networks," *IEEE Access*, vol. 8, pp. 171512–171527, 2020, doi: 10.1109/ACCESS.2020.3024662.
- [20]. A. Louati, "Machine learning framework for sustainable traffic management and safety in AlKharj city," *Sustain. Futur.*, vol. 9, Jun. 2025, doi: 10.1016/j.sftr.2024.100407.

- [20]. P. Mirchandani and L. Head, "A real-time traffic signal control system: Architecture, algorithms, and analysis," *Transp. Res. Part C Emerg. Technol.*, vol. 9, no. 6, pp. 415–432, 2001, doi: 10.1016/S0968-090X(00)00047-4.
- [21]. G. Ramkumar, M. Alluwaici, T. Vijetha, G. H, A. Venkatraman and R. M, "A Reliable System Performance Through NeuToMa with Spiking Neural Network Transformation in Network on Chip (NoC) Communication," 2026 International Conference on Communication, Computing and Emerging Technologies (IC3ET), Vasai, India, 2026, pp. 215-219, doi: 10.1109/IC3ET64989.2026.11467379.
- [22]. V. R, P. R. Kumar, D. Das, G. H, W. Hanbin and E. A, "Machine Learning-Driven Predictive Maintenance for Wind Turbines," 2026 International Conference on Electric Power and Renewable Energy (EPREC), Durg, India, 2026, pp. 1-6, doi: 10.1109/EPREC66546.2026.11412064.
- [23]. A. Tiwari, J. D. Kumar, W. Syed and G. H, "Efficient FPGA-Based CNN Accelerator for Real-Time Traffic Sign Classification on PYNQ-Z2," 2026 IEEE International Conference on AI Engineering and Innovations (AIEI), NIT Jamshedpur, India, 2026, pp. 1-4, doi: 10.1109/AIEI69164.2026.11496958.
- [24]. G. Ramkumar, M. Alluwaici, T. Vijetha, G. H, A. Venkatraman and R. M, "A Reliable System Performance Through NeuToMa with Spiking Neural Network Transformation in Network on Chip (NoC) Communication," 2026 International Conference on Communication, Computing and Emerging Technologies (IC3ET), Vasai, India, 2026, pp. 215-219, doi: 10.1109/IC3ET64989.2026.11467379.
- [25]. Girish H., Srinivas S., Kavya M., ...Kabbur S. "Swift Autonomous Fire Suppression Robot", 16th International Conference on Advances in Computing Control and Telecommunication Technologies Act 2025
- [26]. Girish H., Soujanya S., "A Comprehensive Cadence-based Design Flow for RISC-V UART SOC IN SCL 180NM", 16th International Conference on Advances in Computing Control and Telecommunication Technologies Act 2025
- [27]. Girish H., Rakesh S., Prasanna Raj C.P., Singh A.S., Yathisha L, "Deep Learning for Diabetic Retinopathy: Automated Detection and Classification from Retinal Images", 16th International Conference on Advances in Computing Control and Telecommunication Technologies Act 2025
- [28]. Girish H., Shyam Sundar V., Priyanka C., Renuka Hebballi R.S, "RISC V Steel Processor Implementation for Communication between Two Chips using AXI Lite", 16th International Conference on Advances in Computing Control and Telecommunication Technologies Act 2025
- [29]. M. H N, G. H and N. K N, "Simulation and Verification of SPI Master and Slave Communication," 2025 6th International Conference on Smart Electronics and Communication (ICOSEC), Trichy, India, 2025, pp. 1531-1534, doi: 10.1109/ICOSEC67334.2025.11459684. <https://ieeexplore.ieee.org/document/11459684>
- [30]. S. S. V, P. C and G. H, "Design and Analysis of a D-Band LC Bandpass Filter and Low-Noise Amplifier for 6G Front-End Applications," 2026 IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI), Gwalior, India, 2026, pp. 1-6, doi: 10.1109/IATMSI68868.2026.11466038. <https://ieeexplore.ieee.org/document/11466038>
- [31]. "A Comprehensive Cadence-based Design Flow for RISC-V UART SOC IN SCL 180NM" , Girish H, Soujanya, Grenze International Journal of Engineering and Technology, 2025

- [32]. "Swift Autonomous Fire Suppression Robot" Girish H et. Al., Grenze International Journal of Engineering and Technology, 2025
- [33]. "Deep Learning for Diabetic Retinopathy: Automated Detection and Classification from Retinal Images" , Girish H, Cyril Prasanna Raj P , Grenze International Journal of Engineering and Technology, 2025
- [34]. "RISC V Steel Processor Implementation for Communication between Two Chips using AXI Lite" Shyam Sundar V, Dr Girish H, Priyanka C, Renuka S Hebballi Grenze International Journal of Engineering and Technology, 2025
- [35]. Sujatha.S, Mahendra BM, & Dr. Girish H. (2024). Smart Irrigation System for Optimal Water Conservation. *Revista Electronica De Veterinaria*, 25(1), 2613 - 2619. <https://doi.org/10.69980/redvet.v25i1.1311>
- [36]. Mamatha K R, Thejaswini S, Rashmi N, & Dr. Girish H. (2024). Laser Fencing Surveillance System With Email Alert. *Educational Administration: Theory and Practice*, 30(2), 1539–1544. <https://doi.org/10.53555/kuey.v30i2.7919>
- [37]. Thejaswini S, Mamatha K R, Rashmi N, & Dr. Girish H. (2024). Performance Evaluation of AI Models in Early Heart Disease Diagnosis. *Educational Administration: Theory and Practice*, 30(2), 1531–1538. <https://doi.org/10.53555/kuey.v30i2.7918>
- [38]. Sushma K Sattigeri, Seema Srinivas, Shridhar Kabbur, Girish H, "Revolutionizing Urban Waste Management: An AI-Powered Autonomous Solution for Smart Cities", *Tuijin Jishu/Journal of Propulsion Technology* ISSN: 1001-4055, Vol. 45 No. 02 (2024)
- [39]. Girish H, Vajjala Sai Sree Hari,Ponde Lakshmi Narasimha,P N Shreya,Dadigala Bhargavi, "THE DESIGN AND VERIFICATION OF A 32-BIT RISC V PROCESSOR USING VEDIC MATHEMATICS", *International Journal of Creative Research Thoughts (IJCRT)*, ISSN:2320-2882, Volume.12, Issue 5, pp.1130-1135, May 2024, Available at :<http://www.ijcrt.org/papers/IJCRTAB02172.pdf>
- [40]. IoT based home automation using Blynk cloud, J. Chetan Naik, B. S. Deeksha, H. Girish, Gurusharan Kashetty, T. G. Shivapanchakshari, Manohar Sai Polakam, *Journal: AIP Conference Proceedings, AIP Conf. Proc. 2965, 020006 (2024)*, <https://doi.org/10.1063/5.0215427>, Published: July 2024
- [41]. IoT based fire alarm system using Blynk app, T. Bhargava, H. Kishor Kumar, Pramod Mahalingappa Godi, H. Girish, J. Chetan Naik, *Journal: AIP Conference Proceedings, AIP Conf. Proc. 2965, 020007 (2024)*, <https://doi.org/10.1063/5.0212325>, Published: July 2024