IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 16 February 2024, accepted 4 March 2024, date of publication 11 March 2024, date of current version 19 March 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3375335

RESEARCH ARTICLE

Beyond Sensors: IntelliSignal's Map-Integrated Intelligence in Traffic Flow Optimization

K. SREEJITH [1], **SENTHILKUMAR MATHI** [1], **AND PREEJA PRADEEP** [2]
[1]Department of Computer Science and Engineering, Amrita School of Computing, Amrita Vishwa Vidyapeetham, Coimbatore 641112, India
[2]Insight Centre for Data Analytics, School of Computer Science and Information Technology, University College Cork, T12 CY82 Ireland

Corresponding author: Senthilkumar Mathi (m_senthil@cb.amrita.edu)

ABSTRACT The burgeoning growth of vehicular traffic, fuelled by rapid urbanization and an ever-expanding population, has resulted in congested road networks. Traditional and sensor-based adaptive traffic light management systems have shown commendable progress in some scenarios, but they suffer from inherent disadvantages that hinder their effectiveness and scalability. To combat these challenges, a dynamic and adaptable traffic control system is imperative to optimize traffic flow. The present paper explores the limitations of sensor-based adaptive traffic light management and advocates for integrating a novel algorithm to overcome the existing drawbacks. It proposes an intelligent traffic management algorithm called IntelliSignal that leverages the map service for fetching real-time traffic information to calculate the optimal green time and a penalty-based road selection to optimize traffic flow. The proposed IntelliSignal is designed to provide equal chances for all roads while prioritizing higher-density roads with more green time, effectively mitigating traffic congestion and improving overall transportation efficiency. It incorporates Q-learning, a reinforcement learning technique that enables the system to adapt and learn from traffic patterns. The proposed IntelliSignal's performance is assessed through rigorous evaluations conducted on the simulation platform SUMO. The acquired results demonstrate substantial enhancements across various crucial metrics, including average waiting time, vehicle density, travel time, CO_2 emissions, and queue length. Furthermore, the simulation results demonstrate that the proposed IntelliSignal algorithm exhibits a remarkable 30.52% increment in system throughput compared to the traditional approach. This significant enhancement underscores the efficacy of the proposed IntelliSignal in optimizing system performance and merits consideration for practical implementation.

INDEX TERMS IntelliSignal, map service, Q-learning, sensor-free traffic optimization, sustainability.

I. INTRODUCTION

Traffic congestion is a challenging issue in many cities worldwide, including India. The congestion may linger for hours, causing many problems, including increased pollution, decreased productivity, and declining quality of life. Traditional fixed-time traffic controllers are incapable of dealing with the erratic nature of traffic patterns. Emergency vehicles are often caught in traffic jams, which can delay their arrival at the scene of an emergency. The delay can have serious consequences, as every minute counts in an emergency.

The associate editor coordinating the review of this manuscript and approving it for publication was Giovanni Pau.

In some cases, delays in the arrival of emergency vehicles have resulted in the loss of life. Using cutting-edge technology, a lane clearance system for emergency vehicles [1] and emergency notifications can be transmitted to automobiles in an area using vehicular ad hoc networks (VANETs) and multi-node message transmission [2]. A self-adaptive traffic management plan is required because the current traffic system only provides fixed time-based traffic control. By assisting sensor networks with network mobility, image processing can help to establish an intelligent traffic control method for smart cities [3]. Intelligent traffic signal control systems, capable of controlling and monitoring real-time traffic scenarios, are also integrated into smart cities [4].

Sensor-based traffic management systems (SMTS) can potentially improve traffic flows. However, many challenges need to be addressed. One challenge is the vast number of traffic intersections in India, around 10 million intersections, and each intersection would need to be equipped with sensors. It would be very expensive, and ensuring all the sensors were maintained correctly would not be easy. Another challenge is the varying environmental conditions in India. It can affect the performance of sensors. In addition, the traffic patterns in India are extremely complex. Many vehicles are on the road, and traffic patterns can change frequently. The traffic can make it difficult for an SMTS to keep up with the changing traffic conditions. More research is needed to establish the optimum strategy to apply SMTS in India regarding cost, complexity, accuracy, and privacy.

In the bustling realm of urban transportation, the constant struggle against traffic congestion has driven researchers and engineers to seek innovative solutions. Amidst this quest, an automated traffic system equipped with a revolutionary algorithm for time calculation and road selection harnessing the power of reinforcement learning. This advanced system aims to address the challenges associated with traffic management. Ultimately striving for increased efficiency, reduced travel times, and improved overall transportation experiences.

The primary goal of this automated traffic system is to tackle the persistent problem of traffic congestion that plagues modern cities; it endeavours to alleviate the burden on commuters, minimize fuel consumption, and curtail the negative environmental impact caused by prolonged idling in traffic jams.

At the core of this system lies an innovative algorithm that employs reinforcement learning. This artificial intelligence technique enables the system to learn and adapt from real-time traffic data. By leveraging this robust methodology, the system can make informed decisions, dynamically adjusting traffic signal timings to efficiently distribute vehicles across the road network. By integrating this cutting-edge technology into the fabric of transportation infrastructure, the automated traffic system aspires to revolutionize urban mobility. Its potential benefits include reduced travel delays, optimized traffic flow, improved safety by minimizing accidents, and a more sustainable transportation ecosystem. The motivation behind this approach is to create a self-learning traffic control system that can effectively adapt to changing traffic patterns.

The current paper delves into the workings of the innovative automated traffic system, exploring its algorithmic foundations and the role of reinforcement learning. It uncovers how this system addresses traffic congestion challenges, enhances transportation efficiency, and contributes to a greener and more enjoyable urban environment.

The motivation behind the development of adaptive traffic controller systems is to improve the efficiency and effectiveness of traffic management. Traditional traffic signal systems often function based on predetermined timing schedules that cannot adapt to rapidly changing traffic circumstances in real-time. As a result, intersections might experience congestion, delays, and inconsistent traffic patterns, which can cause annoyance for drivers and reduce the overall efficiency of the transportation system. Adaptive traffic controller systems seek to overcome these constraints by utilizing real-time data and ingenious algorithms.

The primary benefit of adaptive traffic controller systems resides in their capacity to swiftly react to variations in traffic patterns. Through the continuous surveillance and examination of traffic data, these systems can make well-informed determinations regarding signal timing, considering variables such as traffic volume, density, and waiting time. The system's adaptability enables it to allot green time efficiently, prioritizing the most congested and stagnant roads and adjusting traffic flows accordingly. There are various advantages of adaptive traffic control systems. Firstly, they have the potential to substantially decrease waiting times at junctions, hence enhancing drivers' travel durations. Additionally, these technologies contribute to reducing fuel consumption and lowering vehicle emissions by optimizing traffic flow, thereby generating beneficial environmental effects.

The primary goal of adaptive traffic controller systems is to optimize traffic flow dynamically. These systems can constantly observe and analyze traffic conditions in real-time, enabling them to modify signal timings promptly. By utilizing data-driven decision-making and intelligent algorithms, this research can revolutionize crowded intersections, significantly contributing to a more sustainable and liveable future.

Traditional traffic lights are fixed in two aspects: the order of states/phases and the length of each state/phase. Some noticeable improvements can be made by dynamically adjusting the length of each state. For example, a green light can be transitioned to red earlier to allow traffic from other directions if no traffic is approaching the traffic junction. However, the model goes a step further by completely removing the order of the states. The states of traffic lights are no longer dependent on the previous state; instead, they are dynamically generated by the intelligent algorithm. Based on the traffic conditions, vehicles on the road are allowed to pass the traffic junction. The road and its green time are dynamically generated to minimize the average wait time. Therefore, neither the order of states nor the length of each state is static. By breaking the fundamental limitation of traditional traffic lights, the system can maximize the utilization of a traffic junction and save people's time. The key contribution of the papers is listed below.

1. **Sensor-Free real-time adaptability and fairness Enhancement:** The proposed algorithm eliminates the need to deploy a multitude of sensors for real-time traffic status, offering a cost-effective and streamlined solution. The algorithm achieves real-time adaptability by leveraging live traffic data and dynamic map information. By assigning importance to roads with high traffic, the system ensures efficient allocation of resources where they are needed most. The innovative incorporation of a penalty concept promotes fairness, prevents congestion on

specific routes, and distributes traffic load equitably across the road network.

2. **Inclusivity for Vehicles without Internet Connectivity:** The algorithm demonstrates a novel capability by considering vehicles without Internet connectivity, a crucial aspect in diverse traffic scenarios in calculating traffic intensity. This inclusivity allows for a more comprehensive assessment of traffic conditions. This feature enhances the robustness and reliability of the system, and the algorithm provides a more accurate representation of the overall traffic landscape in real-time traffic management catering to the varied connectivity landscape in Indian heterogeneous traffic conditions.
3. **Optimised System performance and enhanced sustainability:** By integrating reinforcement learning, the system continually fine-tunes its performance based on real-world feedback. This dynamic adaptation ensures optimal traffic flow in response to evolving conditions, enhancing overall system efficiency and responsiveness. This enhances the algorithm's effectiveness in optimizing intersection throughput, reducing total travel time, and consequently minimizing CO2 emissions, a crucial contribution towards sustainable and eco-friendly urban mobility. The algorithm's positive impact on sustainability aligns with global efforts to mitigate environmental concerns associated with urban traffic, making it a valuable contribution to the field of intelligent transportation systems.

The paper continues with a literature survey, which explores and summarizes existing research and works in the domain. Chapter 3 presents the proposed IntelliSignal approach, providing an overview of each module and flow diagrams to illustrate the solution to the defined problems. It also includes the technical implementation and a proof of concept to validate and support the solution. Chapter 4 presents the results and discussion, where the model is evaluated on their performance. Finally, chapter 5 consists of the conclusion and future enhancements that can be made.

II. LITERATURE SURVEY

In [5], Lilhore et al. used expensive cameras to capture snapshots of all four lanes in a traffic junction. One camera per lane might not cover the whole lane, so more cameras per lane might be needed. Jamil et al. proposed a reward architecture for adaptive traffic signals in [6]. Besides employing image processing techniques for road density prediction, integrating IoT with sensors facilitates gathering road density data. A diverse range of sensors is utilized to accomplish this objective, with each sensor type offering distinct advantages and disadvantages.

In [7], Kazemee et al. present a smart traffic system based on IoT technology and renewable energy sources. The system utilizes RFID technology to scan emergency vehicles, enabling the identification and notification of traffic police. However, the current approach of relying solely on applications used by priority vehicles to determine the approaching direction of emergency vehicles and which road they are destined to take at traffic junctions is time-consuming. Additionally, the use of RFID incurs higher costs compared to barcode scanners.

The work in [8] describes using infrared sensors to improve traffic management efficiency. The study in [9] proposes a solution to the problem of overcrowding and congestion on specified roads by calculating the number of vehicles and allocating green lights based on vehicle density using IR sensors. Furthermore, this new system prioritizes emergency vehicles. In [10], Varshney et al. used only one type of IR to determine the number of vehicles that might be subject to bad weather conditions and might provide distorted results. Krishan et al. [11] proposed a different traffic sensing model using acoustic and biosensors to control the intensity of the vehicles in the intersections.

In [12], Sharon et al. proposed a density-based adaptive traffic control system with the help of V2X and Internet of Vehicles (IoV) technologies. Vehicles have internet connectivity through the traveller's mobile network or IoV. Wang et al. employ connected and automated vehicle (CAV) technologies to predict traffic density and optimize traffic signal control at urban signalized interchanges [13]. The framework integrates infrastructure detectors with CAV technology to enable efficient traffic light signalling based on real-time traffic density predictions.

A separate study conducted by Wang et al. utilizes a novel wireless electronic license plate system platform to determine the location of vehicles [14]. By leveraging the data obtained from this platform, they develop a traffic light scheduling mechanism that considers the real-time vehicle positions. This approach enables more effective and efficient traffic light management based on the collected vehicle location information. As mentioned earlier, the research primarily focuses on internet-connected vehicles, meaning that the data used for predicting traffic density may not be reliable since it excludes non-internet-connected vehicles.

Zhihong Yao et al. investigate using connected vehicle (CV) data to improve signal management efficiency and traffic flow [15]. For signal control optimization, they used genetic algorithms and rolling horizon optimization. The investigation discusses the pros and cons of employing CV data for signal control and how this technology can be used in real-world circumstances. The work in [16] describes an integrated traffic control model that optimizes vehicle arrival time and signal timing. It addresses the challenge of allocating green time to each phase and calculating the optimal travel speed for approaching connected vehicles, especially when they are coming from conflicting movements. The model in [16] uses a sliding time window technique for dynamic optimization and considers factors such as vehicle arrival time, speed guidance, and signal control.

The study in [17] discusses the development of optimization models for the traffic signal control (TSC) problem. It briefly describes population-based metaheuristics, such as evolutionary algorithms and swarm intelligence, that tackle non-linear optimization problems. The document also highlights the application of these metaheuristics in solving the TSC problem, which involves optimizing traffic signal settings to minimize delay, number of stops, and other objectives. The model in [18] proposes a new design for intersections with limited traffic lanes and short queuing space. The proposed design combines the advantages of the tandem and exit lanes for left turn (CTE) designs to improve operational efficiency. This model also establishes an optimization model to maximize intersection capacity under the CTE design. The work in [19] proposes a reinforcement learning-based signal optimization model with constraints for dynamic traffic flow. The work aims to minimize traffic congestion by learning an optimized signal pattern that reduces delay and the number of vehicles stopped. The model is trained using a traffic simulator and evaluated in a virtual environment like real roads with multiple intersections.

The investigation in [20] discusses a study on optimizing the on-time performance of bus rapid transit systems by implementing conditional transit signal priority at stop-to-stop segments. The study proposes an optimization model that considers both the efficiency of transit vehicles and the impact on private vehicles. The model aims to minimize transit vehicle delay against the schedule while minimizing the total transit priority time assigned to intersections. The research in [21] focuses on developing a distributed coordination management system for autonomous vehicles at intersections, specifically prioritizing the crossing of emergency vehicles. This article aims to minimize the impact on the flow of non-priority vehicles while ensuring the efficient movement of emergency vehicles. In [22], Hanyu Zhu et al. discussed the joint control of traffic signals and CAVs to improve traffic efficiency. It presents a system model of a traffic network with a bottleneck intersection and multiple other intersections, and the model aims to reduce travel time, waiting time, and fuel consumption. Li Tang et al. examined the management of traffic signals in streets that are designated as shared space streets (SSS), where several forms of transportation, including autos, buses, and light rails, utilize the same lane. They introduced an optimization formulation to tackle this issue and suggested a model that takes into account the movement of various transportation types. The proposal also presents a technique for choosing an optimized signal plan and examines the utilization of the particle swarm optimization (PSO) algorithm to address the signal control problem [23].

In the study of [24], Namazi et al. thoroughly examine the approaches used to handle crossings involving autonomous vehicles (AVs), encompassing both situations with exclusively AV traffic and those with a combination of AVs and traditional cars. The evaluation categorizes methodologies into four primary classes: rule-based, optimization-based, hybrid, and machine-learning methods. It additionally analyses the objectives of these approaches, encompassing efficiency, safety, ecology, and passenger comfort. James Ault et al. discussed the importance of developing understandable signal control principles for optimizing traffic signals in their work cited [25]. The researchers provided empirical evidence that supports the utilization of value-based reinforcement learning for training the control function. Their findings suggest that a regulatable control function can be as effective as a deep neural network in approximating an optimized signal actuation policy. The work in [26] highlights the importance of managing and mitigating traffic congestion in urban areas, as the increasing number of vehicles leads to deteriorating traffic conditions and various negative impacts on health, the environment, and the economy. The work categorizes traffic signal timing optimization methodologies into two significant categories: microsimulation-based optimization models and computational intelligence models.

Myungeun et al. discussed finding efficient schedules for intersection traffic signal settings to maximize traffic flow. It surveys the problems, methods, and practices in evaluating the intersection traffic signal control problem [27]. The work in [28] proposed a method for globally controlling traffic signals in an urban city using quantum annealing. It explains how the problem of traffic signal optimization can be formulated as an Ising model, which is compatible with quantum annealers like the D-Wave machine. The research in [29] critically reviews signalized intersection control methods in a mixed traffic environment of AVs and regular vehicles (RVs). It discusses the challenges and limitations of implementing these methods and explores alternative solutions. The paper emphasizes the need to balance computational complexity and control performance while considering the characteristics and behaviour of AVs and RVs. In [30], Lili et al. proposed a new space-time resource scheduling model and a bi-level optimization control method for urban intersections. The model explains the traditional methods of intersection traffic control and their limitations in effectively allocating road space resources. It then introduces the concept of lane genes and the use of reinforcement learning and model predictive control for control optimization.

Due to potential challenges and limitations, relying solely on sensors for traffic density prediction may not be practical in all scenarios. The deployment and maintenance costs associated with sensors can be high, making it less feasible for widespread implementation. Additionally, sensors might encounter adverse reactions in extreme conditions such as severe weather, impacting their accuracy and reliability. Depending solely on sensors could compromise the fairness and effectiveness of the traffic density prediction model. Therefore, developing a solution that can be deployed at any traffic junction and function reliably in various circumstances is crucial, ensuring a comprehensive and robust approach.

From the literature survey of adaptive traffic schedulers,there are about lakhs of traffic signals in India. Installation, maintenance, and repair of cameras at each junction is time-consuming and expensive. Periodically captured real-time images at a junction from all the cameras mounted in all four lanes must be stored and processed. It is not efficient in India due to its heavy vehicle density. Complexity in processing and computing the real-time images may create delays that impact Indian traffic worse. Images with bad light conditions or image artefacts can reduce the correctness of the model, which in turn impacts Indian streets in a worse way. Using only a sensor or a radar alone is not sufficient for Indian scenarios as the weather condition degrades the performance of the sensors, and radar is vulnerable to electromagnetic waves from power lines, base stations, etc. It reduces the correctness of the model. The use of RFID for priority vehicles in India has its challenges where the driver must mention the lane he is coming from, and there must always be a communication signal between that vehicle and the receiver side.

Analyzing all the drawbacks and Indian scenarios, moving towards map source data with reinforcement learning for base timers is more efficient. The map source data is passed as a parameter to an algorithm that has the potential to revolutionize traffic management by significantly reducing waiting times, optimizing travel time, and reducing congestion on the roads, ultimately resulting in a more efficient transportation system for all.

III. THE PROPOSED INTELLISIGNAL APPROACH

An adaptive traffic control system that combines HERE map API data and reinforcement learning (RL) techniques is proposed. This paper aims to leverage the rich information provided by HERE map data and the adaptive decision-making capabilities of RL algorithms to optimize traffic signal control and improve traffic flow in urban areas. In the proposed IntelliSignal algorithm, the Q learning algorithm is employed to learn from the real-time map data and adjust traffic signal timings dynamically. Through engagement with the surrounding environment and the acquisition of feedback, the RL agents will fine-tune signal timings to minimize congestion, diminish delays, and enhance the overall flow of traffic. A system is constructed by integrating map data and RL algorithms, enabling it to make intelligent judgments using real-time and historical information. This leads to enhanced efficiency in the transport system and a more satisfactory experience for road users.

A. HERE API – MAP DATA

The HERE API - Map Data is a flexible set of tools for developers, providing a range of features to include maps and location-based services in their applications. Developers can utilize this technology to utilize mapping, geocoding, routing, directions, places, and real-time traffic information for various purposes, such as visualization, geospatial analysis, navigation, and contextual information retrieval. With these capabilities, developers can create robust applications that enhance user experiences, optimize routes, display points of interest, and provide up-to-date traffic information. Using the GET request URL, the user provides the required coordinates (latitude, longitude, and radius) for various designs, such as corridors and circles. The current speed, jam density, free flow speed, and other relevant factors are provided when GET API is run using JavaScript or Python. The module makes use of the functionality of HERE API by providing latitude, longitude, and squared boundary as area, thereby obtaining coordinates of each road of a junction and gaining jam factors of each of those roads through API response, which further gets used by other parts of the module of the system.

B. JAM FACTORS FROM HERE API

Necessary modules were imported, including requests for making HTTP requests and JSON for handling JSON data. The roadJamFactor function takes two parameters: road (the road ID) and name. It constructs the HERE API URL with the provided road ID and makes a GET request to retrieve traffic flow data for that road. The JSON response is parsed, and the jam factor value is extracted and returned. Then, the road data that includes its latitude and longitude from a file that contains road IDs and their corresponding names are read. It iterates over each road, calls the function to obtain the jam factor, and stores the results in a dictionary. Finally, the dictionary is written into a JSON file. HERE API key and token variables contain the API key and token for accessing the HERE Traffic API.

C. ROAD SELECTION

The current traffic signal has a rule of letting the vehicles pass clockwise or anticlockwise. For a more efficient traffic flow, selecting the most optimal road when vehicles are provided green time is important. To avoid confusion on algorithm-based road selection, some yellow time was allotted to ensure the next vehicle section was updated and ready. An initial penalty value for each road was set, i.e., 1, and jam factor values for each road from here map API were obtained. The cost for each road was calculated as the penalty value of each road * jam factor. The total loss value for each road was calculated as the sum of the cost of other roads with the cost difference for the current road. The road with the most negligible loss is selected. This algorithm uses a penalty value that increases exponentially and will ensure that the same road is not selected multiple times and that no road is kept waiting for a long duration.

Using a greedy algorithm to schedule the traffic light states using only the jam factor from Here API does not provide fairness between the entities. Waiting time must also be considered. So, this algorithm considers the time that vehicles have waited. For every traffic light state change, assign a penalty value to each road based on how long the vehicles wait for their turn in the junction. An array structure can represent the penalty with 4 elements (roads) as P = [P0, P1, P2, P2].

$$p_n = \begin{cases} 1, & \textit{Initial penaltyorvehicles are moving} \\ (p_{n-1} + 1)\,, & \textit{otherwise} \end{cases} \tag{1}$$

Assuming that the penalty value in the previous step is p_{n-1}, the penalty value in the current step p_n should be set to $(p_{n-1}+1).\ p_{n-1}$.

'$(p_{n-1}+1).\ p_{n-1}$' is a non-linear growth pattern to ensure the penalty value increases as time passes so that no one is blocked for too long. When traffic is allowed on the road in the previous step, the penalty is fixed to 1.

To find out the optimal states of traffic lights for the current time, the algorithm considers the cost and reward of a road if traffic is allowed on that specific road. The cost and reward values can be calculated from the penalty value. The reward value R for a road represents the benefit of allowing traffic on the corresponding route. It is defined as the product of the penalty and jam factor of the road.

$$R_i = ((p_n)i).JF_i \tag{2}$$

Here, R, P, and JF represent the reward, penalty at moment n, and jam factor of road i, respectively. The cost of a road is computed as the summation of the reward of all other roads.

$$C_i = \sum\nolimits_{J=1}^{4} R_j - R_i \tag{3}$$

Therefore, the total loss value for a road is the difference between the reward and the cost.

$$L_i = C_i \times R_i \tag{4}$$

By substitution,

$$L_i = \sum\nolimits_{j=1}^{4} [R_j - R_i] - R_i \tag{5}$$

$$L_i = \sum\nolimits_{j=1}^{4} R_j - 2R_i \tag{6}$$

A road with minimum loss value is continuously found, and a green traffic light state is set. A penalty breaks ties between roads with the same loss value. The longer a road is disabled since it was enabled last time, the larger priority it has. If there is more than one road with the same penalty and loss value, it is selected based on its index order by default.

D. NON-INTERNET CONNECTED VEHICLES

Jam factors received from Here API calls do not include non-internet-connected vehicles. Constants must be introduced following the road's jam factor and added to it. Some of the congestion (jam factor) is contributed by non-internet-connected vehicles.

The reward of a road is a combination of penalty (waiting time), jam factor (internet-connected vehicles), and constant (non-internet-connected vehicles).

$$\propto = (0.9) \times JF_i \tag{7}$$

$$JF_i = JF_i + \propto \tag{8}$$

$$R_i = (P_n)i \times JF_i \tag{9}$$

E. TRAFFIC SIGNAL TIME ESTIMATION

Ensuring the amount of green time allotted for a particular road is important. The road selection algorithm ensures that the most optimal road is chosen for green time allocation. Considering the base time provided by the RL algorithm, min and max values for traffic light duration were set. The cost value of the roads was used for comparison, and the fraction of green time for that road was calculated. The green time for the selected road was set. The green time allotted to the road chosen is given by,

$$GT = \left(\left(\frac{JF_r}{JF_t}\right) \times BT\right) - 3 \tag{10}$$

Here, GT is green time, JF_r is the jam factor of the selected toad, JF_t is the total jam factor, and BT is the base time. The yellow time (YT) is constant, as below.

$$YT = 3 \tag{11}$$

F. RL APPROACH

RL has emerged as a valuable approach for enhancing traffic control systems. Using RL algorithms, traffic control systems can autonomously learn and adapt signal timings based on real-time traffic data. This adaptive approach enables the system to make intelligent decisions on adjusting signal timings to optimize traffic flow, reduce congestion, and minimize delays. RL agents interact with the environment, observing traffic patterns and congestion levels, and iteratively improve their decision-making process over time. The algorithm works based on trial and error with training included. The reward is positive (+1) if the expected output improves and negative the other way (−1). Feedback is used to compare and set rewards. This way, selecting a base timer improves the Q-learning method used by reinforcement learning. The algorithm runs for fixed episodes and trains based on reward. It eventually produces the most profitable output base timer.

Q-learning-based RL method is deployed, which learns optimal traffic signal policy based on trial and error with training included. By iteratively interacting with their environment, Q-learning agents update the Q-values representing rewards for acting. The reward is positive when the predicted output enhances and negative when it deteriorates. Feedback is employed to evaluate and establish incentives. The Q-learning mechanism employed by RL can be improved by choosing a suitable baseline timer. Q-learning agents constantly update the Q-values in response to real-time feedback as traffic patterns change throughout the day. This enables the system to modify signal timings adaptively to accommodate fluctuating traffic demands. The algorithm executes for a predetermined number of episodes and undergoes training based on the reward received. Ultimately, it generates the most lucrative output using a timer as its foundation.

G. INTELLISIGNAL ALGORITHM

Figure 1 displays the suggested IntelliSignal algorithm.

The proposed IntelliSignal algorithm is composed of two key components:

1. A road selection algorithm that chooses the optimal road to give a green light based on traffic conditions.

```
roadPenalty ← [1, 1, 1, 1];
jamFactors ← [];
lossValues ← [0, 0, 0, 0];
alphas ← [1, 1, 1, 1];
baseTime ← 100;
while True do
    getJamFactorRoads();
    for i in range(0, 4) do
        alphas[i] ← jamFactors[i] × 0.1;
        jamFactors[i] ← alphas[i] + jamFactors[i];
        jamFactors[i] ← round(jamFactors[i], 2);
    end
    reward1 ← round(roadPenalty[0] × jamFactors[0], 2);
    reward2 ← round(roadPenalty[1] × jamFactors[1], 2);
    reward3 ← round(roadPenalty[2] × jamFactors[2], 2);
    reward4 ← round(roadPenalty[3] × jamFactors[3], 2);
    reward ← [reward1, reward2, reward3, reward4];
    for road in range(0, 4) do
        cost ← reward[0] + reward[1] + reward[2] + reward[3];
        lossValues[road] ← cost − 2 × reward[road];
    end
    minLoss ← min(lossValues);
    for y in range(len(lossValues)) do
        if minLoss == lossValues[y] then
            minLossRoad ← y;
            break;
        end
    end
    totalReward ← round(sum(reward), 2);
    Timer ← int((reward[minLossRoad]/totalReward) × baseTime);
    baseTime ← baseTime − Timer;
    for z in range(len(roadPenalty)) do
        if z == minLossRoad then
            roadPenalty[z] ← 1;
        else
            roadPenalty[z] ← (roadPenalty[z] + 1) × roadPenalty[z];
        end
    end
end
```

FIGURE 1. The proposed IntelliSignal algorithm for smart intersection management.

2. A RL model that adapts the duration of the green light phases over time to minimize congestion.

The road selection algorithm aims to provide fairness between roads while prioritizing high-congestion areas.

I. **Initialization:** Variables for road penalties, jam factors, loss values, base timer, and other parameters are initialized.
II. **Data Gathering:** Real-time traffic data is collected to update jam factors for each road segment. Penalty values are maintained for each road, representing the waiting time experienced by vehicles on that road. Roads that have waited longer have higher penalties.
III. **Reward Computation:** The reward for giving a green light to each road is computed as the product of the road's penalty and jam factor. Roads with higher rewards are more congested and have waited longer.
IV. **Loss Estimation:** The total loss value of selecting each road is determined using the rewards of all roads. The road with minimum loss is prioritized to receive a green light next. This adaptive approach ensures high-congestion roads are prioritized efficiently while providing fairness between roads over time.
V. **Optimization Decision:** Once the selection algorithm selects the optimal road, a Q-learning-based RL agent controls the duration of the green phase for that road. The key steps are:
   - The agent uses the aggregate jam factor across roads to estimate a fair green time for the selected road.
   - It allocates this green time and observes the resultant traffic flow.
   - A positive or negative reward signal provides feedback on whether the allocated green time enhanced traffic conditions.
   - Over many learning episodes, the agent determines optimal green phase durations to minimize congestion, using the rewards to update its decisions.
VI. **Penalty Adjustment:** Once a road receives a green light, its penalty resets 1. For other roads, penalties grow exponentially as waiting time escalates. This modification reflects the changes in traffic conditions post-optimization, guaranteeing the algorithm adapts to new traffic patterns.

H. SYSTEM DESIGN

Figure 2 provides a general overview of the model design, offering a high-level understanding of the system's structure. The proposed system employs an advanced methodology to enhance traffic signal control by leveraging real-time traffic data and reinforcement learning techniques. The model gathers dynamic traffic information from all four intersecting roads by integrating the HERE map API. This data is the primary input for the subsequent computations and decision-making processes.

The model takes in the real-time traffic data from all four roads using the HERE map API's. The reward computation block and the penalty-based road selection compute the reward and penalty described in the algorithm. It then selects a road and computes a green time for that road. The model then receives a reward based on the traffic flow and the state of the intersection. This feedback is used to refine the model's policy for selecting and timing green lights. The reward computation module and the penalty-based road selection module collaborate to evaluate the current traffic conditions and determine the most appropriate course of action to identify the most suitable road for signal prioritization.

Once the optimal road has been nominated, the model proceeds to compute the apt green time duration for that particular road. This computation considers various factors, including the current traffic density, anticipated traffic patterns, and the overall system objectives. The estimated green time is then applied to the selected road, allowing vehicles to flow through the intersection. During this duration, the model continues to monitor the traffic conditions and gathers data on the resulting traffic flow and the state of the intersection. This real-time feedback is then used to refine the model's policy for selecting and timing green lights in future iterations.

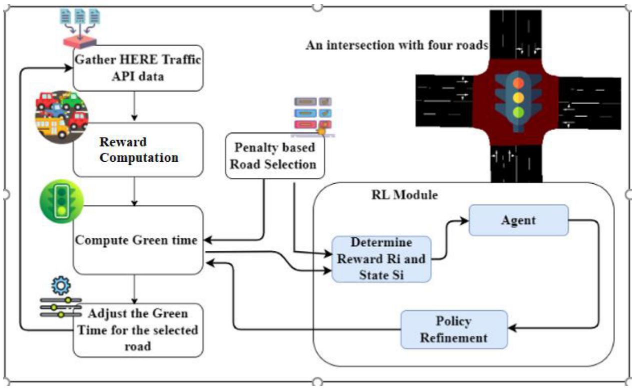

FIGURE 2. IntelliSignal's approach for optimized intersection control.

TABLE 1. Simulation environment specifications.

Parameter	Value	Description
Intersection Details		
Intersection Type	Four-way	A standard four-way intersection with traffic signals.
Traffic	Left-hand	Default Indian traffic style
Lanes per Direction	2	Each side of the intersection has two lanes.
Signal Cycle	45 seconds green, 3 seconds amber	Each direction receives a green light for 45 seconds, followed by a 3-second amber phase before the transition.
Simulation Duration	5000 seconds	The total length of time for which the simulation runs.
Total edge length	1.52 km	The total length of the road
Vehicle Parameters		
Vehicle type	Car	Default passenger car in SUMO
Length	4 meters	The length of a car in the simulation.
Max Acceleration	1 m/s²	The maximum rate at which a vehicle can accelerate.
Max Deceleration	3 m/s²	The maximum rate at which a vehicle can decelerate (brake).
Max Speed	55 km/h	The highest speed a vehicle is allowed in the city
Car-Following Model	Krauss	The model is used to simulate how vehicles follow each other.
Lane Change Model	Default SUMO model	Governs the behaviour of vehicles changing lanes.

IV. SIMULATION AND EXPERIMENTAL PROCEDURE

A. SIMULATION OF URBAN MOBILITY (SUMO)

SUMO is an open-source traffic simulation tool that is extensively used for modeling and analyzing traffic patterns in metropolitan environments. Users can utilize this software to replicate and evaluate the movement of vehicles, traffic patterns, and road networks, which assists in assessing traffic control systems and infrastructure designs. Researchers and urban planners can utilize SUMO to analyze congestion, trip times, and performance metrics, thus enabling the optimization of transportation systems. The selection of SUMO as the preferable traffic simulation software is based on its vast capabilities and detailed documentation, which surpasses that of other open-source platforms.

The SUMO simulation scenario involved modeling a standard four-way intersection representing typical traffic junctions in left-hand traffic regions like India. The purpose was to analyze the dynamics of traffic flow, the efficiency of signal timing, and the effectiveness of different traffic management strategies in reducing congestion and improving vehicle throughput. The testing process began by configuring the SUMO environment to correctly simulate the authorized traffic rules and road layout particular to the intersection.

The simulation scenario utilized the route and flow models for vehicle creation. By employing both the route and flow models in a SUMO simulation, the user can obtain a combination of the accuracy provided by manually defined routes and the scalability offered by automatic traffic demand generation. The routing model provides precise control over specific vehicle behaviours, while the flow model efficiently creates large amounts of background traffic. Collectively, they enhance the adaptability and extent of the simulation by allowing tailored routes for vehicles in specific areas while also facilitating the modeling of substantial traffic volumes and needs. Combining the complementary strengths allows crafting a hybrid approach tuned for the particular needs of the simulation. The simulation parameters are exposed in Table 1.

To simulate realistic traffic conditions, traffic signals were programmed initially for fixed time signals with a green time of 45 seconds and 3 seconds amber timings. The simulations were conducted under various conditions with actuated control signals and with the proposed IntelliSignal algorithm to examine their impact on traffic flow and the efficiency of intersections. Gathering and reviewing data about crucial transportation performance metrics such as delay durations, travel time, queue length, CO2 emissions, waiting time, and throughput to detect trends, bottlenecks, and potentials for improvement. The SUMO simulation scenario depicted in Figure 3 accurately replicates the attributes of a specific road network within a virtual environment. It includes a detailed representation of road segments, intersections, and traffic signals, allowing for an accurate representation of vehicular interactions.

B. TraCI

TraCI stands for Traffic Control Interface and is a software interface that interacts with traffic simulation programs, particularly the widely-used microscopic traffic simulator called "SUMO". TraCI controls and retrieves information from the SUMO simulation in real-time. It enables external programs (such as traffic management algorithms, intelligent transportation systems, or custom applications) to connect to the

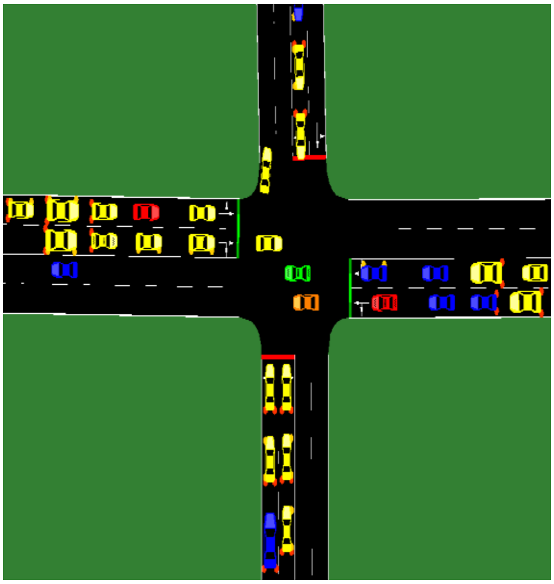

FIGURE 3. A SUMO simulation of a four-way intersection with left-hand traffic dynamics.

SUMO simulation, modify the state of the simulation, and extract relevant data for analysis.

C. PROGRAMMING LANGUAGES

JavaScript for running API queries and storing the result in JSON format, Python for running the algorithm and creating a graphical simulation of the traffic flow system.

The model showcases its adaptability to various types of traffic jams by utilizing detectors in SUMO, which provide valuable vehicle information during the simulation. By default, SUMO employs traditional static scheduling for traffic lights. A Python script interacts with the simulation in real-time to overcome this limitation through the TraCI feature. TraCI enables the script to control and monitor the simulation's progress, access various simulation statuses, and modify the states of traffic lights. In SUMO, each traffic junction is represented by a single traffic light element responsible for controlling the traffic lights for all the roads. The Python script retrieves the vehicle count information from SUMO during each simulation step. This vehicle count is then transformed into a jam factor, which the algorithm utilizes to generate an optimal traffic light state for that simulation step. The script then sets the traffic light to the generated state. SUMO independently controls the acceleration and slowdown of traffic by accurately configuring the traffic lights. This enables flexible and reactive movement of vehicles, efficiently adjusting to varying degrees of traffic congestion and optimizing traffic conditions within the simulation.

V. RESULTS, DISCUSSIONS AND BENCHMARKING AGAINST EXISTING APPROACHES

To evaluate the model's efficiency, comparative experiments were conducted to analyze its performance in different circumstances. The purpose of these tests was to assess the

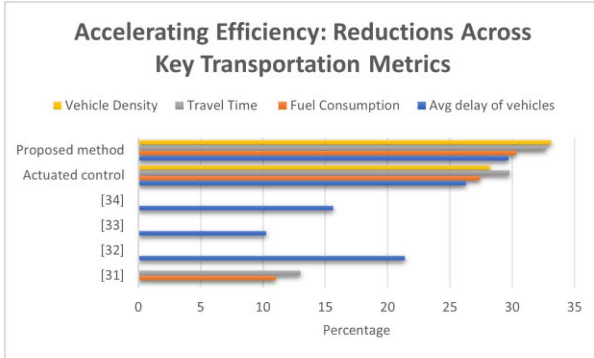

FIGURE 4. Reductions across key transportation metrics benchmarked against fixed-time control, actuated control and four relevant research innovative methods.

enhancement of the algorithm in contrast to the default fixed-time scheduling approach, the actuated control, and four different recent methodologies [31], [32], [33], [34]. The actuated control scheme is common in Germany. It works by extending the traffic phases whenever a prolonged flow of vehicles is detected. The system switches to the next phase after an appropriate time interval between consecutive transports is identified. It enables a more efficient allocation of green time among the signal cycle phases and adjusts the cycle length in response to changing traffic conditions. The research predominantly assessed the fixed-time scheduling approach and the actuated control using essential variables such as vehicle density, waiting time, travel duration, queue length, CO_2 emissions, fuel consumption, and intersection throughput. This work seeks to showcase the efficacy and impartiality of the algorithm through these evaluations. Figure 4 compares the reductions in transportation metrics produced by the proposed work, actuation control approaches, and previous research findings compared to the standard fixed-time traffic control.

As shown in Figure 4, the proposed technique exhibits higher performance in various crucial parameters than traditional fixed-time methods, actuated control systems, and other research efforts recorded in papers [31], [32], [33], and [34]. More precisely, the suggested approach demonstrates a notable improvement in minimizing the delay of vehicles, reducing fuel usage, decreasing travel time, and reducing the number of vehicles in the intersection, indicating a more effective traffic flow and energy utilization.

The studies were classified into eight sections, each focusing on distinct facets of the model's performance. The many components included diverse traffic settings, enabling us to evaluate the algorithm's efficacy thoroughly. By comparing the outcomes derived from the analysis, it is possible to measure the enhancements accomplished and confirm the effectiveness of the proposed model.

A. VEHICLE DENSITY

The data depicted in Figure 4 illustrates that the proposed strategy effectively reduces vehicle density at the intersections by 33.1%, resulting in smoother traffic flows and alleviating congestion. Urban regions face a chronic difficulty of high vehicle density, which significantly influences mobility and air quality. Consequently, this element is vital in such areas. The decrease in density can be attributed to the algorithm's integration of real-time traffic data, which allows for adaptive and data-driven decision-making. In contrast, the standard algorithm operates without access to real-time data, leading to suboptimal vehicle routing and increased congestion. The ability to leverage current traffic conditions allows the proposed algorithm to more efficiently distribute vehicles across the transportation network, thereby decreasing overall density. These results highlight the benefits of incorporating dynamic data sources into traffic management algorithms to improve urban mobility.

B. TRAVEL TIME

As discerned from Figure 4, The proposed method achieves a 32.7% saving on journey time, which is considerably more than the reductions achieved by [31] (13%) and the actuated control method (29.8%). This enhancement indicates that the suggested approach efficiently mitigates congestion and optimizes traffic flow, resulting in expedited passage throughout the network. This noteworthy outcome enhances traffic efficiency and carries consequential environmental benefits. The algorithm reduces ecological pollution by minimizing travel durations and conserves fuel resources. The observed improvements in travel time underscore the algorithm's potential to impact both traffic dynamics and broader sustainability goals positively.

C. FUEL CONSUMPTION

As depicted in Figure 4, the proposed technique achieves a reduction of 30.3% in fuel consumption, surpassing the improvements described in [31] (11%) and the actuated control method (27.4%). The proposed method can improve fuel efficiency by optimizing the signal timings, adjusting speed, and reducing stop-and-go driving situations, which are well-known for causing increased fuel consumption. The proposed methodology utilizes real-time traffic inputs to adjust signal phases more accurately according to current demand. It entails prolonging the duration of green traffic signal phases to align with continuous vehicle platoons, minimizing the time wasted due to inconsistent phase timings or early transitions. The adaptive control technology optimizes traffic patterns by reducing abrupt braking and repeated engine restarts. Furthermore, it helps alleviate traffic congestion that worsens fuel inefficiency due to frequent stopping and starting of vehicles and prolonged idling in queues. The integration and computational analysis of traffic data and responsive orchestration of dynamic signal operations lead to overall gains in fuel economy throughout the urban area.

D. DELAY OF VEHICLES

Automobile delays are measured as the additional travel time induced by signalized intersections. As observed in

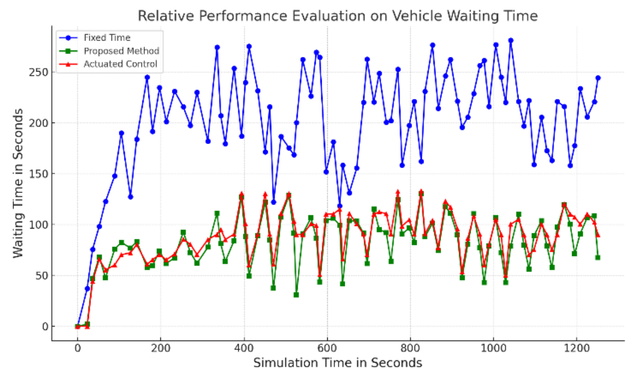

FIGURE 5. Performance evaluation of vehicle waiting time of the proposed method benchmarked with fixed-time and actuated control methods.

Figure 4, the proposed innovative method enabled considerable diminution of mean vehicle delay, exhibiting a 29.70% attenuation relative to the fixed time scenario. It outperforms literature-documented diminutions of 21.39% [32], 10.25% [33], and 15.64% [34], as well as the 26.3% attained via actuated signal control implementation. The substantial advancements are attributed to the methodology's efficacy in optimizing traffic progression by integrating real-time vehicular volumetrics for the dynamic management of signals. The substantial decreases in vehicle immobilization facilitate more efficient network performance and capacity usage, generating technical, economic, and environmental benefits for transportation systems.

E. WAITING TIME

The waiting time for a vehicle is calculated by measuring the time it remains static due to a red traffic signal. The graphic in Figure 5 illustrates a comparative comparison of vehicle waiting time across three distinct traffic signal control systems plotted over a simulated duration. The x-axis depicts the simulation time in seconds, while the y-axis measures the vehicle waiting time in seconds. The data indicates that the fixed time technique yields the most extended waiting times, suggesting lower efficiency in traffic flow management. The actuated control method performs better than the fixed-time method, reducing waiting times. Overall, the proposed method exhibits the shortest waiting periods compared to the other two methods, indicating its superior efficiency in lowering vehicle waiting times at intersections. As inferred from Figure 5, integrating the proposed penalty-based algorithm yields a substantial reduction in the overall waiting time experienced by vehicles.

F. CO_2 EMISSION

As depicted in Figure 6, integrating the proposed penalty-based algorithm leads to a substantial decrease in CO_2 emissions from vehicles compared to the standard algorithms. The fixed-time model has the highest emissions levels, which is implied by its inflexible operational nature.

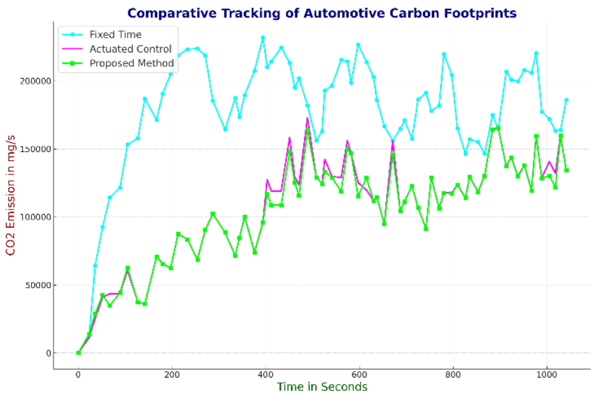

FIGURE 6. Comparison of CO_2 emission of the proposed method with fixed-time and actuated control strategies.

On the contrary, the actuated control exhibits variable emissions that are generally reduced, indicating a semi-dynamic reaction to traffic stimuli. The proposed method exhibits a continuously low emission footprint, underscoring its potential for eco-efficient traffic management. However, an intriguing observation emerges, wherein, at specific points, the emissions from this algorithm align somewhat with those generated by the standard algorithm. This trend can be attributed to increased vehicle density outweighing the travel time benefits of the proposed algorithm under extreme congestion. At very high densities, vehicles experience significant queuing even under optimized routes, diminishing the emissions advantage compared to the standard algorithm.

Nonetheless, the proposed algorithm demonstrates considerable emissions reductions under normal traffic conditions. The penalty-based approach remains an effective strategy for mitigating environmental impact by minimizing CO_2 production from traffic, especially during periods of moderate to high, but not extreme, network congestion. Further optimization may enable sustaining lower emissions at the highest vehicle volumes.

G. QUEUE LENGTH

This stacked area graph in Figure 7 illustrates a comparison representation of vehicle queues under alternative signalization systems, using queue length as a proxy for traffic congestion. The abscissa represents time sequentially, while the ordinate measures the number of vehicles present. The fixed time control is the highest level, which shows that it has minimal flexibility and results in long lines.

The actuated control is situated in the middle layer and demonstrates a reasonable level of effectiveness in reducing queues. The proposed method serves as the fundamental basis, consistently demonstrating the shortest lines, thereby indicating excellent performance in improving traffic flow. The visual depiction emphasizes the need for adaptive traffic control systems to reduce automobile congestion. However, a notable observation arises under certain circumstances: the proposed algorithm's queue length approaches parity with that of the other two methods. This phenomenon can be rationalized by considering specific operational scenarios where the penalty-based algorithm, while generally effective in minimizing queue lengths, encounters specific conditions or congestion patterns that lead to momentary alignments with the queue lengths observed under the standard algorithm. Further detailed analysis, including real-world validation and fine-tuning algorithmic parameters, is warranted to identify the operational contexts contributing to this observed behaviour and optimize the penalty-based algorithm for sustained and enhanced performance in diverse traffic scenarios.

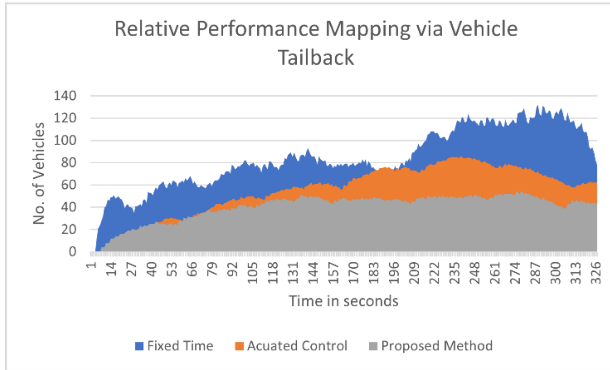

FIGURE 7. Optimizing vehicle queues: A comparative study of proposed, fixed-time, and actuated control methods.

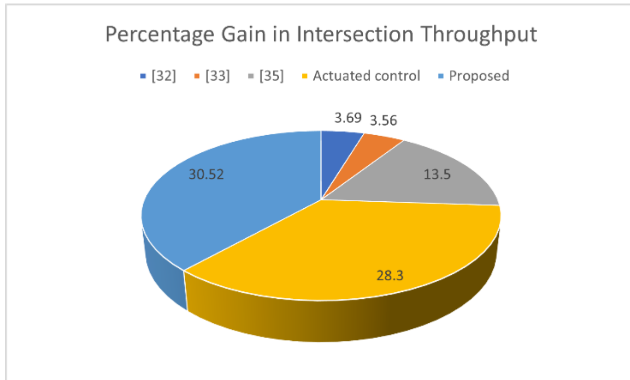

FIGURE 8. Comparison of intersection throughput gain benchmarked against traditional fixed-time control, actuated control and with three recent research efforts.

H. INTERSECTION THROUGHPUT

Intersection throughput, the rate at which vehicles and pedestrians traverse an intersection, is a critical metric for assessing intersections' performance and overall efficacy within a transportation network. The pie chart in Figure 8 illustrates the relative improvement in intersection throughput achieved by different traffic signal control methods benchmarked against fixed-time traffic control. The proposed IntelliSignal methodology employed intersection traversal counts over a fixed interval to estimate throughput. Simulations revealed the traditional approach accommodated 3,282 vehicle traversals, while IntelliSignal enabled 4,725 traversals over identical intervals. This equates to a 30.52% improvement in throughput under IntelliSignal versus standard fixed time control. The stark divergence in throughput is visually encapsulated in Figure 8, which elucidates the substantial gains in intersection capacity afforded by the IntelliSignal approach. These results underscore the potential of IntelliSignal to enhance the throughput of signalized intersection infrastructure through intelligent, adaptive control mechanisms. Implementing the actuated signal control strategy resulted in a 28.3% improvement in intersection throughput compared to the base scenario. Although it showed improvement, the rise was not as substantial as achieved with the proposed strategy. Prior studies have observed very modest enhancements in intersection throughput. Reference [32] demonstrated a 3.69% increase, [33] a 3.56% increase, and [35] a 13.5% increase using their respective signal control techniques.

The suggested strategy demonstrated superior performance in increasing junction throughput compared to existing methods, most likely attributed to utilizing real-time traffic data and reinforcement learning techniques to optimize cycle lengths and green light allocations. It enables us to respond more to dynamic traffic situations than static or reactive control techniques.

VI. CONCLUSION

Our proposed penalty-based traffic signal management algorithm combining jam factor data from HERE maps with a time allocation algorithm enhanced by reinforcement learning demonstrates superior performance across key transportation metrics. This solution effectively utilizes HERE maps traffic data to analyze real-time traffic conditions and employs the advanced Q-learning algorithm to optimize traffic signal durations. As a result, it eliminates the requirement for physical sensors, representing a significant transition towards more sustainable and efficient urban planning. The empirical evidence collected from thorough assessments indisputably shows that this technology outperforms classic fixed-time traffic management systems, actuated traffic control mechanisms, and many modern methodologies in enhancing important transportation metrics. Implementing this approach has significantly resulted in a remarkable 30.52% improvement in throughput and significant decreases in CO_2 emissions, journey durations, fuel consumptions, intersection queue length, and vehicle waiting times. These improvements not only enhance the environmental sustainability of urban centers but also significantly improve the quality of urban life by reducing traffic congestion and improving mobility. The significant influence of this approach highlights the possibility of combining artificial intelligence and real-time data analytics in traffic management systems, signaling the arrival of a new era of intelligent transportation systems that are more flexible, effective, and sustainable.

REFERENCES

[1] A. Khatri and M. Senthilkumar, "Lane clearance approach for emergency vehicles in highways network," *PLoS ONE*, vol. 17, no. 11, Nov. 2022, Art. no. e0276988.

[2] K. Sreejith and S. Mathi, "A prototype design for emergency notifications between vehicles in vehicular ad hoc networks," in *Inventive Communication and Computational Technologies*. Singapore: Springer, 2023, pp. 221–235.

[3] V. Bhardwaj, Y. Rasamsetti, and V. Valsan, "Traffic control system for smart city using image processing," in *AI and IoT for Smart City Applications*. Singapore: Springer, 2022, pp. 83–99.

[4] K. Adwani and N. Rakesh, "Smart city traffic control system," in *Intelligent Communication Technologies and Virtual Mobile Networks*. Cham, Switzerland: Springer, 2019, pp. 421–430.

[5] U. K. Lilhore, A. L. Imoize, C.-T. Li, S. Simaiya, S. K. Pani, N. Goyal, A. Kumar, and C.-C. Lee, "Design and implementation of an ML and IoT based adaptive traffic-management system for smart cities," *Sensors*, vol. 22, no. 8, p. 2908, Apr. 2022.

[6] A. R. M. Jamil and N. Nower, "Dynamic weight-based multi-objective reward architecture for adaptive traffic signal control system," *Int. J. Intell. Transp. Syst. Res.*, vol. 20, no. 2, pp. 495–507, Aug. 2022.

[7] S. R. Kazemee, M. S. Mahmud, Y. Rahman, M. A. R. Khan, B. B. Pathik, and M. Kabiruzzaman, "Design and implementation an IoT based smart traffic system using renewable energy sources," in *Proc. 2nd Int. Conf. Image Process. Robot. (ICIPRob)*, Mar. 2022, pp. 1–6.

[8] S. V. Raut, S. A. Jangam, and B. Rajpathak, "Improving vehicular traffic efficiency by infrared sensors," in *Proc. IEEE 1st Int. Conf. Smart Technol. Power, Energy Control (STPEC)*, Sep. 2020, pp. 1–6.

[9] H. Agarwal and J. N. Rai, "Traffic control system based on density with emergency priority mechanism," in *Proc. Int. Conf. Electron. Renew. Syst. (ICEARS)*, Mar. 2022, pp. 192–197.

[10] G. Varshney, A. Jaiswal, U. Mittal, A. Pawar, and Satyajeet, "Density-based remote override traffic control system," in *Machine Learning, Advances in Computing, Renewable Energy and Communication: Proceedings of MARC*. Singapore: Springer, 2020.

[11] T. T. Krishan, R. S. Alkhawaldeh, I. Al-Hadid, R. A. Azawi, and S. H. Al-Sharaeh, "An impact of smart traffic sensing on strategic planning for sustainable smart cities," in *Proc. 2nd Amer. Univ. Emirates Int. Res. Conf.* Cham, Switzerland: Springer, 2020, pp. 25–31.

[12] S. Sharon, A. R. Krishnamoorthy, and V. E. Salis, "Design study on actuated traffic control system using Internet of Vehicles for smart cities," *ECS Trans.*, vol. 107, no. 1, pp. 19253–19263, Apr. 2022.

[13] P. Wang, P. Li, and F. R. Chowdhury, "Development of an adaptive traffic signal control framework for urban signalized interchanges based on infrastructure detectors and CAV technologies," *J. Transp. Eng., A, Syst.*, vol. 148, no. 4, Apr. 2022, Art. no. 04022004.

[14] Z. Wang, M. Li, L. Tang, and J. S. Huang, "Research and application of intersection traffic signal control algorithm based on vehicle location," *Int. J. Commun. Netw. Distrib. Syst.*, vol. 24, no. 3, pp. 249–261, 2020.

[15] Z. Yao, Y. Jiang, B. Zhao, X. Luo, and B. Peng, "A dynamic optimization method for adaptive signal control in a connected vehicle environment," *J. Intell. Transp. Syst.*, vol. 24, no. 2, pp. 184–200, Mar. 2020.

[16] W. Wu, L. Huang, and R. Du, "Simultaneous optimization of vehicle arrival time and signal timings within a connected vehicle environment," *Sensors*, vol. 20, no. 1, p. 191, Dec. 2019.

[17] P. W. Shaikh, M. El-Abd, M. Khanafer, and K. Gao, "A review on swarm intelligence and evolutionary algorithms for solving the traffic signal control problem," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 1, pp. 48–63, Jan. 2022.

[18] J. Zhao and W. Ma, "An alternative design for the intersections with limited traffic lanes and queuing space," *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 3, pp. 1473–1483, Mar. 2021.

[19] J. Gu, M. Lee, C. Jun, Y. Han, Y. Kim, and J. Kim, "Traffic signal optimization for multiple intersections based on reinforcement learning," *Appl. Sci.*, vol. 11, no. 22, p. 10688, Nov. 2021.

[20] J. Wang, Y. Han, and J. Zhao, "Conditional transit signal priority optimization at Stop-to-Stop segments to improve BRT on-time performance," *IEEE Access*, vol. 10, pp. 33512–33526, 2022.

[21] C. L. González, S. L. Delgado, J. M. Alberola, L. F. Niño, and V. Julián, "Toward autonomous and distributed intersection management with emergency vehicles," *Electronics*, vol. 11, no. 7, p. 1089, Mar. 2022.

[22] H. Zhu, Z. Wang, F. Yang, Y. Zhou, and X. Luo, "Intelligent traffic network control in the era of Internet of Vehicles," *IEEE Trans. Veh. Technol.*, vol. 70, no. 10, pp. 9787–9802, Oct. 2021.

[23] L. Tang, Q. He, D. Wang, and C. Qiao, "Multi-modal traffic signal control in shared space street," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 1, pp. 392–403, Jan. 2022.

[24] E. Namazi, J. Li, and C. Lu, "Intelligent intersection management systems considering autonomous vehicles: A systematic literature review," *IEEE Access*, vol. 7, pp. 91946–91965, 2019.
[25] J. Ault, J. P. Hanna, and G. Sharon, "Learning an interpretable traffic signal control policy," 2019, *arXiv:1912.11023*.
[26] S. S. S. M. Qadri, M. A. Gökçe, and E. Öner, "State-of-art review of traffic signal control methods: Challenges and opportunities," *Eur. Transp. Res. Rev.*, vol. 12, no. 1, pp. 1–23, Dec. 2020.
[27] M. Eom and B.-I. Kim, "The traffic signal control problem for intersections: A review," *Eur. Transp. Res. Rev.*, vol. 12, no. 1, pp. 1–20, Dec. 2020.
[28] D. Inoue, A. Okada, T. Matsumori, K. Aihara, and H. Yoshida, "Traffic signal optimization on a square lattice with quantum annealing," *Sci. Rep.*, vol. 11, no. 1, p. 3303, Feb. 2021.
[29] M. Al-Turki, N. T. Ratrout, S. M. Rahman, and K. J. Assi, "Signalized intersection control in mixed autonomous and regular vehicles traffic environment—A critical review focusing on future control," *IEEE Access*, vol. 10, pp. 16942–16951, 2022.
[30] L. Zhang, Q. Zhao, L. Wang, and L. Zhang, "Urban intersection signal control based on time-space resource scheduling," *IEEE Access*, vol. 9, pp. 49281–49291, 2021.
[31] M. Kolat, B. Kővári, T. Bécsi, and S. Aradi, "Multi-agent reinforcement learning for traffic signal control: A cooperative approach," *Sustainability*, vol. 15, no. 4, p. 3479, Feb. 2023.
[32] J. Guo, X. Huang, R. Li, Z. Li, N. Sun, and H. Dong, "Based on MOPSO algorithm of real-time traffic signal optimization control for intelligent transportation intersections," *J. Phys., Conf. Ser.*, vol. 2477, no. 1, Apr. 2023, Art. no. 012085.
[33] X. Fu, H. Gao, H. Cai, Z. Wang, and W. Chen, "How to improve urban intelligent traffic? A case study using traffic signal timing optimization model based on swarm intelligence algorithm," *Sensors*, vol. 21, no. 8, p. 2631, Apr. 2021.
[34] H. Zhang, H. Yuan, Y. Chen, W. Yu, C. Wang, J. Wang, and Y. Gao, "Traffic light optimization based on modified webster function," *J. Adv. Transp.*, vol. 2021, pp. 1–10, Aug. 2021.
[35] Ł. Kuźmiński, P. Maśloch, M. Bazan, T. Janiczek, K. Halawa, H. Wojtaszek, I. Miciuła, T. Chajduga, A. Kawecki, R. Czwartosz, and J. Stawik, "Management of delay optimization at intersections," *Energies*, vol. 13, no. 12, p. 3087, Jun. 2020.

K. SREEJITH received the B.Tech. degree in computer science and engineering from Cochin University of Science and Technology (CUSAT), the M.Tech. degree in wireless networks and applications from Amrita Vishwa Vidyapeetham, Coimbatore, India, and the M.B.A. degree in human resources from Sikkim Manipal University. He is currently pursuing the Ph.D. degree with the Amrita School of Computing, Amrita Vishwa Vidyapeetham. He possesses more than eight years of expertise as an Assistant Professor. He has authored and published three papers in internationally recognized conferences indexed in Scopus. His research interests include intelligent transportation systems, artificial intelligence, computer networks, and machine learning.

SENTHIL KUMAR MATHI received the B.E. degree in computer science and engineering from Bharathiar University, India, the M.E. degree in computer science and engineering from Anna University, India, the M.B.A. degree in human resources management from Bharathiar University, and the Ph.D. degree in internet protocol mobility and security from the Faculty of Information and Communication Engineering, Anna University.

Since 2004, he has been an Associate Professor with the Amrita School of Computing, Amrita Vishwa Vidyapeetham, India, Coimbatore. He has around 20 years of teaching and research experience. He has guided many B.Tech. and M.Tech. student projects/thesis and currently guiding B.Tech. students and M.Tech. and Ph.D. scholars for their project/research/dissertation work. He has published research papers in reputed journals and conference proceedings, most of which are indexed in SCOPUS, SCI, and Web of Science. His research interests include IPv4 mobility and IPv6 mobility–next-generation internet protocol mobility, wireless networks, mobile computing, cryptography and information security, machine learning and formal languages, and automata theory. He is a member of IETE. He was a recipient of the best paper awards for his publications.

PREEJA PRADEEP received the Ph.D. degree in context-aware Internet of Things ecosystems. She is currently a Postdoctoral Researcher with the Insight Centre for Data Analytics, University College Cork, Ireland. She has eight years of technical experience working in various interdisciplinary national and internationally funded research projects in an academic research and development setting. She is an active member of European collaborative project Intelligent Sharing of Explanation Experience (iSee). She was also involved in designing India's first remote-triggered laboratory in the area of computer science. Her research interests include context-aware intelligent systems, explainable AI, the IoT, Semantic Web, ontology, data analysis, microservices, and probability and statistical models.