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A Comparative Survey of Smart City Traffic Management Solutions: Taxonomy, Tools, and Emerging Trends

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ABSTRACT

Artificial intelligence (AI) has become a critical component of modern urban environments, driving the development of smart cities that promise enhanced efficiency, sustainability, and improved quality of life. Despite these advancements, traffic congestion remains a significant challenge in urban mobility. Addressing this challenge requires further investigation to develop innovative and effective solutions. This paper reviews recent research on traffic management in smart cities, providing a comprehensive analysis of current strategies. It emphasizes the need for adaptive, integrated approaches to traffic control in the context of rapidly evolving urban systems.

Keywords: Traffic congestion, Smart City, Vehicle Rerouting, Traffic Management, Signal Control.

I. INTRODUCTION

The number of people on Earth exceeded eight billion in 2022, researchers estimate that there are 1.32 billion motor vehicles between cars, trucks and buses are driven on the road while automobile companies produce more than 100 million motor vehicles every year. Therefore, our roads suffer from traffic jams, accidents, pollution, and other issues, particularly those related to public health [1].

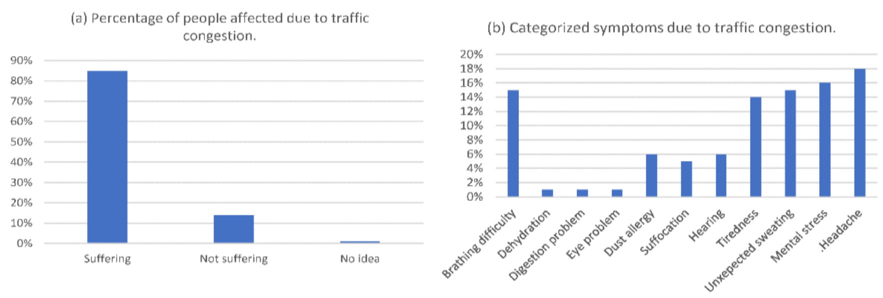

Figure 1: Impact of traffic congestion on public health.

Source: U. K. Lilhore et al, (2022).

Recent research [2] was conducted to examine the impact of traffic congestion on public health, as shown in figure 1 which offers a detailed breakdown of the study's findings, shedding light on the significant health effects caused by traffic congestion. The chart (a) of figure 1 shows that 85% of the participants in the study reported being affected by traffic congestion, while chart (b) illustrates the various symptoms experienced by these individuals, including headaches and breathing difficulty

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The term Smart City was first used in the late 20th century, referring to urban areas that exploit operational data, such as that arising from traffic congestion, power consumption statistics, and public safety events, to optimize the operation of city services [3]. In the middle of the aforementioned challenges, the concept of Smart Cities emerges as a beacon of hope, offering rational and practical solutions to address urban issues, particularly traffic congestion. Effective traffic management plays a pivotal role in the lives of city residents and can enhance their quality of life on multiple levels. Firstly, ensuring the smooth and timely movement of people within the city is essential for the functionality of smart cities. Secondly, proactively mitigating traffic congestion offers significant economic benefits, such as reducing fuel consumption and its associated costs. Finally, it contributes to a positive environmental impact by curbing carbon emissions.

Although there is no universally accepted definition for traffic congestion, it is widely recognized as a major urban transportation issue and refers to the condition where road demand exceeds supply, leading to slower speeds, longer travel times, and vehicular queuing. This condition often occurs when the volume of vehicles surpasses a road's capacity, leading to various negative effects such as increased air pollution, wasted fuel, and decreased economic productivity. However, the previous definition is purely descriptive, and we need to develop other definitions that enable the measurement of traffic congestion.

I.1 PROBLEM BACKGROUND

The majority of the papers and projects analyzed in this review, as highlighted by [1] [4] [5], revolve around three central objectives: time efficiency, reducing environmental pollution, and minimizing fuel consumption. These objectives also serve as the primary criteria for evaluating work in this domain. On the other hand, there are several indices for measuring the traffic congestion, among which we cite:

1. Traffic density: Traffic density (TD) is a widely used concept for proposing computational solutions to traffic congestion [1], [6], [7]. It is defined based on two variables: the Traffic flow (TF) and the Speed (S)

$$TD = TF/S \qquad (1)$$

Where traffic flow is the number of vehicles in certain time, and speed is the average speed of vehicles in certain time

2. Congestion index: The authors of the paper [3] argue that classical traffic data, such as traffic flow, speed, and travel time, do not provide a robust representation of traffic congestion. To address this limitation, they propose a new metric called the congestion index, where vt and vlimit represent the real-time speed and the speed limit of a road segment, respectively. The variable Ct is a decimal value ranging from 0 to 1, where 0 signifies the absence of congestion and 1 indicates a state of significant congestion.

$$c_t = \begin{cases} 1 - {v_t}/{v_{\lim it}} \; if \; v_t \leq v_{\lim it} \\ 0 \; if \; v_t \succ v_{\lim it} \end{cases} \qquad (2)$$

3. Carbon Emission: the most used equation for CO2 emission estimating is the one based on energy consumption and emission factors [8]:

$$co_2 Emission = \sum_{i=1}^{n} E_i * EF_i \qquad (3)$$

Where: Ei : Energy consumed by activity/source i (in kWh, liters, etc.).

EFi: Emission factor for activity/source i (e.g., kg CO2 per kWh).

n: Number of emission sources (e.g., buildings, vehicles, street lighting, etc.).

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I.2 THE OBJECTIVES OF THE RESEARCH

The objective of this research is to provide an in-depth analysis of studies that focus on traffic management in smart cities, it is relevant for this kind of papers to give a logical and powerful classification of the related work to give the reader a mind map to follow the sequence of information, therefore, we found that it useful to cite the classification of the previous reviews.

Following a comprehensive review of prior surveys and studies on traffic management in smart cities, we identified multiple methodologies for categorizing research. For instance, the authors in [9] classify studies according to their key objectives, such as safety, efficiency, passenger comfort, and environmental sustainability. Conversely, other researchers employ thematic analysis for categorization. Additionally, some categorize the research based on the specific approaches used to address the problem of traffic congestion. For example, certain authors [6] adopt a classification framework that organizes studies according to:

1. Traffic Signal Control: This category focuses on optimizing traffic signal timings using real-time data to manage traffic flow efficiently. It includes adaptive traffic signal systems and synchronization of traffic lights.
2. Traffic Routing: Traffic routing involves directing vehicles along optimal routes to reduce congestion and travel times. This can include real-time navigation apps and systems that provide drivers with alternative routes based on current traffic conditions.
3. Turning Restrictions: Implementing turning restrictions can be a traffic management strategy to improve safety and reduce congestion at specific intersections or during certain times of the day.
4. Congestion Pricing: Congestion pricing is a strategy where drivers are charged a fee for using certain roads or areas during peak traffic times to reduce congestion.

This variation in categorization reflects the diverse priorities and methodologies in the field, underscoring the need for a unified framework to compare and evaluate the effectiveness of traffic management strategies in smart cities. We will present our classification based on our perspective in section II-B.

I.3 SIMULATION TOOLS

A diverse set of simulation tools have been employed to validate and implement various methodologies proposed in recent studies about traffic management and congestion control. MATLAB has emerged as a popular tool, with its specialized functionality that allow an easy simulation of traffic flow such as the Simulink and Vehicle Network Toolbox, these toolboxes provide built-in functions and blocks for simulating vehicle dynamics, traffic flow, and communication systems. [1]. While the objective modular network testbed in C++ (OMNeT++), the simulator for urban mobility (SUMO), and Veins are frequently used together, especially when focusing on inter-vehicle communication and graph theory-based congestion estimations [5], [10].

When it comes to traffic light control using image and video processing, the Raspberry Pi, mainly known as a hardware platform, has been paired with the OpenCV tool [4]. In approaches that concentrate on connected vehicle-based traffic signal control, the Intelligent Driver Model (IDM), JAVA, and AIMSUN have proven indispensable[11]. Reinforcement learning methodologies targeting traffic signal control have notably adopted CityFlow as their primary simulation environment [12]. Meanwhile, for methods utilizing decision trees, linear regression, and neural networks, Python's versatility, along with TensorFlow, have been favored [13]. When venturing into the realm of V2V architectures and real-time traffic congestion identification, the combination of OMNeT++, SUMO, and Veins once again takes precedence [14]. Moreover, Vissim has been highlighted in methodologies that leverage deep reinforcement learning to manage green light times [15]. Other tools, such as ANYLOGIC and the Android application, cater to traffic light optimization and traffic congestion identification, respectively [16], [17].

This paper is organized as follow: The first section is an introduction accompanied with three main points: the background of the problem, the objectives of the research, as well as the simulation tools that are widely used in this kind of research. section II presents the methodology employed while writing this survey. Section III, IV, and V are dedicated to give the state of the art about the aforementioned problem respecting to our taxonomy. And Section VI conclude the paper by giving final remarks and additional comments.

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II. METHODOLOGY

The methodology section outlines the process employed for conducting the literature review, which is structured around two key steps: 1) The selection of the related work, involving the identification and filtering of relevant studies, articles, and resources based on predefined criteria such as relevance, quality, and publication date. 2) The classification of the related work, where the selected studies are organized into categories or themes to facilitate analysis and identify trends, gaps, and patterns in the existing research. This structured approach ensures a comprehensive and systematic review of the literature, providing a solid foundation for further analysis and discussion.

II.1 THE SELECTION OF THE RELATED WORK

The primary stages within this methodology encompass the following steps: The identification of keywords that we consider relevant for our research, gathering a set of articles and scientific papers from academic databases, the filtering process, and the establishment of eligibility and inclusion/exclusion criteria.

To initiate the search, keywords were carefully identified and rescreened before being used to scour the databases. Some examples of these keywords include" smart city","traffic congestion", "traffic jam", "deep reinforcement learning", "passenger", "convolutional neural network", "air pollution", "deep belief network", "parking", "traffic" and "vehicle detection". These keywords were injected in the search engine of several reliable academic databases, such as Springerlink and ScienceDirect. To build our survey on solid foundations, we used a three steps selection method, first, the set of articles included in this survey must be peer reviewed and sourced from reputable journals, conferences, or edited books written in English. Second, each one of these selected articles was rescreening based on its title and abstract to remove any duplication. Finally, a deep read of the articles' full text was conducted to ensure they aligned with the eligibility criteria and they were compatible with the survey's objectives.

II.2 THE CLASSIFICATION OF THE RELATED WORK

Based on an in-depth analysis of the selected articles in this survey, we observe that while the papers share some similarities, each exhibits distinct features in terms of methodology, objectives, or focus. Through this analysis, we have identified three primary categories within this domain (see figure 2): 1) Traffic Congestion Detection and Prediction (TCDP), 2) Vehicle Rerouting and Traffic Management (VRTM), and 3) Traffic Signal Control (TSC). Each of these categories represents a crucial aspect of the overall spectrum of traffic management, with specific methodologies designed to address their unique challenges and objectives.

In the sections that follow, we will highlight a selection of papers from each category, providing a comprehensive overview of the current state of the art of this domain.

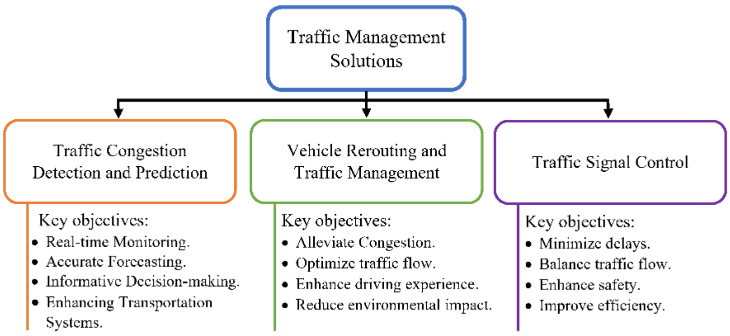

Figure 2: Subcategories of Traffic Management Solutions.

III. TRAFFIC CONGESTION DETECTION AND PREDICTION

This category focuses on methodologies and systems designed to identify, quantify, and/or forecast traffic congestion in real-time or future scenarios. It encompasses the use of diverse data sources, advanced algorithms, and computational models to detect existing traffic bottlenecks or predict potential congestion patterns.

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The papers under this category share a set of common objectives:

1. Real-time monitoring to identify areas of congestion as they occur.
2. Accurate forecasting to predict potential traffic congestion based on historical data.
3. Informative decision-making: To provide transportation authorities, planners, and drivers with accurate information to make informed decisions.
4. Enhancing transportation systems by understanding congestion patterns.

The first paper in this survey that deals with the detection and the prediction of traffic congestion is the paper [18], which describes the implementation of a fuzzy inference model for traffic congestion detection, this model takes flow and density as inputs to give the level of congestion as output. Linguistic variables are assigned to input and output parameters, while fuzzy rules are defined to connect these variables using the AND operator, each rule result is a fuzzy set, and an aggregation is performed using the maximum aggregation operator, which gives a fuzzy set as a final result for this step. Therefore, De-fuzzification is carried out using the centroid method to obtain a single value for congestion from the final fuzzy set obtained in the previous step. The fuzzy rules are formulated using an if-then structure, for example: 'If Flow is Stable and Density is High, then the Road is Unstable.' is a rule where 'Flow is Stable' and 'Density is High' are the input variables, while 'Unstable' (pertaining to the road segment) is the output variable, which can take several values: Congestion Free, Stable, Unstable, Near Congestion, Congestion, and Severe Congestion, which represent the fuzzy set in this model.

The model is applied to real data from a specific highway, and the results show the detected levels of congestion for each road segment demonstrating that the proposed fuzzy inference model offers several advantages, like providing a flexible and intuitive approach to modeling traffic congestion, taking into account subjectivity, ambiguity, and uncertainty. However, it also has limitations, such as the simplicity of its input variables and the need for more sophisticated fuzzy rules.

In summary, the paper presents an innovative approach to traffic congestion detection and modeling using fuzzy logic, emphasizing the advantages of its flexibility and ability to capture the subjective nature of traffic conditions.

The methodology presented in the paper [19] adopts a fuzzy logic approach to quantify congestion levels on expressways, this measurement is based on two primary parameters: traffic flow speed and density, which is a pivotal element of a traffic stream and derived from the occupancy of loop detectors. Conversely, speed stands out as a prevalent congestion indicator since it mirrors the traffic stream's mobility. In simple terms, congestion is considered as a function of decreasing speed. The authors of this paper conduct a comparative study to evaluate the proposed approach using three variables: congestion indices, speed and density, the congestion indices are defined based on the two former parameters, the output of this approach is a value between 0 and 1 called the congestion level, which is mapped into a set of linguistic categories composed of FreeFlow, Light, Moderate, Heavy, VeryHeavy. The system defines 19 fuzzy rules that take density and speed as predicates and give the level of congestion as an output, the following rule represents one of the 19 used in the system:

If speed is "VeryLow" and density is "VeryHigh" then congestion level is "VeryHeavy"

After testing the proposed approach on the inductive loop detector dataset, the fuzzy inference system (FIS) was compared to the Level of Service of the highway capacity manual (LOS) for assessing congestion. Although there was some correspondence between them, FIS offers a more detailed and flexible representation of congestion by combining multiple traffic variables, whereas the Manual is more limited in scope. Comparisons using both speed and density as variables indicated that using both is vital for accurate congestion representation, especially in heavy traffic.

A cooperative technique to identify and minimize traffic congestion in vehicular networks, called CARTIM, was proposed in the paper [14]. It uses V2V and V2I communication along with fuzzy logic to estimate local congestion levels based on vehicle speed and density, powered with a cooperative validation process propagating messages from the front to the back of traffic jams to reach a consensus on congestion levels. For congestion minimization, CARTIM employs heuristics to suggest new routes to vehicles when congestion exceeds a user defined threshold, this can use either V2V communication or infrastructure units, the system is designed to avoid overloading the communication

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channel. Simulations in an urban scenario demonstrate that CARTIM reduces average travel times and CO2 emissions compared to only detecting congestion without route changes.

The key results show that the fuzzy logic system and the validation process make CARTIM adaptive to different environments beyond the freeways. The paper concludes that CARTIM is an effective cooperative and context-aware technique for congestion detection using vehicle communication and fuzzy logic. The system minimizes congestion through suggested route changes, validated through simulations.

Finally, to conclude this section a comparative overview of the selected studies is presented in Table 1 to highlighting their key characteristics.

Table 1. Comparative Overview of the Reviewed Papers.

Study	Inputs	Level of congestion	Number of rules
[18]	Flow and density	Completely Congestion Free Congestion Free - Stable Unstable-Near Congestion Congestion- Severe Congestion	31
[19]	Speed and density	FreeFlow, Light, Moderate, Heavy, VeryHeavy.	19
[14]	Speed and density	free flow, weak flow, moderate flow, harsh conditions.	16

IV. VEHICLE REROUTING AND TRAFFIC MANAGEMENT

This category focuses on the dynamic management of traffic by suggesting alternative routes for vehicles or optimizing the overall traffic flow within a network, it involves the use of real-time data, algorithms, and communication systems to redirect traffic away from congested areas or to manage the flow efficiently.

The scientific research under this category shares a set of common objectives:

5. Reduce traffic bottlenecks by directing vehicles away from congested areas.
6. Ensure smooth flow and minimize traffic-related delays by effectively managing the vehicular movement.
7. Enhance driving experience with real-time route suggestions to avoid congestion, thus reducing travel time.
8. Reduce environmental impact by minimizing congestion and improving traffic flow, which allow to decrease fuel consumption and reduce carbon emissions.

In their publication [10], the researchers propose an AI based rerouting system designed to mitigate road congestion, through simulations conducted using the SUMO simulator, the system has shown a reduction in both travel time and distance for rerouted vehicles. One of the major challenges addressed is traffic congestion in areas with high population density, such as Cairo, the solution presented revolves around the road side unit (RSU), a key component that collects, processes, and communicates rerouting information to vehicles, these RSUs are organized within a structured hierarchy consisting of areas, zones, and maps, with the study predominantly focusing on operations within a single area. The core of the solution lies in its algorithmic approach; in addition, a graph structure is employed where nodes denote specific points on a map. The primary routing technique used is the Dijkstra's algorithm, though the k-shortest paths algorithm is also explored as a potential alternative. Furthermore, the data processing aspect of the system is anchored on four principal tasks: optimizing graph weights, accurately identifying road congestion, strategically selecting vehicles for rerouting, and effectively ranking the rerouting processes. In general, this research presents an innovative AI-driven approach using RSUs to intelligently reroute vehicles, offering a potential solution to the pervasive issue of traffic congestion.

The AI-based traffic management system was assessed using the SUMO simulator incorporating the traffic control interface (TraCI) library, the system offered real-time traffic management. Concurrently, CO2 emissions were calculated using the EMIT model, with variables like vehicle acceleration and speed playing pivotal roles.

The examination primarily centered on two map configurations:

9. A foundational customized map, explicitly designed to evaluate the algorithm, defined by nodes representing intersections and bidirectional roads.

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10. A more complex representation mirroring the intricacies of New Cairo, Egypt, sourced from OpenStreetMap.

Building on the aforementioned maps, real-world traffic simulations were synthesized, one simulation randomly designated start and end points for 100 vehicles, creating congestion by extending wait times at a selected traffic junction. In contrast, an alternative simulation that marks two primary routes for these 100 vehicles, with using extended traffic light intervals to emulate congestion. The findings of these simulations, show that it is evident that the optimized parameters, had a profound impact on system efficiency, their integration, coupled with a range of congestion detection methods, further underscored the system's potential, laying the groundwork for promising future enhancements.

Machine learning is a powerful tool that transforms raw data into meaningful knowledge, revolutionizing the way we solve complex problems. The Paper: Intelligent Traffic Management for Vehicular Networks Using Machine Learning [20] is a compelling attempt to integrate advanced machine learning techniques, specifically the support vector machines (SVM) combined with radial basis function (RBF) kernels, into the domain of traffic management. The heart of this research beats around the creation of an intelligent traffic management system that is able to predict, interpret, and react to the complexities of modern traffic in real-time. The combined power of SVM and RBF has been heralded for its capability to capture non-linear relationships within dynamic traffic environments.

The Methodology of this paper adopts a multi-faceted approach begins with comprehensive data collection, gathering real-world traffic data, including variables like vehicle speed, density, and historical traffic patterns, this data forms the foundation upon which the SVM, armed with the RBF kernel, generates detailed traffic predictions. Furthermore, an ITS architecture is established, comprising layers from communication to decision support. This methodology is composed of the following key components:

11. Data collection: Real-world traffic scenarios provide a myriad of data points, crucial for accurate machine learning.
12. SVM with RBF: SVM is renowned for handling nonlinear relationships, and its pairing with the RBF kernel augments its ability to interpret intricate traffic patterns.
13. ITS System architecture: A detailed structure, featuring a communication layer, data processing, decision support, and an information service layer, underscores the holistic approach.
14. Traffic prediction: With SVM-RBF at its core, the system continuously processes real-time data to predict future traffic conditions, ensuring decisions are proactive rather than reactive.
15. Signal timing optimization: The dynamic nature of the model enables timely adjustments to traffic signals, further ensuring smoother flow and reduced congestion.

Across a range of tests and iterations, the SVM-RBF model demonstrated a superior performance, outclassing its peers (like SVM, BPNN, DBN) in terms of accuracy metrics, such as MAE, MSE, and RMSE. Another noteworthy result was its computational efficiency, marking the SVM-RBF model as particularly suitable for real-time operations.

While the SVM-RBF model emerges as a front-runner in predictive accuracy, it's essential to tailor the choice of model to the unique requirements of a traffic management system, the research also hints at the untapped potential of other models which, with additional hyper parameter tuning, could narrow the performance gap witnessed.

The objective of the paper [5] is to maximize the vehicle traffic flow (minimize congestion) using an estimation about the congestion level which is spread between vehicles via messages exchanges, the map of the city was modeled based on a weighted and oriented graph G = (V, A), where V (G) and A(G) are the vertices and edges of the graph respectively. V = {v1, v2, ..., vi} represents the set of intersections of the map, on the other hand, A = {a1, a2, ..., ai} represents the set of roads interconnected to the intersections, i.e., each ai represents the association between two vertices vi and vi+1 ∈ V |vi ≠ vi+1|. For weighting G = (V, A), each road ai ∈ A has a set of weights W = {w1, w2, ..., wj}, i.e., w are attributed to the directed edge a(x, y) ¸ w(z).

Based on the previous model, the authors propose a solution named TRAFFIC composed of four steps:

1. Data model for estimating congestion: based on the speed obtained from the OBU and the density, which represents the number of vehicles nearby, the classification model can provide three levels of congestion.

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2. Mechanism for detecting congestion: The detection mechanism employed by TRAFFIC relies on a classification algorithm to estimate road congestion levels based on the velocity and density of nearby vehicles. To obtain more accurate decision, the authors use an aggregation of three distinct classification algorithms (Fuzzy logic, KNN and ANN-MLP) defined in previous work.
3. Mechanism for disseminating data: in the proposed method, the authors claim that the asynchronous sharing of information is the best way for inter vehicles communication, there for they adopt the Pub/Sub paradigm to ensure the exchange of information between vehicles.
4. Mechanism for recommending routes: The recommended method in TRAFFIC to prevent traffic from entering congested areas involves sharing knowledge between vehicles, allowing them to determine alternative routes. When a vehicle receives information about a congested road, it checks whether it is scheduled to travel on that road thus, it uses the Dijkstra algorithm to find an alternative route.

In the results discussion phase, the authors show that their proposition helps reduce travel time, fuel consumption, and CO_2 emissions of the vehicle.

Table 2. Summary of the Reviewed Papers and Their Key Features

Study	Inputs	Level of congestion (outputs)	Rerouting algorithm	Evaluating criteria
[5]	Velocity andvdensity of vehicles	Free, moderate, and congested	Dijkstra	- Travel time - Fuel consumption, - co2 emissions
[10]	Real world map as a graph	Alternative paths	Dijkstra k-shortest paths	Travel time and travel distance
[20]	Dataset: Speed Traffic, Density Weather condition, Road type, Signal status	Traffic flow, congestion level	- adaptive control of traffic signals - adaptive speed limit recommendations	-Mean Absolute Error (MAE) - Root Mean Squared Error (RMSE)
[21]	Travel distance Expected distance	Equation based	unknown	- Travel time. - Time loss. - Distance. - Speed and density.

According to the work of [21], the primary focus of the paper is on the use of Vehicular Adhoc Networks (VANETs) to manage traffic conditions by locally observing and estimating traffic congestion, the proposed system detects signs of congestion and disseminates this information to nearby vehicles, which then use this information to potentially reroute to avoid congestion. The traffic management systems (TMS) discussed in the paper emphasizes traffic monitoring, congestion detection, and route suggestion to minimize congestion impacts.

The proposed" ON-DEMAND" Vehicular traffic management system operates in three steps: 1) Road traffic analysis, where vehicles determine the road's congestion level; 2) Communication model, where vehicles decide if they should share their congestion assessments with nearby vehicles and also seek traffic data if unavailable; and 3) Rerouting, where alternative paths are calculated based on received traffic data. In road traffic analysis, vehicles compare their actual traveled distance (TD) with an expected distance (ED) calculated under ideal traffic conditions to determine a contention factor, this factor quantifies traffic congestion, with values helping identify road conditions ranging from

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free-flowing to heavily congested. The simulation results show that ON-DEMAND reduces travel time and delay compared to other approaches like PANDORA, DIVERT, and s-NRR, with lower network overhead. The distributed estimation and sharing of congestion levels enables effective distributed traffic management.

In summary, this paper presents a fully distributed and adaptive traffic management system for VANETs that relies on local congestion monitoring and information sharing between vehicles to improve traffic flow and reduce congestion, and the system is shown to outperform other approaches through simulations.

This section concludes with Table 2, which compares the selected studies emphasizing their key characteristics.

V. TRAFFIC SIGNAL CONTROL

This category focuses on the techniques and frameworks developed to regulate and coordinate traffic signals, aiming to enhance the efficient flow of vehicles through intersections, crossroads, or any signalized points. It involves adapting signal timings based on traffic conditions, vehicular density, or other relevant parameters.

The research in this category shares a set of common objectives:

1. Minimizing vehicle waiting times at intersections or any signalized points.
2. Preventing any specific direction from being overly prioritized or neglected.
3. Enhance safety by minimizing the risk of collisions or accidents at intersections.

Video processing-based techniques for traffic signal management aim to enhance traffic control and alleviate congestion by utilizing real-time video data. These systems employ cameras and computer vision technologies to monitor traffic conditions at intersections. By analyzing video feeds, they can dynamically adjust signal timings, detect abnormal traffic patterns, and optimize traffic flow, ultimately improving the efficiency of traffic routing in urban areas. The research presented in [4] tackles the pressing challenge of urban traffic congestion, which is exacerbated by population growth and the rising number of vehicles. The authors propose a smart traffic management system that integrates Internet of Things (IoT) technology with advanced image and video processing. Traditional traffic systems, which rely on fixed schedules, often lead to inefficient traffic flow. To overcome this limitation, the researchers introduce two innovative models designed to address these inefficiencies and improve overall traffic management.

4. Model based on vehicle density: This model uses image processing to analyze traffic conditions at each direction of an intersection. It calculates the overlapping percentage of the current traffic image with a reference image and uses this information to dynamically schedule green lights for each direction.
5. Model based on the number of vehicles: This model uses video processing to estimate the number of vehicles traveling along the main streets approaching the intersection. By applying filters to detect and track moving vehicles, the system counts the vehicles and dynamically adjusts green light timings based on the observed traffic volume. This approach ensures that signal timings are responsive to real-time traffic conditions, optimizing flow and reducing delays at the intersection.

These models were implemented using Raspberry Pi boards and OpenCV tools, showcasing promising results in improving traffic management efficiency. The system's adaptability and potential for prioritizing emergency vehicles make it a valuable contribution to addressing urban traffic challenges.

One of the primary challenges in mitigating traffic congestion is the absence of interconnectivity between traffic signals at different junctions. Currently, signals at one junction often operate independently from those at neighboring junctions, resulting in inefficient traffic flow both along the same road and across interconnected roads. Interconnected traffic signal management systems seek to address this issue by coordinating signals across multiple intersections in real-time. These systems leverage data from sensors, cameras, and communication networks to dynamically adjust signal timings, alleviate congestion, and optimize traffic flow. By enabling synchronized and adaptive signal control, such systems enhance transportation efficiency, reduce delays, and improve overall traffic management in urban areas.

The article [22] investigates the application of the teacher student framework in reinforcement learning (RL) for adaptive traffic signal control. While RL has proven effective for traffic signal control, the teacher-student framework,

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a type of RL, has not been extensively applied in this domain because of challenges in determining hyper-parameters and the number of state-action pairs. In this framework, RL agents are tasked with controlling traffic intersections, an agent observes the current traffic scenario and decides on an action, all with the goal of enhancing traffic flow. The observed state provides details on vehicles, queue lengths, and the present phase of the traffic light.

Elaborating on the methodology, the entire approach rests on the Teacher-Student framework. While the teacher has already been trained in a distinct traffic scenario, the student, with its freshly initialized parameters, is nurtured under this experienced teacher.

At a specific time t, both the student and the teacher observe the same environmental state, which could represent various scenarios, such as current traffic conditions at an intersection or the configuration of a game board. While both observe the same state, the student takes the initiative by selecting an action based on its current understanding and policy, this chosen action is then executed in the environment. Once the student makes its decision, it communicates the action to the teacher, who does not alter or intervene in the student's choice but instead records it to evaluate the student's decision and preparing to provide feedback.

In their study, as outlined in [12], the authors explore the application of reinforcement learning for traffic signal control (RL-TSC) to address the challenges of urban traffic congestion, particularly under over-saturated traffic conditions. The key contribution of the paper is the adaptation of the RLTSC method to accommodate varying traffic signal phasing designs, which is especially useful in high-traffic scenarios. Additionally, the authors introduce a strategy search process for RL-TSC in real-world contexts, drawing inspiration from AlphaGo's virtual game exploration. The approach leverages a virtual simulation environment along with a new kinematic wave-based mesoscopic model to estimate traffic conditions that are difficult to measure directly.

The proposed RL-TSC algorithm uses a virtual simulation environment to model traffic strategies using real-time traffic data. Based on the virtual environment's state, the RL-TSC agent makes decisions regarding traffic signal control. The model employs a kinematic wave-based mesoscopic model, which divides approach links into cells and calculates traffic density over time, providing an accurate representation of traffic dynamics at intersections. Built upon a prior study, the agent's design relies on this mesoscopic model to represent traffic conditions. Its state space, which defines how it interprets traffic situations, is primarily based on traffic density.

The reward function of the RL-TSC is designed to reduce intersection delays, which is derived from the traffic density state variable, the intersection delay caused by a new action is compared with the previous one, and rewards are given based on the reduction. The agent's model training employs a pre-training strategy based on a prototype intersection's simplified geometry, its parameters, including learning rate, soft target updates, and discount factor, are optimized for fast learning and stable convergence. In summary, the study provides a comprehensive outline of a virtual traffic simulation environment and the design and training of an RLTSC agent, the primary focus is on accurately modeling and simulating traffic conditions, validating the model's accuracy, and enhancing the RL-TSC system's performance and reliability.

Table 3 summarizes and compares the key features of the selected studies, bringing this section to a close.

Table 3. Comparative Summary of the Selected Research Works

Study	Year	Problem Formulation	Methods/Algorithm	Simulators & tools
Traffic light control [4]	2019	Based on the density and the number of vehicles	Image and Video processing	Raspberry
The teacher-student framework [22]	2023	Markov Game	RL using teacher-student framework	CityFlow
RL-TSC method [12]	2023	Agent with Environment state	Reinforcement learning	Vissim

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VI. TRAFFIC MANAGEMENT DATASETS

Reliable datasets are crucial for traffic management and smart city research, enabling benchmarking, simulation validation, and AI model training. Public datasets help compare algorithms, test models, and improve congestion forecasting, vehicle detection, and signal optimization. High-quality data ensures reproducible and scalable research.

To assist researchers, we provide a table (Table 4) summarizing key datasets by type, use cases, and geographic coverage.

Table 4. Example of available datasets for traffic management solutions.

Dataset	Type	Use case	Region
NGSIM [23]	Trajectories	Congestion modelling	U.S
METR-LA [24]	Speed sensor data	Forecasting	U.S. (LA)
GeoLife [25]	GPS traces	Routing, travel patterns	China
urban traffic dataset [26]	Weather conditions Traffic incidents road classifications	Congestion prediction	London, UK
LuST) [27]	Traffic Signal Data	Testing traffic management algorithms	City of Luxembourg

VII. CONCLUSION

A city is the cornerstone of our modern society, built and populated by humans, who constantly search for construct the ideal cities. In other hand, artificial intelligence has become part of our daily life, from the simple application in our mobile phones to systems that make critical decisions such as the control and the management of a nuclear station, and among the applications of artificial intelligence that affects a very large number of people, is the application of AI in our cities.

Table 5: Example of available datasets for traffic management solutions.

Study	Problem formulation	Methods/Algorithm	Key Objectives	Simulators & tools	Category
ATM [1]-2022	Platoon-based traffic flow	IoT and ML	Adaptive congestion reduction and accident detection	MATLAB	VRTM
Hybrid approach [28] 2020	Hybrid Approach with signal inter-linking	SVM	improving traffic flow and reducing congestion	MATLAB	TSC
Signal Control Algorithm [11]-2020	Location and speed of all vehicles	ConnectedVehicle-based	Balancing efficiency and equity at intersections	JAVA IDM AIMSUN	TSC
PrePCT [29]-2020	Matrix of congestion index	ConvolutionalLSTM	Traffic congestion prediction	/	TCDP
[13]-2020	Collected Data	Decision tree, LR and NN	Accurate Congestion prediction	Python 3	TCDP
ITS for IOV [30]-2023	Collected Data	Decision tree XGBoost	Congestion prediction	Python 3	TCDP

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Cooperative Multi-Agent [31]-2023	Multi-Agent System	Deep Reinforcement Learning	traffic signal controls	CityFlow	TSC
Traffic Congestion Prediction [32]-2023	Neural network	NN and LR	Congestion prediction to reduce traffic	/	TCDP
Dynamic adaptive vehicle re-routing [33]-2023	Mesh-grid	k-shortest path algorithm	Mitigate traffic congestion	MATLAB	VRTM
IV/ PL [15]-2023	Matrix based	Deep Reinforceme nt Learning	Manages green light time for vehicles and pedestrians	Vissim	TSC
DR Q-learning [34]-2021	DQN Agent	DR Q-Learning	TSC at isolated intersections	Sumo	TSC
Traffic Light Optimizatio n [16]-2021	Multi Agent System	Multi-agent system	Traffic Light Optimization	ANYLOGIC	TSC
dynamic traffic environmen t [35]-2023	bi-level optimization problem	Several Algorithms	minimize the Average Travel Time with priority	Sumo	VRTM
NRSD [17]-2023	Proposed framework	Several Algorithms	Identify traffic congestion and estimate air quality	Android	TCDP

In conclusion, traffic congestion remains a persistent and complex challenge in urban areas, significantly impacting transportation efficiency and quality of life. This survey has explored a wide range of proposed solutions, highlighting their strengths and potential limitations. In addition, Table 5 provides a summary of a set of studies whose detailed summaries were not included in the paper, in order to offer a clearer understanding and evaluation.

It is clear that while numerous solutions have been proposed, their effectiveness is highly dependent on local context, infrastructure, and community engagement. Future research should focus on developing adaptive and integrated solutions that account for the evolving dynamics of urban environments. Collaboration among stakeholders, continued innovation, and increased public awareness will be crucial in driving progress toward sustainable and congestion-free urban mobility. By addressing these challenges holistically, cities can move closer to achieving efficient, equitable, and environmentally friendly transportation systems.

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