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A Systematic Review Of Multi-Agent Systems And Mobile Edge Computing In Intelligent Transportation Systems

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Abstract

The Internet of Vehicles (IoV) can be identified as the most progressive evolutionary stage in the development of Intelligent Transportation Systems (ITS), being, in fact, the result of a merging of modern communication technologies with the traditional vehicle network. This review provides an in-depth survey of the current state of knowledge regarding Multi-Agent Systems (MAS) and Mobile Edge Computing (MEC) applications in Intelligent Transportation Systems. The review further explored the MEC and MAS mechanisms as technological solutions of modern times, as they enable real-time data processing and intelligent decision-making at the edge of the network. This analysis ascertains the gaps in the literature. Further, it explores the subject within the broader scholarship, thereby defining the study objectives in the arena of improving ITS through Internet of Vehicles (IoV) technologies.

1. Introduction

The Internet of Vehicles (IoV) is a concept in which vehicles are connected to the Internet and other forms of communication through Vehicle-to-Everything (V2X) communication, which is part of an Intelligent Transportation System (ITS) [1]. V2X aims to establish a connected environment that enables vehicles, infrastructure, and other devices to communicate with each other in real-time. It should be noted that due to the wide range of measurements carried out in V2X with a multitude of various requirements, it primarily presents specific and stringent claims on mobile cellular networks. IoV is a technology that, just a few decades ago, seemed like a realm of science fiction, and has now evolved into a complex, intelligent network. It has emerged from the simple idea of cars talking to each other through messages. This notion has evolved, ripped by smartphones that became ubiquitous and connectivity changes thrust upon us by 5G technology [2], [3]. The importance of IoV is profound and far-reaching, for having an ITS with a worldwide presence can make our roads safer [4]. It's as if every vehicle and traffic light has been transformed into a driving assistant watching over our journeys, making roads and cities smarter, in which an efficient and safe travelling experience is viable [5]. Figure 1 shows a basic network model for IoV.

With IoV comes a revolutionary idea that opens a new era for the transportation system, where the nature of the interactions between vehicles and their surroundings will be completely changed. Though the range of opportunities for IoV to improve linkage, traffic management, or safety issues is undeniable, for the complete realization of IoV, many challenges need to be managed in this way [6]. These challenges are conflicts in decentralized decision-making [7], scalability [8], security and privacy [9], interoperability [10], latency [11-12], real-time traffic management [9], predictive analysis for road safety [13], enhanced vehicle safety features [14], infrastructure improvements [9], and legislation and policy support [15].

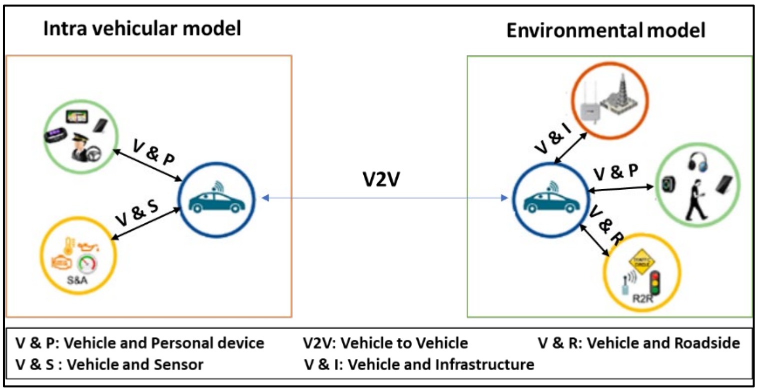

Fig. 1 *An IoV network model*

The intelligence of advanced IoV road networks is controlled and governed by Mobile Edge Computing (MEC), which operates discreetly behind the scenes [16]. MEC takes cloud computing facilities right to the edge of the IoV network, where it is needed on roads and vehicles. This capability ensures high response times and instantaneous decision-making as data processing is done at the edge location, rather than being moved to central data centres far away [17]. MEC is critical in the IoV implementation environment, representing a world where milliseconds make the difference between safety and danger. Imagine this as having a supercomputer at the side of the road, capable of analyzing and responding to evolving traffic flow conditions, allowing you to drive safely immediately. It is akin to providing each vehicle with the capacity for rapid thinking capabilities and movement to prevent accidents, resulting in a smooth traffic flow [18]. As Figure .2 illustrates, the deployed MCE-based IoV-empowered task offloading is modelled by IoV.

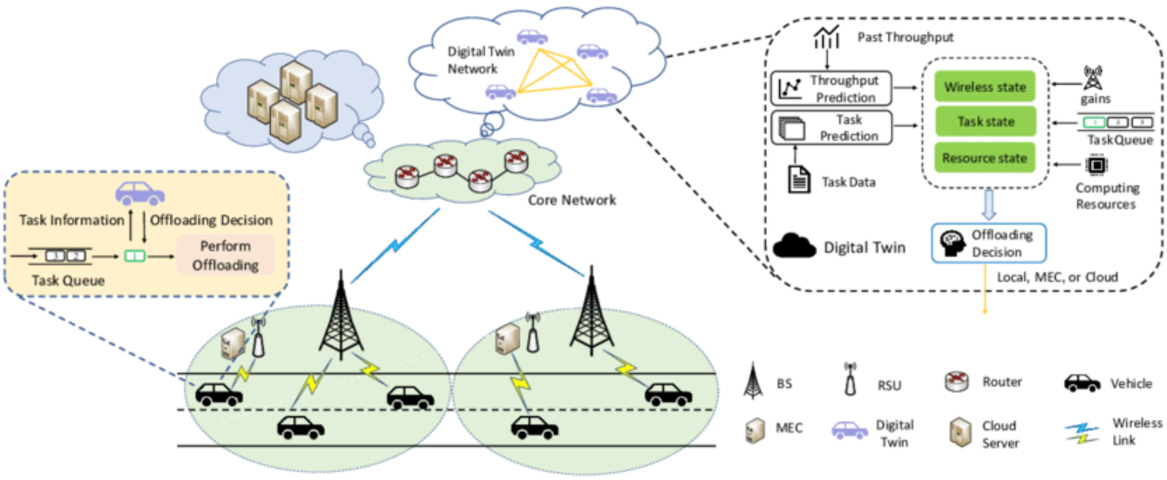

Fig. 2 *An MCE-based IoV architecture of the empowered task offloading for IoV*

In the paradigm of IoV dynamic systems and complexity, Multi-Agent Systems (MAS) act as helpers or ardent followers under the veil, infusing interconnectedness and interactivity between multiple ends [19]. The MAS creates a collective intelligence system in that individual agents develop a larger intelligent network ambient within the MEC structure. The MAS is the decision-making network within the landscape of IoV, comprising numerous vehicles and devices that communicate continuously and exchange data. Every single agent in the system dynamically scrutinizes data streams from vehicles, traffic lights, and other IoT devices and accordingly reacts with the required actions [20], [21]. The agents cooperate to take comprehensive measures to assess the current traffic situation, improving traffic management and ensuring road safety [19], [22]. This MAS collective intelligence transforms the complexity of traffic into a coordinated unification, in which every step and every movement is measured to maximize the efficiency of the IoV system. Figure .3 shows a generic MAS architecture in which n agents observe an IoV environment state, s, and reactions r and respond to the environment with a course of action.

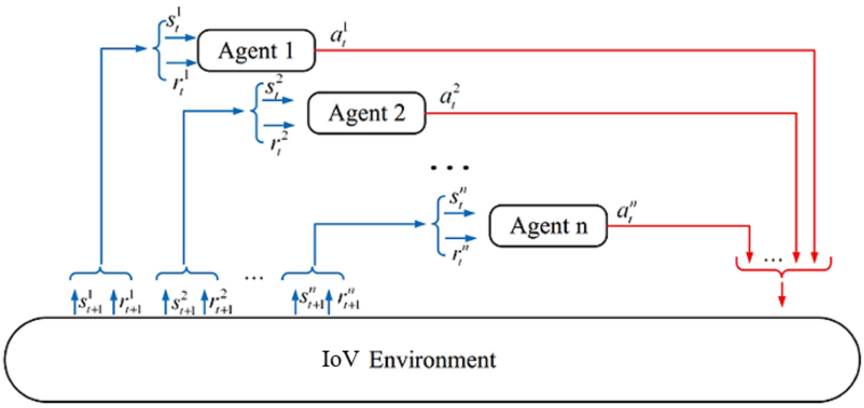

Fig. 3 *A MAS architecture in the IoV environment*

MEC can provide high levels of processing speed and immediate response, and MAS can contribute robustness and agility as well. The agents of the MEC operate on the network's edge and process data locally at the source, where it is created. The ultra-rapid at which decisions can be made from this proximity to the data sources is similar to a reflex action due to road environmental changes [20]. In a hypothetical scenario, a sudden road closure could occur, resulting in immediate traffic congestion. In this case, MAS needs to quickly engage with its agents, communicating actively and cooperatively to redirect traffic flow, update the navigation system, and provide real-time warning messages for drivers and operators, while maintaining the overall network load to avoid system overloads. Providing safety, efficacy, and serenity capabilities in the IoV system by integrating MAS in the MEC entails overcoming various research challenges [22, 24].

This review paper aims to identify and analyze existing literature and ongoing studies on the topic of IoV in the context of ITS. This review paper aims to provide readers with an understanding of IoV domains that can be utilized, such as MEC and MAS applications. In addition, the paper further explores MEC and MAS as technological solutions of modern times, as they enable real-time data processing and smart decision-making at the edge of the network. This analysis ascertains the gaps in the literature. Further, it explores the subject within the broader scholarship, thereby defining the study's objectives in the arena of improving ITS through Internet of Vehicles technologies.

2. Methodology

We carried out an SLR for this survey, which includes preparation, research, and reporting (Figure 4). This survey's goals are to examine the most recent research on the function of MAS and MEC in ITS.

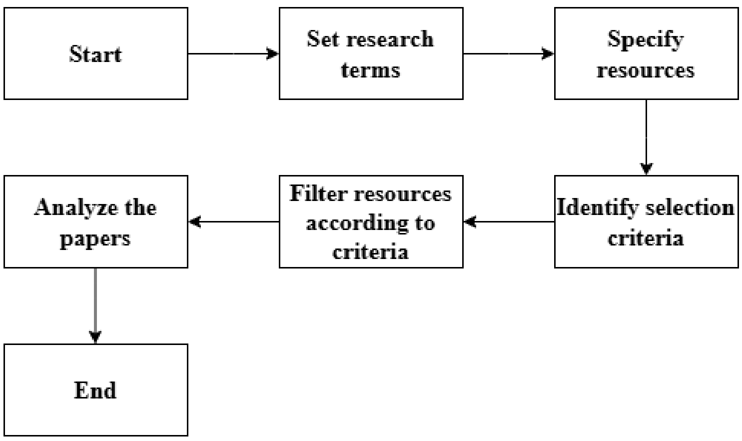

Fig. 4 *Review stages*

2.1 Search Strategy

The advanced search phrase ("Multi-Agent Systems" OR "MAS") AND ("Mobile Edge Computing" OR "MEC") AND ("Intelligent Transportation Systems" OR "ITS" OR "Smart Transportation"), ("Multi-Agent Systems" AND "Mobile Edge Computing") AND ("Traffic Optimization" OR "Traffic Management" OR "Vehicle Coordination"), ("Mobile

Edge Computing" AND "Multi-Agent Systems") AND ("Real-Time Data Processing" OR "Traffic Prediction" OR "Resource Allocation"), ("Multi-Agent Systems" AND "Mobile Edge Computing") AND ("Smart Cities" OR "Urban Mobility" OR "Connected Vehicles"). The aforementioned digital libraries were searched to locate the required publications (from journals and research papers):

- IEEE Explorer
- Google Scholar
- Science Direct
- ACM Digital Library
- Springer.

To eliminate duplicate research, the chosen publications were exported to the Mendeley software. The titles and abstracts of the selected studies were vetted. To determine their eligibility, the qualifying studies underwent an extensive review of full-text articles. Figure 5 presents the selection process using PRISMA techniques along with the rationale for exclusion.

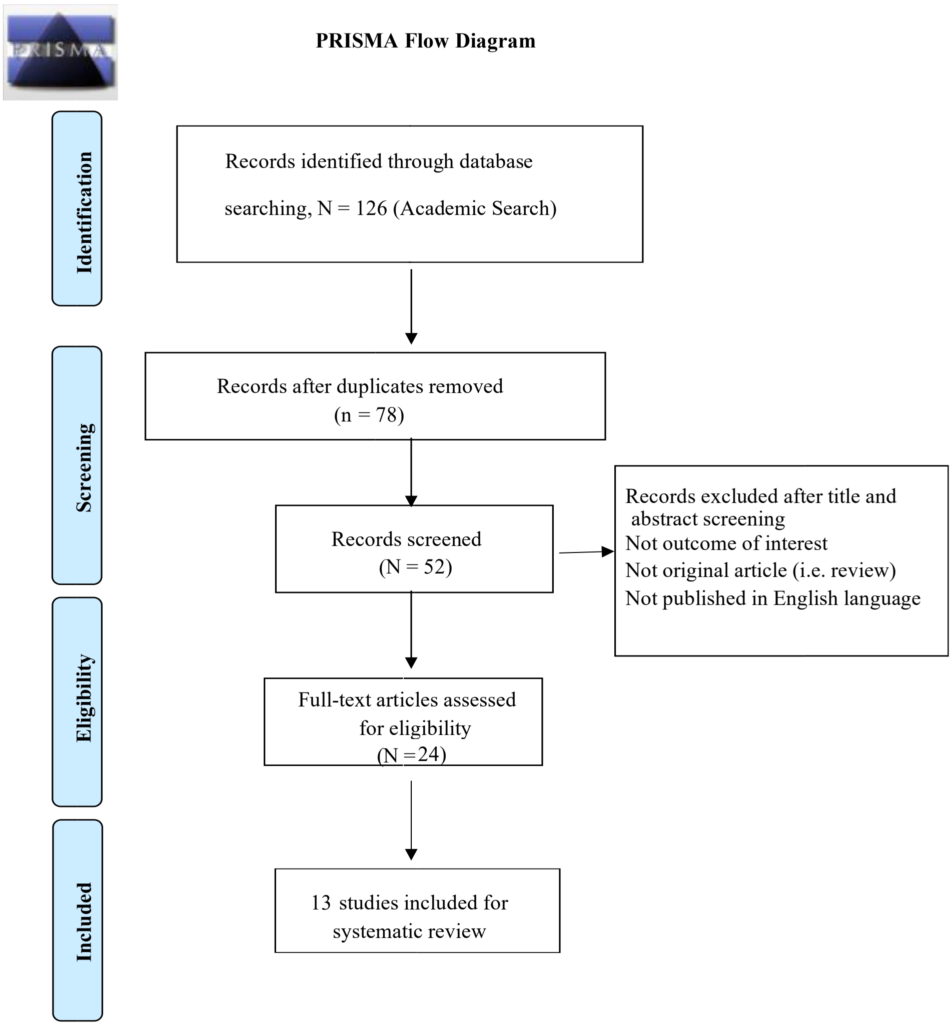

Fig. 5 *PRISMA diagram*

2.2 Inclusion and Exclusion Criteria

As a result, when discussing the inclusion and exclusion criteria, we shall discuss the types of papers that must be included and those that must be excluded. Therefore, the papers we will submit for this SLR must address topics such as Multi-Agent Systems, Mobile Edge Computing, autonomous vehicles, emergency response, Intelligent Transportation, and dynamic traffic management.

- Criteria for Inclusion
  - Peer-reviewed journal articles, conference papers, and theses that focus on the application of Multi-Agent Systems (MAS) and Mobile Edge Computing (MEC) in Intelligent Transportation Systems (ITS).

- Peer-reviewed journal articles, conference papers, and theses that focus on theoretical frameworks, algorithms, or methodologies involving MAS and MEC in traffic management, vehicle coordination, or related areas.
- Date from 2010 to the present.

- Criteria For Exclusion
  - Remove the non-English paper.
  - Not having valid findings.
  - Not related to the topic.
  - Studies published before 2015.

3. Findings and Results

Every research paper was analyzed and summarised in Table 1 according to the study domain, methods, results, and limitations.

Table 1 *Efforts in constructing and expanding the Arabic ontology*

Reference	Study Domain	Methods	Results	Limitation
Buzachis et al. [24]	Smart city, improving traffic flow and safety in smart cities	IoV, MEC, MAS	It presents the integration of multiple cutting-edge technologies to address pressing urban transportation challenges.	The evaluation did not adequately address real-world environments, the solution's scalability, and the experimental nature of the blockchain implementation.
Yuan et al. [12]	ITS, optimizing traffic flow and road safety within the IoV through a dynamic controller assignment	IoV, MAS	The study highlights significant contributions in reducing network latency and enhancing data packet management.	The limitation is represented by scaling controller resources under peak load conditions.
Zhou et al. [7]	ITS, to optimize traffic signal control across a network to enhance traffic management, aiming to alleviate urban congestion	IoV, MAS	The study breaks down the complexity of managing multiple traffic lights into more manageable, decentralized tasks.	It assumes consistent vehicular communication capabilities, which might not be accurate in all real-world scenarios.
Zhang et al. [25]	Smart city, dynamic and demanding nature of smart vehicle networks which vary in their capacity and computational demands	IoV, MAS,	It shows improved task offloading efficiency and reduced computational costs, contributing to optimizing vehicular networks.	The evaluation did not satisfy the requirements for adapting to highly dynamic network conditions.
Zhou et al. [26]	Smart city, optimization of task offloading decisions in MEC networks	IoT, MEC MAS	It can handle MEC environments' complexity and stochastic nature effectively, leading to improved system performance.	The assumptions on queueing dynamics and wireless channel conditions may not always hold true in real-world scenarios.

Wang et al. [27]	ITS, alleviating urban traffic congestion through CEC	IoV, MEC, MAS	It demonstrates the utility of MAS and DRL in optimizing traffic flow in an urban setting, underscoring the potential for scalability and adaptability in diverse traffic conditions.	The scalability of the solution across different urban layouts and the computational demands of such systems are acknowledged as limitations.
Xu et al. [28]	ITS, optimizing computation offloading with traffic flow prediction in the IoV environment	IoV, MAS	It reduces energy use and delays, validated through comparative experiments against other methods.	Implementing the proposed models and algorithms in diverse IoV environments is highly complex.
Wang et al. [29]	Smart city, minimizing delays for both V2I and V2V communications	IoV, MAS	The improvements in reducing transmission delays highlight the potential of MAS in optimizing IoV network operations.	It suggests that integrating EC can further refine the model.
Shinde et al. [11]	Smart city, optimization of network-wide latency and energy consumption in a multi-service IoV environment.	IoV, MEC	It significantly enhances computational offloading efficiency in IoV environments.	The increase in the number of vehicles and service demands may lead to more complex problem spaces that are harder to optimize in real-time scenarios.
Cai et al. [30]	ITS, optimization of traffic flow and road safety through enhanced vehicular perception	IoV, MAS,	It improves service migration efficiency and resource management in IoV scenarios.	The evaluation did not satisfy the applicability and efficiency in diverse operational contexts and real-world settings.
Shao et al. [31]	ITS, collaborative intersection driving decisions for connected and automated vehicles	IoV, MAS	It promotes safer and more efficient traffic flow of automated vehicles in IoV environments.	There is a need for further exploration into the cooperative interactions and system integrations within larger IoV environments.
Chen et al. [32]	Service migration for MEC in transportation networks	MAS, MEC	Reduced service delay and improved Quality of Experience (QoE) for mobile devices traversing different edge zones	Simulation-based evaluation; scalability in highly dynamic, real-world traffic conditions remains untested
Yi et al. [33]	Edge–cloud collaboration for mobile automation with potential application in ITS	ITS, MEC	Achieved task success rates comparable to cloud-only frameworks while significantly reducing communication overhead and token consumption	Validated on mobile automation tasks; direct application to ITS (e.g., vehicle coordination) requires further investigation

The research of Zhou et al. [7] focuses on the improvement of task offloading in MEC networks via a multi-agent, distributed method where queue dynamics are incorporated. The work for which we give this context belongs to the broad category of IoT applications, within which task offloading is so important because of the stochastic dynamics of task queueing and wireless interference. The key problem is concerned with the system of optimization of the offloading decisions in the multi-agent case without using a centralized, coordinated system, which implies the problem of unpredictability of the network queues as one of the interfering factors, as well as the wireless communications interference on the agency in question. The authors introduce a new optimization model that makes the best utilization by choosing the most suitable offloading thresholds of multiple agents. They apply a game-theoretical rigmarole and a distributed best-response iterative optimization scheme, thus providing a basis for the functionality of decision-making on a decentralized level. The presented framework is evaluated by simulating results in favour of this method over the distributed techniques and comparing it to the centralized approaches. The research has modelled the offloading threshold optimization in a game-theoretical approach and used a best-response method for decentralized optimization. The simulations provide a testing ground where the method is verified with metrics such as offloading success rate and system-wide performance. The model has the capacity to handle complexity and uncertainty, which are important features of the MEC systems. As a result, shifting towards better performance and quality is possible. Nevertheless, the workboat research also acknowledges limitations, such as assumptions about line queuing and wireless channel models, which may not always hold true in real-world scenarios. Such work fills this gap by designing a fault-tolerant algorithm for IoT networks, which is very useful for environments where centralized coordination is challenging. It portrays such endeavours, and thus, it encourages research into models that are more ideal and strategies that respond adaptively to network changes.

In their study, Shinde et al. [11] discussed the IoV domain, aiming to minimize overall latency and energy consumption in a multi-vehicle environment. The central issue associated with this problem is optimal RSUs placement and computation offload among the vehicle nodes for the given number of vehicles. In fact, they developed an approach involving collaborative Q-learning that allows for V2I and V2V communications. The action and state spaces are facing a high dimensionality problem. The DQN approach supplements this method. Models were experimented with a Python-based simulator with ML libraries such as NumPy and Pandas, which were loaded into the simulator to run simulations of different vehicular network cases and measure the latency and energy metrics. The results obtained had such an effect, as the new approach was much better than the traditional one in terms of latency and energy consumption. The study presents a new algorithmic solution that effectively accelerates traffic offloading in V2X communication. Nevertheless, the scalability of the solution has a drawback as it becomes more shared; the number of taxis and service demands grows, which could cause an increase in the complexity of the optimization problem-solving that will be harder to achieve in a real-time environment.

Yuan et al. [12] focus on pipeline optimization through a dynamic controller, assigning multi-agents based on deep reinforcement learning. Our research is situated in the SDN-IoV domain, which concerns the use of intelligent software defaults for incident handling and ensuring that vehicle traffic flow rates and movements are efficient. The approach constructs the problem set as a MAS with MDP dynamics. Cooperative multiple-agent deep reinforcement learning (MADRL) is then used to dynamically assign controllers based on on-site real-time vehicle location and network traffic information. Their proposed approach relies heavily on simulations based on actual vehicle mobility data and shows that their model outperforms conventional methods when tested on real-world situations in terms of time lags and dropped packets. The study also revealed enhanced system performance and high reliability, which are essential features of ITS applications, such as security-critical applications. The study focuses on more essential tasks, such as data transmission delay and data packet security, but also has weak points related to the controllers' load during peak traffic.

The work of Buzachis et al. [24] falls within the scope of ITS, focusing on the development of a new Multi-Agent Autonomous Intersection Management (MA-AIM) system that aims to achieve safety and smooth traffic in smart cities. This scheme is based on V2I and I2V communication systems. They are advanced by MEC and blockchain technologies to coordinate urban traffic lights more effectively and securely. The proposed system comprises an Intersection Manager Agent (IMA) that communicates with vehicles through Driver Agents (DA) and aims to ensure that vehicles pass an intersection safely without disturbing other traffic. Blockchain, in general, becomes important for providing a secure and reliable platform for the orchestration of the entire process, as it makes it impossible to modify the system and makes it more resistant to failures. A proof-of-concept implementation shows the full spectrum of the solution by integrating these functions into the existing simulators and conducting initial experiments. These experiments demonstrate the system's ability to reduce congestion and enhance overall traffic flow management by highlighting the importance of blockchain in providing additional assurance and security. The paper describes how the latest computational technologies, when integrated into traditional traffic management systems, can have numerous positive effects on the town's road network. However, it also mentions the challenges posed by the complexity and resourcefulness required to put such advanced systems into real-world practice. The contribution of this thesis stems from the application of the latest technologies in a given field, which enables the resolution of the most pressing problem concerning urban transportation, despite the limited scale and immaturity of the blockchain implementation.

The research by Zhang et al. [25] is conducted on the subject of Vehicular Edge Computing (VEC) and Networks that apply the technologies of Digital Twin (DT) and MAS and DRL for the purpose of improving vehicular connections and EC efficiency. The first thing worth mentioning is that smart vehicle networks are designed for dynamic environments, which is why their capacities vary; they depend on the computational demands. The scientists developed a model that utilizes a DT to imitate and predict fringe service needs, while allocating duties and resources according to the MAS learning principles. In addition to the data set, which simulated real city traffic conditions, they also included an evaluation scan of their model to ensure its applicability in real-life scenarios. The results establish the trend of task offloading, loading improvement, and reduction in computational costs, thus demonstrating the scientific fundamental nature of their work in optimizing vehicular networks. In addition to the study, some caution is also necessary due to the weakness in adapting to a fast-varying network environment, which requires some improvements.

The work by Zhou et al. [26] aims to improve traffic light control in the V2X ecosystem by utilizing decentralized reinforcement learning on the edge (DRLE). It achieves this through the collection of real-time data from vehicles and roadside units, aiming to enhance traffic management in urban areas and reduce congestion. The study brings in a new DRLE model characterized by the use of MAS with RL algorithms for optimizing traffic signal control across a given network; consequently, the system is decomposed into several simpler systems, each dedicated to a specific aspect of traffic control. The system's effectiveness was demonstrated by performance statistics from simulations, which clearly showed that several state-of-the-art methods were significantly outperformed in terms of convergence speed and training efficiency. Significant contributions have been made to traffic management at the ground level, and the model has been proven correct through traffic flow simulations. Nevertheless, this investigation does not examine the scalability feature with different urban planning systems, and it expects that the vehicles' communication abilities will always be homogeneous. It is possible that the drivers do not actually use the same protocols for their vehicles. This constraint means that the system is similar to that in different capital cities or under varying network performance conditions.

The study by Wang et al. [27] is about the application of the IoV and offloading urban traffic congestion with CEC. The problem being addressed is the issue of traffic efficiency in the social IoV environment, which is complex due to factors such as the heterogeneity of the network and the mobility of the vehicles. The solution entails applying MAS and DRL to ensure that the MEC servers interact with the IoV and traffic lights properly. This system strives to produce green waves at the intersection that flow at different speeds/rates to minimize the vehicles' waiting time at signals. The implementation is performed by the utilization of simulations via a CEC-backed traffic management system (CEC-TMS) targeting DRL strategies throughout city-wide Mobile Edge Computing servers. The mentioned study indicated that the model could do just this by considerably cutting down on average waiting times, demonstrating that a sensor distribution management system using edge computing can be effective. The impacts include the utility of MAS and DRL for optimal traffic flow in an urban environment, which also points out the scale and versatility of diverse conditions. Nonetheless, the scalability of the solution across various urban landscape plans and the maintenance of high-performance systems in this case are the realized limitations.

The work of Xu et al. [28] deals with the study of the optimization of computation offloading in an Internet of Vehicles environment. The concern is centering around achieving a similar effect using EC, which allows data mobility to proximate servers for optimal performance. The paper introduces a graph-weighted convolution network (GWCN) for traffic flow prediction and employs a deep deterministic policy gradient (DDPG) method to optimize offloading decisions. Such an approach could be useful to avoid high energy consumption and delay development, which can be confirmed by the study in which their method is compared with other methods. The research focuses on the benefits of exploiting such data by combining it with sophisticated modeling techniques in order to sort out the difficulties of real-time computing involved in intelligent transport systems. The research is a response to the vehicles' vital data processing issue, which indicates that priority resource allocation and predictive modeling elements are necessary tools for contemporary transport systems.

Wang et al. [29] studied the designing of communication efficiency in vehicular networks by dealing with edge information-sharing delays. Focused on minimizing delays for both V2I and V2V communications: the study's objective is delay reduction, and individual delay reduction is the main one within the PPO-based MAS-RL framework. The methods are validated through a comprehensive set of simulations to show comparisons to the perturbed and baseline models. Findings present a remarkable decrease in delay times that MAS may be, to a large extent, helpful in increasing the level of IoV network effectiveness. The article indicates how the model dealing with delays in communications is practical, yet more studies could focus on incorporating/incorporating EC to refine the model.

The research of Cai et al. [30], published recently in the domain of IoV, especially on enhancing traffic flow optimization and road safety through improved vehicular perception, is being discussed here. The research takes on the challenge of the poor unsensed perception of the individual vehicle, and with the help of emergency communication along with V2I communication, it is able to provide a cooperative perception. Thus, the dynamic extraction and transfer of interim perception characteristics remove barriers such as buildings and vehicles, preventing the exactness of the sensor data from being spoiled. To handle the computation responsibility of edge servers, this study has employed a MADRL framework that can optimize resource allocation. The graph model employed in this model is specific and varies with time. It effectively and efficiently schedules and migrates perception services such as perception data analysis and response to ensure minimal end-to-end latency and maximize utilization of the resources. The offered approach shows great progress in sense migration speeds and resource management, which validates its possible relevance to autonomous driving applications to increase responsiveness in real-time. It is worth highlighting the novel utilization of reinforcement learning with multi-agent dynamics for service scheduling in mobile edge computing infrastructure and introducing a graph-based approach to model and optimize service interactions and migrations. Yet the paper underlines that using complex simulation models in real-world environments is complicated, thereby putting forward the requirement for more work in terms of shaping this type of framework to be applicable in various operational scenarios.

The research article from Shao et al. [31] puts forward a suite of traffic management tools in the IoV context, which refers to intelligent transportation system communications with connected and automated vehicles to enhance the safety and efficiency of autonomous intersections. The solution's core deals with the implementation of real-time and coordinated decision-making for traffic lights at unsignalized intersections (without lights) by 6G technology to leverage the system's capacity and maintain safety. The proposed methodology is based on a multi-agent reinforcement learning (MARL) approach, including a parameter-sharing mechanism within an efficient Proximal Policy Optimization (PPO) algorithm that is adaptable to a dynamic setting of intersections and places extra emphasis on local reward systems in order to make learning more efficient and scalable. In practice, the approach is tested through extended simulations that prove its capacity to reduce travel time and collision rate during high traffic conditions, making traffic flow safer and more effective. The study illustrates the algorithm's potential role in managing intersections embedded in the IoV. At the same time, it also pinpoints the need to clarify cooperation between components and integrate components into more complex designs of IoV environments.

4. Discussion

The MEC design serves as the framework for bringing cloud computing capabilities and the IT service environment close to the edge of the network. The MEC principle involves placing computing units, data storage, and intelligence closer to where their functionality is needed and as close to the edge of the network as possible, adjacent to where the data is being generated [10]. Therefore, it drastically decreases delay, promotes the use of large bandwidth, and improves the overall network performance because nearby cloud servers are avoided, and data is processed locally. MEC provides support for various services and applications, including those that utilize real or near real-time processing by decentralizing process tasks and reducing the distance data must be transmitted [26]. Such practice is beneficial in all areas of IoV, where rapid response leads to improved management, safety, and user satisfaction. MEC-based technology enables organizations to create more reactive and context-aware services that promote innovation, which are highly data-intensive and require rapid processing and analysis close to the edge of the network [22].

Under the IoV scheme, MEC serves as a crucial component responsible for processing and analyzing the large quantity of data produced by vehicles and infrastructure. MEC closes the gap between primary computational resources and data sources, thereby lowering latency, a prominent feature in real-time functions of IoV, namely automated driving and traffic governance systems [34]. This closeness enables immediate data processing and decision-making at the edge of the network, enhancing the facility's ability to respond quickly in dynamic traffic situations and address potential safety issues. Furthermore, IoV scalability is advanced as MEC relieves the core network of supporting data transmission. Hence, the distributed data computing continues [29]. Through this, the response and effectiveness of IoV services are significantly increased, ultimately leading to new possibilities, such as advanced analytics and AI-driven insights into traffic patterns, vehicle behavior, and predictive maintenance, which contribute to better safety and increased fluidity for transportation systems [13].

MEC applies a set of algorithms and technologies to data processing, data exchange, and data management in real-time to make the traffic management process more effective. Such programs demonstrate that the MEC, providing processing power close to where data is used, brings numerous benefits for traffic management, resulting in enhanced efficiency, safety, and overall quality of driving. The MEC applications include real-time traffic monitoring and management [34], enhanced safety systems [24], autonomous vehicle support [35], emergency vehicle prioritization [36], intelligent parking solutions [37], predictive traffic analysis [38], and data offloading [26].

The term MAS represents a type of computing architecture where autonomous agents, capable of deciding, acting, and interacting within a common environment, work together. The essence of these decentralized systems is that each agent is capable of performing their own task autonomously, yet collectively fulfilling the system's purpose [34]. The agents have sensors that allow them to perceive the outside world, actuators to take actions, and routines to make decisions based on the information they process [34]. MAS embodies the skills of communication and teamwork with other agents, enabling them to solve complex problems more intricately than can be done by a single agent. The capacity to work jointly is integral, particularly in dynamic and complex environments such as traffic management in the IoV, where instant and interactive interventions are vital. MAS's inherent flexibility, scalability, and robustness make them great tools for applications that require distributed coordination and intelligence. Example: automated traffic systems to smart grid management and beyond. Thus, they might be a key element of the future where technology will change in many domains [39].

MAS has been applied in the IoV and traffic coordination fields, contributing to new public transportation concepts that utilize different types of physical vehicles. Such applications demonstrate that MAS can influence IoV and traffic coordination by leveraging distributed intelligence and cooperation to solve complex traffic management problems. The result is improved transportation system performance. Here's a concise overview of MAS applications [12]. The MAS applications include traffic flow optimization [12], accident avoidance and safety [7], emergency vehicle routing [40], real-time information sharing [23], autonomous vehicle coordination [38], and environmental impact reduction [28].

Although these advancements bring some efficiency, widespread use of these technologies in conjunction with the large number of participants and the range of unpredictable urban environments is a major challenge [45]. Besides, the integration complications and the high computational power of the latest AI algorithms represent some restrictions that are encountered in real-world implementations. The overarching theme that correlates with all these studies is that IoV can better leverage distributed computing, group decision-making, and advanced data analysis to foster safety and functionality in the system. They point to the capacity that these technologies have to change the way urban transportation operates as we know it and are already laying the foundation for future-oriented and robust city transport systems.

In an environment where decision-making power is decentralized, like in IoV systems utilizing MAS and MEC, there is a risk of inconsistent decisions, failure, complexity, and inefficiency. These issues can arise due to several factors: These issues can arise due to several factors:

- Incomplete information: The IoV entity operates based on the information that is locally available in the network. Moreover, this may include only a limited part of the network's state. Such a scenario may lead to local decisions that prove efficient, but from a broader perspective, they may be inefficient and even a bad idea.
- Different objectives: The IoV system will operate under conflicting or differing objectives and priorities. For instance, a simple scenario of an ICV regulating traffic flow can be prioritized to be congestion-free, whereas an emergency system can be designed to give way to emergency vehicles even if it results in traffic being delayed, creating a situation with contradictory behaviours.
- Communication failures: Communication is a vital and active factor in the convergence of decisions among IoV entities. Miscommunication in communication networks could provoke different versions of shared information, causing early detection illusions.
- Edge computing complexity: Along with the spread of edge computing in the context of IoV, the fulfillment of management tasks connected with edge nodes and their protection represents an important challenge. This requires the development of novel frameworks to manage edge computing resources efficiently.
- Training and learning: Besides, there is a need to investigate the algorithms to improve the training and learning for IoV purposes that would have high potential applications in traffic management and forecasting accidents.
- Advanced simulation models: Reliable simulation models that can more appropriately reflect the dynamics of real-world IoV systems will be more useful in creating and testing new IoV applications and concepts without the risk of jeopardizing the established infrastructure.
- Energy Efficiency: As the IoV grows, more energy is required to support its activities. The interdisciplinary study of energy-efficient communication protocols and systems is required to scale the Internet of Vehicles (IoV) in an environmentally sustainable way.

The management of road flow and assurances of road safety within the inter-vehicle communications environment are challenged by a wide range of complex issues, which can be tackled by applying IoV, MEC, and Collaborative MAS. As for the primary problem, it relates to scalability. The rise in the number of connected vehicles will also increase the workload of the overarching IoV infrastructure, resulting in the need to process a large volume of data efficiently. A benchmark function that prevents the system from being flooded may cause delays in traffic management and emergency responses.

Delays are another major bottleneck; a high delay in an IoV environment can hinder the real-time data processing required for swift decision-making and action. The failure to make quick decisions and take prompt actions can be disastrous for road safety and efficient traffic management. Moreover, the interoperability problem of different device manufacturers and systems needing to interact smoothly at the same wave will result in the wide management of the whole IoV spectrum. Integrating MEC into the system allows computing power to be placed where data is produced and through devices that can perceive environmental changes, such as vehicles and road sensors. This setup eliminates latency by reducing the distance data travels, which significantly improves real-time processing and is essential for timely traffic management, safety measures, and mitigating traffic congestion. MEC also plays a role in augmenting IoV systems by moving tasks from the central data centre to edge nodes, easing the workload burden and making the system more levelled.

5. Conclusion and Recommendations

This review highlights current issues and potential solutions for managing traffic flow and ensuring road safety from the perspective of the Internet of Vehicles (IoV) system. It identified key problems, including scalability, latency, interoperability, and the need for accurate real-time computation, which could limit IoTV's effectiveness. The combination of MEC and MAS solutions offers an efficient way to address these challenges. MEC enhances the need for low delay and fast data processing close to data sources, while MAS provides the infrastructure for vehicles to make decisions directly without relying on centralized control. Additionally, the review points out major gaps that need attention, such as AI optimization for advanced systems, integrating IoV with other smart technologies, and developing energy-efficient solutions. It also emphasizes that CRS is an essential part of MAS, and that robust communication protocols are crucial for resolving decision conflicts within the local network. The review also discusses solutions for maintaining network security and user privacy, managing the complexity of edge computing devices, and establishing legal frameworks to regulate autonomous and connected vehicles. These issues highlight the importance of multidisciplinary research and development efforts. Addressing these challenges, IoV has the potential to significantly enhance urban public transportation and road safety through more sustainable and effective transportation principles. The final section stresses that IoV can transform transportation infrastructure, provided that technological, legal, and operational challenges are successfully addressed.

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Conflict of Interest

Authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Hassan Mohamed;* ***data collection:*** *Hassan Mohamed;* ***analysis and interpretation of results:*** *Hassan Mohamed, Ahmed Fakhfakh;* ***draft manuscript preparation:*** *Hassan Mohamed, Hend Marouane, Ahmed Fakhfakh. All authors reviewed the results and approved the final version of the manuscript.*

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