Multi-Agent Systems for Urban Traffic in Smart Cities

Abstract. Access to urban services has improved over the last century, leading to a higher quality of life. However, increasing heavy industrialisation and population growth have presented challenges to urban planners, architects and administrators [1]. On the other hand, the continuous development of smart cities has significantly changed the daily lives of citizens [2]. In line with a recent report, "As cities get smarter, they are becoming more livable and more responsive - and today we are seeing only a preview of what technology could eventually do in the urban environment" [3]. This concept of smart cities introduces technologies that lead to lower crime rates, health impacts and carbon emissions due to massive real-time data collection and transmission between Internet of Things (IoT) devices. Such technologies also aim to improve urban transport, which will be the object of study in this article. The goal is to analyse and compare the different approaches and solutions with multi-agent systems for urban traffic in smart cities.

Keywords: Multi-agent · Smart City · Urban Traffic · Traffic Control · Traffic Congestion · UTC

1 Introduction

Urban traffic modeling is done from different points of view and with different technologies, along different ages. In a recent article [4], the history of urban traffic control system is highlighted, starting with gas-powered signals manually operated by traffic officers to control railroads (which contained only red and green lights), through the introduction of electric-powered signals fixed from time to time, to automatic and responsive integrated systems. In the past decades, communication and interaction between the various components of urban traffic were a difficult undertaking, but nowadays with everything connected via Internet, we have the opportunity to design optimized traffic management strategies. The purpose of this paper is to explore the different solutions for urban traffic management that use multi-agent systems in the context of smart cities. "What aspects of urban traffic do these systems deal with? What are their architectures? What data are used and how do the system entities interact?" – these are the questions addressed in this article.

At first, a brief definition and characterization of the areas and fundamental concepts of this study are offered. Then, the state of art of the available solutions is explored through a quick overview of some existing projects and a more in-depth analysis of three articles that describe the proposed solutions. Finally, a comparison of the solutions under consideration is given, followed by a review of the state of art for multi-agent solutions for urban transport.

2 Definition of the Research Domain

Defining the domain of a research is crucial because it sets the scope and boundaries of the investigation. A well-defined scope characterizes the specific study area and objectives, ensuring its success and impact by allowing researchers to identify the relevant questions, methods and theories. This, in turn, leads to more efficient results and facilitates the application of findings to the field.

2.1 The concepts of urban traffic and smart cities

A notable concept covered in this article is **urban traffic**, which can be defined as the movement of vehicles and other means of transport within a densely populated urban area. Since this is a complex and multi-faceted issue, several studies have explored the causes and impacts of traffic congestion in cities, as well as possible solutions to mitigate its negative effects.

According to a study by Rizvi et al. (2020), one significant contributor to urban traffic congestion in several Indian cities is the rapid growth of urban populations [5]. As more people move to cities, the demand for transportation increases, leading to more vehicles on the road and higher levels of congestion.

Another study by Jiang et al. (2019), based on Chinese cities, indicated that poor road design and infrastructure quality are also predictors of traffic congestion [6]. However, the triggers are wide-ranging and diverse. Road maintenance, adverse weather conditions, distracted driving and other factors can equally contribute to the problem and have negative public health impacts by increasing air pollution [7] and leading to a decline in economic growth [8].

In order to mitigate the negative effects of congestion in cities, one popular solution is the use of intelligent transport systems (ITS), a technology promoted by smart cities [9]. A **smart city** is a concept that entails the use of advanced technology and data-driven approaches to improve the life quality of its citizens, promote environmental sustainability and optimize urban services. According to the British Standards Institute (BSI), smart cities are urban settlements that combine digital and human systems to provide a prosperous and participatory future for their residents [10]. Therefore, a wide collection of data, including traffic flow, energy consumption, air quality and public safety, is collected and analysed in real time by advanced monitoring systems and built-in sensors to enable informed decisions, regarding urban planning and management [11].

The integration of technologies such as the Internet of Things, artificial intelligence and cloud computing enables the simulation of intelligent behaviour to achieve consistent decision outcomes without human intervention [2]. Take intelligent traffic management systems as an example: these can alleviate traffic congestion by using real-time data to regulate traffic lights and reroute vehicles.

Furthermore, smart cities place great emphasis on citizen participation and want residents to take part in decision-making processes [11]. This way, the aim is to create a more proactive and inclusive city that gives residents the opportunity to help shape its services and, thus, foster a sense of community.

2.2 The concepts of multi-agent systems

Before contextualizing which role multi-agent systems play on the urban traffic of smart cities, let us first analyze what an agent is and the need for its existence. The initial paradigm of computing is conformed to the notion of obedience, within knowing what to do with an anticipated programming, planned by someone. However, nowadays with the exponential increase in applications (that often interact with each other), it's required systems that can decide for themselves what they need to do in order to satisfy their design objectives [12]. Such computer systems are known as agents. Gerhard Weiss still tries to formulate a definition for agent, even agreeing that there is no definitive consensus: an agent is a computer system situated in some environment, that is capable of autonomous action in this environment in order to meet its design objectives [12].

Once defined what an agent is, the concept of multi-agent systems emerges along with distributed computing. Several problems need cooperation to be solved. Others, due to complexity, require a modular structure, not always centralized. Information processing is ubiquitous. There are computer processors seemingly everywhere, embedded in all aspects of our environment. And that being said, multi-agent systems are the best way to characterize or design distributed computing systems [12].

Paul Davidsson et al. concludes that agent technology is indeed a promising approach for the transport logistics area. Often, these agent approaches are distributed and very complex by nature, such as: planning and scheduling, fleet management, transport scheduling, traffic management, and traffic control [13]. Urban traffic requires applications with the characteristics involved in a multi-agent technology: modular, decentralized, changeable, Ill-structured and complex [13]. These characteristics are justified by the high number of behaviors and interactions that urban traffic entities have, and the structure of these systems can change frequently by nature. The issue of urban traffic also distinguishes several entities with a set of state variables, including transport vehicles, traffic lights, intersections, and so on, with a well-defined actions interface in the environment [13].

Thus, as urban traffic is allied with distributed IoT devices, in the context of smart cities, with an immense amount of data exchanged between them, that needs a certain degree of autonomy to perform their tasks in real time, it is conclusive that multi-agent systems perfectly fit this theme.

3 State of Art Analysis

In this section, we will characterize some pertinent solutions that have been worked on in the field during the last decade and summarize the objectives, models, and results achieved by the proposals. Following a quick overview of several studies, some intriguing proposals will be individually explored, and all the studies will then be contrasted and resumed in Table 1.

3.1 Search criteria

Our search string included relevant keywords to the topic: "smart cities", "urban traffic", and "multi-agent systems". We limited the time period to 2010 to 2023 in order to obtain information from the last decade. The articles were searched on reputable platforms in the field of scientific dissemination, such as: MDPI, IEEE Xplore, Semantic Scholar, Springer Link and Research Gate.

3.2 Quick overview of existing solutions

In recent times, smart cities have led to develop and implement numerous multi-agent systems with the purpose of improving traffic in urban areas.

One project is the coordinated autonomous road transport system, currently evaluated in several European cities, which utilizes a fleet of autonomous vehicles to communicate and collaborate with one another to optimize traffic flow and reduce congestion. It includes a fleet management system and a virtual traffic control center that utilizes real-time data to observe traffic conditions and alter the behavior of these vehicles. In reality, using a multi-agent system enables autonomous cars to exchange knowledge while making decentralized decisions about their course of action. As a point of reference, the article [14] offers a comprehensive overview of the goals, methods and outcomes of the multi-agent system used to coordinate autonomous vehicles, as well as a critical examination of its drawbacks and advantages.

Yet there are many other techniques for dealing with this subject. In the paper by Papadopoulos et al., the authors suggest a solution for coordinating the charging of electric cars (EVs) in a manner that minimizes the cost of energy usage and guarantees that the EVs are completely charged by the time they are intended to depart [15]. They propose a multi-agent system in which each EV is portrayed as an agent that interacts with other agents to coordinate its charging schedule. The potential solution also considers the limitations of the power infrastructure and the accessibility of renewable energy sources. The document presents simulated results that demonstrate the effectiveness of this approach in decreasing the cost of electricity consumption and increasing the use of energy from renewable sources.

Because of Singapore's Mobility as a Service (MaaS) system, users are provided with a consistent and integrated transportation experience. The system mixes many forms of transportation, such as ride-sharing, bike-sharing, and public transit, into a single platform that is accessible through a mobile app [16]. To optimize the transportation network and enhance the user experience, the MaaS system employs a multi-agent system that gathers real-time data on traffic circumstances, user behavior, and transportation preferences. The MaaS system has produced positive outcomes in Singapore, including greater use of public transportation and bike-sharing programs, and improved air quality in the city.

In addition to reducing congestion, smart cities must solve parking issues. Actually, "Finding a parking space in big cities is becoming more and more impossible. (...), the emergence of car has created several problems relating to urban mobility for the city." [17]. In response to this challenge, Los Angeles has implemented a smart parking system that guides drivers to available parking spaces using real-time data. The system incorporates parking-space sensors that can recognize when a car is parked and send that information to a central database. Via a mobile application, drivers may access the data to receive directions to the closest parking spot available and to reserve it in advance [18]. This innovative technology is one of many multi-agent approaches being developed to improve the sustainability and efficiency of urban transport.

3.3 A decentralized network bimodal approach

Our first analyzed modeling of urban traffic is the one proposed by Neïla Bhouri et al. [19]. What distinguishes this work from others is the proposal of a bimodal traffic control strategy. That is, both public and private vehicles are taken into account. This results in another relevant feature of the article: it models traffic both at a microscopic level (e.g., modeling the behavior of each bus) and at the macroscopic level (modeling traffic flows). It is therefore a hybrid proposal, modeling at the macroscopic level for private vehicles and microscopically for the management of public transport.

One of the objectives of this solution is to regulate traffic not only locally, but in a whole network, not just at a single intersection. Before going into the structure and the agents used, let us understand what the study has achieved, so that we have an idea of where we want to go. The proposed multi-agent system aims to create a traffic signal plan to minimize the time that vehicles lose when stopping at traffic signals. In this way, the model has the autonomy to vary the traffic light phases to consider, for example, the urgency of acceleration of some bus routes with delayed buses. One of the results – Figure 1 – shows that the multi-agent system improves times by about 50%, compared to a fixed timing strategy at traffic lights when the number of vehicles in the simulation is varied.

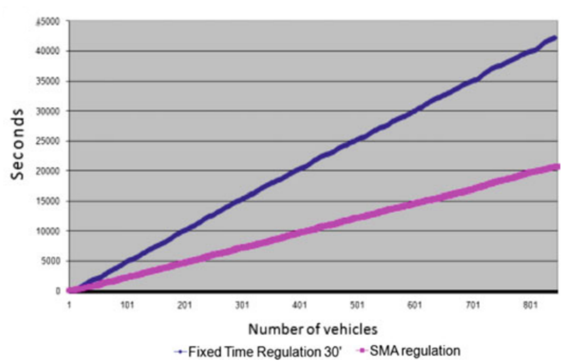

Fig. 1: Study results - fixed time vs MAS regulation [19]

Regarding the modeling of the multi-agent system, both static (e.g., size of arcs that connect intersections and the maximum number of vehicles that the arc supports) and dynamic information (e.g., number of vehicles on the arc and their average speed) are used. From the vocabulary used, another characteristic of this model can be derived: its network-based architecture through a graph where the arcs represent the “traffic lane” and the nodes represent the intersections.

Taking this into account, the following agents were used: Intersection agent, responsible for controlling an intersection with traffic lights and developing the schedule for these lights, based on the information sent by the approaching buses; Stage agent (abstraction of the public road, i.e., a set of traffic lanes), which communicates the roads’ current state to the Intersection agent, aiming to determine the optimal time of the green light to evacuate vehicles in the arcs.

In a microscopic modeling approach, there is also the Bus agent, which represents an individual vision of a bus in a particular way and on a particular route. Its goal is to reduce time at traffic lights to minimize its trips, and its behavior includes both stopping at traffic lights (as other vehicles do) and stopping to pick up carriers. The second one is important to control the behavior of the other buses on the same route. For this reason, there is also the Bus Route agent, which communicates with the buses on a route to synchronize their movements.

Considering this relationship, the bimodal micro-macro control of traffic becomes visible: “The Intersection Agent ensures a bimodal micro-macro regulation process. It calculates the plan of traffic lights according to two criteria: (1) the demand of the corresponding Stage Agents, which is based on a macroscopic modeling of the global traffic, and (2) the priority demands of Bus Agents which are based on a microscopic modeling of the buses.”

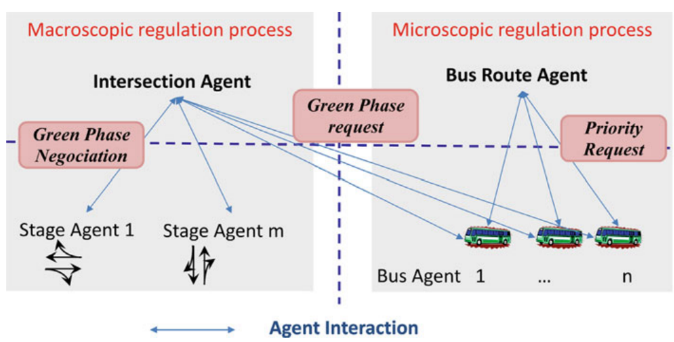

Fig. 2: Agents interaction [19]

Back to the results: in this work, the solution was simulated on the platform JADE for a small network with 6 intersections. In addition to the one already shown, another relevant result is the reduction and considered stabilisation of the times between bus stops on a route with these required priorities – Figure 3, highlighting the agents’ individual contribution in the microscopic modelling.

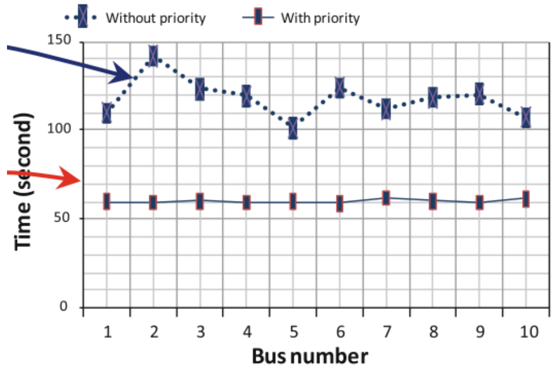

Fig. 3: Study results - Bus delay with and without priority [19]

3.4 Microscopic modeling through a market-based network

In order to explore other aspects of modeling multi-agent systems, [20] was chosen. This study explores the use of dynamic demand models and innovative methods, where Big Data and a multi-agent system are used to determine the close to optimal dynamic operation of public transport in a given area. It proposes to control traffic at a microscopic level by collecting data from sensors that track the movement of passengers in vehicles and monitor traffic flow. The distribution of the network is centralized, since this study is being done locally and there is a single entity in charge of directing the results to the designated destination, depending on the processed input it receives. The same might no longer be true, though, when seen globally.

The context of the study is a region with many small villages with low transport demand, where public transport accessibility must be ensured. The problem arises when the main lines of public transport have to provide service to these villages, resulting in complicated and confusing timetables with delays. The proposed solution is a shared and integrated dynamic public transport system that can use different types of vehicles and styles of transport, such as bikesharing and carsharing. The system is based on passengers' orders and combines different modes of transport to find an optimal outcome, taking into account the current state of traffic in the area. In addition, the study highlights the importance of considering not only buses and streetcars, but also other ways of transport, as well as the potential of walking and cycling for the last mile problem. When building a multi-agent model, the environment must be defined as:

- **Inaccessible**: the complete information about the system cannot be obtained in the moment;
- **Non-deterministic**: the effects of the agents' actions are neither certain nor intended;
- **Dynamic**: the environment evolves over time as new decisions and adjustments are made;

- **Continuous**: the number of possible actions is unlimited;
- **Non-episodic**: the agents cannot operate independently in parts, instead they depend on each other.

The input parameters are also critical in determining how the agents can respond to the environment and to each other. In this article, the input parameters are: demand, offer, infrastructure and environment.

In this multi-agent system, the goal is the dynamic creation of routes on a given graph, considering different routes that can pass through the same stops, detours and intersections. Constraints about the routes, such as their start and end points, minimum and maximum length, maximum capacity, operating price of vehicles and ticket price, are considered. The system includes a market-based architecture of the urban transportation network with three types of agents: Order agent, Fleet agent and Route agent.

The Order agent creates deliverers who have financial resources and gathers the input data from passengers, seeking transportation to analyse it and then choose the most effective and economical path for the passengers' transportation. Always aiming to fulfill as many orders as possible going in the same direction, the Order agent does this computation and then passes the results to the Route agent, which builds the route back and forth as a sequence of stops based on those results. To choose the best path, the Route agent considers the requirements of the Order and Fleet agents, as well as the accessibility of bus entities and other resources. The Fleet agent, on the other hand, must determine the travel time and cost for a route while taking into consideration the parameters for speed and the quantity of passengers to load and unload at stops. Therefore, it creates a schedule, bargains with the roads and pays for the labor. Later then, it informs the Route agent about the appropriate fleet as it identifies a certain route. The Fleet agent can also make requests to the Route agent to modify the route or fleet if needed. After accepting this amount of data, the Route agent determines the duration of the route and notifies each bus stop with the time schedule. The flow of these interactions can be described in Figure 4.

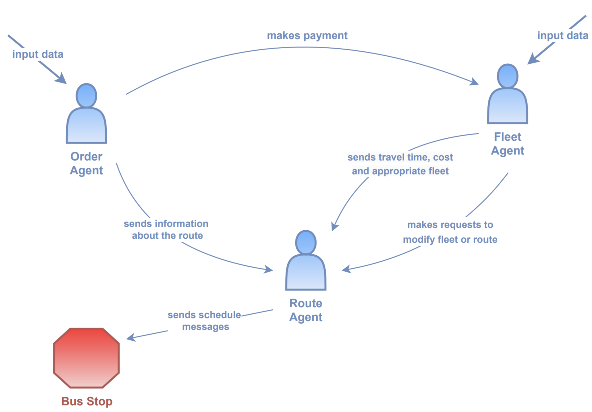

Fig. 4: Agents interactions

A negative aspect in this article was the lack of results' discussion. However, this analysis will be completed afterwards by comparing all these three studies analysed in the Section 4. In contrast, it illustrates an example of a possible, but poorly explained, outcome, where its evolution is represented in order by the Figures 5, 6, 7 and 8 and by their respective captions. Suppose that the just-emerging stops are portrayed as the red dots. Once a preliminary version of the pathways is constructed, the routes 2 (blue colored) and 4 (yellow colored) are removed since, in comparison to the other ones, they are inefficient in terms of length and cost. A reschedule is, thus, initiated. The Order agent elevates the weight for the probability of loops on route 3 (orange colored), by increasing the number of people transported or the prices at 2.

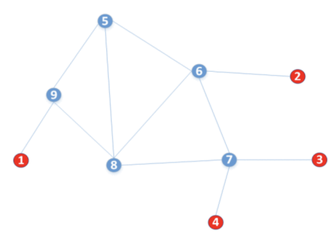

Fig. 5: Starting points of routes [20]

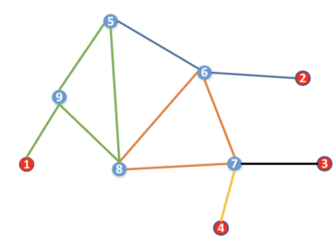

Fig. 6: Routes created after the first stage of agent's negotiation [20]

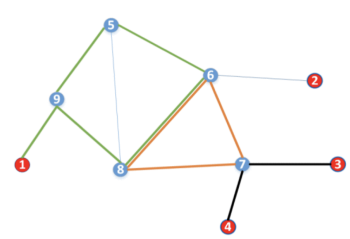

Fig. 7: Route structure after the first intervention of the city agent [20]

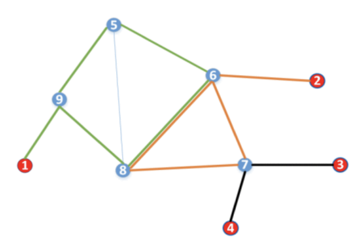

Fig. 8: Final route structure [20]

3.5 Macroscopic modeling through a centralized architecture

Compared to other multi-agent solutions, even though the general goal remains the same, which is improving urban traffic, the way it is proposed by [21] differs significantly. For this reason, we decided to cover this article to show that the diverse problem approaches using multi-agent systems can be very different.

The main difference is the specific goal of the purpose system: it is not about finding the best route or an optimal traffic light plan. Its purpose is to deal with real-time data and to notify a human expert when an anomaly occurs in terms of occupancy rates related to traffic flow, intersections and parking. That being said, we are dealing with a multi-agent system in conjunction with prediction and classification models.

The system has an agent for each task: predicting the utilization of traffic flows, road junctions and parking spaces (as pointed out earlier), and classifying errors. The conclusion that we are dealing with a decentralized architecture may therefore seem a bit susceptible. However, a closer look reveals a more "centralized" dependency due to another agent not yet mentioned – the System Monitor agent. This agent "coordinates" the other agents, i.e., it is responsible for submitting the datasets that the agents use to build their predictive models and for receiving the results of the data processed by each agent. These results are then analyzed by a human expert who can make decisions about what to do.

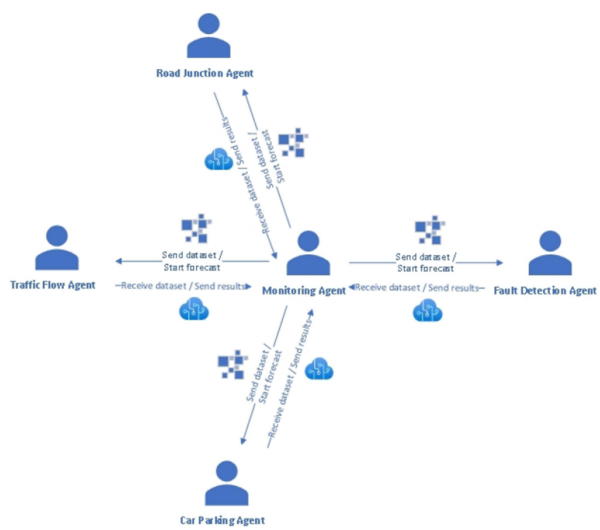

Fig. 9: Agents interactions [21]

To illustrate the practicality of this system, imagine that a dataset about a road junction is sent to the Road Junction agent to predict the occupancy of the road intersection at a given time. From this, the peak traffic hours can be inferred and, from there, the human expert can take the necessary precautions to prevent bottleneck from occurring at a particular road junction at that time.

In addition to this proposed MAS architecture, the article pays special attention to the k-nearest neighbor and decision tree techniques used for prediction and classification, which is what most of the tests and results are about. However, this is not addressed in this analysis since it is not its focus.

The platform JADE is mentioned again as it is used to simulate communication between agents. As a data source, the multi-agent system uses four real-time traffic datasets published by Birmingham and West Midlands Councils[1].

[1] Birmingham City Council decided to make the real-time datasets available for predictive traffic forecasting as an open source solution.

In short, the patterns discovered by the agents can promote different actions to optimize urban traffic management and control. A mechanism that can be realized due to the high real-time data flow generated by the sensors, as well as the MAS architecture designed to process the data as fast as possible.

3.6 Summary of each paper

The characteristics of the three studies addressed are summarized in the table 1. As can be seen, the selected studies approach the proposed problem in very different ways, each examining a particular aspect of urban traffic, which makes it even clearer how complex an "overall solution" to this issue would be.

Table 1: Summary table of studies

Paper	**Paper 1**[a]	**Paper 2**[b]	**Paper 3**[c]
Bimodal traffic control	Yes	No (Public only)	Yes
Micro-Macro level	Micro/Macro	Micro	Micro/Macro
Local/Global traffic	Local and Global	Local	Global
Static/Dynamic	Static and Dynamic	Dynamic	Dynamic
Agents	• Intersection; • Stage; • Bus; • Bus Route.	• Order; • Route; • Fleet.	• Traffic Flow; • Monitor; • Road Junction; • Car parking; • Faults detection.
Architecture	Network-based	Market-based	Subordination
Distribution	Decentralized	Centralized	Centralized

[a] "An agent-based computational approach for urban traffic regulation"
[b] "Dynamic Public Transport in Smart City using Multi-agent system"
[c] "Multi-Agent System for Intelligent Urban Traffic Management Using Wireless Sensor Networks Data"

4 Conclusions and Critical Analysis

The papers that were more carefully studied demonstrated various applications of multi-agent urban traffic systems in smart cities. From our point of view, articles 3.3 and 3.4 benefit more from a multi-agent system that is directly involved in urban traffic and is characterized by a number of interactions, as opposed to 3.5, which can be seen as a slave system that responds to a central process without necessarily having the "DNA" of a multi-agent system.

The absence of simulations of events that put these technologies into use was another thing we confirmed from these three articles. Regarding 3.3, only a scenario with 6 junctions and 2 bus routes was used for the experiment. However, no experiment was ever performed in the instance of 3.4 to simulate the outcomes of the object of study. The modeling of the multi-agent system was not well addressed in article 3.5, but even so, such a system does not provide a solution or automatic decisions based on the data processed by the agents. In other words, once the result predictions have been received by the Monitor agent, the multi-agent system is no longer useful and it is up to a human to continue the analysis process.

3.3 has the benefit of dealing with both traffic optimization for public and private cars, which is in line with the autonomous management of urban traffic. Yet, since public transportation is managed by the traffic entity (Bus Route agent), only explicit interactions between agents and public vehicles occur there. This implies that private transport do not fully profit from this technology on an individual level. This turns out to be a concern for two reasons: so far, these cars are currently dependent on the drivers' choices and each choice does not always include the same destination. The maximum potential of MAS technology may not be achieved until autonomous cars are fully integrated into society.

Real-time data collecting is a crucial component shared by all of these three papers. Every proposed solutions rely on real-time data transfer between agents, whether they are measuring the number of vehicles on a particular route, the number of people transported by a vehicle, or the occupancy stats of a parking lot. Consequently, the notion of IoT, which is being achieved with the introduction of smart cities, and the viability of this MAS technology are intrinsically related. The success of these models is thus challenging in the absence of an abundance of technological resources.

Contrary to what we previously assumed, there are many aspects of urban traffic that go beyond figuring out the optimal routes for vehicles. In reality, the prediction of peak hours, especially the management of traffic light cycles is an important factor in the modeling of these systems. Therefore, modeling multi-agent systems for the management of traffic signal lights with complex simulations scenarios is a suggestion for future work.

Acronyms and Abbreviations

UTC Urban Traffic Control
IoT Internet of Things
MAS Multi-Agent System
BSI British Standards Institute
ITS Intelligent Transport System
EV Electric Vehicles
MaaS Mobility as a Service

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