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A Fuzzy Logic Supported Multi-Agent System For Urban Traffic And Priority Link Control

Abdelouafi Ikidid
(Cadi Ayyad University Marrakesh, Morocco,
https://orcid.org/0000-0002-7850-639X, a.ikidid@gmail.com)

Abdelaziz El Fazziki
(Cadi Ayyad University Marrakesh, Morocco,
https://orcid.org/0000-0002-0302-234X, elfazziki@uca.ma)

Mohammed Sadgal
(Cadi Ayyad University Marrakesh, Morocco,
https://orcid.org/0000-0002-1087-0988, sadgal@uca.ma)

Abstract: Artificial technologies are rapidly becoming one of the most powerful and popular technologies for solving complicated problems involving distributed systems. Nevertheless, their potential for application to advanced artificial transportation systems has not been sufficiently explored. This paper presents a traffic optimization system based on agent technology and fuzzy logic that aims to manage road traffic, prioritize emergency vehicles, and promote collective modes of transport in smart cities. This approach aims to optimize traffic light control at a signalized intersection by acting on the length and order of traffic light phases in order to favor priority flows and fluidize traffic at an isolated intersection and for the whole multi-intersection network, through both inter- and intra-intersection collaboration and coordination. Regulation and prioritization decisions are made on real-time monitoring through cooperation, communication, and coordination between decentralized agents. The performance of the proposed system is investigated by implementing it in the AnyLogic simulator, using a section of the road network that contains priority links. The results indicate that our system can significantly increase the efficiency of the traffic regulation system.

Keywords: Fuzzy Logic, Multi-agent modelization, Priority vehicles, Priority links
Categories: H.3.1, H.3.2, H.3.3, H.3.7, H.5.1
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1 Introduction

Artificial transportation systems (ATSs) have evolved significantly following the development of artificial intelligence and computer technology. Otherwise, the transportation systems are major factors affecting urban areas, which not only influence the overall cost of community mobility but also play a key role in society and the economy. According to United Nations, two-thirds of the world's 9.7 billion people will reside in urban areas by 2050 [US/DESA, 2021]. This growing urbanization increases the number of vehicles seeking to use the road infrastructure and puts traffic and mobility infrastructures under a specific challenge. An optimized transportation system can therefore support many aspects of life in metropolitan areas and provide better services for road users. Moreover, Promoting the use of public transport can significantly increase infrastructure capacity and alleviate the phenomenon of congestion. In this paper, we combine agent technology and fuzzy logic to design an intelligent traffic signal regulation system that controls traffic flow at multi-intersection network and prioritizes certain vehicles using priority links.

Agent technologies have been widely accepted as one of the most responsive tools to deal with distributed systems. That's why agent-based systems are well suited for the traffic and transportation domain, since these systems are geographically distributed in a dynamic environment [Chen and Cheng, 2010]. Moreover, the intersections environment is characterized by uncertainty, fuzzy circumstances, inexact data, and typically controlled by rules, which make fuzzy logic suitable for handling the control of a single intersection [Collotta et al., 2015].

With this being considered, we develop a decentralized multi-agent system (MAS) to regulate traffic signals and prioritize certain vehicles using priority links. The proposed traffic signal control system (TSCS) uses fuzzy logic to deal with the uncertainty in traffic road data, and is based on an MAS architecture with two levels of collaboration: inter-junction and intra-junction collaboration. In this approach, each group of agents is assigned to a signalized intersection and has full control over the local streams, while control over the whole intersection network is fully distributed, and is accomplished through collective coordination between groups of agents.

The aims of the proposed system are to reduce the travel time, to promote the use of public transport, and to maximize the road network throughput. Our work makes three main contributions: (i) real-time optimization and traffic monitoring are applied to allow the system to frequently adapt to the continuously changing traffic conditions; (ii) two levels of coordination are used with parallel tasking: intra-junction coordination (which allows for interactions and collaboration between the agents controlling a given intersection) and inter-junction coordination (which permits collaboration between adjacent intersection control groups); and (iii) specialization is used, in which each agent in the system plays a specific role; this develops the adaptability of each agent to the required tasks, and allows to give the agent a more structural and behavioral feature to improve its efficiency and master its roles.

The rest of the paper is organized as follows: Section 2 introduces the proposed system and the methodology applied. Section 3 describes the implementation phase of the methodology and reports the performance of our proposed system. Finally, section 4 summarizes the results and suggests directions for future work.

2 Related works

In what follows we analyse and discuss relevant studies that use a multi-agent system and artificial intelligence techniques to perform intelligent traffic signal control and priority vehicles management. Additionally, we present any aspect beneficial to realizing our research.

2.1 Adaptative Urban Traffic Control with priority

Pre-timed signal control cannot adapt to the non-stationary traffic state. It has been a while since interactive system control became a trend in traffic management. The first appearance of adaptative traffic control was in the last decade of the second millennium, with the release of the cycle and offset optimization technique (SCOOT) in the 1980s, the Sydney cooperative adaptive traffic system (SCATS), and the green link determining (GLIDE) system. Thereafter, these adaptative control systems were implemented in many countries to manage traffic control in metropolitan areas, and others have been developed, such as RHODES [Mirchandani and Head, 2001] and TUC [Diakaki et al., 2002] (for a review of the self-adaptive traffic signal control, see [Wang et al., 2018]). The Green wave system is one of the initial approaches providing the priority in these control systems[Mittal and Bhandari, 2013], this approach aims to fluidize the priority vehicle path by turning all the red signals to green ahead of the vehicle, thus generating a route without stop time to the desired vehicle. In addition to the green wave path, the system will track a stolen vehicle when it passes through a traffic light. Moreover, the system will be able to track any type of vehicle. Nonetheless, the green wave path presents some limits when the wave is asynchronous, which disturbed the whole traffic network and may overload the infrastructure. Also, this priority system doesn't take into consideration the impact of signal intervention in the roads surrounding the green travel path.

Karmakar et al [Karmakar et al., 2021] designed an intelligent emergency vehicle priority system by assigning to each priority vehicle a priority level based on its task and estimating the number of necessary signal changes while considering the impact of those changes on the road traffics surrounding the priority vehicle's travel path. However, it is not clearly mentioned if the system considers the dynamic changes in the traffic environment after designing the traffic strategy and determining the optimal route for the priority vehicles.

In [Ariffin et al., 2021] the authors propose a real-time emergency vehicle priority system based on radio frequency identification (RFID) readers, the system adjusts frequently the cycle layout to enable priority vehicles control. The proposed system consists of three modules; (i) the traffic light control module defines the cycle length based on the lane density; (ii) the emergency RFID module to handle priority vehicles approaching the intersection; and (iii) the internet module allows the management of traffic light signals by an authorized person. However, this model supports only the vehicles with an RFID tag attached and ignores other vehicles.

Other research investigates the prioritization of adaptive traffic management methods. Deveci *et al.* [Deveci et al., 2021] propose an efficient fuzzy combined compromise solution (CoCoSo) model based on the logarithmic method and power heronian function for solving the advantage prioritization of real-time traffic management methods. According to this study results, integrating autonomous vehicles into other traffic management systems is the best method for real-time traffic management compared to five others traffic management methods which are dynamic speed limits, lane control systems, variable message signs, ramp metering, and traffic diversion. This comparison is based on economic, public and political, environmental, and traffic safety criteria. Despite advantages of the autonomous vehicles, the use of such vehicles presents many complex concerns and issues. Moreover, reducing carbon emissions should be selected as the first criteria to reach an optimized transport Strategy [Pamucar et al., 2021], also an Interval Agreement Approach (IAA) should be utilized to prioritize and evaluate such management projects [Deveci et al., 2020].

2.2 Multi-agent systems and fuzzy logic for traffic signal control

The most appealing characteristics for an MAS used in traffic and transportation management are autonomy, collaboration, and reactivity [Evans and Elston, 2013]. Agents can use perceptive data and received information from other agents to achieve their goals. Each agent can cooperate with neighboring agents and adjust its reaction online to its surroundings' changes. Thus, multi-agent technology treats a complicated system in a distributed manner. It splits the complex control system into a simple subsystem, therefore permitting parallel and fast decision-making [Evans and Elston, 2013]. Moreover, agents can run, learn new contexts and skills, and make autonomous decisions in the complete or partial absence of human supervision.

Many studies have reported using a hierarchical scheme [Roozemond, 2001][Abdoos et al., 2013] to manage the traffic signal, where agents are arranged in a tree-like architecture with two levels: top-level agents known as authoritative agents and bottom-level agents that interact with other agents via their upper agents. The authoritative agents have an overview of the system and treat much data coming from low levels. This hierarchical model can limit the autonomy of the agents; agents at the bottom level work to achieve goals given by top-level agents. Hence, more flexible coordination mechanisms need to be reached [Bazzan and Klügl, 2013]. Jin and Ma, [Xu et al., 2018] introduced a three-layer optimizing control system that includes intersection controller agents (ICAs), sub-zone controller agents (SZCAs), and network controller agents (NCAs), which represent the lowest, middle, and highest layers, respectively. The interaction takes place across all levels to optimize the signal timing strategy, while coordination is granted by the SZA. Nonetheless, besides the overcharge data at higher levels, the focal decision process might produce a bottleneck in these levels, lengthen the response time, and limit the system's scalability. Flat [Darmoul et al., 2017] and holonic [Tchappi et al., 2020] structures are also proposed for multi-agent-based traffic signal control. Otherwise, it is widely recognized that there is no specific operating multi-agent architecture that is absolute for all traffic signal control systems; additionally, various operating models can be combined.

Urban traffic management requires particular abilities that an MAS cannot guarantee alone, so to create intelligent traffic signal controllers, an MAS integrates various intelligent techniques [23]. Thence, [Daeichian and Haghani, 2018] uses fuzzy Q-learning (QL) and agent technologies to develop a traffic lights control framework. Each agent interacts with neighbor agents by getting a reward from each decision. The control decision is made by using the number of vehicles input to schedule green phase duration. The aim is to maximize the reward and decrease average delay time. [El-Tantawy et al., 2013] improve the travel time and overall delay using QL and a decentralized junction-based model. The model-free Reinforcement Learning can be implemented when dealing with a non-deterministic model of the environment, as it does not require pre-assignment of the environment. . On the other hand, the model-based RL adopted in [Wiering, 2000] [Steingröver et al., 2005] omitted disturbances, such as lane changing, which makes them less adaptable.

Concurrently, some researchers investigated the potential of fuzzy-logic-based control, which has a rule-based inference system and is based on human reasoning. FL is suitable for handling the control of a single intersection [Collotta et al., 2015] characterized by uncertainty, fuzzy circumstances, inexact data, and typically controlled by rules. Because the MAS has a restricted capability to deal with fuzzy circumstances, the incorporation of an MAS and fuzzy inference can show considerable effectiveness in enhancing signal settings in traffic light control [Latif and Megantoro, 2020] [Bi et al., 2014].

In these studies, the cooperation mechanism is mainly limited at the inter-junction level, which reduces the local control efficiency in favor of global control. Also, the concentration of fuzzy logic in one level creates an overload at fuzzy components. Our proposed multi-agent control system is a model based on the two levels of coordination and collaboration, local at the intersection and within the surrounding neighbors. Each intersection is represented by a controller group in which the decision is made via two levels of fuzzy logic and coordination with adjacent group controllers. We propose a fuzzy logic supported multi-agent system for urban traffic management and priority link control, the system aims to reduce the travel time for all types of vehicles, promote the use of public transport and prioritize the priority vehicles. Our work makes three main contributions: (i) real-time optimization and traffic monitoring; (ii) two levels of coordination are used with parallel tasking; and (iii) agent specialization.

3 Methodology

The organizational design of a TSCS is spatially and functionally distributed. Each intersection is viewed as a sub-section of a network, and is controlled by a community of autonomous, cooperative, and intelligent agents. Agents are commonly perceived as carrying out analysis at a higher level of abstraction than components and objects, meaning that an MAS is suitable for complex and distributed problems.

The proposed MAS has a decentralized architecture with two levels of collaboration. Each signalized intersection is controlled by an intersection control group (ICG), which defines the signal control strategy. This strategy optimizes the phase layouts and is responsible for meeting the needs of the continuously changing surrounding environment, whereas the control of the whole intersection network is fully distributed and is accomplished through the collective and coordination capability of ICGs.

- Inter-junction collaboration, which allows for coordination between connecting ICGs.
- Intra-junction collaboration, which allows for interactions between agents belonging to the same ICG.

The members of a group of agents attempt to fulfill the roles required by the overall goal of the group. Groups of agents attempt to coordinate their actions through the exchange of data and via predetermined interactions.

The TSCS is based on 6 cooperative methods [Ferber, 1995]

- **Grouping**: Agents in the same group are in physical proximity. The group operates as a distributed organism in which each type of agent has a particular role.
- **Communication**: Agents communicate to build a collective perception of the environment and to exchange data; communication is allowed between agents both within a group and between groups.
- **Specialization**: Each agent in the system plays a specific role that develops its adaptability to the required tasks, and allows to give the agent a more structural

and behavioral feature to improve its efficiency and master its roles (where there is a one-to-one mapping between these roles and the types of agent).

- **Collaboration**: The agents cooperate to reach a common goal; for each group, the goal is to optimize the traffic light signal at a local intersection, while the goal of the system is to optimize operation over the whole network. These goals are divided into sub-tasks, which are allocated to the agents in the system.
- **Coordination**: The behaviors and actions of agents are scheduled and synchronized to guarantee a high rate of consistency as well as performance.
- **Conflict resolution**: We use arbitration by rules to resolve conflicts between agents, based on a fuzzy inference system containing a set of rules that apply to all agents.

To build an agent system, as for any software, an engineering process must be applied, and in this case we used agent-oriented software engineering (AOSE). This aims to represent the development process of an agent-based approach, as well as the acquired features brought by using the agents in the deployed systems (for surveys see [Akbari, 2010] [Cossentino et al., 2010]). To develop our system, we used a model that became increasingly detailed at each stage, from an abstract idea to a concrete implementation. This development model consisted of six stages, as follows:

1. Analyze the system requirements.
2. Select the organizational structure of the MAS.
3. Structure the TSCS into groups of agents.
4. Structure the groups into agents.
5. Identify the roles of the agents and the interactions between them.
6. Implement the system.

3.1 System requirements

The aim at the requirements stage is to define the components of the system, their functions and interactions, and to describe the scenario under study. For our system, there were three tasks in this phase: (i) modeling of a multi-intersection network; (ii) definition of the traffic light control components; and (iii) a description of the scenario.

3.1.1 Multi-intersection network modeling

The idea of this task is to extend the TSCS to give precedence to priority vehicles. The traffic flow is divided into two types of vehicles: priority and regular vehicles. Regular vehicles can use only the regular links, while priority vehicles can use both priority and regular links. The urban road network can therefore be viewed as a strongly connected oriented graph $N = (I, A)$, where I is the set of nodes representing the intersection, and A is the set of arcs that connect these intersections. We have two types of arcs: priority arcs, which represent the priority links and regular arcs, which represent regular links. We assume that in order to control an intersection, we need to take into consideration both upstream and downstream flows. Hence, each arc has a set of successors $succ(A_{ij}) = \{ A_{jk}, (i,j,k) \in I \}$ and a set of predecessor arcs $pred(A_{ij}) = \{ A_{ki}, (i,j,k) \in I$. Fig. 1 shows an intersection between two regular roads and two priority roads.

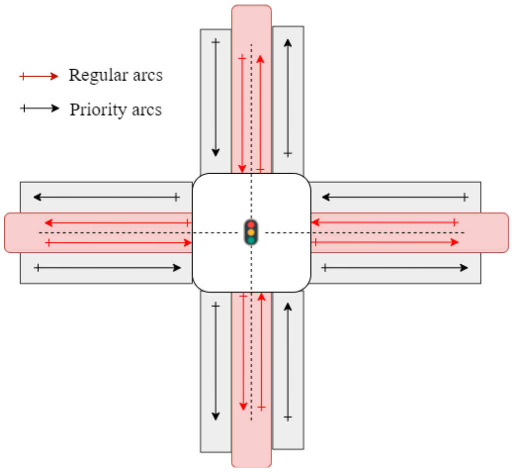


Figure 1: Intersection between two ordinary roads and two priority roads

3.1.2 Traffic light control components

Each intersection in the system is a signalized intersection, and is managed by an intersection control unit (ICU). The urban road traffic model is made up of the following components:

- **ArcMonitor**: Each incoming arc is monitored by an ArcMonitor. The monitoring process consists of collecting data from the sensors to define the arc traffic parameters (Table 1), and to calculate the arc state factors. When the signal is red at the arc stop line, these factors are the stop ratio (SR) (Equation 1) and the congestion ratio (CR) (Equation 2), and when the signal is green, these are the CR and congestion ratio at the arc successor (CRS). The SR represents the waiting time ratio in the arc, while the CR is the ratio of queuing vehicles to the capacity of the arc.

Parameter	Definition
T_{max}	Maximum concentration of vehicles in the arc
T_t	Concentration at an instant t
t_s	Vehicle stop time at a red signal
t_y	Length of the yellow signal
c	Length of the cycle

Table 1: Arc parameters

$$\mathrm{SR} = \frac{\mathrm{t_s}}{\mathrm{c\text{-}ty}}\,\mathrm{SR} = \frac{\mathrm{t_s}}{\mathrm{c\text{-}ty}}\;SR = \frac{t_s}{c-ty} \qquad (1)$$

$$CR = \frac{T_t}{Tmax} \qquad (2)$$

- **Phase manager**: The ICU contains a phase manager, which defines the urgency level of the red phases and the priority level of the current green phase. A phase is represented by the arc with the highest state factors. The urgency and priority levels of the phase are obtained using the fuzzy mechanism presented in [Ikidid and Abdelaziz, 2019]. The phase with maximal urgency level will be proposed as a candidate for the next green time.
- **Controller**: The controller is the axis component of the traffic light control. It defines the cycle layout (i.e. the phase sequence and length). It uses fuzzy inference to decide whether to extend the current green phase or to switch to the candidate phase.
- **Coordinator**: The main roles of this component are to coordinate with the neighboring intersections and to exchange local state data to develop an overview of the environment. Fig. 2 represents the components of the generic TSCS.

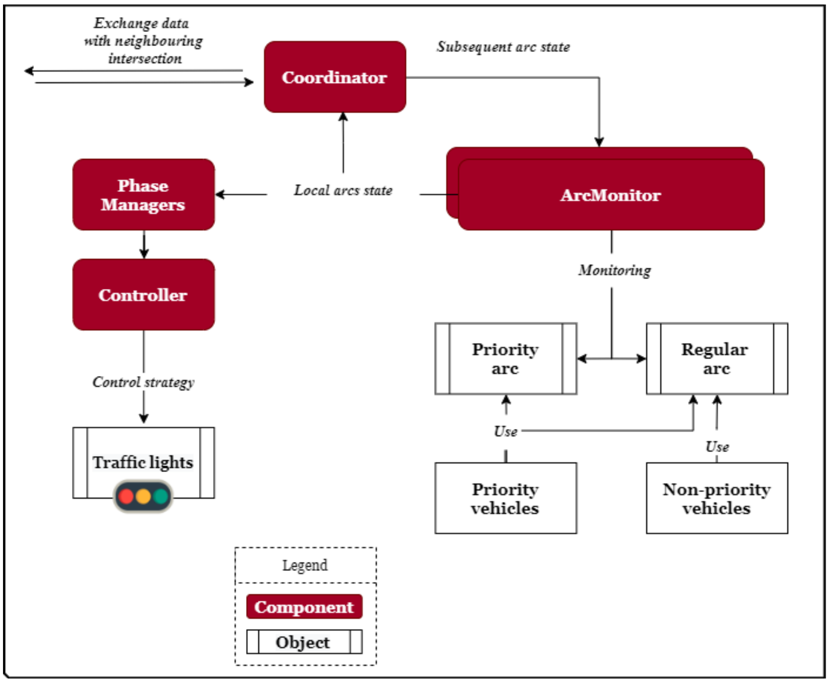


Figure 2: the components of the generic TSCS

3.1.3 Scenario description

The system uses the traffic signal plan to grant precedence to the priority arcs. It updates the phase layout during system operation by deciding when to interrupt the current green phase and which phase will replace it. It also creates a cases-base decision that contains historical data on the traffic conditions and the corresponding decisions that were made.

The task of the components shown in Fig. 2 is to create a traffic light strategy that respects a set of constraints and functional exigencies, as follows:

- The regulation process is initialized after each recurring interval with a group of phases $P \{ P_r, P_p \}$, where P_r represents the phase set of regular arcs, and P_p represents the phase set of priority arcs.
- All the arcs are monitored and state data are collected. The indicators of the traffic conditions in each arc are defined by observing the local state, and by considering the traffic state in succeeding arcs.
- During the cycle, if the degree of saturation in the succeeding arc is above a certain limit, the urgency of the preceding arc is reduced, in order to retard evacuation and to relieve saturation.
- The candidate for the green phase will be chosen from the priority phases with at least one enqueued vehicle. If all priority phases are empty, it is chosen from the regular phases.
- All types of phases have the right to be allocated green time once and only once in the cycle, although phases with no enqueued vehicles in their arcs can waive their turn.
- No phase can be allocated green time twice in the same cycle.
- The control strategy consists of phase sequencing and timing.
- The pedestrian phase is outside of the scope of our approach.

3.2 Organizational structure

The selection of the organizational structure is a key stage in the development of an MAS. It defines the general structure of the roles, interactions, and authority that govern the behaviors of the system and the relationships between entities. Several types of organizational structures for MASs have been proposed over the years, and surveys of these are presented in [Dorri et al., 2018] [Horling and Lesser, 2004].

To build a federation organization that contains a set of groups, we apply the AGR (agent, group, and role) model, with the AALAADIN metamodel [Gutknecht and Ferber, 1999]. Fig 3 shows a representative diagram of this model. The group is an atomic aggregation of agents sharing services with other groups. In our system we have a community of agents that should be optimally aggregated into multiple groups, this aggregation can be based on trust relationships where agents are mutually connected by strong trust relationships [Comi et al., 2017]. Otherwise, in Cooperation-Competition Network, the community can be divided into two groups, the agents cooperate with their neighbors in the same group, while they compete with the neighbors from different groups [Hu et al., 2016]. However, satisfying all group members in an even way still remains as a challenge [Villavicencio et al., 2016].

in traffic road control, where the system is geographically and functionally distributed, to structure the system into groups we use the classically structured programming guideline: low coupling and high cohesion. Therefore, agents sharing more roles will be in the same group while agents not sharing roles (or having few roles in common) will be in two separate groups.

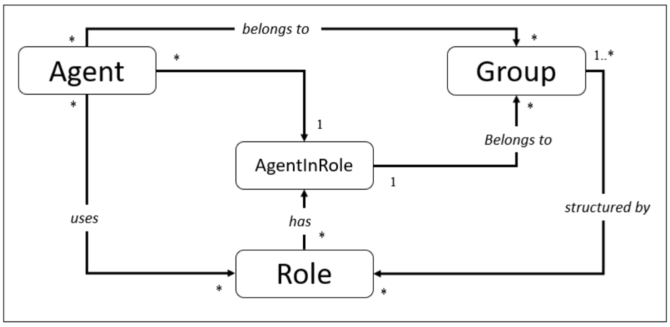


Figure 3: Organizational structure

3.3 Structuring the organization into groups

The multi-intersection network is decomposed into regions controlled by an ICU, which coordinate with neighboring control units by communicating. In an MAS, the role of an ICU is played by an ICG. Each ICG is assigned to an intersection and is responsible for full control over the local flows.

Our multi-agent system has a decentralized architecture in which the ICGs are structured into federation organizations. A federation organization is a system containing a group of agents. Group members have common goals and a single delegate that represents the group. They can interact either directly among themselves or with the external environment through the delegated agent. The group is capable of making its own decisions in a collaborative way between group members, and without any central supervising agent. Fig. 4 depicts a network with three intersections and their corresponding control groups.

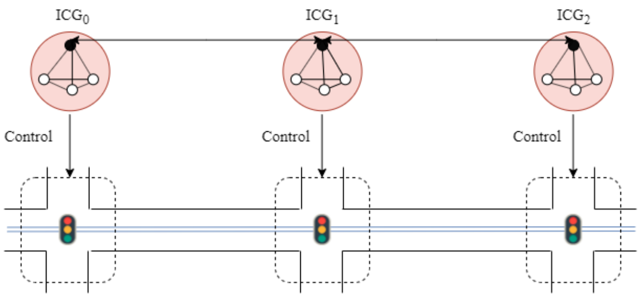


Figure 4: Example of three intersections and their control groups

3.4 Structure the groups into agents.

Since the multi-intersection network is decentralized, most approaches usually divided the network into regions or sub-parts that cover one or more intersections. Using the aforementioned structured programming guideline (low coupling and high cohesion). To define the group members of the ICG, we will use a one-to-one mapping between the components of the TSCS and the MAS. Each active component of the regulation system is represented by an agent. The agent fulfills a specific role in the system, and this specification improves its adaptability and efficiency in the requested role. We use the UTS/MAS correspondence shown in Table 2. The ICUs are represented by ICGs, each of which includes several agents that are classified into four types: an ArcMonitor agent, which is associated with each incoming arc; a phase manager agent; a controller agent; and a coordinator agent. Table 2 summarizes the different types of agents and their roles.

UTC component	**MAS**	**Roles**
ArcMonitor	ArcMonitor agent	• Online monitoring of the traffic state of the arc. • Providing the traffic state factors.
Phase manager	Phase manager agent	• Controlling the phase sequences. • Defining the urgency and priority of phases • Selecting a phase candidate for the next green period.
Controller	Controller agent	• Regulating the phase layout • Updating the signal control plan in a timely manner
Coordinator	Coordinator agent	• Coordinating with the neighboring ACG • Playing the role of mediator in all external communications. • Exchanging data on the traffic state

Table 2: TSCS and MAS correspondence

3.5 Identifying the roles and interactions of agents

The proposed system contains a set of ICGs, each of which is assigned to a signalized intersection with a priority lane. Agents attempt to fulfill the roles required to meet the goal of the group. Coordination between the agents in the group is achieved through exchanging data and predetermined interactions. Each agent seeks to accomplish its own goals while also taking into consideration the goals of the other agents and the group as a whole. The goals and roles of each agent are described below.

3.5.1 ArcMonitor agent

This type of agent is assigned to each incoming arc, and its goal is the online monitoring of the traffic state of that arc. It then passes the traffic state factors to the phase manager and coordinator agents. The state factors for the succeeding arc are obtained through collaboration with the coordinator agent.

The state factors for the arc differ based on the state of the light signal at the stop line of the arc. When the signal is red, the state factors are the stop ratio (SR), the congestion ratio (CR), and the congestion ratio downstream (CRD), and when the signal is green, these factors are the CR and CRD. The linguistic variables and the membership functions of SR, CR, and CRD are standardized as shown in Fig. 5. There are four membership functions: small (S), medium (M), large (L), and very large (VL).

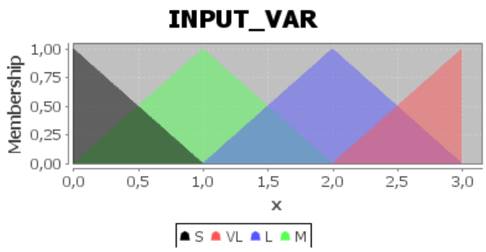
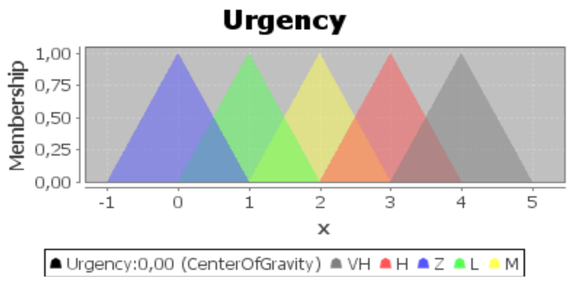


Figure 5: Membership function and linguistic of state variables

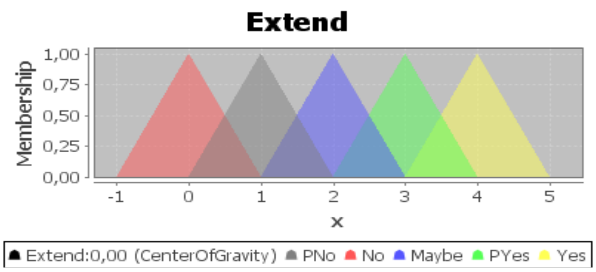
3.5.2 Phase manager agent

The phase manager agent controls the phase sequences, and selects a candidate phase for the next green period. Phases with a priority arc are given precedence, and the urgency and priority are defined using a fuzzy mechanism. The phase manager provides the results to the controller agent. The linguistics and the membership functions of the urgency and priority variables are shown in Figs. 6(a) and (b), respectively.



Z: Zero - M: Medium - L: Large - H: High - VL: Very High.

(a)



No - PNo : perhaps no – Maybe - PYes : perhaps yes - Yes.

(b)

Figure 6: Membership function and linguistic of Urgency and Extend variables

3.5.3 Controller agent

The objective of this agent is to regulate the phase layout by updating the signal control plan in a timely way. The updating decision is made collaboratively, and aims to give precedence to the priority arc and to optimize the management of other traffic flows. The linguistic variables and membership functions of the decision variable are presented in Fig. 7.

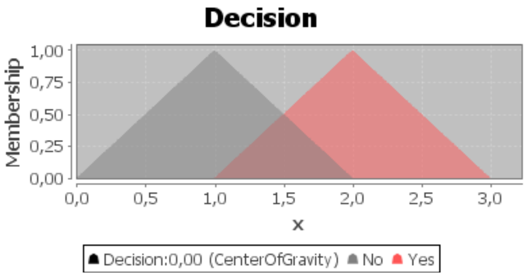


Figure 7: Membership function and linguistic of the decision variable

3.5.4 Coordinator agent

The objective of this agent is to coordinate with the neighboring ICG. It represents the communication interface of the group and plays the role of mediator in all external communications. The coordinator agent shares the local state of each incoming arc with adjacent coordinator agents.

Fig. 8 shows an overview of the proposed multi-agent system, along with the different interactions between agents.

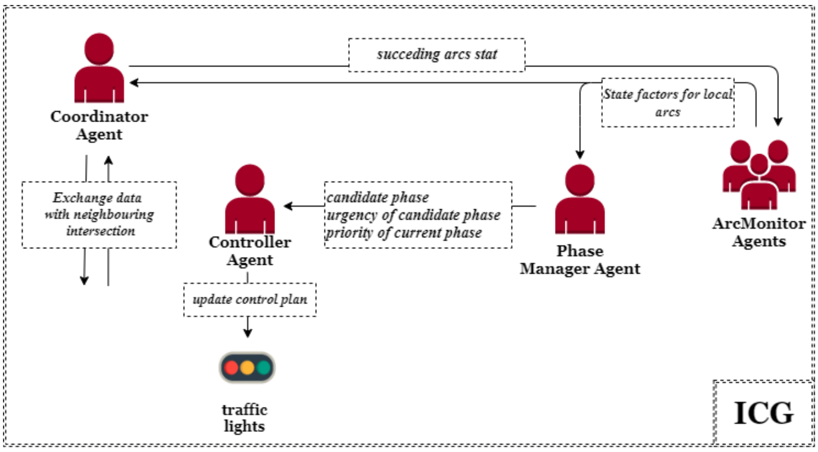


Figure 8: Overview of the interactions between agents

4 Experimental results and performance analysis

To evaluate the performance of our system, we implemented it using the AnyLogic simulator. AnyLogic is a Java-based development environment that includes a graphical model editor and code generator. We used the JFuzzyLogic library to represent the fuzzy inference system. The simulation focused on a section of the Marrakesh road network that included a priority link for electric buses and emergency vehicles. Fig. 9 illustrates the different intersection agents used in the simulation model.

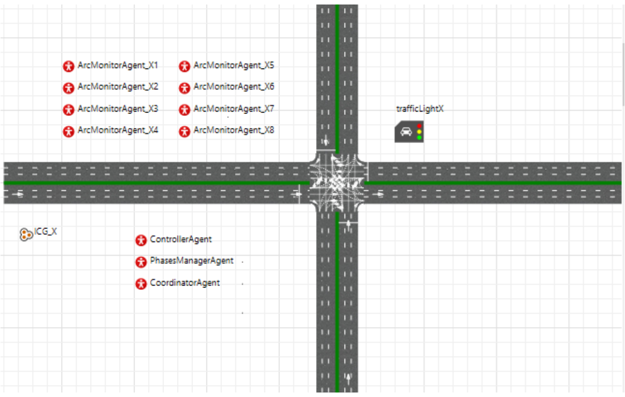


Figure 9: Representation of the intersection during the simulation

We used the vehicle travel time and travel speed as mean evaluation criteria, where the travel time was defined as the period between the departure of the vehicle from the point of origin and the arrival at the destination. These criteria provided us with the optimization level of our approach, and included the average stop time and network throughput indices.

Two alternative approaches to traffic signal control were used to conduct a comparative analysis with the proposed TSCS method (method 3): a fixed-time controller (method 1) and the controller used in the current system but without agents (method 2).

- Fixed-time controller: This was a fixed cycle controller in which the same phase layout was repeated with a fixed length and sequence. We used Traffic Light Phase Optimization, an AnyLogic model that applies the Road Traffic Library to determine the optimal phase layouts by minimizing the travel time.
- Adaptive traffic signal optimization (ATSO): This was a standard version of the proposed MCTSO without agents.

Since a feasible system should smoothly handle a range of different traffic conditions, all control systems were tested under similar conditions and in three different scenarios. In the first scenario, the performance of each method was assessed under low traffic conditions, with an arrival rate of 18,000 PVU/hour. The second scenario involved medium traffic flow, representing a situation with moderate congestion, with an arrival rate of 27,000 PVU/hour. In the third scenario, there was a high traffic load, with an arrival rate of 36,000 PVU/hour. Each method was run for 180 minutes for each scenario, and all experiments were repeated for 30 iterations to ensure the reliability of the results.

Fig. 10 shows the average travel time for all vehicle types and for each set of traffic conditions. It can be seen that our proposed approach gave the fastest travel time in all scenarios, thereby improving the network capacity and the number of vehicles that could use the network and reach their destinations compared to the other control methods.

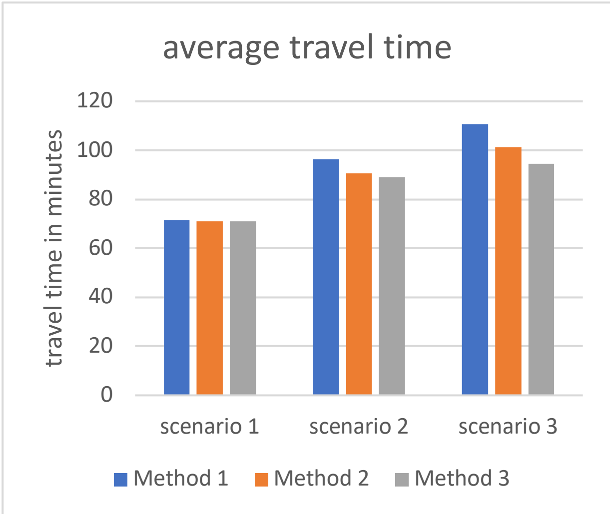


Figure 10. Average travel times

The travel times for the priority vehicles in our system were also compared with those under perfect stationary conditions (SC), representing a situation in which priority vehicles passed all intersections without stopping at any stop-line, and with a fixed speed. Otherwise, the travel stop time was null. Fig. 11 shows the travel times for three different scenarios. The first with stationary ST. The second represents our approach, in which the priority of the traffic is taken into consideration.

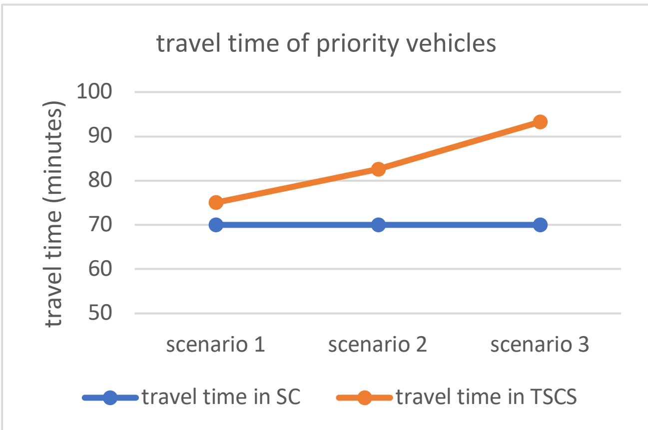


Figure 11: Travel times for priority vehicles

The results showed that a strategy based on the priority link transport using multi-agent technology and fuzzy logic gave a reduced travel time that was very close to the value for perfect conditions.

This reduction in travel time was due to a reduction in the set of key performances and as a consequence, in a set of intersection indices. Fig. 12 summarizes the key performance metrics for the intersection. These measurements were first locally aggregated at each intersection and for each period in the evaluation scenarios. The average performance and other indices were then calculated. The results show that our proposal outperformed other controllers on almost all metrics. The other methods failed to optimize the management of green time to mitigate the traffic conditions.

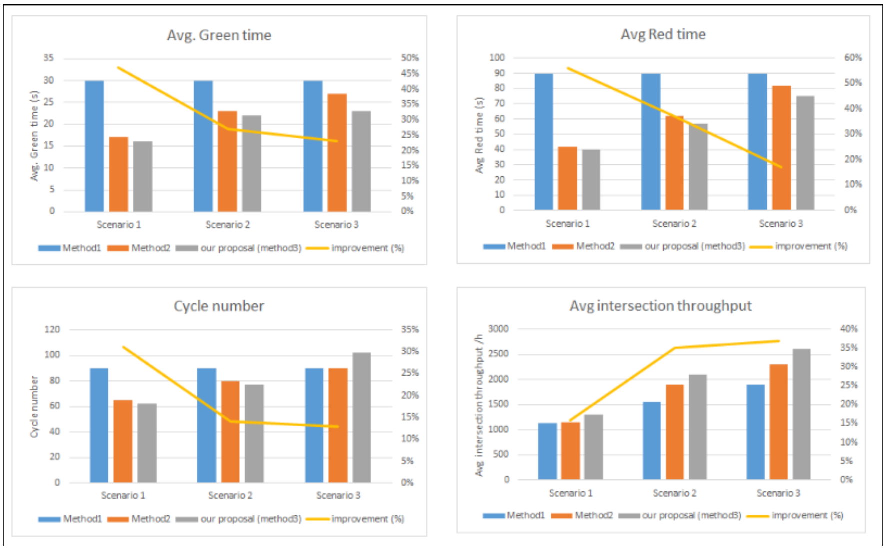


Figure 12: Performance results

The standard deviation in the vehicle's intersection key Performances of the proposed approach was 5.75 lower than for Method 2 which was 7.32. A high standard deviation means that there is a large amount of variability among the data, while a low standard deviation means that the data is less spread out, and thus more reliable. Our proposed approach can be seen to be more reliable than the alternatives.

In addition, a two-factor ANOVA test with replication yielded a p-value of ≈ 0 (3.39E-40 for the travel time and 2.18E-97 for the travel speed), which was much lower than the 0.05 level of alpha significance, meaning that the changes in the control methods had a statistically significant impact on the travel time under different traffic conditions

5 Conclusion

In this paper, we have presented a fuzzy logic-supported multi-agent system for urban traffic and priority link control, with the aim of promoting the use of public transport and enabling the flow of emergency traffic. The agents in our system communicate in order to cooperatively determine an optimized traffic light plan in real-time. Two levels of cooperation are used (inter-junction and intra-junction) to avoid local optimization and to ensure that our control plan takes into consideration all neighboring intersections.

The proposed system was simulated in an AnyLogic simulator, and the results showed that the use of the multi-agent organization generated significant improvements in the travel times for the traffic network. Our proposed system also significantly improved the travel times for priority vehicles under different road traffic conditions. Although the proposed system shows a better result and can adapt smoothly with different traffic demands, it is still an open question on how to optimally deal with the communication failures and their effects on regulation and traffic system, essentially when numerous intersections are involved in the multi-intersection network. The complexity of such problem extends exponentially since the communication failures probability extends proportionally to the increased number of intersections. To tackle this problem, an efficient case-based reasoning model should be designed, such case-based model is required to handle the failures issue. This will be processed in our future work.

In the future, the system shall be further extended to other traffic control fields. For traffic signal control, one extension of this approach is to include an Intelligent path recommendation, and add a protocol that aims to find the best path based on the relative location of the vehicle and takes into consideration the road traffics state. Meanwhile, it is necessary to develop the intelligent optimization approach to deals with the system failures and their effects.

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