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Smart Mobility Using Multi-Agent System

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Abstract

In this paper, we propose a self-adaptive mechanism for traffic regulation based on cooperative agents. We focus our study on the intersection behaviour, using intelligent agents to represent the infrastructure elements, which cooperate among each other in order to minimize traffic congestion. While the agents are capable of cooperating among themselves, the cooperative behaviour is not pre-defined, as it emerges from the agent interactions at a local level. We also explain our results from simulation experiments involving the proposed mechanism, comparing it with other traffic congestion regulation systems currently in use.

Keywords: MAS; Self-adaptation; Traffic regulation; AVT,

1. Introduction

Traffic congestion occurs when road capacity is exceeded, resulting in slower average speeds and ultimately in increased vehicular queuing. Different circumstances can cause or increase traffic congestion, such as traffic incidents, weather, road work, or even recurrent conditions (i.e. people moving between their residences and workplaces). Several strategies for mitigating traffic congestion have been studied, from zoning and development planning [16] to mechanisms based on queuing and fluids flow theory [8], or even colony optimization [28]. Depending on the chosen approach, traffic congestion mitigation can be studied in different scales: land development strategies rely on macro-models, attempting to mitigate the problem from a higher perspective (i.e., keeping residences and workplaces close to each other for most of the people living in a city should empirically minimize traffic congestion). Localized traffic regulation techniques, on the other hand, rely on micro-models: if the problem is locally mitigated (i.e. within the

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radio of a small number of blocks), the solution can be scaled and replicated throughout the city, resulting in overall congestion mitigation.

Among the different mechanisms that can be used for localized traffic regulation, intelligent regulation can be achieved through the use of Vehicle Ad-hoc Networks (VANETs) [32, 22]. VANETs are networks composed by vehicles, and also by roadside units (intelligent infrastructure devices such as semaphores, sensors, and cameras) that provide each other information, allowing the use of more complex regulation strategies. Based on their composing elements, communication in VANETs can take place in terms of: Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), and Infrastructure-to-Infrastructure (I2I), each of which can be used with specific regulation strategies. Average vehicle speed can be regulated using V2V communication, for example, while traffic lights timing can be dynamically optimized in I2I communication. Depending on the VANET available support, different solutions can be used for traffic regulation. V2V communication allows vehicles to cooperate among themselves, resulting in mechanisms such as virtual traffic lights [11]. When both vehicles and infrastructure elements can exchange information among themselves (V2I communication), cooperation mechanisms between vehicles and traffic lights [9] [23] [4] can be used. Also, I2I communication can be used to regulate traffic without any vehicle communication, i.e. allowing traffic lights to coordinate among themselves in order to create ”green waves” [25]. There are also hybrid approaches that use different types of VANETs, allowing both traffic lights and the cars to dynamically adapt to traffic [19] [29]. However, none of these solutions are able to guarantee a satisfactory global solution for traffic congestion mitigation. As a result most of the countries are still using the Standard Traffic Light System (STLS) [26], where there is a predefined traffic light period which is not modified with time and there is no communication facility.

With the considerations above, we propose a self-adaptive mechanism for traffic regulation based on cooperative agents. This mechanism is intended to be as a traffic congestion mitigation solution based on I2I communication, reducing the total time spent by vehicles in intersections.

This paper is organized as follows: Section 2 describes the case of automated traffic regulation using I2I communication, along with some of the existing work in the area. Section 3 details our proposition on how intelligent agents can be used in I2I communication for traffic regulation. A simulation of the proposed solution is shown in Section 4, along with the experimental results obtained. Finally, Section 5 concludes this paper and presents some perspectives for future work.

2. Related Work

The focus of our work resides on regulation mechanisms that (i) are able to dynamically adapt to the traffic conditions, and (ii) do not depend on interactions with vehicles, relying only on infrastructure elements. Due to these restrictions, we do not consider mechanisms such as dynamic vehicle routing [21] or adaptive cruise control [2]. More specifically, we focus on mechanisms that involve dynamically controlling the traffic lights.

Traffic regulation solutions, involving the adjustment of the duration of traffic lights, date back from the 80s. In SCOOT (Split Cycle and Offset Optimisation Technique) [17], electromagnetic sensors are installed in the asphalt to detect the number of cars at intersections and an optimization is applied in order to reduce this number. SCATS (Sydney Co-ordinated Adaptive Traffic System) [27], on the other hand, uses optimization criteria such as period of day (night), congestion, fluidity and the time of the day. MOTION (Method for the Optimization of Traffic signals In On-line controlled Networks) [6] is an adaptive traffic signal network control system where each intersection determines a minimal cycle duration for a traffic light set based on the estimated vehicle flow. Then, a common cycle time for all intersections is determined. Finally, a coordination takes place in the form of a phase shift to create green waves. However, this kind of method would not work if the traffic flow is not the same for all intersections. To this end, Krajzewicz et al. [20] discuss flow-sensitive traffic lights. In their approach, the size of the incoming queues at each intersection is compared and then vehicles in the larger queue are given priority to cross the intersection. However, in this study, only one intersection is studied.

More recently, Fleck *et al* [12] propose a quasi-dynamic adaptive system for a single intersection, which is modeled as a stochastic hybrid system. Their solution is a policy ”based on partial state information defined by detecting whether vehicle backlogs are above or below certain thresholds” *(sic)*. Another solution, by Qi *et al* [24], propose the use of additional warning lights in conjunction with a traffic flow recommendation model. Some of the most recent works also involve the use of intelligent agents. Different works [30, 10, 18] propose the use of multi-agent reinforcement learning for dynamic traffic regulation.

Despite the new developments in the area, however, most of the countries still use the Standard Traffic Light System (STLS) [26], where the traffic light periods are fixed. This is mainly due the fact that none of the existing solutions solely based on infrastructure elements can guarantee a satisfactory, scalable mitigation alternative for traffic regulation. For this reason, we use the STLS as a reference in our simulation experiments, described later in this paper. Moreover, despite the development of systems where infrastructure elements collaborate to manage traffic, it is still not clear if it is interesting to have a selfish or a collaborative behaviour. In that direction, we compared our approach in two ways, one as non cooperative approach and another way as a cooperative approach. To convenient represent our approach, we use Multi-Agent System (MAS) abstraction [7]. MAS allows a suitable abstraction to support the whole software development process.

3. MAS-based I2I Traffic Regulation

For our traffic regulation, we consider a traffic light management system modelled as a quintuple $\mathcal{L} = (\mathcal{I}, \mathcal{CR}, \mathcal{T}, \mathcal{V}, C)$ where $\mathcal{I}$ denotes the intersection set, $\mathcal{CR}$ denotes the crossroad set, $\mathcal{T}$ denotes the traffic light set, $\mathcal{V}$ denotes the view set and C denotes the dynamic car set. An example of traffic management system is illustrated in Figure 1.

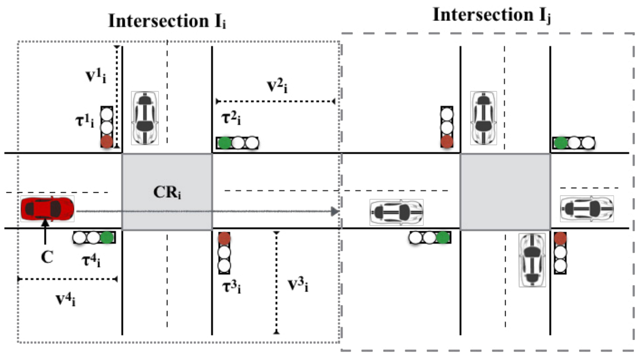

Fig. 1. An example of traffic light management system $\mathcal{L}$ composed of two adjacent intersections $\mathcal{I}_i, \mathcal{I}_j \in \mathcal{I}$.

Given an intersection $\mathcal{I}_i \in \mathcal{I}$, $\mathcal{I}_i = (\mathcal{CR}_i, \mathcal{I}_j, \mathcal{T}_i, \mathcal{V}_i)$ such as $\mathcal{CR}_i \in \mathcal{CR}$ that represents the central symmetry of the intersection $\mathcal{I}_i$, where $|\mathcal{CR}_i| = 1$. $\mathcal{I}_j \subset \mathcal{I}$ denotes the neighbors of the intersection $\mathcal{I}_i$ such as $i \neq j$ and $\mathcal{I}_i$ and $\mathcal{I}_j$ are connected by the edge $(\mathcal{CR}_i, \mathcal{CR}_j)$ and there is no other $\mathcal{CR}_h$ between $\mathcal{CR}_i$ and $\mathcal{CR}_j$.

We pose that $0 \leqslant |\mathcal{I}_j| \leqslant 4$, $\mathcal{T}_i \subset \mathcal{T}$ denotes the traffic light set of i where $|\mathcal{T}_i| = 4$ and $\mathcal{V}_i \subset \mathcal{V}$ denotes the view set of an intersection i where $|\mathcal{V}_i| = 4$.

We model a traffic light $\tau \in \mathcal{T}$ as $\tau = \langle d^G_\tau, d^R_\tau \rangle$ where d^G_τ and d^R_τ are the duration of the green and the red lights of τ respectively, $0 < t_{min} \leqslant d^G_\tau, d^R_\tau \leqslant t_{max}$ and $\forall \tau \in \mathcal{T} : d^G_\tau + d^R_\tau = \mathbf{C}$ where $\mathbf{C}$ is constant. Precisely, for an intersection $\mathcal{I}_i$, we consider $\tau^1_i, \tau^2_i, \tau^3_i \wedge \tau^4_i \in \mathcal{T}_i$, where,

$$d^G_{\tau^1_i} = d^G_{\tau^3_i} = d^R_{\tau^2_i} = d^R_{\tau^4_i} \wedge d^G_{\tau^2_i} = d^G_{\tau^4_i} = d^R_{\tau^1_i} = d^R_{\tau^3_i} \tag{1}$$

We model a set of views $\mathcal{V}_i \subset \mathcal{V}$ for an intersection $i \in \mathcal{I}$ as $\mathcal{V}_i = \{v^1_i, v^2_i, v^3_i, v^4_i\}$ where $v^1_i, v^2_i, v^3_i, v^4_i$ are the views of the traffic lights $\tau^1_i, \tau^2_i, \tau^3_i, \tau^4_i$, respectively. In other words, views represent the road segment, that traffic lights control. Each view $v \in \mathcal{V}$ has a static capacity of cap number of cars and for all v there can be η_v number of cars. The total number of cars η_i in an intersection $i \in \mathcal{I}$ is then defined as $\eta_i = \eta_{v^1_i} + \eta_{v^2_i} + \eta_{v^3_i} + \eta_{v^4_i}$ where $0 \leqslant \eta_i \leqslant (cap * 4)$. Each view $v \in \mathcal{V}$ has two end points $Start$ and End where $Start$ is the point the cars enter to v and End is the point the cars exit from the view v of the associated traffic light τ. Thus, the End point of v is also the point where the associated traffic light τ is situated.

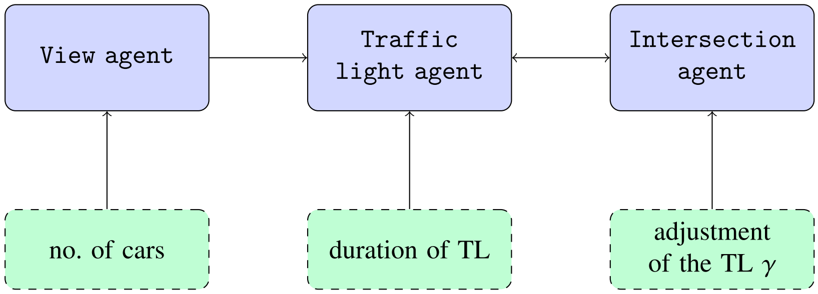

Fig. 2. Proposed system architecture with agent interactions.

We denote a car $c \in C$ as $c = \{s, \varphi\}$ where s is the speed and φ is the type of c. Depending of φ, the length of c may vary. Each car $c \in C$ continuously travels in the system. As they travel, cars enter to and exit from views.
In the following subsections, we describe the defined agents, their interactions and their behaviours.

3.1. Agent Role

We define three types of agents: `view agents`, `traffic light agents` and `intersection agents`:

1. `View agents` are responsible for specific views and detect the number of cars for their view. Then, they send the information to their related `traffic light agent`.
2. `Traffic light agents` are responsible for the traffic lights, where they change the duration of the green and the red light. They continuously collect car count information from their corresponding `view agents`. Then, send their state and the state of the traffic light to their related `intersection agent`.
3. `Intersection agents` are responsible for intersections. They continuously collect car count information from their corresponding `view agents` and the duration of the traffic light from their corresponding `traffic light agents`. `Intersection agents` are computing the required duration of the green light of their `Traffic light agents`.

3.2. Agent Interactions

Three types of interactions exist between the three types of agents defined as follows:

1. `View agent`→ `Traffic light agent` (I2I). Each `view agent` v continuously communicates with the agent that is responsible of the traffic light τ_i^n where their view belongs to in order to send the car count information. We model sending the number of cars η_v to the `traffic light agent` τ_i^n as with the action of the form $sendNumberOfCars(\tau_i^n, \eta_v)$.
2. `Traffic light agent` ↔ `Intersection agent` (I2I). Each `traffic light agent` τ_i^n collects continuously car count information η_v from their corresponding `view` agent and sends this information together with their status (the duration of its lights: $d^G_{\tau_i^n}$, $d^R_{\tau_i^n}$) to their corresponding `Intersection agent`. We model this message as $forwardState(i, \eta_v, \tau_i^n, d^G_{\tau_i^n}, d^R_{\tau_i^n})$, where $1 < n \leqslant 4$.
   Each `Intersection agent` then computes and sends the duration adjustments γ_i for all its related `traffic light agents` τ_i^n. We model this as $sendAjustment(\tau_i^n, \gamma_i)$.
3. `Intersection agent` ↔ `Intersection agent` (I2I). Depending on the agent behaviour (selfish or collaborative), an intersection agent i can send its adjustment (γ_i) to its neighboring intersection agent j. We model this sending as $sendAdjustment\ Intersection(j, \gamma_i)$.

3.3. Agent's behaviour

In the following, the behaviors of the three types of agents are given. In addition, a summary of the interactions is depicted in Figure 2.

View Agent. This agent is continuously sending the count number of cars that are passing by its view.

Traffic Light Agent. `Traffic light agents` have twofold behavior:

1. They continuously collect car count information from corresponding `view agents`. τ_i^n then sends this information together with their status (the duration of its lights) to the corresponding `intersection agent` i.
2. They continuously receive adjustments from their corresponding `intersection agent` The `traffic light agent` τ_i^n continuously receive adjustments from its corresponding `intersection agent` i. Each `traffic light agent` τ_i^n $(1 \leqslant n \leqslant 4)$ then updates the duration of their lights. Updating the duration of traffic lights uses the action of the form $updateDurations(\gamma_i)$, where γ_i is the adjustment value for modifying the duration of green d_τ^G and red lights d_τ^R by adding and reducing γ_i respectively.

Intersection Agent. `Intersection Agents` are responsible of specific intersections. An `intersection agent` i receives state information coming from its `traffic light agent` τ_i^n. It then calculates the duration adjustments for all `traffic light agents` and sends for each `traffic light agent` τ_i^n its adequate duration adjustment γ_i.

`Intersection Agents` can use two different behaviors for calculating the duration adjustments: (β_1) the selfish (non-collaborative) behavior in which it does not take into account its neighbours or (β_2) the collaborative behavior in which it considers its neighbours. The behaviours are explained as follows:

- `Intersection agent` receives state information coming from its four `Traffic Light agents` τ_i^n : $1 \leqslant n \leqslant 4$.
- `Intersection agent` computes the adequate duration of the traffic light for all $\tau_i^n : 1 \leqslant n \leqslant 4$ using an Adaptive Value Tracking (AVT) [4, 1, 31, 15, 14, 13]. We model this computation as $avt.adjust()$. The computed value is embedded in γ_i, where $\gamma_i \leftarrow avt.adjust()$. Depending on the agent behaviour, the γ_i is computed using two ways:
  - (β_1) Selfish behaviour:
    $$\gamma_i \leftarrow \eta_{v_i^1} - \eta_{v_i^2} + \eta_{v_i^3} - \eta_{v_i^4} \tag{2}$$
  - (β_2) Cooperative behaviour: The computation of γ_i is computed as in equation (2), however it is introducing also the computed γ_j from its intersection neighbour as follow.
    $$\gamma_i \leftarrow \eta_{v_i^1} - \eta_{v_i^2} + \eta_{v_i^3} - \eta_{v_i^4} + \gamma_j \tag{3}$$
    If the computed γ_i is greater than zero, then the traffic lights (τ_i^1 and τ_i^3) need to INCREASE ($\uparrow$) its green duration. Otherwise, they need to DECREASE ($\downarrow$). In the case where γ_i is equal to zero, then it is PRESERVING ($\approx$) the actual green light duration.
- `Intersection agent` sends this adjustment to its `Traffic Light agents` τ_i^n.
  We model this as $sendAjustment(\tau_i^1, \gamma_i)$

4. Experimental results

In our model, we used collaborative and non-collaborative agents. Thus, we conduct an experimental evaluation to verify how collaborative and non-collaborative agents impact in the system behaviour. In our work, we used two tools to evaluate our developed algorithm: Simulation of Urban MObility (SUMO) [3] and Java Agent DEvelopment Framework (JADE) [5].

We experiment our approach, first for one intersection then we extended to two intersections. Initially, we use a restricted scenario with only one intersection to evaluate without noise as the proposed strategy acts. To discuss the obtained results, we compared our approach that uses AVT with a Standard Traffic Light System (STLS) [26]. STLS has a predefined traffic light period and is not modified with time. As a second experiment, we evaluate the impact of

(a)

(b)

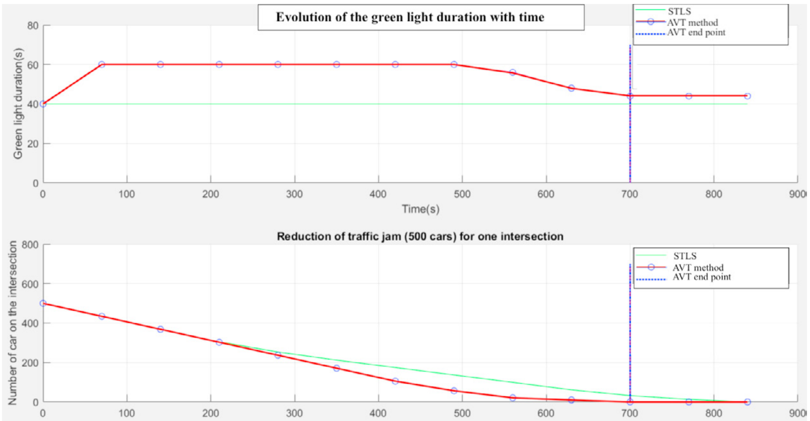

Fig. 3. Evolution of the green light duration by time (a) and reduction of traffic congestion (b) results for Scenario 1.

our approach using two intersections. Thus, we compared the two predefined behaviours of `Intersection agents` (`selfish` and `collaborative`) with STLS using different scenarios and discuss the obtained results.

Scenario 1. In this scenario, we defined one intersection $i \in \mathcal{I}, i = 1$ and a predefined number of vehicles. We suppose that at the end of the experiment, 500 vehicles will pass by this intersection i, where their distribution in the four views is as follow: $v_1^1 = 220$, $v_1^2 = 40$, $v_1^3 = 180$ and $v_1^4 = 60$. In the simulation, the vehicles are not coming all at the same time, there is a frequency factor which is defined in which each vehicle appears in the view each 2 u.t. Additionally, we suppose that all vehicles while entering to the view have the same starting speed.

Figure 3 represents the obtained results using one intersection. The red line represents our developed method based on AVT and the green line represents the Standard Traffic Light System. Figure 3(a) represents the duration of the green light of the `traffic light` agent $d^1_{\tau_1}$. From our model, knowing the duration of the green light of one traffic light, we can deduce the duration of all other traffic lights.

Figure 3(b) shows the evolution of the number of cars in the intersection $i = 1$. We can see that using our approach AVT, there is no remaining car in the intersection after 700 u.t. However, using STLS the intersection becomes empty only after 800 u.t. We can conclude that our approach outperforms STLS.

In this continuity, we perform another experiment, where we used different car flow for different hours of the day (morning and afternoon). Table 1 represents the obtained results. We defined a density in a view as the number of cars in the view divided by the view's capacity. From the table, we can conclude that our AVT method was able to adapt for different flows and it reduces the density (Vertical and horizontal) in a better way than STLS.

Table 1. Achieved statistical results with different flows for AVT and STLS

	(Vertical, Horizontal density)	AVT (Vertical, Horizontal density)	STLS (Vertical, Horizontal density)
Morning	(0.9, 0.2)	**(0.6, 0.1)**	(0.7, 0.18)
Afternoon	(0.3, 0.95)	**(0.15, 0.7)**	(0.22, 0.8)

Scenario 2. In this scenario, we consider two intersections with different vehicle densities for each view. For the intersection $\mathcal{I}_1$ the car distribution is as follow: $v_1^1 = 1100$, $v_1^2 = 200$,$v_1^3 = 300$, $v_1^4 = 900$ and for the second intersection $\mathcal{I}_2$ is as follow: $v_1^1 = 200$, $v_1^2 = 1100$, $v_1^3 = 900$, $v_1^4 = 300$. We suppose that at the end of the experiment, 5000 vehicles will pass by these two intersections. Like in Scenario 1 and Scenario 2, each car appear at each $2u.t$ after the previous car appears.

At the same time and in order to simulate as close as possible the behaviour of cars for the two intersections, we measured in a real context the cars direction. For the intersection at Ivry-sur-Seine (France), we notify that: 25% of cars are turning left, 25% of cars are turning right and 50% of cars are going straight. Based on this evaluation, we simulate our car traffic.

(a)

(b)

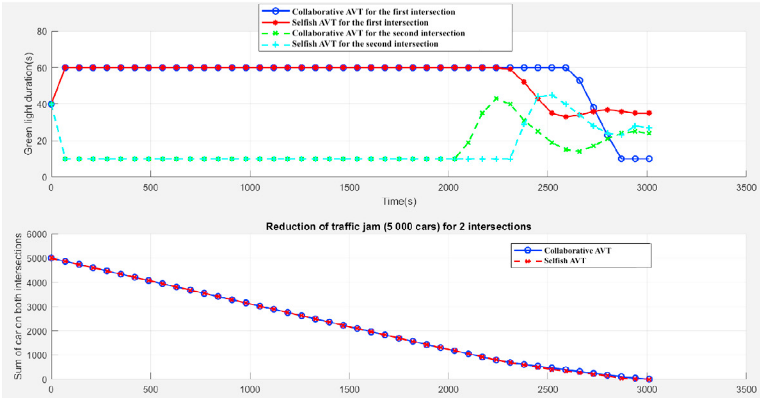

Fig. 4. Evolution of the green light duration by time (a) and reduction of traffic congestion (b) results for Scenario 2.

Moreover, in this scenario, we evaluate the two possible behaviours of `intersection agents` given in Section 3: β_1 selfish behavior and β_2 collaborative behavior. In β_2, each `intersection agent` calculates the γ of its intersection for AVT while taking into account the estimated number of vehicles which will be send by the other intersections for the next period of time. Thus, it uses the formula (3) (see section 3.3).

Figure 4 presents the obtained results for a simulation of 5000 cars passing through the two intersections. On these initial conditions we notice that the collaborative `intersection agent` can regulate the traffic faster than the selfish `intersection agent`. Where, for collaborative `intersection agent` at 2950 u.t the traffic is regulated, however, for the selfish `intersection agent` it stays until 3000 u.t. Thus, according our experiments results, the introduction of selfish agents did not impact the expected system behavior.

From our experiments, we concluded that using a self-adaptive traffic regulation mechanism produces interesting results not only for one intersection, but also for several intersections. Additionally, when intersection agents have a collaborative behaviour the traffic is regulated faster.

5. Conclusion

In this paper we proposed a self-adaptive mechanism for traffic regulation based on cooperative agents. The proposed mechanism was designed for I2I communication, in scenarios where multiple traffic lights can coordinate among themselves to mitigate traffic congestion in intersections. For this purpose, we modeled intersections using three types of agents: `View agents`, `Traffic light agents`, and `Intersection agents`. `View agents` are responsible of car counting, `Traffic light agents` put in place the traffic light duration and `Intersection agents` are managing the duration adjustment of a specific traffic lights using Adaptive Value Tracking (AVT). Due to the complexity of traffic networks, developing an efficient and scalable solution for mitigating traffic congestion is a challenging task. While different approaches can be used in order to develop such solution, our work focuses on cooperative infrastructure elements. The proposed mechanism is innovative in its method for capturing the dynamics of traffic networks and allowing traffic lights to self-adapt accordingly, alleviating traffic congestion when it is perceived. It is important to notice that this perception can occur preemptively, such as in the case where the traffic lights duration in one intersection change according to the perceived traffic in its neighbouring intersections.

We used Jade to implement the proposed mechanism and SUMO to validate it on different scenarios. By changing the number of intersections, the number of cars, and the traffic behaviour we were able to observe better congestion mitigation results using the proposed mechanism, when compared to the STLS. In addition, our experiments showed that traffic congestion is mitigated more efficiently when intersection agents are collaborative.

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