



**HAL**  
open science

# COALITION: CAVs-enabled Probabilistic Offloading of Congested Lanes for Reduced Urban Traffic Congestion

Soufiene Djahel, Yassine Hadjadj-Aoul, Renan Pincemin, Celimuge Wu

► **To cite this version:**

Soufiene Djahel, Yassine Hadjadj-Aoul, Renan Pincemin, Celimuge Wu. COALITION: CAVs-enabled Probabilistic Offloading of Congested Lanes for Reduced Urban Traffic Congestion. VTC 2023-Fall - IEEE 98th Vehicular Technology Conference, Oct 2023, Hong Kong, France. pp.1-7, 10.1109/VTC2023-Fall60731.2023.10333813 . hal-04368543

**HAL Id: hal-04368543**

**<https://inria.hal.science/hal-04368543v1>**

Submitted on 1 Jan 2024

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution 4.0 International License

# COALITION: CAVs-enabled Probabilistic Offloading of Congested Lanes for Reduced Urban Traffic Congestion

Soufiene Djahel\*, Yassine Hadjadj-Aoul†, Renan Pincemin‡, and Celimuge Wu§

\*University of Huddersfield, UK

†University of Rennes, France

‡Telecom Physique Strasbourg, France

§The University of Electro-Communications, Japan

{s.djahel@hud.ac.uk, yassine.hadjadj-aoul@irisa.fr, renan.pincemin@outlook.fr, celimuge@uec.ac.jp}

**Abstract**—The number of vehicles in developed countries has grown more rapidly than available road capacity, resulting in increased congestion, air pollution, and more accidents. A recent UN report predicts that the increasing size of cities and levels of population mobility will mean 2.9 billion vehicles on the road in cities alone by 2050. To mitigate the consequences of this increase without dramatically increasing the number of built roads, novel methods to better utilise existing road capacity are required. To that end, this paper introduces COALITION, a cognitive radio-enabled probabilistic offloading of congested lanes, as an innovative solution to efficiently handle traffic congestion in urban areas. This solution builds upon and improves the performance of our previous work, named CRITIC, and makes use of Electric Connected and Autonomous Vehicles (ECAVs) features to maximize the usage of road capacity through opportunistic exploitation of under-utilized reserved lanes while fostering the use of electric vehicles to support carbon neutral transportation objectives. Simulation results have proven the effectiveness of COALITION and its potential impact in real-world scenarios.

**Index Terms**—Smart Transportation, Smart Cities, Road Traffic Congestion, Cognitive Radio

## I. INTRODUCTION

According to the study made by INRIX and published in its Global Traffic Scorecard<sup>1</sup> London was the most congested city in the world in 2022 followed by Chicago, Paris and Boston. In average, the delay experienced by drivers in London was 156 hours due to congestion in 2022. Obviously, this delay can be translated into a colossal economic cost in addition to its negative impact on the environment. This study analyzed traffic congestion data in over 1000 cities from 50 countries, which makes it an accurate representation of traffic congestion problem worldwide. Traffic congestion [1] is caused by the excessive demand for roadway travel which usually exceeds the road infrastructure capacity. As vehicular traffic flow increases, drivers and public transport riders waste time and consume more fuel in an unproductive manner.

Reducing urban traffic congestion is among top priorities of smart cities and transportation authorities, especially in big urban areas. To that end, many solutions are designed and

some of them are tested by cities through pilot studies [2], [3]. These solutions include a myriad of advanced features and concepts underpinned by the unprecedented advancement in sensing, monitoring and electrification technologies. Modernizing and expanding the capacity of road networks is among the solutions adopted by some wealthy cities, in addition to significantly shifting towards transport electrification by adopting electrified public transport means such as electric buses. Mobility-as-a-Service (MaaS) [4] is another emerging concept that aims to facilitate access to multiple transport modes through a single platform for the end users so that more sustainable transport options could be used and better control of traffic congestion could be achieved. MaaS is expected to benefit from the emerging Connected and Autonomous Vehicles (CAVs) and Electric CAVs (ECAVs) to further widen its adoption and support its long term Net Zero transport objectives.

Other advancements in Intelligent Transportation Systems (ITS) represent also potential affordable solutions to traffic congestion problem. ITS is Considered a key enabler of smart cities as the efficiency and availability of other services are reliant on their robustness and security level [5]. Transport experts foresee that CAVs, ECAVs and Unmanned Aerial Vehicles (UAVs) will play major role in realizing the ITS vision, through reduced traffic congestion and more sustainable passengers and freight transport. Indeed, an increased use of CAVs, subject to adequate regulations in place by the transport policy makers, will lead to more efficient usage of road capacity, relatively safer driving thus reducing the occurrence of unexpected traffic congestion due to road accidents, and more economic driving with less impact on the environment. To achieve this, an upgraded road infrastructure is required through the extensive use of smart and adaptive traffic light control systems [6] capable of interacting with CAVs for more efficient traffic routing [7].

To complement the above efforts, we propose an efficient yet affordable (i.e., limited cost in terms of upgrading the available road network infrastructure) traffic congestion reduction solution that builds upon and extends our previous

<sup>1</sup><https://inrix.com/scorecard/>

work published in [8] named CR-TMS (Cognitive Radio based Traffic Management System). In CR-TMS, two traffic mitigation solutions were proposed, CRITIC and its extension CRITIC+. In this paper, a more robust solution is introduced, named COALITION - a Cognitive radiO enABled probabiLIstic offloading of cONGested lanes - in which we propose a deterministic model for the vehicles and the road lane statuses along with a new control strategy based on Proportional Integral Derivative (PID) controller.

## II. AN OVERVIEW OF CR-TMS

The Traffic Management System (TMS) shown in Fig. 1 represents the framework under which CRITIC, CRITIC+ and COALITION could be deployed and used to reduce urban traffic congestion. The left-hand side of the figure depicts an intersection equipped with heterogeneous traffic sensing devices that can sense and report traffic flow volume and speed to the road traffic data collection component of the TMS. This component will aggregate such data and forward it to the Intelligent Traffic Light Controller (ITLC) to make local adjustments, if necessary, such as those proposed in [9], as well as to the Global Congestion Evaluation Engine (GCEE) for deeper analysis of the collected data to recommend adjustments at a larger scale. These recommendations will be communicated to the Intelligent Traffic Lights (ITLs) controlling the different intersections. The ITLs are equipped with Cellular vehicle to everything (C-V2X) technology for communication with CAVs or ECAVs. Based on its global view of the traffic situation, the GCEE can further optimize local adjustments made by the ITLCs. The purpose of defining two levels of decision-making is to improve the TMS flexibility while making it easy to scale up to a larger urban road network.

Among the recommended adjustments by the ITLC or the GCEE is the decision to exploit an under-utilized priority lane (e.g., Lane 3 reserved for buses shown on the right-hand side of Fig. 1) to offload other congested lanes (e.g., Lane 2 in this scenario). To that end, a subset of the vehicles (private or ECAVs) using the congested lanes will be selected to temporarily use the priority lane. The selection of these vehicles is made based on CRITIC, CRITIC+, or COALITION schemes. If an ECAV is chosen, it will then be notified by the corresponding ITL using C-V2X communication technology. In order to efficiently and safely move to the priority lane, coordination among the ECAVs (e.g., for lane change manoeuvre) is required using an adequate protocol, such as the one proposed in [10].

The proposed CR-TMS's primary aim is to reduce traffic congestion on regular (i.e., non-priority) road lanes (e.g., Lane 2 in Fig. 1), allowing vehicles to move faster to increase traffic throughput. This is achieved by optimizing the usage of priority lanes' capacity under certain conditions without any negative impact on buses, which are the primary users of the priority lanes. ITLCs are responsible for creating access opportunities, for non-prioritized vehicles (private or ECAVs), to priority lanes if the access conditions, which are evaluated either locally, by the ITLC, or at a global level by

the GCEE, are met. As a result, optimal actions are taken by triggering CRITIC, CRITIC+, or COALITION schemes. These conditions are summarized below:

- Traffic on non-priority lanes is moving at a slow speed compared to the speed limit, which can be expressed as follows:

$$\frac{|FF_{speed} - C_{speed}|}{FF_{speed}} \geq threshold_1 \quad (1)$$

where  $FF_{speed}$  refers to the free flow speed and  $C_{speed}$  denotes the current measured speed on this road lane.  $threshold_1$  is a dynamic value that controls how fast CR-TMS should react to traffic congestion occurrences on non-priority lanes.

- At least one priority lane (e.g., bus lane) is under-utilized, as expressed below:

$$\frac{|RU_{rate} - CU_{rate}|}{RU_{rate}} \geq threshold_2 \quad (2)$$

where  $CU_{rate}$  defines the Current Usage (CU) rate observed on the priority lane while  $RU_{rate}$  represents the Recommended Usage (RU) rate of such lane by the priority vehicles.  $threshold_2$  is a dynamic value that controls how fast CR-TMS should exploit access opportunities to priority lanes.

In CR-TMS three classes of vehicles are defined, as explained below.

- **Prioritized vehicles (P-vehicle):** any vehicle in this class (such as buses and carpool vehicles) will, by default, use any Priority Lane (PL) in its route to the destination.
- **Non-Prioritized Vehicles (NP-vehicle):** any regular vehicle that does not belong to the above class. By default, any vehicle in this class will use the Non-Priority Lanes (NPL) during its route to the destination.
- **VIP-vehicle:** this class is defined dynamically, where a number of vehicles belonging to NP-vehicle class are selected to temporarily use the available priority lanes.

### A. The promotion process in CRITIC and CRITIC+: from NP-vehicle to VIP-vehicle

The main difference between CRITIC and CRITIC+ is that the latter takes into account the accumulated delay during a vehicle journey to compute a fair probability of access to the priority lanes. Also, while in CRITIC all vehicle classes have the same priority of access to priority lane, CRITIC+ assigns a different priority for each class.

When the conditions for the promotion are met, the hosting capacity of the priority lane (see Equation 3) and the required traffic load reduction on the Non-Priority Lanes (see Equation 4) are calculated to determine the number of vehicles to be promoted (see Equation 5).

$$PL_{Hosting-capacity} = \frac{Length(PL) + Safety\ Distance}{AVG_{VL} + Safety\ Distance} \quad (3)$$

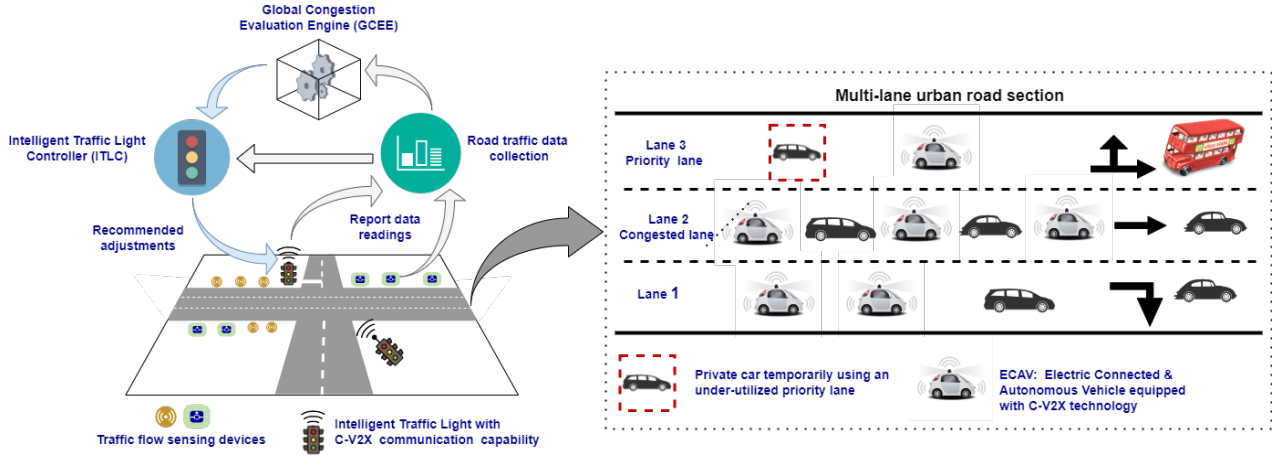


Figure 1: CR-TMS overview: from traffic flow sensing to ECAVs-enabled congestion reduction

$$NPL_{Load-reduction} = \left( \frac{FFS_{NPL} - AVG_{Speed}(NPL)}{FFS_{NPL}} \right) \times \#Vehicles \quad (4)$$

$$Subset_{size} = \min(PL_{Hosting-capacity}, NPL_{Load-reduction}) \quad (5)$$

where  $Length(PL)$  represents the priority lane's length,  $AVG_{VL}$  is the average length of a vehicle,  $FFS_{NPL}$  refers to the Free Flow Speed of the congested non-priority lane while  $AVG_{Speed}(NPL)$  denotes its current average speed. Safety Distance is calculated using the maximum speed allowed in the priority lane.

The selection of vehicles to be promoted to the VIP-vehicle class is made based on three criteria:

- Their power source (i.e., electricity, hybrid, and fossil fuel), where an ECAV has a higher chance of promotion as it contributes more to transport sustainability.
- The remaining travel distance towards the destination. Here, vehicles with longer trips have higher chances of being selected for promotion.
- The accumulated waiting time, at intersections and due to traffic congestion, since the start of the vehicle trip. Vehicles with longer waiting times are given preferential consideration for promotion.

For each non-prioritized vehicle  $i$ , normalized values of the above three criteria along with their corresponding weight values are used to compute its probability for promotion to the VIP-vehicle class, as shown in Equation 6.

$$Pr(i) = (W_{power} \times Power_{value}(i)) + (W_{trip} \times Trip_{value}(i)) + (W_{waiting-time} \times Waiting-time_{value}(i)) \quad (6)$$

such that  $Power_{value}$  is set to different values, in  $]0,1]$ , for electric, hybrid and fossil fuel vehicles.  $Trip_{value}(i)$  is a normalized value representing the remaining travel distance

for the vehicle  $i$  trip and calculated according to Equation 7.  $Waiting-time_{value}(i)$  is a normalized value that denotes the accumulated waiting time of the vehicle  $i$  and is computed according to Equation 8.

$$Trip_{value}(i) = \frac{Trip(i)}{Maximum_{trip}} \quad (7)$$

where  $Trip(i)$  denotes the remaining distance to the destination for the vehicle  $i$ , while  $Maximum_{trip}$  represents the maximum value of this distance among all the vehicles using this congested non-priority lane.

$$Waiting-time_{value}(i) = \frac{Waiting-time(i)}{Maximum_{waiting-time}} \quad (8)$$

such that  $Waiting-time(i)$  represents the accumulated waiting time of the vehicle  $i$  during its trip so far, while  $Maximum_{waiting-time}$  refers to the maximum experienced accumulated delay among all the vehicles using this congested non-priority lane. Now, the ITLC selects the non-priority vehicles with the highest  $Pr(i)$  values (i.e., the top  $Subset_{size}$  vehicles) and notify them that they have been promoted to the class VIP-vehicle and are now able to move to the under-utilized priority lane(s).

### III. COALITION

In this section, we will introduce the key principle and the model underlying our proposed contribution - COALITION.

#### A. System model

To model the road traffic management system, we develop in this section a simple deterministic model, allowing a high-level analysis of the system and giving some insights into its performance.

The proposed model is a fluid one (see Fig. 2), meaning that the involved quantities and the whole numbers are seen as real quantities. We considered a simplified model in which the vehicle is in one of the states:  $S_y$  and  $S_x$ . The vehicles

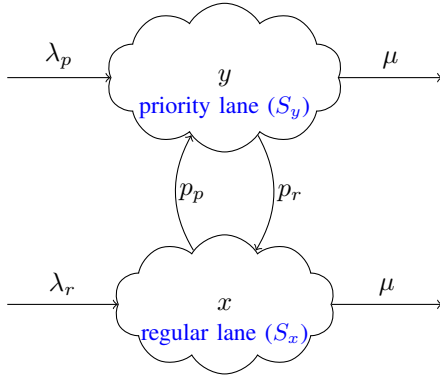


Figure 2: System model

using the priority lane(s) are within  $S_y$ , while the ones using the regular lanes are within the state  $S_x$ .

without loss of generality, we consider, in the following, only one regular lane and one priority lane. Indeed, in the case of multiple regular lanes, the model is still valid as the different lanes could be aggregated into one lane.

The considered parameters of the model are as follows:

- $x(t)$  number of vehicles in the regular lane at time  $t$ ;
- $y(t)$  number of vehicles in the priority lane at time  $t$
- $\lambda_p$  arrival rate of priority vehicles (e.g. Bus, Taxi or ambulance)
- $\lambda_r$  arrival rate of regular vehicles
- $\mu$  rate at which the vehicles of different categories leave the system
- $p_p$  rate at which regular vehicles move to priority lane
- $p_r$  rate at which vehicles (from different categories) of the priority lane move to the regular one

Now we are ready to describe the evolution of the state variables  $x(t)$ ,  $y(t)$ , based on the model described in Fig. 2. The model's dynamic is described by the following system of differential equations:

$$\begin{cases} \frac{dx(t)}{dt} = -(p_p + \mu)x(t) + p_r y(t) + \lambda_r, & (9) \\ \frac{dy(t)}{dt} = p_p x(t) - (p_r + \mu)y(t) + \lambda_p. & (10) \end{cases}$$

with the constraints that  $x(t)$  and  $y(t)$  should be non-negative and the rates  $\lambda_p$ ,  $\lambda_r$ ,  $p_p$ ,  $p_r$ ,  $\mu$  are all strictly positive.

Note that the system described in (9) and (10) is nonlinear and non affine in the control [11].

### B. Steady state performance

Having described the details of the proposed model, let's direct now our focus on the analysis of its steady-state performance.

The state matrix  $A$  of the system represented in equations (9) and (10), is as follows:

$$A = \begin{bmatrix} -(p_p + \mu) & p_r \\ p_p & -(p_r + \mu) \end{bmatrix}$$

It can be easily checked that the eigenvalues of the system state  $A$  are equal to  $(-\mu, -\mu + p_p + p_r)$ . As both of the eigenvalues are strictly negative, this means that the system is stable and converges to its steady-state equilibrium.

The study of the steady state of the system comes back to consider that

$$\frac{dx(t)}{dt} = \frac{dy(t)}{dt} = 0$$

We get from the equations (9) and (10):

$$\begin{cases} -(p_p + \mu)\bar{x} + p_r\bar{y} + \lambda_r = 0, & (11) \\ p_p\bar{x} - (p_r + \mu)\bar{y} + \lambda_p = 0. & (12) \end{cases}$$

where  $\bar{x}$  and  $\bar{y}$  represent the equilibrium values for  $x(t)$  and  $y(t)$ .

By solving the linear system represented in equations (11) and (12), we obtain

$$\begin{aligned} \bar{x} &= \frac{(\lambda_p + \lambda_r)p_r + \lambda_r\mu}{\mu(\mu + p_p + p_r)}, \\ \bar{y} &= \frac{(\lambda_p + \lambda_r)p_p + \lambda_p\mu}{\mu(\mu + p_p + p_r)}. \end{aligned}$$

Now suppose that a vehicle that has taken the priority lane only exits at the end of the lane (i.e.  $p_r = 0$ ). The equation for  $\bar{y}$  can be simplified

$$\bar{y} = \frac{(\lambda_p + \lambda_r)p_p + \lambda_p\mu}{\mu(\mu + p_p)} \quad (13)$$

From equation (13), we can deduce that knowing the system parameters  $\lambda_p$ ,  $\lambda_r$ ,  $\mu$  and  $p_p$  one can obtain the average number of vehicles in the priority lane.

As described in [8], the congestion in a lane depends not only on the number of vehicles in that lane but also on the difference between the optimal speed (i.e., Free Flow Speed "FFS") and the average speed of the lane. Thus, if the congestion level is to be controlled, equation (13) could be used to derive an upper bound of parameter  $p_p$  knowing the different system's parameters and a targeted number  $\bar{y}$  of vehicles in the priority lane.

The upper bound of  $p_p$  is, thus, equal to

$$\bar{p}_p = -\frac{\mu(-\mu\bar{y} + \lambda_p)}{-\mu\bar{y} + \lambda_p + \lambda_r} \quad (14)$$

with the constraints that  $\lambda_p + \lambda_r \neq \mu\bar{y}$ .

### C. Designing a control strategy

As we are focusing, in this paper, on controlling the number of vehicles in the priority lane, we consider, in the following, a simple, model agnostic, Proportional Integral Derivative (PID) controller [12]. The main objective of the control strategy is to ensure that the number of vehicles  $y$  converges to the optimal number  $y_{ref}$ . In fact, the proportional action allows reacting to the error, the integral part allows reacting to the average error and the derivative part allows reacting to the slope of the error, which may give a kind of predictive action.

The PID controller can be written as follows [12]:

$$u(t) = K_p e(t) + K_i \int_0^t e(s) ds + K_d \frac{de(t)}{dt} \quad (15)$$

where  $u$ ,  $e$ ,  $K_p$ ,  $K_i$  and  $K_d$  represent, respectively, the control input, which will be used to compute  $p_p$ , the error between the number of cars  $y$  in the priority lane and the targeted number of cars  $y_{\text{ref}}$  ( $y - y_{\text{ref}}$ ), the proportional gain, the integral gain and the derivative gain.

Using the Ziegler-Nichols method [12],  $K_p = 0.6K_u$ ,  $K_i = 2K_p/T_u$  and  $K_d = K_p T_u/8$ , where  $K_u$  is the ultimate gain at which the output of the system has stable and consistent oscillations and  $T_u$  is the oscillation period.

From (15), we can obtain a dynamic expression for  $p_p$

$$p_p(t) = \min(\max(\min(u(t), 1), 0), \bar{p}_p) \quad (16)$$

#### IV. PERFORMANCE EVALUATION

To assess the performance of CRITIC, CRITIC+, and COALITION, we performed a number of experiments using the microscopic traffic simulator SUMO and TraCI packages. For comparison purposes, a baseline scenario is defined wherein non-priority vehicles are not allowed to access priority lanes. We used two road network topologies:  $7 \times 7$  and  $10 \times 10$  Grid network topologies consisting of  $2 \times 2$  lanes and set the distance between every two consecutive junctions to 250m, similar to the Manhattan Road network in New York City. Two scenarios were tested, in the first one, the most outer lane on 25% of the network edges was used as a priority lane (i.e., a lane reserved for buses) while in the second scenario, 50% of the edges have such a reserved lane. As an example, if we examine an area of  $2 \text{ km}^2$  around the Grand Central Terminal in Manhattan, we can find that 23% of edges have a reserved bus lane. The experiments were run 30 times with a varying seed value at each run to get more representative results. The simulation considers three vehicle categories: buses, private vehicles, and ECAVs. The details of the simulation setting are summarized in Table I. The weight values for the three selection criteria, used in equation (6), are set to  $1/3$  each in our simulation, but different values could also be used if traffic authorities want to give more importance to one specific criterion, for example. During the simulation, non-prioritized vehicles with promotion probability greater than or equal to 0.6 are promoted to the VIP-vehicle class until the  $Subset_{\text{size}}$  is reached or there is no further non-prioritized vehicle that meets the promotion conditions.

Table I: Simulation setting

Parameter	Value
Map	2 Grid networks: $7 \times 7$ and $10 \times 10$
Edge length	250m
% of bus lanes	25% and 50% of total number of lanes
# of Vehicles	2200 (for Grid 7) & 5500 (for Grid 10)
% of buses	4%, 8% and 12%
% of ECAVs	10%
# of Simulation epochs	30

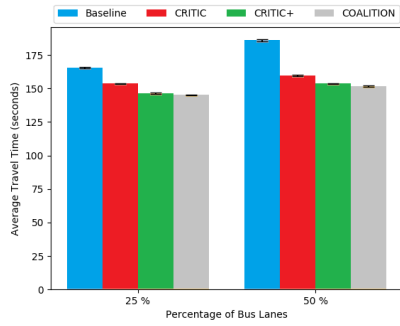
Fig. 3 shows the achieved Average Travel Time (ATT) in seconds for buses, private vehicles, and ECAVs in a  $7 \times 7$  Grid network with 4% of the traffic flow pertaining to buses. We can observe that when the percentage of bus lanes is 25% the three schemes significantly outperform the baseline with COALITION achieving the highest reduction in ATT. This shows the advantage of selecting a subset of vehicles to use the priority lane, instead of allowing all vehicles by assigning them the same priority, as the latter may shift the congestion to the priority lane instead of using it to virtually increase the road capacity and relieve the congestion situation. This also highlights the benefit of the probabilistic model used in COALITION, as well as the control strategy applied to control the load on the priority lane when a subset of vehicles is promoted to the VIP-vehicle class. The plotted results reveal also that even the buses will see their ATT reduced as during their journey they will also use non-priority lanes, which are now less congested due to the impact of the schemes applied, thus their overall travel time is reduced. When the percentage of bus lanes increases to 50% almost the same trend is observed with ECAVs achieving the highest reduction in their ATT. This is expected as the proposed schemes encourage the use of more sustainable transport options like ECAVs. Similar results could also be seen in Fig. 4 when the percentage of buses is increased to 8%.

We can also notice that the achieved travel time improvement by all schemes is higher when the percentage of bus lanes is 50% because in this case, the congestion is worse since the capacity of non-priority lanes is reduced with more vehicles using them.

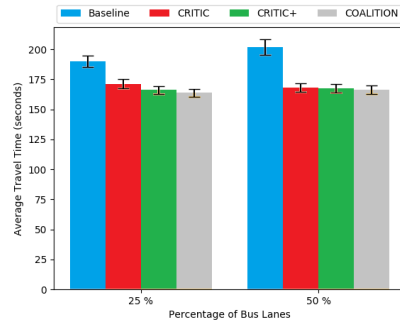
A summary of the achieved improvement in ATT (i.e., the average ATT reduction over 30 runs of the experiments) by the three schemes on  $7 \times 7$  Grid network and  $10 \times 10$  Grid network are shown in Table II and Table III, respectively. In Table II, it is clear that COALITION outperforms the other schemes, especially for ECAVs, where the improvement in ATT is 6% and 2% more than that achieved by CRITIC and CRITIC+ when the percentage of bus lanes is 25% and percentage of buses is 12%. For private vehicle type, a similar trend is maintained in the same scenario, with 17% more reduction in ATT compared to CRITIC and 2% further reduction in ATT compared to CRITIC+. The performance of COALITION is slightly reduced on  $10 \times 10$  Grid network as the traffic load is excessive (5500 vehicles, which is more than double the traffic load used in  $10 \times 10$  Grid network).

#### V. CONCLUSION

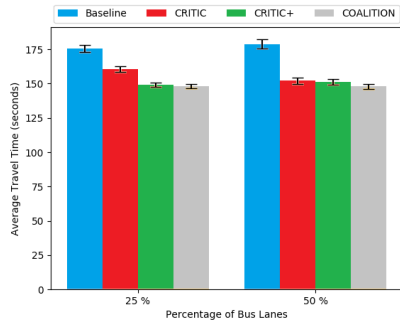
Faced with the rapid increase in the number of vehicles in developed and emerging countries, we presented COALITION, an innovative, probability-based system leveraging cognitive radio technology to alleviate congestion in overcrowded road lanes. The core concept of COALITION involves the strategic and dynamic allowance of selected non-priority vehicles to traverse the priority lane, with the objective of enhancing overall traffic flow and conditions. By prioritizing eco-friendly vehicles in our system (i.e., ECAVs), we are not only



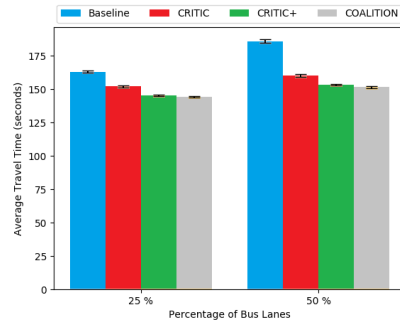
(a) All vehicles



(b) Buses

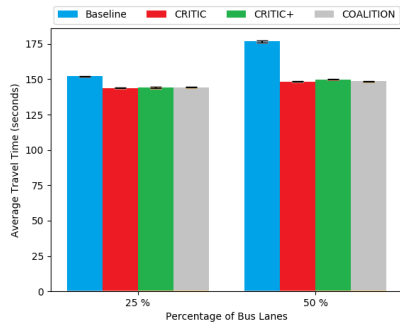


(c) Electric vehicles

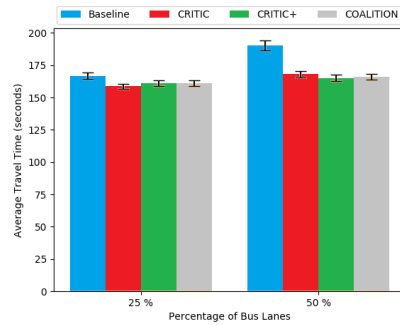


(d) Private vehicles

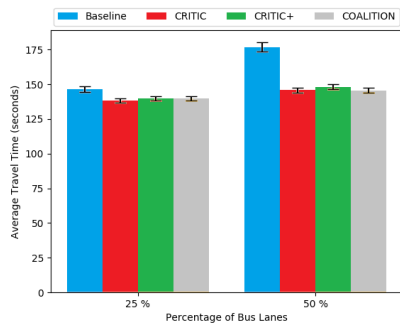
Figure 3: Impact of the percentage of available bus lanes on the efficiency of CRITIC, CRITIC+ and COALITION: a scenario of 7\*7 grid map with 4% of buses in the traffic



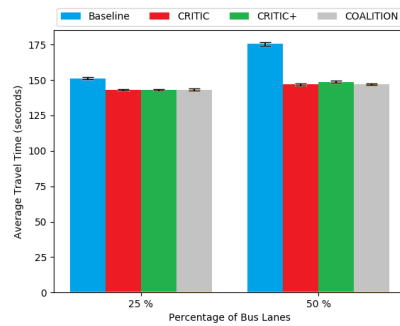
(a) All vehicles



(b) Buses



(c) Electric vehicles



(d) Private vehicles

Figure 4: Impact of the percentage of available bus lanes on the efficiency of CRITIC, CRITIC+ and COALITION: a scenario of 7\*7 grid map with 8% of buses in the traffic

Table II: Summary of the achieved improvement of ATT in CRITIC, CRITIC+ and COALITION: case of 7\*7 grid map

Vehicle type	% bus lanes	The achieved ATT improvement								
		CRITIC			CRITIC+			COALITION		
		4% buses	8% buses	12% buses	4% buses	8% buses	12% buses	4% buses	8% buses	12% buses
ALL	25	-7%	-5%	-13%	-11%	-5%	-17%	-12%	-5%	-18%
	50	-14%	-16%	-20%	-15%	-15%	-16%	-18%	-15%	-17%
BUS	25	-9%	-4%	-13%	-12%	-3%	-14%	-13%	-3%	-15%
	50	-16%	-11%	-17%	-16%	-13%	-14%	-17%	-12%	-16%
PRIVATE	25	-6%	-5%	-2%	-10%	-5%	-17%	-11%	-5%	-19%
	50	-13%	-16%	-20%	-17%	-15%	-15%	-18%	-16%	-16%
ECAVs	25	-8%	-5%	-14%	-15%	-4%	-18%	-15%	-4%	-20%
	50	-14%	-17%	-24%	-15%	-16%	-24%	-17%	-17%	-24%

Table III: Summary of the achieved improvement of ATT in CRITIC, CRITIC+ and COALITION: case of 10\*10 grid map

Vehicle type	% bus lanes	The achieved ATT improvement								
		CRITIC			CRITIC+			COALITION		
		4% buses	8% buses	12% buses	4% buses	8% buses	12% buses	4% buses	8% buses	12% buses
ALL	25	-4%	-8%	-7%	-8%	-11%	-9%	-8%	-10%	-9%
	50	-17%	-21%	-25%	-18%	-17%	-19%	-19%	-18%	-20%
BUS	25	-5%	-5%	-5%	-5%	-2%	-4%	-5%	-4%	-5%
	50	-16%	-20%	-19%	-5%	-9%	-10%	-7%	-11%	-11%
PRIVATE	25	-4%	-8%	-7%	-9%	-11%	-10%	-8%	-11%	-10%
	50	-18%	-21%	-25%	-18%	-18%	-21%	-19%	-19%	-21%
ECAVs	25	-4%	-7%	-9%	-7%	-11%	-11%	-7%	-12%	-11%
	50	-17%	-21%	-26%	-18%	-16%	-19%	-19%	-17%	-19%

contributing to improved traffic conditions but also promoting the widespread adoption of these environmentally friendly vehicles in the years to come. Extensive performance evaluation results have demonstrated the effectiveness of COALITION and its potential for significant impact in real-world scenarios. Our current results, while encouraging, pave the way for various research opportunities in the future. In particular, we intend to explore the application of Graph of Neural Networks (GNN), which could significantly improve the estimation of traffic conditions and optimise overall decision-making in terms of traffic management.

#### REFERENCES

- [1] W. Yue et al. What is the root cause of congestion in urban traffic networks: Road infrastructure or signal control? *IEEE Transactions on Intelligent Transportation Systems*, 23(7):8662–8679, 2022.
- [2] H. Zhu et al. Intelligent traffic network control in the era of internet of vehicles. *IEEE Transactions on Vehicular Technology*, 70(10):9787–9802, 2021.
- [3] F. Gao et al. Distributed urban freeway traffic optimization considering congestion propagation. *IEEE Internet of Things Journal*, 9(14):12155–12165, 2022.
- [4] Yen Tran and Naohisa Hashimoto. Mobility-as-a-service trials in japan: Initial result from a national project. In *2022 IEEE International Conference on Consumer Electronics (ICCE)*, pages 1–5, 2022.
- [5] S. Djahel et al. A communications-oriented perspective on traffic management systems for smart cities: Challenges and innovative approaches. *IEEE Communications Surveys Tutorials*, 17(1):125–151, Firstquarter 2015.
- [6] X. Huang et al. Dynamic trajectory-based traffic dispersion method for intersection traffic accidents in an intelligent and connected environment. *IEEE Intelligent Transportation Systems Magazine*, 15(1):84–100, 2023.
- [7] Zheng Wang and Shen Wang. Xrouting: Explainable vehicle rerouting for urban road congestion avoidance using deep reinforcement learning. In *2022 IEEE International Smart Cities Conference (ISC2)*, pages 1–7, 2022.
- [8] S. Djahel et al. Cr-tms: Connected vehicles enabled road traffic congestion mitigation system using virtual road capacity inflation. In *2020 IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC)*, pages 1–6, 2020.
- [9] ALEKO Dex R. and Soufiene Djahel. An efficient adaptive traffic light control system for urban road traffic congestion reduction in smart cities. *Information*, 11(2), 2020.
- [10] J. Hodgkiss et al. An advanced coordination protocol for safer and more efficient lane change for connected and autonomous vehicles. In *2019 16th IEEE Annual Consumer Communications Networking Conference (CCNC)*, pages 1–4, 2019.
- [11] Tayfun Cimen and Stephen P. Banks. Global optimal feedback control for general nonlinear systems with nonquadratic performance criteria. *Systems Control Letters*, 53(5):327 – 346, 2004.
- [12] J.C. Doyle et al. *Feedback Control Theory*. Prentice Hall Professional Technical Reference, 1991.