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CONTROL DE CONGESTIÓN Y ASIGNACIÓN DE RECURSOS EN REDES VEHICULARES MEDIANTE ALGORITMOS DE OPTIMIZACIÓN E INTELIGENCIA ARTIFICIAL

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Resource Allocation and Congestion Control in Vehicular Ad-Hoc Networks through Optimization Algorithms and Artificial Intelligence

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Abstract

The ever-increasing growth of the transportation industry demands combined with new safety requirements has triggered the development of vehicular communications. These communications among vehicles are based on the exchange of periodical messages or beacons containing valuable information about vehicle state. This gives rise to the socalled cooperative awareness, which allows extending the capabilities of numerous driverassistance systems and safety applications. Disseminating information among vehicles certainly lessens the risk of collision and other undesired events. Nevertheless, the aggregated beaconing load can rapidly jam the channel, compromising packet reception, and therefore endangering the advantages offered by such communications. To guarantee the availability of the channel for emergency messages and the minimum beacons receptions that satisfy safety application requirements, a given fraction of the channel capacity should be available. This congestion control has been addressed by adjusting several transmission parameters but some challenges are still unresolved. Although these parameters are usually optimized individually because of the convexity of the optimization problem, we show the advantages of combining them. In this thesis, we propose the use of different distributed algorithms that reach the desired congestion level without explicitly requiring any costly infrastructure. The first part of this thesis addresses beaconing rate allocation. We propose several distributed solutions based on Network Utility Maximization (NUM) and different risk metrics such as time-to-collision and advisory road speed. In the second part, we not only study different combinations of well-coupled parameters but also dive into the paradigm of noncooperative algorithms, in which no information from neighboring vehicles or centralized infraestructure are required. We formulate the congestion control problem as a Markov Decision Process and solve it by means of different reinforcement learning techniques. In particular, we propose different solutions ranging from tabular methods suitable for simple and discrete environments, like Q-learning, to more complex functions approximations for continuous action-state spaces, such as Semi-gradient SARSA or artificial neural networks.

Resumen

En los últimos años la creciente demanda de la industria del transporte junto con reguisitos de seguridad cada vez más estrictos han promovido el rápido desarrollo de las comunicaciones vehiculares. Tales comunicaciones se basan en el intercambio de mensajes periódicos (beacons) que contienen información crítica de los vehículos. Esta difusión de información da origen a lo que comúnmente se denomina conciencia cooperativa, que permite ampliar las capacidades de numerosos sistemas de asistencia en carretera y las diferentes aplicaciones de seguridad. Ciertamente, la difusión de información entre vehículos es la base de la conducción autónoma y reduce drásticamente el riesgo de colisión y otros eventos indeseados. Sin embargo, es importante tener en cuenta que la carga agregada de los beacons transmitidos puede congestionar rápidamente el canal, comprometiendo la recepción de paquetes y, por lo tanto, poniendo en peligro las ventajas que ofrecen tales comunicaciones. Para garantizar la disponibilidad del canal tanto para la recepción correcta de mensajes de emergencia y de las mínimas balizas necesarias para satisfacer los requisitos de las aplicaciones de seguridad, una determinada fracción del canal debe de ser reservada. En la literatura relacionada, el control de la congestión se ha abordado mediante el ajuste de varios parámetros de transmisión (tasa de mensaje, potencia y tasa de bit), pero todavía existen numerosos desafíos por abordar. Por ejemplo, aunque los parámetros de transmisión suelen ajustarse individualmente debido a la simplicidad del problema de optimización, aquí se muestran las ventajas de ajustar varios parámetros de forma simultánea. En esta tesis, se propone el uso de diferentes algoritmos distribuidos que alcancen el nivel de congestión deseado sin requerir infraestructura ninguna en carretera. La primera parte de esta tesis aborda la asignación de la tasa de balizamiento mediante la maximización de la utilidad de red (NUM) y diferentes métricas de riesgo como el tiempo de colisión y la velocidad de la carretera de aviso. En la segunda parte, no solo se estudian diferentes combinaciones consistentes de parámetros, sino que también nos sumergimos en el paradigma de los algoritmos no cooperativos, en los que no se requiere información de los vehículos vecinos. El problema de control de la congestión es formulado como un Proceso de Decisión de Markov (MDP) y resuelto mediante técnicas de inteligencia artificial, más concretamente, mediante aprendizaje por refuerzo (RL). Se proponen diferentes soluciones que van desde simples métodos tabulares, adecuados para entornos discretos, como Q-learning, hasta funciones de aproximación más complejas adecuadas para espacios continuos, como SARSA basado en semi-gradiente o redes neuronales artificiales.

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Part I

Introduction, motivation and background

Introduction

1.1 V2V communications and DCC

The transportation industry has evolved according to the escalating demand of a globalized scenario for carrying goods, raw materials, and millions of passengers from increasingly larger and overpopulated cities [1]. Unless current trends do change, the number of vehicles is estimated to triple by 2050, reaching 3 billion vehicles [2] along with vehicle-related crashes, injuries, and death ratios. Intelligent Transportation Systems (ITS) are designed to avoid this detrimental traffic impact on mankind by sharing information among vehicles [3, 4]. This exchange is conducted using vehicle-to-vehicle (V2V) communications, which extend the capabilities of numerous driver-assistance systems and driverless vehicles. Cooperative actions, such as platoon driving, collision avoidance [5], spotting pinch points and routing the traffic flow automatically, or detecting suspicious and harmful driver behavior, would suppose a huge step toward the safety and efficiency of transportation systems. Undoubtedly, the number of fatal events on roads and accident severity will be diminished.

The European Telecommunications Standards Institute (ETSI) defines the ITS-G5 radio channel, a 10 MHz control channel for vehicular communications at the 5.9 GHz band of the IEEE 802.11p standard [6]. The ETSI Cooperative Awareness Service (CAS) [7] transmits periodical broadcast single-hop messages, called beacons, throughout this control channel (or Channel 172 in the US). Formally called Cooperative Awareness Messages (CAM) in Europe or Basic Safety Messages (BSM) in the US, beacons are responsible for disseminating status and environmental infomation among vehicles. Data, such as position, speed, acceleration, heading angle, or vehicle dimensions are employed to track and predict the behavior of neighboring vehicles ¹. This broadcast information supports many safety applications and is crucial for reducing the risk of collision among vehicles [8–10] or other undesired events. Apart from beacons, vehicles send other data over the ITS-G5 radio channel, such as service announcements and event-related messages. Finally, it should be noted that cooperative actions not only improve the safety of the vehicles but also benefits the environment. A

¹In V2V communications, neighbors are defined as the set of vehicles from which at least one message has been correctly received during a given time interval.

more coordinated traffic flow allows the removal of unnecessary braking and accelerating, which results in a remarkable reduction in fuel consumption and longer vehicle lifespan.

As the number of vehicles on the road increases, the aggregated load due to the CAS beacons can easily saturate the channel, compromising packet reception, and therefore endangering vehicle situation awareness. Many safety applications [8–10] based on beacons could be using outdated and inaccurate information and therefore stop working properly. Congestion also affects other services based on the ITS-G5 radio channel, like the Decentralized Environmental Notification (DEN) service, which notifies emergency services whenever an accident occurs on the road [11]. Not receiving such event-related messages, called DEN Messages (DENM), is a critical issue to the safety and health of the road users (drivers, passengers, and pedestrians) [11]. To guarantee the delivery of these emergency-related messages (DENM), as well as to provide cooperation awareness (CAM) enough to satisfy safety application requirements, a certain fraction of the channel capacity should be available. Broadly speaking, this is what congestion control does and why is it of great importance in V2V communications.

The ETSI standard defines the Cross-Layer Decentralized Congestion Control (DCC) Management Entity [12] to prevent the ITS-G5 radio channel overload. The use of channel congestion control mechanisms is established in a distributed manner among several layers of the architecture (cross-layer). Optionally, congestion control is also carried out in a distributed manner among all the vehicles of the network, which allows us to dispense with costly infrastructures. This is what is known in the ETSI standards as DCC (Decentralized Congestion Control). More to the point, the DCC is in charge of controlling channel congestion and allocating radio resources. As shown in 1.1, the DCC is mainly comprised of the DCC_CROSS entity, which manages the cooperation between different layers. The standards specify that the DCC function will be executed by prioritizing traffic classes, queue management, flow control, transmission frequency, transmission speed, and power, among others. Nevertheless, despite the fact that the CAS beaconing provides the basic support for the development of cooperative applications and, above all, for determining the reliability of most of them, there are not completely satisfactory DCC mechanisms to date.

Two different approaches can be drawn to solve the resource allocation problem in V2V communications, awareness control (CA) [13] and congestion control (CC). On the one hand, CA satisfies first *some application* requirements. Although there is no widely accepted definition for awareness, it is usually related to the notion that the beaconing rate should adapt to traffic or vehicle situations [14], especially as regards safety [15], and not only to the channel load. In contrast, pure CC refers to the mechanisms intended to maintain the channel load under a certain target level, regardless of whether or not the needs of the applications on top of the service are fulfilled. Some of these proposals adjust transmission parameters separately or jointly, but there is still plenty of room for improvement. For instance, current European standards [7] state some generation rules only depending on the vehicle's own dynamics, which results in a type of limited awareness control, as we have pointed out, but that result in underusing the channel. The underlying issue seems to be how to integrate congestion and awareness control, including beacon generation, into a more coherent

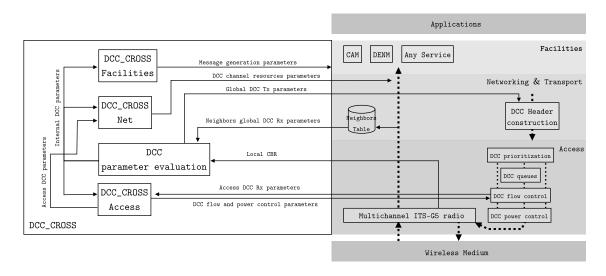


FIGURE 1.1: DCC architecture.

framework with more clearly defined goals. Additional desirable features of the procedure are that it is distributed, allocates resources according to vehicle requirements (fairness), and stable. This thesis will discuss some of these points, as well as different ways of allocating resources, as explained below.

1.2 Toward optimal resource allocation

Channel congestion can be alleviated by prioritizing traffic classes, managing queues, or controlling the transmission flow. Variations in transmission frequency, transmission speed (data rate), and transmission power of the vehicles have a great impact on the overall channel load. The most widespread solution lies in adjusting the transmission frequency of beacons, which is popularly called beaconing rate. This kind of approach was so effective that was included in the standard [16, 17]. Secondly, numerous approaches reduce transmission power to alleviate congestion. Since the transmission range is lowered, the number of messages received by neighboring vehicles is also reduced, along with overall channel congestion [18–20]. Finally, despite being less popular, increasing the data rate can also relieve channel congestion. Adjusting a single parameter usually results in successfully control congestion, but presents some drawbacks. Despite reducing channel congestion, some detrimental effects to vehicle awareness and application layer, especially in highly congested scenarios. For example, insufficient beaconing rates to mitigate congestion may also entail a lack of situation awareness of the surrounding vehicles. Likewise, if the transmission power is decreased too much to maintain channel load under control, vehicles would only communicate with a few close neighboring vehicles due to low transmission ranges, leading to poorer cooperation among vehicles.

To deal with this problem, a combination of two or more parameters can be used. Since channel load is balanced between the different parameters employed, no drastic changes,

detrimental to cooperative awareness, are required. Therefore, an optimal joint allocation of two or more parameters would be ideal but the associated optimization problems are usually not convex [21] and consequently, ordinary optimization methods become ineffective. As mentioned in the previous section, and given the nature of the DCC entity, we focus on distributed algorithms that can reach their goals without any centralized entity or base-station. Within this type of algorithms, some solutions employ game theory [22] or decision theory to deal with joint optimization [23], being beaconing rate and transmission power combination one of the most popular. It should be noted that this set of parameters works well, but it is more consistent to combine data rate and transmission power. Despite the fact that the IEEE 802.11p standard [6] defines up to 9 different data rates from 3 to 27 Mbps, a data rate of 6 Mbps is usually recommended and set by default, but there is actually no reason not to vary the data rate. On the one hand, high data rates lessen transmission times and, therefore, overall channel congestion is reduced. As a drawback, they employ high-order modulations, which are less robust against unfavorable channel conditions, and their efficiency depends on the transmission power radiated. To mitigate this effect, higher transmission power is required to maintain an adequate Packet Delivery Ratio (PDR) at a given target distance. On the other hand, low data rates provide more reliable communications but increasing the transmission time and therefore, the channel load. This thesis will investigate this novel trade-off between transmission power and the data rate.

1.3 Motivation and Objectives

In the previous section, we have commented the operation mode of vehicular networks and the importance of controlling congestion, leaving a certain fraction of the channel free, to guarantee the delivery of CAM and DENM messages. Two of the most relevant problems of these networks are why and how resources are allocated. In other words, the performance of the different congestion control algorithms depends on whether they are focused on purely alleviating congestion (CC) or satisfying application layer requirements (CA). Note that these two approaches are usually associated, and a balance between them is required. In this work, we cope with the design of distributed congestion control algorithms based on different requirements and transmission parameters adaptation, such as beaconing rate and transmission power, and data rate. We formulate the following general objectives:

- 1. To investigate congestion awareness (Chapter 3) and congestion control problems (Chapters 3, 4, 5, 6, 7, 8) in vehicular networks using distributed algorithms.
- 2. To address the congestion control problem using a combination of transmission parameters and applying artificial intelligence (Chapters 6, 7, 8).

In order to accomplish these general objectives, we define the following specific objectives:

1. To address joint congestion and awareness control by using a Network Utility Maximization (NUM) [24, 25] problem formulation. Consider the constrained version of the

- problem taking into account several metrics as constraints. Related to general objective 1 and addressed in Chapter 3.
- 2. To evaluate the CAM dissemination mechanism stated in the standard and propose different improvements. Related to general objective 1 and addressed in Chapters 4 and 5.
- 3. To address the congestion control using tabulated methods within the reinforcement learning framework for joint transmission parameter adaptation. Related to general objectives 1 and 2 and addressed in Chapter 6.
- 4. To address congestion control using approximate reinforcement learning methods and evaluate the gains with respect to tabulated methods. Related to general objectives 1 and 2 and addressed in Chapters 7 (function approximation) and 8 (neural networks).
- 5. To investigate data rate adaptation, alone or together with other parameters and its effects on safety applications. Related to general objectives 1 and 2 and addressed in Chapter 8.

Related Work

As mentioned in the previous chapter, vehicles are expected to cooperate with each other and provide drivers with assistance, improving safety on the road significantly. Such advantages could be compromised if the channel load is too high and the transmitted information among vehicles and emergency services (CAM and DEMN messages) is not successfully received. In this chapter, we analyze the different mechanisms that have been proposed to alleviate congestion in vehicular networks.

The ETSI standard states the DCC management entity [26] to control congestion of the ITS-G5 radio channel. The algorithm included in this standardization process, called CAM-DCC, combines some CAM generation rules that rely on vehicle dynamics [7] (cooperative awareness), and the simple reactive congestion control algorithm suggested in [12]. On the one hand, CAM-DCC triggers a new CAM message when the difference between current values of position, speed, and heading, and those included in the previously transmitted message, surpasses some predefined thresholds. This mechanism offers poor responsiveness [27] and the motivation of the triggering rules is not always related to the risk of the vehicles. On the other hand, congestion is limited using a finite state machine, which results in oscillations [28] and channel underuse since no target channel load is defined. CC and CA should be highly related. As studied in Chapters 3, 4 and 5, respectively, undesired outcomes result when they are used independently, as in the case of CAM-DCC. For this reason, numerous proposals have emerged to improve the standard in some way.

2.1 Common congestion control approaches

Several transmission parameters, such as beaconing rate, transmission power or data rate, can be varied over time according to channel requirements and how much is it congested. Given the wide scope of solutions, let us first review the beaconing rate, which is the most relevant parameter and easiest to adjust. One of the most widespread solutions based on variations of the number of beacons transmitted per second is LIMERIC [16]. With LIMERIC, each vehicle linearly updates its own rate depending on the total channel load, which driven towards a required goal. Note that this is a pure CC mechanism since only channel load is used to update the rates, whereas vehicle dynamics, application requirements, and traffic

situation are completely ignored. PULSAR [17] is another popular rate-based control algorithm that uses Additive Increase Multiplicative Decrease (AIMD) with feedback from 2-hop neighbors. Since the convergence of LIMERIC is not proved in multi-hop scenarios, PULSAR was used in combination with LIMERIC to resolve this issue [28]. Concerning awareness control, numerous approaches can be found in the literature. These solutions regulate the beaconing rate depending on some kind of prioritization, improving the awareness of the vehicles and allocating resources more fairly (achieving *fairness*). For instance, there is a set of proposals that adjust the beaconing rate to minimize the position tracking error with respect to other vehicles, such as [29–31]. This is actually the mechanism employed in the US DCC standard [32]. EMBARC [33], which is a more recent variation of LIMERIC, also integrates the tracking error algorithm of [31]. Other solutions assess the risk estimated of some specific traffic situations [15, 34–36].

Among the solutions that successfully integrate CC and AC, NORAC [37] provides a distributed control based on non-cooperative game theory. Each vehicle adjusts the beaconing rate according to application requirements and without exchanging control information with its neighboring vehicles. ABC [34] also integrates AC and CC in the context of a TDMA-based protocol. In this case, the potential risk of a rear-end collision is incorporated in an optimal resource allocation problem to assign more resources to more dangerous vehicles. Similarly, in Chapter 3, we formulate the CC problem as a Network Utility Maximization problem [24, 38] and integrate the AC by means of a general vector form of the time-to-collision between neighboring vehicles. Consequently, we prioritize the rate allocated according to the risk of collision between vehicles.

In addition to the beaconing rate, transmission power is also widely used to prevent the channel from being saturated. If the transmission range is lowered, the number of vehicles that receive broadcast messages is reduced and thus channel congestion is alleviated. Despite not being as much popular as the beaconing rate, numerous works proposed also controlling transmission power depending upon different variables. For instance, authors in [39] used the channel state information (CSI) to improve energy efficiency. In [18], the speed of the vehicle was employed to allocate transmission power. The higher the speed, the greater the transmission power radiated to counteract the adverse impact of low time-to-collisions. Vehicle density was also introduced in [19] to decide whether to increase or decrease transmission power. Likewise, the signal-to-noise-interference ratio (SNIR) is estimated in [40], or the vehicle position prediction error [41], to determine whether to increase or decrease transmission power. Other proposals allocate transmission power directly as a function of the channel congestion [20, 42]. Different congestion controls based on single parameter adaptation have been summarized in Table 2.1.

2.2 Joint and intelligent parameters adaptation

Instead of handling congestion using transmission parameters individually, more advanced proposals combine two or more simultaneously [21, 32, 43–47]. This prevents excessive variations of the transmission parameters while alleviating congestion, which has a detrimental

impact on the safety application performance and context awareness of the vehicles. For instance, if the beaconing rate is lowered too much, the aforementioned services might receive outdated information and become useless in enhancing safety. Likewise, sharp and inadequate reductions of transmission power while mitigating congestion result in transmitted messages reaching only a few close neighboring vehicles. Cooperative actions are undoubtedly meaningless when they are not able to go farther than humans' perception. These problems are solved by using two or more parameters at a time since they compensate each other and reduce congestion without sharp reductions. However, joint adaptation (usually beaconing rate and transmission power) is usually a non-convex optimization problem, which makes ordinary optimization methods ineffective. Each emerging approach deals with the allocation problem in a different way. Some proposals are based on measuring different factors to carry out resource allocation and improve specific aspects. For example, the packet Inter-Reception Time (IRT) at a given distance to optimize packet reception is measured in [48]. Authors in [44] proposed the algorithm ECPR, which varies transmission power to obtain a certain awareness ratio by estimating the Path Loss Exponent (PLE), whereas channel load is individually controlled by LIMERIC [16].

The vast majority of approaches mentioned above require including additional information in the messages. This technique is usually called piggybacking and makes congestion control depending on the channel state, which may degrade the awareness in unfavorable channel conditions with fast variations. As suggested in [46], tracking error should be considered to protect the congestion control against the channel instabilities. But there is a more straightforward solution: not relying on neighbors' information for the proper operation of congestion control. These algorithms are commonly known as non-cooperative. The first approach of this type was introduced in the J2945/1 standard by the Society of Automotive Engineers (SAE). In particular, the J2945/1 standard states a congestion control based on the CBR and vehicle density, which regulate transmission power and beaconing rate when the channel is congested [32, 43]. Later, the J2945/1 proposal has been updated to allocate beaconing rate and transmission power in cellular V2X communications [47]. Using also a non-cooperative scheme and game theory to successfully maintains congestion at a certain desired level, authors of NORAC [37] introduce BFPC [22]. Unlike NORAC, which only uses the beaconing rate, BFPC includes also transmission power. Nonetheless, some parameters must be adjusted experimentally depending on the scenario to obtain the desired CBR level.

Note that game theory has been used to find optimal congestion control and endow a certain level of intelligence to vehicles, handling the complexity of mixed optimization problems. Likewise, given the nature of the problem, in which no a priori information or data about the (road) environment is available, the Markov Decision Process (MDP), which is one of the decision-making techniques of choice and the basis of reinforcement learning (RL) [49], has also been employed in recent years. With RL, each vehicle takes actions, performs transitions among different states, and obtains different rewards depending on how well congestion is alleviated. For instance, congestion control to adapt transmission power using Q-learning is proposed in [50] for the particular case of LTE-V2V communications. A multiagent approach is also suggested in [51]. Concerning joint allocations that optimize more

than one parameter, authors in [52] combine the selection of the optimal frequency subband and transmission power in a decision-making problem. Simultaneous beaconing rate and transmission power adaptation are addressed in [53]. This work formulates the different states, the reward function, and the learning method in the downlinks of cellular networks (C-V2X). These solutions mentioned above are focused on cellular networks, but none of them have applied reinforcement learning to deal with congestion in a non-cooperative and distributed manner. For this reason, we propose (Chapter 6) a novel approach, called MDPRP, to derive the best beaconing rate and transmission power based on transmission policies. A Markov Decision Process is modelled and resolved with Q-learning techniques to fully prevent congestion while maximizing channel utilization and preserving the proper performance of safety applications. Despite allocating resources properly, tabulated methods (e.g., Q-learning) become unstable if the state space is large due to the substantial amount of memory needed for large tables and also due to the time and data needed to fill them accurately. The use of more general approximation functions allows solving complex problems with sophisticated environments and continuous action-state spaces. As a first step before the full use of artificial neural networks within the RL framework, we apply function approximation in discrete action-state space to resolve a simple beaconing rate allocation in Chapter 7. This allows us to generalize previous states to derive sensible decisions when new states are encountered. The resulting parameterized model can be applied by vehicles through limited computational resources.

2.3 Balancing transmission power and data rate

Even though up to 9 different data rates, from 3 to 27 Mbps, are defined by the standard [6], a data rate of 6 Mbps is recommended and even fixed by default. Some research assumed this data rate as optimal and provided a method to identify it according to multiple scenarios [54]. In [54], transmission power was adjusted to obtain the same PDR as the reference value obtained for 6 Mbps. However, this was later discussed in [55], whose authors claimed that it is not clear whether the selected transmission power levels in [54] guarantee the communication range required by vehicular applications. Using both simulations and field experiments, authors in [55] demonstrated that 6 Mbps is not always the optimum data rate. In fact, the data rate can be also used to alleviate congestion, and there is no reason not to vary it with that end. On the one hand, higher data rates result in shorter packet transmission times, which reduces channel load and congestion effectively. As a drawback, they employ more complex modulations less robust against unfavorable channel conditions over distance. This issue could be compensated by using a higher transmission power and guaranteeing an adequate Packet Delivery Ratio (PDR) at a given distance. On the other hand, lower data rates increase transmission time and congestion but provide more reliable communications over distance. There is limited research work aimed at handling data rate variations. For instance, the study [56] should be highlighted, which is a non-cooperative approach based on game theory to successfully maintain congestion below a certain level.

Concerning combining more than one parameter to control channel congestion, the most popular solutions integrate the beaconing rate and transmission power parameters in their formulations. However, using transmission power and data rate jointly is more consistent and appropriate due to the channel condition dependence of the data rate; that is, high data rates are more affected by fading and attenuation, and thus, the effective transmission range is reduced, which can be counteracted by increasing transmission power. To the best of our knowledge, only two works are aimed at combining data rate and transmission power in vehicular ad-hoc networks to alleviate congestion in a distributed manner [57, 58]. The first study employs a look-up table to select pairs of transmission power and data rates according to the PDR and end-to-end delay metrics. As a drawback, the available pairs of data rate and transmission power parameters are scarce. The second work [58], called CACC, senses the Received Signal Strength (RSS) to determine the cause of packet loss, discerning between weak signal or collisions. Then, the algorithm decides to decrease or increase the transmission power or data rate. Even though CACC attains good results in terms of packet delivery, the channel is usually underused or overused depending on the scenario. As in the previous solution, only a few data rates among all the available ranges in the standard are considered. Having these weaknesses in mind, a more sophisticated solution is necessary to consider the full ranges of the transmission parameters and to select them accordingly. To contribute to filling this research gap, we propose a novel deep reinforcement learning approach (Chapter 8), called NNDP, (i) to alleviate congestion, leaving a fraction of the channel capacity free to guarantee the delivery of DENMs. On top of this, (ii) transmission power is intended to provide safety applications with an adequate performance at a certain safety distance, whereas (iii) the lower possible data rate (most robust) is set. In Table 2.2, joint parameter adaptations have been summarized according to different features, such as the transmission parameter used, the optimization technique, and whether they require a centralized entity or not.

	[26]	[16, 17, 28]	[15, 29-36]	[38]	[37]	[18, 19, 39-41]	[20]	Chapter 3	Chapter 7
Cooperative	No	No	No	Yes	No	No	Yes	Yes	No
Awareness control	Yes	No	Yes	No	Yes	Yes	No	Yes	No
Beaconing control	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
Power control	No	No	No	No	No	Yes	No	No	No
Data rate control	No	No	No	No	No	No	No	No	No
Target load	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Distributed (V2V)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Approach	CGR	OA	OA	NUM	GT	OA	NUM	NUM	MDP

TABLE 2.1: Comparison of distributed congestion control related works (single parameter adaptation).

TABLE 2.2: Comparison of distributed congestion control related works (joint parameter adaptation).

	[32, 43-46]	[21]	[47]	[22]	[52]	[53]	[57, 58]	Chapter 6	Chapter 8
Cooperative	No	Yes	No	No	No	No	No	No	No
Awareness control	Yes	No	Yes	Yes	Yes	Yes	No	No	No
Beaconing control	Yes	Yes	Yes	Yes	No	Yes	No	Yes	No
Power control	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Data rate control	No	No	No	No	No	No	Yes	No	Yes
Target load	No	Yes	No	No	No	No	No	Yes	Yes
Distributed (V2V)	Yes	Yes	No	Yes	No	Yes	Yes	Yes	Yes
Approach	OA	NUM	OA	GT	DRL	DRL	OA	MDP	DRL

Part II Article summaries

Article 1: Time-to-Collision-Based Awareness and Congestion Control for Vehicular Communications

3.1 Summary

Connected vehicles extend the capabilities of multiple advanced driver-assistance systems and automated vehicles by enabling the possibility of performing cooperative actions and increasing the awareness of vehicle sensor systems [59]. These communications among vehicles are based on single-hop status messages (beacons) over a control channel to provide detailed information about vehicle position, speed, heading, acceleration, and other data of interest [7]. Beacons, called Cooperative Awareness Messages (CAM) in European standards and Basic Safety Messages (BSM) in the US standard, are transmitted periodically at a certain beaconing rate. Excessive beaconing activity may hinder the delivery of other messages called Decentralized Environmental Notification Message (DENM), which is triggered whenever a fatal situation occurs to warn both emergency services and other vehicles. Therefore, the adaptation of transmission parameters becomes vital to guarantee the availability of a fraction of the channel load (using Maximum Beaconing Load threshold, MBL) for the proper delivery of event-related messages. This problem has been really analyzed previously (p.e. [16, 28, 31, 37, 38, 60], but some aspects still deserve further consideration.

There are two different approaches to the control problem: pure *congestion control*, (CC) and *awareness control*, (AC) [13]. Congestion control refers to the mechanisms used to maintain the channel load at a certain level, disregarding the needs of the safety applications on top of the service. Meanwhile, awareness control refers to the mechanisms employed to satisfy *some application* requirements. Although there is no widely accepted common definition for awareness, it is usually related to the notion that the beaconing rate should adapt to traffic or vehicle situations [14], especially as regards safety [15], and not only to the channel load. Most current approaches ignore the traffic situation and only adapt the beaconing rate, which is the most common parameter, to the channel congestion state.

In this chapter, we propose and validate a novel approach, combining both congestion and awareness control. The proposed algorithm is based on distributed allocation of beaconing rate using Network Utility Maximization (NUM) [24, 25, 38, 61, 62] and satisfying the constraints on channel availability. The safety (risk) of the surrounding traffic situation is captured with a time-to-collision (TTC) metric to assign priorities in the optimal allocation problem. The lower the TTC metric, the higher the risk. The performance of the proposed approach is validated and compared to other popular algorithms in several road scenarios. Results show that our proposal automatically anticipates a potential increase in rate due to a critical safety situation (AC), but does not interfere with the reserved bandwidth for safety applications (CC).

3.2 Methodology

We first made a deep review of the state-of-the-art with regards to congestion control algorithms based on the beaconing rate adaptation. We paid particular attention to work focusing on awareness control, which usually refers to the mechanisms employed to satisfy some application requirements. We formulated the problem as a NUM problem that complements the pure congestion control of [38] by taking advantage of the algorithm's capability to shape the resulting allocation via fairness and priority parameters. As shown in Figure 3.2, we first made some theoretical computations in Java to prove whether the proposed algorithm converged properly under those parameters variations.

- The fairness parameter, α , allowed us to adjust the notion of fairness. For instance, if α = 0, the throughput is maximized but unfair solutions may result. In contrast, with α = 1, proportional fairness, as defined by Kelly [24], is achieved. As $\alpha \to \infty$, the allocation tends to max-min fairness.
- Regarding priority parameter, ω_v , is used to prioritize the rate allocated to particular vehicles to achieve the so-called weighted fairness.

Unlike other proposals, we used a general vector form for the computation of TTC between vehicles. We assign the value of the TTC to the priority parameter to prioritize the rate allocated according to the risk of collision between vehicles. To evaluate this, we employed a simulation environment using OMNeT++ 5.3 [63] and its INET 3.5 library [64], which implements the IEEE 802.11p standard and realistic propagation and interference models, also considering the capture effect. To this end, we developed our own Network Interface Card (NIC) based on IEEE 802.11p [7], disregarding both agent and classifier properties. An additional mobility module, which implements the Intelligent Driver Model (IDM), was also developed to simulate more realistic driver behavior [65]. The whole simulation environment in which different scenarios were tested is illustrated in Figure 3.1.

We set 5 consecutive vehicles in movement on a lane moving at high speeds, and other parallel lanes in the opposite direction with a traffic jam to produce channel congestion. The first group is led by a vehicle that moves at a slower speed than the rest of the vehicles. Such

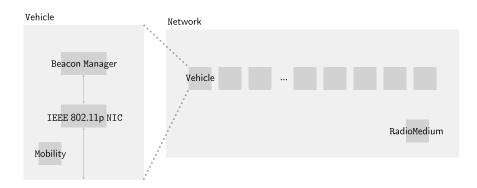


FIGURE 3.1: Simulation environment developed in OMNeT++.

initial differences in speed and separations forced the following vehicles to decelerate with different intensities due to the IDM model embedded in the vehicle mobility module. With this scenario, we intended to reflect the risk of the vehicle deceleration on the beaconing rate. Since all vehicles were in range with each other, this was an ideal single-hop scenario to test whether the proposed algorithm works properly. Then, this simple scenario turned to be multi-hop, where vehicles only saw a bunch of vehicles as neighbors. Two realistic scenarios were also developed to test the robustness of the proposed algorithm under moving conditions: two approaching clusters and a 2×2 grid road comprised of 9 intersections and 600 m edges with 4 lanes each.

3.3 Results and contributions

We proved that the algorithm provided a good response by varying the priority parameters and that it still converged, so the awareness metric (TTC) could be used to prioritize vehicles according to their environmental situation. As shown in Figure 3.3, vehicles with a lower time-to-collision provide a higher beaconing rate. It is important to highlight that congestion is still alleviated, and a certain fraction of the channel is left free to guarantee the proper delivery of event-related messages. The main contributions of this work can be summarized as follows:

- Awareness control is fully integrated with the congestion control and complies with the MBL constraint.
- The awareness control takes the surrounding traffic situation and neighboring dynamics into account.
- · Safety services are guaranteed a reserved bandwidth.
- · Vehicles are prioritized in terms of risk by embedding TTC in the beaconing rate.
- · A higher channel usage is provided.

3.4 Conclusions

In this chapter, we have integrated awareness and congestion control as a Network Utility Maximization (NUM) problem. The proposed algorithm, called TTCC, maintains the channel load under a certain threshold while assessing the safety of the surrounding traffic situation with a time-to-collision metric suitable for realistic traffic scenarios. unlike other approaches, which only control congestion, the proposed algorithm uses the TTC metric to assign priorities in the optimal allocation problem. The formulation for the computation of the TTC is one of the distinctive features of TTCC. It allows us to seamlessly assess the risk in curves and intersections and aligns well with the CAM management alternatives discussed in European safety signaling standards. Results show that TTCC effectively increases the beaconing rate of the vehicles involved in more dangerous situations.

3.5 Scientific outcome

The proposals discussed in this Chapter has been published in [66] (see full-text version in Chapter 9).

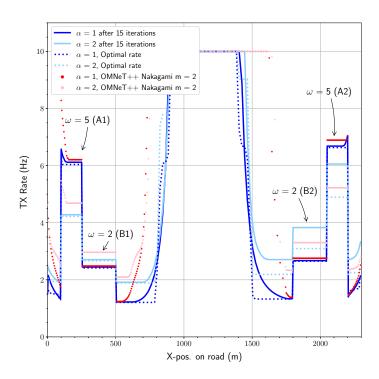


FIGURE 3.2: Exact optimal allocation and FABRIC with different values of fairness (α) and priority (ω) parameters for selected vehicles after 15 iterations. Vehicle density (vehicles/m) was set to 0.05 in the middle of the road, between 750 and 1750 m, and 0.2 otherwise (edges).

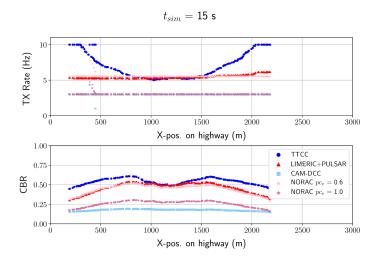


FIGURE 3.3: Beaconing rate and CBR versus position.

Article 2: Cooperative Awareness Message Dissemination in EN 302 637-2: an Adaptation for Winding Roads

4.1 Summary

In the previous chapter, we proposed a beaconing rate adaptation aimed at controlling congestion while providing vehicles with priority according to their environmental situation using a time-to-collision metric. In this chapter, we address some issues of the Cooperative Awareness Message (CAM) dissemination, stated in the European Standard EN 302 637-2 [7]. This mechanism, called CAM-DCC, alleviates congestion by setting some CAMs generation rules and mechanisms dependent upon vehicle kinetics. However, instead of using the maximum beaconing rate (10 Hz) whenever there is no congestion, CAM-DCC sets the minimum rate (1 Hz). From our point of view, there is no point in getting the channel underused. We study more profoundly the awareness control of this standardized mechanism and do further research related to prioritization. More to the point, we evaluate the performance of the EN 302 637-2 dissemination mechanism in risky sharp bends and winding roads. We propose a novel triggering condition based on the dynamic estimation of the road curvature radius, used as a risk metric. In this way, the lower the radius, the higher the risk while driving, and consequently, a high beaconing rate could help to prioritize the transmission of information of such vehicles.

4.2 Methodology

The methodology of this work is divided into four parts. Firstly, we evaluated the performance of the CAMs dissemination stated in the standard [7]. To do this, we also reviewed the state-of-the-art related to the CAM-DCC mechanism, allowing us to discover the strengthens and

weaknesses of the CAM triggering algorithm. We realized that CAM-DCC sets the minimum rate (1 Hz) when the channel is uncongested. The second stage entailed implementing this beaconing rate adaptation on the simulation environment mentioned in the previous chapter. Thirdly, we did some research about how CAM-DCC could be easily improved by using minor changes that can be directly implemented by vehicle industry. In particular, we proposed a new CAM triggering condition based on the dynamic estimation of the risk under which the vehicles are. One way to quantify the risk of a road is to measure the crash rate (CR), defined as the number of crashes per Million Vehicle Kilometer (MVKm), which is in turn highly related to the radius of curvature (R). Indeed, this is a common metric used to design the radius of curvature of a road (R, in ft), which depends in turn on the vehicle's speed (V, in mph), the superelevation rate (e, %), which is the lateral inclination of the road, and the side friction (f, %), which is taken at right angles to the line of movement of the vehicle. In short, vehicles estimate the radius of curvature during driving to increase the number of messages transmitted per second, improving the channel awareness and channel use with respect to the CAM-DCC algorithm. The radius is estimated by finding the equation of the circle passing through the points of the position of the vehicle, as shown in Figure 4.1. As a case study, two real road sections, with different lengths and angles, were simulated in OMNeT++ to test the new triggering condition based on the road radius. Finally, congestion constraint is also tested to check that no significant interferences are found in the described behavior.

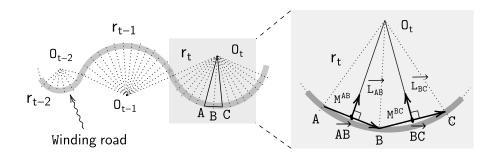


FIGURE 4.1: Radius estimation while driving based on the last positions of the vehicle.

4.3 Results and contributions

Results proved that better awareness and responsiveness are achieved in the vehicles to ensure a higher application layer functioning than in the original version of CAM-DCC stated in the standard. As can be observed in Figure 4.2, the proposed CAM-DCC-R triggers some extra beacons when the vehicles take a curve whose estimated radius is lower than 20 m, increasing the awareness of the traffic situation and prioritizing those vehicles with high risk. The sharpener the curve, the higher the risk, as illustrated in Figure 4.3 for different radiuses of curvature of the road. It is important to mention that the algorithm is implemented to prioritize congestion control, so these extra beacons will not be transmitted if the channel is

4.4. Conclusions 25

congested. To prove that, we finally test a scenario subject to channel congestion, obtaining the same results as the original version of the algorithm. The main contributions of this work can be summarized as follows:

- The radius of curvature of the road is estimated while driving as a risk metric.
- A novel triggering condition, easy to implement, is used to integrate this metric and provide vehicles with higher awareness.
- · A higher channel usage is achieved with respect to the original version.

4.4 Conclusions

We have presented a novel triggering condition for the CAM dissemination mechanism of the European Standard EN 302 637-2 to address its deficiency in uncongested roads (i.e. allocation of low beaconing rates). Our premise is that channel underuse might cause a failure in the application layer if the information update is insufficient, which is especially important under dangerous circumstances like winding roads. Therefore, we have proposed a triggering condition as a function of the radius of curvature of the road, periodically estimated and used as a risk metric. In this way, the higher the road curvature, the higher the beaconing rate allocated and higher awareness achieved. The extra beacons transmitted could not only be used to help to provide vehicles with more information in risky curves but also to support emergency services on recording more accurately the zones with a high crash ratio.

4.5 Scientific outcome

The proposals discussed in this Chapter has been published in [67] (see full-text version in Chapter 10).

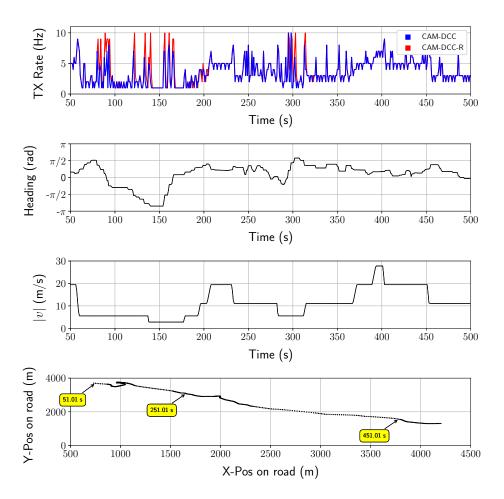


FIGURE 4.2: Comparison between original and radius-metric adapted CAM-DCC under real speed limitations.

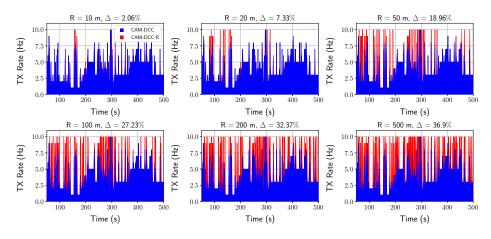


FIGURE 4.3: Evaluation of CAM-DCC-R for different radiuses values.

Article 3: Advisory Speed Estimation for an Improved V2X Communications Awareness in Winding Roads

5.1 Summary

As shown in the previous chapter, in uncongested scenarios, the default CAM dissemination mechanism of the ETSI standard underuses the channel. The amount of data supplied to the safety applications and therefore its proper operation could be drastically improved by increasing the number of transmitted messages. This is especially important in those situations under which vehicles are subject to risks and require being aware of their environment more carefully. Winding roads usually imply low vehicle dynamics when curves are traversed, but become dangerous as vehicles surpass the advisory speed. To better evaluate the risk while driving, we introduce diverse magnitudes and parameters of the road design in the CAM algorithm, instead of using vehicle parameters only. Unlike in the previous conference, where the proposed CAM generation rule depended on the radius of curvature of the road, we take a step forward, employing the difference between the vehicle speed and the estimated advisory speed over time. In particular, we first derive the radius of curvature of the road, to later apply some common road design rules, from which the advisory speed is obtained for a given road section. Then, the proposed approach generates a new message whenever the vehicle's current speed overcomes the advisory one.

5.2 Methodology

Firstly, we analyzed some concerns of the CAM triggering condition previously proposed. Using the radius of curvature, which is calculated while driving through several GPS location points, assigned a high beaconing rate (transmission priority) to those vehicles moving across a risky curve. However, it is important to clarify that risk or danger is not implicit in curves, but arises as long as the advisory speed is exceeded. In this way, a more clear way to

identify the risk is to estimate the advisory speed for each road section and compare it with the vehicle's current speed. The number of messages transmitted per second is increased as a function of this realistic concept of risk, improving the channel awareness and channel use with respect to the CAM-DCC algorithm. As a case study, two real road sections located in Cartagena, Spain, and Kentucky, US, with different lengths and angles, were simulated in OMNeT++ to test the new triggering condition based on the advisory speed derived. Finally, different speed limits were also tested to check the proper behavior of our proposal.

5.3 Results and contributions

Results revealed that a greater level of information exchange among vehicles is achieved in the vehicles, which is denoted as context-awareness. As can be observed in Figure 5.1, the proposed CAM-DCC adaptation triggers a certain number of additional CAM messages when the vehicles take a curve faster than recommended by the road design rules, prioritizing those vehicles with higher risk. The more severe the speed violation, the higher the risk. It is worth noting that the triggering condition is implemented after checking congestion control, so these extra beacons shall not be transmitted if the channel is congested. The main contributions of this conference article can be summarized as follows:

- The advisory speed of the road is derived while driving as a risk metric.
- A novel triggering condition, easy to implement, is employed to endow vehicles with higher awareness.
- · A greater channel usage is obtained with respect to the original CAM-DCC algorithm.

5.4 Conclusions

In summary, this work is aligned with the previous chapter, where a novel adaptation of the EN 302 637-2 standard is proposed to avoid channel underuse as well as to improve cooperative awareness in winding roads. Risk or danger is not implicit in curves, as suggested in the previous article, but arises as long as the advisory speed is exceeded. To endow the CAM generation mechanism with a more realistic concept of risk, we employ a comparison between the advisory and current speeds to determine whether transmit or not additional beaconing. Higher awareness and beaconing rates are successfully achieved by adding the estimated advisory speed in the triggering conditions.

5.5 Scientific outcome

The proposals discussed in this Chapter has been published in [68] (see full-text version in Chapter 11).

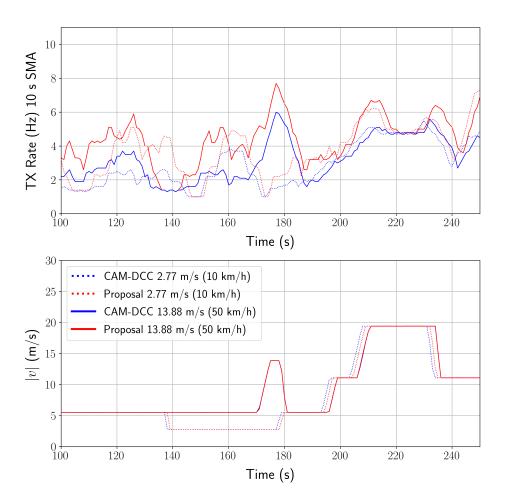


FIGURE 5.1: Evaluation of the CAM-DCC using the proposed triggering condition.

Article 4: MDPRP: A Q-Learning Approach for the Joint Control of Beaconing Rate and Transmission Power in VANETs

6.1 Summary

The adaptation of transmission parameters is of great importance to prevent excessive beaconing load, which might compromise the proper operation of safety applications and driverassistance systems, especially regarding the exchange of emergency-related messages. Previous chapters addressed beaconing rate adaptation, which is the most popular congestion control in the literature [7, 27, 60]. The success of these solutions in reducing congestion by decreasing the number of transmitted messages is clear. However, in high congested scenarios, the beaconing rate shall be drastically reduced, therefore threatening situation awareness and vehicle safety [69]. In addition to beaconing rate, numerous studies have also studied the transmission power adjustment to control congestion. Reducing the transmission power decreases the number of vehicles that receive the broadcast messages, and, consequently, channel load is also reduced. Many works have proposed controlling transmission power depending upon different variables, such as the Channel State Information (CSI) [39] to improve energy efficiency, the speed of the vehicle [18], or vehicle density [19], among others [20, 42]. Despite the fact that transmission power variations are capable of alleviating channel congestion properly, a clear drawback arises in high congested scenarios. If the vehicle density on the road is high, transmission power could receive too low values to fulfill the MBL constraint, and the number of receivers might drop drastically, harming the overall context awareness of vehicles. In this way, only a few neighboring vehicles will be aware of the behavior of the transmitting vehicle.

Instead of using transmission parameters individually to handle congestion, more advanced proposals combine two or more simultaneously [57, 58]. This avoids excessive changes

in transmission parameters, therefore easing the proper operation of the safety applications requirements. Nonetheless, joint optimization of parameters usually result in non-convex problems and entails employing heuristic algorithms instead of ordinary optimization methods.

In this chapter, we propose a novel control congestion based on joint beaconing rate and transmission power adaptation. To optimally balance the available channel load between both parameters, we model a Markov Decision Process (MDP), illustrated in Figure 6.1. To this end, a set of simplifying assumptions are applied to obtain a transition model, actions, and states within the complex road environment. This MDP characterization, denoted as MDPRP, was later solved using Q-learning techniques. The proposed algorithm MDPRP is non-cooperative, disregarding additional information from neighbors. This makes it suitable to be deployed in a distributed fashion in infrastructure-less (ad-hoc) networks. The results obtained show that MDPRP leads the channel load to the optimal MBL, which, in turn, improves the packet delivery ratio. Finally, the robustness of MDPRP is also proved since the algorithm works well even when the assumptions made are no longer true.

6.2 Methodology

The optimization problems associated with transmission parameter adaptation to control congestion are usually convex and thus can be solved by ordinary optimization methods, as the NUM approach suggested in our previous work [66]. However, these methods turn ineffective when parameters are allocated jointly and the optimization problem is not convex anymore. As methodology, we first investigated a new way to solve the beaconing rate and transmission power problem. Recent approaches used Artificial Intelligence (AI) techniques, such as Reinforcement Learning (RL) [52, 53], but assuming cellular networks and requiring high-cost infrastructures for their deployment. Similarly, we employed the Markov Decision Process (MDP) framework, which is the basis of the RL, to solve the proposed problem but without assuming any centralized entity to coordinate its operation. Some simplifying assumptions of the road environment were made to obtain a feasible transition model.



FIGURE 6.1: Three-dimensional state-space used to model the joint power and rate allocation problem as an MDP. Axes represent each constituent element of the available states of the MDP: beaconing rate, estimated number of neighbors, and transmission power.

- On the one hand, we assumed that close neighboring vehicles have a similar requirements and, therefore, similar channel load as well.
- · On the other hand, we assumed a Nakagami-m channel model, from which we derived the average carrier sense (r_{CS}) :

$$r_{CS} = \frac{\Gamma(m + \frac{1}{\beta})}{\Gamma(m)(SA\frac{m}{p})^{\frac{1}{\beta}}}$$

$$\tag{6.1}$$

With these two assumptions, we were able to relate the Channel Busy Rate (CBR) measured with the transmission parameters under study: beaconing rate (b) and transmission power (p). The beaconing rate relationship stems from the vehicle similarity assumption since the CBR, which is calculated as the sum of all the beaconing rates between the channel capacity $\frac{\sum_{v}^{N}b_{v}}{C}$, could be estimated as $\frac{(n+1)b}{C}$. The second assuption allowed us to update the number of neighboring vehicles according to the transmission power employed, included in the carrier sense range estimation, as follows:

$$n' = n \frac{r'_{CS}}{r_{CS}} = n \frac{\left(SA\frac{m}{p'}\right)^{\frac{1}{\beta}}}{\left(SA\frac{m}{p}\right)^{\frac{1}{\beta}}} = n \left(\frac{p}{p'}\right)^{\frac{1}{\beta}}$$
(6.2)

Not only do these assumptions allow us to obtain a feasible MDP model that can be solved to derive a certain desired behavior, but also it can be deployed in infrastructure-less (ad-hoc) networks. The MDP model was resolved by using Q-learning techniques, implemented in the Python programming language. Due to the way the reward was shaped, the channel congestion could be maintained below the MBL constraint. To prove that, we finally assessed the performance of the proposed MDP-based algorithm (MDPRP) using OMNeT++ 5.3 [63] together with the INET 3.5 library [64]. Once the learning process finished, and the optimal policy was obtained, the tabulated policy was loaded into the OMNeT++ framework. This could be interpreted as storing the policy in the vehicles' memory.

The proposed algorithm was evaluated in different scenarios and compared against other related congestion control algorithms [22, 32]. Since the MDP has been trained using a row of evenly spaced vehicles to satisfy the assumptions made, this is precisely the first scenario we tested. Then, a more realistic scenario was simulated; that is, two moving clusters, in which vehicles were randomly distributed and the assumptions made did not hold. Finally, different channel conditions were also tested.

6.3 Results and contributions

The actions prescribed by the obtained policy maximize the reward function, which specifically controlled the channel busy rate (CBR) in a non-cooperative manner; that is, without the need for additional information from neighbors. The proposed algorithm implements fully distributed congestion control in which every single vehicle contributes to reducing

overall congestion. Since every vehicle had the same trained policy, the overall congestion was conducted to the same level or MBL. The main contributions of this work can be summarized as follows:

- The policy derived was successfully applied in a fully distributed fashion, without the need for a centralized network infrastructure.
- The policy was evaluated in realistic scenarios, including those cases not satisfying the model assumptions, thereby, demonstrating the robustness of our congestion control method.
- As shown in Figure 6.2, channel load was kept below the MBL, reducing packet loss significantly but also preventing channel underutilization. This leaves a certain space of the channel free, guaranteeing the proper reception of emergency-related messages or DENMs.
- Finally, no information from neighboring vehicles is required to carry out the actions, so any exchange with the application layer is disregarded for a proper resource allocation operation.

6.4 Conclusions

Channel overload caused by excessive periodical beacons may compromise the proper functioning of many safety applications. This is of great relevance in the case of messages triggered in emergency cases. In this chapter, joint beaconing rate and transmission power congestion control is proposed. Since the associated problem is not convex, ordinary optimization methods are ineffective. Instead, we have modeled the beaconing rate and transmission power control problem, by making several simplifying assumptions in the road environment, to apply the Markov Decision Process (MDP) framework. The proposed solution, called MDPRP, alleviates congestion in a non-cooperative and fully distributed fashion, disregarding additional information from neighbors, where every single vehicle contributes to reducing overall congestion. Simulation results reveal that MDPRP successfully keeps the channel load under the desired level and offers good outcomes in terms of packet delivery ratio. Since every vehicle uses the same trained policy, all they are geared towards the same congestion level or MBL. The robustness of the solution is also proved since the algorithm operates well even in those cases in which the assumptions made do not hold. In future chapters, we will focus on different reward functions as well as on applying approximating functions such as Semi-Gradient SARSA or aritificial neural networks to resolve more complex problems.

6.5 Scientific outcome

The proposals discussed in this Chapter has been published in [23] (see full-text version in Chapter 12).

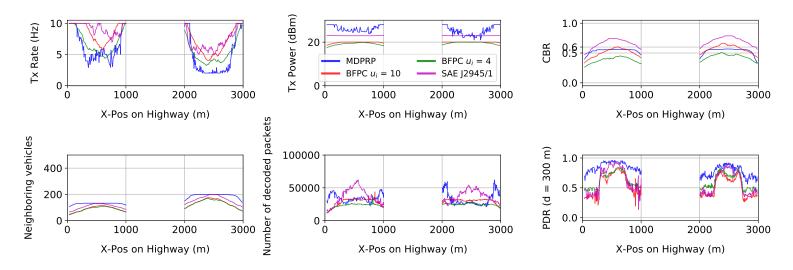


FIGURE 6.2: Comparison of the different congestion control algorithms by using two randomly distributed moving clusters evaluation.

Article 5: Approximate Reinforcement Learning to Control Beaconing Congestion in Distributed Networks

7.1 Summary

As the number of disseminated beacons increases, packet receptions can be compromised and vehicle situation awareness endangered. To guarantee the delivery of both beacons and emergency-related messages (DENM), a given fraction of the channel capacity is usually reserved. Despite the fact that a wide range of transmission parameters can be adjusted over time to alleviate congestion, the most widespread mechanism is the beaconing rate (i.e., how many beacons are transmitted per second).

Given the nature of this resource allocation problem, in which no a priori information or data about the (road) environment is available, we formulate it as a Markov Decision Process (MDP) and solve it using Reinforcement Learning (RL) algorithms. In such a way, each vehicle takes actions, performs transitions among different states, and obtains different rewards depending on how well congestion is alleviated. One simple way of solving such a problem would be to use tabular methods, such as Dynamic Programming, Monte Carlo methods, or Temporal Difference (TD) Learning, which includes the well-known Q-learning used in the previous chapter. However, this tabular way of mapping states and actions is not appropriate when the state space is large and continuous, as occurs in our case (road environment).

In this chapter, we apply on-policy control with function approximation, as an intermediary step towards the full implementation of artificial neural networks, which will be implemented in the next chapter. The function approximations employed generalize previous states to derive sensible decisions when new states are encountered. The resulting parameterized model can be applied by vehicles so the most appropriate beaconing rate is arrived at very efficiently in terms of runtime and computational cost, which is of great importance in congested scenarios. With our approach, not only very good outcomes are obtained, as shown in the results section, but also in relatively short training times.

7.2 Methodology

The use of artificial neural networks within the RL framework allows solving complex problems with sophisticated environments and continuous action-state spaces. As will be shown in the next chapter, in spite of their numerous advantages, this solution entails tough reward modeling as well as longer training times and subtle hyperparameter tuning. In some cases, agents learn unintended things that result in high rewards. Therefore, they should not only maximize the reward obtained, but also satisfy every single rule of the game or environment defined. Numerous iterations and training attempts are usually required to rigorously tell the agent what is correct and what is wrong. In this work, we provide an intermediary step towards the use of complex function approximations (i.e. artificial neural nets) to alleviate congestion straightforwardly and easily in realistic scenarios. We propose simple approximation functions that make the congestion control not rely so much on the reward shaping, which eases the training process significantly. To this end, we first formulated the problem as a Markov Decision Process (MDP).

As can be observed in Figure 7.1, the resulting MDP model considers numerous congestion levels (channel busy rate, CBR) which vehicles can theoretically sense. Note that these CBR levels sensed already reflect many external environment conditions. For instance, given a beaconing rate, a low measured CBR may be due (i) to a channel with high fading (lost packets results in a lower measured CBR) or (ii) because of having few neighbors. From the point of view of our solution, the action to perform would be the same irrespective of the real cause. In that sense, the CBR captures well the particularities of different scenarios. Because of this, given a common transmission power, the performance of our proposed solution is robust to variations in the channel model or radio propagation effects, as corroborated by the results obtained from the different simulations carried out.

Once the MDP model was defined, we solved it by using approximation methods instead of tabular ones. In particular, we employed Semi-Gradient SARSA with function approximation. This allowed us to leverage the advantages of approximation functions but with the

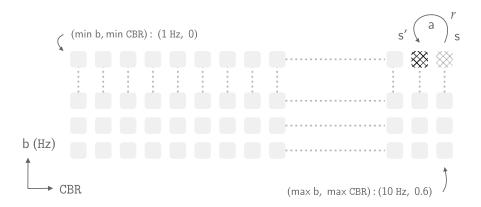


FIGURE 7.1: Two-dimensional state-space used to model the beaconing rate allocation problem as an MDP. Axes represent each constituent element of the available states of the MDP: beaconing rate and CBR.

simplicity of discrete state-action spaces. The state-action value function can be parameterized according to different approximation functions $\overline{x} = \langle x_1, x_2, ..., x_n \rangle$, as follows:

$$Q(s,a) \approx \hat{Q}(s,a) = \theta_0 + \theta_1 x_1(s,a) + \dots + \theta_n x_n(s,a)$$
(7.1)

Then, we tested different combination of approximation functions \overline{x} to improve the beaconing rate allocation and make the algorithm not depend so much on how the reward is shaped. A well-trained SSFA model was evaluated in different realistic scenarios. In the first scenario, the performance of our solution is assessed under training conditions (free-space) for a row of 650 static vehicles. The second scenario introduces realistic conditions and employs a row of 400 static vehicles. Note that the number of neighboring vehicles will be lower than 400 due to the limited transmission power (27 dBm). Finally, in the third scenario, we evaluate an increasing number of moving vehicles in a realistic urban environment (i.e., city of Pereira, see Figure 7.3), from 1 to 400 vehicles.

7.3 Results and contributions

As can be observed in the results achieved, overall congestion is not only successfully alleviated but also the CBR sensed is always kept below or around the optimal value (o.6). When necessary, the algorithm would set the minimum (too many vehicles) or maximum (few vehicles) beaconing rates allowed (1 Hz and 10 Hz, respectively). It is worthy of mention that the results obtained are close to the optimal values proposed by baseline works (e.g., FABRIC), and more general approximators, like artificial neural networks, might not mean a significant improvement. In short, the main contributions of this work are the following:

- SSFA generalize previous states to derive sensible decisions when new states are encountered. The resulting parameterized model can be applied by vehicles so the most appropriate beaconing rate is arrived at very efficiently in terms of runtime and computational cost.
- A well-trained SSFA model is straightforwardly deployed in a distributed manner, without the need for a centralized network infrastructure.
- The proposed SSFA was evaluated in realistic scenarios. Not only very good outcomes are obtained but also in relatively short training times.
- · As shown in Figure 7.2, channel load is kept below the optimal value, i.e., MBL.

7.4 Conclusions

In vehicle-to-vehicle communications, the control channel can be saturated by excessive periodical beacons and compromise the proper functioning of most safety applications. In this chapter, we aim to control congestion through the adaptation of beaconing rates without requiring any additional infrastructure. Given the nature of the problem, we define it as a

Markov Decision Process (MDP) and solve it using Reinforcement Learning (RL). Unlike tabular solutions, we employ approximating functions, which allow us to make sensible decisions when new states are encountered. In particular, the proposed algorithm is based on Semi-Gradient SARSA, whose resulting parameterized model can be trained very rapidly compared to the use of artificial neural networks. The performance of our proposed solution is robust to variations in the channel model or radio propagation effects, as corroborated by the results obtained from the different simulations carried out.

7.5 Scientific outcome

The proposals discussed in this Chapter has been published in [68] (see full-text version in Chapter 13).

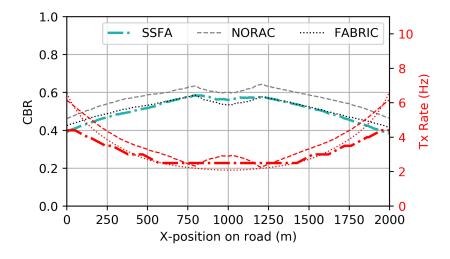


FIGURE 7.2: Beaconing rate and CBR measured versus the vehicles' position on the road of our proposed congestion control approach compared to FABRIC and NORAC.



FIGURE 7.3: Traffic map (Map data ©2021 Google) of the city of Pereira (Risaralda, Colombia), used in the simulations.

Article 6: Simultaneous Data Rate and Transmission Power Adaptation in V2V Communications: A Deep Reinforcement Learning Approach

8.1 Summary

As we studied in previous chapters, limiting the beaconing load has great significance to make safety applications work properly, avoiding packet loss and collisions due to high congestion. This might especially endanger event-related messages triggered whenever an emergency situation occurs. As mentioned before, a vast number of solutions are aimed at reducing channel congestion through varying transmission parameters somehow. The most widespread approaches decrease the number of messages transmitted per second (beaconing rate) or reduce the transmission power and thus the coverage area and the number of receivers. Unlike single transmission parameter congestion controls, more advanced proposals employ two or more parameters simultaneously [43–47]. Such combinations avoid severe variations, harmful for context awareness of the vehicles, but they are no longer convex. To resolve this issue, different approaches based on decision or game theory emerged, usually using transmission power and beaconing rate [22, 23, 50, 52, 56].

Even though the IEEE 802.11p standard defines 9 different data rates, as shown in Table A.1, 6 Mbps is usually recommended and set by default, while varying transmission power or beaconing rate. Nonetheless, there is no reason not to control congestion by dynamically varying data rates. This actually allows us to fix the beaconing rate to the maximum allowed (i.e., 10 Hz), which improves the context-awareness of the vehicles. Reducing the data rate means decreasing transmission time, so congestion is also alleviated, but higher-order modulation schemes are required. This implies less robustness against unfavorable channel conditions over distance. Therefore, the transmission power can be used along with the data rate to guarantee an adequate Packet Delivery Ratio (PDR) at a given target distance. In

TABLE 8.1: Data rates, modulation schemes and coded bits per Orthogonal Frequency Division Multiplexing (OFDM) symbol stated in the IEEE 802.11p standard.

Data rate (Mbps)	Modulation	Coded bits per OFDM symbol
3	BPSK	48
4.5	BPSK	48
6	QPSK	96
9	QPSK	96
12	16-QAM	192
18	16-QAM	192
24	64-QAM	288
27	64-QAM	288

fact, the combination of transmission power and data rate is much more physically consistent than transmission power and beaconing rate due to the channel condition dependence of the data rate. As mentioned above, high data rates are more affected by fading and attenuation, and thus, the effective transmission range is reduced, but it can be readjusted by increasing transmission power. The related works based on balancing both transmission power and data rate are scarce and employ fairly limited ranges of these parameters, which may make them ineffective in some cases.

In this chapter, we apply the Deep Reinforcement Learning (DRL) framework to alleviate channel congestion through optimizing data rate and transmission power simultaneously. Basically, after making some reasonable assumptions, we train a single Deep Neural Network (DNN) whose resulting model is loaded into the vehicles of the network. Since every vehicle is geared toward the same goal, they converge to a proper congestion level. This mechanism not only prevents us from tackling with multi-agent approaches, complex to train and deploy, but also from training using any simulator or real implementations with enormous computing times. The proposed mechanism denoted Neural Network for Data rate and transmission Power (NNDP) alleviates overall congestion while assuring a certain packet delivery ratio and the most robust data rate possible.

8.2 Methodology

The first step of this work was to profoundly review the state-of-the-state in congestion control in vehicular communications. We realized that data rate was scarcely used in spite of its significative advantages. Little efforts were also found with regards to adjusting more than one transmission parameter jointly. Therefore, a combination of transmission power and data rate became a great research line, but the associated optimization problems were no longer convex, so we investigated the way to solve them as optimally as possible. Recent approaches used game theory and decision theory, which is the basis of the well-known Reinforcement Learning (RL). In the previous chapter, we were focused on solving a MDP

8.2. Methodology 45

model using tabulated methods. However, when the state space is large and continuous, it is unfeasible to store such amount of states and actions in a table. In this chapter, we resolve this issue by employing approximation methods. More to the point, we now apply DRL to find the optimal pair of transmission parameters more accurately. The nature of vehicular communications implied to use Multi-Agent Reinforcement Learning (MARL), which increases remarkably the complexity of the training. To avoid this, some simplifying assumptions were made:

- On the one hand, we assumed that neighboring vehicles sense a similar channel load. This brings two consequences. First, the DNN could be trained using a single agent whose resulting policy was deployed in the vehicles of the network. This assumption allows us to avoid using MARL and its related complexity. And second, the model could be trained off-line, in a simplified environment rather than conducting the training in discrete event simulators (e.g., OMNeT++), in which the required computing time would have escalated.
- · On the other hand, we assumed a realistic Nakagami-m channel model.

Then, we formulated the allocation problem as a simple MDP, by linking both transmission power and data rate parameters with the congestion of the network, as follows:

$$CBR = \frac{2r_{CS}\rho b}{C} \tag{8.1}$$

where r_{CS} is the average carrier sense range 6.1, b the maximum beaconing rate allowed (10 Hz), ρ the estimated vehicle density in the neighborhood, and C is the channel capacity in messages per second. Note that this is only an estimation to express the channel load as a function of the transmission power and data rate used by every single vehicle, without using any information from the neighboring vehicles. Recall that transmission power is included in the carrier sense range, whereas the data rate is implicitly included in the channel capacity.

Once this simplified environment was formulated, the next step was to obtain the optimal policy $\pi*$, which determines the best action for every single state. To this end, we shaped the reward function according to different goals. The main objective was to maintain the CBR around a certain level (typically 0.6-0.7) to avoid congestion and channel underuse. Once this has been satisfied, the reward made the vehicles select such transmission power that the PDR at a certain distance, called the safety distance (d_s) , was above 0.9. This was performed using a one-slope path loss model and the aforementioned sensitivities, $l=Ad_s^\beta$, and guaranteed the proper operation of the safety applications. The algorithm also rewarded the most robust modulation schemes (low data rates) as much as possible in terms of congestion.

To solve the MDP model, we employed Deep Neural Networks (DNN) so the policy was represented not as a table but as a parameterized functional form with a vector of weights $\pi:=f(\theta)$. In our case, the DNN was trained and evaluated using different RL algorithms [70–76], but only PPO [75] and SAC [76] provided good behavior (transmission power and data rate) in terms channel load. Then, the trained model was deployed in the vehicles of the

network. We assessed the performance of the PPO and SAC agents more thoroughly using OMNeT++. The entire DNN model could not be directly exported due to numerous compatibility problems between OMNeT++ and the python server where the DNN was implemented. We designed and developed a TCP/IP socket connection between the simulator and a Python server, as illustrated in Figure 8.1.

The two variants of the proposed algorithm NNDP, using PPO and SAC agents, were evaluated in different scenarios and compared with the CACC algorithm. First, NNDP was evaluated in a row of evenly spaced vehicles. There is channel load similarity among neighboring vehicles, so it satisfies the assumption made. Then, a more realistic scenario was simulated through two moving clusters. Finally, different channel attenuation was also assessed.

8.3 Results and contributions

Every time the algorithm is executed, OMNeT++ sends a request to the Python server, which responds by the recommended actions of the trained DNN. Then, vehicles apply the received actions and vary their transmission parameters accordingly. Simulation results reveal that this mechanism (i) successfully maintain channel loads at the optimal desired value, around 0.6-0.7. As shown in Figure 8.2, NNDP leaves channel capacity free enough for successful DENM reception. Once congestion is alleviated, NNDP also (ii) prevents transmission power from being reduced too much, guaranteeing a given packet delivery ratio at a certain distance. Finally, (iii) NNDP set the most robust data rate against fading and attenuation whenever possible. These goals, which were previously imposed in the reward function, are achieved for every scenario under test. Therefore, the main contributions of this article are the following:

• The policy is implemented using a DNN and trained with different algorithms. The DNN accepts the whole ranges of transmission power and data rate stated in the standard, both continuous and discrete values.

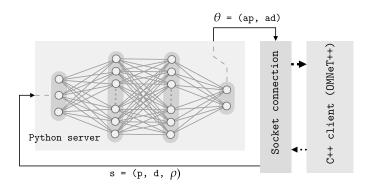


FIGURE 8.1: Evaluation of the trained DNN to control congestion through transmission power and data rate adaptation in vehicular networks simulated with OMNeT++.

8.4. Conclusions 47

• As shown in the results section, NNDP works well even in those scenarios where the assumptions taken are not satisfied. Therefore, the proposed congestion control successfully avoids the use of more complex MARL approaches.

- NNDP maintains the channel load around a certain threshold, which remarkably decreases packet loss. Channel underutilization is avoided as well.
- Transmission power is adjusted to the necessary level to guarantee a given packet delivery ratio at a certain distance, whereas low data rates with more robust modulation schemes are rewarded as much as possible.
- Finally, no information from neighboring vehicles or centralized network infrastructure is required.

8.4 Conclusions

In short, an increase in beaconing loads results in higher packet loss and endangers the proper functioning of these applications. Therefore, maintaining a certain fraction of the channel available is vital for the successful delivery of periodical and emergency-related messages. In this chapter, we propose a novel congestion control based on transmission power and data rate adaptation. The proposed mechanism, called NNDP, employs DNNs trained with different DRL algorithms (PPO and SAC agents) to alleviate congestion in a non-cooperative way, without requiring any additional information from neighbors or centralized infrastructure. NNDP successfully control congestion, and obtains a higher throughput (number of decoded packets) with similar PDR to other proposals. The proposed solution operates reasonably well even in scenarios with different channel attenuation from that used in the training environment.

8.5 Scientific outcome

The proposals discussed in this Chapter has been published in [77] (see full-text version in Chapter 14).

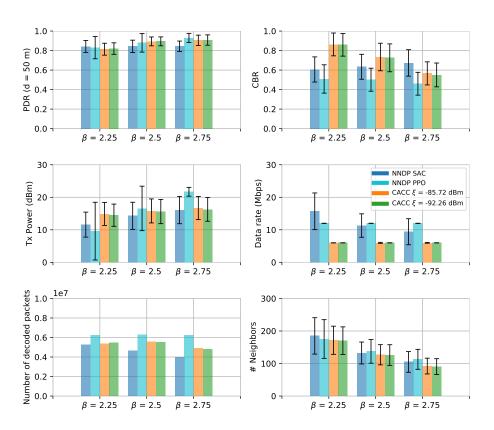


FIGURE 8.2: Comparison between the proposed algorithm and CACC for different path loss exponents and for two approaching clusters.

Part III Article list

CHAPTER 9

Article 1 (Full text)



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Time-to-Collision-Based Awareness and Congestion Control for Vehicular Communications

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ABSTRACT Vehicular wireless communications require both congestion control to guarantee the availability of a fraction of the bandwidth for safety-related event-driven messages in emergency cases, and awareness control to adapt the beaconing activity to the application needs and surrounding traffic situation. Most current approaches either ignore the traffic situation and only adapt the beaconing rate to the channel congestion state or override the congestion control limits, leading to questionable results in both cases. In this paper, we conceive and validate a novel approach, combining both aspects. Based on distributed Network Utility Maximization (NUM), our algorithm satisfies the constraints on channel availability, whereas the safety of the surrounding traffic situation is captured with a time-to-collision metric, used to assign priorities in the optimal allocation problem. The performance of the proposed approach is validated and compared to other popular algorithms. Results show that our proposal automatically anticipates a potential increase in rate due to a critical safety situation, but does not interfere with the reserved bandwidth for safety applications.

INDEX TERMS Awareness control, beaconing rate control, congestion control, time-to-collision, vehicular communications.

I. INTRODUCTION

Connected vehicles extend the capabilities of multiple advanced driver-assistance systems and automated vehicles by enabling the possibility of performing cooperative actions, such as Cooperative Automated Driving (CAD) or increasing the awareness of a vehicle's sensor systems [1]. CAD can improve safety and efficiency by introducing Cooperative Adaptive Cruise Control (CACC) applications [2], including not only platoon driving, but also cooperative collision avoidance [3], among others.

Cooperative inter-vehicular applications usually rely on the exchange of broadcast single-hop status messages (*beacons*) among vehicles on a single control channel, which provides detailed information about vehicle position, speed, heading, acceleration, curvature, and other data of interest [4]. Beacons, called Cooperative Awareness Messages (CAM)

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in European standards and Basic Safety Messages (BSM) in the US standard, are transmitted periodically at a certain beaconing rate. The aggregated load on the wireless channel due to periodic beacons can rise to a point where it can limit or prevent the transmission of other crucial messages, which is called *channel congestion due to beaconing activity*. Even though this problem has been previously analyzed by different related proposals [5]–[10], some aspects deserve further consideration.

In this regard, there are two different approaches to the control problem: pure *congestion control*, (CC) and *awareness control*, (AC) [11]. Congestion control usually refers to the mechanisms used to keep the channel load at the desired level, irrespective of the needs of the applications on top of the service. In contrast, awareness control usually refers to the mechanisms employed to satisfy *some application* requirements. To the best of our knowledge, although there is no widely accepted common definition for awareness, it is usually related to the notion that the beaconing rate



should adapt to traffic or vehicle situations [12], especially as regards safety [13], and not only to the channel load. Although related, both approaches call for different solutions, with different results, requirements, and inputs.

To illustrate the differences between both approaches, consider the following situations from the adopted solutions in the standards: purely CC, such as LIMERIC [5], updates the beaconing rate only according to the locally measured state of the wireless channel. This immediately raises the question of what to do when the same channel is shared by vehicles with different traffic states, such as a free flow of high-speed vehicles in one direction of a highway, and a traffic jam in the opposite direction. An AC oriented solution is to let vehicles generate beacons according to their own dynamics, as specified in [4], and proposed in [7], [10], [14], [15] among others. Which in turn raises more questions. First, should this mechanism always be limited by the CC or should it be able to violate the CC-imposed limits on bandwidth usage in some circumstances? In the former case, the previous problem persists, while in the latter case, the effectiveness of the CC has to be evaluated, as well as potential interference with other services, such as Decentralized Environmental Notification (DEN), which requires the access network not to be in a congested state. Second, if the CC only limits but does not trigger beacon generation, the channel is underused, at least with the generation rules of [4], so why not use all the available resources if the quality of services of applications benefits from a higher rate? Moreover, non-reactive CC mechanisms [5], [6] are usually designed to drive the load to a desired point. If they are just used to limit the rate, the results and performance may not be as designed. Reactive controls, such as the one in the standard [16], on the other hand, suffer from instabilities [8]. Third, if the vehicle does not evaluate the safety of its surrounding traffic situation but generates beacons only according to its own dynamics, some particular situations yield questionable results. For instance, a vehicle stopped in the middle of a highway may be a danger, but current beacon generation rules [4] force it to transmit at the minimum beaconing rate. This particular example is actually mentioned in the standards for various collision risk warnings [17]–[19].

Current European standards specify the separation of beacon generation and congestion control [4]; the latter strictly limits the rate, reproducing the aforementioned concerns. The beacon generation rules only depend on the vehicle's own dynamics, which results in a type of limited awareness control, as we have pointed out. The underlying issue seems to be how to integrate congestion and awareness control, including beacon generation, into a more coherent framework with more clearly defined goals. Additional desirable features of the procedure are that it is distributed as well as providing provable fairness, stability, and convergence.

In this paper, we discuss these issues and propose a novel awareness control mechanism that complements the pure congestion control of our previous FABRIC protocol [6], by taking advantage of the algorithm's capability to shape the resulting allocation using fairness and priority parameters. Our goals are, first of all, that the surrounding traffic situation and neighboring dynamics be taken into the account by the awareness control. To this purpose, vehicles evaluate the safety of the traffic situation by computing the Time-To-Collision (TTC) with their known neighbors with a simple but generic procedure, and the result is used to set the priority parameter, which provides weighted fairness. Based on a Network Utility Maximization (NUM) problem with constraints, it assigns differentiated rates but enforces a Maximum Beaconing Load (MBL) constraint. So, in this way, we achieve our second goal, which is to effectively integrate awareness control with congestion control. Road safety signaling services, such as DEN, maintain a reserved bandwidth and eliminate the potential interference. Finally, our approach also provides guarantees of convergence to a fair allocation solution, supported by the rigorous developments of the NUM theory [6].

In Sect. II, we discuss related work. Then, a brief review of our previous work, as well as an illustration of its capabilities is provided in Sect. III. We describe our proposal in Sect. IV, and simulate it in Sect. V, providing a comparison with other algorithms, and discussing the obtained results. Finally, Sect. VI summarizes the main conclusions.

II. RELATED WORK

ETSI standards define, as one of the basic network access technologies, a 10 MHz control channel for vehicular communications at 5.9 GHz [20], the ITS-G5 radio channel. Transmissions over this access network are broadcast in nature and use CSMA-based medium access control (MAC), with no acknowledgment or retransmission. The ETSI Cooperative Awareness Service (CAS) [4] requires periodic beaconing over one-hop broadcast communications to support cooperative awareness by disseminating status and environmental information to vehicles on the control channel [4]. In addition, ETSI standards specify the Cross-Layer Decentralized Congestion Control (DCC) Management Entity [21], whose goal is to avoid overloading the ITS-G5 radio channel.

The algorithm specified by European standards, which we call here CAM-DCC, is the combined operation of two procedures: the vehicle dynamics dependent CAM generation rules, specified in [4], and the simple reactive congestion control algorithm suggested in [16]. More specifically, CAM-DCC measures the absolute difference between a current heading, position, and speed, and those included in the previously transmitted CAM. If the time elapsed since the last generation and one of these conditions overcome pre-defined thresholds, a new CAM will be generated. This procedure presents two drawbacks: i) a lack of clear motivation for the triggering rules, and ii) a CAM synchronization problem for cooperative maneuvers that seriously degrades its performance, as discussed in [9]. Moreover, a lack of responsiveness for faster vehicles is found in [22], which results in an absence of fairness. The second part, the reactive congestion control, is based on a finite state machine which

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results in oscillations, as reported in [8]. In contrast, most of the available proposals do not separate CAM generation from congestion control.

To limit the load on the channel, several transmission parameters can be controlled, such as the beaconing rate, transmission power [23], data rate and joint combinations of them [15], [24]. Given the broad scope of solutions and to keep the review focused, we first discuss relevant beaconingrate CC proposals and later AC proposals which in some cases incorporate joint control of other parameters. In the category of rate-based controls, LIMERIC [5] is a distributed and adaptive linear rate-control algorithm in which each vehicle linearly updates its own rate depending on the total load, which is driven towards a required goal. This a pure CC mechanism, since only the channel load is used to update the rates, whereas vehicle dynamics, application requirements, and traffic situations are completely ignored. PULSAR [25] is another pure rate control algorithm that uses Additive Increase Multiplicative Decrease (AIMD) with feedback from 2-hop neighbors. The convergence of LIMERIC is only proved when all the vehicles are in range of each other; not for multi-hop scenarios. Therefore, authors of LIMERIC propose some modifications [26] to use the rate adaptation employed in LIMERIC in multi-hop scenarios by combining it with the PULSAR proposal [8]. The outcome, however, of this combination is that all the vehicles sharing a link converge to the rate of the most congested link, which unnecessarily decreases the rate of some vehicles, even though they do not measure channel congestion. A more detailed discussion and examples of this problem can be found in our previous work [6].

Regarding awareness control and the application requirements that determine the beaconing rate, different alternatives can be found in the literature. There is a set of proposals whose aim is to adjust the rate in order to minimize the position tracking error with respect to other vehicles, such as [27] and [7], which is actually the mechanism for the US DCC standard [28], or EMBARC [14], a variation of LIMERIC, which integrates the tracking error algorithm of [7]. Other proposals assess the estimated risk of some traffic situations, especially intersections, such as [13], where an estimated collision probability for intersections triggers the transmission rate adjustment. CAM-DCC can be considered another proposal for awareness control, as it adapts the beaconing rate to current vehicle dynamics. Several works define [29], [30] some risk metrics based on the vehicle dynamics and traffic situation, similar to our TTC metric, but with less general models. Finally, there are some application-agnostic proposals, such as INTERN [12], which directly assigns the rate that an application demands and then equally shares the excess capacity.

Regarding the way AC is integrated with CC one can find approaches that directly *override or ignore* congestion control [13], [27], [30], and others that *integrate* congestion control in some way [4], [7], [10], [12], [14], [15], [29]. Among the proposals that actually integrate CC and AC

effectively, NORAC [10] is a rate and awareness distributed control based on non-cooperative game theory, whose more relevant feature is that it does not require the exchange of control information. Each vehicle can independently use a utility parameter and a price parameter to adjust the behavior of the algorithm. The utility parameter is used to assign a rate to a vehicle proportional to its requirements, which is the way to provide priority or weighted fairness and, consequently, AC when it is demanded by some application. In this sense, it is quite similar to our proposal, where we also use a per-vehicle parameter to provide weighted fairness, as described below. However, in contrast to our proposal, constraints are not considered in NORAC and so an MBL cannot be explicitly set. The resulting channel load and shape of the allocation is determined by the combinations of price and utility parameters and no systematic procedure to select them is provided. These same limitations apply also to BFPC [15], a recent proposal, which incorporates joint power control to NORAC. ABC [29] also integrates AC and CC in the context of a TDMA-based protocol. In this case, the potential risk of a rear-end collision is incorporated in an optimal resource allocation problem in order to assign more resources to more dangerous vehicles. In our proposal, we also prioritize the rate vehicles involved in potentially riskier situations, but with a more general kinematic model, not limited to rear-end collisions, and which integrates seamlessly in our algorithm, without the computational and communication overhead of ABC.

The problem of beaconing rate control for vehicular networks has been modeled as a NUM problem [31], [32] in our previous work [6]. The different fairness notions that can be induced on rate allocations and its fast convergence are shown in multi-hop and dynamic scenarios. The NUM approach has also been applied to power control [23], and joint power and rate control [24]. For a different problem, in [33], the probability of transmission under a slotted *p*-persistent vehicular broadcast medium access is formulated as a NUM problem, which takes the driving context into account to prioritize packets.

A further discussion about the limitations of these approaches is deferred to Sect. IV-A, where we link it to our proposal.

III. BACKGROUND

In a previous paper [6], we derived an optimal congestion control algorithm for the beaconing rate based on a NUM approach. The key advantage of this approach is that it allows us to design a broad family of decentralized and simple algorithms with proven convergence guarantees to a fair allocation solution. That is, the rate allocation is guaranteed (i) to be optimal, (ii) to comply with the constraints, and (iii) to enforce a particular fairness notion. We remark that this approach leads to a *family of algorithms* because different results are achieved depending on the values of a couple of parameters, which will be described later in this section. In our previous paper, we did not discuss how to select these parameters, but their appropriate choice provides

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further enhancements to the algorithm. Before we discuss this, we briefly review the procedure and provide the algorithm for the sake of completeness.

Let V be a set of vehicles in a vehicular network. Each vehicle $v \in V$ transmits beacons at a rate r_v beacons/sec, $r_v \in [R_v^{min}, R_v^{max}]$, with a constant transmission power. Beacons are broadcast and received by surrounding neighbors within the reception range. Let n(v) denote the set of neighbor vehicles of v, which also includes v. Let us note that each vehicle has its own set of neighbors, i.e., not all vehicles are in range of each other. The total rate received by each vehicle is the sum of the rates in its set of neighbors and we are interested in limiting this amount to a maximum C (beacons/s) to avoid channel congestion. Let $U_{\nu}(r_{\nu})$ be a utility function, $\mathbf{R} \rightarrow \mathbf{R}$.

With our approach, the beaconing rate allocation is the solution to the optimization problem (1) given by:

$$\max_{r_{\nu}} \sum U_{\nu}(r_{\nu}) \quad \text{subject to:} \tag{1a}$$

$$\max_{r_{\nu}} \sum_{v} U_{v}(r_{v}) \quad \text{subject to:}$$

$$\sum_{v' \in n(v)} r_{v'} \leq C \quad \forall v \in V$$

$$R_{v}^{min} \leq r_{v} \leq R_{v}^{max} \quad \forall v \in V$$

$$(1a)$$

$$R_{v}^{min} \le r_{v} \le R_{v}^{max} \quad \forall v \in V$$
 (1c)

Problem (1) achieves two goals: (i) to control congestion, while (ii) maximizing the allocated rates in a controllable and fair way. Congestion control is enforced by constraints (1b), which means that the beaconing load of a given vehicle, given by the rates generated by the neighboring vehicles, plus its own must be below C, which is a fraction of the available channel capacity. Constraints (1c) force the vehicle rate to be within a minimum (R_v^{min}) and maximum (R_v^{max}) range as required by the standards. The objective function to be maximized is the sum of the utility $U_{\nu}(r_{\nu})$ of each vehicle, which is a function of the rate r_v allocated to it. Therefore, the shape of the utility function determines how the rates are maximized.

In fact, the link to the enforced fairness notion comes from an appropriate selection of the utility function: the use of the so called (α, ω) utility functions, shown in equation (2), guarantees that the solution to problem (1) is also fair according to well-defined fairness notions, as shown in [32].

$$U_{\nu}(r_{\nu}) = \begin{cases} \omega_{\nu} r_{\nu}, & \text{if } \alpha = 0\\ \omega_{\nu} \log r_{\nu}, & \text{if } \alpha = 1\\ \omega_{\nu} \frac{r_{\nu}^{1-\alpha}}{1-\alpha}, & \text{if } \alpha > 1 \end{cases}$$
 (2)

Let us now discuss the selection of the parameters of problem (1) when we insert the (α, ω) utility functions:

• The Maximum Beaconing Load (MBL), given by C, is usually set at a fraction of the available channel capacity, which depends in turn on the transmission rate used. A transmission rate of 6 Mbps is usually selected because of its robustness, though this has recently been questioned [34]. A 60% of the whole available capacity is usually selected because it is the optimum beaconing

load concerning several metrics [7], [35]. The remaining 40% of the available capacity is left unused to guarantee the delivery of event-driven messages in emergency

- The minimum R_v^{min} and maximum R_v^{max} beaconing rates are set by the standards [4], at 1 and 10 beacons/s respectively. However, with our approach, each vehicle may independently set its minimum and maximum rates if necessary, to guarantee minimum application reliability, and the algorithm will allocate the remaining rates to meet the constraints.
- The fairness parameter, α , allows us to adjust the notion of fairness. In particular, $\alpha = 0$ maximizes the throughput but may result in arbitrarily unfair solutions where some nodes are granted all the resources and others, none. With $\alpha = 1$, proportional fairness, as defined by Kelly [31], is achieved. Finally, as $\alpha \to \infty$, the allocation tends to max-min fairness.
- The priority parameter, ω_{ν} , is used to prioritize the rate allocated to particular v vehicles; that is, to achieve weighted fairness.

The above optimization problem is solved via its dual problem in a distributed way including a gradient-descent based algorithm [6], shown in Algorithm 1.

Algorithm 1 FABRIC [6]

1 Set initial vehicle prices π_{ν}^{0} and rates r_{ν}^{0} .

2 foreach interval k do

Each vehicle v receives the prices of neighbor vehicles $\pi_{v'}^k, v' \in n(v)$

At the end of interval k, each vehicle updates its rate

$$r_{\nu}^{k}(\pi) \text{ according to:}$$

$$r_{\nu}^{k+1}(\pi) = \left[\left(\frac{\omega_{\nu}}{\sum_{\nu' \in n(\nu)} \pi_{\nu'}} \right)^{\frac{1}{\alpha}} \right]_{R_{\nu}^{min}}^{R_{\nu}^{max}}$$
6 Finally, each vehicle computes its new price:

$$7 \quad \pi_{v}^{k+1} = \left[\pi_{v}^{k} - \beta \left(C - \sum_{v' \in n(v)} r_{v'}^{k} \right) \right]_{0}$$

8 end

In [6], the evaluation of the influence of ω was left as future work, setting $\omega_{\nu} = 1$ for all vehicles. Also, it was remarked that there is no consensus about which particular value of α is best suited for vehicular networks. The criteria for selecting a particular fairness notion are application dependent. We demonstrated and discussed its effects with examples, which, in our opinion, tend to favor proportional fairness versus max-min fairness.

In this way, in this paper, we return to the question of parameter selection to achieve the full potential of the algorithm and the best way to tune it to vehicular network requirements.

Before putting forward our proposal, in the next section, we evaluate the influence of the parameters to determine its sensitivity and potential to determine the results according to a particular goal.

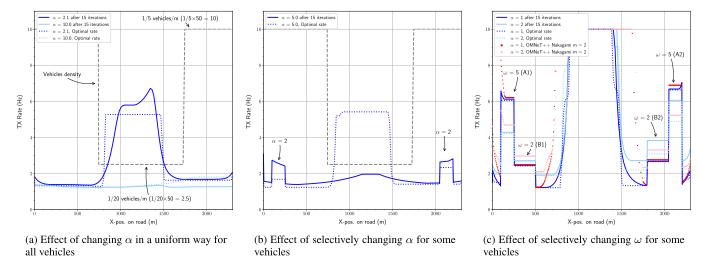


FIGURE 1. Exact optimal allocation and FABRIC with different values of fairness (α) and priority (ω) parameters for selected vehicles after 15 iterations. Vehicle density (vehicles/m) marked in a dotted gray line and scaled by 50 to match the beacon rate axis.

A. INFLUENCE OF PARAMETERS ON THE ALGORITHM

We have evaluated Algorithm 1 (FABRIC) of [6], for different values of α and ω . In this evaluation, neither propagation nor additional protocol layers are considered, as our goal at this point is to characterize only the influence of each parameter without distortions due to other effects. The behavior of the algorithm with realistic settings is shown in the results section. Besides, the exact optimal allocation has been computed using a numerical solver implemented with the Java Optimization Modeler (JOM) library. The exact solution as well as the results of FABRIC after 15 iterations, starting from the maximum rate, are plotted in Fig. 1. A simple highway scenario has been recreated, consisting of 310 vehicles evenly spaced in the x axis every 5 m (high-density region), except those vehicles between numbers 150 and 200, which are spaced every 20 m (low-density region). In the following explanation, we always consider the x axis to be the longitudinal axis of the highway, and the y axis, the traversal axis. The MBL has been set to C = 200 beacons/s and a deterministic transmission range of 400 m is assumed.

In the first test, we set an equal weight, $\omega=1$, for all the vehicles and vary the parameter α . As can be seen in Fig. 1a, the effect of increasing α is to equalize the allocated rates, as expected. As α grows, the allocation tends to a max-min solution where the rates are determined by the bottleneck links, that is, the congested channel regions force vehicles in not congested channel areas to reduce their rates. These are actually the results obtained with other proposals, such as LIMERIC+PULSAR, as was also shown in [6]. We do not think this is generally desirable, because the rate of vehicles in areas with a not congested channel is unnecessarily reduced, even though there is available channel capacity; that is, the load is below the MBL.

In the second test, we examine whether it is useful to prioritize the beaconing rates by selectively changing the α parameter for some vehicles in the network. In Fig. 1b,

we show the results of setting $\alpha=2$ for vehicles 20 to 50 and 260 to 290, while leaving $\alpha=5$ for the rest of the vehicles, and keeping $\omega=1$ for all of them. The results show that it is actually possible to prioritize those vehicles, but there is no clear mapping between the values of α and the allocated rates. Moreover, the use of a high value of α is detrimental to the convergence and we would need more iterations to achieve a better match. Let us also note that the differences between the rates obtained in each cluster of vehicles (20-50 and 260-290) are due to the different number of neighboring vehicles located in their surrounding area, since, as can be observed in the figures, the vehicle density is not symmetric.

Finally, we set the parameters in the natural way; that is, we use ω to prioritize some vehicles and α to induce a global fairness notion. We have set $\omega = 5$ for vehicles 20 to 50 (group A1) and 260 to 290 (group A2), $\omega = 2$ for vehicles 50 to 100 (group B1) and 210 to 260 (group B2), and $\omega = 1$ for the remaining ones. In addition, we have plotted the results for $\alpha = 1$ (proportional fairness) and $\alpha = 2$. The MBL has been increased to C = 400 beacons/s to give more leeway to the allocation of the rates. As can be seen in Fig. 1c, if there is enough capacity, with proportional fairness, the allocated rates are proportional to the ω ratios, as expected. For instance, for vehicles in A1 and B1, we have $\frac{r_{A1}}{r_{B1}} = \frac{6.09}{2.437} = \frac{\omega_{A1}}{\omega_{B1}} = \frac{5}{2}$ and the ratio of A1 for the rest of the vehicles in the high density area $\frac{r_{A1}}{r} = \frac{6.09}{1.219} = \frac{\omega_{A1}}{\omega} = \frac{5}{1}$. Similarly, $\frac{r_{B1}}{r} = \frac{\omega_{B1}}{\omega} = \frac{2}{1}$. Moreover, in the low density area, even though here $\omega = 1$, the vehicles set the maximum rate because there is available capacity. Let us note that this behavior is general; not dependent on this particular scenario. From eq. (7), later, it follows that the ratios of rates of vehicles i and j, measuring the same congested channel state, are given by $\omega_i^{\dot{\bar{\alpha}}}/\omega_i^{\dot{\bar{\alpha}}}$. These results suggest that fine tuning of the allocated rates can be achieved by appropriately setting the ω



parameter, while the α parameters allow us to smooth out the differences. Since the algorithm adapts to these parameters dynamically, we can use them to support further application requirements. In other words, fairness and congestion control are automatically fulfilled by directly applying the algorithm with equal parameter settings; but by selectively assigning values to the parameters, weighted fairness and therefore awareness control can be achieved.

To illustrate the behavior in a more realistic scenario, we have simulated it with OMNeT++ [36], setting a Nakagami-m propagation model and a IEEE 802.11 MAC. The results after 15 iterations are also plotted in Fig. 1c. It can be seen that even when we include fading and collisions, the results are reasonably close to the values of the ideal setting. They cannot be equal because the sharp differences in the ideal case are a consequence of the deterministic number of neighbors of the vehicles, whereas fading smoothes the shape of the allocation.

Let us conclude with a brief discussion on the convergence of the algorithm, since both α and ω affect in it [6]. We consider the basic synchronous algorithm, due to that their influence is more clearly seen, while the conclusions apply qualitatively to other variants. According to [37], the convergence of the gradient descent depends on the value of the gradient step β (line 7 in Algorithm 1) and, in the considered case, it must satisfy the following inequality (3):

$$\beta < \frac{2}{\bar{L}\bar{N}\bar{c}} \tag{3}$$

where \bar{L} is the length of longest path (links or hops in our context) used by the sources ($\bar{L}=1$), \bar{N} the number of vehicles that share the most congested link, and \bar{c} is a bound of the second derivative with respect to the beaconing rate of the utility function [37]:

$$-\frac{d^2U(r)}{dr^2} \ge \frac{1}{\bar{c}} \tag{4}$$

By introducing the utility function (2) in equations (4) and (3) and considering the maximum rate, we have:

$$\beta < \frac{2\alpha\omega}{R_{max}^{\alpha+1}\bar{N}}\tag{5}$$

This leads to the following guidelines: (i) The higher the α parameter is, the slower the convergence since we are forced to use a smaller gradient step β . And (ii), by the opposite reason, a greater ω parameter helps to improve the convergence. We will come back to these parameters in Sect. IV-D, when we describe our proposal more in detail.

Now, the question is how to set these parameters to effectively enforce some notion of awareness control while maintaining a high convergence speed. From the previous discussion and results we favor the use of a low α : A value of 1 allows us to obtain proportional fairness and quick convergence, but values around 2 may be used to get more balanced allocations without degrading convergence.

As for the awareness control via weighted fairness including the ω parameter, in the next section, we will discuss several approaches and propose our own.

IV. PROPOSED ALGORITHM

In this section, we first discuss the limitations of other awareness and congestion control algorithms. Then, based on the conclusions we introduce our proposal.

A. LIMITATIONS OF CURRENT PROPOSALS

In Sect. I and II, we pointed out that the main problem with pure CC approaches is that they ignore the traffic situation of the vehicle and only use channel information, with additional problems if the beacon generation is separated from the congestion control. Regarding AC, some of them integrate CC in some way, but most of them ignore or override it. However, care should be taken when overriding beaconing congestion control. One of the goals of congestion control is to facilitate the operation of event-driven messages, such as those of DEN in ETSI standards, by guaranteeing that a given fraction of the channel capacity is available for this service. The intended functionality of each service, CAS and DEN, should be kept separate in our opinion. For instance, using estimated collision probability at an intersection [13] seems more suitable for a road hazard signaling (RHS) application that uses periodic event-driven messages, as suggested in [17, Annex B], rather than CAM messages. And by not actually enforcing the MBL, some proposals may interfere with the DEN service even though they take congestion control into account in some way. This is the case of INTERN, whose authors recognize the difficulties of ubiquitously satisfying application requirements and discuss feasible regions where this is possible. The issue, then, is how to avoid those regions, which again points to a clearer mapping between the CAS or DEN service and the nature of the application. In fact, they have recently proposed a coordination methodology described in [38].

Many AC proposals aim to adapt the rate to minimize the position tracking error with respect to other vehicles, such as [27] and [7], which is the mechanism for the US DCC standard [28], or EMBARC [14], a variation of LIMERIC which integrates the tracking error algorithm of [7]. The proposals that use tracking error to trigger new beacon generations [7], [14], [27], essentially adapt the beaconing rate to their own vehicle dynamics. Therefore, CAM-DCC also falls into this category. In the absence of variations, few or even no additional beacons are generated. Our main concern with this approach is that it ignores the surrounding traffic situation. The previously discussed example of a highway with a traffic jam in one direction, resulting in a congested channel, and a free-flow condition in the opposite direction with highspeed vehicles, applies here. The vehicles in free-flow are forced to decrease their rates due to the congested channel and, even with error tracking control, if they do not change their speed or heading significantly, no additional beacons are generated. Some others, such as NORAC [10] and explicitly BFPC [15], address the problem by setting the rates

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proportional to the speed, but again they only consider the dynamics of each vehicle, in particular, the speed, not the surrounding traffic, which, for instance, leads to that a single stopped vehicle in the middle of a highway reduces the rate instead of increasing it. It must be said that both NORAC and BFPC only introduce the speed as an example of a potentially suitable weight function and that others, such as our own TTC proposal, might be used with these algorithms.

In fact, the single stopped vehicle example is used in ETSI standards for safety-related applications, such as RHS [17], ICRW [18], LCRW [19], when discussing CAM adaptation, saying that, in some situations, the solutions based on "highly dynamic data evolutions", that is, the dynamics of the ego vehicle *may* not be suitable and adjustment by the corresponding safety application, "based on the perceived criticality of the traffic safety situation around the vehicle [...], would be more meaningful" [17, Annex F]. In other words, the traffic situation should be taken into account. From our point of view, even though some recent proposals address these issues, some aspects are missing and potentially more satisfactory solutions can be still explored.

B. TIME-TO-COLLISION CONGESTION CONTROL (TTCC)

We propose a type of awareness control that complements the pure congestion control of [6] by taking advantage of the algorithm's capability to shape the resulting allocation via fairness and priority parameters. The considerations of the previous section suggest the following goals:

- The awareness control should be fully integrated with the congestion control and comply with the MBL constraint. This way, safety services are guaranteed a reserved bandwidth. If this is not feasible because of application requirements, one should consider whether the application should use the CAS as the main dissemination service.
- The awareness control should take the surrounding traffic situation and neighboring dynamics into account.

A usual metric to assess the criticality of a safety situation is Time-to-Collision (TTC), as discussed in ETSI standards [17]–[19] and other works [39]. We use it as the basis for prioritizing beaconing rates. To compute it, we use simple kinetics, but formulated in a general vector form, which can be applied to most situations without assuming limiting simplified models [29], [30], such as one-dimensional (1D) models or just ahead-vehicle tracking. Let us assume a three-dimensional (3D)¹ scenario, such as the scenario depicted in Figure 2. We represent each vehicle as a sphere of radius r_{ν} , and its movement with three different vectors of acceleration, velocity, and position, \vec{A} , \vec{V} , and \vec{P} , respectively.

Assume that TTC will be computed at regular intervals of time, which are short enough to presume that the acceleration in that interval will remain constant. In this case, we can ignore complex real-vehicle dynamics and use simple

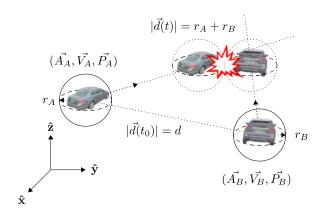


FIGURE 2. Notation and scenario used to derive the time-to-collision (TTC) metric, used in this article.

constant-acceleration kinetics as estimations of future vehicle position: $\vec{P}(t) = \vec{P}_0 + \vec{V}t + \frac{1}{2}\vec{A}t^2$.

A collision between two vehicles occurs at time t when their corresponding spheres overlap. To compute this, it is easier to use a relative formulation, where the R subscript denotes the difference between A and B vectors: $\vec{S}_R = \vec{P}_A - \vec{P}_B$, $\vec{V}_R = \vec{V}_A - \vec{V}_B$ and $\vec{A}_R = \vec{A}_A - \vec{A}_B$.

Therefore, d(t), the distance between two vehicles at time t is $\vec{d}(t) = \vec{S}_R + \vec{V}_R t + \frac{1}{2} \vec{A}_R t^2$. And there is a collision when $\vec{d}(t) \cdot \vec{d}(t) = |d(t)|^2 = |r_A + r_B|^2$. For the sake of simpler notation, we set $r_A + r_B = r$, and expand the dot product to get the following 4th order polynomial equation in t, eq. (6), whose solution gives the TTC between the two vehicles involved:

$$\frac{1}{4}A_R^2t^4 + \vec{V}_R \cdot \vec{A}_Rt^3 + (\vec{S}_R \cdot \vec{A}_R + V_R^2)t^2
+2t\vec{S}_R \cdot \vec{V}_R + (S_R^2 - r^2) = 0$$
(6)

where each $\vec{u} \cdot \vec{u} = |u|^2 = u^2$. If a constant-speed model is used, a straightforward quadratic equation is obtained, but we prefer to include the acceleration information.

The outline of the algorithm is: A vehicle computes the TTC_{ν} for all its known neighbors, using the data contained in the beacons received from them and using the inverse of the minimum one to set its priority ω_{ν} in the utility function of Problem (1), as will be described in Sect. IV-D later.

Let us first discuss some qualitative features of this approach:

- It is obvious that the quality of the computed TTC depends on the quality of the received data. Alternatives that take noise into account can be considered. Just as the *suspected tracking error* is used by [7], [14], [27], a suspected TTC error may be also used. However, we focus here on the basic approach.
- The sphere radius can be set as half of the vehicle length to get a conservative value. Real or average values can be used. Trucks, buses, and long vehicles can be represented by multiple spheres. In general, further adjustments can be made to tune the procedure, but let us highlight how this concept aligns well with the notion of the *dynamic safety shield* mentioned in the ETSI safety

¹A two-dimensional (2D) scenario is enough in most practical situations. The vector equations are the same in any number of dimensions.



- standards [17]–[19], which set a vehicle in a state of increased alert when it detects that a neighbor is within a TTC threshold.
- Let us remark that our scheme aids, but does not overlap the DEN functionality. As TTCs decrease, our proposal increases the beaconing rate of potentially involved vehicles, which is absorbed by non-involved ones in advance. If a critical safety situation eventually occurs, the congestion control is overridden, if necessary, from the DEN. Therefore, this algorithm *automatically anticipates a potential increase in rate by the DEN due to a critical safety situation* as discussed in standards [17]–[19]. But only up to a point, since the MBL constraint is satisfied so it does not interfere with the reserved bandwidth, which is entirely available for the safety signaling application.



FIGURE 3. Intersection of 100 S mays St and main St, Round rock, Austin, Texas, USA. Image captured from google maps street view.

C. ILLUSTRATION OF TTC

Figure 3 shows a real situation which illustrates the need to consider the surrounding traffic situation globally. A vehicle i will compute a different TTC_{ij} for each of its neighbors, which depends upon the particular state of movement of the neighbor. For example, for vehicle A, TTC_{AE} may be long or short, depending on whether E accelerates or brakes. TTC_{AC} is very long (or infinity) because there is no collision risk, but TTC_{AD} may be low because the acceleration of D sets it on a collision course. The TTC has been represented in Figure 4 as a function of the relative speed for different separation distances and accelerations in a 1D scenario.

As expected, TTC reflects the risk related to the different combinations of parameters well. When a real root for TTC does not exist, it means an absence of risk. A collision would occur later as the separating distance increases and earlier as it decreases. Similarly, sudden deceleration owing to abrupt braking implies short values of TTC, and light braking, longer values of TTC. Let us note that this metric correctly reflects the risk in cases that may seem dubious. For instance, a closely tailgating vehicle with a very low relative speed and acceleration actually has a long TTC. In fact, one

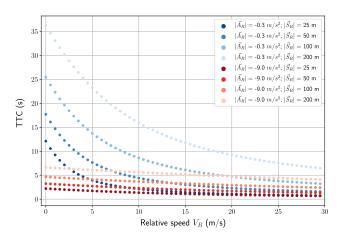


FIGURE 4. Time-to-collision evaluation between two vehicles for different accelerations, separation distances, and relative velocities V_R

of the goals of CAD and cooperative platooning is to keep controlled relative speeds and accelerations to increase the capacity of the roads. Of course, in a normal situation tailgating vehicles would likely soon develop a non-zero relative speed or acceleration. But at that moment, the TTC would quickly decrease, reflecting again an increased risk.

D. TTCC ALGORITHM

Finally, here we describe the implementation of our TTCC algorithm. We have modified our previous algorithm by introducing the priority parameter in the optimization problem, determined by the computed minimum TTC, as we will discuss below. With this change, and checking the derivation [6, Sect. 4] mentioned in Section III, it directly follows that the optimal rate with the ω parameter included is:

$$r_{\nu}^{*}(\pi) = \left[\left(\frac{\omega_{\nu}}{\sum_{\nu' \in n(\nu)} \pi_{\nu'}} \right)^{\frac{1}{\alpha}} \right]_{R_{\nu}^{min}}^{R_{\nu}^{max}}$$
(7)

whereas the rest of the steps do not change. Therefore, the only necessary modification to our previous algorithm is the inclusion of the ω parameter in eq. (7) and the selection of its value.

We now turn to the details of how *each vehicle v sets its* ω_v : a vehicle v computes the TTC_{vi} for all its known neighbors i from eq. (6). Only the real positive roots of eq. (6) give a valid TTC. The first approach is to use the inverse of the minimum valid TTC, found as the priority parameter $\omega_v = \frac{1}{\min(TTC_{vi})}$. But then, a solution with only imaginary roots means that no collision is possible with the given input: it would translate into a $w_v = 0$. In addition, TTC values can be arbitrarily large, which makes ω_v tend to zero as well. We would prefer to assign $w_v = 1$ to all the vehicles in the case that no minimum TTC is found, which more clearly conveys the idea that the vehicle does not need prioritization. We also introduce the σ parameter to rescale ω to approximately match the scale of the rates and favors a quicker convergence as discussed below.

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In addition, we introduce a speed term, *S*, to differentiate the speed among vehicles, so faster vehicles, even in absence of risk, are prioritized with respect to slower ones. Besides, it reflects the severity of a collision in case it may occur. This is done by means of the *S* term below:

$$S = 1 + \frac{v}{v_{MAX}} \tag{8}$$

which is the ratio of the vehicle speed to some maximum allowed speed v_{MAX} , plus one to guarantee that ω is greater or equal to one. These parameters included in ω have an influence on both the convergence of the algorithm and the ratios of the rates that we allocate to vehicles:

• First, to study the influence in the convergence of the algorithm, that is, its performance, we introduce the parameters in eq. (5) and get:

$$\beta < \frac{2\alpha}{R_{max}^{\alpha+1}\bar{N}} \left(\frac{\sigma}{TTC} + 1 + \frac{v}{v_{MAX}} \right) = \beta_0 \omega \qquad (9)$$

We can observe how scaling the TTC with σ benefits the convergence by not forcing us to decrease the gradient step when the TTC is long. For the sake of clarity, we use a numerical example, and consider two TTCs, a short one, $TTC_s = 0.5$ s, a long one, $TTC_l = 50$ s, and v = 32 m/s. Without scaling and S, TTC_l would force us to decrease the step two orders of magnitude to ensure convergence, $\beta < 2\beta_0 10^{-2}$. With scaling of $\sigma = 10$ we would only need to reduce one order of magnitude. But if we introduce the S term we achieve more stability, since when adding it to the scaled term, we make $\omega \approx S$, so making it be in the order of units. In the example, we get $\beta < \beta_0(2 \cdot 10^{-1} + 1 + 32/34) = 2.14\beta_0$. In summary, the longer the TTC, the less relevant it becomes and we can keep the same gradient step even for long TTCs. On the contrary, with TTC_s in the example, we obtain $\beta < 21.94\beta_0$. That is, σ makes the TTC term be on the order of tens, with $\omega \approx \frac{\sigma}{TTC_s}$, which would even allow us to increase the gradient step to achieve quicker convergence.

• Second, the parameters establish the ratios of the allocated rates in presence of channel congestion as:

$$\frac{r_i}{r_j} \approx \left(\frac{w_i}{w_j}\right)^{\frac{1}{\alpha}} = \left(\frac{\frac{\sigma}{TTC_i} + 1 + \frac{v_i}{v_{MAX}}}{\frac{\sigma}{TTC_j} + 1 + \frac{v_j}{v_{MAX}}}\right)^{\frac{1}{\alpha}} \tag{10}$$

where TTC_x refers to the minimum TTC computed by vehicle x. For long TTCs, that is, in absence of substantial risk, the ratio is determined by the S term basically: For $\alpha=1$ and realistic speeds, the maximum ratio is around 2. Let us note how that ratio tends to 1 as α increases, that is, as we argued previously, it tends to max-min fairness or more equal allocations. On the other hand, for short TTCs, σ again makes the maximum ratio depend basically on the ratio of the TTCs. Similarly, in the case of a short TTC and a long one, the former prevails over the S term.

In summary, with these parameters, we have an additional degree of control over the convergence speed and the allocations. In any case, we treat them as global parameters, in the sense that they do not need fine tuning. In our tests, we have set them to $\sigma = 15$ and $v_{MAX} = 34$ m/s, values which should work well in a very broad range of situations, legal limits and types of roads.

Thus, the updated procedure with respect to our previous algorithm in [6] is outlined in Algorithm 2.

```
Algorithm 2 TTCC
```

```
1 Set initial vehicle prices \pi_v^0 and rates r_v^0.
 2 foreach interval k do
          Each vehicle v receives \vec{A_v}, \vec{V_v}, \vec{P_v}, \vec{P_v}, \pi_v^k, r_v^k from its
          neighbors n(v).
          At the end of interval k:
 4
 5
          Compute the TTCs and store them in ttcs:
          for i in n(v) do
 6
                TTC_{vi} \leftarrow \text{Roots of eq. (6) for } v \text{ and } i;
 7
                ttcs \leftarrow TTC_{vi}
 8
 9
10
          Get the minimum real positive root among ttcs:
          TTC_{min} \leftarrow min(ttcs \in \mathbb{R}^+)
          if \exists TTC_{min} then
11
              \omega_v \leftarrow \frac{\sigma}{TTC_{min}} + S
12
13
           \omega_v \leftarrow S
14
15
          Then, each vehicle updates its rate r_v^k(\pi) according
16
         r_{v}^{k+1}(\pi) = \left[ \left( \frac{\omega_{v}}{\sum_{v' \in n(v)} \pi_{v'}^{k}} \right)^{\frac{1}{\alpha}} \right]_{R^{min}}^{R^{max}}
          Finally, each vehicle computes its new price:
          \pi_{v}^{k+1} = \left[\pi_{v}^{k} - \beta \left(C - \sum_{v' \in n(v)} r_{v'}^{k}\right)\right]_{0}
```

As shown in Algorithm 2, at regular k intervals, each vehicle collects both its current acceleration, speed, and position, and those of the neighboring vehicles from their corresponding received beacons. With this information, the vehicle under study computes the root of eq. (6) for each neighbor, which corresponds to the TTC for that neighbor.

If a collision is possible, at least one of these roots (t) is real and positive. The TTC used in the algorithm is the minimum real positive root among all the obtained roots for all neighboring vehicles. The remaining steps of the iteration are identical to those of [6] and solve the problem (1) in a distributed way. We finish this section with a clarification of some features of TTCC:

• The procedure is *local and fully distributed*. Each vehicle independently sets its priority ω_{ν} with the information received from one-hop neighbors. Similarly, the

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20 end



- weights and rates are computed with only local information from one-hop vehicles.
- The information required for TTCs: position, velocity, and acceleration can be extracted from the fields already present in the beacons; specified in the standards. The only additional information each vehicle has to insert in a beacon, required to solve the NUM problem, is the weight (π) and, optionally, 2 rate (r); just two real numbers. This small overhead is similar to other proposals, such as LIMERIC+PULSAR, which requires the sending of two real numbers, local and one-hop Channel Busy Ratio (CBR).
- Let us remark that priorities are only enforced if there is not enough capacity, as shown in Fig. 1c. If the MBL constraint is not active, that is, the load is below MBL, the beaconing rates are always set to the maximum rate, R_{max} , for all vehicles.

V. RESULTS

In this section, we evaluate the performance of the TTCC versus other approaches previously discussed, namely: (i) LIMERIC+PULSAR, as a pure CC solution, (ii) CAMDCC, specified in the standards with AC and CC, (iii) EMBARC, which integrates AC with LIMERIC, and (iv) NORAC, an integrated AC and CC solution based on game theory which provides weighted fairness. Unless explicitly mentioned, all the simulations have been made with OMNeT++ 5.3 [36] and its INET 3.5 library [40], which implements the IEEE 802.11p standard and realistic propagation and interference models, also considering the capture effect. An additional mobility module, which implements the Intelligent Driver Model (IDM), has been developed to simulate more realistic driver behavior [41].

In Table 1, we summarize the simulation parameters, common to the simulation studies in this and the following section. We use a 6 Mbps channel and a beacon size of 500 bytes, which gives a total message size of 536 bytes including the MAC headers, and according to [20], the resulting PHY packet duration is 760 µs. With these channel settings, the MBL constraint is set to C = 789.47 beacons/s to reserve 40% of the capacity for the DEN service, as explained in previous sections. In the particular case of NORAC, the utility parameter has been set, as a reference, to $u_v = |v_v/4|_4$, being u_v the speed of each vehicle v. As we discussed in Sect. II, an intrinsic problem of NORAC is that it requires adjusting a proper combination of parameters for different scenarios. Following the scheme of the authors in [10], we have tested $\lfloor u_v \rfloor_4$ and $\lfloor u_v / 2 \rfloor_4$, but since the maximum speed for which they tested the algorithm is 20 m/s, the

TABLE 1. OMNet++ simulation parameters.

Algorithm	Parameter	Value
*	Frequency (f)	5.9 GHz
*	Power (P)	251 mW
*	Sensitivity (S)	-92 dBm
*	Data rate (D)	6 Mb/s
*	SNIR Threshold (T)	4 dB
*	Background Noise (N)	-110 dBm
*	Path loss	Nakagami-m
*	Old neighbor removal	5 s
*	Beacon duration	$760 \mu { m s}$
*	Capacity (C)	789.47
		beacons/s
*	Maximum rate (R_v^{max})	10 Hz
*	Minimum rate (R_v^{min})	1 Hz
TTCC	π_v^0	1.252×10^{-3}
TTCC	$\mid r_v^{ 0} \mid$	5 Hz
TTCC	α	1
TTCC	β_F	2.8×10^{-7}
LIMERIC (+PULSAR)	α_L	0.1
LIMERIC (+PULSAR)	β_L^-	1/150
LIMERIC+PULSAR	CMDI	300 ms
CAM-DCC	$T_CheckGenCam$	10 ms
CAM-DCC	N_GenCam	3
EMBARC	$ \alpha_L $	0.1
EMBARC	$\mid eta_L$	1/400
EMBARC	T'	0.2 m
EMBARC	δ_s	100 ms
EMBARC	δ_l	300 ms
NORAC	$\mid u_v \mid$	$\lfloor v_v/4 \rfloor_4$
NORAC	pc_v	0.6, 1.0

^{*} Common parameters for all the algorithms.

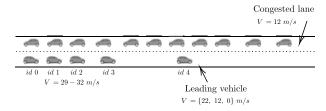


FIGURE 5. Free-flow direction scenario with all vehicles in range and leading vehicle 4 limiting the speed.

resulting beaconing rates are too high when we now employ higher speeds (e.g. 20-34 m/s) and the MBL constraint is not met. Other functions could be introduced, such as our own TTC, but further parameter adjustment would be required.

A. CONGESTED AND FREE-FLOW DIRECTIONS WITH ALL VEHICLES IN RANGE

In the first scenario, we set up 5 consecutive vehicles in movement on a lane at high speeds, and other parallel lanes in the opposite direction with a traffic jam to induce channel congestion. We call this the congested/free-flow direction scenario. The first group is led by the vehicle with ID=4 (vehicle 4, hereinafter), which has a lower speed than vehicles 0, 1, 2 and 3, as shown in Table 2 and Fig. 5. With the implemented IDM model, such initial differences in speed and separation force the following vehicles to decelerate with different intensity.

We intend to show the effect of vehicle deceleration on the beaconing rate. This is a situation where the TTC of

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²The algorithm requires that each vehicle know the load it measures in the channel, which is either the sum of the rates or approximately equal to the CBR. Therefore, only the weights need to be broadcast and CBR can be locally measured. We prefer to send the rate because it generally tends to be more stable. When the CBR is not equal to the sum of the rates, for instance in cases of severe fading, using the measured CBR allows us to adjust the allocation better to the actual channel load. Otherwise, in those cases, the load is overestimated and the allocation is slightly below the optimal.

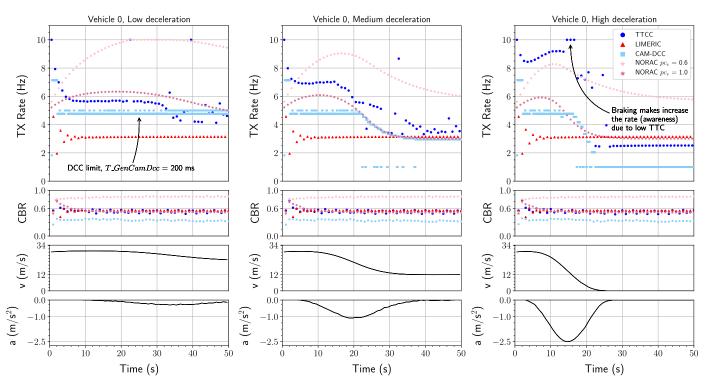


FIGURE 6. Rate control approaches comparative for vehicle 0, evaluated in different deceleration cases being all vehicles in range. From top to bottom: beaconing rate, channel busy rate, velocity and deceleration.

TABLE 2. Simple scenario, initial positions and speeds.

Vehicle ID	0	1	2	3	4	5	 235
v ₀ (m/s)	29	30	31	32	22, 12, 0*	12	 12
x_0 (m)	15	60	130	210	450	5	 1996
y_0 (m)	8	8	8	8	8	15	 15

^{*} Variable employed to generate different deceleration cases.

the following vehicles must increase due to a risky situation created by the slower leading vehicle. Note that the vehicles in the traffic jam are not stopped, but moving at a slow uniform speed of 12 m/s, to prevent CAM-DCC from decreasing the beaconing rate down to one. They have been randomly positioned according to a Poisson distribution of average density $\rho=0.14$ vehicles/m. There is a total of 236 vehicles in the network, all in range of each other. A Nakagami-m propagation model is used, and, as a consequence, the packet reception is not deterministic. The average carrier sense range [42] for this scenario is 1805 m, corresponding to a shape parameter m=2 and path loss exponent $\beta_{PL}=2$.

In Figure 6, we show the results for vehicle 0, the last of the high-speed vehicles, for 50 seconds and three different deceleration profiles, corresponding to IDM behavior in response to the initial speed of the leading vehicle 4. In the first case, where this speed is set at 22 m/s, we obtain light deceleration, which corresponds to a natural driver fit of the optimal speed in the road and which barely entails risk. Secondly, the initial speed of the leading vehicle is set at 12 m/s, which results in a moderate deceleration and risk; and finally, abrupt deceleration of about -3 m/s² is forced when the leading vehicle is completely stopped.

As might be expected, LIMERIC does not take the movement of the vehicle into account and allocates resources only according to the locally measured CBR. Particularly, with 236 vehicles all in range, all rates go to 3.668 Hz, which is an equal share of the available bandwidth.

Regarding CAM-DCC, it triggers a new CAM generation when there have been certain variations in speed, heading, or position during the last interval. That is, it reacts to the dynamics of the vehicle. It is always limited by the DCC entity, which constrains the CAM rate according to the congestion measured in the channel by a finite state machine, as in [4], [8], [21]. Results show that for the CAM-DCC algorithm, the speed of the vehicle proportionally determines the beaconing rate until it is limited by the DCC entity. In Fig. 6, we can see that even though the velocity is still high, the beaconing rate drops to 5 beacons/s ($T_GenCamDcc =$ 200 ms) due to the CBR limit, as a result of the CBR created by the vehicles in the congested direction, not shown in the aforementioned figure, but which have a similar rate to those of LIMERIC. This is an unnecessary limitation for a vehicle in a potentially unsafe situation; even more so when the CBR is only slightly above 0.3 and there is ample margin before reaching the MBL. In the moderate and sudden deceleration cases, again the DCC entity unnecessarily prevents the vehicle from raising the rate above 5 beacons/s. Moreover, the rate decreases as the speed decreases, independently of the traffic situation. The appropriateness of this behavior is questionable, as a vehicle stopped in the middle of a highway would transmit at just 1 beacon/s, oblivious to the state of the rest of vehicles, and in fact, this case is questioned in the standards



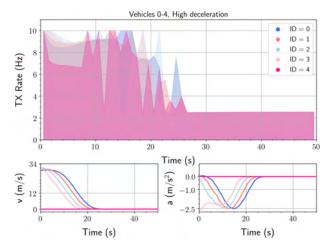


FIGURE 7. TTCC rate control for vehicles 0-4 evaluated in the high-decelerated case, with all vehicles in range with each other and leading vehicle 4 limiting the speed.

for safety applications [17, Annex F]. On the contrary, TTCC effectively takes into account the surrounding traffic situation and prevents this issue: with TTCC, vehicle 4, the leading one, also keeps a higher rate. Especially, in the case of high deceleration, where it is completely stopped, it still keeps a high rate until the risk is over, as shown in Fig. 7.

The behavior of NORAC depends on the combination of parameters, as we commented. The beaconing rate results are in accordance with CAM-DCC, except that setting the lower limit of speed to 4 m/s avoids dropping the rate to 1 Hz. But depending on the value of the price, the MBL may be violated, for instance, when using the recommended values in [10], or when establishing $pc_v = 0.6$. As shown in the next sections, NORAC requires its parameters to be tuned for each road scenario.

With TTCC, however, the beaconing rate adjusts to the risk of the situation, while keeping the CBR at the desired limit. In all the cases, as an example of weighted fairness in action, the ω parameter makes the beaconing rate of the free-flow vehicles stay well above the vehicles in the direction of the traffic jam, which are transmitting at around 3.5 beacon/s. That is, they have reduced their rates slightly to allow for the increase of the beaconing rates of the vehicles in the high-speed direction. Moreover, in the case of abrupt deceleration, it may seem odd that vehicle 0 sets the rate below 3.66 beacon/s, but, in fact, this is intended behavior. Since after t = 25 s, all the vehicles in the high-speed direction are stopped, there is actually no risk; that is, no TTC and $\omega = 1$, whereas the vehicles in the jammed direction are moving at 12 m/s, so their $\omega > 1$ and they transmit at around 3.5 beacon/s.

As a final remark, the CBR for TTCC is always slightly below the 0.6 limit because of the algorithm implementation. At step 15 of Algorithm 1, to compute the difference between the MBL and the load, vehicles use the beaconing rate that their neighbors are using piggybacked in the received beacons. But, due to the fading of the propagation model, some of those beacons are lost. LIMERIC, however, adjusts to the

MBL better because it uses the measured CBR. If a more precise fitting were necessary, TTCC could also compare the MBL to the measured CBR in step 15.

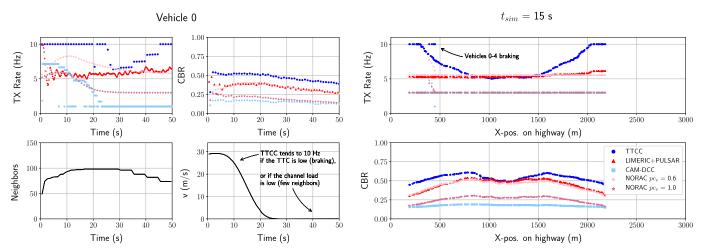
B. CONGESTED AND FREE-FLOW DIRECTIONS WITH MULTI-HOP

This scenario is the same as the previous one, but in this case, we change the path loss exponent of the Nakagami-m propagation from 2 to 2.5, which reduces the transmission range from 1805 to 403 m, approximately. Unlike the previous case, the vehicles have a different number of neighbors in range depending on their position, and so they set different beaconing rates depending on their position. We evaluate the sudden deceleration scenario.

In Figure 8a, we plot the time evolution of the beaconing rate, CBR, and the number of neighbors, while in Fig. 8b, we plot the beaconing rate and CBR vs the position of all the vehicles at t = 15 s, because from Fig. 6, the greatest deceleration occurs approximately at that time. Regarding the overall rate allocation, in Fig. 8b, we can see how CAM-DCC only assigns a rate of 3 beacons/s proportional to vehicle speeds, which results in an under-use of the capacity, with CBR below 0.2. Unlike the all-in-range scenario, the DCC limit is not met in this case, and so we can observe in Fig. 8a, that the decelerating vehicle can set a higher beaconing rate in the interval from 0 to 18 s. LIMERIC+PULSAR (shown as L+P), NORAC and TTCC try to maximize the capacity up to the MBL. In the case of TTCC, we can see the typical "U" allocation for proportional fairness [6], where the throughput is being maximized when possible. So the vehicles on the edges of the scenario set a much higher rate, since they have fewer neighbors and therefore, experience less load. LIMERIC+PULSAR, on the contrary, yields a typical maxmin allocation, and so the bottleneck links, in this case, the vehicles in the middle of the scenario, limit the maximum rate for the others: all vehicles set their rate equal to the rate of the more loaded ones. This is the typical trade-off between resource usage and fairness, which manifests itself also as a CBR below the MBL.

If we look at the time evolution for vehicle 0, we see that the LIMERIC+PULSAR beaconing rate goes to the common final allocation with a slight oscillation, independently of the dynamics of the vehicle. TTCC, on the contrary, keeps the beaconing rate to a maximum due to the risk, and only when it is over is it decreased to the level of the neighbors in the congested area. Later, as the congested cluster moves away, the beaconing rate is raised again, contrary to LIMERIC+PULSAR, which maintains the rate of the most congested vehicle level as long as there is a multi-hop link to the bottlenecked area. Concerning NORAC, we use the same utility and price parameters than in the previous scenario, where using $pc_v = 0.6$ resulted in a remarkable surpassing of the MBL. But, nevertheless, in this case, makes the CBR keep below the MBL. This outcome confirms again that NORAC requires fine parameter tuning for different scenarios or a more clear selection procedure.

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(a) Time evolution of vehicle 0 for beaconing rate, CBR, number of neighboring vehicles and speed.

(b) Overall beaconing rate and CBR versus position at t=15 s.



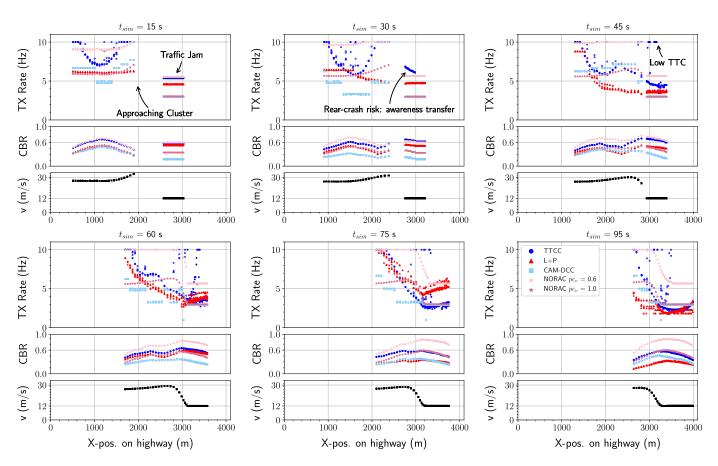


FIGURE 9. Comparison of different beaconing rate control algorithms in a realistic scenario with a cluster of moving vehicles approaching a traffic jam.

We have also simulated EMBARC in this scenario. However, the results are very similar to those of LIMERIC+PULSAR, because the tracking error does not change noticeably in this scenario, and so no additional beacon is triggered. Once the main features of both congestion and awareness control both for all the vehicles in range and multihop for a simple scenario have been analyzed, we turn to

evaluate a more realistic road situation, consisting of a large number of vehicles in motion.

C. REALISTIC TRAFFIC JAM WITH MULTI-HOP

To observe the TTCC response in a real scenario with a large number of moving vehicles, we generate two approaching clusters of vehicles: one (Cluster A) at very high speed



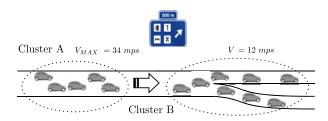


FIGURE 10. Realistic multi-hop scenario consisting of moving cluster approaching a jammed area.

TABLE 3. Realistic traffic jam scenario, initial positions, and speeds.

Vehicle ID	0, 1, 2	 147, 148, 149	150, 151, 152	 297, 298, 299
v ₀ (m/s)	34	 34	12	 12
x_0 (m)	20	 1285	2294	 2641
y_0 (m)	5, 8, 11	 5, 8, 11	5, 8, 11	 5, 8, 11

 $(V_{MAX} = 34 \text{ m/s})$ and another (Cluster B) congested due to a traffic jam (12 m/s), as depicted in Figure 10. We now require more realistic separation distances. Otherwise, the TTC would yield values that are too low. Therefore, we position the vehicles according to a Poisson process, separating vehicles with distances of between 10 and 40 m for those in free flow and distances of between 5 and 10 m for those located in the congested road section. In addition, we introduce channel congestion by adding 2 more lanes in different y-axis positions. Altogether, we have 300 vehicles, divided into two clusters of 150 vehicles each, separated by 1000 m, as shown in Table 3. This distance is introduced for two reasons: (i) to give the algorithms time to converge and leave the transient phase, and (ii) to clearly observe the priority of speed before the vehicles start to measure risk and, therefore, the TTC priority mechanism is applied. The transmission range used in this section is set at 403 m as in the previous scenario. In Figure 9, the beaconing rate is plotted versus the position of the vehicles for different simulation times to allow us to observe the channel management and behavior of each studied approach. In addition, we show the speed versus position of the vehicles to discuss their influence.

15 seconds

In the first 15 seconds, when the clusters are still isolated, we see a typical allocation pattern in a multi-hop scenario for TTCC for the approaching cluster, with higher speed vehicles prioritized. In contrast, the allocation is flatter for the other proposals, equal for LIMERIC+PULSAR, and proportional to speed for NORAC and CAM-DCC, except in this latter for the middle of the approaching cluster, where a higher load triggers the DCC entity, which limits the rates to 5 beacon/s. In the congested flow cluster, since all the vehicles are in range due to higher vehicle density, all the proposals result in a flat rate allocation, but TTCC and NORAC set a higher value due to its design.

30, 45 seconds

As time passes, some leading vehicles from the front of the moving cluster start entering the range of those located in the traffic jam. For TTCC, the approaching vehicles start detecting the jam and the risk involved, so the TTCs begin to decrease, while the rates increase. The effect is more clearly visible in the front section of the congested cluster, marked with an arrow in the figure, where the risk assessed as TTC makes the vehicles increase their rates, balanced by a decrease in the rates of vehicles in the rear section. This is a behavior not shared by other proposals and shows how weighted fairness operates in TTCC.

In this interval, the speed is still high because free-flow vehicles are far from the congested cluster. However, they are already in communication range, and the measured channel load increases, which triggers the DCC limit for CAM-DCC and forces vehicles to decrease their rates. This behavior is questionable, since high speed, potentially more risky vehicles are forced to reduce their rates unnecessarily. NORAC solves this point by keeping high the beaconing rates until vehicles begin braking. With LIMERIC+PULSAR, the rates are directly reduced to match those of the congested cluster. Again, the max-min approach forces vehicles to adopt the rate of the most congested link.

60, 75, 95 seconds

When the approaching cluster of vehicles comes close to the traffic jam, the risk of collision is more significant due to a low relative distance and a high relative speed. TTCC increases the rates of the vehicles involved to a maximum, shown in Figure 9 between 2600 and 3400 m. Over time, as drivers brake, the risk of collision is gradually moving along the cluster, from the front (3500-4000 m) to rear (1800-2600 m), depending on the measured TTC at each moment. Also, as more vehicles join the congested queue, the channel load increases. TTCC forces beaconing rates to decrease gradually along the merging clusters, lowering the rates of those in the queue without risk and keeping the rates of both vehicles with low risk high or not really measuring congestion on the channel. In comparison, LIMERIC+PULSAR cause the rates to drop more drastically and with oscillations, shown in t = 60, 75, and 90 s. CAM-DCC again tracks the speed in the sense that it assigns rates proportionally to speed in general, decreasing the rate as the vehicles brake. Similarly, NORAC decreases the beaconing rate in function of the vehicle speed, but, as the number of neighboring vehicles increases, the CBR may grow also without any limitation or not, again depending on the selected value of the price parameter.

D. GRID ROAD

Finally, we test TTCC in a scenario with intersections, where vehicles approach intersections at different speeds and stop in queues before crossing them, according to their right of way. We have used SUMO [43] to simulate realistic traffic patterns. We have set up a 2×2 grid road network with 9 intersections and 600 m edges with 4 lanes each, where vehicles tend to a top speed of 34 m/s whenever possible and no other vehicle is ahead. The minimum distance traveled for each vehicle has been set at 12 km with 15 intermediate

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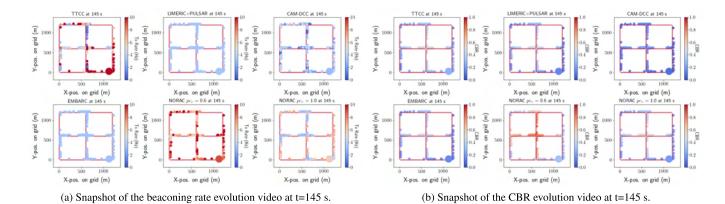


FIGURE 11. Grid scenario with multihop range. Vehicle 192 highlighted with a larger marker.

TABLE 4. SUMO configuration.

Parameter	Value
Grid number	3
Grid length	600 m
Default speed	34 m/s
Lanes	4
Trip beginning time	0 s
Trip ending time	10 s
Repetition rate	0.03 s
Minimum distance	12 km
Intermediate way-points	15
Fringe factor	100

way-points, which allows us to record the same number of data once the algorithm is stable (from 150 s to 450 s). The number of vehicles is fixed in the network since all of them have already been inserted and neither has completed their trip. A summary of the SUMO simulation parameters is shown in Table 4. We have tested TTCC, LIMERIC+PULSAR, CAM-DCC, NORAC, and EMBARC.

Due to the multidimensional nature of the results of this scenario and the difficulties of drawing them on a picture, we have included supplementary videos (MPEG4 files) which show the time evolution for the beaconing rate and CBR on the road overlay. A sample image is shown in Fig. 11, and the videos will be available at http://ieeexplore.ieee.org. As can be seen, TTCC vehicles typically set their maximum beaconing rate on clear road sections, as well as when they approach intersections. While vehicles are stopped on queues, they tend to reduce their beaconing rate unless they detect a potentially dangerous approaching vehicle. LIMERIC+ PULSAR, being a pure CC algorithm, keeps an almost constant beaconing rate independently of the road section and traffic situation, whereas CAM-DCC and NORAC basically set the beaconing rate proportional to the speed. Although not shown either in the video or in Figure 12, if we combine CAM-DCC with LIMERIC+PULSAR, the results are very similar, because the beacon generation is separate from the CC and the latter only limits the maximum rate. The results for EMBARC are very similar to those of LIMERIC+PULSAR and only some additional beacons are

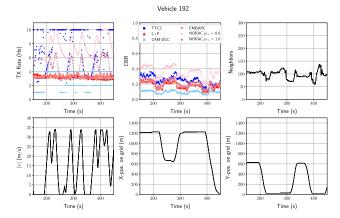


FIGURE 12. Comparison of different beaconing rate control algorithms with SUMO in a grid scenario for a representative vehicle (192).

sent when the suspected tracking error of the vehicles reach a certain threshold (T'=0.2 m), which occurs when vehicles are turning, braking, or accelerating. Nevertheless, this mentioned extra transmission does not occur very often (see Fig. 12) with a representative vehicle with id = 192, which confirms that it is only active in noticeable curvy scenarios.

Overall, as shown in Fig. 12, TTCC vehicles maintain a higher beaconing rate, often the maximum, for longer times, without violating the MBL, which should always benefit the QoS of applications on top of the service. In the case of NORAC, given the number of vehicles implied and the given speeds, this is also satisfied, since the CBR is above average but the MBL is not exceeded. EMBARC, on the other hand, oscillates unless we set its β_L parameter to 1/400 [5], which stabilizes the control, but results in an unnecessarily low beaconing rate, even though the CBR is not close to the MBL.

VI. CONCLUSION

We have described and discussed TTCC, integrated awareness and congestion control algorithm based on distributed Network Utility Maximization (NUM). TTCC keeps the channel load under a given threshold while assessing the safety of the surrounding traffic situation with a time-to-collision metric, valid in general traffic situations, which is



used to assign priorities in the optimal allocation problem. This simple, but general vector formulation for TTC is one of the distinctive features of TTCC. It allows us to seamlessly assess the risk in curves and intersections and aligns well with the CAM management alternatives discussed in European safety signaling standards.

Results show that TTCC effectively raises the beaconing rate of the vehicles involved in more dangerous situations, and, in general, TTCC yields higher rates and better usage of channel capacity. In any case, its behavior can be further tuned through the σ parameter to be more or less sensitive to the computed TTC. As for the next steps, we intend to continue evaluating the suitability of the metric and parameters regarding the risk of the surrounding traffic situation. Finally, we plan to study how to integrate our control in multi-access scenarios with cellular communications.

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CHAPTER 10

Article 2 (Full text)

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Cooperative Awareness Message Dissemination in EN 302 637-2: an Adaptation for Winding Roads

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Abstract—This paper evaluates the performance of the Cooperative Awareness Message (CAM) dissemination stated in the European Standard EN 302 637-2 in risky sharp bends and winding roads. We propose a novel triggering condition based on the dynamic estimation of the road radius, used as a risk metric. So as lower the radius, the higher the beaconing rate. As a case study, two real road sections, with different lengths and angles, have been simulated to prove that both a better awareness and responsiveness are achieved in the vehicles, to later ensure a proper application layer functioning. Finally, congestion constraint is also tested to check that no significant interferences are found in the described behavior.

Index Terms—Vehicular communications, CAM dissemination, Rate control, Winding roads, Congestion control.

I. INTRODUCTION

NTELLIGENT transportation systems (ITS) [1] have been widely studied in recent years since drivers' safety could substantially be preserved in many ways. Supplementary assistance and more intelligent embedded apps may reduce the risk caused by the human factor. The efficiency reached by emergency services in a traffic incident can be significantly improved thanks to these kinds of wireless communications in a vehicular environment. And, also, among other advantages, from a routing viewpoint, traffic control can be optimized by taking into account real-time data of the surrounding traffic conditions.

Given the importance of these networks, as a step towards its implementation in the automotive industry, different entities and governments have started standardization works. Both American and European standards adopted the Dedicated Short Range Communications (DSRC) 5.9 GHz band (5.850-5.925 GHz) to accommodate inter-vehicle communications. This band was considered and proposed by the Institute of Electrical and Electronics Engineers (IEEE, hereinafter) through IEEE 802.11-2012 standard (IEEE 802.11p), which defines the medium access control (MAC) and physical layers (PHY) for wireless communications among vehicles. Furthermore, the IEEE 609 group has set the IEEE 609.x protocol stack, called Wireless Access in Vehicular Environment (WAVE), as an extension of the aforementioned IEEE 802.11p MAC layer, management, and security. The European profile standard ITS-G5, drafted by European Telecommunication

Spanish MEC, AIM, ref. TEC2016-76465-C2-1-R, BES-2017-081061

Standard Institute (ETSI), is based on IEEE 802.11-2007 and includes physical features of the IEEE 802.11p and data-link layers of the IEEE 1609 framework. ITS-G5 also defines the required regulations to allow cooperative awareness, which is one of the basics to guarantee safety.

The awareness concept can be defined as the information that a vehicle has about the surrounding traffic and the environment whereby it is located in a given time. This information exchange among vehicles is conducted through the so-called Cooperative Awareness Messages (CAM) in Europe or the Basic Safety Messages (BSM) in the US, also known as beacon, defined in EN 302 637-2 standard [2]. Since the road is a highly dynamic environment with short-life communications and severe fading effects, periodical beaconing broadcast is required to keep the information updated. Several problems may occur if the beaconing rate is not adequately allocated. On one side, if the rate is too low, the application layer may receive outdated or wrong data. In contrast, if the aggregated load caused by beacons in the wireless channel is too high, unexpected and severe errors may also be produced as a result of channel congestion, especially if the event-driven messages from DEN service are lost. This bandwidth unavailability is referred to as channel congestion.

In carrying out these kinds of congestion solutions in a real-world environment, some important considerations must be followed, in addition to keeping channel usage below a certain limit: the channel capacity must be assigned fairly. This means that each vehicle must reflect in its beaconing rate the current status of the surrounding area. To disregard the fairness concept can cause not only a high resource waste but also jeopardize the safety of the road since a fair beaconing rate implies to favor a proper application layer functioning. For example, some vehicles in a dangerous situation could not be differentiated if an algorithm assigns a similar rate to all the vehicles.

The algorithm stated by European standards, which we call here CAM-DCC, satisfies the mentioned requirements by combining the operation of two procedures:

 A fair allocation is provided by some vehicle dynamics dependent CAM generation rules, specified in [2]. More to the point, CAM-DCC measures the absolute difference between a current heading, position, and speed, and those included in the previously transmitted CAM. If the time elapsed since the last generation and one of these conditions overcome some predefined thresholds, a new CAM is generated. CAM-DCC results in a beaconing rate which is a function of the vehicle speed. In this way, vehicles with higher speeds are considered to have more risk than slower ones, and consequently, they will allocate a higher rate.

 As regards the congestion mitigation, the ETSI defined the Cross-Layer Decentralized Congestion Control (DCC) Management Entity [3]. The main aim of the DCC is to avoid overloading the ITS-G5 radio channel. This entity was tested and validated through two of the most extended pure rate control algorithms in the standardization tasks: (i) a reactive control [2], where the message rate is controlled by a finite state machine, and (ii) an adaptive linear control, called LIMERIC [4], one of the most extended congestion control.

Some drawbacks can be found in the mentioned CAM-DCC procedures. First, a CAM synchronization problem for cooperative maneuvers seriously degrades its performance, as discussed in [5]. Secondly, according to [6] [7], the CAM-DCC stability leaves room for improvement as channel load measurement presents considerable fluctuations when only the facility layer control is applied and severe state oscillation when different DCC control methods are combined. Finally, CAM-DCC lacks clear motivation for the triggering rules. In the absence of abrupt variations, few or even no additional beacons are generated, which leads to ignoring risk when vehicles operate at low and medium speed. For instance, a vehicle in curvy roads, urban environments, or motorway entrances and exits.

In this paper, we propose a novel CAM dissemination for EN 302 637-2 standard to try to meet most of the requirements imposed by vehicular scenarios. A more sophisticated approach is introduced to increase the risk awareness through prioritization with higher rates in low and medium speed curves, whereas the original algorithm only limits the beaconing rate as a function of the speed and decreases the rates even if in presence of risk. To this purpose, vehicles evaluate the safety of the traffic situation by computing the bending radius of the road, and the result is used to set a new CAM triggering condition.

The rest of this article remains as follows. In Section II we introduce the basic background and formulates the proposed model. Section III validates the model, compare it against the original congestion control approach, and discuss the obtained results. Finally, Section IV summarizes major conclusions.

TABLE I: Look-up table for FSM-DCC rate control

Channel state	CBR	T_GenCam_Dcc (s)	TX Rate (Hz)
Relaxed	< 0.30	0.1	10
Active	0.30-0.39	0.2	5
Active	0.40-0.49	0.3	3.33
Active	0.50-0.59	0.4	2.5
Restrictive	>0.60	0.5	2

II. SYSTEM DESCRIPTION

CAM-DCC was defined in the EN 302 637-2 standard and updated in the newest 1.4.1 version in 2019, and consists of setting some CAMs generation rules and mechanisms dependent upon vehicle kinetics. Since the congestion control is out of the scope of this article, we use the default DCC finite states machine (FSM, hereinafter), whose states are depicted in Table I. The rates are limited between 1 and 10 Hz, or between times $T_GenCamMax = 1$ s and $T_GenCamMin = 0.1$ s, and the algorithm is executed every $T_CheckCamGen$ seconds. The congestion is controlled using the time between CAMs provided by the DCC, called T_GenCam_Dcc time, which depends on the measured CBR. If the elapsed time reaches this limit, congestion avoidance is satisfied, and then, a new beacon may be triggered. First, CAM-DCC measures the absolute difference between the current heading, called Heading Condition (HC), position (PC), and speed (SC), and those included in the previous transmitted CAM. If one of these conditions overcome 4°, 4 m or 0.5 m/s, respectively, a new CAM message shall be generated. Conversely, if there are no vehicle changes in speed, position or heading, a new CAM is generated if the elapsed time since the last message sent is higher or equal to the called T_GenCam . In this latter case of low dynamics, the algorithm will send until $N_GenCam =$ 3 consecutive CAMs before setting the minimum rate (1 Hz). The whole algorithm is summarized in Algorithm 1.

Algorithm 1: CAM generation frequency

```
1 foreach interval T_CheckCamGen do
2
      T \ GenCam \ Dcc \leftarrow look-up \ result \ from \ FSM
      Check T\_GenCam\_Dcc boundaries
      if lastCam\_elapsed\_time \ge T\_GenCam\_Dcc
       then
         if HC OR SC OR PC then
             Generate a CAM
6
             T\_GenCam \leftarrow lastCAM\_elapsed\_time
7
             N\_GenCam \leftarrow 0
8
          else if
          lastCAM\_elapsed\_time \ge T\_GenCam
             Generate a CAM
10
             N\_GenCam++
11
             if N\_GenCam > 3 then
12
               T\_GenCam \leftarrow T\_GenCamMax
13
14
             end
         end
15
      end
16
17 end
```

In this paper, a new triggering condition is developed and tested to achieve a more adequate rate even when the vehicle dynamics are low. This is due to that in some cases, the current triggering conditions based on heading, position, and speed of the CAM-DCC mechanism may not be enough to send a significant number of CAM messages to fulfill the application

layer requirements, so we think that there is also still room for improvement in this sense. Let us first define the curve risk, the road design to set the most suitable and realistic parameters, and then give an example of a road to prove the aforementioned weakness.

One way to quantify the risk of a road is to measure the so-called crash rate (CR), defined as the number of crashes per Million Vehicle Kilometer (MVKm). As studied in [8], the CR is highly related to the radius of curvature (R), being the most dangerous curves the sharpen curves with a low R (<250 m). According to US Department of Transportation [9], the inferred design of the radius of curvature of a road (R, in ft) depends in turn on the vehicle's speed (V, in mph), the superelevation rate (e, %), which is the lateral inclination of the road, and the side friction (f, %), which is taken at right-angles to the line of movement of the vehicle, as follows:

$$0.01e + f = \frac{v^2}{15R} \tag{1}$$

In this way, we can illustrate a real risky curve with a high CR. For example, given a vehicle that is traveling in a simple semicircular curve, with a single radius, at a steady speed of 30 mph (13.41 m/s), its maximum side friction will approximately be stated as 0.2%. The maximum allowed side friction factor is studied by the American Association of State Highway and Transportation Officials [10] and depends upon the intended speed of the vehicles in that road section. Finally, if the superelevation rate is supposed as 6.6%, the radius will be around 225.56 ft (68.75 m), which effectively entails that the curve is more sharpen and has a higher CR.

Once the road has been characterized, let us prove that the achieved beaconing rate may be insufficient. The traveled distance in the aforementioned semicircular curve will be $\pi \times R = 215.98$ m. Likewise, the traveled distance until the vehicle heading varies 4° is 4.80 m, and hence, the minimum elapsed time required to trigger a CAM message due to heading variation is $\frac{4.8 \text{ m}}{13.41 \frac{m}{2}}$ = 358 ms. According to [2], $T_CheckGenCam$ time must be equal or lower than 100 ms. The lower this parameter, the higher motion resolution, and responsiveness will be achieved. If, for example, we set $T_CheckGenCam$ to 10 ms, which is a very good resolution, we will need more than 35 steps until a new CAM is triggered due to heading condition. The algorithm would allocate $\frac{1 \ s}{0.358 \ s}$ = 2.79 Hz due to heading condition. Similarly, the position condition will be sent a new CAM every time the position changes 4 m, which is equal to $\frac{4 m}{13.41 \frac{m}{s}} = 298$ ms, or $\frac{1 s}{0.298 s}$ = 3.35 Hz. Finally, the speed condition will depend on both the acceleration and deceleration experienced while traveling the curve or will be null (0 Hz) if the speed of the vehicle is constant, as in the example above. The CAM message sending is carried out if the elapsed time reaches T_GenCam_Dcc , not always that the triggering conditions are satisfied. So, the beaconing rate of this curve is not the sum of all the aforementioned individual contributions (2.79 Hz + 3.35 Hz + 0 Hz), but approximately the same as those which results from position condition, 3.35 Hz, plus some peaks from heading and

speed conditions. This is a low rate for a curve with a high CR and risk, which results in channel bandwidth underuse and awareness degradation in the neighboring vehicles.

Since the radius of curvature is related to the CR, it is considered a risk factor, and a new CAM triggering condition could be based on this metric. In particular, we propose to dynamically estimate the radius of curvature of the road as vehicle moves from different positions. A schema of the proposed mechanism and the notation employed are summarized in Figure 1. Before moving to further details, it is important to mention that in a real implementation, these positions may be sensitive to noise from the onboard GPS. There are two worstcases depending upon where the wrong position is located. On one hand, some extra beacons could be triggered by false sharp bends, producing unnecessary channel usage. In contrast, a risky curve may go unnoticed losing the awareness. The aforementioned inaccuracies can be solved by supporting the radius metric with other ones such as heading change rate or the heading threshold degree variation; this has been left as future work.

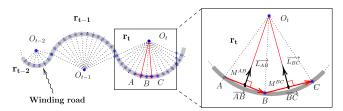


Fig. 1: Notation and schema used to derive the radius metric.

Let us define A, B and C the last three vehicle positions, being C the current position and A the older one. There are different ways to estimate the radius of an arc from three position points, but, in our particular case, we employ the perpendicular bisectors of two chords that meet at the center of the circle. First, we define \overrightarrow{AB} and \overrightarrow{BC} as the chords of the arc described by the road, and M^{AB} and M^{BC} as their corresponding midpoints. Secondly, we calculate the gradients of the chords, $\nabla(\overrightarrow{AB})$ and $\nabla(\overrightarrow{BC})$, to obtain the tensors that tell us how they change in any direction. Since \overrightarrow{AB} and \overrightarrow{BC} are perpendicular to their bisectors, called $\overrightarrow{L_{AB}}$ and $\overrightarrow{L_{BC}}$, their gradients will also be perpendicular to each other: $\nabla(\overrightarrow{AB})\bot\nabla(\overrightarrow{L_{AB}})$ and $\nabla(\overrightarrow{BC})\bot\nabla(\overrightarrow{L_{BC}})$. Using the gradients of $\overrightarrow{L_{AB}}$ and $\overrightarrow{L_{BC}}$ and the midpoints, we find the equations of the aforementioned bisectors, as follows:

$$y - M_y^{AB} = \nabla(\overrightarrow{L_{AB}})(x - M_x^{AB})$$
 (2a)

$$y - M_x^{BC} = \nabla(\overline{L_{BC}})(x - M_x^{BC}) \tag{2b}$$

Finally, solving these equations we obtain the center point (x,y), called O. The radius is easily obtained through the module of the vector formed from a position point and the estimated center, R = |AO| = |BO| = |CO|. As vehicle moves, the position points stored in the system are updated and a

new radius r_t is estimated. If and only if the time between updates is sufficiently low, the next radius can be assumed to be similar to the current one. With this in mind, we update the radius every second (t = 1 s), which is regarded as a low time interval from a vehicular viewpoint. The proposed CAM-DCC adaptation introduces a new CAM triggering condition based on a radius threshold, similarly to speed, heading and position. More details about our proposal performance and the radius employed as threshold are given in the following.

III. RESULTS

In this section, we evaluate the performance of the proposed mechanism against the original CAM-DCC. To this, OMNet++ v5.3 together with the INET v3.5 library, are used to replicate some realistic vehicular environments regarding the wireless channel. Concretely, the INET library implements the IEEE 802.11p standard (PHY and MAC layers), a realistic propagation and interference model for computing the Signal to Interference-plus-Noise Ratio (SINR) and determining the packet reception probabilities, considering also capture effect. In Table II, we summarize the simulation parameters.

TABLE II: Simulation parameters

Parameter	Value
Frequency (f)	5.9 GHz
Power (P)	251 mW
Sensitivity (S)	-92 dBm
Data rate (D)	6 Mbps
SNIR Threshold (T)	4 dB
Background Noise (N)	-110 dBm
Path loss	Nakagami-m
Beacon size	$760~\mu s$
Maximum rate (R_v^{max})	10 CAM/s
Minimum rate (R_v^{min})	1 CAM/s
$T_CheckGenCam$	10 ms
N_GenCam	3

In the first stage, we intend to observe only the turning effect of the vehicle in the proposed algorithm, so channel congestion is ignored by adding a few numbers of cars. We take a winding road section belonging to the State Hwy 22 from Kentucky, US, and set a uniform speed of 20 m/s throughout it. In Figure 2, we plot the transmission rate of a vehicle running both the original CAM-DCC and the proposed, named CAM-DCC-R, the heading angle of the vehicle to better appreciate the curves effect, the speed, and a birds-eye-view sketch of the road, including the times whereby the vehicle passes through these points. As can be observed, the proposed CAM-DCC-R triggers some extra beacons when the vehicles take a curve, and every time that the estimated road radius is lower than 20 m, increasing the awareness of the traffic situation.

A more realistic scenario is replicated in Figure 3, where the different road sections have been adapted to the real speed limitations, which means that the equation (1) is satisfied. In this case, we have used the mountain road section of E-22 road, located between Cartagena and Puerto de Mazarrón, in Murcia, Spain; the radius employed as a threshold the same as in the previous case, 20 m. In the speed profile, we can observe

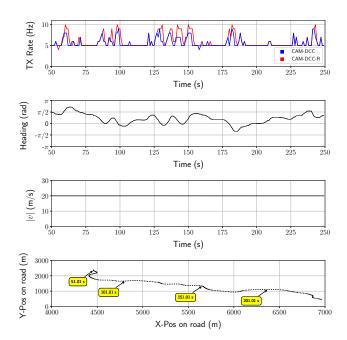


Fig. 2: Comparison between original and radius-metric-adapted CAM-DCC evaluated in a section of the State Hwy 22, Kentucky, US. A uniform speed of 20 m/s have been set in the whole road section to study only the turning effect of the vehicle.

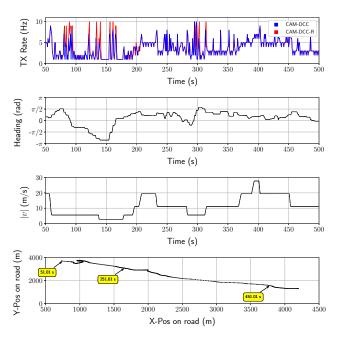


Fig. 3: Comparison between original and radius-metricadapted CAM-DCC evaluated in the mountain road E-22, located between Cartagena and Puerto de Mazarrón cities, Murcia, Spain. Sections between edges have been adapted to real speed limitations.

that several sharp turns are located about 1000 m, between 75 and 175 seconds of the recorded vehicle's path. Also, a curve is located at 2000 m, about 300 s. The extra transmissions produced by the proposed CAM-DCC are quantified as the ratio between the average beaconing rate of the original CAM-DCC over those of the proposed one, called $\Delta(\%)$. The radius R used as a threshold, that determines if a new CAM is sent or not, will make the extra transmissions percentage Δ vary. For instance, a high R means that a higher number of curves will be included in the CAM triggering, whereas if R is very low, CAM-DCC-R will only take into account the most sharpen curves. This behavior is depicted in Figure 4, where different radiuses between 10 m and 500 m are evaluated, and different Δ are obtained between 2.06 to 36.9%, respectively.

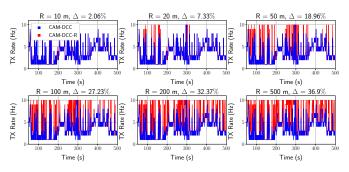


Fig. 4: Evaluation of CAM-DCC-R for different radiuses values in road E-22.

In the previous scenarios, we have used the default CBR limits of the DCC-FSM, and, since we have introduced a few vehicles, the congestion mechanism is not used. Once we have assessed the performance of including new extra CAMs in the standard, it is necessary to prove that it still works in the presence of congestion limitations. Rather than append more vehicles to the simulations, in an equivalent manner, we have reduced the CBR limitations stated by the FSM. More concretely, we have divided by 10 the CBR intervals shown in Table I. For instance, the CBR values lesser than 0.3 becomes to be lesser than 0.03, the 0.30-0.49 interval become to be 0.03-0.049, and so on. The study of packet collisions, losses, fading, and further effects is outside the scope of this article, so maintain a few vehicles is a good approach. We have plotted the results obtained in the E-22 road of the original CAM-DCC with the default FSM scale, and those of the radiusbased CAM-DCC-R both with the original and the scaled FSM using a radius threshold of 20 m. As can be shown in Figure 5 for CAM-DCC-R 1/10, notwithstanding the scaled congestion limits, the curves are still reflected with a higher rate, and the CBR is under the stated limits.

IV. CONCLUSION AND FUTURE WORK

We have presented a novel triggering condition for the CAM dissemination mechanism of the European Standard EN 302 637-2 to address the likely deficiency of CAM messages in winding roads. Our premise is that this deficiency could cause a failure in the application layer if the information update is

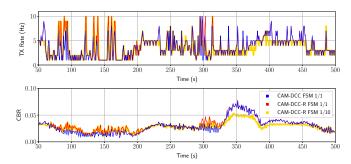


Fig. 5: Study of CBR in the presence of channel load limitations using a 1/10 scaled FSM.

insufficient. Therefore, we propose a triggering condition as a function of the radius of curvature of the road, periodically estimated and used as a risk metric. We have evaluated different radius, and their effect in some real scenarios, for both congestion limited and unconstrained cases, obtaining promising results with regards to extra beaconing and turning awareness.

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Article 3 (Full text)

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Advisory Speed Estimation for an Improved V2X Communications Awareness in Winding Roads

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ABSTRACT

The European Telecommunications Standards Institute (ETSI) establishes a Decentralized Congestion Control (DCC) which triggers the so-called Cooperative Awareness Message (CAM) depending on vehicle kinematics. However, this algorithm hence called CAM-DCC represents a challenge in the triggering rules of these messages. In particular, it lacks (i) awareness of the neighboring vehicles and (ii) efficient use of the channel bandwidth. Consequently, information gaps related to the road environment might give rise to non-compliances in the application layer requirements of the vehicles, which could potentially threaten the drivers' safety, most particularly in hazardous roads. To overcome these flaws, we first study the CAM generation trigger focused on the vehicle heading in risky curves or winding roads. Then, we evaluate both scenarios tuning different triggering thresholds and including additional mechanisms such as the comparison of the current speed respect to the estimated advisory speed over time. Different computer simulations have been conducted in two real road sections to validate our proposal. Results reveal significant better performance in terms of awareness and channel usage.

Keywords: Vehicular networks, Cooperative Awareness Message, Rate control, Winding and curved roads, Congestion, Awareness

1. INTRODUCTION

In recent decades, road accidents involved large mortality ratios [1]. Given the self-evident high importance of the passengers' safety and their protection, many of the technological advances in the vehicular industry are addressed to avoid accidents or reducing their severity through different measures. In general, current safety developments fall into two main groups depending on when they are applied. First, passive systems. They come into play once the accident is unavoidable to minimize the passengers' injuries since they remain passive until some car sensors are triggered. Examples include smart airbags, seat belts, the vehicle body, chassis or headrests. In contrast, active systems are those preventing accidents or crashes anytime while driving, such as adaptive headlights, collision avoidance, lane departure warnings, blind-spot vehicle alerts, electronic stability program (ESP), or antilock brake systems (ABS).

Most of the aforementioned active safety systems are based on data obtained from neighboring vehicles. Data, usually called awareness, are dispatched by periodical broadcast messages denoted as Cooperative Awareness Messages (CAM), also termed beacons, as defined in EN 302 637-2 standard [2] by the European Telecommunications Standards Institute (ETSI). Furthermore, having in mind the road as a highly dynamic environment, a careful periodical beaconing broadcast is required to keep the information updated. For instance, if the beaconing rate is not appropriately allocated, different problems may arise motivated by requirements not satisfied. On the one hand, if the number of messages received is too low, the channel is underused and, therefore, the application layer handles outdated information. This would imply unsatisfactory solutions while driving, especially in risky roads. Conversely, if the load caused by beacons in the wireless channel is high, errors produced by channel congestion must be considered, especially if the event-driven messages from Decentralized Environmental Notification (DEN) service are lost. Under these circumstances, the beaconing rate must be fairly allocated among vehicles. This means that the surrounding traffic situation must be an input parameter in the resource allocation in order to discern those *hazard vehicles*, and thus provide more useful information to their application layer services.

To overcome the overloading case in the ITS-G5 radio channel, the ETSI defined the Cross-Layer Decentralized Congestion Control (DCC) Management Entity [3]. This entity was tested and validated by two pure rate control algorithms: (i) a reactive control, denoted as CAM-DCC [2], where the message rate is controlled by a finite state machine, and (ii) an adaptive linear control, called LIMERIC [4]. In this paper, we focus on reactive control, which manages the congestion issue by calculating the elapsed time from the last beacon sent to restrict the generation of new ones. Regarding the CAM allocation, it is fairly prioritized and controlled by certain generation rules based on vehicle dynamics. However, these rules lack clear motivation and, in the absence of abrupt vehicle dynamic variations, few or even no additional beacons are generated. This low number of beacons may entail underestimating the risk on certain roads.

In this paper, we contribute to the two following aspects. Firstly, we evaluate the current behavior of CAM-DCC by tuning the heading threshold. Secondly, in view of the obtained results, a novel triggering condition is designed to improve the awareness in winding roads or sharp bends. Vehicles evaluate the same physical parameters involved in the design of the road, more specifically comparing the current speed of the vehicle with the estimated advisory speed (calculated theoretically during driving), to later set a new CAM triggering condition.

The rest of this paper is organized as follows. In Section 2, we describe in detail the CAM-DCC standard for facilitating the reader's understanding. We discuss the shortcomings of the aforementioned standard to later point out the value of our proposal to achieve better performance in winding roads and sharpen curves. Section 3 validates the model, compares it against the original congestion control algorithm and discusses the obtained results. In Section 4, we summarize this paper and state future research lines.

2. BACKGROUND AND PROPOSAL

Concerning the EN 302 637-2 standard, CAM-DCC triggers a CAM depending on the vehicle dynamics and the channel congestion status. As a rule, the algorithm is executed every T CheckCamGen seconds (typically a low enough value to reach a good time resolution) and sets 1 and 10 Hz as the minimum and maximum reachable beaconing rate. Now, we describe the reactive control mechanism provided by the DCC entity without going into details of the congestion control methodology. A finite state machine (FSM) based on channel busy rate (CBR) measurements regulates the channel congestion by limiting the elapsed time between CAM transmissions (configured by the T_GenCam_Dcc variable). Once this condition is satisfied and the elapsed time between transmission is below T_GenCam_Dcc, the congestion is controlled. At this moment, the vehicle kinetic is checked just before transmitting a new CAM. In particular, CAM-DCC measures the absolute difference between the current heading, position and speed, and those sent in the previous CAM. If any of these conditions exceeds the values of 4°, 4 m and 0.5 m/s, respectively, a new CAM is then dispatched. On the contrary, if no changes are detected in the vehicle heading, position or speed, a new CAM is generated only if the elapsed time from the last CAM transmission is higher than or equal to the value stored in the T GenCam variable. If this situation of low dynamics remains over time, the algorithm will send N GenCam messages (usually three messages) before setting the minimum rate (1 Hz) to T GenCam. In any other case, when a CAM is transmitted by kinetic rules, T GenCam is set to the elapsed time from the previous transmission. In short, the CAM-DCC algorithm is based on measuring the speed, position, and heading changes over time to decide whether or not a new beacon is transmitted. These premises ignore the risk of the curves, since vehicle dynamics are lower than in other types of roads (e.g. highway), and therefore a lower number of CAMs are transmitted. This entails a poor awareness in scenarios as winding roads or sharp bends.

To consider road risks, we design a novel proposal conceived for enhancing the CAM-DCC. The result is a new triggering condition whose basis are the road design parameters. This new CAM-DCC release is achieved by increasing the number of CAM transmissions for the scenarios under study, and allowing appropriate operation of diverse road safety and traffic efficiency applications, as described in ETSI TR 102 638 [5]. The new triggering condition included in the CAM-DCC algorithm after checking the congestion condition is as follows. If the current speed is higher than 85% of the estimated advisory speed, a new CAM is transmitted. The advisory *speed* will be briefly explained in the following paragraphs.

The Federal Highway Administration, which belongs to the U.S. Department of Transportation, defines different parameters to quantify the risk of a road [6], being the top five: radius, superelevation, tangent speed, vehicle type, and curve deflection angle. These parameters allow us to (i) set the road restrictions and speed limits, and (ii) to be aware of those physical magnitudes that must be measured to provide a better awareness. In particular, a combination of the road radius together with the advisory speed estimation is included in the CAM-DCC algorithm as a priority triggering condition. On the one hand, the radius is the parameter most directly related to the risk of a curve [7]. It is easy to observe that the lower the road radius, the larger the risk. Regarding the advisory speed, it is also an important risk indicative; if this value is exceeded, it could denote a serious accident. There are different methods to determine the advisory speeds of specific stretches of road. The oldest empirical method is the so-called Driver Comfort Speed Method, whose main idea is based on "which causes an occupant of the vehicle to feel an outward pitch" and later refined as "that speed at which the driver's judgment recognized incipient instability." This is a very subjective method and provides inconsistent results. A current method, employed in our proposal, is the called AASHTO (American Association of State Highway and Transportation Officials) Geometric Design Method, which calculates the advisory speed from physical parameters obtained in the traditional highway design process, as described in equation (1):

$$V_a = \sqrt{15R(0.01e + f)} \tag{1}$$

where the advisory speed (V_a) is derived from the radius (R), the superelevation (e), and the road friction coefficient (f). Typical values for superelevation and friction coefficient are 0.066 and 0.2, respectively. The radius can be geometrically calculated though the different GPS positions of the vehicle in temporal intervals of

T_CheckCamGen seconds. Since GPS data may be noisy, a bad estimation of the radius may result. To overcome this shortcoming, vehicle positions are computed employing also their initial position, speed, and acceleration vectors. In detail, given an initial position in a given time, we estimate the next position of the vehicle through its speed and acceleration vectors and averaging it with the next GPS position. Once at least three positions have been calculated and stored in the vehicle engine control unit (ECU), the radius is determined and then the estimated advisory speed is obtained by (1).

3. RESULTS

In this section, we evaluate the performance of our proposed mechanism and compare it against the original CAM-DCC. For this purpose, OMNeT++ v5.3 and its INET v3.5 libraries are used to replicate realistic vehicular environments and wireless communications. In particular, INET libraries include the IEEE 802.11p standard module (PHY and MAC layers) comprising, among other features, a realistic propagation and interference model to (i) compute the Signal to Interference-plus-Noise Ratio (SINR) and (ii) determine the packet reception probabilities. Two real winding road sections have been simulated: (i) a section of the State Hwy 22 from Kentucky, US, with a uniform speed of the vehicles of 20 m/s, and (ii) a section of the E-22 mountain road located between Cartagena and Puerto de Mazarrón, Spain, considering the real speed limits of the road. A birds-eye view of both road sections is illustrated in Figure 1.

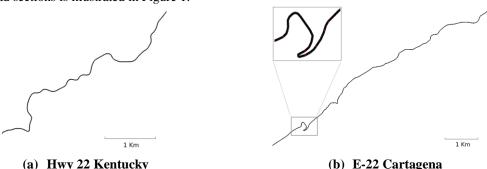


Figure 1. Birds-eye view of the different road sections under study: (a) State Hwy 22 from Kentucky, US and (b) E-22 Cartagena, where most sharpen bend has been zoomed for a better viewing.

First, we perform tuning of the heading threshold (*ht*) in the original CAM-DCC algorithm, which is set by default at 4°. The speed, heading, and the beaconing rate parameters evolution for a random vehicle that drives through the road section are illustrated in Figure 2. The moving average of the beaconing rate using 10 s intervals has been calculated to remove excessive peaks and easily observe the effect of the tuning in the *ht*.

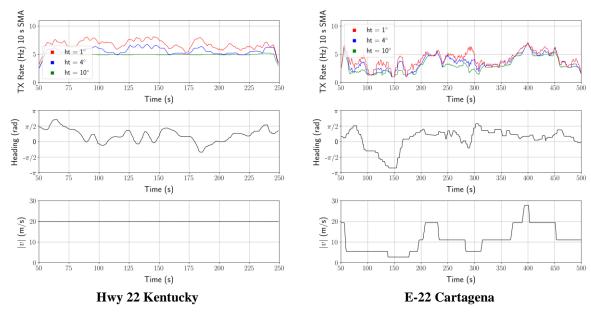


Figure 2. Tuning of the heading threshold (ht) for values 1°, 4°, and 10°.

As can be observed for both sections, the CAM-DCC algorithm tends to follow the behaviour of the speed magnitude if the ht value is too high (i.e. 10° or larger). This is because the heading condition rarely triggers a new CAM, and only the position and speed conditions cause transmissions. Conversely, if the heading threshold is lower than 4°, a higher heading resolution is obtained, and the rate generated by the CAM-DCC algorithm is due to the speed plus some extra transmissions from the heading changes. Following this reasoning, a low ht (i.e. 1°) provides a better awareness in winding roads where the speed is lower (and also the rate). The triggering condition based on the advisory speed is depicted in Figure 3, where the tightest curve of the E-22 road (170-180 s period) has been simulated for two speeds: the advisory speed and a much higher value (2.77 m/s and 13.88 m/s). Note that for a lower ht value, the mechanism here proposed allows us to obtain a higher information exchange when the advisory speed is exceeded and, therefore, the risk increases. This is why this awareness improvement is not reached only in the curve where the speed has changed to 13.88 m/s, but also in other curves, as can be seen in the intervals 110-130 s, 150-

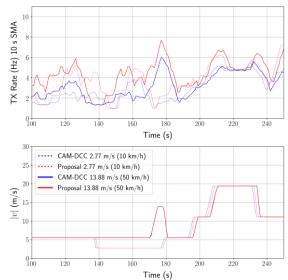


Figure 3. Evaluation of the CAM-DCC for the tightest curve belonging to the E-22 road using the proposed triggering condition.

160 s, 200-220 s, and 230-245 s. If we had applied the original CAM-DCC, it would had provided a lower beaconing rate in these curves, just reacting when the speed is drastically varied (170-180 s).

4. CONCLUSIONS

In summary, the default mechanism of the ETSI standard for generating cooperative awareness messages, i.e. the CAM-DCC, results in low transmissions even in situations that require a higher information exchange. One of these situations are the winding roads since usually imply low vehicle dynamics when curves are traversed. Therefore, this scenario in CAM-DCC underestimates the risk of the curves. To approach this problem and better evaluate the risk while driving, we propose to introduce in the CAM algorithm diverse magnitudes and parameters of the road design instead of vehicle parameters only. Higher awareness and beaconing rate are successfully achieved by adding both the road radius and advisory speed in the triggering conditions. In doing so, the congestion control is not practically affected since it is previously checked according the FSM of the algorithm. Further changes and optimizations have been left for future works.

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Article 4 (Full text)



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MDPRP: A Q-Learning Approach for the Joint Control of Beaconing Rate and Transmission Power in VANETs

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ABSTRACT Vehicular ad-hoc communications rely on periodic broadcast beacons as the basis for most of their safety applications, allowing vehicles to be aware of their surroundings. However, an excessive beaconing load might compromise the proper operation of these crucial applications, especially regarding the exchange of emergency messages. Therefore, congestion control can play an important role. In this article, we propose joint beaconing rate and transmission power control based on policy evaluation. To this end, a Markov Decision Process (MDP) is modeled by making a set of reasonable simplifying assumptions which are resolved using Q-learning techniques. This MDP characterization, denoted as MDPRP (indicating Rate and Power), leverages the trade-off between beaconing rate and transmission power allocation. Moreover, MDPRP operates in a non-cooperative and distributed fashion, without requiring additional information from neighbors, which makes it suitable for use in infrastructureless (ad-hoc) networks. The results obtained reveal that MDPRP not only balances the channel load successfully but also provides positive outcomes in terms of packet delivery ratio. Finally, the robustness of the solution is shown since the algorithm works well even in those cases where none of the assumptions made to derive the MDP model apply.

INDEX TERMS Vehicular ad-hoc networks, connected vehicles, vehicle-to-vehicle (V2V) communications, congestion control, power control, rate control, reinforcement learning, IEEE 802.11p, SAE J2945/1.

I. INTRODUCTION

The transportation industry has evolved according to the growing demand for moving goods and passengers. The number of vehicle registrations is projected to triple by 2050, reaching 3 billion vehicles [1], stimulated by the displacements required by millions of citizens in increasingly larger and overpopulated cities [2].

In this crowded situation, future Intelligent Transportation Systems (ITS) and connected vehicles are expected to improve safety, reducing the number of fatal events on roads and accident severity. In particular, connected vehicles exchange information wirelessly through what is called vehicle-to-vehicle (V2V) communications [3], [4]. In turn, V2V services rely on the exchange of periodical broadcast

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single-hop messages, called beacons, containing information about the vehicle [5]. Data such as position, speed, acceleration, steering angle, or vehicle type are part of these messages' payload aimed at tracking and predicting the behavior of neighboring vehicles. This information empowers vehicles with context or situation awareness [5] and is the basis of many safety applications, which are essential for reducing the risk of collision among vehicles [6]-[8], among other things. As vehicle density increases, situation awareness may be compromised by channel congestion. Channel overload results in high packet and information loss, a critical issue in the case of event-related messages triggered in emergency cases [9]. Therefore, congestion control is vital to guarantee

¹In V2V communications, neighbors are usually defined as the set of vehicles from which at least one message has been correctly received during a given time interval.

1



the safety of the drivers. Basically, it consists of limiting the channel usage in some way (typically to 0.6), leaving unused a certain fraction of the channel to guarantee the timely delivery of event-driven messages.

More to the point, channel congestion can be controlled with different transmission parameters, and a significant number of proposals have dealt with adapting them. The most common solutions are aimed at reducing the number of transmitted messages per second or beaconing rate, such as [10]-[14]. Other approaches addressed congestion by adjusting transmission power, which means varying the number of receiving vehicles and then influencing overall congestion [15]-[18]. These solutions focused on adjusting a single parameter pose some challenges. On the one hand, insufficient beaconing rates to relieve congestion may entail a lack of situation awareness of the surrounding vehicles. Likewise, a sharp reduction in transmission power can result in messages reaching only a few close vehicles, failing to reflect the real situation. That is, independent settings of each parameter may produce a similar effect to congestion itself, which should be avoided. In contrast, a combination of beaconing rate and transmission power may result in a trade-off benefitting both meaningful parameters. An optimal allocation of beaconing rate and transmission power would be ideal; however, the associated optimization problem is not convex [19], making ordinary optimization methods ineffective. Recent approaches for joint optimization use Artificial Intelligence (AI) techniques, such as Reinforcement Learning (RL) [20], [21]. Nevertheless, most of these proposals assume a centralized infrastructure; that is, they are better designed for cellular networks, where in addition to vehicles, base stations have a pre-eminent role. Furthermore, they tend to be remarkably complex, requiring highly demanding computing power.

In this article, we apply the Markov Decision Process (MDP) framework, which is the basis of the well-known RL, for joint transmission power and beaconing rate congestion control. Unlike previous solutions [20], [21], the proposed MDP model can be used in infrastructureless (ad-hoc) networks, namely, with ETSI ITS-G5, incorporating a set of simplifying assumptions. Then, the MDP model is resolved by using Q-learning techniques. Results show that the proposal is still robust even to violations of these assumptions. The MDP model solution, known as policy, can be loaded onto vehicles, becoming very efficient at runtime since it only requires a table lookup search. The prescribed actions maximize the reward function, which specifically controls the channel busy rate (CBR) and the transmission power used, maintaining an appropriate level of congestion. Moreover, the MDP framework allows congestion to be alleviated in a non-cooperative manner; that is, without the need for additional information from neighbors. Also, the proposed algorithm implements fully distributed congestion control in which every single vehicle contributes to reducing overall congestion. In short, the main contributions of this research work can be summarized as follows:

- The policy derived can be applied in a fully distributed fashion, without the need for a centralized network infrastructure.
- The policy is evaluated in realistic scenarios, including those cases not satisfying the model assumptions, thereby, demonstrating the robustness of our congestion control method.
- It is shown that channel load is kept below a certain level to avoid congestion, which reduces packet loss significantly. Moreover, channel underutilization is prevented.
- The packet delivery ratio achieved is similar to other approaches under comparison at short coverage distances but improves at long distances, which enhances the overall level of vehicle awareness of the network.
- Finally, no information from neighboring vehicles is required to carry out the actions, so any exchange with the application layer is disregarded for a proper resource allocation operation.

The remainder of the paper is organized as follows. First, Section II states the related work and delves into the congestion control problem for vehicular ad-hoc communications from a beaconing rate and transmission power viewpoint. Then, in Section III we formulate the mathematical model used and its particularization to the problem mentioned in Section II. Section IV conducts the performance evaluation, discussing simulation environments, defined metrics, and comparison results with other proposals of interest. This will show the effectiveness of the proposed algorithm. Finally, Section V summarizes the main conclusions.

II. RELATED WORK

The European Telecommunications Standards Institute (ETSI) defines a 10 MHz control channel for vehicular communications at the 5.9 GHz band [22], called the ITS-G5 radio channel, as one of the basic network access technologies. Transmissions over this kind of network are of a broadcast nature and employ Carrier-Sense Multiple Access with Collision Avoidance (CSMA/CA) as a medium access control (MAC) protocol. The ETSI Cooperative Awareness Service (CAS) states periodic beaconing over one-hop communications as the basis of cooperative awareness. Formally called Cooperative Awareness Messages (CAM) in Europe or Basic Safety Messages (BSM) in the US, beacons are responsible for disseminating status and environmental information to vehicles on the control channel (G5CC in Europe and Channel 172 in the US, respectively). The excessive aggregated load caused by these beacons results in inaccurate and outdated information for safety applications. In addition, the Decentralized Environmental Notification (DEN) service, in charge of notifying about risk-related road events [9], requires certain channel availability to guarantee the delivery of the event-related messages in emergency cases, called Decentralized Environmental Notification Messages (DENM). In this way, the Cross-Layer Decentralized Congestion Control (DCC) Management Entity [23] is aimed at

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preventing the overloading of the ITS-G5 radio channel by tuning the beaconing rate. DCC combines the operation of two procedures: adaptive control, based on some CAM generation rules dependent on vehicle dynamics [5], [24], [25], and straighforward reactive control called LIMERIC [10]. LIMERIC is a distributed and adaptive linear rate-control algorithm in which each vehicle updates the beaconing rate in accordance with the locally measured channel busy rate (CBR), which is driven towards a certain goal. LIMERIC only converges when all vehicles are within the coverage range of each other, so it has been combined with the PULSAR mechanism [26] to extend its application to multi-hop scenarios. PULSAR is another popular rate-based solution [11] that uses Additive Increase Multiplicative Decrease (AIMD) with feedback from two-hop neighbors. Unlike the aforementioned proposals employing channel information, other solutions set the beaconing rate as a function of some context information, such as the tracking error of neighboring vehicles [27]–[29], detecting rear-end collisions [30], [31], predicting vehicle trajectory [32], and estimating collision probability [12] or vehicle density [13], [14]. Overall, these approaches succeed in reducing congestion by varying the message rate. Nevertheless, in some cases, the only way to alleviate congestion is to excessively decrease the beaconing rate, which may especially threaten situation awareness and vehicle safety [33].

The other parameter widely used in congestion control is transmission power. Congestion is thus alleviated by reducing transmission power, decreasing the number of vehicles that receive the broadcast messages. Several works proposed controlling transmission power depending upon different variables. Authors in [34] employed the channel state information (CSI) to improve energy efficiency. The work in [15] used the speed of the vehicle to allocate transmission power. This approach extended the transmission range in the case of high speeds to raise awareness in neighboring vehicles of their respective lower time-to-collisions. Vehicle density is also employed in [16] to decide whether to increase or decrease transmission power. Likewise, [35] includes an SNIR estimation. Conversely, some proposals allocate transmission power directly as a function of the channel load [17], [18]. The vehicle position prediction error is also used in [36] to determine whether to increase or decrease transmission power. However, congestion management considering only transmission power has a clear drawback: if transmission power receives insufficient values, the number of receivers drops, and, consequently overall awareness is harmed. On top of this, excessive transmission power variations may give rise to instabilities, as is dealt with in [17].

Instead of using beaconing rate or transmission power individually to handle congestion, more advanced proposals combine both simultaneously [37], [38]. However, joint beaconing rate and transmission power control usually makes the optimization problem non-convex, which entails employing heuristic algorithms instead of ordinary optimization methods. Even though hybrid solutions clearly improve the

usefulness and flexibility of congestion control [39], there is no silver bullet to jointly resolve beaconing rate and transmission power control. Thus, each emerging approach faces the allocation problem by claiming several contributions but inevitably falling short in other aspects. In this sense, some proposals are based on measuring different factors to carry out resource allocation and improve specific aspects. For instance, authors in [40] measured the packet Inter-Reception Time (IRT) at a given distance to optimize packet reception. The algorithm proposed in [39], called ECPR, varies transmission power to reach a certain awareness ratio by estimating the Path Loss Exponent (PLE). Meanwhile, channel load is individually controlled by LIMERIC [10]. FABRIC-P [19] modeled rate allocation as a Network Utility Maximization problem, maximizing the beacons delivered at each transmission power. Other examples are MERLIN and PRESTO mechanisms [41], not only focused on reducing congestion but also on satisfying the requirements for different safety applications simultaneously. Most of the algorithms mentioned above require piggybacking additional information embedded in the messages, which makes congestion control dependent on the channel state. This piggybacking process may degrade the quality of awareness in those cases in which the environment changes rapidly, so tracking error should also be considered in the congestion avoidance mechanism, as suggested in [42].

The solution to this problem is to isolate congestion control from fluctuating parameters that rely on neighboring vehicles or channel conditions. This is known as non-cooperative algorithms since no additional information from neighbors is required for the proper operation of congestion control. This approach was introduced in the J2945/1 standard by the Society of Automotive Engineers (SAE). In particular, the J2945/1 standard specifies a congestion control algorithm based on two input parameters, the CBR and vehicle density, which regulate transmission power and beaconing rate when the channel is congested [43], [44]. The J2945/1 algorithm has been adjusted to manage beaconing rate and transmission power allocation in cellular V2X communications [45]. Also using the aforementioned, non-cooperative scheme, BFPC is introduced in [46]. BFPC is a beaconing rate and transmission power control algorithm based on non-cooperative game theory that successfully maintains congestion at a certain desired level. However, the CBR level is not automatically reached and some parameters must be manually adjusted for each scenario.

Given the complexity of the optimization problem, which is similar to that of game theory, decision-making theory has also been used to find optimal congestion control and endow a certain level of intelligence to vehicles. In this context, the Markov Decision Process (MDP) is one of the decision-making techniques of choice and the basis of reinforcement learning (RL) [47]. Congestion control based on transmission power is proposed using both Q-Learning, in the particular case of LTE-V2V communications [48], and a multi-agent approach for overall wireless

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communications [49]. Regarding hybrid solutions whereby more than one parameter is optimized, authors in [21] included the selection of the optimal frequency sub-band in the decision-making problem, in addition to transmission power. In [20], both beaconing rate adaptation and the transmission power control problem are dealt with. This work characterizes the system state, the reward function, and the method of learning the control policy in the downlink of base stations for the case of cellular networks C-V2X. Therefore, such solutions are intended for cellular networks. To the best of the authors' knowledge, none of them have proposed a non-cooperative, distributed algorithm to control both the beaconing rate and transmission power of the vehicles using an MDP-based model. To contribute to filling this research gap, we propose the MDPRP scheme, an approach to derive MDP-based transmission policies (Rate and Power), resolved by Q-learning techniques, that fully prevent congestion while maximizing channel utilization and helping to preserve the performance of safety applications.

III. CONGESTION CONTROL USING MDP

Congestion control is addressed to maintain the channel load, usually measured using the CBR, around a certain target value. This value is defined as Maximum Beaconing Load (MBL), whose optimal value is assumed to be around 0.6 and 0.7, according to several works [27], [46], [52]. A higher load may increase packet loss and hinder safety application operations, so congestion control is a crucial aspect. In this article, we aim to control congestion by using both the beaconing rate and transmission power. However, this is not trivial. For instance, an absence of awareness and instabilities in the resource allocation may give rise if they are not properly assigned. Consequently, a subtle trade-off between both parameters is required to achieve an appropriate level of CBR, as closely as possible to the MBL.

To this aim, as mentioned in Section I, we model the problem using the formal framework of finite Markov Decision Processes. This framework addresses the congestion control in ad-hoc vehicular communications as an optimization procedure over discrete actions, taken by the vehicles themselves in a distributed fashion. Despite the complexity of the V2V environment, some simple assumptions are made to model the MDP. However, it is worth mentioning that positive outcomes are still obtained even in those scenarios that differ from the ones used in the training phase of the proposed mechanism. Moreover, unlike other solutions that require additional processing tasks to compute the optimal action, our proposed solution can be preloaded in tables, which is quite efficient in terms of reading speed.

A. MARKOV DECISION PROCESS FRAMEWORK

MDPs are used to formulate and study optimization problems, because they provide a mathematical framework for deriving optimal sequences of actions. This is especially useful in those challenging environments where outcomes may be partially random or difficult to predict. Formally, MDPs consist of the following elements:

- The agent (in our particular case, a vehicle) is the decision-maker or learner entity that continuously seeks optimal behavior.
- The *environment* is defined as everything outside the agent that is capable of perturbing it (e.g. road conditions, other vehicles, pedestrians, etc.). In order to reach the desired behavior, the agent is continuously sensing the environment to accordingly select an action.
- The agent is able to perform an *action* $a \in A(s)$. This action belongs to the available set of actions for each state
- This environmental situation, along with the properties of the agent is called *state*. Usually, the state is defined as a vector $s \in \mathcal{S}$ that embraces both the outer and inner properties of the agent, with \mathcal{S} being the set of possible states.
- Every time the agent acts, the environment is modified, presenting a new situation to be explored. In this change of state from s to s', the agent obtains a *reward* r. This reward is considered feedback from the environment that the agent seeks to maximize through its choice of actions over time. Therefore, it can be modeled as a function of the state s and the action taken a, i.e. $r(s, a) = f(s, a) \in \mathbb{R}$.

The solution for *complete knowledge* of the MDP is given by deterministic state-transition models, depicted by the probabilities of transitioning among states. Nevertheless, this is not available in realistic environments such as V2V communications. Instead, MDP-solving algorithms employ what is called *policy*, denoted as π , a mapping between states and actions; that is $\pi: \mathcal{S} \to \mathcal{A}$. The main objective, through solving MDPs, is to reach the optimal policy π^* , which maximizes the accumulated sum of rewards over the entire lifespan of the agent during training. As shown in (1), the total reward is usually computed using a discount factor γ [50], a number less than one (typically 0.9 or closer to 1), which determines the present value of future rewards. This discounted formulation allows the algorithm to converge more easily in continuing tasks in which the agent-environment interaction does not naturally break into episodes but continues without limit.

$$\pi^* = \underset{\pi}{\operatorname{arg\,max}} \sum_{\tau=0}^{\inf} \gamma^{\tau} r(s_{\tau}, a_{\tau})$$
 (1)

It is worthy of mention that the state s_{τ} , where the agent is, the taken action a_{τ} , and consequently, the reward obtained also refer to a specific time. This is because Markovian systems operate using discrete spaces, so the agent and environment interact with each other in a sequence of discrete-time steps, or slots τ . As occurs in our particular case, more complex problems comprising continuous variables could hinder their MDP formulation, requiring some approximations to be defined and solved. This will be detailed in the following

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subsection while particularizing the elements making up the proposed MDP model.

B. PARTICULARIZATION OF THE MODEL

1) AGENT OR LEARNER

To start with, the *agent* is represented by each single vehicle, which continuously senses the environment to adequately adjust its transmission power and beaconing rate. The goal is to reduce overall channel congestion in a distributed manner. This means that vehicles control their transmission parameters, only making use of their own metrics, without relying on any centralized infrastructure, in contrast to the practice in the cellular communications scheme.

2) SET OF ACTIONS

Concerning the *actions* undertaken by the agent, they consist of a tuple of both beaconing rate (b) and transmission power (p) actions, a=(b,p). These two parameters can be easily discretized to properly satisfy the MDP requirements. In particular, the beaconing rate appended in the joint action can be increased, decreased, or maintained, selecting among the set $b=\{0,\pm 1\}$ Hz (also expressed in beacons per second). Likewise, the transmission power is defined by 3 dBm steps, resulting in the set $p=\{0,\pm 3\}$ dBm. All available actions are logically constrained to the bounds stated in the standards [22], [23]. For instance, if a vehicle is already using the maximum transmission power, the available actions for this particular state will exclude those that involve a power increase.

3) ENVIRONMENT

The *environment* is depicted by the road on which the vehicle and its neighbors pass. Roads are fairly complex environments in which many factors are involved, not only the physical parameters of the road and vehicles (e.g. speed, position, acceleration, etc.) but also several human factors (e.g. driver fatigue, drug ingestion, lack of focus, among others). In terms of congestion (both network and traffic), roads are also quite unpredictable since they depend on vehicle density variations which are directly affected by abrupt changes in traffic conditions, such as accidents and other undesired events. Actions should change the state, leading the vehicle to a certain desired behavior, such as handling congestion. However, each vehicle is unable to alleviate overall congestion by itself since its contribution to channel utilization (beaconing rate or transmission power) is just a fraction of the total capacity. Let us take the very simple example of 200 neighboring vehicles transmitting at 5 Hz with a channel capacity of 1200 beacons per second. If a vehicle decides to decrease its beaconing rate from 5 to 1 Hz, the CBR will be reduced by only 0.003 $(\frac{|5-1|}{1200})$, from 0.833 $(\frac{5\times200}{1200})$ to 0.83. Even though this change is slight from a global perspective, it affects the CBR sensed by each neighboring vehicle, hindering the MDP states' definition and preventing the problem from being addressed as a clear transition model. In other words, the next state

would also depend on neighboring vehicles' actions, resulting in an exponential increase in the dimensionality needed to characterize the state. Transmission power also causes the model to be even more complex and unpredictable by varying the number of available vehicles receiving the transmitted beacons. Some solutions employ a multi-agent scheme, such as that designed for base stations in [49], but the aspiring MDP model for controlling congestion in a distributed fashion would become too complex.

4) ASSUMPTIONS

To characterize the aforementioned problem as an MDP, let us state some simplifying assumptions about the environment. As can be expected, these assumptions are related to control variables; that is, channel load (CBR), beaconing rate, and transmission power, allowing us to completely address the transition model.

Assumption 1: Firstly, let us assume that the channel load sensed by nearby vehicles is approximately the same. This is a reasonable assumption when the density of vehicles (ρ) barely differs within the same neighborhood. For instance, in congested areas, as illustrated in Figure 1, the closer the vehicles to each other, the more similar the channel load they perceive. Likewise, the resources required will be also similar (in our case, beaconing rate and transmission power). Because of this assumption, vehicles decide their actions as if their neighbors had precisely its same channel load. In other words, agents suppose that their neighbors select the same actions they do. This allows CBR to be expressed as a function of the selected beaconing rate b, the number of neighbors sensed n (we add one to include the vehicle's own load), and the channel capacity C (beacons per second), as follows:

$$CBR = (n+1)\frac{b}{C} \tag{2}$$



FIGURE 1. Assumption of channel load similarity among nearby vehicles within the same area. The carrier sense ranges of two close neighbors (e.g. *A* and *B*) are represented by yellow and blue circles.

Assumption 2: Secondly, a realistic Nakagami-m [51] fading and path loss propagation model is assumed in order to characterize a wide range of fading conditions realistically. This is key to model the number of neighbors and channel load. In our particular case, we employ the average carrier sense range (r_{CS}) to estimate the number of neighbors as a function of the transmission power. The carrier sense range is defined as the distance from the transmitter in which the power sensed by the receiver is above its sensitivity (S),

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as suggested in [17], as follows:

$$r_{CS} = \frac{\Gamma(m + \frac{1}{\beta})}{\Gamma(m)(SA\frac{m}{p})^{\frac{1}{\beta}}}$$
(3)

where $\Gamma(x)$ is the *gamma function*, p the transmission power, β the *path loss exponent*. $A = (\frac{4\pi}{\lambda})^2$, with λ the wavelength of the carrier, and S the sensitivity of the receiver. Finally, m is the so called *shape* parameter, which indicates the severity of the fading conditions. The lower the m parameter, the more severe the fading.

Combining the assumed fading model with Assumption 1, we can derive an estimate of neighbors using the carrier sense range itself, as explained in the next subsection. In short, Assumption 1 allows us to define the transition model and obtain a feasible MDP that can be solved in a distributed manner. Meanwhile, Assumption 2 provides concrete formulation to compute clear transitions among states in terms of transmission power. With these two assumptions, we relate the CBR measured with the beaconing rate and transmission power. In the next subsection, we will see how the MDP states are defined using the assumptions made.

5) SET OF STATES

Once the requirements to generate a transition model between states have been specified, it is time to define the states of our proposed MDP. The states allow the agent to model the current situation of its environment so both the beaconing rate and the transmission power must be part of them. Moreover, since the main goal of the algorithm is to alleviate overall congestion and maintain the measured CBR under a certain level, the CBR itself must also be considered in the configuration of the state. Basically, we derive an estimate of neighbors to reflect the CBR as part of the states in the MDP, using the relationship between the CBR and the number of neighbors shown in (2). The states are thus defined as a 3-tuple containing the beaconing rate, the estimated number of neighbors, and the transmission power, s = (b, n, p). The resulting space of states can be represented in a three-dimensional fashion, as shown in Figure 2, where axes depict each of the aforementioned parameters. When a vehicle executes an action a = (b, p), the environment response leads the vehicle to a new state s', as follows. The beaconing rate and transmission power just apply the action values to the state. If, for instance, the current state transmits at 10 Hz (beaconing rate) and 23 dBm (transmission power), and a = (0, -3), the new state maintains the beaconing rate and reduces the transmission power to 20 dBm. Concerning the estimated number of neighbors, given the old (p) and new (p') transmission powers, what the environment does first is to assume a Nakagami-m model and to compute the carrier sense ranges using (3). Then, Assumption 1 makes similar the resources needed among nearby vehicles, so neighbors act in the same way. To associate transmission power changes with the channel load, we derive an estimate of the updated number

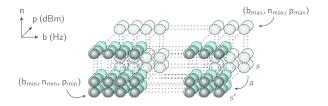


FIGURE 2. Three-dimensional state-space used to model the joint power and rate allocation problem as an MDP. Axes represent each constituent element of the available states of the MDP: beaconing rate, estimated number of neighbors, and transmission power.

of neighbors, as shown in (4).

$$n' = n \frac{r'_{CS}}{r_{CS}} = n \frac{(SA\frac{m}{p'})^{\frac{1}{\beta}}}{(SA\frac{m}{p})^{\frac{1}{\beta}}} = n \left(\frac{p}{p'}\right)^{\frac{1}{\beta}}$$
(4)

Therefore, the transition to a new state s' = (b', n', p') (comprised of the updated beaconing rate, the estimated number of neighbors, and transmission power), are calculated depending on action a = (b, p).

6) REWARD FUNCTION

Every time the agent performs an action and moves from the state s to the state s', a reward $r(s, a) \in \mathbb{R}$ is obtained. Maximizing the total reward allows the agent to learn the most suitable actions and finally obtain the optimal policy (1). As previously mentioned, the desired behavior is to maintain the sensed CBR value around a certain limit, called MBL, which is typically assumed between 0.6 and 0.7. Note that a higher channel load may increase packet loss, hindering suitable safety application operations, and jeopardizing the delivery of event-driven messages in emergency cases. Conversely, a lower load implies a loss in the levels of situation awareness and channel underutilization. This behavior is obtained by modeling the reward function properly, which is specifically shaped to be proportional to the CBR and maximized up to the MBL. This is achieved through the following function g(x, k):

$$g(x, k) = x(H(x) - 2H(x - k))$$
 (5)

where H is the Heaviside function. As can be observed in Figure 3, we use a linear combination (h(x, k)) of the H function and the same function shifted (by k) to discriminate the input values between negative or positive outputs depending on whether they are above or below the threshold k, respectively. Then, we multiply h(x, k) by f(x) = x to endow the overall function with slope, which means that higher inputs offer higher rewards, but once k is exceeded the rewards become more and more negative. Using negative rewards allows us to speed up the learning process [47] since this tells the agent how unwanted the action is as the reward becomes more negative. The resulting g(x, k) function is the basis of the reward function, defined by (6).

$$r(s, a) = \pi_b g(CBR, k_b) - \pi_{p_1} |p - p'| - \pi_{p_2} g(p', k_p)$$
 (6)

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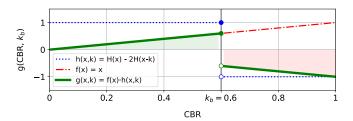


FIGURE 3. Illustrative example of g(x, k) function to restrict the CBR up to $k_b = \text{MBL} = 0.6$. Different areas represent both a positive (green) and negative (red) reward, depending on whether or not the input CBR is above threshold k_b , respectively. Note that generic g(x, k) is also employed in the reward function to constrain transmission power, using p' as input within the standard limits (1-30 dBm) and k_p as threshold and target.

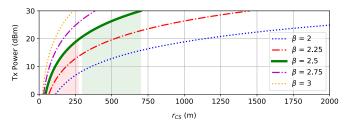


FIGURE 4. Evaluation of the carrier sense range estimation r_{CS} (3) for different transmission powers and path loss exponents.

This expression consists of three terms. The first term is the g(x, k) function in which the CBR is the input parameter and the threshold $k = k_b$ is the MBL,² set, in this case, to 0.6. Note that the CBR is estimated by equation (2) once the action is executed, thus using the pair (b', n'), and, consequently, also p' included in the n' estimate given by expression (4). So, this first term not only prioritizes CBR values close to MBL = 0.6 but also penalizes higher values. The second term is related to excessive variations in transmission power, which may hinder the whole algorithm convergence. Its objective is to inhibit consecutive power actions (p and p') unless they significantly overcome the benefit of the main CBR term. Also associated with transmission power, the third term prevents the algorithm from reaching those states with insufficient power values. These low power states are fairly undesired in terms of awareness since they prevent other vehicles from becoming aware of the presence of the vehicle under study and vice versa. In this case, the g(x, k) function is used introducing transmission power. Regarding the power threshold k_p , we first evaluate the carrier sense ranges resulting from the Nakagami-m fading model (3). We assume a worst case, thus setting severe fading to m = 2 and a path loss exponent to $\beta = 2.5$. As can be seen in Figure 4, carrier sense ranges higher than 250 m are reached with a transmission power of about 20 dBm or greater. Keeping these values in mind, we focus on maintaining carrier sense ranges higher than or equal to 250 m, so we have fixed the power threshold to $k_p = 20$ dBm. Finally, each term of the reward function is normalized and weighted. Weights have been set experimentally to the following values: $\pi_b = 75$, $\pi_{p_1} = 5$, $\pi_{p_2} = 20$, after several iterations. This iterative process was performed assessing the results of different combinations of weights. For instance, too high values of π_b with respect to π_{p_1} and π_{p_2} entail satisfying the CBR limit ($k_b = \text{MBL} = 0.6$), but transmission power would vary widely or below the target value ($k_p = 20 \text{ dBm}$). On the contrary, lower values of π_b could violate the desired MBL objective, which means that congestion is not controlled anymore. In essence, a trade-off among weights is required to satisfy the different constraints appropriately.

7) POLICY DERIVATION

Now that the entire MDP model has been defined, we can resort to efficient MDP-solving algorithms, such as Q-learning [53], to determine the best action to take in every single state (i.e. following the optimal policy π^*). In essence, Q-learning is an iterative algorithm that provides the desired behavior of any action-state pair Q(s, a). So, the optimal policy π^* improves iteratively with the updated estimation of Q(s, a), as shown in equation (7):

$$Q(s, a) \leftarrow (1 - \alpha)Q(s, a) + \alpha \left[r(s, a) + \gamma \cdot max_{a'}[Q(s', a)] \right]$$
(7)

where $\alpha \in (0, 1]$ is a learning rate factor determining how much of the newly-acquired information is incorporated into the current estimation of Q(s, a).

The MDP model and the solving algorithm have been implemented in Python using several interrelated classes and objects as well as advanced libraries, such as NumPy [54] or Pandas. The environment is represented by a simple set of vehicles evenly spaced in a row, satisfying the vehicle density assumption. This allows us to easily model the transition between states. The agent-environment interaction and action-state relationships are also implemented, as previously explained, through the state, action, and reward definitions. Due to the way the reward is shaped, the overall CBR sensed by vehicles can be controlled in a distributed fashion. In the first stage, each action-state pair or Q value is stored in a table, called Q-table, which is initialized to zero, as written in Algorithm 1. Then, it iteratively calculates the maximum expected future rewards for each action at each state. Throughout training, the algorithm attempts to reach the optimal policy π^* , which maximizes the accumulated reward over time. As this policy is a simple mapping between states and actions, it can be also effectively stored in a table; which, in turn, would be programmed into the memory of vehicles before deploying them. It is also important to mention that reaching an optimal policy is not guaranteed, but the training performed was enough to achieve the desired behavior (CBR close to 0.6). To illustrate this, the learning curve of the proposed algorithm has been plotted using the biggest change of consecutive action-state pairs (Q values), called ΔQ . This is carried out in given time intervals for the whole training time. As shown in Figure 5, the higher the

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²A different MBL value can be used. In our particular case, we employ a value of 0.6 value as an optimistic case within the optimal 0.6-0.7 interval.



Algorithm 1 (Python) MDP-Solving Q-Learning

```
1: Step size \alpha \in (0, 1], small \epsilon > 0
2: Initialize Q(s, a) = 0, \forall s \in \mathcal{S}, a \in \mathcal{A}(s)
    for each episode do
        Initialize S
 4:
 5:
        for each step of episode do
             Choose a from S using \epsilon-greedy
 6:
             Take action a
 7:
             Compute reward r(s, a) using (6)
 8:
             Observe the next state s'
 9:
             Update Q(s, a) using (7)
10:
             s = s'
11:
12:
        end for
13: end for
```

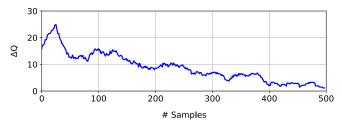


FIGURE 5. Biggest change of successive Q values for a given time interval during the whole training.

TABLE 1. Policy derivation and MDP parameters and their values.

Parameter	Value
Channel frequency	5.9 GHz
Channel model fading	Nakagami-m
Path loss exponent (β)	2.5
Shape parameter (m)	2
Sensing power threshold (S)	-92 dBm
Channel capacity (C)	1315.78 msgs/s
Data rate, modulation and coding rate	6 Mbps (QPSK ½)
Learning rate (α)	0.1
Discount factor (γ)	0.9
Min, Max beaconing rate (b_{min}, b_{max})	1 Hz, 10 Hz
Min, Max number of neighbors (n_{min}, n_{max})	1, 500
Min, Max transmission power (p_{min}, p_{max})	1 dBm, 30 dBm
Set of beaconing rate actions	$\{0,\pm 1\}$ Hz
Set of transmission power actions	$\{0, \pm 3\}$ dBm
Total number of actions	9
Total number of states	500×10×10

training time, the lower the biggest changes between consecutive Q values. Note that this biggest change is a worst-case metric since lower differences between consecutive Q values imply a better performance. The most meaningful features of the proposed MDP model and the parameters used in the Q-learning algorithm have been summarized in Table 1. In the next section, the resulting policy is fed into realistic simulation software to evaluate the algorithm's performance in terms of channel congestion. The assumptions and estimates stated in this section given by expressions (2) and (4) will also be thoroughly tested using different scenarios to confirm their validity and the robustness of the proposed algorithm.

IV. PERFORMANCE EVALUATION

In this section, we assess the performance of the proposed MDP-based algorithm (MDPRP) using OMNeT++ 5.3 [55] together with the INET 3.5 library [56], which implements the IEEE 802.11p standard along with realistic radio propagation and interference models. Once the learning process is finished, and, therefore, the optimal policy is obtained, results are loaded into the OMNeT++ framework. This could be interpreted as storing the policy in the vehicles' memory. As can be observed in Algorithm 2, each time t that MDPRP is executed, it first reads the current beaconing rate and transmission power and measures the CBR. Then, the estimated number of neighbors n is computed, isolating it from expression (2). This allows the vehicle to determine its current state s. Once the vehicle knows its state, the action prescribed by the policy is taken. The action tuple comprising both beaconing rate and transmission power will take us to the next state. To do so, the estimated number of neighbors is also updated using equation (4), after computing the corresponding carrier sense ranges by formula (3), in turn derived from the power action. This whole process is repeated as many times as there are available actions (per state) to guarantee that the most optimal state is reached in a single execution time of the algorithm, which is especially useful in highly variable scenarios.

Algorithm 2 (OMNeT++) Policy Evaluation for MDPRP

```
1: Load policy \pi file
2: loop
                                                              \triangleright Over time t
3:
         Measure CBR(t)
         Read rate and power (b, p)
4:
 5:
         Compute n using (2)
         s \leftarrow (b, n, p)
 6:
                                                                \triangleright Set state s
         for i = 1 \rightarrow \text{size}(\mathcal{A}(s)) do
 7:
              a \leftarrow \pi(s) = (b, p)
                                                    \triangleright Take action a(b, p)
 8:
              b' = b + a[0]
9:
10:
              p' = p + a[1]
              Compute r_{CS}(p) and r_{CS}(p') using (3)
11:
12:
              Then n' using (4)
               n \leftarrow n'
13:
         end for
14:
    end loop
```

Bearing in mind that MDPRP allocates both beaconing rate and transmission power in a distributed and non-cooperative fashion, disregarding neighbors' information, we compared it with two similar and well-accepted congestion control algorithms. The first algorithm in the comparison is the so-called BFPC [46], which employs game theory to allocate the aforementioned parameters depending on the measured CBR. However, as discussed in Section II, BFPC is unable to reach a target CBR level by itself. Instead, it requires its own internal (utility) parameters³ to be selected for a given

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³These parameters control the utility function employed by BFPC, therefore tuning beaconing rate and transmission power as well.



situation; they cannot be calculated a priori to achieve a given desired CBR level. This means that sometimes the MBL constraint is not met, while on other occasions the channel is underutilized. For the sake of clarification, we will show that by setting different values to the frequency utility parameter $(u_i = 4 \text{ and } u_i = 10)$ for all vehicles, a different CBR level is obtained in each scenario. Similarly, the power parameter could be used for this purpose. The second algorithm in the comparison is the congestion control protocol suggested in the SAE J2945/1 standard [43], in which each vehicle adjusts their beaconing rate and transmission power as a function of the number of surrounding vehicles and the CBR sensed. In order to carry out the experiments, the parameters of the simulation are carefully selected, aiming to reduce packet losses, as suggested in [44]. Overall, the comparisons among the different approaches are performed by making use of the following metrics:

- Channel Busy Ratio (CBR) is defined as the fraction of channel in which the radio is busy either due to transmissions or receptions. It is usually measured each second.
 The CBR indicates channel utilization. Thus, a high CBR is related to a higher number of packet collisions and packet losses, reducing the situation awareness level and hindering the adequate operation of safety applications.
- Packet Delivery Ratio (PDR) is usually defined as the ratio of successfully received packets by all the receivers to the total number of packets transmitted [37], [51]. PDR is also an estimate of the situation awareness achieved, closely related to radio channel propagation and medium access control packet losses. Therefore, the highest possible PDR is desirable. In our case, the PDR is transmitter-centric and computed as a function of the distance at which transmitted packets are successfully received. More to the point, PDR is calculated in 50 m wide steps, providing more accurate information in terms of transmission power changes and their effects on the coverage range. Finally, PDR is also averaged for each distance over the entire time period of the simulation.
- Number of decoded packets (NDP). The number of beacons successfully received in the whole network under the same scenario also provides additional information about the proper operation of the different algorithms.

The simulations are conducted using a data rate of 6 Mbps and a beacon size of 500 bytes. This gives rise to a total message size of 536 bytes, including the MAC headers. The resulting PHY packet duration is 760 μ s, according to [22], and thus, the total channel capacity is C=1315.78 beacons per second. All the simulation parameters are specified in Table 2. The different scenarios tested to assess the appropriate operation of our proposal are described below.

A. UNIFORMLY SPACED VEHICLES

The MDP has been trained using a row of evenly spaced vehicles to satisfy the assumptions made. Therefore, this is

TABLE 2. OMNeT++ simulation settings.

Parameter	Value
Channel frequency	5.9 GHz
Channel model fading	Nakagami-m
Path loss exponent (β)	2, 2.5, 3
Shape parameter (m)	2
Sensing power threshold (S)	-92 dBm
SNIR threshold	4 dB
Background noise	-110 dBm
Message size	536 B
Channel capacity (C)	1315.78 msgs/s
Data rate, modulation and coding rate	6 Mbps (QPSK ½)
Min, Max beaconing rate (b_{min}, b_{max})	1 Hz, 10 Hz
Min, Max transmission power (p_{min}, p_{max})	1 dBm, 30 dBm

exactly the initial scenario that we evaluate in OMNeT++ to prove that the proposed MDP-based algorithm works appropriately under the same conditions of training. In particular, we employ a single row of 400 vehicles uniformly distributed along 2000 m. The results of this scenario, after a simulation time of 50 s, are shown in Figure 6. As can be observed, the policy leads the algorithm to the desired behavior previously described, basically defined by a CBR limited to 0.6 and not too low transmission power. Although all the algorithms provide a similar response, some of them fail to meet the desired CBR level, such as SAE J2945/1 standard (around 0.8), as well as BFPC, using a utility parameter $u_i =$ 4, which indicates that the channel is underused. In contrast, MDPRP and BFPC, with $u_i = 10$, reach the 0.6 constraint well. In our particular case, the variations of beaconing rate and transmission power between adjacent vehicles are due to the fact that the allocation is non-cooperative, but especially because each vehicle attempts to search for the optimal response by itself. In any case, these variations have no significant effects on resource allocation. MDPRP reduces the beaconing rate of the central congested area (vehicles surrounded by neighbors) to increase it around those vehicles located at the ends of the row (not completely surrounded by neighbors). This behavior makes sense in terms of situation awareness since these latter vehicles are precisely the most exposed to risk due to the arrival of other vehicles and their consequent braking. What is more, the vehicles located in the middle of the row are supposed to be stopped in the gridlock, so little risk is involved, and they thus require fewer resources. It is important to highlight that our algorithm is working properly even at the ends of the road, even though the model assumptions are not satisfied in these areas. This shows the robustness of the proposed algorithm in scenarios that differ from that used for training. This also means that the formulated assumptions are reasonable and fit well with the road environment. Concerning the results obtained, MDPRP achieves a higher PDR (taking 300 m as a reference) in comparison with the other solutions, mostly at the edges. Recall that these areas are subject to higher risk, and an upper PDR guarantees the proper operation of the safety application. This fact is also reflected by the number of decoded packets.

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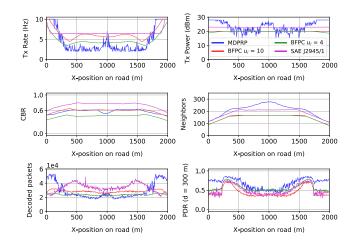


FIGURE 6. Comparison of MDPRP with BFPC and J2945/1 algorithms. This evaluation is conducted under the same conditions as for the training of the MDP. That is, a congested scenario based on a single row of vehicles evenly spaced.

B. TWO RANDOMLY DISTRIBUTED MOVING CLUSTERS

The robustness of MDPRP is thoroughly tested using a worstcase, in which none of the assumptions made to define the transition model are satisfied. The simulated scenario significantly differs from that used to generate the policy. To begin with, vehicles are not evenly spaced, so there is no channel load similarity between close vehicles. Instead, we employ two different clusters bounded within a road section 1000 m long each and located 1000 m away. Vehicles are randomly positioned in a row according to a Poisson distribution of average density $\rho = 0.15$ and 0.3 vehicles per meter, respectively. This results in a first cluster (A) comprised of 150 vehicles located from 0 to 1000 m, an empty road section from 1000 to 2000 m, and a second cluster (B) composed of 300 vehicles distributed along the next 1000 m (2000 to 3000 m). A realistic traffic jam scenario is represented, in which all the vehicles have the same drive direction. The vehicles located in the front of cluster A are approaching the rear of cluster B. They are forced to brake abruptly and this entails a higher risk of vehicle collision. To this end, the speed of cluster A is set at 40 mps (144 km/h), supposing free flow, whereas vehicles in cluster B are completely stopped (0 mps).

This scenario demands an adaptation of the resource allocation throughout the whole simulation time. In our particular case, we simulate until both clusters come together, causing dense network congestion, i.e. 50 s. All the algorithms compared show similar behavior. Basically, as clusters get closer, they all attempt to reduce channel congestion, mainly by decreasing beaconing rate, as illustrated in Figure 7. Concretely, channel congestion is properly alleviated by maintaining the CBR around 0.6-0.7, with the only exception being the SAE algorithm, which exceeds this desired CBR range during the entire simulation time. Keeping the CBR at that level optimizes the achieved situation awareness. This is not the case of BFPC for $u_i = 4$, which remains below

the MBL value, and thus showing channel underutilization. Meanwhile, transmission power is intended to be as high as possible to avoid insufficient carrier sense ranges, which may produce a lack of awareness even of closer neighbors. In fact, both BFPC and SAE mechanisms assign almost the same transmission power to all vehicles and never decrease it by less than 20 dBm. In contrast, MDPRP better exploits the transmission power usage, which acting together on the beaconing rate, notably alleviates channel congestion. This effect can be observed in Figure 7d, where MDPRP reduces overall congestion when clusters come together and overlap. Since the proposed algorithm is non-cooperative, this is achieved after some fluctuations in transmission power, without any noticeable impact on performance.

Regarding PDR, the bar plot of Figure 9a reveals that good performance is obtained with respect to SAE and BFPC algorithms. Three different runs generated with random seeds have been simulated and averaged. The standard deviation is included for 14 different distances from 0 to 700 m. The plotted PDR has also been averaged for all vehicles, largely due to the fact that the scenario is now moving, and a more global and robust sight is required. In essence, results show that our proposal improves the PDR, especially at long distances. This means that transmitted beacons reach the farthest neighbors with higher probability, which makes the vehicle aware of risks earlier.

C. ROBUSTNESS UNDER CHANNEL CONDITIONS

The assumption related to the fading model employed should also be tested to prove the robustness of the proposed MDPRP algorithm beyond the training conditions scenario. By updating the number of neighboring vehicles, as shown in equation (4), all the parameters are common factors of numerator and denominator, except for the path loss exponent β . For instance, the shape parameter m, or the receiver sensitivity are compensated among closer vehicles, allowing the expression to be simplified. This is not so in the case of β because it is an exponent of a different base in the numerator (p) and denominator (p'). So, resource allocation depends on the path loss exponent. Under this premise, we evaluate the previous moving scenario IV-B for different values from those used in training to demonstrate that the algorithm still works properly. Results using three simulation runs at an arbitrary time (e.g. 20 s) are illustrated in Figure 8. On the one hand, by setting $\beta = 2$, namely free space attenuation, the carrier sense range is remarkably higher. This value allows the vehicles to receive messages from more and more vehicles, so the transmission parameters are forced to decrease. In contrast, using $\beta = 3$, the number of neighbors is reduced, and consequently, the scenario is free of congestion and the transmission parameters can be maximized. The policy π trained with $\beta = 2.5$ seems to work well even with different path loss exponent values ($\beta = 2, 3$). That is, MDPRP behaves similarly to those compared algorithms which do not depend on β . Both BFPC using $u_i = 10$ and the SAE J2945/1 standard dramatically neglect the MBL constraint



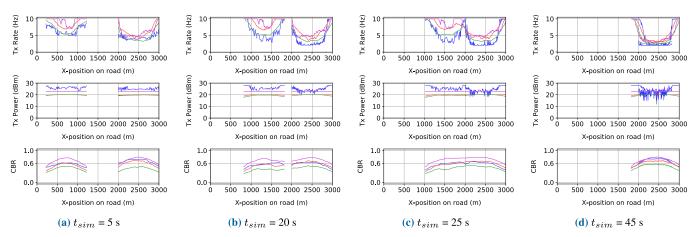


FIGURE 7. Evaluation of different beaconing rate and transmission power congestion control algorithms in a realistic traffic jam scenario comprised of two approaching clusters of vehicles. The response evolution is described by using several simulation times (i.e. 5, 20, 25, and 45 s respectively).

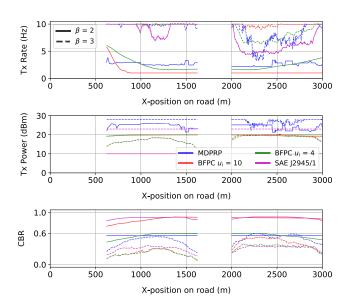


FIGURE 8. Path loss exponent assessment at $t_{sim} = 20$ s for values differing from those used in training or policy derivation.

with channel utilization above 90%. Note that, unlike in the previous scenario (IV-B), BFPC for $u_i = 4$ satisfies the MBL constraint, but for $u_i = 10$, it breaches it. This demonstrates that BFPC needs an online parameter adjustment to obtain the proper CBR level for different scenarios. However, MDPRP still controls congestion well and in a stable manner, even when trained in a completely different scenario. The resulting PDR, depicted in Figures 9b and 9c, is aligned with the result previously provided for $\beta = 2.5$. In addition, the proposed MDP-based algorithm keeps a high PDR with respect to its counterparts. The PDR results also highlight the importance of channel load management. That is, overly congested scenarios (i.e. SAE and BFPC using $u_i = 10$) clearly decrease the packet delivery ratio, whereas well-controlled congestion guarantees proper PDR (MDP and BFPC using $u_i = 4$). In the case of high fading $\beta = 3$, our proposal also provides a high PDR along with the SAE standard.

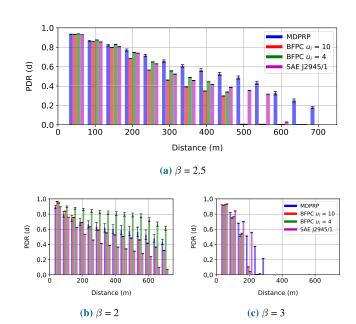


FIGURE 9. Packet delivery ratio evaluation using different path loss exponents in a realistic traffic jam scenario comprised of two clusters of vehicles.

V. CONCLUSION

Vehicular ad-hoc communications rely on real-time periodic messages, called beacons, to allow vehicles to be aware of their surroundings and act accordingly. Indeed, most of the applications that guarantee driver safety are based on the situation awareness provided by this exchanged information. Channel overload caused by this periodic beaconing results in data loss, which may compromise the proper functioning of many safety applications. This is especially important in the case of event-related messages triggered in emergency cases. Therefore, congestion control capable of maintaining a certain fraction of the channel free is crucial. In this article, joint beaconing rate and transmission power congestion control is proposed. Since the associated problem posed is not convex, ordinary optimization methods are usually ineffective. Instead, we have modeled the beaconing



rate and transmission power control problem, making several simplifying assumptions in the road environment to apply the Markov Decision Process (MDP) framework. The proposed solution, called MDPRP, alleviates congestion in a non-cooperative and fully distributed fashion, disregarding additional information from neighbors, where every single vehicle contributes to reducing overall congestion. Simulation results reveal that MDPRP successfully keeps the channel load under the desired level and offers good outcomes in terms of packet delivery ratio. Note that despite being noncooperative, all vehicles are geared towards the same goal, which successfully alleviates congestion. The robustness of the solution is also demonstrated since the algorithm operates reasonably well, even in those cases which do not satisfy any of the initial assumptions defining the MDP transition model. In a future work, we will focus on different reward functions as well as on applying powerful techniques such as deep reinforcement learning in order to resolve the new problems presented. The study of their implications in real implementation issues will also be a part of the future investigation.

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OPEN Approximate reinforcement learning to control beaconing congestion in distributed networks

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In vehicular communications, the increase of the channel load caused by excessive periodical messages (beacons) is an important aspect which must be controlled to ensure the appropriate operation of safety applications and driver-assistance systems. To date, the majority of congestion control solutions involve including additional information in the payload of the messages transmitted, which may jeopardize the appropriate operation of these control solutions when channel conditions are unfavorable, provoking packet losses. This study exploits the advantages of non-cooperative, distributed beaconing allocation, in which vehicles operate independently without requiring any costly road infrastructure. In particular, we formulate the beaconing rate control problem as a Markov Decision Process and solve it using approximate reinforcement learning to carry out optimal actions. Results obtained were compared with other traditional solutions, revealing that our approach, called SSFA, is able to keep a certain fraction of the channel capacity available, which quarantees the delivery of emergency-related notifications with faster convergence than other proposals. Moreover, good performance was obtained in terms of packet delivery and collision ratios.

Transportation is evolving in increasingly overpopulated cities due to a growing demand for goods and human transit. Unless current trends change, the number of vehicles on the road is predicted to triple by 20501, which will also contribute to increasing vehicle-related crashes, injuries, and death ratios. Under these circumstances, Intelligent Transportation Systems (ITS) and Vehicle-to-Vehicle (V2V) communications are expected to reduce these detrimental effects and extend the capabilities of numerous driver-assistance systems and driverless vehicles². The European Telecommunications Standards Institute (ETSI) defines V2V communications over the ITS-G5 radio channel, a 10 MHz control channel at the 5.9 GHz band of the IEEE 802.11p standard³. The ETSI Cooperative Awareness Service (CAS)⁴ transmits periodic broadcast single-hop messages, called beacons, throughout this control channel (Channel 172 in the US). Formally called Cooperative Awareness Messages (CAM) in Europe or Basic Safety Messages (BSM) in the US, beacons are responsible for disseminating status and environmental information among vehicles, where specific information such as position, speed, acceleration, direction, or vehicle dimension are employed to track and predict vehicle behavior. This broadcast information supports many safety applications and is crucial to reducing the risk of collision among vehicles or other undesired events⁵⁻⁷.

As the number of CAS beacons increases, the aggregated load can easily saturate the communication channel, compromising packet reception, and therefore endangering vehicle situation awareness. In this scenario, many safety applications^{5–7} based on beacons could receive outdated and inaccurate information. Furthermore, congestion negatively affects other services transmitted over the ITS-G5 radio channel, like Decentralized Environmental Notification (DEN), which notifies emergency services whenever an accident occurs on the road⁸. Not receiving such event-related messages, called DEN Messages (DENM), is of critical importance to the safety and health of road users (drivers, passengers, and pedestrians). To guarantee the delivery of these emergencyrelated messages (DENM), as well as to provide enough cooperation awareness (using CAM messages) to satisfy safety application requirements, a certain fraction of the channel capacity should be available. The upper limit of the channel load that can be dedicated to be aconing is usually called Maximum Beaconing Load (MBL). To satisfy the MBL constraint, the ETSI standard defines a Cross-Layer Decentralized Congestion Control (DCC) Management Entity⁹ to prevent the ITS-G5 radio channel from overloading.

Several transmission parameters can be tuned over time according to channel requirements and congestion. Keeping this in mind, the most widespread mechanism used to restrict congestion is decreasing the number of beacons transmitted per second. In¹⁰, authors proposed the LIMERIC method, in which each vehicle linearly updates its own rate (metric) depending on the total channel load, thus orienting rates toward a certain

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target value. This algorithm became so extended that even the standardization process included it in the DCC mechanism9. PULSAR11 was another popular rate-based control algorithm using Additive Increase Multiplicative Decrease (AIMD) with feedback from 2-hop neighbors. Since the convergence of LIMERIC has not been tested when some vehicles are out of range with each other, PULSAR was used in combination with LIMERIC to solve this issue¹². With this combination, every vehicle sharing a link converges to the beaconing rate employed by the most congested link. The disadvantage of this solution is that it might unnecessarily decrease the beaconing rate of some vehicles, even though they are not congested. In13, authors proposed FABRIC, which dealt with congestion control as a Network Utilization Maximization (NUM) problem 14,15 to optimally allocate beaconing rates. This approach allowed the design of simple algorithms with proven convergence. Note that these previous solutions are pure congestion controls in which only channel load is used to update beaconing rates. Conversely, other approaches found in the literature cope with the beaconing rate metric from some kind of prioritization. For instance, beacon inter-reception time is employed in 16 to improve vehicle awareness. Similarly, other works adjust the beaconing rate in an attempt to minimize position tracking error with respect to other vehicles¹⁷. This was actually included in the US DCC standard¹⁸. Under this umbrella, the work in ¹⁹, called EMBARC, is based on LIMERIC but integrates the tracking error algorithm of 20. Several works define some risk metrics related to vehicle dynamics and traffic situations, such as²¹⁻²⁴. In²¹, collision probability was employed to adjust the message or beaconing rate at intersections. The works^{22,23} employed tailgating collision risk to assign more resources to more dangerous vehicles. TTCC²⁴ extended FABRIC to transmit beacons using a more generic time-to-collision metric. Vehicle density was also used to fit beacon generation over time^{25,26}.

Most of the approaches mentioned above involve including additional information in beacon payloads. This implies that the congestion control procedure depends on beacon reception, which may disrupt congestion control performance in unfavorable channel conditions. As suggested in²⁷, tracking errors should be included in the congestion alleviation mechanisms. However, there is a more straightforward solution: not relying on neighbors' information to control congestion. These kinds of algorithms, commonly known as non-cooperative, are able to obtain a global change by means of individual actions. The most representative one is NORAC²⁸, a distributed beaconing rate control that employs game theory as its optimization core. As expected, NORAC does not involve exchanging control information, so each vehicle independently fits its beaconing rate according to the channel load measured. Despite the fact that some parameters can be used to adjust the behavior of NORAC, the MBL cannot be explicitly set. This leads to an insufficient or excessive channel load unless an appropriate combination of parameters is selected. However, non-cooperative proposals provide simple but effective resource allocation with very low computational cost, which results in a faster convergence speed to appropriate beaconing rates.

In this paper, we thoroughly discuss all these aforementioned aspects and conceive novel, non-cooperative congestion control capable of attaining an optimal MBL. Similar to game theory, we explore how decision theory and novel reinforcement learning (RL) techniques²⁹ can be applied to resolve a distributed optimization problem. As far as we know, most of the RL-based works require some kind of infrastructure; that is, they are designed for cellular networks^{30–32} or employ a more complex combination of parameters^{31,33–36}. However, none of them introduce simple, reliable, and fast beaconing rate control to alleviate congestion for V2V communications. We make use of a finite Markov Decision Problem (MDP) to formulate both the road environment and congestion control, which is later solved using approximate solution methods. In particular, we apply on-policy control with function approximation, which, unlike tabular solutions, allows us to generalize previous states to derive sensible decisions when new states are encountered. The resulting parameterized model can be applied by vehicles so the most appropriate beaconing rate is arrived at very efficiently in terms of runtime and computational cost, which is of great importance in congested scenarios. Results show that the policy, together with the model evaluated, called SSFA, successfully adjusts the channel load to an appropriate level. This means that road safety services, such as DEN, maintain a certain reserved bandwidth to guarantee the delivery of DENM notifications. Also, the proposed congestion alleviation mechanism does not require the installation of any costly infrastructure on the road (distributed) and does not depend on channel conditions to work properly (non-cooperative).

The remainder of this article is organized as follows. In "MDP formulation for congestion alleviation" section, we describe the resource (beaconing rate) allocation problem of V2V communications more thoroughly and introduce our proposal. Then, we validate it in "Results" section, comparing it with other algorithms and discussing the obtained results. Finally, "Conclusion" section summarizes the main conclusions.

MDP formulation for congestion alleviation

Excessive channel load might increase packet loss and hamper the operation of safety applications with outdated information, not to mention the fatal consequences of not receiving emergency notifications or DENMs. To overcome this problem, congestion control maintains the channel load near a certain target value, defined as the Maximum Beaconing Load (MBL). According to several works^{13,28,37,38}, the MBL is assumed to be around 60 or 70 percent of channel capacity (C), leaving the remaining percentage of the channel free to guarantee the delivery of DEN-related messages and other essential services. Since no a priori information or data about the (road) environment is available, we model the beaconing rate allocation problem as a finite Markov Decision Process (MDP), which is the basis of Reinforcement Learning (RL), to optimally satisfy this MBL constraint using discrete actions. In such a way, each vehicle takes actions, performs transitions among different states, and obtains different rewards depending on how well congestion is alleviated. This will be solved by means of approximated reinforcement learning techniques. The parameterized model resulting from these learning techniques can be easily evaluated by vehicles, causing the algorithm to converge significantly faster than other approaches^{13,28}.

MDPs are often employed to formulate optimization problems and later solve them by deriving optimal sequences of actions. This is particularly appropriate for complex environments that are partially random and difficult to predict. MDPs are mainly comprised of several entities. Firstly, *agents* are the learner entities that

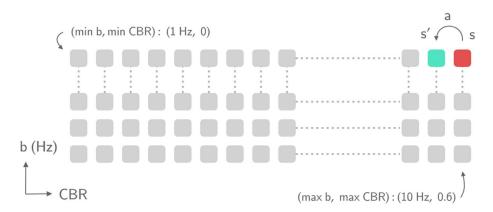


Figure 1. Two-dimensional space of states employed to model the beaconing rate allocation problem as an MDP. Axes represent each constituent element of the available states of the MDP: beaconing rate and CBR.

continuously seek for optimal behavior. In our case, vehicles evaluate policies to keep channel congestion under control. Secondly, the *environment* (road) is everything outside the agent (pedestrians, roads, or other agents) able to alter the agent *state*. The external environmental situation and the internal agent conditions are called *state*, usually defined as a vector $s \in \mathcal{S}$, with \mathcal{S} being the set of possible states. The agent is able to vary its state, from s to s, by carrying out actions $a \in \mathcal{A}(s)$. Every time this happens, the environment is modified, and the agent obtains a *reward r* according to how appropriate the behavior of the agent has been. The agent acts over time in a bid to maximize the reward obtained, which can be modeled as a function of the state s and the action taken a, i.e., $r(s, a) = f(s, a) \in \mathbb{R}$.

The relationships among the different entities are usually determined by state-transition models, depicted by probabilities of transitioning among states. Nonetheless, in realistic scenarios with fast variations and partial information, MDP-solving algorithms employ a mapping between states and actions called policy; that is $\pi:\mathcal{S}\to\mathcal{A}$. Consequently, the main goal of the MDP-solving algorithm is to reach the optimal policy π^* that maximizes the accumulated sum of rewards during the entire training of the agent.

Particularization of actions and states. As mentioned above, the agents of the proposed MDP model, represented by vehicles, sense their environment to adequately adjust their beaconing rate, and thus reduce overall channel congestion. These changes are called *actions*, and they allow vehicles to reduce, maintain, or increase their current beaconing rate within the limits stated in the standard $(1-10 \text{ Hz})^4$. The set of available discrete actions is called action space and is crucial to obtain a good training efficiency and later algorithm accuracy. For instance, too small actions (e.g. < 0.1 Hz) may lead to a more accurate solution but involving a huge state space, which takes much longer to be trained without incurring inaccuracies since many states may never be visited after a while. Once deployed, the convergence of our algorithm could also be affected if too many steps are required. In contrast, too big actions (e.g. > 1 Hz) simplify the training of the model at the expense of accuracy, so that the optimal value would rarely be reached over time. Note that the number of available actions can also make the dimension of the state space grow exponentially, to the detriment of effective training process. Therefore, an appropriate balance should be struck between training efficiency (directly related to the size of the state space) and proximity to the optimal value, in order to appropriately select the set of actions. In our particular case, the action space $\mathcal{A}(s) = \{0, \pm 0.5\}$ Hz was used.

Congestion is usually measured by using the Channel Busy Ratio (CBR), defined as the fraction of time (typically 1 s) during which the channel is busy due to transmissions or receptions. Another way of understanding the CBR is as the fraction of the channel load (sum of the neighbors' beaconing rates), over channel capacity. Note that this metric reflects external environment conditions. For instance, given a beaconing rate, a low measured CBR may be due (i) to a channel with high fading (lost packets results in a lower measured CBR) or (ii) because of having few neighbors. From the point of view of our solution, the action to perform would be the same irrespective of the real cause. In that sense, the CBR captures well the particularities of different scenarios. Because of this, the performance of our proposed solution is robust to variations in the channel model or radio propagation effects, as will be shown in the results section.

Taking this into account, let us define the states of the MDP model as the tuple comprised of the current beaconing rate and the CBR measured s = (b, CBR). Up to 789 different CBR values (60% of the channel capacity in beacons per second) from 0 to 0.6 (MBL/C) are included in the MDP model, which results in 15,780 different tuple states. Every sensed state above or below these limits would result in a decrease or increase of the beaconing rate, respectively. As shown in Fig. 1, the proposed space of states can be illustrated on a two-dimensional plane, where the axes represent both the current beaconing rate and the CBR measured. When executing an action $a \in \mathcal{A}(s)$, the environment gives a new state s back to the vehicle. The beaconing rate only applies the action value to the state. If, for instance, a lot of vehicles are transmitting at 10 Hz (beaconing rate) but suddenly they experience slight congestion and a = -0.5, they will decrease their beaconing rate to 9.5 Hz.

Reward function. With each transition among states, the agent obtains a reward $r(s, a) \in \mathbb{R}$, which denotes how much the current behavior differs from the desired behavior. In other words, maximizing the accumulated reward allows the agent to approach the optimal transmission parameters recommended by the optimal policy π^* . In our case, the desired behavior is to maintain the channel load around the MBL, typically between 60 and 70 percent of channel capacity. Note that higher loads may increase packet loss, jeopardizing vehicle context awareness and preventing emergency-related messages from being decoded. In contrast, a lower CBR would imply that the channel is underused, causing a loss of awareness. To overcome these drawbacks and thus achieve an optimal channel load, the reward is shaped according to the following function:

$$r(x) = -x sign(x - \delta), \tag{1}$$

where sign is the signum function shifted by target value δ . In our case, the input x is the CBR, whereas the target value δ would be the MBL over channel capacity. Let us denote this upper CBR limit as the Maximum Beaconing Ratio (MBR = MBL/C). With this function, an increasing positive reward is obtained as the CBR approaches the target value MBR (0.6–0.7). However, if the CBR overruns this limit, a decreasing negative reward is obtained. These negative rewards speed up the learning process compared to using only positive ones, as proved in 29 . In short, reaching the MBR limit not only allows us to reduce congestion and leave a certain fraction of the channel free to guarantee the delivery of emergency-related messages but also prevents channel underutilization.

Policy derivation. Once the states, actions, and rewards of the MDP have been defined, agents should learn the most advantageous policy; that is, to determine the sequence of actions for which the total reward is maximized. To this end, we employ Semi-gradient SARSA with Function Approximation (hence the name of our congestion alleviation mechanism: SSFA). SARSA iteratively updates the policy to achieve as large a reward as possible over time. Its name comes from the fact that the action is updated in function of the current state (s), the action selected (a), the reward obtained (r), the new state (s'), and the next action selected by the agent (a') in the new state. In difference to the training environment described above which was defined with discrete MDP states, the state space is continuous in real conditions (or their simulated counterparts) while evaluating the policy. Making sensible decisions in these unknown states entails generalizing from previous states that are similar to the current one. To this end, we attempt to generalize using function approximation; that is, we approximate the state-action value function, Q(s, a), as a parameterized function $\widehat{Q}(s, a)$, as follows:

$$Q(s,a) \approx \widehat{Q}(s,a) = \theta_0 + \theta_1 x_1(s,a) + \dots + \theta_n x_n(s,a), \tag{2}$$

where $\theta \in \mathbb{R}^n$ is an n-dimensional weight vector to be learned and $\overline{x} = \langle x_1, \dots, x_n \rangle$ the n-tuple (n = 5) comprised of the following features:

- $x_1(s, a)$ represents an additional reward given whenever ideal behavior is reached. Therefore, it has a value of 1 if the vehicle senses a CBR = MBR and 0 otherwise.
- $x_2(s, a)$ and $x_3(s, a)$ are congestion indicators, which are useful to lead the vehicle to the desired behavior and to define whether the channel load is congested or not. They have a value of 1 if the vehicle has high or low congestion, respectively; that is, the CBR experienced is above or below the MBR, and 0 otherwise.
- $x_4(s, a)$ and $x_5(s, a)$ provide subtle information about how the algorithm should proceed in detail. They assess whether the associated action is approaching or moving away from the desired behavior. In particular, they have a value of 1 if the CBR measured after carrying out the action is closer or further from the MBR, respectively, and 0 otherwise.

As can be observed, these five functions are modeled to obtain the desired behavior so the algorithm does not depend so much on how the reward is shaped. In short, using function approximation not only allows better generalization when assessing the policy but also speeds up the learning process and eases reward tuning. It is worth noting that more sophisticated RL algorithms, suitable for continuous action spaces, could be used to directly predict the optimal beaconing rate. Nevertheless, these solutions entail tough reward modeling to obtain the desired behavior in the right way as well as longer training times and subtle hyperparameter tuning. In contrast, we provide a simple congestion alleviation mechanism that can be trained straightforwardly and is ready to be deployed in realistic scenarios. Furthermore, as will be seen in the next section, the results obtained are close to the optimal values proposed by baseline works, and more complex algorithms might not mean a significant improvement.

The complete environment and the solving algorithm of the MDP model proposed have been implemented in Python, using different classes, objects, and advanced libraries, like NumPy³⁹, to obtain efficient data processing. The environment is represented by a set of vehicles arbitrarily located on a two-dimensional plane, as would occur on realistic roads. The interactions between the agents and the environment, such as rewards and transitions among states, are also implemented. In this (training) environment, each vehicle includes its current state (CBR and beaconing rate), transmission power, spatial location, and the set of allowed actions. Note that the proposed congestion control algorithm is not influenced by channel model or propagation effects so we assume here a free-space channel model and sufficient transmission power to permit vehicles to be in coverage with each other. In this way, numerous congestion levels represented by different numbers of vehicles allow a policy able to respond quickly to each CBR measured, from 0 to 0.6, to be obtained. This CBR is controlled in a distributed fashion by each vehicle according to the way the reward is modeled.

The semi-gradient SARSA with function approximations described in Algorithm 1 was implemented in a different class from the environment. Firstly, the parameterized action-state pairs, or \widehat{Q} -values, are initialized to

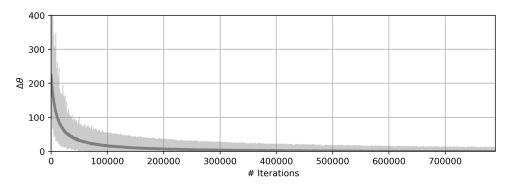


Figure 2. Biggest variation of consecutive θ values for each episode.

zero. For each episode, the environment generates as many vehicles as required to represent the CBR indicated in the current state and iteratively calculates the expected rewards and updated \widehat{Q} -values. For instance, if the initial state is s=(b,CBR)=(10Hz,0.5), the environment will create as many vehicles transmitting at 10 Hz as possible to obtain a CBR = 0.5. The algorithm will recommend actions to every vehicle equally until reaching the optimal policy $\pi^*=f(\theta^*)$ and maximizing the accumulated reward during the training. Note that the policy is shared among vehicles and that overall channel congestion is successfully controlled in this training scenario. As will be shown in the following section, this shared policy will work appropriately even when all the vehicles are not in range of each other since individual contributions lead to the right overall channel load. This is the advantage of non-cooperative algorithms: they can obtain a global change by means of individual actions.

```
Algorithm 1 Pseudocode of semi-gradient SARSA with function approximation
Inputs
   Step size \alpha \in (0,1], small epsilon \epsilon > 0, discount factor \gamma \in [0,1]
   Set of features \bar{x} = (x_1, ..., x_n)
   Initialize value-function weights \theta \in \mathbb{R}^d arbitrarily
Loop for each episode
   Initialize s and select action a
   Loop for each step of episode
       Act a
       Observe reward r and new state s'
       Select action a' using policy derived from \hat{Q}(s', \theta) (e.g., \epsilon-greedy)
       \theta \leftarrow \theta + \alpha [r + \gamma \hat{Q}(s', a', \theta) - \hat{Q}(s, a, \theta)] \nabla \hat{Q}(s, a, \theta)
       s \leftarrow s'
       a \leftarrow a'
   End loop
End loop
```

It should be noted that attaining the optimal policy is not guaranteed. For this reason, we continued training until we achieved the desired behavior ($CBR \approx MBR$). To illustrate this, the learning curve of the proposed algorithm has been plotted in Fig. 2 through the biggest change of consecutive θ vectors, called $\Delta\theta$. This value was calculated as the sum of the difference between the elements of successive θ vectors. As can be observed, the biggest changes between consecutive θ values decrease as training moves forward, which implies better performance.

The most meaningful parameters of the environment as well as those employed in the MDP-solving algorithm have been summarized in Table 1. In the next section, the performance of the proposed congestion alleviation mechanism in different motorway and urban scenarios will be thoroughly assessed.

Results

In this section, a well-trained SSFA model is evaluated using different studies ranging from simple, theoretical evaluations to more complex and realistic simulations in urban and motorway scenarios. To this end, the resulting policy is loaded onto vehicles to execute the SSFA mechanism, as shown in Algorithm 2. Firstly, each vehicle measures the CBR and initializes the beaconing rate (10 Hz by default). Once the vehicles become aware of their state, the policy function modeled by the weights gives the optimal action back. Then, the policy is evaluated as many times as there are different available rates ($|\mathcal{B}|$) as a preemptive measure to avoid overlooking possible inaccuracies in the trained policy. This way, vehicles are led to reduce overall congestion in a distributed and non-cooperative fashion. Note that this is achieved thanks to the individual contributions of all the vehicles in

Parameter	Value
Discount factor (γ)	0.9
Step size (α)	0.1
Epsilon-greedy probability (ϵ)	0.1
Channel capacity (C)	1315.78 beacons/s
Maximum Beaconing Load (MBL)	789.47 beacons/s
Maximum Beaconing Ratio (MBR)	0.6
Transmission power	500 mW (27 dBm)
Min., Max. beaconing rate	1, 10 Hz
Number of available actions ($ \mathcal{A} $)	3
Number of available rates (B)	20
Number of available CBRs ($ \mathcal{L} $)	789
Total number of states ($ S $)	$ \mathcal{B} \times \mathcal{L} $
Episodes	$(\mathcal{S} \times \mathcal{A})/MBR$
Steps of episode	100

Table 1. Training parameters and their values.

the network, which follow the same policy and act equally under similar states. Finally, according to the received action, SSFA (each vehicle) adjusts the beaconing rate that will be used until the next update.

```
Algorithm 2 Pseudocode of the non-cooperative SSFA mechanism

Inputs

Load trained policy \pi \coloneqq f(\theta)
s \leftarrow (b_o, CBR_0)

Loop over time t

For each vehicle

Measure CBR

For i = 1 \rightarrow |\mathcal{B}| do
s \leftarrow (b, CBR)
b \leftarrow b + \theta(s)

End For

End For

End loop
```

SSFA allocates beaconing rates without cooperation among vehicles and without relying on any base station or road infrastructure. Therefore, we compare it with two similar congestion control mechanisms found in the literature. The first solution in the comparison is NORAC28, which employs game theory to allocate the beaconing rate depending on the measured CBR. Nevertheless, as discussed in "Introduction" section, no channel load limit can be explicitly set. In other words, the proper combination of parameters to reach a given MBL is, a priori, unknown, which means that the MBL constraint might not be met when traffic conditions vary. The second comparative solution is FABRIC¹³, which approaches the beaconing rate allocation as a Network Utilization Maximization (NUM) problem with proven convergence. Despite providing optimal allocation, FABRIC entails including Lagrange multipliers in the header of the transmitted messages (these multipliers, also known as prices, π , should not be confused with the policy that defines agent behavior). This means that vehicles require additional information about their neighbors, which may increase the convergence time. It is noteworthy that the authors of NORAC criticized FABRIC for piggybacking these prices. Nonetheless, we consider that adding a few extra bytes in the heading is not as serious a problem as longer convergence time. The comparison of (i) our non-cooperative approach based on decision theory (RL), (ii) FABRIC, which is a cooperative solution employing NUM, and (iii) NORAC, a non-cooperative solution based on game theory, is performed by making use of the following metrics:

- Channel Busy Ratio (CBR). The CBR is defined as the ratio between channel load and channel capacity. Furthermore, it can be interpreted as the fraction of busy time (typically 1 s) due to transmissions or receptions. As seen throughout this work, this metric represents how much of the channel is used (congested) so it is closely related to packet loss.
- Neighboring vehicles. Finally, together with the CBR, the number of neighbors detected provides valuable
 insight into the distribution of resources (and context awareness) among vehicles, which should also be
 considered when assessing the aforementioned algorithms.

Parameter	Value
Frequency band	5.9 GHz
Channel model	Nakagami-m
Carrier sense threshold	- 92 dBm
Noise floor	-110 dBm
SNIR threshold	4 dB
Data rate	6 Mbps
Transmission power	500 mW (27 dBm)
Beacon size	4288 bits
Channel capacity (C)	1315.78 beacons/s
Maximum beaconing load (MBL)	789.47 beacons/s
Maximum beaconing ratio (MBR)	0.6
Min., Max. beaconing rate	1, 10 Hz
FABRIC parameter	
α	1
β	2.8e-7
ω	1
π_0	0.001252
NORAC parameter	
u _i	5
pc _i	0.2

Table 2. OMNeT + + simulation parameters.

- Packet Delivery Ratio (PDR). The PDR is usually defined as the sum of successfully decoded packets with
 respect to the number of packets transmitted in the network^{40,41}. In our particular case, we employ a transmitter-centric approach in which the PDR is measured as the transmitted packets that are successfully received
 at a certain distance over the total number of packets transmitted. More to the point, the PDR is calculated
 every 50 m from the source vehicle.
- Packet Collision Ratio (PCR). We assume the PCR as the number of packets lost due to a collision (n_c) between the packets successfully decoded (n_s) and those lost due to a collision, $n_c/(n_c + n_s)$, as suggested in 36 .

The scenarios simulated below are not only conducted using different channel conditions and environments, but also a variable number of vehicles. In the following sections, we simulate 650 static vehicles under training conditions, 400 static vehicles under realistic conditions, and up to 400 moving vehicles gradually introduced in a realistic urban scenario. For all these scenarios, a beacon size of 536 bytes and a fixed data rate of 6 Mbps were employed. According to the standard³, this results in a total PHY packet duration of 760 μs and channel capacity of C = 1315.78 beacons per second. The whole set of simulation parameters are depicted in Table 2.

Evaluation under training conditions. As a first step, we evaluate the proposed congestion control using the Python environment, maintaining most of the training conditions. Therefore, resource allocation is performed theoretically, without sending messages or considering any interference phenomena, headers, or further MAC or PHY protocols. However, unlike the training, in which vehicles were randomly distributed and transmission power was high enough to reach every other vehicle, we now introduce a limited communication range of 400 m. We employ a single row of 650 vehicles evenly spaced along 2000 m. Every algorithm under comparison was run for 100 successive iterations. This evaluation is useful to check whether our proposed mechanism obtains the desired overall congestion (CBR) even when vehicles act in a non-cooperative way. As shown in Fig. 3, the beaconing rate obtained by evaluating the resulting policy (SSFA) is similar to the optimal response of FABRIC. NORAC has a rougher, oscillating shape, although the allocation tends toward the same limit as SSFA and FABRIC by the middle of the row of vehicles. Concerning the CBR, the three algorithms perform well in terms of reaching the MBR constraint, which is satisfied except in the transition to the edges, around 350 and 1600 m. The evolution over time for a vehicle located in the middle of the row was also obtained to study the convergence time. In this case, our proposed SSFA algorithm converges faster (around 15 iterations) than NORAC (40 iterations) and FABRIC (30 iterations).

Realistic uniformly spaced vehicles. In this subsection, we rigorously assess the performance of each comparative algorithm with the well-known discrete event simulator of networks OMNeT $+ + 5.3^{42}$. The INET 3.5 library⁴³ was used to implement the IEEE 802.11p standard as well as realistic channel, propagation, and interference models. To observe whether these realistic conditions affect the process of how resources are allocated, we deploy a similar scenario to the previous subsection. In particular, a row of 400 static vehicles uniformly spaced along 2000 m is simulated for 30 s. As illustrated in Fig. 4, SSFA obtains reliable beaconing rate

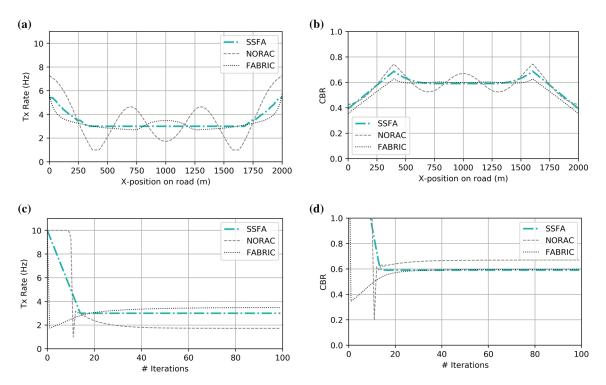


Figure 3. Theoretical comparison (implemented in Python) of the proposed congestion control approach with FABRIC and NORAC. (a) Recommended beaconing rate and (b) CBR measured for a row of vehicles versus their position on the road; (c) Evolution of the beaconing rate and (d) CBR of a vehicle located in the middle area of the road over time.

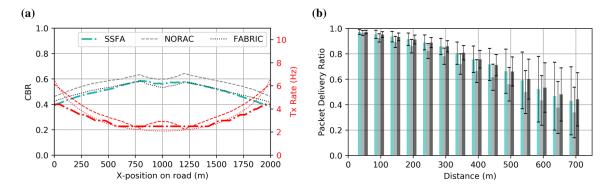


Figure 4. Realistic simulation (OMNeT ++) of our proposed congestion control approach compared to FABRIC and NORAC for an evenly spaced row of vehicles. (a) Beaconing rate and CBR measured versus the vehicles' position on the road; (b) Packet Delivery Ratio over different distances.

allocation, comparable to the optimal rate proposed by FABRIC, and similar also to NORAC. Regarding the CBR measured, SSFA and FABRIC provide identical responses, whereas NORAC slightly exceeds the MBR limit. Recall that NORAC does not allow the upper CBR limit to be specified. Therefore, not reaching the desired CBR of 0.6 exactly means that the parameters selected were probably not optimal. This non-compliance brings interesting outcomes in terms of packet delivery ratio, decoded packets, and packet collision ratio, as shown in Fig. 4b and Table 3, respectively. As expected, SSFA and FABRIC reach a similar packet delivery ratio, but that of NORAC is reduced. Such an effect highlights the importance of congestion control and proves that the MBR used (0.6) is the value which allows us to obtain the best performance, as studied in numerous works^{13,28,37,38}. Since NORAC surpasses the MBR limit, the beaconing rate, and thus the number of decoded packets, is slightly higher than with the FABRIC and SSFA algorithms. However, the packet collision ratio is significantly higher than in the SSFA and FABRIC approaches. So far, not only does our proposal improve the convergence time but it also obtains excellent results in terms of PDR and PCR. Moreover, it is important to note that, unlike FABRIC, which is based on exchanging prices among neighboring vehicles, SSFA does not depend on channel conditions or packet delivery to operate properly.

Algorithm	PCR±std	Decoded packets			
Realistic uniformly spaced vehicles					
SSFA	0.1115±0.0886	6,706,167			
NORAC	0.1530 ± 0.1040	6,851,859			
FABRIC	0.1144±0.0902	6,736,288			
Realistic urban scenario					
SSFA	0.1341 ± 0.0620	1,368,140			
NORAC	0.1344±0.0619	1,286,087			
FABRIC	0.1536±0.0649	1,457,903			

Table 3. Packet Collision Ratio and total number of decoded packets.

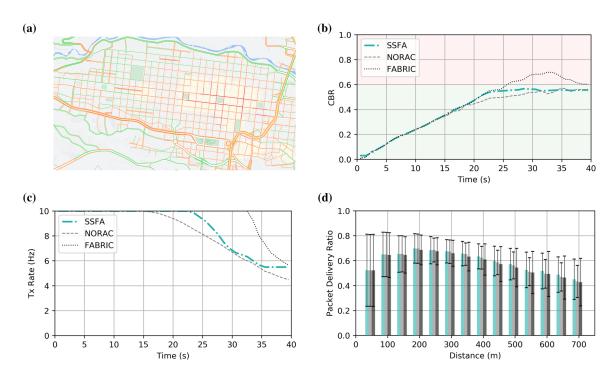


Figure 5. Realistic urban simulation (OMNeT ++ and SUMO) of the proposed congestion control approach compared to FABRIC and NORAC. (a) Traffic map (Map data ©2021 Google) of the city of Pereira (Risaralda, Colombia), used in the simulations, illustrating different levels of congestion (from low; green, to high; red) during the peak period (4 p.m.); (b) CBR measured and (c) allocated beaconing rate of a sample vehicle over time; (d) average packet delivery ratio for different vehicles over distance.

Realistic urban scenario. Finally, we evaluate SSFA in a realistic urban scenario where, unlike in the previous subsections, vehicles are not uniformly spaced. This will put the non-cooperative scheme to the test because the requirements of the vehicles might differ significantly among neighboring vehicles. For instance, some vehicles could experience congestion while stopped in a traffic jam or at a traffic light, whereas others could flow at higher speeds in a secondary street. In short, this realistic scenario will show how well SSFA performs under congested and stressful conditions considering rapid variations. To this end, in addition to OMNeT++ and INET, we use Simulation of Urban MObility (SUMO)⁴⁴, a traffic simulation package designed for large networks. The OSM web wizard of SUMO allowed us to select a geographic region and specify traffic mode and demand. We imported the traffic map of the city of Pereira, Colombia. The different levels of congestion in this city (from low; green, to high; red) during the peak period (4 p.m.) are illustrated in Fig. 5a. To simulate this congestion, we sequentially introduce up to 400 vehicles, which will be randomly traveling around the city during the whole simulation time (40 s). The behavior of the first vehicle introduced in the network will be studied so that the congestion experienced by this vehicle increases over time. The goal of this experiment is to observe whether the SSFA approach performs well in terms of convergence time as well as to obtain an adequate CBR compared to other solutions. As can be shown in Fig. 5b, SSFA and NORAC cause the CBR to be the set MBR. However, FABRIC maintains the maximum beaconing rate even after experiencing congestion (Fig. 5c) so the CBR takes longer to converge and to reach the target MBR. This is a disadvantage of cooperative schemes under varying conditions. Concerning the PDR (Fig. 5d), SSFA obtains higher values than its counterparts in almost every distance measured, from 0 to 700 m. It should be noted that the location of vehicles is now random around the simulated urban environment so the PDR has a different distribution than in the previous scenario. The PCR obtained, shown in Table 3, is also similar to or lower than that of FABRIC and NORAC. Therefore, not limiting the CBR properly may lead the algorithms to transmit pointless beacons that not only will be lost but that will impede the reception of DENM messages. In other words, we want to transmit only those messages that will be successfully decoded (Table 3) in order to not congest the channel. Finally, note that vehicles are now introduced gradually so that the total number of decoded packets is smaller with respect to the previous scenario.

Conclusions and future work

V2V communications are based on transmitting periodic messages (beacons) which support most safety applications and driver assistance systems. However, the associated channel load stemming from beacons should be controlled since it might saturate the channel and hamper the appropriate operation of these applications and services. For this reason, congestion control algorithms aimed at maintaining a given fraction of the channel free are of great importance to preserve the safety of road users, especially by guaranteeing the delivery of emergency-related notifications (DENMs). In this work, we introduce innovative beaconing rate control to alleviate congestion. We make use of approximate reinforcement learning, which allows vehicles to take sensible actions with low computational cost and converge in a short period of time. Our proposal, called SSFA, restricts the channel load by adapting the beaconing rate in a non-cooperative way. Since no additional information from neighbors is required and vehicles work independently, the algorithm is robust even in unfavorable conditions in which packet losses are significant. Moreover, SSFA operates in a distributed manner, thus no pre-installed infrastructure is required for its operation. Results reveal that SSFA successfully maintains channel usage at the desired level, leaving channel capacity free enough for successful DENM reception. Also, a higher packet delivery ratio and a lower number of collisions than other related mechanisms are achieved. In future works, we will focus on the design of algorithms with improved learning capabilities while driving in real implementations.

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Author contributions

Conceptualization, J.A.P.; methodology, J.A.P., A.J.G.S., E.E.L.; software, J.A.P. and E.E.L.; validation, J.A.P. and E.E.L.; formal analysis, J.A.P., A.J.G.S., E.E.L.; investigation, J.A.P., A.J.G.S., E.E.L.; writing—original draft preparation, J.A.P.; writing—review and editing, J.A.P., A.J.G.S., E.E.L., and J.G.H.; visualization, J.A.P.; supervision, A.J.G.S., E.E.L., and J.G.H.; project administration, A.J.G.S., E.E.L., and J.G.H.; funding acquisition, A.J.G.S., E.E.L., and J.G.H. All authors have read and agreed to the published version of the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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Simultaneous Data Rate and Transmission Power Adaptation in V2V Communications: A Deep Reinforcement Learning Approach

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ABSTRACT In Vehicle-to-Vehicle (V2V) communications, channel load is key to ensuring the appropriate operation of safety applications as well as driver-assistance systems. As the number of vehicles increases, so do their communication messages. Therefore, channel congestion may arise, negatively impacting channel performance. Through suitable adjustment of the data rate, this problem would be mitigated. However, this usually involves using different modulation schemes, which can jeopardize the robustness of the solution due to unfavorable channel conditions. To date, little effort has been made to adjust the data rate, alone or together with other parameters, and its effects on the aforementioned sensitive safety applications remain to be investigated. In this paper, we employ an analytical model which balances the data rate and transmission power in a non-cooperative scheme. In particular, we train a Deep Neural Network (DNN) to precisely optimize both parameters for each vehicle without using additional information from neighbors, and without requiring any additional infrastructure to be deployed on the road. The results obtained reveal that our approach, called NNDP, not only alleviates congestion, leaving a certain fraction of the channel available for emergency-related messages, but also provides enough transmission power to fulfill the application layer requirements at a given coverage distance. Finally, NNDP is thoroughly tested and evaluated in three realistic scenarios and under different channel conditions, demonstrating its robustness and excellent performance in comparison with other solutions found in the scientific literature.

INDEX TERMS Vehicular ad-hoc networks, connected vehicles, Vehicle-to-Vehicle (V2V) communications, congestion control, power control, data rate control, deep reinforcement learning.

I. INTRODUCTION

Future Intelligent Transportation Systems (ITS) aim to reduce both the number and severity of accidents using connected vehicles. In ITS, Vehicle-to-Vehicle (V2V) communications [1], [2] periodically exchange broadcast single-hop messages, called beacons, to announce information which enables the tracking and prediction of neighboring vehicle behavior [3]. The goal is to achieve context awareness by means of cooperation among vehicles [3]. As the number

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of vehicles on the road increases, this context awareness is crucial, laying the foundations for many safety applications that reduce the risks of collision [4]–[6]. An overloaded channel compromises this feature because high packet losses may occur; affecting both periodical beaconing and event-related messages triggered in emergency cases [7]. Context-awareness can help leave a certain fraction of the channel capacity available to be used to deliver relevant messages, guaranteeing, a priori, the safety of drivers, passengers, and pedestrians.

Channel congestion may be controlled by different transmission parameters. The most common approach adjusts



the beaconing rate [8]–[10]. Another approach fine-tunes transmission power, thus regulating the number of messages received by vehicles [11]–[13]. Finally, the data rate is also a parameter used to relieve channel congestion. However, very few proposals for data rate adaptation have been discussed in the scientific literature [14].

Adjusting a single parameter often entails worse outcomes in reducing channel load in highly congested scenarios. For instance, if the transmission power is decreased too much, messages would reach only a few neighboring vehicles; those located very near, leading to poorer cooperation among vehicles. In contrast, fine-tuning a combination of two or more parameters may yield better performance results since no drastic changes that would be detrimental to cooperative awareness occur. With this line of action, the most common approaches jointly consider transmission power and beaconing rate [15]-[17]. An optimal joint allocation of both parameters would be the best solution; however, the associated optimization problems are not always convex [18]. This issue may result in mixed-integer problems (MIPS), escalating computing complexity. To deal with this problem, some proposals in the literature suggested applying artificial intelligence (AI) techniques to reach an optimal joint allocation of beaconing rate and transmission power [19]. Although this set of parameters works significantly well, it is more consistent to combine data rate and transmission power since they are intrinsically interrelated. That is, high data rates reduce channel load but use more complex modulations, which are less robust against unfavorable channel conditions, and their efficiency depends on the transmission power radiated. Therefore, high transmission powers should be employed to balance the weakness of fading and attenuation at longer distances. Joint data rate and transmission power solutions are rarely found and simply treated in the scientific literature, which means they have limited ranges of data rates and transmission powers [20], [21].

In this paper, we apply the Deep Reinforcement Learning (DRL) framework to alleviate channel congestion through optimizing data rate and transmission power simultaneously. Given the nature of this problem, in which no a priori information or data about the (road) environment is available, we formulate it as a Markov Decision Process (MDP) and solve it using Deep Reinforcmeent Learning (DRL) algorithms. Previous proposals applying DRL to this problem are focused on infrastructure networks and disregard data rate control [22]-[24]. Our solution is addressed to an ITS G5 infrastructure-less (ad hoc) network; that is, a distributed environment where cooperation among vehicles naturally leads to Multi-Agent Reinforcement Learning algorithms (MARL) [25], [26]. However, the solution given in these papers are difficult to train and are not yet mature enough, especially regarding future real implementations. In our case, we train a single agent, whose resulting policy could be easily stored on-board any vehicle belonging to the network. Moreover, this shared policy obtains suitable results without the need to tackle the complexities associated with MARL

approaches. In fact, in our previous paper [19], we demonstrated that this single agent, when appropriately trained, controls beaconing rate and transmission power by using a tabulated Q-learning method. Unlike [19], in this work we employ DRL, which is appropriate when the state space is large and continuous, as occurs in our case (road environment). The outcoming actions (data rate and transmission power) of the trained Deep Neural Network (DNN) are then applied by vehicles in a non-cooperative fashion, without the need to request additional information from neighboring vehicles.

This proposed mechanism, denoted Neural Network for Data rate and transmission Power (NNDP), controls overall channel congestion while assuring a certain transmission range with the most robust data rate possible. In short, we verify that training a single agent using our DRL approach is an appropriate solution to jointly adapt data rate and transmission power and thus adjust congestion levels in an effective way. The main contributions of this research work are summarized as follows:

- The policy is implemented through a DNN solution, which accepts continuous values as input. All the values stated in the standard are taken into consideration. This endows the algorithm with greater flexibility and accuracy than previous approaches [20], [21].
- The proposed method keeps the channel load below a certain threshold to avoid congestion, which notably reduces packet loss. At the same time, channel underutilization is avoided.
- Transmission power is adjusted to the necessary level to guarantee a given packet delivery ratio at a certain distance.
- Low data rates with more robust modulations schemes are rewarded, whenever possible, if the channel load allows their usage.
- The model obtained can be applied in a fully distributed fashion, without the need for a centralized network infrastructure.
- Finally, no information from neighboring vehicles is required to carry out actions, so any exchange with the application layer is disregarded for an appropriate resource allocation operation.

The remainder of the paper is organized as follows. First, Section II discusses the related work and congestion control from the viewpoint of the existing trade-off between transmission power and data rate. Then, in Section III, we detail the model proposed and the solving method used. Section IV conducts the performance evaluation, discussing different simulation scenarios and metrics, and compares the achieved results with other proposals of interest. Finally, Section V summarizes the main conclusions.

II. RELATED WORK

Vehicle communications are specified by the European Telecommunications Standards Institute (ETSI). In



particular, ETSI defines the ITS-G5 radio channel comprising a 10 MHz control channel at the 5.9 GHz band of the IEEE 802.11p standard [27]. Transmissions over these networks are broadcast and employ Carrier-Sense Multiple Access with Collision Avoidance (CSMA/CA) as a medium access control (MAC) protocol. The ETSI Cooperative Awareness Service (CAS) also features periodic beaconing over one-hop communications as the basis of cooperative awareness. Such periodic messages or beacons, formally called Cooperative Awareness Messages (CAM) in Europe or Basic Safety Messages (BSM) in the US, are responsible for disseminating status and environmental information to vehicles on the control channel (G5CC in Europe and Channel 172 in the US, respectively). However, the aggregated load generated by dispatching beacons may cause packet loss, thereby negatively impacting safety applications. In addition, the Decentralized Environmental Notification (DEN) service, which is in charge of notifying about risk-related road events [7], needs some channel availability to guarantee the appropriate delivery of event-related messages in emergency cases, called Decentralized Environmental Notification Messages (DENM). To this end, the Cross-Layer Decentralized Congestion Control (DCC) Management Entity [28] is aimed at preventing ITS-G5 radio channel overload by adjusting different transmission parameters.

Regarding single-parameter control, beaconing or message rate is the most frequently employed congestion control parameter, and different authors have implemented algorithms which relate beaconing rate to the measured Channel Busy Rate (CBR) [8], [9], vehicle dynamics [3], [29], [30], or context information [10], [31]–[33], among others. However, in some cases, the only way to alleviate congestion is to decrease the beaconing rate excessively, which may degrade the necessary context awareness capabilities and hence vehicle safety [34].

Another widely used parameter in congestion control is transmission power. Reducing transmission power means decreasing coverage distance and thus, the number of vehicles that receive the broadcast messages, so overall congestion is also alleviated. Several works propose controlling transmission power as a function of different metrics. Authors in [35] employed channel state information (CSI) to maximize energy efficiency in wireless cellular networks. The work in [11] exploited vehicle speed as a parameter to allocate transmission power. In particular, this approach extended the transmission range in the case of high speeds to raise awareness in neighboring vehicles with less time-to-collision. Vehicle density is also employed in [12] to decide whether to increase or decrease transmission power. Likewise, authors in [39] included an SNIR estimation in their study. Conversely, some proposals directly allocate transmission power as a function of the channel load [13], [40]. In [41], a parameter denoted as vehicle position prediction error determined the increase/decrease in transmission power. In general, if transmission power takes inadequately low values while attempting to mitigate congestion, the number of receivers would

drop too much and overall awareness would be jeopardized. On top of this, abrupt transmission power variations also cause variations in the resource allocation mechanisms, as is dealt with in [13].

More advanced proposals combine two or more parameters simultaneously to take advantage of the benefits of each them as much as possible. In this case, an algorithm for joint optimal allocation of several parameters could be a good solution, but we find an important drawback in many cases: the optimization problem is usually non-convex. Even though there are solutions involving two or more parameters that clearly improve the usefulness and flexibility of congestion control [15], [18], [37], [38], [42]-[44], there is no silver bullet to resolve congestion control from a multiparameter perspective. Given the complexity of the optimization problem, different advanced solutions have emerged. Similarly to [14] but including beaconing rate and transmission power as control parameters in the mathematical problem, an algorithm based also on game theory was proposed in [16]. Decision-making theory has also been an important tool to achieve optimal congestion control and endow a certain amount of intelligence to vehicles. In particular, the Markov Decision Process (MDP) framework is one of the decision-making techniques that provide the basis of reinforcement learning (RL) [45] commonly employed to solve complex problems. Congestion control is proposed by varying transmission power using both Q-Learning, in the particular case of LTE-V2V communications [22], and a MARL approach for overall wireless communications [25], [26], [36]. Regarding solutions where more than one parameter is optimized, authors in [23] derived the best selection of the frequency sub-band together with transmission power through a deep decision-making approach. In the case of C-V2V networks, a reinforcement learning framework offers a smart solution for balanced power control and rate adaptation [24]. Finally, in the context of the IEEE 802.11p standard, and consequently, in a distributed fashion, discrete Q-learning has also been proposed in [19] to optimize both beaconing rate and transmission power allocation.

Despite the fact that the IEEE 802.11p standard [27] defines up to 9 different data rates from 3 to 27 Mbps, a data rate of 6 Mbps is usually recommended. Moreover, authors in [46] provided a method to identify the optimum data rate according to different scenarios, assuming and fixing the 6 Mbps data rate. Higher data rates entail shorter packet durations, reducing the channel load, but these data rates employ high-order modulation schemes and coding rates. This means less robustness against adverse channel conditions over distance. To mitigate this effect, higher transmission power is required to guarantee an adequate Packet Delivery Ratio (PDR) at a given target distance. On the other hand, low data rates reduce the required transmission power levels to provide reliable communications at a certain target distance but increasing the transmission time and therefore, decreasing the throughput. The trade-off between data rate and transmission power in terms of transmission range and

TABLE 1. Comparison of our congestion control proposal (NNDP) and other related work	TABLE 1. Com	parison of our cong	estion control pro	posal (NNDP) and	d other related works
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	[8], [9]	[10], [31]	[12], [35]	[25], [45]	[14]	[16]	[40], [43]	[19], [23]	[20], [21]	NNDP
Controlled parameters	BR	BR	TP	TP	DR	BR, TP	BR, TP	BR, TP	DR, TP	DR, TP
Centralized/Distributed	D	D	D	C	D	D	D	D	D	D
Type of algorithm	O	O	О	RL	G	G	O	RL	O	\mathbf{RL}
Non-cooperative	Yes	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes

(BR): Beaconing Rate; (TP): Transmission Power; (DR): Data Rate; (O): Optimization; (G): Game theory; (RL): Reinforcement Learning.

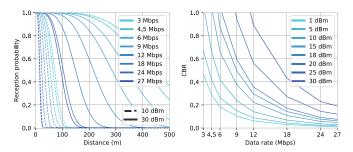


FIGURE 1. Reception probability variation over distance (left) and channel busy ratio (right) for different data rates and transmission powers using a Nakagami-m fading model.

reception probability is depicted in Figure 1. In [46], transmission power was adjusted to obtain the same PDR as the reference value obtained for 6 Mbps. However, this was discussed in [47], whose authors claimed that it is not clear whether the selected transmission power levels in [46] guarantee the communication range required by vehicular applications. Using both simulations and field experiments, authors in [47] demonstrated that 6 Mbps is not always the optimum data rate. As a consequence, there is limited research work which tackles data rate variations. We can highlight the study in [14], which is a non-cooperative approach based on game theory to successfully maintain congestion below a certain level.

As can be observed in Table 1, most of the aforementioned proposals integrate the beaconing rate and transmission power parameters to control channel congestion in their formulations. In light of the existing trade-off between data rate and transmission power, as explained above and in Figure 1, data rate variations could be compensated by simultaneously fine-tuning transmission power. Therefore, this double-parameter perspective is much more physically consistent due to the channel condition dependence of the data rate: high data rates are more affected by fading and attenuation, and thus, the effective transmission range is reduced, although it can be adjusted by increasing transmission power. Moreover, data rate and transmission power parameters can be directly controlled by the DCC Management Entity as defined by the standard [3]. In contrast, other parameters (e.g. receiver sensitivity) are more dependent on the particular hardware of each vehicle and may affect the MAC operation. We consider this issue out of the scope of this work. To the best of the authors' knowledge, there are only two works aimed at combining data rate and transmission power in vehicular ad-hoc networks [20], [21]. The first work proposed

a look-up table to optimally select pairs of transmission power and data rates in terms of the PDR and end-to-end delay. However, available pairs of data rate and transmission power parameters are very limited, which leads to undesired behavior whenever the environment is slightly modified. Moreover, the validation results of this work are scarce and therefore weak. The second work, called CACC [20], analyzed the Received Signal Strength (RSS) of the received packets to determine whether their losses were due to weak signal or collisions and, based on this, decided to decrease or increase the transmission power or data rate. Despite obtaining fairly good results in terms of the PDR, the channel is underused or overused depending on the scenario, and only a few data rates among all the available range are analyzed for simpler scenarios. Keeping these weaknesses in mind, a more sophisticated scheme would be necessary to consider the full range of each parameter and select them according to different goals. Consequently, to contribute to filling this research gap, we propose a deep reinforcement learning approach, called NNDP, to (i) prevent congestion, leaving some of the channel capacity to deliver event-related messages available. Also, (ii) transmission power is intended to preserve adequate performance of safety applications at a certain distance, while (iii) the most robust data rate is set whenever possible.

III. CONGESTION CONTROL USING DRL

Congestion control is developed to guarantee an appropriate channel load, usually measured by the CBR metric, around a certain target value denoted Maximum Beaconing Load (MBL). According to several works [16], [48], [49], its optimal value is around 0.6 and 0.7. Higher channel loads may increase packet loss and hinder proper safety application operations. In this paper, we propose to control congestion by jointly adjusting both the data rate and transmission power. However, this is not trivial, and a subtle trade-off between both parameters is required to satisfy application layer requirements. In the case of transmission power, values that are too high increase congestion while values that are too low endanger vehicles' awareness. In terms of data rates, high rates alleviate congestion due to shorter packet transmission intervals. Nonetheless, high order modulations are required and robustness against fading and attenuation is lessened as distance increases. To this aim and as already mentioned in Section I, we first model the problem through a Markov Decision Process (MDP) framework. In general, MDP addresses congestion control in ad-hoc vehicular communications as an optimization procedure over discrete actions taken by



the vehicles themselves in a distributed fashion. However, when the state space is large or continuous, novel approaches employ approximation methods, as in our proposal. Unlike in our previous work, where we used beaconing rate and transmission power [19] and the MDP was solved using tabulated policies, in this work we apply Deep Reinforcement Learning (DRL) to find the optimal transmission parameters more accurately. Within the DRL framework, we train DNN models using a simplified environment programmed in Python. Once the training is completed, we check whether the trained DNN (agent or model) successfully alleviates the channel congestion through individual actions of the vehicles in realistic scenarios using a discrete event simulator for networks.

A. REINFORCEMENT LEARNING FRAMEWORK

MDPs provide a mathematical framework to derive optimal sequences of actions, so they are commonly applied to formulate optimization problems. This is especially useful in those challenging environments where outcomes may be partially random or difficult to predict, as happens in vehicular settings. Formally, MDPs consist of the following elements:

- The agent is the learner entity that continuously seeks optimal behavior. In our case, the agent is every single vehicle on the road, whose goal is to reduce overall channel congestion in a distributed manner, jointly employing transmission power and data rate parameters.
- The environmental situation, along with the properties
 of the agent is called *state*. Usually, the state is defined
 as a vector s ∈ S that embraces both the outer and inner
 properties of the agent, with S being the set of possible
 states.
- The agent is able to perform an action $a \in A(s)$. This action belongs to the available set of actions for each state. In our case, actions are a tuple consisting of the transmission power and data rate to be set in forthcoming transmissions.
- Every time the agent takes an action, the environment is modified, presenting a new situation to be explored. In this change of state from s to s', the agent obtains a *reward* r, considered as the feedback from the environment. It can be modeled as a function of the state s and the action taken a, i.e., $r(s, a) = f(s, a) \in \mathbb{R}$.

MDP-solving algorithms employ what is called *policy*, denoted as π , a mapping between states and actions; that is, $\pi: \mathcal{S} \to \mathcal{A}$. The main objective is to reach the optimal policy π^* , which maximizes the accumulated sum of rewards over the entire lifespan of the agent during training. This decision policy can be determined by the state-action function, also called the Q-function, Q(s,a), which can be approximated using Deep Neural Networks (DNN). In general, Markovian systems operate from discrete spaces so the agent and environment interact with each other in a sequence of discrete-time steps. However, as occurs in our particular case, more complex problems comprising continuous variables could

require some approximations to be solved. This will be detailed in the following subsection while particularizing the constituent elements of the proposed MDP model.

B. DATA RATE AND TRANSMISSION POWER

Roads are fairly complex environments which are influenced by many factors, not only the physical parameters of the road and vehicles (e.g., speed, position, acceleration, etc.) themselves but also numerous human factors. In this way, traffic conditions are quite unpredictable due to unforeseen events. The associated number of neighboring vehicles and their beaconing loads may increase both channel congestion and packet collisions, therefore drastically reducing packet reception probability. Furthermore, there is an additional randomness due to the channel fading and attenuation produced by the surroundings of the road. For instance, rural areas generally represent more favorable channel conditions, while urban areas cause higher fading (e.g., multipath effects caused by objects and buildings) and increase the number of weak signals in the environment. We assume a well-accepted Nakagami-m [50] fading and path loss propagation model in order to realistically characterize a wide range of channel conditions. From this model, we compute the average carrier sense range, r_{CS} (m) as a function of the transmission power. Basically, carrier sense range is defined as the average distance from the transmitter where the power is sensed by the receiver over its sensitivity (S), as suggested in [13]:

$$r_{CS} = \frac{\Gamma(m + \frac{1}{\beta})}{\Gamma(m)(SA\frac{m}{p})^{\frac{1}{\beta}}}$$
(1)

where $\Gamma(x)$ is the *gamma function*, p the transmission power, β the path loss exponent, A is defined by the expression $(\frac{4\pi}{\lambda})^2$ (λ is the wavelength of the carrier), and S is receiver sensitivity. Finally, *m* is the so called *shape* parameter, which indicates the severity of the fading conditions. For instance, m = 1 means severe fading, while m = 5 denotes the most favorable fading. As previously shown in Figure 1 in which the reception probability was computed from a Nakagamim model, the carrier sense range depends on transmission power. This can be observed in the carrier sense range expression (1) as well. Therefore, as transmission power increases, a larger number of packets received from neighboring vehicles that are located at greater distances could be successfully decoded. That is, there is information available from a greater number of vehicles thus enriching context awareness. However, this increase in power also implies increasing the channel load. In contrast, if transmission power is excessively reduced, vehicles would receive packets only from closer neighbors. Therefore, there is a trade-off for achieving a certain channel load level without jeopardizing context aware vehicle information. To set appropriate transmission power while controlling congestion, a second parameter is usually considered. The most common approach consists of varying the beaconing rate by fixing the data rate by default to 6 Mbps. However, there is no reason not to propose



TABLE 2. IEEE 802.11p Data rates.

Data rate (Mbps)	Modulation	CR	Data bits per symbol	Coded bits per symbol	S _r [47] (dBm)
3	BPSK	$\frac{1}{2}$	24	48	-85
4.5	BPSK	$\frac{3}{4}$	36	48	-84
6	QPSK	$\frac{1}{2}$	48	96	-82
9	QPSK	$\frac{3}{4}$	72	96	-80
12	16-QAM	$\frac{1}{2}$	96	192	-77
18	16-QAM	$\frac{3}{4}$	144	192	-73
24	64-QAM	$\frac{2}{3}$	192	288	-69
27	64-QAM	$\frac{3}{4}$	216	288	-68

controlling congestion by dynamically adjusting data rates while fixing the beaconing rate to the maximum allowed (i.e., 10 Hz). Indeed, the IEEE 802.11p standard [27] defines up to 9 different data rates, from 3 to 27 Mbps. Note that, as shown in Table 2, higher data rates imply higher-order modulation schemes.

On the one hand, high data rates are more beneficial in terms of network throughput since packet transmissions are shorter, but they are also more prone to packet error due to interference and noise. Therefore, the higher the data rate, the higher the Signal-to-Interference-plus-Noise Ratio (SINR) threshold required for successful packet reception and the shorter the effective transmission range. Table 2 can be used to illustrate the trade-off (related to different data rates) between generated channel load and transmission power requirements over distance. Note that the receiver sensitivities stated in the standard [47], [51], denoted by S_r , are the minimum required values to keep the Packet Error Ratio (PER) below 10%; which means that, in the absence of interference/noise, at least 90% of the packets with that power level will be successfully received. Under these circumstances, the selection of the appropriate data rate should be based on its capacity to reduce the channel load while simultaneously guaranteeing the application requirements using the most suitable transmission power [47]. In short, we mainly combine both transmission power and data rate to make sure that channel loads are kept below the required MBL. Once congestion is alleviated, we determine the transmission power to ensure that, at a certain target distance, the received power is above the S_r required by a given data rate. In the following section, the safety distance, transmission power, and data rate for the measured CBR are related to each other.

1) AGENTS, ACTIONS, AND STATES

Agents, which are represented by every single vehicle on the road, continuously sense their environment to adequately adjust both transmission power and data rate. As previously stated, they are mainly intended to reduce overall channel congestion in a distributed manner by making use of their own metrics and without relying on any centralized infrastructure. To this end, each vehicle first computes the channel capacity (C, messages per second) that would be available according

to the selected data rate, as illustrated in Equation (2).

$$C = \left(C_d \left\lceil \frac{b_{st} + M}{C_d} \right\rceil + t_{ps}\right)^{-1} \tag{2}$$

The data field of the Medium Access Control (MAC) frame/packet layer [27], also called MAC Protocol Data Unit (MPDU), is comprised of the packet length M in bits (536 B), plus 22 bits of service and tail (b_{st}), and additional padding destined to reach multiple coded bits (C_d) per Orthogonal Frequency Division Multiplexing (OFDM) symbol. This padding is represented in Equation (2) by the ceiling function and, according to Table 2, each data rate entails a different number of coded bits per OFDM symbol. Before transmission, the Physical layer (PHY) also includes a preamble and a signal field (t_{ps} , in seconds), which are transmitted applying the most robust data rate (3 Mbps), which translates into 40 μs . The whole packet structure is summarized in Table 3. Once the data rate has been selected and the channel capacity is calculated, each vehicle estimates the CBR that would be measured if all vehicles employ the same operating parameters. To this end, we use the average carrier sense area $(2 \times r_{CS})$, the vehicle density detected in the neighborhood (ρ) , and the average beaconing rate (b), which is set to 10 Hz for every vehicle.

$$CBR = \frac{2r_{CS}\rho b}{C} \tag{3}$$

The set of Equations (1), (2), and (3) allows vehicles to carry out congestion control. We also consider actions consisting of 2-tuples of transmission power (p) and data rate (d), $a = \langle a_p, a_d \rangle$. As stated in the standard [27], [28], transmission power may take both discrete and continuous values ranging from 1 to 30 dBm, whereas the data rate is constrained to some discrete values, as shown in Table 2. Notice that Equation (3) is only an estimation to express channel load as a function of the transmission parameters of every single vehicle. A more realistic calculation would include information from neighboring vehicles, which would turn the problem into a multi-agent approach. This type of approach is very complex to address, train, and deploy. Instead, we train a single agent to recognize and act against different levels of congestion. Agents define states to model their situation and their environment, so both data rate and transmission power should be relevant parts of these states. In addition, channel congestion has been included in the state by using the estimated vehicle density (ρ) within the neighborhood of each vehicle. The states are then defined as a 3-tuple containing the currently used transmission power, data rate, and estimated vehicle density, $s = \langle p, d, \rho \rangle$. When a vehicle executes an action $a = \langle a_p, a_d \rangle$, the environment response leads the vehicle to a new state s', as follows. The transmission power and data rate are applied as the action values to the state. For instance, if the current state transmits at 15 dBm and 6 Mbps and $a = \langle -4.8, 12 \rangle$, the new state will reduce the transmission power to 10.2 dBm and increase the data rate to 18 Mbps. Since each vehicle applies the same



TABLE 3. Packet structure for MAC and PHY layers.

MAC			Service	PSDU	Tail	Pad bits
PHY	Preamble	Signal		Dat	а	

trained policy, the channel load measured by the vehicles will be also changed to the corresponding value, given by Equation (3). Therefore, the transition to a new state $s' = \langle p + a_p, d + a_d, \rho \rangle = \langle p', d', \rho \rangle$ is calculated depending on action $a = \langle a_p, a_d \rangle$. These state transitions describe the behavior of the vehicles, which is governed according to the rules imposed by the reward function.

2) REWARD FUNCTION

Every time the agent (or the vehicle) performs an action and changes from state s to state s', a reward $r(s, a) \in \mathbb{R}$ is received. Maximizing accumulated rewards over time allows agents to learn the most suitable actions and, as a consequence, obtain an optimal policy. As mentioned above, the desired behavior is to maintain the channel load around a certain MBL, whose ratio over the channel capacity is typically between 0.6 and 0.7. Higher channel loads may increase packet loss and jeopardize the delivery of event-driven messages if an emergency arises. Conversely, lower channel loads decrease awareness of the surroundings and may cause channel to be underutilized. In order to achieve the desired behavior, we include the following function in our characterization:

$$g(x) = -sgn(x - x_T)x \tag{4}$$

where sgn is the signum function shifted by some target value x_T (in our case x = CBR and $x_T = MBL$). As can be observed, a positive reward increase is obtained as long as the CBR approaches the target value (MBL). However, if the CBR exceeds that target value, an increasing negative reward is achieved. These penalties (negative rewards) intensify learning speed [45]. In this way, reaching the MBL = 0.6 not only allows us to reduce congestion and leave a certain fraction of the channel free to guarantee the delivery of emergency-related messages but also prevents channel underutilization. To move the agent toward this optimal behavior, we add +10 to the reward whenever the CBR reaches the MBL within a ± 0.025 error interval and -0.1 otherwise.

In addition to CBR control, some restrictions should be included to prevent the model from reaching undesired combinations of transmission parameters. For instance, the agent could learn to set the most robust data rate (longer transmission times) at the expense of reducing transmission power and thereby reaching a fewer number of neighbors. Despite achieving adequate channel load levels, overall awareness on the road would be seriously impacted; that is, transmitted messages would only reach the closest neighboring vehicles. To overcome this problem, we include a second term in the reward function aimed at satisfying reliability and awareness at a given distance. As already discussed in [47], higher data rates reduce congestion in an effective manner but entail less

robustness against fading. This reduces the effective transmission range, requiring an increase in transmission power to obtain the same PDR at a certain distance. The sensitivities (S_r) specified in Table 2, also called *reliability sensitivities*, depend on the selected data rate and are used to improve the performance of the application layer, guaranteeing that at least 90% of the packets received are successfully decoded. Using a one-slope path loss model and the aforementioned sensitivities, $l = Ad_s^\beta$, we can shape the reward function to provide an acceptable PDR for safety applications, at least, up to a certain distance, called the safety distance (d_s) . Therefore, the higher the received power over sensitivity, the higher the reward obtained, as indicated by the following equation:

$$r = -|(S_r + l) - p| \tag{5}$$

Note that this expression is aligned with the fact that from a logarithmic scale perspective, transmission power (p) minus path loss (l) results in power received (p - l) at a certain safety distance, which, in turn, should be greater or equal to sensitivity. It is true that lower data rates entail lower sensitivities, and the effective transmission range can be much higher than that for higher data rates (more vulnerable to channel conditions). This aspect is already included in expression (5). However, we also encourage low data rate usage whenever possible by adding a third term, so, the higher the data rate, the more negative the reward. In this way, excessive variations among higher data rates are most likely avoided. The total reward function is therefore aimed at controlling channel loads (see Equation (4)) while guaranteeing the proper operation of safety applications (Equation (5)) by intelligently exploiting the trade-off between transmission power and data rate, as shown in Equation (6):

$$r = \omega_c g(CBR) - \omega_p |(S_r + l) - p| - \omega_d(d)^{\omega_e}$$
 (6)

Each term of the reward function is normalized and weighted using an iterative process to the following values: $\omega_c = 2$, $\omega_p = 0.25$, $\omega_d = 0.1$, and $\omega_e = 0.8$. As can be observed, channel load control assumes greater importance, while those terms that control single parameters play a minor role. For instance, excessive values of ω_c with respect to ω_p and ω_d result in satisfying the CBR limit, but some transmission power and data rate combinations may be undesired (e.g., too low transmission powers). In contrast, lower values of ω_c could violate the desired MBL objective, which means that congestion is no longer being controlled. Concerning the exponent of the data rate term, named ω_e , it governs how negative the rewards are as long as data rates increase. A 0.8 value is set to obtain a similar range for the rest of the terms. In essence, a balance among weights is required to satisfy the different constraints appropriately within the bounds of the parameters stated in the standard.

3) DERIVATION OF π^*

Once the proposed MDP model has been formulated, the next step is to derive the optimal policy (π^*) , which determines the

TABLE 4. Environment and learning parameters and their values.

Parameter	Value
Channel frequency	5.9 GHz
Channel model fading	Nakagami-m
Path loss exponent (β)	2.5
Shape parameter (m)	2
Sensing power threshold (S)	-92 dBm
Safety distance (d_s)	100 m
Message size (M)	536 B
Learning rate (α)	0.0001
Discount factor (γ)	0.9
Batch size	128
Beaconing rate (b)	10 Hz
Min, Max vehicle density (ρ_{min}, ρ_{max})	0.0001, 0.8
Min, Max transmission power (p_{min}, p_{max})	1 dBm, 30 dBm
Min, Max data rate (d_{min}, d_{max})	3 dBm, 27 Mbps

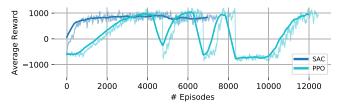


FIGURE 2. The average accumulated reward for PPO and SAC algorithms.

best action for every single state. Traditional MDP-solving algorithms, such as Q-learning [19], [52], use tabular methods which map $\pi:\mathcal{S}\to\mathcal{A}$ merely by employing a table. Despite achieving a convergent solution, and, a priori, good results, tabular methods are not appropriate to map every single state onto a suitable action, in particular when the state space is too large or continuous, as occurs in our case. Instead, we make use of Deep Neural Networks (DNN) to model π . Therefore, the policy is represented not as a table but as a parameterized functional form with a vector of weights, that is $\pi:=f(\theta)$. By adjusting these weights θ , a wide range of functions can be implemented by the DNN. In our case, the DNN learns the best transmission parameters based on the road environment and vehicle situation.

There are many DRL algorithms based on DNNs [53]–[58] but not all of them accept the same type of states and actions. Recall that in our case, transmission power and vehicle density are continuous parameters. Concerning data rate, we consider it to be continuous, to later take the closest discrete value that satisfies the requirements stated in the standard. In this way, we resort to algorithms that feed on continuous actions, such as [53], [55]-[58], highlighting [57] and [58] for their good performance. The first one to consider is the so-called Proximal Policy Optimization (PPO) algorithm [57], which inputs multiple epochs of stochastic gradient ascent to perform each policy update. PPO exhibits the stability and reliability of trust-region methods (TRPO) but it is much simpler to implement. The second algorithm that also presents good results is the Soft Actor-Critic [58], whose main feature is entropy regularization. With SAC, the policy maximizes a trade-off between the expected return and entropy, a measure of randomness in the policy, which ensures greater robustness

and stability. In our work, both algorithms were implemented in Python through RL-dedicated libraries [59], [60]. Basically, they iteratively calculate the maximum expected future rewards for each action at each state according to different policies. In particular, we selected a policy that implements the actor-critic method based on a multilayer perceptron (2 layers of 64 nodes). A hyperbolic tangent activation function is employed for PPO by default, whereas a Rectified Linear Unit (ReLU) is used for SAC. The initial weights of the DNN models for both PPO and SAC agents were randomly initialized. In practical terms, as shown in Figure 2, PPO results in much faster training than SAC, but eventually, the rewards decrease, which means that the algorithm forgets the good behavior learned. To avoid this situation, we automatically save the best model every few episodes. Conversely, SAC offers more stable rewards.

It is also important to highlight that the training process is performed by a single vehicle that monitors different levels of congestion, represented by the density of the vehicles sensed (ρ) . Then, the trained model is loaded onto every single vehicle in the network to be evaluated (this process will be further explained in the following section). The rationale behind this is that channel loads are similar among neighboring vehicles so all of them will have the same requirements and thus, similar transmission parameters. This is just an assumption that enables channel loads to be estimated by taking the information from the vehicles (Equation (3)) into account. This estimation will be fairly close to the real load. Overall congestion is properly controlled in a distributed fashion as will also be shown in the next section. Note that as each vehicle applies the same policy with a similar channel load among neighbors, our proposal successfully converges to the same congestion level per vehicle. Finally, the environment and learning parameters used for the training of the PPO and SAC agents have been summarized in Table 4. In the next section, the trained DNN models are fed into realistic computer simulation software [61] to evaluate the performance of the algorithms in terms of channel congestion. The channel load estimate stated in this section and given by the expression (3) will also be thoroughly tested for different scenarios to prove the validity and robustness of the proposed algorithm.

IV. PERFORMANCE EVALUATION

In this section, we evaluate the performance of our proposed congestion control mechanism (NNDP), using OMNeT++ 5.3 [61] and including the INET 3.5 library [62]. This library implements the IEEE 802.11p standard along with realistic radio propagation and interference models. This simulation software as well as the RL libraries must be the cornerstones of the learning process. Once the learning process is finished and the weights of the DNN model have been thoroughly optimized, the vehicles will apply the resulting actions to alleviate any channel congestion episodes. In a real implementation, this would be achieved by installing the trained DNN model in the vehicle controller. The entire DNN model could be



FIGURE 3. Diagram of the training process of the DNN in a simplified environment developed in Python (left), and the subsequent evaluation of the trained model to control congestion in realistic vehicular networks (right). Different road scenarios have been simulated in OMNeT++, in which each vehicle individually sends its state over the socket and receives the optimal actions of transmission power and data rate from the DNN model (previously trained in Python).

directly exported for this purpose but numerous compatibility problems may arise between OMNeT++ and RL libraries written in Python. To resolve this issue, one option is to use tables to store both actions and states, which would evaluate the DNNs, but at the expense of losing accuracy and reducing the potential advantages of DNNs against tabular methods like Q-learning. As a simple solution to evaluate the trained DNN model, we create a TCP/IP socket connection between Python, in which the model is contained, and OMNeT++, in which realistic road scenarios are simulated. The training process of the DNN model in Python using different DRL algorithms (PPO and SAC) and the subsequent evaluation of the resulting trained DNN models are illustrated in Figure 3.

After opening the aforementioned socket connection between Python and OMNeT++, which saves us from exporting the whole trained model to the OMNeT++ simulator, each vehicle initialize its transmission parameters (23 dBm and 6 Mbps), and our proposed congestion alleviation mechanism (NNDP) starts to run. As can be observed in Algorithm 1, it first reads the current transmission power and data rate and calculates the vehicle density of the environment. To this end, each vehicle uses the average carrier sense range along with the number of neighboring vehicles detected. Note that the vehicle density is only an estimation that represents the channel load measured in the environment at a given time. Once the vehicles are aware of their state, they send these 3-tuples (p, d, and ρ) to the Python server. Before giving actions back to OMNeT++, the server evaluates the model as many times as there are available actions (per state) to avoid overlooking possible inaccuracies in the training process and to guarantee that proper transmission parameters are reached for every state. From the simulator's viewpoint, the server immediately responds with the action recommended for that state in a single execution time of the algorithm, so our solution is also useful in highly variable scenarios. Finally, each vehicle adjusts its transmission parameters according to the received action.

NNDP allocates data rate and transmission power in a distributed and non-cooperative manner, without relying on any base station or infrastructure. Therefore, we compare it with a similar existing congestion control mechanism called

```
Algorithm 1 NNDP Evaluation (OMNeT++)
```

```
1: s \leftarrow \langle p_0, d_0, \rho_0 \rangle
 2: loop over time t
 3:
             for all v \in \mathcal{V} do
 4:
                    Calculate r_{CS} according to Eq. (1)
                    \rho \leftarrow \frac{n}{2r_{CS}}
 5:
 6:
                    s \leftarrow \langle p, d, \rho \rangle
 7:
                    a \leftarrow \theta(s) = \langle a_p, a_d \rangle
 8:
                   p \leftarrow p + a_p
                    d \leftarrow d + a_d
 9.
             end for
10:
11: end loop
```

Channel-Aware Congestion Control (CACC) [20]. Basically, CACC adjusts transmission power and data rate according to the cause of packet loss. This is discerned by the Packet Delivery Ratio (PDR) and Packet Collision Rate (PCR) metrics, which, in turn, are based on a given RSS threshold (ξ). Therefore, CACC is able to achieve the optimal MBL = 0.6 but only when the RSS threshold is properly set. For the sake of clarification, we will show how setting different values for the RSS threshold (ξ = -85.72 and 92.26 dBm) may result in different CBR levels. In general, the comparison among the different approaches is conducted for the following metrics:

- Channel Busy Ratio (CBR) is defined as the fraction
 of time (typically 1 second) in which the channel is
 busy either due to transmissions or receptions. The CBR
 indicates the best channel utilization so higher CBR
 values are closely related to a greater number of packet
 losses. In these cases, situation awareness is damaged,
 and the adequate operation of safety applications may
 be hindered.
- Neighboring vehicles (N). Together with the CBR, the number of neighboring vehicles is essential to provide insight into how information is distributed on the road
- Packet Delivery Ratio (PDR) is usually defined as the ratio of successfully received packets by all the receivers with respect to the total number of packets

TABLE 5. OMNeT++ simulation settings.

Parameter	Value
Channel frequency	5.9 GHz
Channel model fading	Nakagami-m
Path loss exponent (β)	2.5
Shape parameter (m)	2
Sensing power threshold (S)	-92 dBm
SNIR threshold	4 dB
Background noise	-110 dBm
Message size (M)	536 B
Beaconing rate (b)	10 Hz
Min, Max transmission power (p_{min}, p_{max})	1 dBm, 30 dBm
Min, Max data rate (d_{min}, d_{max})	3 dBm, 27 Mbps

transmitted [21], [50], [63], [64]. The PDR is said to be an estimate of situation awareness, intrinsically related to radio channel propagation and medium access control packet losses. Therefore, the highest possible PDR is desirable. Instead, authors of CACC [20] established their own interpretation of the PDR as the relation between the number of decoded packets (N_s) and the sum of decoded packets and packets lost due to weak signal reception (N_w) . From our point of view, this definition differs notably from the original definition of the delivery ratio [21], [50], [63], [64] since the authors of CACC did not consider collisions in the total number of packets lost. Despite using the PDR proposed in [20] to implement CACC reliably, we compute the PDR in a traditional way. In our case, the PDR is a transmittercentric approach, defined as the ratio between the number of packets transmitted that are successfully received at a certain distance and the total number of packets transmitted. Note that this PDR is a function of the distance from which packets are successfully received. More concretely, the PDR is calculated at 50 m steps. This provides more accurate information in terms of transmission power changes and their effects on coverage range, which is of major interest for the problem addressed here.

Total number of decoded packets (N_s). The total number of beacons successfully received in the entire network under the same scenario also provides additional information about the proper operation of the different algorithms.

The simulations are conducted using a fixed beaconing rate of 10 Hz and a beacon size of 536 bytes. The resulting PHY packet duration and channel capacity will depend on the data rate [27]. For instance, 6 Mbps means a packet duration of 760 μ s and a total channel capacity of C=1315.78 beacons per second. All the simulation parameters are specified in Table 5. The different scenarios tested are described below.

A. UNIFORMLY SPACED VEHICLES

To validate our proposed congestion control mechanism, we compare the trained agents (PPO and SAC) in our NNDP solution versus CACC. To this end, we first deploy a simple scenario consisting of a row of evenly spaced vehicles in

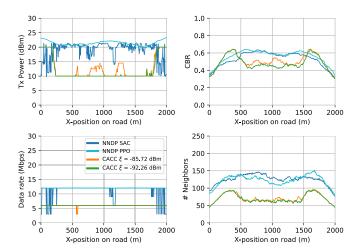


FIGURE 4. Comparison of NNDP and CACC in a congested scenario based on a single row of evenly spaced vehicles.

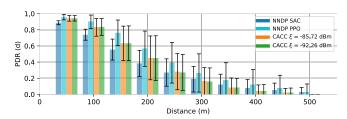


FIGURE 5. The PDR versus distance for a single row of evenly spaced vehicles.

OMNeT++. This scenario seeks a situation in which the channel loads measured by the different neighboring vehicles are similar. In particular, we employ a single row of 400 static vehicles, uniformly distributed along 2000 m. The outcomes of this scenario, after an exhaustive simulation during intervals of 25 s, are shown in Figure 4. As can be observed, the trained PPO and SAC agents lead the vehicles to the desired behavior previously described; that is, the CBR is properly limited to 0.6 by adjusting both transmission power and data rate. Although all the algorithms provide a similar response in terms of channel load, CACC leaves the channel underused with a CBR = 0.4, clearly below the MBL. This may be a consequence of its narrower range of available parameters (transmission power is subject to discrete steps of 0.5 dBm and only 3 and 6 Mbps data rates are available). Moving back to NNDP, on top of CBR control, the data rate is intended to be robust against channel fading so NNDP agents attempt to always set the lowest rate while the channel load is successfully limited. Such an effect is illustrated by NNDP SAC at the end of the road, where there is less congestion, and therefore, lower data rates are used. Instead, NNDP PPO chooses not to vary the data rate and to increase transmission power. Note that despite having been trained according to the same rules, each algorithm learns in a different way, which results in different behavior for the vehicles. Higher data rates are allocated by NNDP with regards to CACC while matching the PDR levels. This means that more information has been shared among vehicles so better context awareness



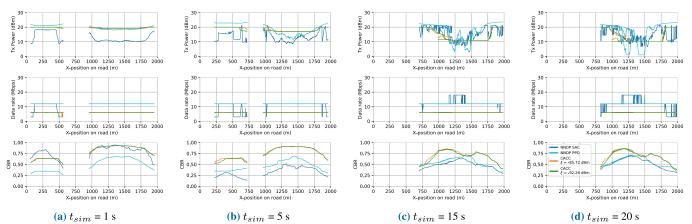


FIGURE 6. Evaluation of different algorithms jointly controlling transmission power and data rates in a realistic traffic jam scenario comprised of two approaching clusters of vehicles. The ongoing progress is described for several simulation times (i.e. 1, 5, 15, and 20 s).

is achieved. Regarding transmission power, it is high enough to satisfy application layer requirements at a certain safety distance ($d_s = 100$ m). More specifically, we seek such received power 100 m away from the transmitter, where the PDR metric is equal to or greater than 0.8, as shown in Figure 5. It should also be pointed out that, on average, NNDP variants reach a similar PDR value to the CACC algorithm, which does not employ any CBR target. This contributes to supporting the idea that 0.6 is a suitable target fraction of channel utilization.

B. TWO RANDOMLY DISTRIBUTED MOVING CLUSTERS

The robustness of NNDP is thoroughly tested in a realistic scenario in which the assumption related to channel load is not satisfied. In this situation, vehicles are not evenly spaced so channel load similarity between close vehicles does not hold. Unlike the first scenario, we employ two different clusters of vehicles bounded within a 500 m and 1000 m long road section, respectively, and located 450 m away from each other. The vehicles are also randomly located in a row in a Poisson distribution of average density $\rho = 0.2$ and 0.4 vehicles per meter, respectively. This results in the first cluster (A) being comprised of approximately 100 vehicles located from 0 to 500 m, an empty road section from 500 to 950 m, and the second cluster (B) composed of about 400 vehicles distributed along the next 1000 m (950 to 1950 m). A realistic traffic jam scenario is represented, in which all the vehicles are heading in the same direction. The vehicles located in the front of cluster A are approaching, supposing free flow, the rear of cluster B. For this purpose, the speed of cluster A is 40 mps, which is considerably higher than the maximum permissible speed of 34 mps, whereas vehicles in cluster B are moving very slowly (2 mps).

This dynamic scenario certainly requires an adaptation of the transmission parameters throughout the entire simulation time to alleviate congestion. For instance, cluster A is lightly congested at the beginning, and this congestion increases as it approaches the second cluster (B). We simulate this scenario for 25 seconds until both clusters come together, increasing vehicle density and provoking channel congestion. Under this premise, all the compared algorithms attempt to reduce channel congestion, mainly by decreasing transmission power, although they show slightly different behavior. As illustrated in Figure 6, both NNDP PPO and NNDP SAC alleviate channel congestion properly by maintaining the CBR around 0.6-0.7. Conversely, CACC exceeds this desired CBR range during the entire simulation time, which would jeopardize the delivery of event-related messages broadcast in emergency cases. Meanwhile, the data rate is set at a constant 6 Mbps by the CACC algorithm. In contrast, NNDP agents better exploit data rate usage, which, acting together with the transmission power, notably reduces channel congestion. However, the NNDP SAC approach attempts to lower the data rate to provide transmissions with more robust modulations. Since the main priority of NNDP is to reduce congestion, this is only possible when the channel is not congested. In fact, when the two clusters join and congestion drastically increases, NNDP SAC increases the data rate to avoid reducing transmission power too much and to maintain PDR levels. As shown in the previous scenario, NNDP PPO is an algorithm that tries to not vary the data rate in a similar way as CACC. The only difference is that, in NNDP PPO the MBL is satisfied through sharp decreases in transmission power, as shown at $t_{sim} =$ 15 and 20 s. As regards the PDR, the bar plot of Figure 7 reveals similar performance to the CACC algorithm. The PDR has been averaged for the entire simulation time and for all the vehicles. This is largely due to the fact that the scenario is now moving, and a more global and robust perspective is required. The standard deviation is included for 10 different distances from 50 to 500 m. In essence, the results obtained illustrate that our proposal attains a similar PDR to CACC. However, NNDP clearly improves it at long distances both for NNDP PPO and NNDP SAC. This means that transmitted beacons reach the farthest neighbors with higher probability, which makes the vehicles aware of risks earlier (e.g., jams).

C. ROBUSTNESS AGAINST ATTENUATION

Despite being trained for certain channel conditions, as stated in Section III, the goal is to demonstrate that NNDP works

well even when these conditions vary. To do this, different path loss exponents are tested to verify the robustness of NNDP beyond the training conditions. As described in Algorithm 1, channel load is represented by vehicle density, which is derived from the number of neighboring vehicles divided by twice the average carrier sense range. The carrier sense range depends greatly on channel conditions so it should be updated over time to provide the most accurate estimation. The shape parameter m and the path loss exponent β characterize the severity of fading and attenuation, respectively, whereas the sensitivity of the receiver and the frequency of the carrier remain constant. The shape parameter barely varies vehicle density since the gamma functions in both the numerator and denominator are compensated and, in the remaining terms, the influence of m is almost negligible with regards to changes of the exponent $1/\beta$, as shown in equation 1. Indeed, this is why the path loss exponent β takes a more important in vehicle density estimation than m. This can also be inferred from the results obtained in the simulation of the CACC algorithm [20]. Keeping this premise in mind, we evaluate the previous moving scenario IV-B for different path loss exponent values to demonstrate that the proposed NNDP works properly.

The results achieved are illustrated in Figure 8, employing bar plots and averaging throughout the entire simulation time. Firstly, the carrier sense range is remarkably high when the value of β is set to 2.25, which is considered close to free space attenuation. In this scenario, vehicles receive messages from more vehicles separated by large distances so the channel load increases rapidly. Under these circumstances, all the compared approaches reduce transmission power. Particularly, as congestion increases, NNDP SAC raises the data rate to transmit faster and thus reduces the beaconing load. Conversely, NNDP PPO and CACC keep constant data rates of 12 and 6 Mbps, respectively. The CBR is properly adjusted to the MBL by both NNDP algorithms and, as occured in the previous scenarios, the CACC solution results in a much more congested channel. This could threaten the delivery of event-related messages triggered in emergency situations. Concerning the PDR at 50 m, similar values are obtained by each one of the algorithms analyzed. The rest of the distances, which are not shown in Figure 8, are aligned with the results previously provided for $\beta = 2.5$ in Figure 7. Moreover, as β increases ($\beta = 2.75$), channel attenuation is higher, which (i) reduces the average carrier sense range and, in turn, (ii) senses a fewer number of neighboring vehicles. In this context, the CACC algorithm remains indifferent in terms of data rate, while NNDP and, in particular, the SAC agent, decides to reduce the data rate, resulting in greater robustness over attenuation. This is immediately reflected by reaching a higher PDR. Given less congestion due to higher attenuation, transmission power is slightly increased, which brings the CBR to suitable values. In short, the DNN trained (using both PPO and SAC algorithms) with $\beta = 2.5$ operates appropriately, even when channel conditions vary (i.e. using $\beta = 2.25$, 2.75). NNDP behaves similarly to CACC, which does not

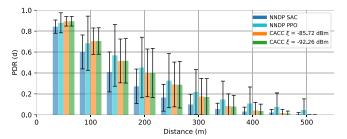


FIGURE 7. The PDR versus distance for two approaching clusters.

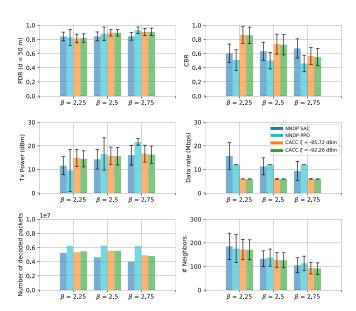


FIGURE 8. Comparison of NNDP and CACC for different path loss exponents and for two approaching clusters.

depend on channel conditions (β). In fact, it is worth noting that our proposed mechanism not only alleviates congestion but also supports the transmission of information much faster while reaching a similar PDR and greater throughput (total number of decoded packets) than CACC. In other words, NNDP obtains a similar PDR to CACC but with greater throughput and employing higher data rates, which results in improved channel availability for DENM messages (lower CBR).

V. CONCLUSION

Vehicular communications support the transmission of real-time periodic messages (beacons), which allow vehicles to be aware of their changing environment. Most of the safety applications which are conceived to guarantee driver and passenger protection are based on the information exchanged by beacons. However, an increase in beaconing loads may result in higher packet loss and compromise the appropriate functioning of these applications. Therefore, the design of effective congestion control mechanisms, while maintaining a certain fraction of the channel free, is essential for the successful delivery of messages, especially those triggered under emergency incidences. In this paper, we propose an innovative congestion control mechanism that simultaneously tunes



transmission power and data rate parameters. Since the associated optimization problem is not convex, ordinary optimization methods are usually inapplicable. Instead, we employ different Deep Reinforcement Learning algorithms.

The proposed mechanism, called NNDP, alleviates congestion in a non-cooperative way, without requiring any additional information from neighbors or centralized infrastructure. Simulation results reveal that NNDP (i) successfully keeps channel loads at the desired levels, leaving channel capacity free enough for successful DENM reception. Once congestion is alleviated, NNDP is intended to (ii) prevent transmission power from reducing too much, guaranteeing a given packet delivery ratio at a certain distance, and (iii) setting the most robust data rate against fading and attenuation whenever possible. Despite being a non-cooperative scheme, all vehicles are geared toward the same goal, which successfully alleviates congestion while reaching higher throughput (number of decoded packets) and a similar PDR to other related mechanisms. The proposed solution operates reasonably well, even in conditions that differ notably from those used in the training environment. Our future work will focus on the study of its cost-effective implementation and improved capabilities to allow the algorithms to learn while driving. Other transmission parameters dependent on the particular hardware of vehicles and their effect on the MAC layer will be also studied.

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ests include vehicular networks and MAC protocols.

Part IV Conclusions and future work

Conclusions and future work

Overview of the problem relevance

Vehicular communications are envisioned to be a crucial element in the development of driver assistance systems and safety-related applications. Many of these safety applications are supported by beacons, responsible for disseminating status and environmental information among vehicles and thus reducing the risk of collision or other undesired events. However, if the amount of beacons increases too much, the aggregated load can easily saturate the channel, compromising packet reception, and therefore endangering vehicle situation awareness. Outdated and inaccurate information might make safety applications and services stop working properly. To guarantee the delivery of beacons enough to satisfy safety application requirements, as well as messages of other services, like emergency-related messages (DENM), a certain fraction of the channel capacity should be available. Some technical challenges are still unsolved regarding how congestion could be alleviated optimally. For instance, several transmission parameters can be jointly varied over time according to channel requirements and how much is it congested. In this thesis dissertation, we mainly study how to dynamically adapt different transmission parameters to control congestion, individually or combining two or more simultaneously. Joint control prevents excessive variations of the transmission parameters while alleviating congestion, which has a detrimental impact on the safety application performance and context awareness of the vehicles. Since joint adaptation is usually a non-convex optimization problem and ordinary optimization methods are ineffective, we apply artificial intelligence techniques (reinforcement learning) in a bid to endow vehicles with a certain intelligence and the capability to assign resources in an optimal way. Depending on whether vehicular communications are based on any kind of infrastructure (V2I) or not (V2V), different advantages and disadvantages will arise. In this work, we defend distributed algorithms (V2V) that do not require any costly infrastructure or base station to work, so that our proposals could be easily deployed in real scenarios from across the world. Finally, some congestion control approaches require including additional information within the transmitted messages to work properly. If channel conditions are unfavorable and some packets are lost, the congestion control itself could be also affected. We also study the paradigm of non-cooperative algorithms, in which vehicles do not require information from neighboring vehicles to carry out that congestion alleviation.

Summary of contributions

In this section, we summarize the contributions of this thesis, which can be divided into two parts.

In the first part, we bring congestion control and awareness control together. This means not only to control the channel load but also prioritize vehicles somehow, for instance, according to the requirements of the safety applications and/or danger on the road. In Chapter 3, we have formulated the beaconing rate control as a NUM problem, in which the channel congestion was optimally controlled and prioritized as a function of the time-to-collision (TTC) metric. Our numerical results showed that the lower the TTC, the higher the risk and therefore, a higher beaconing rate is allocated. Conversely, vehicles with low risk and unlikely to collide maintain lower their beaconing rate but keeping them as high as possible to guarantee the best packet delivery possible. This algorithm, called TTCC, (stemming from the risk metric embedded in the congestion control) was compared with its predecessor and CAM-DCC, which defines different CAM generation rules in the standard. While implementing this latter algorithm, we realized their drawbacks and lacks, so we further studied it in Chapters 4 and 5.

In Chapter 4, we address some issues of the Cooperative Awareness Message (CAM) dissemination, stated in the European Standard EN 302 637-2 [7]. This mechanism, called CAM-DCC, alleviates congestion by setting some CAMs generation rules and mechanisms dependent upon vehicle kinetics. However, instead of using the maximum beaconing rate (10 Hz) whenever there is no congestion, CAM-DCC sets the minimum rate (1 Hz). From our point of view, there is no point in keeping the channel underused. We study more profoundly the awareness control of this standardized mechanism and do further research related to prioritization. In uncongested scenarios, the default CAM dissemination mechanism of the ETSI standard underuses the channel. The amount of data supplied to the safety applications and therefore its proper operation could be drastically improved by increasing the number of transmitted messages. This is especially important in those situations under which vehicles are subject to risks and require being aware of their environment more carefully. Winding roads usually imply low vehicle dynamics when curves are traversed, but become dangerous as vehicles surpass the advisory speed. Therefore, we evaluate the performance of the EN 302 637-2 dissemination mechanism in risky sharp bends and winding roads. We propose a novel triggering condition based on the dynamic estimation of the road radius, used as a risk metric. In this way, the lower the radius, the higher the risk while driving, and consequently, a high beaconing rate could help to prioritize the transmission of information of such vehicles.

Then, we take a step forward in Chapter 5, employing the difference between the vehicle speed and the estimated advisory speed over time. In particular, we first derive the radius of curvature of the road, to later apply some common road design rules, from which the advisory speed is obtained for a given road section. Then, the proposed approach generates a new message whenever the vehicle's current speed overcomes the advisory one.

The success of the previous chapters, which addressed beaconing rate adaptation, in reducing congestion by decreasing the number of transmitted messages is clear. However, in high congested scenarios, the beaconing rate shall be drastically reduced, therefore degrading situation awareness and vehicle safety. In addition to beaconing rate, numerous studies have also studied the transmission power adjustment to control congestion. Instead of using transmission parameters individually to handle congestion, more advanced proposals combine two or more simultaneously. This avoids excessive changes in transmission parameters, therefore easing the proper operation of the safety applications requirements. Nonetheless, joint parameter control is no longer a convex optimization problem and entails employing heuristic algorithms instead of ordinary optimization methods.

In the second part, we delve into non-cooperative algorithms and artificial intelligence to allocate resources optimally. In Chapter 6, 7, and 8, we formulate the congestion control as a Markov Decision Process (MDP), and solve it using different reinforcement learning techniques.

More to the point, in Chapter 6, we propose a novel control congestion based on joint beaconing rate and transmission power adaptation. To optimally balance the available channel load between both parameters, we model a Markov Decision Process (MDP). To this end, a set of simplifying assumptions are applied to obtain a transition model, actions, and states within the complex road environment. This MDP characterization, denoted as MDPRP, was later solved using Q-learning techniques. The proposed algorithm MDPRP is non-cooperative, not requiring additional information from neighbors. This makes it suitable to be deployed in a distributed fashion in infrastructure-less (ad-hoc) networks. The results obtained show that MDPRP leads the channel load to the optimal MBL, which, in turn, improves the packet delivery ratio. Finally, the robustness of MDPRP is also proved since the algorithm works well even when the assumptions made are no longer available.

Then, as an intermediary step towards the full use of artificial neural networks as value function approximation in reinforcement learning, we come back to the simpler beaconing rate control problem and apply *on-policy control with function approximation* in Chapter 7. Unlike tabular solutions (Q-learning), function approximation allows us to generalize previous states to derive sensible decisions when new states are encountered. The resulting parameterized model can be applied by vehicles so the most appropriate beaconing rate is arrived at very efficiently in terms of runtime and computational cost, which is of great importance in congested scenarios.

Finally, in Chapter 8, we apply the *Deep Reinforcement Learning (DRL) framework to alleviate channel congestion through optimizing data rate and transmission power simultaneously.* Even though the IEEE 802.11p standard defines 9 different data rates, as shown in Table A.1, 6 Mbps is usually recommended and set by default, while varying transmission power or beaconing rate. Nonetheless, there is no reason not to control congestion by dynamically varying data rates. After making some reasonable assumptions, we train a single Deep Neural Network (DNN) whose resulting model is loaded into the vehicles of the network. Since every vehicle is geared toward the same goal, they converge to a proper congestion level. This mechanism not only prevents us from tackling with multi-agent approaches, complicated to

train and deploy, but also from training using any simulator or real implementations with enormous computing times. The proposed mechanism denoted Neural Network for Data rate and transmission Power (NNDP) alleviates overall congestion while assuring a certain packet delivery ratio and the most robust data rate possible.

Future lines of research

We believe the contributions and results of this thesis will be useful for the development of intelligent transportation networks and systems. The congestion control problem has been extensively studied: we have proposed effective methods to dynamically adapt most of the meaningful combinations of transmission parameters. However, there are still numerous research gaps:

- As expected, the simultaneous combination of beaconing rate, transmission power, and data rate is still unexplored. Since this three-parameter problem is not convex, the RL algorithms addressed in this thesis would be useful to find optimal solutions.
- The beaconing rate adaptation is mature in V2V communications. Nevertheless, future connected driving proposals will extend the upper limit of 10 Hz to 50 Hz at the expense of more strict latency requirements. These new conditions and the latency control together with the congestion control will also give rise to numerous research opportunities and applications.
- · Although the non-cooperative mechanisms proposed to control congestion work well, the employment of multiple agents (Multiple Agent RL) could be also explored to alleviate congestion, and then, to control latency and congestion in cooperative driving problems, as mentioned above.
- The IEEE 802.11p standard is undergoing numerous improvements to support advanced vehicle applications in terms of reliability, low latency, and high throughput. As a future research line, it is necessary to reevaluate the needs and requirements of congestion control for this new version called IEEE 802.11bd [78].
- The IEEE 802.11p coexists with Cellular V2X (C-V2X) communications and its corresponding evolution: 5G NR V2X. Coordinating the resource allocation of the base station and the transmission parameters of the vehicles within the coverage area is also an interesting research line.
- Finally, the appropriate selection between the latter two Radio Access Networks (802.11bd or 5G) in multi-access devices (Multi RAT) is also an interesting field of study for the optimal control of latency, congestion, and awareness.

Part V Appendices

APPENDIX A

Quality metrics

TABLE A.1: Quality metrics of the scientific outcomes derived from this thesis. Source: Journal Citation Reports™

Title	Journal and Editorial	Accepted	IF (Released)	JIF Quartile
"Time-to-Collision-Based Awareness and Congestion Control for Vehicular Communications"	IEEE Access, IEEE	19-0ct-2019	3.745 (Jun-2019)	35/156 01 ¹ 61/266 01 ²
"MDPRP: A Q-Learning Approach for the Joint Control of Beaconing Rate and Transmission Power in VANETs"	IEEE Access, IEEE	06-Jan-2021	3.367 (Jun-2021)	65/162
"Simultaneous Data Rate and Transmission Power Adaptation in V2V Communications: A Deep Reinforcement Learning Approach"	IEEE Access, IEEE	26-Aug-2021	3.367 (Jun-2021)	65/162
"Approximate Reinforcement Learning to Control Beaconing Congestion in Distributed Networks"	Scientific Reports, Nature	16-Dec-2021	4.379 (Jun-2021)	17/73 01 3

¹ Computer Science, Information Systems; ² Engineering, Electrical and Electronic; ³ Multidisciplinary sciences.

Other contributions

During the development of this thesis, the doctoral candidate has also contributed to the field of electronics and electrochemical sensing with numerous high-impact journal articles and renowned conferences:

- Aznar-Poveda, J., Lopez-Pastor, J. A., Garcia-Sanchez, A. J., Garcia-Haro, J., Fernández Otero, T. (2018, February). A COTS-Based Portable System to Conduct Accurate Substance Concentration Measurements. Sensors 18 (2), 539.
 DOI: 10.3390/s18020539
- Serafín, V., Martínez-García, G., Aznar-Poveda, J., Lopez-Pastor, J.A., Garcia-Sanchez, A.J., Garcia-Haro, J., Campuzano, S., Yáñez-Sedeño, P., Pingarrón, J.M. (2019, February). Determination of Progesterone in Saliva Using an Electrochemical Immunosensor and a COTS-Based Portable potentiostat. Analytica chimica acta 1049, 65-73.
 DOI: 10.1016/j.aca.2018.10.019
- Serafín, V., Arévalo, B., Martínez-García, G., Aznar-Poveda, J., Lopez-Pastor, J.A., Beltrán Sánchez, J.F., Garcia-Sanchez, A.J., Garcia-Haro, J., Campuzano, S., Yáñez-Sedeño, P., Pingarrón, J.M. (2019, November). Enhanced Determination of Fertility Hormones in Saliva at Disposable Immunosensing Platforms Using a Custom Designed Field-Portable Dual Potentiostat. Sensors and Actuators B: Chemical 299, 126934.
 DOI: 10.1016/j.snb.2019.126934
- Lopez-Pastor, J. A., Martínez Sánchez, A., Aznar-Poveda, J., Garcia-Sanchez, A. J., Garcia-Haro, J., Aguayo, E. (2020, January). Quick and Cost-Effective Estimation of Vitamin C in Multifruit Juices using Voltammetric Methods. Sensors 4 (20), 676.
 DOI: 10.3390/s20030676
- Serafín, V., Arévalo, B., Beltrán Sánchez, J.F., Aznar-Poveda, J., Lopez-Pastor, J.A., Garcia-Sanchez, A.J., Garcia-Haro, J., Campuzano, S., Yáñez-Sedeño, P., Pingarrón, J.M. (2021, July). Simultaneous determination of four fertility-related hormones in saliva using disposable multiplexed immunoplatforms coupled to a custom-designed and field-portable potentiostat. Analytical Methods 13 (31), 3471-3478.

DOI: 10.1039/D1AY01074C

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