Prioritizing Relevant Information: Decentralized V2X Resource Allocation for Cooperative Driving

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ABSTRACT Cooperative driving is a promising approach to increase traffic efficiency and safety. However, cooperative driving requires high communication performance from the application perspective when coordinating and executing a cooperative maneuver, especially in scenarios with high vehicle densities under congested channel conditions. Recent studies identified that content-agnostic congestion control mechanisms deployed in decentralized vehicular networks, e.g., from the European Telecommunications Standard Institute, maintain the radio communication performance under congested channel conditions but can severely degrade the communication performance from the application perspective. In this paper, we propose a collaborative resource allocation mechanism with content-aware congestion control for decentralized vehicular networks that prioritizes vehicles with relevant information under congested channel conditions. Our evaluation results show that our proposed approach maintains the radio communication performance and significantly increases the communication performance from the application perspective compared to content-agnostic congestion control mechanisms.

INDEX TERMS V2X communication, resource allocation, decentralized networks, congestion control, information relevance, cooperative driving

I. INTRODUCTION

THE number of vehicles has grown over the past years and is expected to continue growing in the future [1]. Therefore, traffic jams become more severe, especially in urban areas and on highways [2]. As a result, traffic efficiency, in addition to safety, gets increasingly important [3] to reduce or even avoid traffic jams.

In this context, Vehicle-to-Everything (V2X) communication constitutes an important research area to increase traffic efficiency and safety for both human-driven and autonomous vehicles [4], [5]. V2X extends the environment’s perception beyond the vehicle’s local sensor perception by combining information perceived by the vehicle’s sensing capabilities with information received from other vehicles [6].

As a next step, V2X enables cooperative driving to optimize traffic efficiency on the road by improving traffic flows, i.e., the exchange and cooperative coordination of driving maneuvers [7]. Cooperative driving can be organized in a centralized [8] or decentralized [9] way. In this paper, we focus on decentralized cooperation. The reason is that decentralized cooperation distributes the computation among the vehicles, is independent of infrastructure, and maintains the driving autonomy at the vehicle, i.e., the vehicle is responsible for requesting, granting, or denying cooperation.

As proposed in [9], we assume that vehicles continuously broadcast their future driving intentions to nearby vehicles using planned trajectories. The increased local awareness already enables implicit coordination of driving maneuvers: Vehicles can identify and use a gap in a traffic flow to improve traffic efficiency. If there is no sufficiently large
gap, vehicles can explicitly request cooperation by sending additional desired trajectories and asking other vehicles to adjust their planned trajectories to improve the traffic flow. However, the channel resources of communication networks are limited. The channel congestion increases with an increasing number of exchanged messages required to coordinate a cooperative maneuver. In scenarios with high vehicle densities, the communication channel will frequently be congested [10]. The resulting degradation of the radio communication performance negatively impacts the application performance of cooperative driving because of insufficient channel resources and message collisions [11].

On the application level, different resource allocation mechanisms have been proposed to send messages depending on the respective content of the vehicle’s message. For example, the European Telecommunications Standard Institute (ETSI) defines a resource allocation mechanism for Cooperative Awareness Messages (CAMs) [12] depending on the dynamics of the vehicle. Further, the authors in [13] propose resource allocation mechanisms for cooperative driving depending on the collision risk of vehicles. The proposed V2X resource allocation mechanisms mentioned above are content-aware and aim to fulfill the communication requirements of their respective V2X applications. However, these V2X resource allocation mechanisms solely operate on the application level and do not adapt to the communication channel conditions. Thus, current V2X resource allocation mechanisms on the application level cannot counteract channel congestion to mitigate a severe degradation of the radio communication performance.

On the communication level, different mechanisms and algorithms for Decentralized Congestion Control (DCC) have been proposed [14], [15] to tackle channel congestion in decentralized V2X networks. The ETSI proposes Reactive Decentralized Congestion Control (R-DCC) and Adaptive Decentralized Congestion Control (A-DCC) [16] to counteract channel congestion. Sepulcre et al. show that R-DCC and A-DCC improve radio communication performance under congested channel conditions [17]. However, both approaches degrade the V2X communication performance from the application perspective compared to the case without using the ETSI DCC mechanisms in densities up to 180 vehicles/km on a highway. In the considered scenario, DCC cannot fully exploit the available channel resources. In addition, DCC on the communication level is content-agnostic and acts as a gatekeeper on the communication level to prevent channel congestion. Hence, DCC cannot consider the dynamic communication requirements of the respective V2X application. Moreover, DCC limits the communication resources of vehicles irrespective of their individual, application-specific communication requirements. However, vehicles coordinating and executing a cooperative maneuver require high radio communication performance and sufficient resources [18].

Our paper addresses this problem with a collaborative resource allocation mechanism for decentralized V2X communication networks that accounts for information relevance at the V2X application level and allocates resources w. r. t. the current channel congestion. We link the radio communication performance (message collisions caused by channel congestion) with application-specific communication requirements (information relevance). More precisely, we define the Accessible Information Relevance (AIR) for decentralized V2X networks. Each vehicle contributes to the network’s AIR with its current information relevance and message frequency. The AIR allows us to formulate an optimization problem for deriving the optimal message frequency of each vehicle in a decentralized V2X network.

Our approach works as follows: Vehicles claim the maximum message frequency while the channel is not congested and their information is relevant. For medium to high vehicle densities, the available channel resources will be exceeded, leading to a degradation of the radio communication performance due to message collisions. In our approach, vehicles with low relevant information reduce their message frequencies to decrease channel congestion and improve radio communication performance. In contrast, vehicles with high relevant information claim the maximum message frequency to increase the probability of delivering relevant information to other vehicles in time. That way, vehicles collaboratively increase the network’s AIR because vehicles with low relevant information prioritize vehicles with highly relevant information.

In this paper, we use ETSI ITS-G5 with IEEE 802.11p on the access layer and discuss the computation of information relevance for cooperative driving. We assume that our approach can be extended to any decentralized V2X communication technology and different V2X applications to improve the communication performance from the radio and especially the application perspective.

Overall, we contribute the following:

- We extend Bianchi’s 802.11 Markov Chain model [19] to safety broadcast messages under non-saturated heterogeneous conditions for 802.11p Enhanced Distributed Channel Access (EDCA).
- We formulate an optimization problem that describes the AIR in a decentralized V2X network to maximize relevant information w. r. t. channel congestion.
- We derive content-aware information relevance for cooperative driving messages.
- We perform a numerical analysis of our and reference approaches and compare the communication performance from the radio and application perspective in simulations.

The numerical evaluation results show that our approach maximizes the network’s AIR and presents a fast convergence to the vehicle’s optimal message frequency to maximize the communication performance from the application perspective. We also confirm that our approach maximizes the network’s AIR in simulations, deploying a cooperative driving V2X application under congested channel conditions. The structure of this paper is as follows: In Section II,
we describe our considered scenario and briefly recap the fundamentals of EDCA for 802.11p. We outline our problem description in Section III. In Section IV, we extend Bianchi’s 802.11 Markov Chain model, formulate our optimization problem using the network’s AIR, and describe our resource allocation mechanism for decentralized V2X networks. We analyze the computational complexity of our approach, propose an approximate Packet Delivery Ratio (PDR) model, and discuss information relevance for cooperative driving in Section V. Section VI focuses on the evaluation framework, providing details on the experimental setup and validating our numerical results with simulations. We compare the performance of our approach with reference approaches in a numerical and simulation evaluation in Section VII. In Section VIII, we discuss related work, its limitations, and emphasis on the contributions provided by the work at hand. Finally, Section IX summarizes and concludes the paper.

II. SYSTEM MODEL

In this paper, we propose a novel decentralized Vehicle-to-Everything (V2X) resource allocation mechanism for cooperative driving and apply it to European Telecommunications Standard Institute (ETSI) ITS-G5. For this purpose, we describe our considered urban intersection scenario, where cooperative driving is required to improve traffic efficiency. Furthermore, we outline our V2X communication setup.

A. SCENARIO

Let us consider an urban intersection with four arms, where vehicles can approach from all four directions. Figure 1 depicts a representative urban intersection [21], located in Aschaffenburg, Germany, where traffic lights control each arm. We consider a 3000 m × 3000 m section of the urban scenario. The intersection, depicted in Figure 1, is located at the center of our considered urban scenario.

In this paper, we focus on one specific scenario extracted from real traffic measurements in [22]. As depicted in Figure 1, vehicles approach from the north-west and south-east and wait at a red light. At a green light, vehicles from the north-east drive straight and vehicles from the south-west drive straight or turn left. In the evaluation, the traffic lights will not switch their state such that we remain with the specific scenario described before.

We measured the number of vehicles perceived by the Roadside Unit (RSU) in the center of the intersection within an interference range of 1500 m using the traffic simulator Simulation of Urban Mobility (SUMO) [20] and the network simulator OMNeT++ [23]. The average number of vehicles within the interference range of the RSU is approximately 150 vehicles for the parameters introduced in Table 1.

Let us assume that our Ego vehicle in Figure 1 wants to turn left in the intersection during such a congested scenario. Typically, the Ego vehicle must decelerate and wait in the intersection for the traffic flow from the north-east to end. Instead, our Ego vehicle can ask other vehicles approaching from the north-east for cooperation to avoid waiting in the intersection. A Cooperative Vehicle (CV) from the north-east can share its willingness to cooperate via V2X communication. The CV can prevent the requesting Ego vehicle from waiting in the intersection by slowing down and opening a sufficiently large gap to preceding vehicles.

Let us assume that the Ego vehicle in Figure 1 requests cooperation to turn left. However, the maneuver cannot be coordinated because of a congested communication channel, causing poor radio communication performance. If the cooperative maneuver coordination fails because of poor radio communication performance, the Ego vehicle waits in the intersection for an open gap. Consequently, all subsequent vehicles on the same lane have to stop and wait as well. Thus, the intention to cooperate with other vehicles in the intersection is relevant for the Ego vehicle to turn left and for all subsequent vehicles from the south-west to avoid a traffic jam. In this work, we argue that the information required to coordinate a cooperative maneuver is even more relevant than information from, e.g., the vehicles that drive straight with a low risk of interference by other vehicles.

In summary, cooperative driving requires content-aware communication resources, where poor radio communication performance can negatively impact traffic efficiency.

B. V2X COMMUNICATION

Cooperative driving leverages V2X communication to coordinate and execute a cooperative maneuver for increasing traffic efficiency and safety. In the following, let us formulate our assumptions for V2X communication and recap ETSI ITS-G5 on the access layer.

1) Assumptions

Vehicles periodically broadcast their planned and (if necessary) desired trajectories following the decentralized approach for cooperative driving in [9]. Vehicles send messages in one dedicated communication channel using Single-Hop Broadcast (SHB), i.e., no multi-channel operation, without multi-hop forwarding. As a result, the communication re-
sources are limited to only one channel and vehicles cannot extend their communication range by forwarding messages via other vehicles.

In this paper, all vehicles are equipped with V2X communication and solely operate on the cooperative driving V2X application and the respective facility to send messages within the dedicated communication channel. Additional applications and facilities operating in the same communication channel would further increase channel congestion and increase the need for a content-aware decentralized resource allocation mechanism, such as proposed in this paper.

A vehicle $n$, with $n \in \{1, ..., N\}$ and $N > 1$ denotes the number of vehicles, sends messages with the message frequency $\lambda_n$. The minimum and maximum vehicle message frequencies are denoted as $\lambda_{\text{MIN}}$ and $\lambda_{\text{MAX}}$, respectively. The message frequency $\lambda_n$ is limited for each vehicle $n$, where $\lambda_{\text{MIN}} \leq \lambda_n \leq \lambda_{\text{MAX}}$.

2) ETSI ITS-G5

ETSI ITS-G5 uses 802.11p on the access layer, where the transmission of messages is slotted in the time domain [24]. 802.11p deploys Enhanced Distributed Channel Access (EDCA) on the Medium Access Control (MAC), extending Distributed Coordination Function (DCF) with Quality of Service (QoS) categories for message scheduling [25].

A message from the V2X application arriving at the MAC is immediately sent if the channel was sensed idle for at least the Arbitration Inter-Frame Spacing (AIFS) time $T_{\text{AIFS}}$. If the channel is sensed busy, EDCA goes into one randomly chosen backoff stage, where we have $W$ backoff stages depending on the selected QoS Access Category (AC). In SHB mode, messages are not queued and the maximum number of backoff stages is not increased if the channel is sensed busy [25]. EDCA decrements its backoff counter by one every time the channel is sensed idle for the channel slot time $T_{\text{CH,S}}$. A vehicle sends a message when the respective message is waiting at the MAC, the channel is idle, and the backoff stage is zero. After a successful transmission, EDCA goes into a randomly chosen post-backoff stage to avoid a subsequent message from the same vehicle being sent immediately after its last message.

The behavior of 802.11 DCF has been modeled in [19] using a time-discrete Markov Chain, representing a vehicle’s backoff stage $b$. In [26], the authors propose a heterogeneous DCF model to account for different vehicle message frequencies. The authors in [27] proposed an EDCA model for unicast mode and multiple ACs. In Section IV, we extend the DCF model proposed in [19], the heterogeneous DCF model in [26], and the EDCA model in [27] to describe EDCA in SHB mode under non-saturated conditions for safety messages of the highest access category $\text{AC}_\text{VO}$ with a post-backoff stage after sending a message [25]. Our system model also differs from the work mentioned above because we only transition to the next (post-)backoff stage when the channel is idle.

III. PROBLEM DESCRIPTION

Recently proposed Vehicle-to-Everything (V2X) applications such as collective perception and cooperative driving can increase traffic safety and efficiency under congested vehicle traffic conditions [9], [28]. However, these V2X applications require high radio communication performance [18]. In traffic scenarios with high vehicle densities, the radio communication performance severely degrades because the channel resources are limited and the channel gets congested. On the communication level, LInear MEssage Rate Integrated Control (LIMERIC) [29], an approach adopted from the European Telecommunications Standard Institute (ETSI) for Adaptive Decentralized Congestion Control (A-DCC) [16], limits the message frequency of each vehicle in a decentralized V2X network. This way, a predefined target Channel Busy Ratio (CBR) should not be exceeded. At the target CBR, the number of message collisions is considerably low such that LIMERIC and ETSI A-DCC achieve high channel throughput. Thus, LIMERIC and ETSI A-DCC achieve fairness in terms of an equal distribution of the channel resources among all vehicles in the communication channel.

The authors in [17] conclude that ETSI Decentralized Congestion Control (DCC) negatively affects the V2X communication performance from the application perspective. In their study, ETSI DCC limited the number of sent messages of each vehicle more than required compared to a Naïve approach. The Naïve approach sent messages with the highest message frequency without any congestion control mechanism, accepting message loss due to collisions and degrading the radio communication performance. However, the Naïve approach increased the number of received messages on the application level because messages were not limited on the communication level. That way, ETSI DCC was outperformed by the Naïve approach w.r.t. the communication performance from the application perspective.

On the application level, the communication requirements depend on the message content [30]. Therefore, the message frequency can be limited at the application level creating the messages. However, current approaches on the application level still require congestion control mechanisms such as ETSI DCC to counteract a degradation of the radio communication performance caused by channel congestion [12].

In summary, resource allocation in a decentralized V2X network poses significant challenges: i) V2X applications such as cooperative driving require content-aware channel resources, e.g., only a few vehicles will coordinate a cooperative maneuver in an intersection. Thus, limiting the message frequency of all vehicles to guarantee a fair and equal distribution of channel resources, e.g., as provided by ETSI A-DCC, may harm the communication performance from the application perspective. ii) The overall performance of traffic safety and efficiency V2X applications decreases with a degrading radio communication performance, typi-

1The study considered both ETSI Reactive Decentralized Congestion Control (R-DCC) and A-DCC [16].
ually under highly congested channel conditions. DCC on the communication level acts as a gatekeeper and limits the vehicle’s message frequency to improve the radio communication performance irrespective of application-specific communication requirements. We argue that resource allocation and congestion control cannot be solved decoupled on the application and communication levels because we need to consider the application-specific communication requirement and maintain the radio communication performance. iii) Resource allocation mechanisms targeting cooperative driving are still an open topic in the related work.

We propose a novel resource allocation mechanism that collaboratively maximizes the Accessible Information Relevance (AIR) in a decentralized V2X network, considering the information relevance of messages and the current channel congestion. The idea is that each vehicle’s message has content-dependent information relevance to other vehicles in its vicinity. A vehicle wants to send as many messages as required to satisfy its individual, application-specific communication requirements and allow relevant messages to reach other vehicles in time. However, if a vehicle increases its message frequency, it decreases the reliability (or Packet Delivery Ratio (PDR)) of other vehicles sending relevant messages in the respective communication channel. Following our approach, a vehicle can decide if it is worth increasing its message frequency based on its current information relevance while being aware of the current channel congestion and other vehicles’ information relevance. However, by increasing its message frequency, a vehicle accepts to decrease the PDR of other vehicles sending in the same communication channel. Therefore, a vehicle can also decrease its message frequency to prioritize other vehicles’ information. In this paper, we also discuss our approach to obtain information relevance for cooperative driving and apply it to our proposed resource allocation mechanism.

IV. SYSTEM DESIGN

In this chapter, we describe our numerical heterogeneous 802.11p Enhanced Distributed Channel Access (EDCA) model for safety messages using the Single-Hop Broadcast (SHB) mode. Further, we propose our decentralized resource allocation mechanism, which aims to prioritize relevant information and simultaneously considers the current channel congestion to improve the communication performance from the application perspective. Our approach incorporates the Packet Delivery Ratio (PDR) obtained from our proposed numerical heterogeneous EDCA model to optimize the vehicle’s message frequency w.r.t. the current channel congestion and information relevance of vehicles. For this purpose, we formalize the Accessible Information Relevance (AIR) to account for each vehicle’s message frequency and information relevance. After that, we explain how we adjust each vehicle’s message frequency to achieve convergence w.r.t. content-aware resource allocation in a decentralized Vehicle-to-Everything (V2X) network.

A. NUMERICAL HETEROGENEOUS EDCA MODEL

In the following, for the tractability of this model, we neglect hidden terminals [31], path loss, and assume constant propagation delay $T_{PD}$ of messages. We analyze the impact of these effects on the performance of our approach in our simulation evaluation in Section VI.

Let $b_k$ denote the current backoff stage, where $k \in \{0, \ldots, W-1\}$ is the current backoff stage. The post-backoff stage is denoted as $b_{P,k}$. We need to obtain the probability $\tau_n$ that a vehicle $n$ sends a message in a randomly chosen time slot [19]. Let $q_n$ denote the probability for vehicle $n$ that a message is waiting at the Medium Access Control (MAC) and let $p_B$ denote the probability that the channel is busy. A vehicle sends a message in stage $b_{-1}$. Stage $b_{-1}$ is reached if the vehicle transitions from the idle stage $b_1$ (we have finished the post-backoff stage), has a message ready to be sent, and the channel is idle, as depicted in Figure 2. We can use the stage $b_{-1}$ to obtain the probability $\tau_n$ that a vehicle $n$ sends a message in a randomly chosen time slot and get

$$\tau_n = \frac{2q_n(1-p_B)}{2(1+q_n)(1-p_B)+q_n(1+p_B)(W+1)}.$$  \hspace{1cm} (1)

The derivation of $\tau_n$ can be found in the appendix.

The probability that the channel is busy can be expressed as the counter probability that no vehicle sends in a randomly chosen time slot, giving

$$p_B = 1 - \prod_{n=1}^{N} (1-\tau_n).$$  \hspace{1cm} (2)

Hence, we can obtain the probability that the channel is idle as $p_I = 1 - p_B$.

Equations (1) and (2) recursively depend on each other, i.e., (1) depends on $p_B$ and (2) depends on $\tau_n$. Therefore, we can compute (1) using a numerical solver. The authors in [19] assume messages arriving at the MAC under saturated conditions, i.e., a message is always available and waiting to be sent, giving $q_n = 1$. However, V2X applications such as cooperative driving generate messages periodically with an individual, finite message frequency $\lambda_n$, i.e., a message is not always available at the MAC to be sent. Therefore, we need to model a vehicle’s load under heterogeneous, non-saturated conditions. For a vehicle $n$, we
obtain the probability $q_n$ that messages are available at the MAC in a virtual time slot $T_{VS}$ with the message frequency $\lambda_n$. $T_{VS}$ is a virtual duration of a time slot, where the channel is busy or idle. We derive $T_{VS}$ later in this section. We use the load equation from [26], assuming that messages arrive at the MAC in a Poisson distribution as

$$q_n = 1 - \exp(-\lambda_n \cdot T_{VS}).$$

(3)

The probability of a successful transmission $p_s$ for all vehicles $N$ following [26] is

$$p_s = \sum_{n=1}^{N} \tau_n \prod_{j\neq n} (1 - \tau_j),$$

(4)

where $\tau_j$ is the probability that a vehicle $j$ with $j \in \{1, ..., N\}$ and $j \neq n$ sends a message in a randomly chosen time slot. The channel can be idle or the channel can be busy with either a successful or collision transmission, i.e., $1 = p_C + p_s + p_t$. Therefore, the probability of a collision transmission is $p_C = 1 - p_s - p_t$, i.e., no vehicle has a successful transmission and the channel is not idle.

For safety messages using the SHB mode, the time required for a successful transmission $T_S$ and collision transmission $T_C$ can be obtained using the frame duration $T_{FD}$, the propagation delay $T_{PD}$, and the Arbitration Inter-Frame Spacing (AIFS) time $T_{AIFS}$ we wait for the channel to become idle [25]. Further, we might end sending during a time slot because the channel access is scheduled in time slots $T_{CH,S}$. Therefore, we obtain the successful and collision transmission times as

$$T_S = T_C = \left[\frac{T_{FD} + T_{AIFS} + T_{PD}}{T_{CH,S}}\right] \cdot T_{CH,S}.$$  

(5)

We consider the formula suggested in [25] for the frame duration $T_{FD}$ with the message size $M$ as

$$T_{FD} = T_{PRE} + T_{SIG} + T_{OFDM} \cdot \left[\frac{M + 6 + 16}{B_{OFDM}}\right],$$

(6)

where $T_{PRE}$ and $T_{SIG}$ are the durations of the preamble and signal of the physical layer, respectively. $T_{OFDM}$ is the duration of an Orthogonal Frequency-Division Multiplexing (OFDM) symbol and $B_{OFDM}$ is the number of bits per OFDM symbol. Equation (6) also considers the service and tail bits with 16 bits and 6 bits, respectively.

EDCA decrements the backoff stage every $T_{CH,S}$ when the channel is idle. The channel can be idle if no vehicle has a message ready at the MAC or all vehicles are in the backoff stage after the channel was busy. However, if the channel turns busy, EDCA stays in the current backoff stage and waits for the time $T_{AIFS}$ that the channel gets idle again. After that, EDCA again decrements the backoff stage after each time slot $T_{CH,S}$ [24], [25]. Therefore, we modify the virtual time slot proposed in [19] as

$$T_{VS} = p_t(T_{AIFS} + T_{CH,S}) + p_s T_S + p_C T_C.$$  

(7)

Equation (7) considers that the channel is idle for the time $T_{AIFS} + T_{CH,S}$ after a successful or collision transmission, i.e., other vehicles remain in their current backoff stage for the time mentioned above after they perceived a successful or collision transmission.

In (7), we assume the same size $M$ for all messages. If $M$ is different for each message, we need to consider the probability of a successful and collision transmission and the frame duration of each message individually to obtain the virtual time slot $T_{VS}$. In this paper, we assume that $M$ is the same for all messages to limit the model’s complexity.

Vehicles sense the channel before sending a message. However, there is a probability that two or more vehicles send a message simultaneously, causing messages to collide. From [32], we know that the PDR $\rho_n$ of a vehicle $n$ w. r. t. message collisions can be obtained as the probability that no other vehicle $j$ sends in a randomly chosen time slot, giving us

$$\rho_n = \prod_{j \neq n} (1 - \tau_j).$$

(8)

The PDR decreases if the number of vehicles $N$ and their message frequencies are high, i.e., the channel is congested. The channel is busy if we have a successful or collision transmission. However, considering (5), the channel is only busy for the frame duration $T_{FD}$. We propose to obtain the Channel Busy Ratio (CBR) [24] $c$ numerically by considering the probability of a successful and collision transmission, the frame duration $T_{FD}$, and the virtual time slot $T_{VS}$ as

$$c = \frac{(p_s + p_C) T_{FD}}{T_{VS}}.$$ 

(9)

B. ACCESSIBLE INFORMATION RELEVANCE

Let us suppose that a vehicle $n$ wants to send a message with the index $i_n$. Further, we suppose that vehicle $n$ can obtain the information relevance $r_n$ of the respective message $i_n$ based on its current knowledge, where $r_n \in [0, 1]$. For readability, we do not distinguish between the information relevance of different messages of the same vehicle, i.e., $r_n$ represents the information relevance of the current message. However, the information relevance $r_n$ depends on the context of the vehicle $n$ and the content of the message $i_n$ and can be different for subsequent messages and various V2X applications. For example, the authors in [33] obtain the information relevance for the V2X application collective perception. We will discuss our approach to obtain information relevance for cooperative driving in Section V.

Our vehicle $n$ sends the message $i_n$ with the respective information relevance $r_n$ and the message frequency $\lambda_n$. The vehicle $n$ obtains the message frequency $\lambda_n$ for each message $i_n$ individually, where the maximum message frequency is limited to $\lambda_{MAX}$. We also assume that vehicle $n$ only obtains the information relevance $r_n$ once the message $i_n$ is created. Suppose that vehicle $n$ has sent the message $i_n - 1$ at time $t$. Based on the subsequent message $i_n$, the vehicle $n$ updates $r_n$ and $\lambda_n$ and waits for the time $t + 1/\lambda_n$ to send the respective message $i_n$. Vehicle $n$ again updates $r_n$ and $\lambda_n$.
if the subsequent message \( i_n + 1 \) is created and discards the message \( i_n \) if it has not been sent yet. For each sent message, we define the information relevance a vehicle \( n \) provides to other vehicles in the same communication channel as \( \lambda_n \cdot r_n \). From (8), we know the PDR \( \rho_n \) of a sent message of vehicle \( n \). In this work, we only consider the PDR w. r. t. message collisions due to a congested channel within the direct communication range of vehicle \( n \), provided by (8). Radio propagation effects (path loss and fading) and message collisions due to hidden nodes, e.g., analyzed in [31], may also impact the overall PDR. However, radio propagation effects and hidden node collisions are not modeled to limit the complexity of our proposed model. We analyze the effects of path loss and hidden nodes on our proposed resource allocation mechanism in our simulation evaluation in Section VI. We show that our approach allocates resources under challenging radio propagation conditions with hidden node collisions and is superior to the reference approaches w. r. t. the communication performance from the application perspective.

Each vehicle \( j \) receives messages from vehicle \( n \) with the same PDR \( \rho_n \) because we neglect path loss. The PDR \( \rho_n \) reduces the provided information relevance \( \lambda_n \cdot r_n \) of vehicle \( n \) at the respective receivers \( j \). We define the information relevance provided by the message \( i_n \) from vehicle \( n \), which any vehicle \( j \) can successfully receive as the Accessible Information Relevance (AIR) \( \Lambda_n \) of vehicle \( n \), where \( \Lambda_n = \lambda_n \cdot r_n \cdot \rho_n \).

In our approach, each vehicle needs to know the information relevance and message frequency of other vehicles to obtain the AIR of other vehicles. Therefore, each vehicle attaches its current information relevance to its respective message. Hence, each vehicle can obtain the information relevance of received messages. Further, a vehicle can obtain other vehicles’ message frequencies as follows: We attach a unique sequence number [34] to each message. The sequence number is incremented for each sent message at the transmitter. We use the difference of the sequence numbers from the current and last received message divided by the elapsed time between both messages to approximate the message frequency \( \lambda_j \) of a vehicle \( j \). Finally, a vehicle \( n \) can calculate the AIR \( \Lambda_j \) of each perceived vehicle \( j \) within its communication range.

We define the network’s AIR \( \Lambda \) as the sum of the individual AIRs \( \Lambda_n \) of all \( N \) vehicles, giving us

\[
\Lambda = \sum_{n=1}^{N} \lambda_n \cdot r_n \cdot \rho_n. \tag{10}
\]

Equation (10) yields the network’s AIR of all \( N \) vehicles for their current messages in the respective communication channel. We have to note that a vehicle \( n \) can only approximate the network’s AIR \( \Lambda \): i) Vehicle \( n \) only approximates the message frequency \( \lambda_j \) for each vehicle \( j \). ii) The information relevance \( r_j \) of other vehicles \( j \) is already outdated at the reception. A vehicle \( j \) might have already sent a subsequent message with different information relevance and each vehicle evaluates the information relevance of other vehicles at different time steps. iii) Messages with their attached information relevance may not even arrive at the receiver because of unreliable communication.

However, based on the vehicles’ current and (probably) incomplete knowledge, our goal is to let vehicles collaboratively maximize the AIR from their perspective in a decentralized V2X network. A vehicle \( n \) can increase its provided information relevance \( \Lambda_n \) by increasing its message frequency \( \lambda_n \) if \( r_n > 0 \) holds. However, a higher message frequency of vehicle \( n \) decreases the PDR of all vehicles. In contrast, vehicle \( n \) can decrease its provided network’s AIR \( \Lambda_n \) by decreasing its message frequency \( \lambda_n \) such that the PDR of all vehicles increases. Let us define the channel load \( \lambda_L \) as

\[
\lambda_L = \sum_{n=1}^{N} \lambda_n. \tag{11}
\]

Each vehicle \( n \) impacts the channel load \( \lambda_L \) because vehicle \( n \) can increase or decrease its message frequency \( \lambda_n \) following (11). We can argue that for \( \lambda_n \leq \lambda_{\text{MAX}} \ll \lambda_L \), the resulting change in \( \lambda_L \) is negligible if our vehicle \( n \) adapts its message frequency \( \lambda_n \), especially for a large \( N \). However, the change in the channel load and the resulting change in the PDR affects all vehicles. Therefore, even slightly changing the channel load can significantly impact the network’s AIR. We rewrite (10) from the perspective of vehicle \( n \) as a function of its message frequency \( \lambda_n \), using its information relevance \( r_n \), and the approximated message frequency \( \hat{\lambda}_j \) and relevance \( \hat{r}_j \) of other vehicles \( j \) and get

\[
\hat{\Lambda}(\lambda_n) = \lambda_n \cdot r_n \cdot \rho_n(\lambda_n) + \sum_{j \neq n} \lambda_j \cdot \hat{r}_j \cdot \rho_j(\lambda_n). \tag{12}
\]

In (12), the PDRs \( \rho_n \) and \( \rho_j \) depend on the message frequency of vehicle \( n \). In addition, the PDR \( \rho_j \) can be different for each vehicle \( j \) depending on its current message frequency \( \lambda_j \).

For a vehicle \( n \), we search for the message frequency \( \lambda_n \) that optimizes \( \hat{\Lambda}(\lambda_n) \). Equation (12) is a non-linear function and varies with \( \lambda_n \), i.e., a vehicle \( n \) can only adapt its message frequency \( \lambda_n \). Let \( \lambda_{O,n} \) denote the optimal message frequency of vehicle \( n \) that optimizes \( \hat{\Lambda}(\lambda_n) \). However, \( \lambda_{O,n} \) is only optimal from the perspective of vehicle \( n \), according to its current knowledge. Vehicle \( n \) can obtain \( \lambda_{O,n} \) in the limits 0 to \( (1-c)/T_{FD} \) w. r. t. the CBR \( c \) as

\[
\lambda_{O,n} = \arg \max_{\lambda_n \in [0, \frac{1-c}{T_{FD}}]} (\hat{\Lambda}(\lambda_n)). \tag{13}
\]

The upper limit \( (1-c)/T_{FD} \) gives us the theoretical maximum message frequency for the remaining channel resources \( 1-c \) w. r. t. the frame duration \( T_{FD} \) of the respective message. Algorithm 1 depicts the pseudo-code to obtain the optimal message frequency \( \lambda_{O,n} \). First, vehicle \( n \) measures the current CBR \( c \), e.g., using (9) in a numerical environment or the procedure described in [24] in a simulation or real-world
environment. After that, Algorithm 1 assigns our relevance \( r_n \), message frequency \( \lambda_n \), and our PDR \( \rho_n \). We iterate over all vehicles perceived by vehicle \( n \) and add their contributions to the perceived network’s AIR \( \Lambda \). Algorithm 1 considers the last perceived information relevance \( r_j \), the approximated message frequency \( \tilde{\lambda}_j \), and the PDRs \( \rho_j \) of other vehicles \( j \).

In the end, we deploy the non-linear solver provided in [35] using the Simplex algorithm [36]. Simplex is a local derivative-free optimization method and optimizes our given function \( \Lambda \) for its argument \( \lambda_n \) in the limits 0 to \( 1-c/T_{FD} \). Finally, Simplex returns the optimized message frequency \( \lambda_{O,n} \), which maximizes \( \Lambda \) from the perspective of vehicle \( n \).

Let us now explain how each vehicle allocates its messages in a decentralized V2X network.

C. DECENTRALIZED RESOURCE ALLOCATION

Synchronization (all vehicles update their message frequencies simultaneously) poses a significant challenge for resource allocation and congestion control mechanisms in communication networks because it can cause unstable behavior. For illustration, let us assume that a communication channel quickly changes from low to high channel load. According to our design in Algorithm 1, all vehicles with low relevant information would immediately release resources to prioritize more relevant information. Vehicles are unaware of other vehicles’ changes in the current time step because we consider a decentralized V2X network. Hence, in the next time step, the channel load decreases significantly and all vehicles immediately increase their message frequencies again because the vehicles perceive a low channel load. In such a case, the channel load and the individual message frequency of each vehicle start oscillating.

We require an update mechanism that prevents rapid changes in the channel load and avoids oscillation. Linear MMessage Rate Integrated Control (LIMERIC) [29] proposes to let each vehicle adapt its message frequency in a time step \( t \) as

\[
s_n(t) = (1 - \alpha) s_n(t - 1) + \beta (s_T - s_C(t - 1)),
\]

where \( 0 < \alpha < 1 \) and \( \beta > 0 \) are the exponential forgetting and adaptive gain factors, respectively. \( s_n, s_T, \) and \( s_C \) are the vehicle’s, the target, and the current network’s channel capacity shares, respectively. The accumulated vehicles’ share of the respective communication channel converges to the target capacity share \( s_T \). The first summand in (14) denotes the channel capacity share of the last time step \( s_n(t-1) \) of vehicle \( n \). Each vehicle can measure the current channel capacity share \( s_C(t-1) \) of the last time step and assigns a fraction of the remaining channel resources \( \beta (s_T - s_C(t-1)) \) to converge to \( s_T \).

This way, channel resources are distributed fairly among all vehicles because each vehicle aims for the same channel capacity share.

In our work, we argue that each vehicle \( n \) has a different information relevance \( r_n \), depending on the content of the respective messages for V2X applications such as cooperative driving. Consequently, each vehicle should have an individual channel capacity share, depending on its current information relevance \( r_n \). For consistency, in the following, we use the vehicle’s message frequency \( \lambda_n \) instead of the vehicle’s channel capacity share \( s_n \), using the frame duration \( T_{FD} \), where \( \lambda_n(t) = s_n(t)/T_{FD} \). We formulate the update mechanism for the vehicle’s message frequency as

\[
\lambda_n(t) = (1 - \alpha) \lambda_n(t - 1) + \beta (\lambda_{O,n} - \lambda_n(t - 1)).
\]

Equation (15) can be interpreted as a generalization of (14) and allows for an individual message frequency \( \lambda_n(t) \) for each vehicle \( n \) to maximize the network’s AIR considering a heterogeneous information relevance among vehicles. More precisely, we let each vehicle converge to its optimal message frequency \( \lambda_{O,n} \) instead of a static target capacity share \( s_T \) in (14). Similar to \( s_T \) with \( 0 \leq s_T \leq 1 \), the optimal message frequency \( \lambda_{O,n} \) is limited to the remaining channel resources, i.e., \( \lambda_{O,n} \in [0, (1 - c)/T_{FD}] \).

We consider the vehicle’s message frequency of the last time step with the exponential forgetting factor \( \alpha \) in the first summand. \((1 - \alpha)\) scales the first summand in (14) and (15) to promote fairness for \( \alpha > 0 \). For \( \alpha \to 1 \), a vehicle \( n \) forgets about its previous message frequency (behaves altruistically) and only considers the second summand in (14) and (15), allowing other vehicles to increase their message frequencies. For \( \alpha \to 0 \), the vehicle does not forget about its last message frequency (behaves egoistically) and can better converge to its target channel capacity share in (14) or optimal message frequency in (15).

In the second summand of (15), we add the delta message frequency \( (\lambda_{O,n} - \lambda_n(t - 1)) \) to the vehicle’s message frequency of the last time step \( \lambda_n(t - 1) \) to converge to \( \lambda_{O,n} \). The delta message frequency yields i) a positive value if we require a higher message frequency, ii) a negative value if we need to reduce the message frequency, and iii) zero if we already converged to \( \lambda_{O,n} \).

The adaptive gain factor \( \beta \) in the second summand of (14) and (15) avoids exceeding the maximum channel capacity in the next time step. Also, the adaptive gain factor \( \beta \) determines how fast we converge to our optimized message frequency.

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Therefore, \( \beta = 1/N \) is a conservative choice but guarantees that all \( N \) vehicles cannot exceed the remaining channel capacity in the next time step. As derived in [29], convergence for (14) is guaranteed if

\[
\alpha + N\beta < 2. \tag{16}
\]

In the following, let us discuss the applicability of (16) on (15). Let us assume that we have an idle channel, i.e., \( \lambda_L = 0, c = 0 \), and \( (1 - c)/T_{FD} = \lambda_{CH,\text{MAX}} \). \( \lambda_{CH,\text{MAX}} \) denotes the theoretical maximum message frequency for an empty channel w.r.t. a message frame duration \( T_{FD} \). For \( \lambda_L = 0 \) and \( r_n > 0 \), Algorithm 1 decides for \( \lambda_{O,n} = \lambda_{CH,\text{MAX}} \) and updates (15) for each vehicle \( n \) accordingly. For \( \lambda_{O,n} = \lambda_{CH,\text{MAX}} \), we can follow [29] to show that we get an asymptotically stable linear discrete-time system if the condition in (16) for (15) holds. Algorithm 1 obtains the optimal message frequency \( \lambda_{O,n} \) according to the vehicle’s current knowledge and its information relevance \( r_n \), where \( \lambda_{O,n} \leq (1 - c)/T_{FD} \). Each vehicle remains with its optimal message frequency as long as there is no incentive to change it, e.g., a change in the information relevance of the own or other vehicles. We can interpret (15) as a generalization of (14), where each vehicle has an individual, optimal message frequency (instead of a static target capacity share). Similar to \( s_r \), \( \lambda_{O,n} \) cannot exceed the remaining channel resources because \( \lambda_{O,n} \leq (1 - c)/T_{FD} \). Therefore, we also have an asymptotically stable linear discrete-time system if (16) holds.

We limit the resulting message frequency \( \lambda_n(t) \) from (15) for V2X applications [13], [16] such as cooperative driving as

\[
\lambda_n(t) = \max(\lambda_{\text{MIN}}, \min(\lambda_{\text{MAX}}), \lambda_n(t))). \tag{17}
\]

We propose allocating the computation of Algorithm 1 and decentralized resource allocation on the application-support facility layer [37], similar to [12]. The application-support facilities can access the Local Dynamic Map (LDM) [38] to obtain the perceived number of vehicles. We can use the LDM to retrieve the content of the last received message to approximate each vehicle’s message frequency \( \lambda_j \) and information relevance \( r_j \). Further, the application-support facility retrieves the message content and information relevance \( r_n \) from its respective V2X applications.

V. DISCUSSION

In this section, we analyze the computational complexity of Algorithm 1, propose an approximate Packet Delivery Ratio (PDR) model, and discuss information relevance for cooperative driving.

A. OPTIMIZATION PROBLEM

In the following, we discuss the computational complexity of Algorithm 1 from the perspective of a vehicle. Further, we propose an approximate PDR model that significantly reduces the computational complexity of Algorithm 1.

1) Computational Complexity

In general, all vehicles can have a different message frequency, inducing an individual message load \( q_n \) for each vehicle. A vehicle obtains, for example, the PDRs of other vehicles from \( N \) (number of vehicles) coupled non-linear equations using our numerical heterogeneous Enhanced Distributed Channel Access (EDCA) model. We already discussed that the message frequency of Vehicle-to-Everything (V2X) applications is limited, i.e., \( \lambda_{\text{MIN}} \leq \lambda_n \leq \lambda_{\text{MAX}} \). Also, we can assume that V2X applications and their respective facilities, responsible for the message generation, are updated in a discrete (message) frequency interval \( \lambda_S \). Hence, we can group vehicles into \( N_G \) groups (following [26]) to solve the numerical heterogeneous EDCA model, where all vehicles within a group have the same message frequency. Therefore, the number of coupled non-linear equations is

\[
N_G = \left\lceil \frac{1}{\lambda_S} (\lambda_{\text{MAX}} - \lambda_{\text{MIN}}) + 1 \right\rceil. \tag{18}
\]

The computational complexity of this model foremost depends on the number of vehicle groups \( N_G \), inducing \( N_G \) coupled non-linear equations. The complexity of the coupled non-linear equations is assumed constant.

We obtain the computational complexity by analyzing the computation time of our numerical heterogeneous EDCA model as a function of the number of coupled non-linear equations. As an example, let us analyze the computation time of Matlab’s numerical solver \textit{vpasolve}\(^3\) to compute our numerical heterogeneous EDCA model. We elaborate on the overall computational complexity of Algorithm 1 from the perspective of a vehicle later in this section. For the analysis of the computation time, we consider the parameters from Table 1, introduced in Section VI. We analyze \( N_G \) within the range 0 to 20 because our parameters introduced in Section VI result in \( N_G < 20 \) coupled non-linear equations.

\(3\)https://de.mathworks.com/help/symbolic/sym.vpasolve.html
Figure 3 depicts the 0.25 and 0.75 quantiles measurements of the computation time required to solve the PDR in (8) for all vehicle groups and 30 runs per setting. In Figure 3, we fit the computation time with a second-degree polynomial. According to Figure 3, a second-degree polynomial seems to be a good approximation for the computation time. Thus, we approximate the computational complexity of the numerical heterogeneous EDCA model as \( \mathcal{O}(N^2 G) \).

The analysis mentioned above only considers the complexity of one solution for a set of message frequencies from \( N \) vehicles, which already results in more than 15 s computation time using commodity hardware for 19 coupled non-linear equations, as depicted in Figure 3. However, in Algorithm 1, we use a non-linear optimization method to maximize the Accessible Information Relevance (AIR) and obtain the optimal message frequency \( \lambda_{O,n} \). Hence, the computational complexity further increases with the number of iterations \( N_I \) required to find the optimal message frequency. Therefore, we get \( \mathcal{O}(N_I N^2 G) \) for the computational complexity of Algorithm 1.

Finally, let us analyze \( N_I \) for Matlab’s `fminsearch`, which implements the Simplex algorithm. We obtain on average \( N_I = 30 \) iterations for \( N = 150 \) vehicles to find the optimal message frequency \( \lambda_{O,n} \) of vehicle \( n \) in a single time step. From the analysis above, it is evident that we require to reduce the computational complexity. We propose an approximate PDR model to focus on the quadratic increase induced by solving \( N_G \) coupled non-linear equations.

2) Approximate PDR Model

In our approach, each vehicle \( n \) impacts the PDR \( \rho_n \) of all other vehicles (or vehicle groups) by adapting its message frequency \( \lambda_n \). Hence, \( \rho_n \) in (8) depends on the load \( q_n \) of each vehicle \( n \). We can approximate the load \( q_n \) to be equal for all \( N \) vehicles using the properties of the exponential function of the load equation in (3) if \( \lambda_{\text{MIN}} \leq \lambda_n \leq \lambda_{\text{MAX}} \) and \( \lambda_{\text{MAX}} \ll \lambda_{\text{CH,MAX}} \). Hence, we get the same load for all \( N \) vehicles, as \( q_n \approx q \). The assumption above also simplifies the probability of sending in a randomly chosen time slot, giving \( \tau_n \approx \tau \) for all \( N \) vehicles.

Let \( \bar{\lambda} \) denote the average message frequency of the respective communication channel with \( N \) vehicles, where

\[
\bar{\lambda} = \frac{1}{N} \left[ \lambda_n + \sum_{j \neq n} \lambda_j \right]. \tag{19}
\]

In (3), we consider the heterogeneous load equation \( q_n \) from [26]. For the average message frequency \( \lambda \), we require a homogeneous load equation \( q \), e.g., used in [27], and propose

\[
q = 1 - \exp (-\bar{\lambda} \cdot T_{VS}). \tag{20}
\]

Hence, the PDR simplifies to \( \rho = (1 - \tau)^{N-1} \) if \( q_n \approx q \) for \( \lambda_{\text{MAX}} \ll \lambda_{\text{CH,MAX}} \). This way, we reduce the computational complexity to only one non-linear equation. A vehicle \( n \) slightly adapts the average message frequency \( \bar{\lambda} \) of the channel with its message frequency \( \lambda_n \) to optimize the AIR from its perspective in a decentralized V2X network. We have significantly reduced the computational complexity to 1 coupled non-linear equation, resulting in a computation time below 0.2 s using commodity hardware, according to Figure 3. However, we still require a numerical solver to obtain the PDR \( \rho \). In [29], the authors identified a high correlation between the Channel Busy Ratio (CBR)\(^4\) and the vehicles’ message frequencies. Equations (3) and (8) also show a high correlation between the message frequency and the PDR for a given number of vehicles.

Let us compute the PDR using our numerical heterogeneous EDCA model for different numbers of vehicles. In Figure 4, we compute the PDR for 50, 150, and 250 vehicles for the average message frequency 0 ≤ \( \lambda \) ≤ \( \lambda_{\text{MAX}} \). We can approximate the PDR obtained from our numerical heterogeneous EDCA model for different numbers of vehicles as a function of the average message frequency using non-linear least square method. We propose that each vehicle has a set of approximate PDR functions (or, more precisely, the respective coefficients), where each approximate PDR function is valid for a specific amount of vehicles in the communication channel. Hence, a vehicle can perceive the number of vehicles and obtain the average message frequency of vehicles in its communication range and use the respective approximate PDR function to obtain the PDR for all vehicles.

In this paper, we select a Gaussian exponential function using non-linear least square method, which provides a highly accurate approximation of the PDR for a specific amount of vehicles \( N \), as depicted in Figure 4. A polynomial function resulted in oscillation for \( \lambda < 5 \) and \( N > 200 \) up to a ninth-degree polynomial, which has a severe impact when optimizing the network’s AIR because each vehicle only slightly adapts the network’s average message frequency \( \lambda \).

In summary, the proposed approximate PDR model decreases the computation time to 0.02 s because we do not require

\(^4\)The authors in [29] refer to channel busy fraction.
a numerical solver. Further, the computational complexity reduces from $O(N_1N_2^3)$ to $O(N_1)$. We analyze and compare the result of the approximate PDR model in Section VI.

**B. INFORMATION RELEVANCE**

The recent literature has stressed the importance of quantifying information relevance for V2X communication [30], [39]. In the following, let us explain how each vehicle can obtain its information relevance for cooperative driving. For this purpose, we extend our approach proposed in [28], where we determine the Environmental Risk Awareness (ERA). In the mentioned work, the ERA contributes to our proposed safety metric to evaluate the performance of collective perception in a simulation environment. Given the instantaneous approaching time $t_{j,0}$ of the relevant vehicle $j$ towards our vehicle $n$, we can obtain $t_{j,0}$ at time $t = 0$ by solving the following motion equation for $t_{j,0}$ as

$$d_t + \dot{d}_t t_{j,0} + 0.5(\ddot{d}_t + \ddot{d}_{\text{MAX}})t_{j,0}^2 = 0,$$  \hspace{1cm} (21)

where $d_t$, $\dot{d}_t$, and $\ddot{d}_t$ denote the relative distance, velocity, and acceleration of our vehicle $n$ and the other vehicle $j$, respectively. $\ddot{d}_{\text{MAX}}$ modifies the acceleration $\ddot{d}_t$ of the vehicles according to their current situation, e.g., $\ddot{d}_t$ decreases on a slippery road. However, in this paper, we set $\ddot{d}_{\text{MAX}} = 0$ such that the maximum acceleration of vehicles remains constant and tractable.

Both vehicles are approaching each other if $\dot{d}_t < 0$. A vehicle can obtain its perceived ERA to other vehicles using (21) as

$$\theta_p = \frac{\sum_{t_{j,0} \geq 0} \mu_j}{t_{j,0} + u(t_{j,0})},$$  \hspace{1cm} (22)

where $u(t_{j,0})$ is the uncertainty for all state vectors in (21) induced by measurements and $\mu_j$ denotes the collision risk posed by the respective vehicle $j$. We refer to [28] for further details on obtaining $u(t_{j,0})$. In [28], $\mu_j$ is a weighting factor to account for the severity of a collision. $\mu_j$ foremost depends on the other vehicle’s weight, dimension, and the tolerable safety time gap $T_{SG}$. Depending on the other vehicle’s dimension and weight, we may want to select a more conservative $\mu_j$. In simulations, we can obtain the vehicle’s ERA by dividing the perceived risk $\theta_p$ by the real risk. The real risk has no uncertainties and can be obtained from global knowledge, using (22) with $u(t_{j,0}) = 0$.

In this work, we are interested in our vehicle’s perceived ERA from (22) to obtain the information relevance for the planned and desired trajectories. However, in (21), we only obtain the instantaneous approach time $t_{j,0}$ at the current time $t = 0$. The authors in [13] obtain the continuous approaching time between vehicles leveraging trajectories (cf. [9]). In the following, we denote the continuous approaching time as $t_{j,t}$, where $0 \leq t \leq T_{TH}$. $T_{TH}$ denotes the time horizon (or validity time) of the vehicles’ trajectories. Figure 5 depicts the concept of the continuous approaching time. In the most left scenario of Figure 5, the grey vehicle receives a trajectory from the blue vehicle. The grey vehicle can obtain the continuous approaching time of the blue vehicle at different time steps $t$. At each time step, we obtain the distance between both vehicles, indicated as the red dashed line and the velocity and acceleration vectors for both vehicles (bold black arrows). In contrast, (22) only obtains the instantaneous approaching time $t_{j,0}$ at the current time $t = 0$.

The authors denote the risk posed by vehicle $j$ towards the vehicle $n$ using the minimum continuous approaching time at different time steps $t$. Their proposed Risk approach triggers the generation of messages if $t_{j,t} + t \leq T_{SG}$. For cooperative driving, we require an allocation mechanism that assigns sufficient resources to vehicles coordinating a cooperative maneuver. The authors in [13] identified in their evaluation that 95% of the vehicles deploying the Risk approach send messages with the maximum message frequency of 10 Hz. Therefore, the authors coupled the Risk approach with the vehicle dynamics to reduce the message frequency and denote it as Risk Dynamic. Risk Dynamic only triggers a message if the continuous approaching time at the respective time $t$ is below $T_{SG}$. In addition, the distance driven by the respective vehicle since its last message has been sent needs to exceed 4 m, limiting the message frequency to 4 Hz for more than 95% of the vehicles.

In addition, the approaching time in [13] considers the continuous approaching time of vehicles passing each other, as depicted in the middle scenario of Figure 5. For vehicles passing each other, the continuous approaching time is close to zero. Therefore, the message frequency of both vehicles is very high, implying a high collision risk. We argue that only trajectories overlapping in the time and spatial domain have a high collision risk. However, we also need to consider the collision risk of trajectories that cannot yet overlap because both vehicles are too far away from each other, as depicted in the most right scenario of Figure 5. In this case, we do not yet know if the vehicle from the bottom will turn in the intersection and requires coordinating a cooperative maneuver with the vehicle from the top.

In conclusion, a threshold-based approach causes all vehicles to send with either the minimum or maximum message frequency. On the one side, setting the threshold value too low can cause vehicles to coordinate a cooperative maneuver.
vehicles. However, we only consider the safety time gap $T_{SG}$ in (22) considers the weight or dimensions of other vehicles’ trajectories.

The ERA in (22) considers the weight or dimensions of other vehicles’ trajectories. Moreover, we extend our proposed ERA to the Perceived Awareness over Time Horizon (PATH), using the continuous approaching time obtained from the vehicles’ trajectories. Therefore, we propose an approach that assigns more relevance to immediate conflicts and less relevance to conflicts in the near future. More precisely, we extend our proposed ERA to the Perceived Awareness over Time Horizon (PATH), using the continuous approaching time obtained from the vehicles’ trajectories.

The perceived awareness is higher for vehicles that are close and approaching each other (safety-relevant). On the other side, we also obtain the PATH for our planned (grant or deny cooperation) or desired (request cooperation) trajectory such that we assign relevance to potential cooperation (efficiency-relevant). We propose that the information relevance $r_n$, $n$, of the respective message (containing the planned and optional desired trajectory) depends on the maximum PATH of the considered trajectories with their respective time horizons $T_{TH}$ among all perceived vehicles $j$ in the vehicle’s communication range. Finally, we get the information relevance as

$$r_n = \max_{t \in \{0, ..., T_{TH}\}} (\Theta(t)_{n,j}).$$

For $r_n \to 0$, a vehicle $n$ has not perceived any potential collision risks with another vehicle $j$ within the given time horizon $T_{TH}$, i.e., there is no need to coordinate a maneuver with other vehicles to improve traffic safety or efficiency. For $r_n \to 1$, we perceive an imminent collision risk with at least one vehicle and must coordinate the maneuver immediately.

### VI. EVALUATION FRAMEWORK

In this section, we outline our framework for the numerical and simulation evaluation and present the considered parameter settings. Further, we describe the metrics used to compare the performance of our proposed and reference approaches. After that, we summarize the reference approaches. Then, we compare the numerical heterogeneous Enhanced Distributed Channel Access (EDCA) model with simulations. Finally, we validate our approximate Packet Delivery Ratio (PDR) model.

### A. EVALUATION SETUP

In the following, we outline our numerical and simulation evaluation setup. We perform a numerical evaluation to demonstrate the behavior of our proposed approach in a controlled environment w.r.t. the communication performance from the radio and application perspective. Further, we evaluate the performance of our and the reference approaches in a realistic simulation environment.
1) Numerical Setup

We perform our numerical evaluation with Matlab2017b\(^5\) and implement the system model described in Section IV. In the numerical evaluation, vehicles synchronously update their message frequencies in a series of iterations, similar to [29]. Each vehicle considers the channel congestion and other vehicles’ message frequencies of the last iteration. All vehicles may see a low or high channel load in the current iteration and increase or decrease their message frequencies accordingly. Synchronous updates represent a rare but challenging case of reality for congestion control and resource allocation mechanisms w.r.t. convergence because the channel load can rapidly change. We focus on channel congestion in the numerical evaluation causing message collisions and neglect propagation effects and hidden node collisions. We refer to this as the Simple channel model.

2) Simulation Setup

We perform a simulation evaluation to analyze the impact of path loss, fading, and hidden node collisions on our approach. Further, we validate our numerical heterogeneous EDCA model and analyze the performance of our approach in an urban intersection. In the simulation, vehicles update their message frequencies independently and after each other, i.e., asynchronous updates.

We use the event-discrete network simulator OMNeT++ [23] and the vehicle traffic simulator Simulation of Urban MObility (SUMO) [20]. Both simulators are coupled using the Veins [40] framework. Veins also implements 802.11p on the access layer. We use our cooperative driving Vehicle-to-Everything (V2X) application framework for turning at intersections, proposed in [41]. We implement and adapt the Channel Busy Ratio (CBR) measurement model and utilize the European Telecommunications Standard Institute (ETSI) Decentralized Congestion Control (DCC) reference approaches from the Artery framework [42].

We use two channel models in the simulation evaluation: We use the aforementioned Simple channel model to validate our numerical heterogeneous EDCA model and a Realistic channel model from [43] to evaluate the impact of radio propagation effects. The Realistic channel model differentiates between a Line-of-Sight (LoS) and Non Line-of-Sight (NLoS) condition. We obtain the LoS condition following a geometry-based deterministic approach. Our Realistic channel model considers path loss, shadowing, and multi-path propagation. We use the parameter setting from [43] for the Realistic channel model.

All parameters used in the numerical and simulation evaluation are summarized in Table 1. We measured the message size for the cooperative driving application turning at junctions in the Intelligent Maneuver Automation – cooperative hazard avoidance in realtime (IMAGinE)\(^6\) project between 300 and 700 B without security overhead in a real-world scenario. Hence, we consider an average message size of 500 B in this paper.

### Table 1. Parameters used for the numerical and simulation evaluation.

| Symbol | Quantity | Value |
|--------|----------|-------|
| TP | Propagation Delay | 1 µs |
| TP | Preamble duration | 32 µs [25] |
| TSIG | Signal duration | 8 µs [25] |
| TOPDM | OFDM duration | 8 µs [25] |
| TOPDM | Bits per OFDM Symbol | 48 [25] |
| TCHS | Channel Slot Time | 13 µs [24] |
| AC | Access Category | AC, VO |
| W | Backoff Stages | 3 [24] |
| TAIFS | Arbitration Inter-Frame Space Time | 58 µs [24] |
| AIIFSN | Arbitration Inter-Frame Space Number | 2 [24] |
| M | Message Size | 500B |
| λMIN | Minimum Message Frequency | 1 Hz [12] |
| λMAX | Maximum Message Frequency | 10 Hz [12] |
| λS | Message Frequency Step Size | 6.5 Hz |
| ρ | Exponential forgetting factor | 0.1 [29] |
| ρ | Adaptive gain factor | 1/150 [29] |
| TTH | Trajectory time horizon | 10 s [41] |
| TSG | Safety time gap | 1 s |
| NSW, S | Flow from south-west driving straight | 650 veh/h |
| NSW, L | Flow from south-west turning left | 300 veh/h |
| NNE, S | Flow from north-east driving straight | 950 veh/h |

5https://de.mathworks.com/products/matlab.html
6www.imagine-online.de

B. METRICS

We evaluate the V2X communication performance for the different approaches using the CBR and the PDR. Further, we analyze the application performance w.r.t. the network’s Accessible Information Relevance (AIR). The CBR, as defined in [24], is the number of time slots where the channel is sensed busy, divided by the total number of slots within 100 ms. In the simulation, the CBR is measured by a Roadside Unit (RSU) in the center of the considered intersection. In our numerical evaluation, we obtain the CBR using (9).

The PDR is the fraction of successfully received messages and the total sent messages. In the simulation, we can obtain the PDR on the access layer of each vehicle. In the numerical evaluation, we obtain the PDR using (8).

We defined the network’s AIR in (10). For our evaluation, we normalize the perceived network’s AIR to the theoretical maximum provided network’s AIR, giving us the normalized network’s AIR as

\[
\hat{\Lambda} = \frac{1}{\lambda_{\text{MAX}} \cdot r_n} \sum_{n=1}^{N} \lambda_n \cdot r_n \cdot \rho_n.
\]  

In (25), the numerator denotes the perceived network’s AIR and the denominator denotes the theoretical maximum provided network’s AIR (error-free communication, i.e., \(\rho_n = 1\) and maximum message frequency \(\lambda_n = \lambda_{\text{MAX}}\)). In the numerical evaluation, we obtain the normalized AIR for each iteration after all vehicles simultaneously updated their message frequencies. In the simulation evaluation, we obtain the normalized network’s AIR in time intervals of 1 s.
C. REFERENCE APPROACHES
We implement the following reference approaches to analyze the performance of our approach and briefly describe all approaches in the following. For all approaches, the vehicle’s message frequency is limited as $\lambda_{\text{MIN}} \leq \lambda_{n} \leq \lambda_{\text{MAX}}$.

1) Naive
The Naive approach disables any congestion control mechanism and lets all vehicles send with the maximum message frequency $\lambda_{\text{MAX}}$.

2) Reactive Decentralized Congestion Control (R-DCC)
ETSI R-DCC deploys a state machine on the communication level with five states from Relax to Restrictive. R-DCC transitions to the previous or next state if the measured CBR is outside the limits of the current state, as defined in [16]. We consider the mapping table A.1 with $0.5 \, \text{ms} \leq T_{\text{FD}} < 1 \, \text{ms}$ for the given message size $M$ in Table 1. The vehicle’s maximum message frequency is limited according to [16], depending on the current state.

3) Adaptive Decentralized Congestion Control (A-DCC)
A-DCC is adopted from LInear MEssage Rate Integrated Control (LIMERIC) [29] and limits the message frequency such that the target CBR is not exceeded (cf. Section IV-C). A-DCC aims to distribute the available channel resources equally among all vehicles in the decentralized V2X network. We consider the parameters defined in [16].

4) Risk
Risk [13] triggers a message if the minimum approaching time obtained from all other perceived vehicles towards our vehicle is below the threshold safety time gap $T_{\text{SG}}$ (cf. Section V-B). For $T_{\text{SG}}$, the authors in [13] considered $0.5 \, \text{s}, 1 \, \text{s}, 1.5 \, \text{s}$ and we select $T_{\text{SG}} = 1 \, \text{s}$ to be comparable with our approach. We only evaluate the performance of Risk in our simulation with dynamic information relevance, where we compute the approaching times between vehicles.

5) Risk Dynamic
In addition to the Risk approach, Risk+Dyn requires that the vehicle has traveled a minimum of $4 \, \text{m}$ since the last message was sent. Similar to Risk, we only evaluate this approach in our simulation with dynamic information relevance.

6) Priority
We denote our approach as Priority and deploy our proposed Algorithm 1 and the approximate PDR model. We refer to the parameters for $\alpha$ and $\beta$ in Table 1. For $\alpha$ and $\beta$, we select the parameter setting proposed in [29] because they allow for a much faster adaptation of the vehicle’s message frequency compared to $\beta$ suggested in [16]. Fast adaptation is required because the information relevance of messages can rapidly change over time.

D. MODEL VALIDATION
In Section IV, we adapted the Markov Model from [19] to consider the post-backoff stage, only transition to the next backoff stage if the channel is idle, and modified the virtual time slot in (7). In the following, we compare our numerical heterogeneous EDCA model with simulation results and show that our proposed model agrees with the simulation model. Further, we compare our proposed approximate PDR model with the numerical heterogeneous EDCA model.

1) Numerical Heterogeneous EDCA Model
Let us first compare the numerical with the simulation model w. r. t. the PDR and CBR, as depicted in Figure 6. We obtain the PDR and CBR for $N$ vehicles in the range $0$ to $300$ for a message frequency of $5 \, \text{Hz}$ and $10 \, \text{Hz}$. We consider the Simple channel model for this validation because we are interested in message collisions caused by channel congestion. The positions of the vehicles do not impact the PDR and CBR considering the Simple channel model. We obtain the average PDR and CBR for all vehicles over a simulation time of $200 \, \text{s}$ per run and we perform 30 runs for each setting. For a message frequency of $5 \, \text{Hz}$ and between $150$ to $250$ vehicles, we observe negligible more message collisions (lower PDR) in simulations compared to our numerical results. The CBR is comparable between the numerical and simulation results for $5 \, \text{Hz}$ and between $150$ to $250$ vehicles. The CBR in the simulation is negligible lower compared to our numerical heterogeneous EDCA model between $200$ to $300$ vehicles and for $5 \, \text{Hz}$ and $10 \, \text{Hz}$. For $5 \, \text{Hz}$ and $10 \, \text{Hz}$, we can see that our numerical heterogeneous EDCA model matches with the simulation model w. r. t. the PDR and CBR for the considered number of vehicles.

In summary, our numerical results coincide with the simulation results. The numerical heterogeneous EDCA model is the basis of our Priority approach to obtain the PDR. However, we already identified in Section V that the numerical...
For this purpose, we consider a worst-case scenario, where we analyze how much the channel can be considered congested because the theoretical maximum message frequency in an empty channel $\lambda_{\text{CH,MAX}}$ is 1500 Hz. Group A with 1 vehicle varies its message frequency between 0 and 100 Hz. Group B with 149 vehicles sends with a constant message frequency of 10 Hz.

Figure 7 depicts the PDR for both vehicle groups. For our numerical heterogeneous EDCA model, we depict the PDR of group A with 1 vehicle as a dashed line. The PDR of group B with 149 vehicles is depicted as a dotted-dashed line. Note that both groups A and B belong to one evaluation, but we obtain different PDRs for both groups, considering our numerical heterogeneous EDCA model. For our approximate PDR model, we depict the PDR for all 150 vehicles as a solid line. The approximate PDR model does not differentiate the PDR between both vehicle groups.

Let us first analyze the PDR for both groups for the numerical heterogeneous EDCA model. In Figure 7, the PDR of group A is slightly lower than the PDR of group B for a message frequency of group A lower than $\lambda_{\text{MAX}}$. The PDR of the numerical heterogeneous EDCA model is equal for both groups if all vehicles send with the same message frequency of 10 Hz. For a message frequency of group A higher than 10 Hz, the PDR decreases for both groups A and B but decreases faster for group B, sending with a constant message frequency of 10 Hz. The PDR decreases for both groups because the channel load increases with an increasing message frequency of group A. The PDR of group A decreases slower because group A cannot have message collisions with itself. However, the vehicles from group B can have message collisions with each of the other vehicles from the same group and with the vehicle from group A. Hence, the PDR of group B decreases faster compared to the PDR of the vehicle from group A for an increasing message frequency of the vehicle from group A.

Now, we compare the PDR of the numerical heterogeneous EDCA model with the approximate PDR model. Between 0 and 10 Hz, the PDR of the approximate PDR model only deviates with less than 0.37% compared to the PDR of group A obtained from the numerical heterogeneous EDCA model. The deviation is more significant for a message frequency of group A higher than $\lambda_{\text{MAX}}$, which verifies the necessity of $\lambda_{\text{MAX}} < \lambda_{\text{CH,MAX}}$. According to Figure 7, the PDR of the approximate PDR model deviates by 2.2% for a message frequency of 100 Hz compared to the PDR of the numerical heterogeneous EDCA model from group A. However, the PDR of the numerical heterogeneous EDCA model of group B highly matches with the PDR of the approximate PDR model, where the PDR only deviates by 0.67% for a message frequency of 100 Hz.

Our results show that the approximate PDR model obtains similar results and highly coincides with the numerical heterogeneous EDCA model for $\lambda_{\text{MAX}} < \lambda_{\text{CH,MAX}}$. Further, we show that the PDR only deviates by 2.2% between the numerical heterogeneous and approximate PDR model in a worst-case scenario for a group A’s message frequency of 100 Hz.

According to Algorithm 1 the optimal message frequency can
be larger than $\lambda_{\text{MAX}}$. However, we show that the approximate PDR model shows comparable results for a higher message frequency in a worst-case scenario. Further, we also limit our message frequency to $\lambda_{\text{MAX}}$ in (17) after obtaining the optimal message frequency in Algorithm 1.

In summary, our approximate PDR model is suitable to obtain the PDR for Algorithm 1 and allocate resources accordingly.

**VII. RESULTS**

In this section, we compare the performance of our proposed approach with the aforementioned reference approaches in a numerical and simulation evaluation. For this purpose, we first analyze the properties of the approaches w.r.t. convergence using a static information relevance of messages. After that, we analyze the impact of dynamic information relevance.

**A. STATIC INFORMATION RELEVANCE**

Let us assume that the information relevance $r_n$ of each vehicle $n$ is uniformly distributed as $\mathcal{U}(0, 1)$ at the beginning and that $r_n$ does not change over time, i.e., all messages from a vehicle $n$ have the same information relevance $r_n$. In our first numerical evaluation, we analyze the communication performance from the radio and application perspective and the iterations required to achieve convergence w.r.t. resource allocation in a controlled environment. In our first simulation evaluation, we analyze the communication performance in a mobile environment, where all messages of a vehicle have the same information relevance and vehicles are not performing cooperative driving maneuvers. In contrast to the numerical evaluation, the network’s Accessible Information Relevance (AIR) in the simulation cannot converge to a single fixed point because vehicles with different but static information relevance continuously enter and leave the intersection.

1) Numerical Results

We consider that vehicles synchronously update their message frequencies in a series of iterations [29]. The vehicles’ message frequencies are uniformly distributed as $\mathcal{U}(\lambda_{\text{MIN}}, \lambda_{\text{MAX}})$ at the first iteration. Each vehicle considers the current channel congestion and other vehicles’ message frequency to adapt its message frequency accordingly.

We chose the described scenario because synchronous updates pose a significant challenge to the resource allocation mechanism in decentralized Vehicle-to-Everything (V2X) networks w.r.t. stable solutions. In the following, we show that our approach achieves convergence and outperforms the other approaches w.r.t. the network’s AIR. Figure 8 shows the performance comparison for the approaches and different numbers of vehicles w.r.t. the CBR, PDR, and network’s AIR.

Let us first analyze the communication performance with 50 vehicles. Figure 8(a) shows that the CBR is below 0.4 for all approaches, resulting in a high PDR of 0.96, as depicted in Figure 8(b). Further, the network’s AIR is at 0.96 for all approaches, as depicted in Figure 8(c). Interesting to note is that we observe oscillation for all three performance metrics for the Reactive Decentralized Congestion Control (R-DCC) approach, which is caused by the synchronous updates: All vehicles firstly observe a CBR of 0.18 and, therefore, transition to the Relaxed state, which allows for a message frequency of 10 Hz. In the next iteration, the CBR increases to 0.35 because all vehicles send with 10 Hz. The increased CBR causes all vehicles to transition from the Relaxed to the Active 1 state. In the Active 1 state, the allowed message frequency is limited to 5 Hz. Therefore, the CBR decreases again to 0.18 in the next iteration. Hence, R-DCC cannot converge to a stable solution considering that all vehicles update their message frequencies synchronously. In reality, synchronous updates represent an edge case in decentralized V2X networks. However, synchronization can also happen more frequently to a smaller group of vehicles, causing a severe communication performance degradation due to oscillation of the vehicles’ message frequencies. Hence, oscillation should be avoided for resource allocation and congestion control mechanisms. Concluding, the channel is not congested and all approaches except R-DCC can almost achieve the maximum network’s AIR for 50 vehicles, where each vehicle operates on one V2X application with a maximum message frequency of 10 Hz. R-DCC cannot converge to a stable solution because all vehicles synchronously update their message frequencies. The PDR of R-DCC also oscillates between 0.27 and 0.52 and transitions between the Active 1 and Active 2 states. The Naive approach has the highest CBR, which causes the highest number of message collisions and results in the lowest PDR of all approaches with 0.59. Priority and A-DCC achieve a higher PDR of 0.82 and 0.87, respectively. The PDR of R-DCC also oscillates between 0.91 and 0.97. We see that Priority outperforms all other approaches and converges to a network’s AIR of 0.75, as depicted in Figure 8(f). Further, the Naive approach outperforms R-DCC with an AIR of 0.59. However, the Naive approach has the lowest PDR. R-DCC oscillates between a network’s AIR of 0.24 and 0.46 and A-DCC achieves a network’s AIR of 0.52. In summary, we show that our approach has a slightly lower PDR compared to R-DCC and A-DCC but outperforms all other approaches in terms of the network’s AIR. Our results also confirm the results in [17], where the authors identified a performance degradation on the V2X application level using European Telecommunications Standard Institute (ETSI) Decentralized Congestion Control (DCC) compared to the Naive approach. We can also confirm that ETSI DCC shows promising results w.r.t. the radio communication performance.
Let us now analyze the performance of the four approaches for 250 vehicles. We again observe in Figure 8(g) that the *Naive* approach occupies most channel resources and has a CBR of 0.90. In contrast, *Priority*, R-DCC, and A-DCC have a CBR of 0.74, 0.63, and 0.44, respectively. We also observe that R-DCC is not oscillating and transitions to the *Active 2* state, limiting the message frequency to 2.5 Hz. We notice that the CBR for R-DCC decreases in the third iteration and increases again in the fourth iteration. The reason is that R-DCC starts in the *Relaxed* state and transitions to the *Active 3* state after 3 iterations. R-DCC considers the CBR of the previous iteration above 0.6 before finally converging to the *Active 2* state. The *Naive* approach is severely impacted by message collisions considering the PDR in Figure 8(h), which decreases the PDR to 0.23. In contrast to that, R-DCC, A-DCC, and *Priority* can almost maintain the PDR, similar to the previous evaluation with 150 vehicles, and converge to a PDR of 0.94, 0.86, and 0.77, respectively. We see that channel congestion severely degrades the radio communication performance, especially for the *Naive* approach. R-DCC, A-DCC, and *Priority* counteract the radio communication performance degradation by limiting the channel load. For the network’s AIR, we see that *Priority* outperforms the other approaches and converges to a network’s AIR of 0.52. In contrast, A-DCC converges to a network’s AIR of 0.33. The *Naive* approach and R-DCC show similar performance, converging to a network’s AIR of 0.23. Both ETSI DCC approaches can maintain the radio communication performance under highly congested channel conditions. However, our approach also maintains a comparably high communication...
performance from the application perspective by prioritizing relevant information under congested channel conditions. One interesting fact to note is the ripples of A-DCC in all performance metrics. These ripples can be explained because the performance metrics of all approaches are evaluated based on the finite step size of the message frequency, i.e., $\lambda_S = 0.5$ Hz, to reduce the number of vehicle groups for the system model in Section IV. However, A-DCC linearly converges to the target message frequency and requires more than 50 iterations, which causes ripples in the performance metrics.

We identified that Priority outperforms all other approaches in terms of the network’s AIR considering Figure 8. However, ETSI DCC outperforms our approach for all considered numbers of vehicles in Figure 8 w.r.t. the PDR. The reason is that Priority allocates more resources for each vehicle to increase the communication performance from the radio and application perspective. In the following, we analyze the importance of balancing the PDR and message frequency for relevant information to satisfy the communication requirements from the application perspective.

For this purpose, let us assume that vehicle $n$ has an emergency and broadcasts emergency messages with an information relevance $r_n = 1$ periodically. The first emergency message of vehicle $n$ is denoted with the index $i_n = 1$. The index increments by one for each subsequent message sent by vehicle $n$ such that $i_n$ denotes the number of emergency messages sent by vehicle $n$. A vehicle $j$ requires to receive a safety message from $n$ immediately to be aware of its emergency. The PDR $\rho_n$ is $0 < \rho_n \leq 1$ because the channel can be congested. The probability $p$ that vehicle $j$ receives at least one message from vehicle $n$ is given by

$$p = 1 - (1 - \rho_n)^{i_n}. \quad (26)$$

We increase the probability $p$ to receive at least one message at vehicle $j$ from $n$ if the PDR $\rho_n$ and the number of sent messages is high. However, before having an emergency, vehicle $n$ periodically sends cooperative driving messages and informs about its current and future positions and velocities. Hence, vehicle $n$ might have just sent a message immediately before having an emergency. From Figure 8, we know that especially the ETSI DCC approaches limit the message frequency of vehicles irrespective of the message content. As a result, the information of vehicle $n$ at $j$ can be outdated because of message loss and the limited message frequency of vehicle $n$.

The main communication requirement from the application perspective is to minimize the Age of Information (AoI) [11], [44] for messages with high relevance such that the information at vehicle $j$ is current and vehicle $j$ is immediately informed about the emergency of vehicle $n$. The AoI of vehicle $n$ at vehicle $j$ depends on vehicle $n$’s message frequency $\lambda_n$. In addition, the AoI increases because of message collisions, i.e., we have to wait for an entire message cycle if we lost a message. The AoI further increases because of message delay because of a congested channel. However, the effect of message collision on the AoI is far more severe compared to message delay for cooperative driving at intersections [11] and is neglected in the following. We can obtain the AoI $\Delta_n,j$ of vehicle $n$ at $j$ with the probability $p$ considering the PDR $\rho_n$ and the message frequency $\lambda_n$ as

$$\Delta_n,j = \frac{1}{\lambda_n} \ln(1 - p) + \frac{1}{2\lambda_n}. \quad (27)$$

In (27), the first summand is derived from (26) to obtain the number of messages required to receive at least one message with the probability $p$ considering the PDR $\rho_n$. We would wait for an entire message cycle $1/\lambda_n$ if we lost a message. For $\rho_n \rightarrow 1$, the first summand converges to zero because we have no message loss and immediately receive the first message. For $\rho_n \rightarrow 0$, the first summand converges to infinity, i.e., we never receive a message from $n$ at $j$. The second summand considers the time until the first emergency message is sent because of vehicle $n$’s message frequency $\lambda_n$. Vehicle $n$ might have sent the last message an entire message cycle or just before the emergency. Hence, vehicle $j$ waits up to $1/\lambda_n$ to receive an emergency message of $n$. In (27), we consider the average time we wait to receive a message because of the message frequency of vehicle $n$ as $1/(2\lambda_n)$.

In Figure 9, we analyze the AoI for all approaches for 50, 150, and 250 vehicles as bar lines. The lower and upper bar lines depict the AoI, guaranteed with a probability of 5% and 95%, respectively. The marker in the middle of the bar line depicts the AoI, guaranteed with a probability of 50%. In Figure 9, we see that A-DCC, Naive, and Priority have the lowest AoI for 50 vehicles. For R-DCC, the message frequency is already halved, which increases the AoI severely. For 150 vehicles, we observe that Priority provides the lowest AoI of 0.23 s with a probability of 95%. Compared to that, A-DCC and Naive have an AoI of 0.32 s and 0.39 s, respectively, with a probability of 95%. Although R-DCC provides a PDR of more than 0.91, the lower message frequency severely increases the AoI to 0.54 s with a probability of 95%.
250 vehicles, we see that the AoI of the Naive approach further increases to 1.18 s with a probability of 95%, which is caused by the low PDR of 0.23. Here, the high message frequency of 10 Hz cannot compensate for the low PDR, negatively impacting the AoI. In contrast, both R-DCC and A-DCC reduce the channel load and, therefore, still achieve an AoI of 0.63 s and 0.53 s, respectively, with a probability of 95%. For 250 vehicles, Priority provides an AoI below 0.26 s with a probability of 95%.

Concluding, Priority outperforms the reference approaches for all considered numbers of vehicles and provides highly relevant information to other vehicles below an AoI of 0.26 s with a probability of 95% for up to 250 vehicles.

2) Simulation Results
Let us now analyze the performance in a simulation environment and compare the simulation results with our numerical results. We perform 30 runs for each study with a different seed. Similar to the numerical analysis before, we also uniformly distribute the information relevance of vehicles and the information relevance of each vehicle and their respective messages remains static over time. Further, we use the Simple and Realistic channel models and vehicles do not coordinate and perform cooperative driving maneuvers because we consider static information relevance for each vehicle.

We decided to analyze the most challenging scenario with 150 vehicles in our simulation evaluation based on our numerical evaluation. The reason is that for \( N \) between 130 and 150 vehicles, we achieve the highest channel throughput for a message frequency of 10 Hz and our considered parameter settings from Table 1 for the Simple channel model. Hence, the Naive approach performs best for \( N \leq 150 \) vehicles but will degrade for \( N > 150 \) vehicles because the PDR severely decreases. For 50 vehicles and following Figure 8, resource allocation is not challenging because the communication channel is not congested. For 250 vehicles, the Naive approach severely degrades radio communication performance because the channel is heavily congested and the PDR is low. Further, we know that R-DCC and A-DCC significantly reduce the message frequency compared to Priority even for vehicles with high relevant messages and 250 vehicles, as analyzed in Figure 9. Hence, a scenario with approximately 150 vehicles is the most challenging scenario w.r.t. a communication performance comparison from the application perspective. The traffic flow for each route is given in Table 1 and results in approximately 150 vehicles because vehicles enter and leave the simulation environment.

Figure 10 depicts the distribution of the CBR as boxplots for the approaches and approximately 150 vehicles. We perform 30 runs per approach, where each run has a simulation time of 200 s. For comparison, we show the converged solution from our numerical evaluation using the Simple channel model as a solid line. We can observe that the Naive approach again has the highest CBR compared to the other approaches, where the numerical and simulation results are at a CBR of approximately 0.8. The CBR of the Realistic channel model is slightly less for the Naive approach. The reason is that the Roadside Unit (RSU), measuring the CBR in the intersection, perceives fewer messages because the communication range of vehicles is limited considering the Realistic channel model. For R-DCC, we consider the average CBR from the numerical result because R-DCC caused oscillation. In line with Figure 8, R-DCC has only a CBR of 0.4 for the Simple channel model (dashed-dotted line) and we observe that the CBR of the Realistic channel model (dashed line) is higher compared to the Simple channel model. The Realistic channel model reduces the communication range of vehicles, decreasing the perceived CBR of vehicles. Hence, the vehicles transition to a less stringent DCC state, which allows for a higher message frequency. This effect can also be observed for A-DCC and Priority. For A-DCC and Priority, we observe a comparable CBR for both channel models. The CBR of the Realistic channel model is at approximately 0.68 for A-DCC and Priority. Hence, A-DCC and our Priority approach use a comparable amount of channel resources.

Figure 11 depicts the network’s AIR as boxplots for all four approaches for approximately 150 vehicles and different channel models.
30 runs per approach, where each run has a simulation time of 200 s. We observe that the network’s AIR is lower for the Realistic channel model compared to the Simple channel model for all approaches. A vehicle is aware of all other vehicles and can avoid hidden node collisions considering the Simple channel model. We also notice that A-DCC and our Priority approach are more affected by hidden node collisions than the Naive and R-DCC approaches. We observe a severe impact of hidden nodes because R-DCC, A-DCC, and Priority adapt their message frequencies based on channel measurements in contrast to the Naive approach. R-DCC is less affected because it operates in a less congested channel. However, our approach outperforms all other approaches w. r. t. the network’s AIR. Priority achieves a median network’s AIR of 0.6 considering the Realistic channel model. Compared to that, A-DCC and the Naive approach only achieve a median network’s AIR of 0.44 and 0.51, respectively. However, we already know that the Naive approach severely degrades the communication performance for more than 150 vehicles, which has been already analyzed in Figure 8 and Figure 9.

B. Dynamic Information Relevance

In the following, we analyze the communication performance from the radio and application perspective, considering a dynamic information relevance. Hence, the information relevance of messages for each vehicle changes over time and our approach needs to continuously adapt to the new information relevance of vehicles in the decentralized V2X network.

1) Numerical Results

For the numerical analysis, we again consider the Simple channel model and uniformly distribute the information relevance of vehicles to analyze the performance of our approach in a controlled environment. In addition, we uniformly distribute the information relevance of all vehicles after every 10 iterations to analyze the adaptability of our approach w. r. t. a dynamic information relevance. Following our approach, a vehicle converges to its optimal message frequency w. r. t. its and the other vehicles’ current information relevance and the channel load. We expect that the network’s AIR drops once the information relevance of all vehicles changes. The reason is that the message frequency of each vehicle is not yet adapted to the new information relevance of the own and other vehicles. For this purpose, let us analyze the network’s AIR for a series of 50 iterations, as depicted in Figure 12. We perform 30 runs for each study with 50, 150, and 250 vehicles and depict the median network’s AIR of 30 runs for each iteration. The vertical dashed lines indicate a new uniform information relevance distribution for all vehicles. Consequently, we analyze the network’s AIR for 50 vehicles as a solid line. We see that the network’s AIR increases after three iterations to 0.95 and is almost unaffected by a change in the information relevance distribution for all vehicles. For 50 vehicles, the communication channel is not congested. Hence, almost all vehicles can send with the maximum message frequency.

The dashed-dotted line represents the evolution of the network’s AIR for 150 vehicles. The median network’s AIR firstly increases and converges after 7 iterations to 0.72. After we newly distribute the information relevance (dashed vertical lines), the median network’s AIR drops to 0.63 but reaches its maximum again after only 4 iterations. All vehicles need to adapt their message frequencies according to the new distributed information relevance in the decentralized V2X network. The convergence speed of the message frequency for each vehicle depends on the choice of $\beta$. We set $\beta$ to 1/150 to achieve convergence and fast adapt to the optimal message frequency from the vehicle’s perspective.

For 250 vehicles, we observe similar behavior for the median network’s AIR compared to 150 vehicles. The maximum achieved median network’s AIR decreases because the channel is more congested compared to 150 vehicles and reaches its maximum median network’s AIR of 0.50 after 8 iterations. We currently do not starve the message frequency of vehicles [16] with low relevant information, i.e., $\lambda_n \geq \lambda_{\text{MIN}} > 0$. Hence, we could further improve the network’s AIR by starving the message frequencies of vehicles with irrelevant information.

In summary, our approach converges after less than 10 iterations after uniformly distributing the information relevance of all vehicles in the decentralized V2X network. Further, it is interesting to note that the median network’s AIR of our approach is always above the information relevance of the reference approaches because we are not dropping below a median network’s AIR of 0.63 for 150 vehicles and below a median network’s AIR of 0.41 for 250 vehicles (cf. Figure 8).

2) Simulation Results

Finally, we compare the performance in our simulation environment considering a dynamic information relevance and the Realistic channel model. For this purpose, we enable
the cooperative driving V2X application at intersections described in [41] for our scenario in Figure 1. Vehicles with the intention to turn left will ask for cooperation to avoid stopping in the intersection. The vehicles also obtain the information relevance of each cooperative driving message based on our discussed approach in Section V. In addition to Naive, R-DCC, and A-DCC, we also compare the performance of the resource allocation mechanism for cooperative driving proposed in [13], named Risk and Risk+Dyn because we now perform cooperative driving maneuvers in the intersection and can obtain the approaching times of vehicles.

Figure 13 depicts the distribution of the CBR as boxplots for all six approaches with approximately 150 vehicles and a dynamic information relevance depending on the vehicles’ messages for the Realistic channel model.

In conclusion, our approach reduces the channel congestion compared to Naive and A-DCC because we only allocate resources for relevant information. However, Priority allocates significantly more resources than Risk and Risk+Dyn.

Figure 14 depicts the median network’s AIR as boxplots for approximately 150 vehicles in the scenario. We again perform 30 runs per approach, where each run has a simulation time of 200 s. We see that Naive and A-DCC achieve comparable performance with a median network’s AIR of 0.30 and 0.27, respectively. R-DCC only has a median network’s AIR of 0.19. Compared to that, the Risk and Risk+Dyn approaches achieve a significantly less median network’s AIR of 0.05. In our scenario, the time horizon of trajectories is set to 10 s. Therefore, vehicles can already coordinate a maneuver 10 s before arriving at the intersection. The information relevance of the messages to coordinate the cooperative maneuver is increasing before the maneuver is coordinated and the vehicles approach each other. However, the information relevance is close to zero if the maneuver is already coordinated. The Risk approach only triggers a message if the approaching time is less than 1 s, where the cooperative maneuver is already coordinated. In this case, vehicles only send with the minimum message frequency to coordinate the maneuver, which results in a low network’s AIR. In contrast, Priority achieves a median network’s AIR of 0.36. Priority early recognizes the need for cooperation because the Perceived Awareness over Time Horizon (PATH) increases for both vehicles approaching each other. Therefore, the information relevance increases and Priority allocates more resources for both vehicles until the conflict is solved and the cooperative
maneuver is coordinated.

In summary, Priority outperforms the reference approaches w. r. t. the network’s AIR by 20% because we can prioritize relevant information depending on the channel congestion. We have shown in our exhaustive evaluation that our approach is a superior resource allocation mechanism for V2X applications such as cooperative driving. For cooperative driving, only a few vehicles require many channel resources to coordinate a cooperative maneuver. Content-agnostic resource allocation and congestion control mechanisms such as ETSI DCC can negatively impact the communication performance from the application perspective because they limit the message frequency of all vehicles irrespective of their information relevance if the channel gets congested.

In conclusion, we have shown in a numerical and simulation evaluation for static and dynamic information relevance that our approach provides a significantly higher network’s AIR for low and very high channel congestion in a decentralized V2X network compared to all reference approaches. Our approach prioritizes relevant information by considering the current channel congestion and the information relevance of vehicles. Therefore, we prioritize vehicles with higher information relevance under high channel congestion to support the coordination of cooperative driving maneuvers from the communication perspective.

VIII. RELATED WORK

A considerable amount of research effort has been invested into resource allocation and congestion control mechanisms for Vehicle-to-Everything (V2X) communication [14], focusing on two different objectives: First, content-agnostic resource allocation and congestion control mechanisms, which primarily focus on the radio communication performance. Second, content-aware resource allocation mechanisms, which focus on the communication performance from the application perspective. In the following, our literature research focuses on resource allocation and congestion control mechanisms in decentralized V2X communication, where we differentiate between content-agnostic and content-aware mechanisms.

A. CONTENT-AGNOSTIC RESOURCE ALLOCATION

One of the most popular congestion control proposals for decentralized V2X networks that has been considered for the European Telecommunications Standard Institute (ETSI) standard is called Linear MESSAGE Rate Integrated Control (LIMERIC) [29]. LIMERIC adjusts the transmission rate based on the current Channel Busy Ratio (CBR) and converges to a target CBR. However, the application communication requirements w. r. t. individual resources are not taken into account. Bansal et al. [45] refine LIMERIC to the Error Model Based Adaptive Rate Control (EMBARC) that additionally takes vehicular dynamics into account, leading to a reduced vehicle tracking error. However, purely focusing on the own vehicular dynamics does not conform to V2X applications such as cooperative driving.

Gozalvez and Sepulcre [46] propose an awareness control mechanism that depends on the vehicle context, the so-called OPPortunistic-driven adaptive RAdio resource Management (OPRAM). This attempt has been continuously improved in [47]–[49] to maintain the communication performance in congested channels. The authors consider a Minimum Packet Transmission Frequency (MINT) and a maximum transmission time window to reduce channel congestion. All of these proposals build upon the assumption that one received message is sufficient for the V2X application. However, current research studies argue that multiple message exchanges must eliminate divergence while performing a cooperative maneuver [50]. Therefore, Sepulcre et al. [51] investigate INTEgRatioN of congestion and awareness control (INTERN) that combines the previously described approaches. The authors in [52] propose Cross-layer coordination of multiple vehicular protocols (COMPASS), which efficiently coordinates several protocols, including Adaptive Decentralized Congestion Control (A-DCC) and MINT to ensure a better evolution perspective. However, the application communication requirements cannot be satisfied without exceeding the maximum allowed CBR in a high traffic density due to insufficient channel resources.

Noor-A-Rahim et al. [15] provide a comprehensive overview of resource allocation for V2X communication. The authors propose a contention window allocation strategy that adapts the Medium Access Control (MAC) parameters according to the coverage area to overcome problems with fairness while maintaining a high data transfer ratio between slow and fast vehicles. Moreover, grouping vehicles with similar transmission rates into one channel increases throughput. Additionally, the use of dynamic modulation coding schemes lowers the average system response time. The proposed strategy focuses on the own vehicle dynamics. However, for cooperative driving, we also need to consider other vehicles to coordinate a cooperative maneuver.

The authors in [53] consider hidden nodes to adapt the message frequency and improve the radio communication performance. However, the authors cannot prioritize messages with relevant information from the same application. All approaches mentioned above improve the radio communication performance and partially consider the own vehicle dynamics to improve resource allocation in a decentralized V2X network. In the following, we enlarge on content-aware resource allocation mechanisms that consider the content of the respective message to select the optimal resource allocation strategy.

B. CONTENT-AWARE RESOURCE ALLOCATION

Significant contributions in the literature are recently provided for collective perception. Garlichts et al. [54] refer to the ETSI standard in [55] and improve the redundancy control techniques7 by message segmentation, filtering recently transmitted objects. Thandavarayan et al. [56] develop an

7 Formerly known as redundancy mitigation techniques.
algorithm that excludes objects from the current message if incorporated into the subsequent message. Their evaluation reveals a decreased number of messages, increasing reliability as well as perception capability. The same authors introduce a mechanism in [57] that uses A-DCC to limit channel congestion. However, these resource allocation mechanisms are explicitly designed for collective perception, making them applicable to other cooperative V2X applications such as cooperative driving. In addition, these approaches rely on Decentralized Congestion Control (DCC) to cope with channel congestion.

The authors in [30] introduce Value of Information (VoI) for V2X networks and propose to allocate more resources for valuable information. The authors in [33] propose a resource allocation mechanism for collective perception based on the VoI. They obtain the VoI of perceived objects and decide if the respective object should be integrated into the subsequent message. However, this approach is explicitly designed for collective perception and cannot be easily transferred to cooperative driving. Further, the authors do not explicitly balance the radio and application communication performance. There is a paucity of literature on resource allocation addressing cooperative driving. A first study is provided by Correa et al. [58] that applies the statistical analysis of static and dynamic rules based on the Cooperative Awareness Message (CAM) to the generation of Maneuver Coordination Messages (MCMs). The authors show that dynamic rules are superior w.r.t. the CBR, particularly in high traffic densities. In [13], more sophisticated policies for resource allocation targeting cooperative driving are proposed, taking the approaching time of vehicles into account. Triggering conditions incorporate thresholds for sending messages. The evaluation results show an increased awareness at the application level, particularly for high traffic densities. However, the proposed approaches do not consider the radio communication performance and would require DCC to counteract channel congestion. In addition, we already showed in our evaluation that the proposed approaches severely decrease the message frequency even for relevant information in an urban scenario, where vehicles drive with low velocities in contrast to the considered highway scenario in [13].

We offer a more generic approach, leveraging the network’s Accessible Information Relevance (AIR) and taking the radio communication performance into account. In a decentralized V2X network, we can maximize the network’s AIR by adapting the message frequency of vehicles w.r.t. the channel load and the information relevance of vehicles.

To sum up, prior research studies have contributed to an immense advance in resource allocation and congestion control mechanisms covering primarily two perspectives, i.e., optimizing the radio communication performance (content-agnostic) and satisfying the communication requirements of the V2X application (content-aware). The proposed algorithms are highly specific to a particular V2X application type and cannot easily be applied to other V2X applications such as cooperative driving. To the best of the authors’ knowledge, there is no generic approach that considers the radio communication performance and the application communication requirements leveraging information relevance.

**IX. CONCLUSION AND FUTURE WORK**

In this work, we propose a collaborative resource allocation mechanism with congestion control based on the perceived channel load and the vehicles’ information relevance for decentralized Vehicle-to-Everything (V2X) communication networks. Our approach increases the message frequency of vehicles with relevant information while reducing the message frequency of vehicles with less relevant information, depending on the current channel congestion in a decentralized V2X network.

In our evaluation, we compare our approach with a Naive approach and the European Telecommunications Standard Institute (ETSI) Reactive Decentralized Congestion Control (R-DCC) and Adaptive Decentralized Congestion Control (A-DCC) [16]. Further, we consider the recently proposed resource allocation approaches Risk and Risk Dynamic from the Transition Areas for Infrastructure-Assisted Driving (TransAID) project, mentioned in [13].

We show in our numerical evaluation that our proposed approach optimizes the network’s Accessible Information Relevance (AIR) and can quickly adapt to a changing information relevance. We significantly increase the network’s AIR by up to 44% compared to A-DCC and by 23% compared to the Naive approach in a congested traffic scenario with 150 vehicles, i.e., we increase the network’s AIR by allocating more resources to vehicles with relevant information. We also show that our proposed approach guarantees an Age of Information (AoI) for highly relevant information below 0.26 s with a probability of 95% for 250 vehicles. In contrast, the reference approaches guarantee an AoI of only 0.53 s and above with a probability of 95%.

In our simulation, we show that our approach outperforms the reference approaches in an urban intersection scenario using a V2X cooperative driving application by more than 20% w.r.t. the network’s AIR. Our approach considers the V2X communication and application performance to prioritize relevant information under congested channel conditions.

In our future work, we want to apply our approach to different decentralized V2X communication technologies and improve the performance of our approach by targeting the hidden node problem, which negatively impacts the radio communication performance of our approach. For this purpose, we plan to estimate the number of hidden nodes with the approach mentioned in [53]. We also plan to deploy our approach on multiple V2X applications sending in the same channel such as collective perception. The challenge is to balance the information relevance of different V2X applications and allocate communication resources accordingly.
APPENDIX A SYMBOLS

All symbols used in this paper are listed with their corresponding brief explanations and respective units in Table 2.

APPENDIX B TRANSMISSION PROBABILITY

Let us derive the probability for a vehicle \( n \) to send in a randomly chosen time slot \( \tau_n \) considering the Markov Chain depicted in Figure 2.

First, we get the transition probabilities for the post-backoff stages as

\[
P(b_{p,k}|b_{p,k-1}) = \frac{1}{W},\]

(28)

\[
P(b_{p,k}|b_{P,k-1}) = p_{B}, \quad k \in \{0, \ldots, W-1\},\]

(29)

\[
P(b_{p,k}|b_{P,k+1}) = 1 - p_{B}, \quad k \in \{0, \ldots, W-2\}.\]

(30)

Next, we can get the transition probabilities for the backoff stages as

\[
P(b_{k}|b_{1}) = \frac{q_{n}p_{B}}{W}, \quad k \in \{0, \ldots, W-1\},\]

(31)

\[
P(b_{k}|b_{k}) = p_{B}, \quad k \in \{0, \ldots, W-1\},\]

(32)

\[
P(b_{k}|b_{k+1}) = 1 - p_{B}, \quad k \in \{0, \ldots, W-2\}.\]

(33)

The transition probabilities of the idle stage are

\[
P(b_{l}|b_{P,0}) = 1 - p_{B},\]

(34)

\[
P(b_{l}|b_{1}) = 1 - q_{n}.\]

(35)

We can obtain the stationary state of the Markov Chain by considering all stages and get

\[
1 = b_{1} + b_{-1} + \sum_{k=0}^{W-1} b_{k} + \sum_{k=0}^{W-1} b_{p,k}.\]

(36)

We get

\[
1 = \frac{b_{-1}}{q_{n}} + b_{-1} + \sum_{k=0}^{W-1} \frac{W-k}{W} \frac{p_{B}}{1-p_{B}} b_{-1} + \sum_{k=0}^{W-1} \frac{W-k}{W} \frac{1}{1-p_{B}} b_{-1},\]

(37)

using the transition probabilities above. After some transformations, we can solve (37) for \( b_{-1} \). \( b_{-1} \) is the stage where we send a message in a randomly chosen time slot and we get

\[
b_{-1} = \tau_{n} = \frac{2q_{n}(1-p_{B})}{2(1+q_{n})(1-p_{B}) + q_{n}(1+p_{B})(W+1)}.\]

(38)

### Table 2: Parameters used for the numerical and simulation evaluation.

| Symbol          | Quantity                        | Unit  |
|-----------------|---------------------------------|-------|
| \( \alpha \)    | Exponential forgetting factor   | -     |
| \( B_{OFDM} \)  | Bits per OFDM Symbol            | bps   |
| \( \beta \)     | Adaptive gain factor            | -     |
| \( j \)         | Vehicle j                       | -     |
| \( \lambda_{MIN} \) | Minimum message frequency     | Hz    |
| \( \lambda_{MAX} \) | Maximum message frequency     | Hz    |
| \( \lambda_{g} \) | Step size of message frequency | Hz    |
| \( M \)         | Message size                     | b     |
| \( N \)         | Number of vehicles              | -     |
| \( N_{G} \)     | Number of vehicle groups        | -     |
| \( N_{SW,S} \)  | Traffic flow from south-west driving straight | veh/h |
| \( N_{SW,L} \)  | Traffic flow from south-west turning left | veh/h |
| \( N_{NE,S} \)  | Traffic flow from north-east driving straight | veh/h |
| \( T_{PD} \)    | Propagation delay               | s     |
| \( T_{PRE} \)   | Preamble duration               | s     |
| \( T_{SIG} \)   | Signal duration                 | s     |
| \( T_{OFDM} \)  | Duration of an OFDM symbol      | s     |
| \( T_{CH,S} \)  | Channel slot time               | s     |
| \( T_{IFS} \)   | Arbitration Inter-Frame Space Time | s     |
| \( T_{VS} \)    | Duration of a virtual time slot | s     |
| \( T_{D} \)     | Duration of a successful transmission | s     |
| \( T_{C} \)     | Duration of a collision transmission | s     |
| \( T_{FD} \)    | Frame duration                  | s     |
| \( T_{SG} \)    | Safety time gap                 | s     |
| \( T_{TH} \)    | Trajectory time horizon         | s     |
| \( W \)         | Number of Backoff stages        | -     |

### Parameters

| \( \lambda_{n}, \lambda_{a} \) | Accessible Information Relevance (of vehicle \( n \)) | -     |
| \( b_{-1} \) | Stage where we send a message | -     |
| \( b_{1} \) | Stage where we are idle | -     |
| \( b_{p,k} \) | Backoff stage at \( k \) | -     |
| \( c \) | Channel Busy Ratio | -     |
| \( \lambda_{n,j} \) | Necessity for \( n \) to obtain approaching time for \( j \) | -     |
| \( d_{i} \) | Relative distance | m     |
| \( d_{i} \) | Relative velocity | mps   |
| \( d_{i} \) | Relative acceleration | mps   |
| \( d_{MAX} \) | Modification of maximum acceleration | mps   |
| \( \Delta_{n,j} \) | Age of Information from \( n \) at \( j \) | s     |
| \( i, n_{0} \) | Message index (of vehicle \( n \)) | -     |
| \( k \) | Current backoff stage | -     |
| \( \lambda_{n}, \lambda_{j} \) | Message frequency of vehicle \( n \) or \( j \) | Hz    |
| \( \tilde{\lambda}_{j} \) | Approximate message frequency of vehicle \( j \) | Hz    |
| \( \tilde{\lambda} \) | Average message frequency of the channel | Hz    |
| \( \lambda_{i,n} \) | Optimized message frequency of vehicle \( n \) | Hz    |
| \( \lambda_{CH MAX} \) | Maximum message frequency in empty channel | Hz    |
| \( \lambda_{C} \) | Channel load | Hz    |
| \( \lambda_{S} \) | Message frequency step size | Hz    |
| \( n \) | Vehicle \( n \) | -     |
| \( \mu_{j} \) | Risk posed by vehicle \( j \) | 1/h   |
| \( r_{i,j}, r_{i,j} \) | Relevance of vehicle \( n \) or \( j \) | -     |
| \( r_{n}, r_{j} \) | Packet Delivery Ratio (PDR) of vehicle \( n \) or \( j \) | -     |
| \( s_{n} \) | Channel capacity fraction of vehicle \( n \) | -     |
| \( s_{C} \) | Current channel capacity fraction | -     |
| \( s_{T} \) | Current time in discrete steps | s     |
| \( t_{j} \) | Instantaneous approaching time of vehicle \( j \) | s     |
| \( t_{j} \) | Continuous approaching time of vehicle \( j \) | s     |
| \( \tau_{n}, \tau_{j} \) | Probability to send in random time slot (for vehicle \( n \) or \( j \)) | -     |
| \( \theta_{n}, \theta_{j} \) | ERA (perceived by vehicle \( n \)) | -     |
| \( \Theta(t)_{n,j} \) | PATH from vehicle \( n \) for \( j \) at time \( t \) | -     |
| \( u(t)_{j} \) | Uncertainty for state vectors relative distance, velocity, and acceleration | -     |
| \( p \) | Probability | -     |
| \( p_{B} \) | Probability that the channel is busy | -     |
| \( p_{S} \) | Probability that the channel is idle | -     |
| \( p_{S} \) | Probability for a successful transmission | -     |
| \( p_{C} \) | Probability for a collision transmission | -     |
| \( q_{n}, q_{j} \) | Probability that a message (for \( n \)) is ready | -     |
| \( \zeta_{n}, \zeta_{j} \) | Trajectory of vehicle \( n \) or \( j \) | -     |
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