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Analysis and Evaluation of Information **Redundancy Mitigation for V2X Collective Perception**

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ABSTRACT Sensor data sharing enables vehicles to exchange locally perceived sensor data among each other and with the roadside infrastructure to increase their environmental awareness. It is commonly regarded as a next-generation vehicular communication service beyond the exchange of highly aggregated messages in the first generation. The approach is being considered in the European standardization process, where it relies on the exchange of locally detected objects representing anything safety-relevant, such as other vehicles or pedestrians, in periodically broadcasted messages to vehicles in direct communication range. Objects filtering methods for inclusion in a message are necessary to avoid overloading a channel and provoking unnecessary data processing. Initial studies provided in a pre-standardization report about sensor data sharing elaborated a first set of rules to filter objects based on their characteristics, such as their dynamics or type. However, these rules still lack the consideration of information received by other stations to operate. Specifically, to address the problem of information redundancy, several rules have been proposed, but their performance has not been evaluated yet comprehensively. In the present work, the rules are further analyzed, assessed, and compared. Functional and operational requirements are investigated. A performance evaluation is realized by discrete-event simulations in a scenario for a representative city with realistic vehicle densities and mobility patterns. A score and other redundancy-level metrics are elaborated to ease the evaluation and comparison of the filtering rules. Finally, improvements and future works to the filtering methods are proposed.

INDEX TERMS Collective perception, information redundancy mitigation, road safety, sensor data sharing, V2X communications.

I. INTRODUCTION

Sensor data sharing using Vehicle-to-Everything Communication (V2X) is an effective and low-cost solution to enhance the perception range of a vehicle's sensors. It is the basis for various advanced use cases for connected and automated driving. In 2019, the European Telecommunications Standards Institute (ETSI) completed a pre-standardization report for sensor data sharing [1],¹ named Collective Perception Service (CPS). CPS relies on the periodic exchange of messages with other V2X stations, e.g., a vehicle or a Road Side Unit (RSU), within the communication range. The report implies important first design decisions, including the definition of the Collective Perception Message (CPM) and features of the communication protocol that is the basis for the development

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¹Published ETSI standards are available at http://etsi.org/standards.

of the CPS standard $[2]^2$ and considered as a baseline in the present paper. One of the main challenges of realizing CPS is to cope with the bandwidth-limited wireless channels in the 5.9 GHz band allocated for road traffic safety and efficiency. The default channel data rate is assumed at 6 Mbit s⁻¹, which is insufficient to transmit the raw data generated by typical sensors mounted on future V2X stations, e.g., cameras, lidars, and radars.

The first step taken in [1] to address the problem of limited channel resources was to use objects as data representations of safety-relevant information, such as other vehicles or a pedestrian at a crossway. Objects have the advantage of smaller data sizes, which result in a lower communication overhead. Also, they are independent of the used sensor types with their specific technical characteristics. Still, depending on the CPM generation frequency and the number of objects to include, CPS could considerably increase the load on a wireless channel, if not saturate it [3]. Another potential approach to reduce channel resource usage would be V2X message compression as proposed in [4], but this approach is beyond the scope of this work.

The second step to control the channel usage is to reduce the number of objects to include in a CPM by applying the so-called Perceived Object Container (POC) inclusion rules in the standard. Both steps are applied in this paper. The current definitions of these rules [1] consider filtering objects based on their dynamics, the type, e.g., Vulnerable Road User (VRU), and the last inclusion time in a CPM. However, they do not consider the information received by other V2X stations. As shown in the evaluation performed in [1], the inclusion rules can reduce the channel load significantly but still face an important issue: information redundancy. Information redundancy in CPS occurs when different vehicles send CPM carrying similar information about the same objects. While this is beneficial for misbehavior detection or to improve the perception of receiving stations, it comes at the cost of both channel and processing resources, indirectly increasing the end-to-end delay [5].

Consequently, the third step to the control channel load is to improve current filtering methods to control information redundancy. Redundancy control has already been addressed by preliminary work that was fed into [1] and further been analyzed in other publications, see Section II. In this paper, the CPS framework in [1] is reviewed and extended by elaborating on functional and operational requirements for Redundancy Mitigation Rule (RMR). Additionally, four RMR are evaluated by simulations using the *OMNeT*++ -based network simulation framework *Artery* [6] coupled with the microscopic traffic simulator for urban mobility, *SUMO* [7]. In *SUMO*, a realistic urban scenario of the city Ingolstadt in Bavaria, *InTAS* [8], is used to evaluate the performance of the filtering approaches. To better assess the performance of the studied RMR, two new metrics are

TABLE 1. Frequently used abbreviations.

AoR	Area of Relevance
CAM	Cooperative Awareness Message
CAS	Cooperative Awareness Service
CBR	Channel Busy Ratio
CPS	Collective Perception Service
CPM	Collective Perception Message
DCC	Decentralized Congestion Control
EAR	Environmental Awareness Ratio
MPR	Market Penetration Rate
POC	Perceived Object Container
RMR	Redundancy Mitigation Rules
RL	Redundancy Level
RV	Redundancy Valuation
S	Score
SIC	Sensor Information Container
V2X	Vehicle-to-Anything
VRU	Vulnerable Road Users

introduced: redundancy level and score. The redundancy level is the information of the frequency of updates received for an object considering its dynamics, i.e., an object moving faster is expected to receive more updates than a non-moving one. The score is an aggregated metric used to parametrize certain target objectives and compare the performance of the different filtering approaches for these objectives. Based on the performed requirements analysis and the obtained results, filtering characteristics are derived that combine advantageous features from the studied rules and can be regarded as the next research steps.

The remainder of this paper is organized as follows: After reviewing related work in Section II, an overview of ETSI's CPS as defined in [1] is presented in Section III. The RMR investigated in this paper are presented in Section IV. Section V analyzes functional and operational requirements for the rules. Section VI describes our simulation environment and parameters used to assess the RMR performance, analyses the results for each RMR, and discusses the obtained results and a RMR combination. Section VII gives an outlook on future work. Section VIII concludes the paper. For ease of understanding, Table 1 lists the most relevant and frequent abbreviations.

II. RELATED WORK

Initial work on sensor data sharing among vehicles dates back to 2012 [9]. Ideas developed in [10] and others have led to standardization activities and the publication of the ETSI study item TR 103 562 [1] and draft versions of a European standard for CPS in TS 103 324 [2]. From the standardization perspective and according to industry roadmaps, e.g., [11], CPS is regarded as a "Day 2" communication service beyond driver information and warning use cases [11]. Besides message format and other design elements, [1] defines the CPM dissemination concept to determine when to generate a CPM, i.e., CPM generation rules, and filtering rules to determine which objects to include in a message. Several publications, such as [3], [12]–[14], have reviewed the CPS design and

 $^{^{2}}$ At the time of writing the manuscript, the draft standard has not been completed yet. Its publication is expected in 2022.

elaborated on algorithms for message generation and object filtering.

As introduced in Section I, one of the key challenges related to CPS is the created information redundancy of the data transmitted on the wireless channel when multiple V2X stations detect and transmit information about the same objects. This problem has been considered in [1] and different redundancy mitigation approaches designed but not evaluated.

Only a few studies have addressed the redundancy problems for CPS. [15] has investigated two RMR, but applied different CPM generation rules than the currently designed ones [1], [2]. Hence, the results are not suitable for comparison and also not applicable to the standardization development.

The authors of [16] focused on the redundancy mitigation approach, which filters objects based on their dynamics, so-called Dynamics-based RMR; this approach is considered later in Section IV. They have used the same CPM generation rules like the ones described in [1]. The evaluation was performed using the NS-3 simulator coupled to *SUMO* in a highway scenario.

In [17], the authors used another approach for redundancy mitigation than in [1]. To reduce redundant object information on the channel, a probabilistic object filtering approach based on the perceived density of vehicles, market penetration, and road geometry was applied. The paper showed the efficiency of object filtering using a highway scenario and a minimal urban scenario with two roads.

A more recent work [18] provided a novel and promising way of controlling information redundancy. Their RMR filters perceived objects using three criteria: channel load as well as number and type of V2X stations that have already provided information about these objects. The main idea is to adapt the number of V2X stations that send information about the same object and thereby contribute to the channel load, i.e., the lower the channel load, the higher the number of V2X stations that are allowed to provide information about the same object.

Compared to the previous work, the present paper evaluates all RMR proposed in [1]. We assess the performance of four schemes and study the impact of parameter settings with the *Artery* framework in a complex and diverse urban scenario. We design and use novel metrics for a fair comparison, and compute the information redundancy while considering the object dynamics.

III. COLLECTIVE PERCEPTION SERVICE (CPS)

Modern vehicles can be equipped with a multitude of different sensor types such as radar, lidar, and camera. These sensors can have different viewing angles, ranges, and representations of their measurement results. For the vehicle to acquire one coherent view of its environment, sensor fusion is crucial. The idea of CPS is to share the objects included in the local environment model resulting from sensor fusion with surrounding V2X stations. This is achieved by transmitting CPM. A CPM, among other containers that are not further detailed in this paper, has two main components: The Sensor Information Container (SIC) holds information about the sensing capabilities of the transmitting V2X station in form of a list of the sensors it is equipped with. Since this information is static, the SIC does not need to be repeated with a high frequency and is included only once every second. The second and most important component of a CPM is the POC. The POC carries all objects the transmitting station has perceived with its local sensors. For inclusion, objects need to fulfill one of the following conditions:

- 1) The object is newly detected and was not included in a CPM of the transmitter before.
- 2) The position of the object changed by more than 4 m (absolute euclidian distance) since it was last included in a CPM of the transmitter.
- 3) The speed of the object changed by more than 0.5 m s^{-1} since its last inclusion.
- The heading of the object changed by more than 4° since its last inclusion.
- 5) The object was previously included in a CPM of the transmitter more than one second ago.

Following the message generation rules in [1], a CPM is generated whenever the SIC needs to be transmitted, or the POC is not empty (i.e., at least one of the locally perceived objects fulfills at least one of the inclusion conditions), or both. However, the CPM generation interval cannot be higher than 1000 ms or lower than 100 ms The rules were originally proposed [13] with the idea in mind that an object is included in a CPM whenever it would generate a Cooperative Awareness Message (CAM), presuming that it is equipped with V2X technology. The rules will certainly help increase the awareness about unconnected vehicles in the first years of V2X deployment but can overreach the goal when the V2X market penetration ratio grows over the years. This is because the information whether other V2X stations have transmitted data about a perceived object is not considered. As a result, a large amount of data is redundantly transmitted. To address this challenge, several RMR have been proposed in [1] and considered in research publications.

IV. REDUNDANCY MITIGATION RULES (RMR)

This section reviews the different redundancy mitigation rules defined in the pre-standardization study [1]. We note that [1] also presents a conceptual pro-and-con analysis for object filtering in general and specifically for the rules. Fig. 1 shows the overall object processing flow from the creation of sensor data to the generation of a CPM. It indicates the step at which the redundancy mitigation rules are applied.

Following the study in [1], redundancy mitigation techniques have two main advantages: reducing channel utilization and the average message size. As shown in [1] and [13], the former benefit is important as CPS alone can easily fill a wireless channel. Additionally, considering the transmission of different types of V2X messages, such as CPM and CAM,

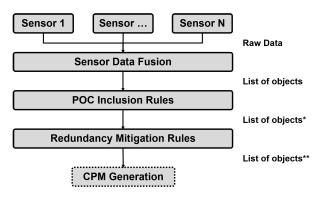


FIGURE 1. Object processing for CPM.

on the same channel, reducing the channel utilization for CPS leaves more transmission resources for the other messages types.

The study in [1] underlines some drawbacks of RMRs as well. First, estimating the relevance of an object for the other V2X stations is not trivial as all V2X stations may not have the same knowledge about an object, e.g., due to network conditions. Second, all RMR rely on the assumption that a V2X station can match its local perceived environment with the received information. This operational requirement is further considered in Section V. Third, filtering objects may increase the processing time and consequently the age-of-information of the objects. Finally, redundancy mitigation techniques consider that all V2X stations perform the same or similar approach. In practice, this may not be the case and should be treated carefully.

A. TECHNIQUES

The different techniques established for the RMR are described in the following subsections.

1) DISTANCE-BASED RMR

The Distance-based RMR filters an object if it has already been received from a remote V2X station within the R_Redundancy range during the recent time window W_Redundancy. This RMR relies on the idea that ideally there is no need for a transmitting V2X station to send information about an object if another V2X station within the W_Redundancy range already communicates CPM containing this object.

The parameter W_Redundancy is the time window during which the received CPMs matter for this RMR. The parameter R_Redundancy needs to be tuned such that the RMR efficiently reduces the channel load while allowing enough transmissions about the same objects. The source of information for this RMR is either an object received in a CPM, the sender of a CPM, or the information received in a CAM.

The additional benefit of this RMR is that it tends to maintain the awareness range. However, how to set R_Redundancy needs to be carefully investigated. A too-small value would result in too few filtered objects, not achieving the desired goal of reducing channel resources. A too high value would result in too many objects being filtered.

An additional drawback not mentioned in the prestandardization study [1] is that the Distance-based RMR, as currently designed, may result in V2X stations not being well placed for the detection of an object to transmit information about this object.

2) DYNAMICS-BASED RMR

The Dynamics-based RMR follows the same logic as the "POC inclusion rules" of the CPM and the CAM triggering rules [19]. An object is filtered if, from the last update received about it, its position or absolute speed changed less than P_Redundancy or S_Redundancy, respectively. However, the heading is not considered in this rule contrary to the CAM and CPS POC inclusion rules. A potential explanation is a difficulty of obtaining an accurate heading from perception sensors.

This approach is beneficial to adapt the number of updates to each object independently, e.g., an object moving fast will be subject to more updates than another one moving slowly. Moreover, an object at a constant speed will have periodic updates, which may be beneficial for tracking algorithms.

3) SELF-ANNOUNCEMENT-BASED RMR

The Self-Announcement-based RMR filters objects that can transmit V2X messages, such as CAM or CPM. The main benefit of this RMR is that its filtering will increase proportionally to the V2X Market Penetration Rate (MPR) and will only target objects that already send information about themselves. A drawback is that it assumes all other V2X stations can receive messages from this V2X station, which may not always be the case.

An additional drawback is that V2X stations sending information about themselves may not always have the most accurate information. For example, a RSU can have better detection capabilities thanks to its fixed position and calibrated sensors.

4) FREQUENCY-BASED RMR

The Frequency-based RMR filters an object if during the last time window of length W_Redundancy, the number of updates received about this object is equal or higher than the threshold N_Redundancy.

An additional benefit of this RMR is that the loss of CPM can be mitigated using the parameter N_Redundancy.

One of the additional drawbacks is that it does not consider the quality of perception. Hence, a few transmissions of objects with bad accuracy might prevent the transmission of more precise information. Additionally, depending on the parameter W_Redundancy, all updates may be received in a short interval of time, blocking any further transmission for the remaining of W_Redundancy.

5) ENTROPY-BASED RMR

The Entropy-based RMR filters an object if within the last time window W_Redundancy, either all neighbouring V2X stations are expected to perceive this object or the measured information novelty is measured lower than E_Redundancy for the other V2X stations within the D_Redundancy range.

In detail, a V2X station is supposed to estimate the prior knowledge of neighbouring V2X stations. To evaluate the prior knowledge of another V2X station, the transmitting V2X station has to assess the CPM received containing the object by this station based on its history of CPM. One proposed way of doing this is to rely on the distance between the transmitting V2X stations of previous CPM and the analyzed station. Yet, the procedure is not indicated in the prestandardization study [1]. Based on the estimated known CPM of the remote station, it is possible to evaluate, e.g., using a Kalman filter, the prior knowledge, such as pose and accuracy, of the remote station. By applying to all V2X stations, it is then possible to estimate the novelty of the information brought by sending this object.

The value suggested for D_Redundancy is to be lower or equal to the typical communication range.

The additional benefit of this rule is that it can mitigate the impact of potential loss of CPM by taking into account the distance between the V2X stations when estimating the received CPM for each station. Additionally, it considers the quality and freshness of the object information to transmit an object. And it may reduce the chance of incorrectly omitting an object.

The additional drawbacks for this RMR are the additional computational overhead and complexity that it creates. Moreover, the anticipated knowledge may depend on the fusion algorithm used and metric to express "knowledge" from another V2X station, making even harder the estimation of a V2X station's prior knowledge.

6) CONFIDENCE-BASED RMR

The Confidence-based RMR filters an object if, during the last time window W_Redundancy, the maximum confidence level of object information received by other V2X stations is higher than the current transmitting station's local perception.

The additional benefit of this rule is that it will prioritize transmission when the estimated knowledge about it is high, i.e., the most confident V2X station will send the information about the object.

The definition of confidence is not yet defined, but it represents a capital challenge for this RMR. Depending on the sensors equipped or the sensor-fusion algorithm used, the confidence level could vary significantly from one V2X station to another. A potential candidate for this confidence metric could be the CPM Object Quality metric proposed in [20].

B. FILTERING ACTIVATION

The activation of the RMR, or in general object filtering, is an important question to solve. As explained above, the

benefit of filtering is to reduce the channel load and object processing and leave more channel resources for other services. However, in case the channel is not loaded when only a few V2X stations are transmitting information, as in the early deployment phase of V2X stations, there are no benefits filtering objects.

In the pre-standardization study [1], the suggestion is to activate the RMR when the observed network channel load is higher than a threshold L_Redundancy. The value for this threshold is currently not specified and can be challenging to establish. The idea of using the channel load to adapt some communication behavior is not new and has already been exploited for Decentralized Congestion Control (DCC) with the reactive approach [21]. The reactive approach consists of several states reached depending on the current channel load. Each state controls the transmission rate of a station by imposing a minimum delay between two consecutive message transmissions. Unfortunately, this approach has been shown to create oscillations in the network load [22], i.e., all vehicles reduce transmission rate, the network load decreases, then all increase their transmission rate due to the lower network load, etc. This kind of result could be expected as well in the case of RMR when a similar approach as the reactive DCC would be applied. Moreover, taking into account resources used by other services running on the same channel is not considered. It may happen that even at a low channel load, a station should reduce the data generated by CPS due to other services with higher priority using most of the resources on the channel.

A better approach is that each station looks at its currently available resources for CPS. The CPM is expected to be released along with other message types such as for maneuver coordination or for platooning. Therefore, the resources allocated for CPM need to be shared with other message types. The resource allocation is expected to happen at the Facilities layer and, it is subject to the standardization item ETSI TS 103 141 [23] for which a first release is expected end of 2022. The activation of the RMRs could then rely on the following principle: activate the filtering of objects when the channel resources available for the CPS are lower than what the CPS would use. For example, if CPS is expected to generate 10 CPM/s when having at least one object to transmit, the activation of the RMR would start from the moment the resource allocated would not be sufficient to maintain this transmission rate. Furthermore, in the scope of this paper, we assume that an RMR is activated independently of the channel load or channel resources, i.e., at all times, when enabled.

V. FUNCTIONAL & OPERATIONAL REQUIREMENTS

Establishing functional requirements for RMR and in more general object filtering is essential to have a picture of what is needed. Functional requirements define what is expected from these rules. Based on these requirements, it is then possible to evaluate, compare, and potentially combine the different RMR to achieve the desired goals. Next to functional requirements, operational requirements of the different RMR describe what each RMR needs to operate. It provides a better understanding of the feasibility of realizing them in a real environment.

The following of this section is divided into two parts: one for the elaboration of the functional requirements and the other analyzes the different operational requirements of the RMR as presented in Section IV.

A. FUNCTIONAL REQUIREMENTS

Object filtering should have the following functionalities:

1) ADAPT TO THE AVAILABLE RESOURCES

Filtering an object should depend on the available resources available for CPS. If resources are abundantly available, there is no reason to filter an object. To determine the available resources, Congestion Control at the Facilities layer will play a vital role [23]. None of the RMR, considering a fixed parametrization, can adapt to the available channel resources. Adapting the parameters to the channel situation may be a way to address this requirement, which would need further studies.

2) PRIORITIZE INFORMATION QUALITY

In case filtering is necessary, the filtering approach should prioritize the exchange of objects with the highest quality of information for transmission. To prioritize the information quality, a RMR could look at the estimated accuracy of measurements or the age of information. The Confidencebased and Entropy-based RMR represent good candidates to achieve this goal. The confidence would need to be defined as the object quality metric defined in [20]. By measuring the estimated brought information, the Entropy-based RMR is a direct approach to reaching this goal.

3) MAXIMIZE V2X STATION'S RELEVANT ENVIRONMENTAL AWARENESS

The filtering should maximize the awareness of relevant objects of the other V2X stations. Maximizing other V2X stations' relevant environmental awareness could be addressed by either the Distance-based and Entropy-based RMR. By choosing an appropriate value for R_Redundancy, the Distance RMR could allow V2X stations to reduce the redundancy of information while maintaining a large range of communication. By estimating knowledge of other V2X stations, the Entropy-based RMR would have the possibility to realize this functional requirement as well.

4) CONTROL OVER THE INFORMATION REDUNDANCY

The information redundancy is significant for misbehavior detection, and it helps improve the perception of objects. An ideal RMR should allow to control it efficiently depending on other criteria such as available channel resources, trust level, or object characteristics. Only the Frequency-based RMR attends to do so by setting a maximum level of updates for all objects.

5) ADAPT TO OBJECT CHARACTERISTICS

As already considered in the Cooperative Awareness Service (CAS), an object not moving does not need as many updates as an object moving at high speed. Additionally, a VRU may require more updates than a vehicle to assert a sufficient safety level. An ideal RMR should take this into account while deciding to filter an object. In the POC dissemination rules, the filtering of objects is adapted already to the object characteristics such as its dynamics and object type. The same applies to the Dynamics RMR. The Self-Announcement rule represents another approach using object characteristics to operate as it only filters the V2X-capable objects.

6) ADAPT TO THE SOURCE OF INFORMATION

Object filtering should be adapted to the V2X station type. For example, an RSU may need different settings for its filtering due to its increased communication range than a mobile station or an emergency vehicle. Currently, none of the RMR has a method to address this functional requirement. Adapting the RMR parameters could be developed similar to [18] which proposed a filtering approach considering RSU.

7) FEASIBILITY

An object filtering approach should be realizable. As shown in Sec. II, most of the studies have been performed using simulations that do not consider enough the perception side of CPS. The operational requirements below are a step in this direction to evaluate the feasibility of the different RMR.

B. OPERATIONAL REQUIREMENTS

Each RMR has different operational requirements that may influence its feasibility and implementability in a real environment. Table 2 summarizes the operational requirements and associated RMR.

The core requirement for any RMR is the ability to accurately match the information received from other V2X stations with its local perception. In the case of a mismatch, an object could be detected as more than one object, making any RMR inefficient. This requirement already imposes a certain level of information quality on the exchanged objects.

Not considering the age of information, the quality of information about an object depends on two main criteria: the accuracy of the transmitting vehicle's estimated pose and its measurement accuracy of an object, whereas the latter depends on the first criterion. Indeed, even in the case of perfect object measurements, if the transmitting vehicle has a high error on its pose estimation, a receiver will have difficulties matching received objects. In comparison to all other RMR, only the Dynamic-Based and Entropy-Based RMR make use of the object pose estimation. If the accuracy level is not sufficient, these RMR will never be activated, which would result in a poor channel resource usage reduction.

Estimating other V2X stations' awareness of their environment to measure the information brought by sending an object is at the same time promising, computationally more intensive, and complex due to the different fusion algorithms and sensor configurations. In the analyzed RMR, only the Entropy-based RMR is attempting to achieve this goal.

Dependency on the equipped sensors matters as it may reduce the efficiency of object filtering. Both, the Entropy-based and Confidence-based RMR are directly dependent on the equipped sensors and the used algorithms to operate them as fusion algorithms.

Another comparison point that is not a requirement is which object a RMR is targeting. The Self-Announcement RMR only addresses information redundancy of a subset of the objects, i.e., the V2X-capable objects.

VI. EVALUATION

A. SIMULATION ENVIRONMENT

For performance evaluation, the discrete-event simulator Artery [6] is used. The simulator relies on Vanetza, INET, and OMNeT++ to implement the ETSI C-ITS communication protocol stack. Furthermore, Artery realizes an environmental model and sensor models that represent vehicles to perceive objects, such as vehicles and bicycles, in their vicinity. To model node mobility, Artery is coupled with microscopic traffic simulator SUMO [7]. To model realistic traffic and vehicle movement, the traffic scenario of the city of Ingolstadt, Bavaria, Germany, referred to as InTAS [8], is chosen. InTAS is 24 hours long and was developed using real daily data traffic from Ingolstadt. The map topology of InTAS and the distribution of vehicles at 9:15am, which corresponds to a rush hour, are depicted in Fig. 2a and 2b, respectively. The following subsections review the relevant parameters of our simulation framework, see also Table 3. Each parameter set is repeated two times with a different set of random seeds to increase the number of samples.

1) COMMUNICATION

To show the prospective impact of CPS and the RMR in the upcoming years, different MPR, i.e., the rate of vehicles with sensors capable to receive and sending V2X messages, are simulated. The investigated MPR are: 0.1, 0.25, 0.5, 0.75, 1.0. For communication, each vehicle is equipped with an ITS-G5 compatible transceiver, an instance of *Vanetza*, which implements DCC, GeoNetworking (GN), and Basic Transport Protocol (BTP), as well as a *middleware*, which runs the services. For DCC, the adaptive approach as specified in [21] and based on the message rate control algorithm LIMERIC [24] has been applied. LIMERIC is extended by the dual-alpha approach [25], which reduces the convergence time of the original approach [26].

2) SERVICES AND MESSAGES

Two services are enabled on vehicles with V2X capabilities: the CAS and CPS. The CAS operates on the control channel $(CCH)^3$ (IEEE channel # 180) while the CPS is assigned to

³The CCH is also named SCH0, where SCH stands for Service Channel

the SCH1 (IEEE channel # 176). Adjacent channel interference is not considered in this paper.

The CAS generates CAM according to ETSI EN 302 637-2 [19]. As described in Section III, the CPS generates CPM based on the rules in the ETSI TR 103 562 [1]. The *itsPduHeader*, the *managementContainer* and the *stationDataContainer* included in all CPM are together 44 B large. Each *sensorInformationContainer*, which is included once a second, amounts to 12 B. A POC in a CPM is 35 B each after encoding. The *FreeSpaceAddendumContainer* is omitted.

3) SENSOR CONFIGURATION

In the simulator *Artery*, perception is assumed to be idealistic, i.e., when an object is perceived, all its information, such as dimensions, position, and speed, are available to the perceiving vehicle without any inaccuracies. For a vehicle to perceive its environment, parameterized sensors can be attached. A sensor can be configured for a given range, opening angle, and attachment position on the vehicle. Also, a direct line of sight from the sensor to the object is required for successful detection. For an object to be perceived, one of its four corners has to be within a sensor detection area. Buildings and other vehicles are considered obstacles to perception.

Vehicles equipped with sensors in our simulation have two radars: one with 80 m range and 325° Field of View (FOV) facing backwards and one with 160 m range and 35° FOV facing forwards. This is directly inspired by the sensor configuration that Tesla states to use for their autopilot on its vehicles.⁴ While these powerful sensing capabilities might not be able to perceive all objects within their sensing range, it can be expected that such perception capabilities exist by the time when "Day 2" services will be deployed in the field.

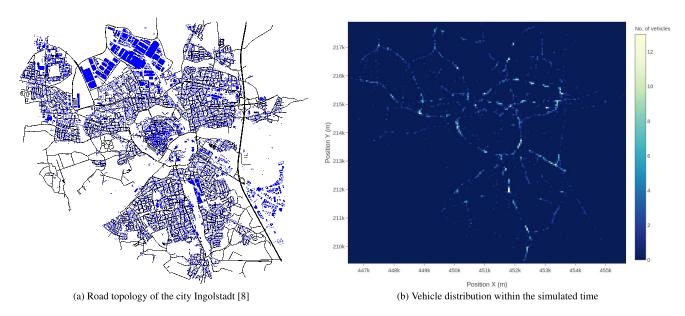
4) AREA OF RELEVANCE (AoR)

Most perception-based use cases of V2X require awareness of objects in the receiver's vicinity with respect to time. In an urban environment, such as the InTAS scenario, where vehicles drive with approx. 50 km h^{-1} , the range of wireless communication exceeds the distance to relevant objects, e.g., for safe braking, by far. Hence, some metrics make use of the Area of Relevance, (AoR) to determine which objects are relevant to the receiver. The AoR for a vehicle is defined as the area delimited by a circle with a radius $AoR_r = 500$ m centered at the vehicle's position. All objects within this area are regarded as relevant. The value of 500 m has been determined such that a non-relevant object should never be safety-critical for the vehicle, i.e., the provided time to reaction is always enough to perform an emergency braking maneuver. It should be noted that two other values for the AoR_r , 50 m, and 100 m, have also been investigated. However, the obtained results did not show a significant difference.

⁴https://www.tesla.com/autopilot. Last accessed: 30. Jan 2022

TABLE 2. Comparison of the studied RMRs with respect to operational and functional requirements, and targeted objects.

Criteria	Non	^e Di st	ance-ba	sed amics-ba Self-	sed Announ Frec	cement. uency-t Entr	based pased opy-base Confi
Functional requirements							
Adapt to available channel resources		×	X	×	X	X	X
Prioritize information quality		X	X	×	X	1	\checkmark
Maximize V2X station's relevant environmental awareness		1	X	X	X	1	X
Control over the information redundancy		X	X	×	1	X	X
Adapt to the source of information	X	X	X	X	X	X	X
Adapt to object characteristics	1	X	1	1	X	X	×
Operational requirements							
Matching local and remote perception		1	1	1	1	1	1
Sender high accurate pose estimation		X	1	X	1	1	X
High received object information accuracy		×	1	×	X	1	X
Anticipation of other V2X stations' current knowledge		X	X	X	X	1	X
Uniform measurement accuracy estimation	×	×	X	X	X	~	1
Targeted objects	All	All	All	V2X	All	All	All





B. RMR PARAMETRIZATION

Due to our characteristics of the used simulator, i.e., assumed ideal perception, the parameter C_Redundancy, which represents the confidence level on an object, was not considered within the scope of this paper. Additionally, this characteristic avoids evaluating either the Confidence-based or Entropy-based RMR.

In this section, we present the parameter settings for the RMR studied in this paper, i.e., Distance-, Dynamics-, Self-Announcement- and Frequency-based RMR. The other two, Confidence-based or Entropy-based RMR, are not considered in the evaluation since they require accurate modeling of the

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perception and hence an alternative approach for modeling and simulation than applied in the paper. Consequently, the parameter C_Redundancy for an object's confidence level is not used.

Table 3 summarizes the chosen parameter values.

1) DISTANCE-BASED RMR

The parameter W_Redundancy is the time window during which the received CPMs matter for this RMR. The chosen value for this parameter corresponds to the lifetime of a CPM, i.e., 1s.

TABLE 3. Summary of the simulation parameters.

Parameters	Values							
Protocol stack	ITS-G5							
Frequency band	5.9 GHz							
Channel model	Two Ray Interference							
Transmission power	23 dBm							
DCC	Dual-alpha LIMERIC							
Services	CAS (SCH0), CPS (SCH1)							
Scenarios	InTAS							
MPR	$\{0.1, 0.25, 0.5, 0.75, 1.0\}$							
Time of simulation	9:15 a.m.							
Number of vehicles	≈ 2755							
Simulation time	13 s (incl. 10 s of warmup)							
Number of repetitions	2							
Vehicle sensor equipment	2 radars: (80 m, 325°) (160 m, 35°)							
AoR	500 m							
Distance-based RMR								
W_Redundancy	1 s							
R_Redundancy	{25, 50, 100, 200}m							
Dynamics-based RMR								
P_Redundancy	$\{2, 4\}$ m							
S_Redundancy	{0.25, 0.5} m/s							
Frequency-based RMR								
W_Redundancy	1 s							
N_Redundancy	$\{1, 3, 5, 10, 15\}$							

The parameter R_Redundancy needs to be tuned such that the RMR efficiently reduces the channel load while allowing enough transmissions about the different objects. In our evaluation, we consider the following set of values for this parameter: R_Redundancy = $\{25, 50, 100, 200\}$ m.

2) DYNAMICS-BASED RMR

Dynamics values have already been analyzed in the context of the CAS and in [16]. Based on these works, the following values were evaluated: P_Redundancy= $\{2, 4\}$ m and S_Redundancy = $\{0.25, 0.5\}$ m/s.

3) SELF-ANNOUNCEMENT-BASED RMR

There is no parameter with this RMR.

4) FREQUENCY-BASED RMR

W_Redundancy can be set either to the lifetime value of a CPM, i.e., 1 s, or could be individually adapted for each object. The latter approach was not considered because W_Redundancy would then be adapted to the object's dynamics or criteria that other RMR use. The parameter N_Redundancy was considered more promising to analyze the potential control over information redundancy that this rule can bring. In our evaluation, the following set of values were evaluated: W_Redundancy = 1 s and N_Redundancy = {1, 3, 5, 10, 15}m.

C. METRICS

The following metrics are recorded periodically by every communicating vehicle and are used to determine the performance of the different RMR:

1) CHANNEL BUSY RATIO (CBR)

As defined in ETSI EN 302 571 [27], the Channel Busy Ratio (CBR) is a time-dependent value between zero and one (both inclusive). The CBR is calculated as the fraction of time that the radio channel is perceived as busy to the total period under observation.

2) ENVIRONMENTAL AWARENESS RATIO (EAR)

The Environmental Awareness Ratio (EAR) describes the ratio of objects known to a vehicle over the actual number of objects within its AoR. An object is defined as known if it can be perceived either by local sensors, by CPM, or CAM.

3) REDUNDANCY LEVEL (RL)

The Redundancy Level (RL) is a metric that represents the number of redundant updates a vehicle received for a perceived object in its AoR. It is defined as follows: For a vehicle v and one of its perceived objects o, the $RL_{v,o}$ is computed every 1 s. Therefore, d_o , s_o , and h_o , representing respectively the distance traveled, speed difference, and heading variation of the object o during the last second is computed. Then, the number of required updates n_req_o for this object for the last second is defined as:

$$n_req_o = \left\lceil max\left(\frac{d_o}{D}, \frac{s_o}{P}, \frac{h_o}{H}, 1\right) \right\rceil$$
(1)

with *D*, *P*, and *H* being the constant triggering conditions for the CAM, i.e., 4m for the distance D, 0.5m/s for the speed P, and 4° for the heading H.

If during the last second, the vehicle v received $n_rec_{v,o}$ updates about the object o, then $RL_{v,o}$ is computed as:

$$RL_{\nu,o} = \frac{n_rec_{\nu,o}}{n_req_o} \tag{2}$$

The advantage of the RL metric is that it keeps track of the redundancy per object considering the object's dynamics, which is not the case with common metrics such as Time Between Updates (TBU). It relies on the CAS standard [19], which defines the triggering rules for the CAM. However, the RL metric is limited since it does not express when updates have been received. Updates close to each other in time might be better for fusion (more redundant information). Equally, distributed updates might be better for things such as path prediction since more points for interpolation are available. The question of knowing when which information should be received is not solved yet and may depend on the algorithms used for processing received objects.

4) SCORE S

The purpose of the metric *S* is to quantify the performance of a RMR, enabling easy comparison between the parameter configurations for a RMR and among the different RMR. The performance of a RMR is determined by considering the conservation of channel resources that the RMR was able to achieve without obstructing the awareness while keeping an object information redundancy at a certain level. The score represents the applicable functional requirements as presented in Section V. Hence, $S \in [0, 1]$ relies on three criteria: the CBR, the EAR, and the Redundancy Valuation (*RV*), and is computed by the following equation:

$$S = (1 - CBR) * EAR * RV$$
(3)

The higher the score S is, the better it is. The CBR can be used to quantify the resource usage of deploying CPS as well as the resource conservation by RMR. Here, the *CBR* is the median of all CBR measurements recorded during a simulation run by every vehicle. For the score, this *CBR* is used to calculate its inverse, i.e., free channel resources. Consequently, the more channel resources are free due to deploying a given RMR, the better the score for the RMR becomes.

However, determining if the filtering by the RMR to free up channel resources was too strict is important. The score accounts for this by integrating the *EAR* which is computed over all periodically recorded EAR by every vehicle in the scenario. Therefore, the score for a RMR is reduced when the RMR determines a locally perceived object as redundant, but omitting its inclusion in the transmission will decrease the reception of its receivers.

Finally, Redundancy Valuation RV is a criterion that quantifies the usefulness of redundant updates for objects while deploying the RMR. Redundancy in the context of the CPS is not bad in itself and improves the reliability of the information. However, too many updates might be hard to process and waste channel resources. Hence, RV is designed to reduce the contribution to the score for each additional redundant update but also penalizes if object updates are too seldom.

Therefore, a vehicle *v* computes periodically the RL $RL_{v,o}$ for each perceived object *o* over the last 1 s. The $RV_{v,o} \in [0, 1]$ for a given object *o* from the perspective of *v* is computed with the following Gompertz function:

$$RV_{\nu,o} = ae^{-be^{-CKL_{\nu,o}}}$$
, with $a = 1, b = 7, c = 2.31337$
(4)

Finally, RV is the median overall recorded $RV_{v,o}$ for a given simulation scenario.

The Gompertz function models the properties of object redundancy in the following way: If $RL_{v,o}$ is 0, $RV_{v,o}$ will be nearly equal to 0, since there is no redundancy without any updates. According to (2), when n_rec_o is significantly smaller than n_req_o , $RU_{v,o}$ will be near 0 and grow exponentially with rising n_rec_o . This behavior penalizes overly aggressive redundancy mitigation techniques. When the n_rec_o reaches n_req_o the function RV = 0.5, indicating that the vehicle received at least the required amount of updates for the object. When n_rec_o exceeds n_req_o , the result will rise above 0.5 and converge toward 1.0 with increasing *RL*. Hence, receiving more updates than necessary yields a better result, but the gain of every further update will decrease.

With the current parametrization of $RV_{\nu,o}$, we define that 20% increased redundancy improves the performance

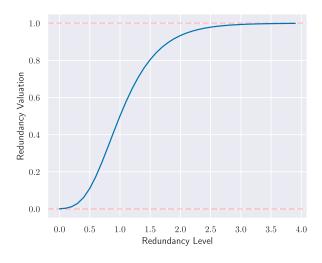


FIGURE 3. Gompertz function with a = 1, b = 7, c = 2.31337.

by 30%, whereas 100% increase in redundancy only improves the performance by about 85%. Receiving 300% more updates than required, the performance is already near its maximum of 198%.

The parametrization of the Gompertz function can be chosen arbitrarily, and therefore, the results are subjective. For this analysis, it is assumed that more than four times the amount of updates than necessary yields very little benefit and, hence, $RV \approx 1$ if $RL \geq 4$. If higher redundancy is required, other parameters for RV could be explored to observe how the scoring of the RMR changes and, therefore, is more suitable to achieve the redundancy level.

D. RESULTS ANALYSIS

1) CHANNEL BUSY RATIO (CBR)

The main objective of the introduction of RMR is to lower the resources required to disseminate the perceived information among the stations. The most relevant resource in this regard is channel capacity. Therefore, the first metric to be evaluated is the channel load, or CBR, caused by Collective Perception Service depending on the applied RMR. Boxplots of the CBR measured while applying each of the rules with different parameters (if applicable) are shown in Fig. 4. Each column represents one RMR. The rows show the results obtained with the five different MPR.

As expected, not applying any RMR results in the highest CBR at all MPR. Any RMR implemented was able to reduce the CBR to some extent at MPR higher than 5%. At 5% however, due to the small amount of V2X-enabled vehicles, CBR are so low that no significant differences can be seen between the RMR or their respective parameterization.

Starting from 5 % MPR, applying the Self-Announcementbased RMR exhibits an interesting effect. As expected, the median CBR increases from around 0.03 at MPR = 0.1 to its maximum of 0.145 at MPR = 0.75. This means that the CBR still grows with increasing MPR but much slower in comparison to the values obtained without any RMR. This is expected as with increasing MPR, a larger proportion of

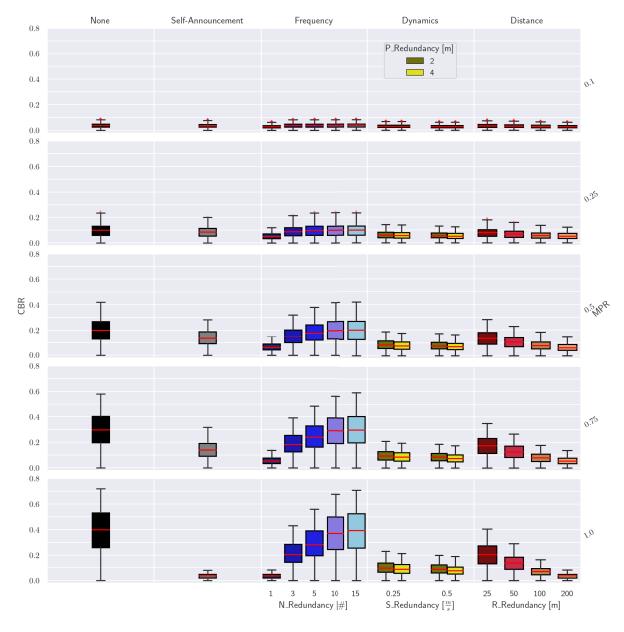


FIGURE 4. CBRs obtained at different MPR for the different RMR.

perceived objects sends CAM and therefore does not need to be transmitted in a CPM.

When increasing the MPR even further to 1.0, the CBR suddenly drops back to a value comparable with the value obtained at an MPR of 0.1. This happens because every single perceived object transmits CAM itself, and therefore the only reason CPM are generated now is that a SIC needs to be transmitted once every second. As a result, those CPM do not contain any perceived objects unless CAM were lost due to, e.g., collisions on the radio medium.

The Frequency-based RMR can result in very low CBR, depending on the value of the parameter N_Redundancy. When N_Redundancy = 1, each object is effectively only included in one CPM of one of the V2X stations in the area.

Therefore, the CBR remains extremely low, even at full market penetration. When choosing the value of N_Redundancy is too high, the RMR has virtually no effect on the CBR at all compared to not using any RMR.

The fourth column of Fig. 4 shows the CBR obtained with the Dynamics-based RMR. Independently of the parameter configuration, all results show a significant CBR reduction. The CBR is reduced between 75 to 80 % at MPR = 1.0 in comparison to the None-RMR case. Among the parameter configurations analyzed, the obtained CBR did not highly differ in comparison to other RMR. In the *InTAS* scenario, both the distance and the speed triggering thresholds contribute equally to the inclusion of objects in a CPM. However, in nonurban traffic scenarios, e.g., on highways, this may not apply.

The last column of Fig. 4 shows the Distance-based RMR and its respective parameter configurations. The parameter R_Redundancy considerably influences the resulting CBR. For example at MPR = 1.0, when R_Redundancy = 25 m, the CBR is at around 0.2. The CBR decreases to 0.14 with $R_Redundancy = 50 \text{ m}$, to 0.07 with $R_Redundancy =$ 100 m, and is reduced to 0.035 when $R_Redundancy =$ 200 m, which represents a reduction of CBR to around 90 % in comparison to the None-RMR. The higher R_Redundancy, the smaller the number of vehicles transmitting the information. R_Redundancy = 200 m represents a corner case because this is further than the maximum perception range of the vehicles which is 160 m (c.f. 3). Therefore, only a single vehicle is allowed to transmit information about an object, resulting in the same behavior as with the Frequency-based RMR at N_Redundancy = 1.

It can be concluded that all RMR have the potential to decrease the CBR by high margins. However, the gain largely depends on the setting of the respective parameter values.

2) ENVIRONMENTAL AWARENESS RATIO (EAR)

RMR can reduce significantly the CBR, however, care must be taken to maintain the awareness of receivers about objects in their AoR. Fig. 5 shows the EAR obtained with the RMR and their parameters settings.

When not applying any RMR, the median of the EAR is already higher than 0.5, even at an MPR of only 0.1. This shows the advantage of CPS, especially at low MPR. With increasing MPR, the EAR grows as well. This is expected as the ratio of vehicles transmitting CAMs and CPMs increases. At an MPR of 0.5, the EAR reaches a value larger than 0.95, and at full market penetration, the cases where not all relevant objects are known to the stations are only outliers. It is evident that neither the RMR themselves, nor their respective parameterization, change the observed behavior considerably. Any object, which is subject to at least one update per second without applying any RMR, is still received at least once per second with any of the simulated RMR.

3) REDUNDANCY LEVEL (RL)

Fig. 6 shows the obtained RL for the different RMR and their respective parameter configurations. For the None-RMR, the higher the MPR, the higher the RL. At MPR = 1.0, the median is at around 8.5, i.e., objects are subject to 8,5 times more updates than if they would send CAM. Some objects can be subject to a RL greater than 25, indicating the necessity of RMR.

The Self-Announcement-based RMR increases from a median at around 1.2 at MPR = 0.1 to 3 at MPR = 0.5. It then reduces to 1.3 again at MPR = 1.0. As this RMR is only active on V2X-capable objects, the redundancy for non-V2X-capable objects can still be high. In the results, this is reflected by a spreader distribution, e.g., the 100th percentile is at around 8.5 at MPR = 0.5 with many outliers as indicated by the red crosses. At MPR = 1, the rule is

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among the ones with the best performance to reduce RL with a median at around 1.5.

Naturally, the higher the N_Redundancy value, the higher the RL for the Frequency-based RMR. The results vary significantly with the different values of the N_Redundancy parameter. Results can be either similar to the Self-Announcement-based RMR and reduce considerably the RL, e.g., at MPR = 1 using N_Redundancy = 1 or similar to the None-RMR when N_Redundancy = 15 by almost not controlling the RL.

For the Dynamics-based RMR, the median of the obtained RL is always between 1 and 2.5. Relatively to the None-RMR, this RMR reduces up to 2.5 times the RL. Among the different parameter configurations, the obtained RL tends to stay around the same value. At MPR = 0.1, the RL median is at around 1 and increases steadily up to around $2 \sim 2.25$ at MPR = 1.0. Hence, the Dynamics-based RMR is among the most efficient rule to reduce the RL.

The RL obtained with the Distance-based RMR depends significantly on the setting of its R_Redundancy parameter. The higher R_Redundancy, the lower the RL. The median value for the RL is always maintained within the range of 1 to 5. Among the parameter values, the RL becomes significant at MPR higher or equal to 0.25. For example, at MPR = 0.5, the median value for RL with R_Redundancy = 25 m is around 3 while around 1 for the R_Redundancy = 200 m. The performance results of None-RM have clearly shown that it is necessary to apply efficient RMR in order to reduce the information redundancy on the channel. However, the selection of appropriate parameter settings is a determining factor for the resulting RL. Especially, the Frequency-based RMR needs to be carefully designed to obtain the desired RL.

4) SCORE

The score represents a subjective view of the authors on the expected RMRs performance (see Section VI-C) and facilitates a performance comparison among the RMRs. Fig. 7 shows the obtained score for the RMR for their respective different parametrizations. As shown in the results, the EAR does not impact the score as all RMRs obtained similar results for equal MPR. Consequently, the score is influenced mostly by the CBR and the RL.

The obtained score for the None-RMR goes from 0.385 at MPR = 0.1 up to 0.77 at MPR = 0.5 and decreases down to 0.62 at MPR = 1. In comparison to the other RMR, this rule performs best at an MPR lower or equal to 0.25.

For the Self-Announcement-based RMR, the score evolves from 0.38 at MPR = 0.1 to 0.83 at MPR = 0.75 than decreases until 0.66 at MPR = 1. Relatively to the other rules, this rule performs as one of the best scorers up to MPR = 0.5. At higher MPR, it starts to underperform compared to others.

The best scores relative to other RMR obtained with the Frequency-based RMR are between MPR = 0.1 to 0.5 with N_Redundancy = 3. At higher MPR, this rule

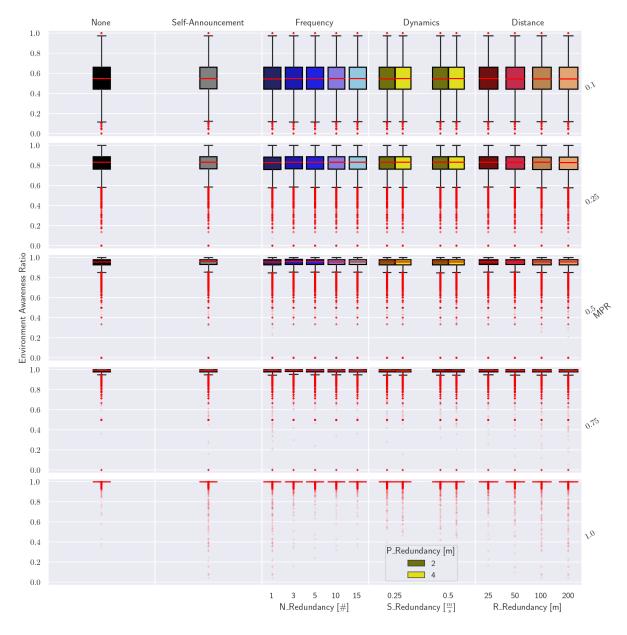


FIGURE 5. EARs obtained at different MPRs for the different RMRs.

underperforms in comparison to the best scores obtained at each MPR.

The scores obtained by the Dynamics-based RMR are lower than the best performing RMR at MPR lower than 0.5. At MPR = 0.5 and higher, independently of the chosen parameter value, this RMR obtains some of the best scores from around 0.83 at MPR = 0.5 to 0.875 at MPR= 1.

For the Distance-based RMR, the results differ chiefly between R_Redundancy = 200 and the other setting configurations. For R_Redundancy = 200, the score obtained is the same as for the Frequency-based RMR with N_Redundancy = 1, even by behaving differently. The reason is that both rules allow only a single vehicle to transmit information about an object. Still, both configurations result in some of the lowest scores obtained independently of the MPR. With R_Redundancy = 50m, the scores are some of the best at MPR higher and equal to 0.25, which corresponds to one of the best performing rules independently of the MPR. The other remaining configurations perform in general well but are either better at low or at high MPR.

In summary, the score as currently configured and studied in our evaluation framework shows that at low MPR, i.e., MPR < = 0.25, a RMR is not necessary. However, at higher MPR, RMR relying on either distance or dynamics criteria perform well to filter objects and maintain a balance between channel usage and information redundancy.

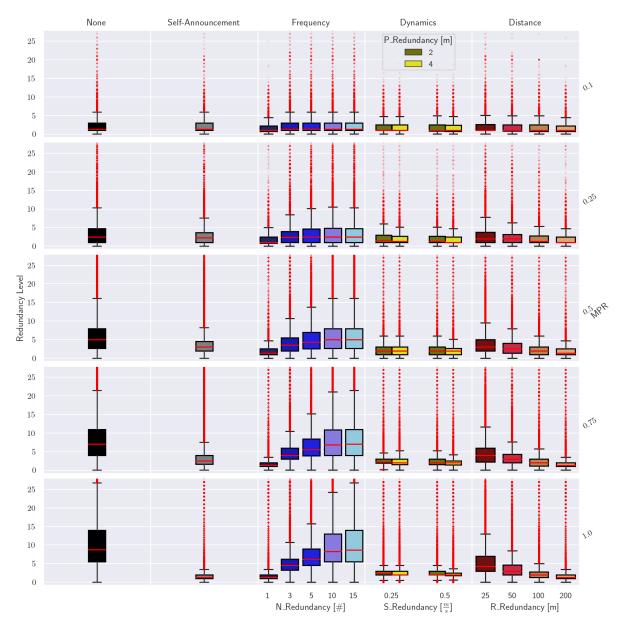


FIGURE 6. RLs obtained at different MPR for the different RMR.

5) DISCUSSION

The obtained results in the above sections and the preliminary analysis performed in Section V provide a better understanding of the RMR, their different requirements, and effects on the channel load, awareness, and information redundancy.

The CP Service can require high channel resources when only the POC inclusion rules are applied. The results indicate that channel resource usage can be controlled efficiently by employing RMRs with well-set parameters. Moreover, we can observe that the EAR was not affected by RMR. Still, the evaluation was made with the idealistic assumption that all objects are perceived and matched without any inaccuracies. Further investigations are needed to understand how error-prone perception would impact the operation of the RMR.

For the Self-Announcement RMR, it may be considered not applying as a standalone rule but complementary to another RMR. As shown in Table 2, this RMR has low operational requirements and only focuses on V2X stations. However, as shown by the score, transmitted updates on V2X-capable objects are kept to a strict minimum while V2X stations may be helpful in the perception of these objects, especially in the case of RSU.

For the Frequency-based RMR, it should not be used as currently defined. First, it may be arduous to choose the value for the parameter N_Redundancy. It could depend on the object characteristics or other criteria used by the rest of

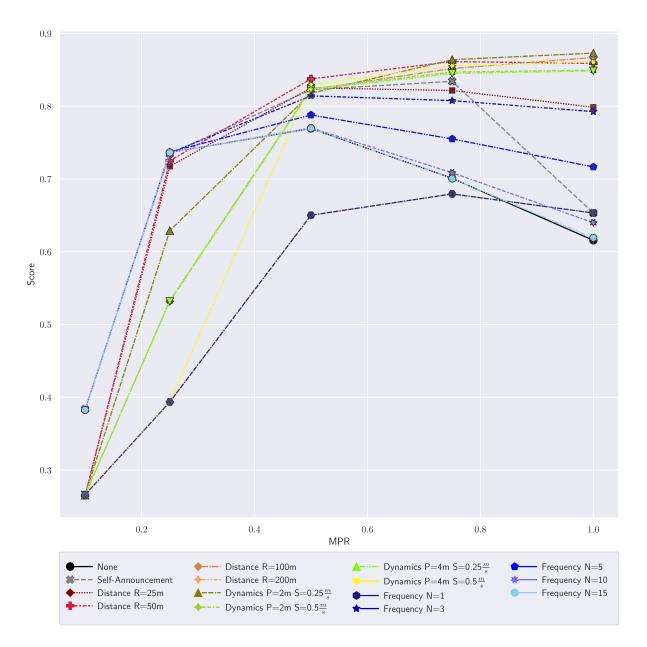


FIGURE 7. Scores obtained for the different RMR at different MPR.

the RMR, but then the behavior of this rule would change. Second, as already discussed in Section IV, many different vehicles may send updates about the same object in a short interval of time, circumventing any additional updates in the rest of the W_Redundancy time. A better approach for this RMR and already analyzed in [18] is to use the number of V2X stations that transmitted information about the same object instead of considering the number of updates received. The advantage of the Frequency-based RMR is the direct control over the number of V2X stations generating information about the same object, which could be helpful, for example, in case of misbehavior detection. The Dynamics-based RMR showed promising results by looking at the metrics such as the score and from other published studies [16]. It deserves further investigation, especially in its feasibility in experimental setups due to its many operational requirements (see Table 2).

The Distance-based RMR showed promising results as well. In terms of operational requirements, this rule seems easier to realize than the Dynamics-based RMR.

As shown with the scoring metric used in this paper and emphasized in other works (e.g., [3]), object filtering does not need to be applied at all times but should be adjusted based on the current situation. Methods, as discussed in Section V, should be used to address this problem, i.e., adapt filtering to the available channel resources.

It is worth mentioning again that we did not evaluate two RMR proposed in [1] because they require detailed and realistic modeling of the environmental data capturing. In fact, the simulator used in our study provides detailed modeling of the communication but does not have the capabilities for realistic sensor modeling and we assume ideal perception (no delay and no errors) in the object measurement. To better understand the impact of realistic sensor models on the RMR performance, enhanced simulation models and alternative simulation tools such as [5] would need to be used.

VII. FUTURE WORK

The functional requirements presented in Section V have provided an insight into the remaining research gaps for object filtering in CPS. In particular, the adaptation of the load to the available channel resources is yet to be addressed. Two approaches could solve this problem: adapting the RMR parameters to the available resources or adjusting the number of objects to filter to the available resources, such as described in [28]. Machine learning techniques could be applied to handle the complexity of channel resource estimation and object filtering, considering the network topology and data received from other vehicles. More work and research are needed to address this requirement.

Additionally, as shown in Section V, combining the RMR can enable better and more advanced filtering rules. The obtained results and performed analysis should be the basis of the decision on which RMR to combine and how.

The algorithm 1 shows the pseudo-code for an exemplary filtering approach that combines different RMR. First, the POC inclusion rules are adopted to pre-filter objects based on their dynamics and type. Second, the number of sources of information for this object is retrieved from received CAM and CPM during the last time window W_Redundancy and within the R_Redundancy range. If the number of sources for an object is lower than N_Redundancy, it is included in a CPM. Else, the confidence level of the transmitter station is compared to the minimum of the N_Redundancy highest confidence level obtained from the same CAM & CPM. If the confidence is lower than this minimum, the object is filtered.

The example of combined filtering approaches enables control over the redundancy level for a defined area and other V2X stations to complement the perception in areas not covered. Moreover, if too many vehicles send information about the same object, relying on the confidence level facilitates to privilege the highest quality of information. Theoretically, this would address the several functional requirements: adapt to object characteristics, prioritize information quality, maximize the V2X station's relevant environmental awareness, and control information redundancy. However, evaluating such an approach requires enhanced simulation tools for evaluation, further developing of the confidence level metric, and understanding its potential and feasibility in real environments. The combination of RMR and its evaluation is considered for future work.

Algorithm 1 Example of RMR Combination.
Input: obj
Output: Is_Filtered
1: Is_Filtered = PocInclusion(obj)
2: if not Is_Filtered then
3: Sources = checkSources(obj, R_Redundancy)
4: if # <i>Sources</i> > <i>N</i> _ <i>Redundancy</i> then
5: <i>min_conf</i> = getConf (Sources, N_Redundancy)
6: if $conf(obj) < min_conf$ then
$Is_Filtered = True$
7: end if
8: end if
9: end if
10: return Is_Filtered

VIII. CONCLUSION

Information redundancy caused by CPS requires control to preserve channel and processing resources. In the present study, different filtering approaches have been evaluated to address this problem. First, their functional and operational requirements have been analyzed. Second, performance was assessed by simulations for four filtering approaches and different parameter configurations. Three criteria were the basis of comparison: the channel load, the environmental awareness, and the information redundancy level. Results showed that RMR are an efficient tool to reduce the channel load while maintaining environmental awareness. The control over information redundancy is possible with fine-grained parameter configurations of the RMR. The scoring metric developed in this paper helps to evaluate a desired redundancy level objective while considering environmental awareness and channel resources. Third, the analysis showed that none of the redundancy mitigation rules achieved all operational requirements. An example of a filtering approach combining different RMR was presented for covering more of these requirements. Such a filtering approach should be analyzed in future work. Finally, more research is needed with a focus on the perception side of CPS to gain a better understanding of how measurements inaccuracies and delays would influence object filtering.

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