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Analyzing and Optimizing Extended-CAM Service Using Simple Stochastic Geometry Model

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Abstract—Vehicular Ad hoc Networks (VANETs) offer a promising approach to enhancing road safety. Cooperative Awareness Messages (CAM) is an essential service in VANETs, allowing vehicles to transmit radio beacons containing their positions and velocities. These messages inform nearby vehicles about the traffic situation. This paper focuses on Extended Cooperative Awareness Messages (ECAM), which include additional information about nearby vehicles. ECAM beacons consist of a vehicle’s speed, position, and data on the positions and velocities of other vehicles in its vicinity. This comprehensive information enables nearby vehicles to understand the traffic situation and take appropriate actions to prevent potential collisions. Studies demonstrate that ECAM has the potential to significantly improve road safety by providing comprehensive and up-to-date traffic information. This paper uses stochastic geometry to evaluate different versions of ECAM services and compare the results with simple simulations. The evaluation assumes random vehicle placement using a homogeneous Poisson Point Process and models the ECAM service using the Matern Point Process.

Index Terms—VANET - CAM - ECAM - Stochastic Geometry - Poisson Point Process

I. INTRODUCTION

Vehicular Ad hoc NETWORKS (VANETs) [13] [14] is a key component of Intelligent Transportation Systems (ITS). They can ensure connectivity between vehicles with or without a fixed network infrastructure. In a VANET, vehicles cooperate to collect and share information with each other, the road infrastructure, and other vulnerable road users. Vehicle-to-vehicle communications have the potential to make a significant contribution to overall traffic control by improving road safety. Two types of messages can be sent: *i.*) Cooperative Awareness Messages (CAMs) [12] and *ii.*) Decentralized Emergency Notification Messages (DENMs). CAM Messages are periodic and usually sent in broadcast and at one hop. They carry the vehicles’ positions and velocities to warn other vehicles and prevent collisions. DENM messages are used when a dangerous event is detected. These messages are thus aperiodic and usually relayed on a few hops.

In dense vehicular networks, CAM messages are typically transmitted at a frequency of 10 Hz, resulting in a substantial amount of data on the radio channel. One approach to address this bandwidth challenge is to adjust the frequency of CAM messages based on the network’s density. However, reducing the message frequency may not always be optimal, as it could

lead to an increased risk of accidents when vehicle density rises. An alternative solution involves employing additional detection techniques, such as sensors or visible light communication units, to gather information about neighboring vehicles, including their speed and position. By incorporating this extra information, vehicles can send Extended CAM messages that encompass their own speed and position and that of nearby vehicles [1], [2]. Despite Extended CAM messages containing more data than simple CAM messages, they help conserve bandwidth by avoiding the constant overhead present in each message.

This paper explores the optimal design of the Extended Car Awareness Message Service and emphasizes the critical role of vehicle selection, referred to as cluster heads, in the protocol’s optimization. Three different approaches are considered in this study. The first approach is a completely random selection aimed at achieving network-wide coverage. The second approach is a greedy algorithm where cluster heads are selected based on the number of neighbors they can cover. This selection process is repeated until all vehicles in the network are covered by at least one cluster head. The third approach utilizes a scheme derived from the Matern hard-core selection process, a classical stochastic geometry point process. We compare the performance of these three techniques along with the optimal selection algorithm, providing insights into their effectiveness. This comparative analysis aims to identify the most efficient approach for building the Extended Car Awareness Message Service.

The remainder of this paper is organized as follows: Section II provides a comprehensive review of studies that focus on the optimization of bandwidth for VANET safety services. Section III presents the selection of nodes sending ECAM messages as an optimization problem namely a binary ILP (Integer Linear Programming) problem.

Section IV introduces the three algorithms that we propose for this optimization. In Section V, we present the simulation results and analyze their impact on performance. Finally, Section VI concludes the paper and outlines potential future work and development in this field.

II. RELATED STUDIES

In Vehicular Ad hoc Networks (VANETs), safety services provided by Cooperative Awareness Messages (CAMs) or Decentralized Environmental Notification Messages (DENMs) are highly influenced by the vehicle density within the network. The density of the vehicles and the channel bandwidth used by the safety services increase simultaneously if no mitigation technique is used. In this section, we examine various solutions that effectively manage and control the bandwidth consumption of safety applications as the vehicle density on the roads increases.

One approach to address the congestion challenge in vehicular networks is to dynamically adjust the packet data rate based on the density of vehicles. [3] propose a congestion control algorithm called Data Rate Decentralized Congestion Control (DR-DCC). This algorithm operates within the ETSI DCC (Decentralized Channel Control) framework [4] and focuses on selecting the optimal data rate at different vehicle densities to mitigate congestion and support various safety applications. The study demonstrates that DR-DCC outperforms schemes based on transmission power control by achieving better Inter Reception Time (IRT). However, due to higher data rates, DR-DCC faces a penalty in transmission range selection in highly dense traffic. It maintains good IRT performance within the critical range of 150 meters. Furthermore, [3] compares DR-DCC with another algorithm called Transmission Power DCC (TP-DCC). The results show that DR-DCC performs better, providing shorter IRT than TP-DCC for the same transmission range. This highlights the efficiency of DR-DCC in reducing congestion and enhancing safety communication.

In another work [8], the authors try to reduce congestion through transmission rate control. This scheme relies on the channel's busy-time as a metric to estimate the traffic density and the number of vehicle nodes in the vicinity.

Another approach to mitigate congestion in vehicular networks is to dynamically adjust the transmission power based on the density of vehicles. [5] present a solution that incorporates a dynamic packet reception model and an adaptive transmission power control mechanism. They aim to reduce congestion and enhance the packet reception rate using the Model Predictive Control (MPC) approach [6]. The proposed solution recognizes that altering the transmission power in CSMA networks can have a similar effect to optimizing the carrier-sense threshold [17]. By leveraging this understanding, the adaptive transmission power control mechanism adapts the transmission power based on the vehicle density, aiming to alleviate congestion and enhance overall network performance.

In this work [7], first, the authors design a dynamic packet reception model and then estimate the vehicle density using the velocity and vehicle flow rate. Based on these two factors, they build an adaptive power control algorithm. Using extensive simulations, the authors show that this mechanism can improve the congestion in a vehicular network.

In [9], a Distributed Fair Power Adjustment scheme is proposed to address congestion on the control channel in

vehicular networks. This scheme utilizes a dynamic control strategy that adjusts the transmission power of beacons for safety applications based on the node density. By decreasing the transmission power and limiting the neighborhood area of nodes, the algorithm effectively reduces congestion on the radio channel.

Similarly, [10] proposes a two-level transmission power scheme named the bi-beacon scheme to reduce the collision rate. The transmission Power Control scheme uses two different transmission ranges decided by the vehicle's speed for disseminating the beacons. The vehicles alternately transmit long-range and short-range beacons with an equal generation rate. Moreover, the authors used a contention window control scheme to minimize collision in a dense vehicle environment. In [11], a protocol selects a minimum CAM transmission power to keep the vehicles connected within a Cooperative Safety Zone. In this algorithm, the distance between the source vehicle and its nearest neighbors, called critical nodes, determines the transmission power. Moreover, Cooperative piggybacking has been used to extend awareness beyond the safety zone in the network.

In contrast to the previous studies that focused on varying data rates or transmission power to reduce channel load and improve CAM transmission in the neighborhood, we propose in a previous study an alternative solution based on cooperative transmission [1], [2]. This solution keeps the data rate and transmission power unchanged. The concept leverages the vehicle's embedded sensors to capture information about their surrounding vehicles. Dedicated vehicles then transmit Extended CAMs, which have their own speed and position and incorporate the speeds and positions of the surrounding vehicles. By leveraging cooperative transmission and sharing this additional information, the objective is to enhance the overall awareness of neighboring vehicles and improve CAM transmission's effectiveness without modifying data rates or the transmission power. This approach allows for a collaborative and cooperative exchange of critical information, thereby contributing to safer and more efficient communication within the vehicular network.

III. SYSTEM DESCRIPTION AND PROBLEM FORMULATION

As introduced before, this paper aims to explore the optimal design of the Extended Car Awareness Message Service and emphasizes the critical role of vehicle selection, noted as vehicle cluster heads. Basically, to optimize the operation of the ECAM, it is crucial to make intelligent selections of the nodes responsible for broadcasting their own information and that of their detected neighboring vehicles. By making intelligent vehicles selection, we can further minimize the number of messages transmitted over the radio channel while ensuring or maximizing the level of awareness that each vehicle has of its surrounding environment. In the following, we start by formulating the optimization problem behind such optimization problem, and then we propose three vehicles selection algorithms to send the ECAM in the next section.

ECAM: vehicle cluster heads selection optimization problem

This section proposes formulating the vehicle cluster head selection in ECAM as an optimization problem. The idea is to find the minimum number of nodes to transmit the ECAM to allow total coverage. This leads to the fact that all the nodes are informed of the position and the speed of any other nodes within their communication radius.

Let us consider that we have a set of vehicle nodes (N) in an area A . We associate to each node a sensing range denoted by s_i , $i \in N$. We also denote by S_i the set of nodes within the sensing range of a node i . In ECAM, each node periodically sends a message that transmits its position and the positions of all nodes that belong to its sensing range (set of nodes j , $\forall j \in S_i$). This message is received by all the nodes in the communication range of a node i , which we denote by r_i . We also denote by R_i the set of nodes within the communication range of i and receive any message it sends.

The objective is that all the nodes have to be aware of the positions of all nodes that belong to their communication ranges. Basically, we need to find the minimum number of nodes that should transmit their ECAM message while ensuring that all the nodes are aware of the nodes that belong to their communication range. Let's consider a binary variable, noted as x_i , that indicates whether a node i transmits its ECAM message. This means that $x_i = 1$ if the node i has to transmit its ECAM message, 0 otherwise.

We also define that a node j is aware of the existence of a node k using a second binary variable, noted as $y_{j,k}^i$. This variable indicates if a node j is informed by the existence (i.e. the position) of node k , by node i . Basically, $y_{j,k}^i = 1$ if the ECAM message transmitted by the node i informs the node j about the position of the node k and the node k belongs to both the sensing range of node i and the communication range of node j , 0 otherwise. $y_{j,k}^i$ is also equal to 1 in the case where the $i = k$, which means that the node transmitting its ECAM (here node i) is also informing the node j about its position. Finally, $y_{j,k}^i$ is also equal to 1 for all nodes k that belong to their sensing range ($\forall i \in R_j$) since all nodes are aware of the nodes that are within their sensing range, thanks to the embedded sensors. According to the last definition, we can easily formulate our problem as a Binary ILP problem as follows:

$$\begin{aligned} & \text{minimize} && \sum_{i=1}^N x_i \\ & \text{subject to} && \sum_{i=1}^N y_{j,k}^i \cdot x_i \geq 1, \quad \forall j \in N, \forall k \in R_j, \\ & && x_i \in \{0, 1\}, \quad \forall i \in N, \\ & && y_{j,k}^i \in \{0, 1\}, \quad \forall i \in N, \forall j \in N, \forall k \in R_j \end{aligned}$$

While the previous formulation enables the selection of vehicles responsible for transmitting ECAM messages, it requires executing such a solution in a fully centralized manner. Nevertheless, such centralization comes with high costs in

terms of computation and communication, which contradicts our objective of reducing the radio channel load. Hence, it is crucial to develop distributed solutions capable of achieving performance levels as close to the optimal solution.

IV. PROPOSALS

In the following, we propose three different algorithms. The first algorithm is a greedy algorithm, which is also a centralized algorithm. We iteratively select the nodes that cover the maximum number of neighbors. We proceed with selection until all the nodes are covered. The second one is a random selection of the vehicles until all the network nodes are covered. Finally, the last algorithm uses the Matern selection process used in stochastic geometry. The idea is to give a random mark to all the network nodes. There will be an auto-selection of the node with the smallest mark. The last two algorithms are fully decentralized. In the following, we describe in detail each of the algorithms.

A. Greedy vehicle selection method

For the greedy algorithm, the steps that follow each of the vehicles are: First, compute the number of neighbors of every node in the network. Second, select the node which has the largest number of neighbors. Third, remove this node and its neighbors. These three steps must be repeated until no more vehicles are covered by the ECAM messages.

We have to notice that this algorithm is centralized. Thus, it is difficult to run it for real. We can think of this algorithm as a basic algorithm to evaluate the improvement obtained from the ECAM scheme.

B. Random vehicle selection method

For this distributed approach, each vehicle randomly chooses to send its ECAM in its neighborhood with a given probability q . As soon as a node receives an ECAM mentioning its speed and position it stops sending its CAM. This algorithm gradually increases the number of nodes sending extended ECAMs and the whole network finishes being completely covered.

C. Matern vehicle selection method

This algorithm is fully distributed. All the nodes in the network receive a random mark, a real number between 0 and 1. The idea is to select one node such as in its neighborhood this node has the largest mark. When the algorithm starts, all the nodes send their ECAMs. These ECAMs carry their random marks. If a node receives an ECAM sent by a node that has a larger random mark, the former node stops sending its ECAM.

This algorithm implements the Matern hard core selection process [15]. Interestingly, when the vehicle follows a homogeneous Poisson point process, it is easy to compute the probability that a node is retained in the Matern process. If we denote by λ the intensity of the Poisson process and we denote by l the sensing range, the probability that a node is retained is:

$$p_r = \frac{1 - \exp(-2\lambda l)}{2\lambda l} \quad (1)$$

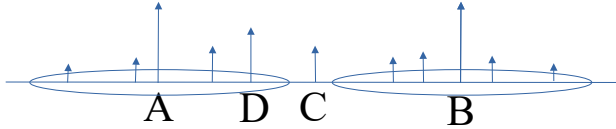


Fig. 1: A selection of sending vehicles with the ECAM - Matern algorithm. Vehicle C is not covered since D is eliminated by C

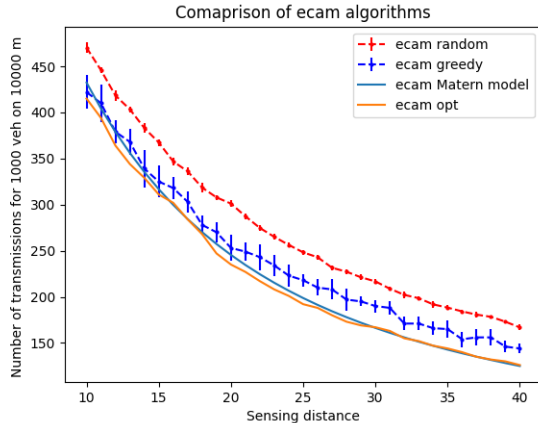


Fig. 2: Comparison between all ECAM algorithms

This algorithm is designed to mimic greedy selection. However, we can not be sure that all the nodes will be covered by the algorithm. For instance, in Figure 1, two nodes (node A and node B) are selected as they carry the largest mark in their neighborhoods. However, node C in-between node A and node B is eliminated by node D , and node D is eliminated by node A . Thus node C is not covered since it should be by node D itself eliminated.

V. EVALUATION

To evaluate our algorithms, we assume we have a ten-kilometer road with 1000 vehicles. These are randomly distributed on the road. We vary the sensing range from 10 to 40 meters.

In Figure 2, we compare the different ECAM algorithms. We show the mean number of nodes selected by the algorithms versus the sensing range of the vehicles. We observe that the ECAM-opt is very close to the ECAM-Matern algorithm. The number of selected vehicles is slightly higher for the ECAM-Greedy algorithm and still higher for the ECAM-Random algorithm, even if the order of magnitude for all the algorithms remains the same.

In Figure 3, we compare for the ECAM M¹ algorithm the mean number of nodes selected by the algorithm and the mean number of nodes selected predicted by the formula of the

¹M for Matern

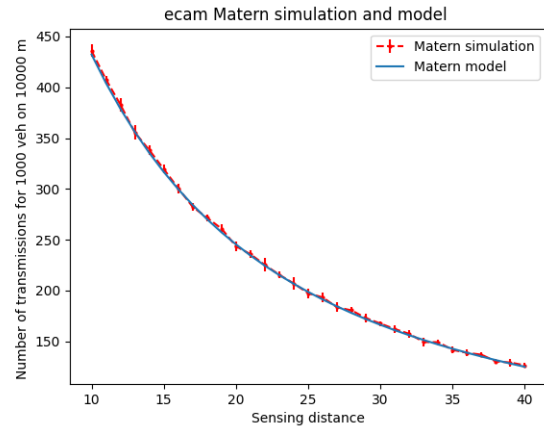


Fig. 3: Comparison between the Matern model and simulation of the Matern process

Matern model. We observe an excellent matching between the two approaches. So in the next comparisons, we can use the analytical formula to evaluate the ECAM M algorithm.

In Figure 4, we evaluate the ECAM Greedy algorithm and we compare to the ECAM M algorithm. The ECAM Greedy algorithm saves 57% in the number of CAM transmissions for a sensing range of 10m, 74% in the number of CAM transmissions for a sensing range of 20m, 81% in the number of CAM transmissions for a sensing range of 30m and 85% in the number of CAM transmissions for a sensing range of 40m. We observe that the algorithm derived from the Matern selection process provides results close to those of the ECAM Greedy algorithm. Therefore, our intuition seems to be correct that the ECAM M algorithm mimics the ECAM Greedy algorithm. Thus, the ECAM Matern analytical model can be an excellent approximation for the performance of the ECAM Greedy algorithm.

In Figure 5, we evaluate the ECAM Random algorithm and compare to a shifted version of the ECAM M algorithm. We show that the ECAM Random algorithm saves 53% in the number of CAM transmissions for a sensing range of 10m, 70% in the number of CAM transmissions for a sensing range of 20m, 78% in the number of CAM transmissions for a sensing range of 30m and 83% in the number of CAM transmissions for a sensing range of 40m. We also show the ECAM Random algorithm.

We can also notice that if we use the following formula:

$$p_r = \frac{1 - \exp(-2\lambda l)}{2\lambda l} + 0.05 \quad (2)$$

we obtain a very good approximation of the ECAM R algorithm, see Figure 5. This approximation will be valid for every linear Poisson point process with $1 < \lambda l < 4$.

In the following, we wish to study to quantify what is gained in bandwidth using the ECAM techniques. If we assume that a resource 1 is necessary to send CAMs we wish to compute

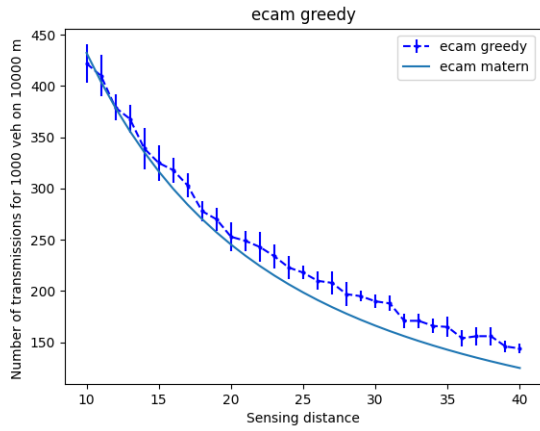


Fig. 4: Comparison between the ECAM greedy and Matern model

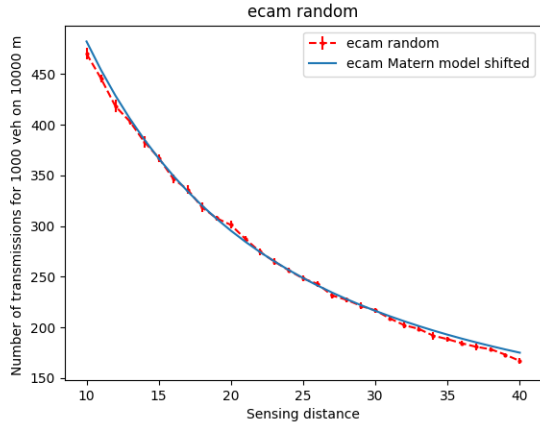


Fig. 5: Comparison between the ECAM random and the Matern shifted model

the resource x necessary if we use ECAM. For this evaluation, we take into account the reduction of the number of messages sent but we also consider that the ECAMs sent are larger than the usual CAM messages. To carry out this evaluation we adopt the the structure of the CAM packet presented in Figure 6 and values for the field length proposed in [16]. The result of this computation is given in Figure 7. For the ECAM Random algorithm, the fraction used by this algorithm is between 0.53 and 0.25 when 1 is the bandwidth needed for the CAM algorithm. For the ECAM Greedy algorithm, the fraction used by this algorithm is between 0.49 and 0.21 when 1 is the bandwidth needed for the CAM algorithm.

VI. CONCLUSION

VANETs are continuously progressing, bringing benefits that can improve road safety at multiple levels. CAMs are messages that carry the nodes' positions and speed and thus can be very useful to increase safety in vehicular networks. But the amount of traffic in terms of the number of packets

Complete Message	Header	Signer Info		
		Generation Time		
	CAM Information	its aid ITS-AID for CAM		
		Basis Container	ITS-Station Type	
			Last Geographic Position	
		High Frequency Container	Speed	
			Driving Direction	
			Longitudinal Acceleration	
			Curvature	
			Vehicle Length	
			Vehicle Width	
			Steering Angle	
		Lane Number		
		...		
Low Frequency Container		Vehicle Role		
	Lights			
Special Container	Trajectory			
	Emergency			
	Police			
	Fire Service			
	Road Works			
Dangerous Goods				
Safety Car				
...				
Signature	ECDSA Signature of this Message			
Certificate	According Certificate for Signature Verification			

Fig. 6: CAM Message with its fields

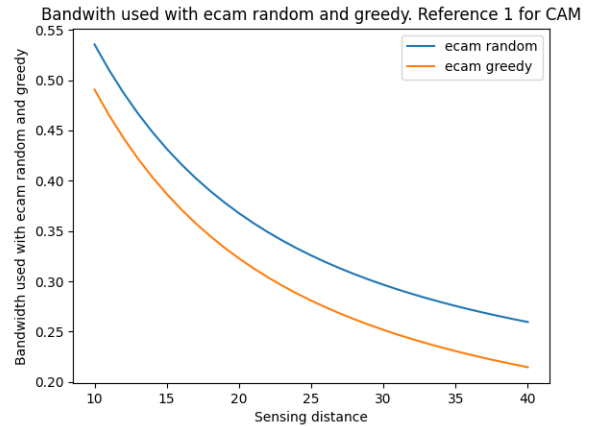


Fig. 7: Fraction of the bandwidth used for ECAMs. Reference for CAMs equal to 1

sent can rapidly be high, and optimizations are very useful. In an ECAM a vehicle sends in addition to its speed and position the positions and speeds of vehicles within its sensors' range. In this paper, we have discussed algorithms to select the vehicles which send these ECAMs. We have shown that the benefit of these algorithms is important. We have also proposed an analytical model based on the Matern process which evaluates the number of vehicles sending ECAMs in the random and greedy approach. Thus one can easily evaluate the gain obtained with ECAMs compared with when every vehicle sends classical CAMs. With reasonable figures, we show that the gain in bandwidth can be easily evaluated using a model derived from the Matern selection process. This gain remains large in normal conditions of utilization.

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