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Cooperative Offloading in Context-Aware Networks: A Game-Theoretic Approach

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ABSTRACT

Vehicles exchange Floating Car Data (FCD) to improve awareness beyond their local perception and thereby increase traffic safety and comfort. If the FCD is required at distant locations, FCD can be shared using the cellular network to notify vehicles early of upcoming road events. However, this monitoring of the roads congests the cellular network, which is already utilized by other applications. The available bandwidth for monitoring is expected to decrease further with the introduction of fully autonomous vehicles.

In this paper, we propose a hybrid dissemination approach for the distribution of road events in vehicular networks. Our approach aims to utilize only a predefined bandwidth for information exchange, which is achieved by two mechanisms: (i) the offloading of information to Wifi-based Vehicle to Vehicle (V2V) communication and (ii) the filtering of low-impact information. We offload the information to Wifi-based communication using non-cooperative game-theory: Each vehicle chooses the minimum impact of information it wants to receive via the cellular network. Through cooperation, the vehicles in proximity might provide information the other vehicles cannot receive. In the evaluation, we show that our approach significantly improves the data quality at the vehicles compared to traditional offloading approaches while sticking to the predefined bandwidth constraints.

CCS CONCEPTS

• **Networks** → *Hybrid networks*; Location based services; • **Theory of computation** → **Network games**; • **Computer systems organization** → *Heterogeneous (hybrid) systems.*

KEYWORDS

non-cooperative games, offloading, heterogeneous networks

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1 INTRODUCTION

Today's vehicles require vast amounts of sensor information to assist the driver [18]. Due to the vehicle's mobility, not only information in the direct proximity is useful, but also distant information. Distant information is not detectable by the vehicle's sensors due to physical restriction like sensor range. To provide distant information to the vehicles, other vehicles near the location of information provide their local perception in the form of FCD. In this work, we focus on the efficient distribution of FCD to concerned vehicles.

This provisioning is typically performed using the cellular network, as the range of Wifi-based communication technologies is limited and the time for information exchange via Wifi over large distances is prolonged due to the necessary relaying at intermediate vehicles. However, the cellular network itself is a limited resource and might not be able to handle the vast amount of exchanged FCD [1]. Additionally, in future fully-autonomous vehicles, the cellular network will additionally be burdened by the occupants of the vehicle. Thus, the bandwidth for the exchange of FCD is limited. In previous work, Meuser et al. reduced the consumed bandwidth by providing only the most essential information based on the vehicle's context [11] to improve the efficiency of the network. However, they did not consider local V2V communication to reduce the load on the cellular channel further. In this work, we consider the availability of local V2V communication.

In the literature, commonly cluster-based approaches as described in [13] are utilized to reduce the load on the cellular network by sending information only to one so-called Cluster Head (CH) which distributes received information to the vehicles in the cluster. Clustering approaches perform well if the number of necessary cluster adaptations is low, i. e., if the network topology remains constant like on highways. In urban scenarios, the road topology might induce frequent changes in the clusters, which leads to temporary disconnects of vehicles. Additionally, the frequent reorganization of clusters induces high load to the local V2V communication network, which reduces the available bandwidth for payload data. Especially for high-density regions, the necessary coordination for forming clusters may lead to issues [26]. Additionally, clustering approaches from the literature often ignore the value of information and assume that all information needs to be received. In this work, we question this approach for our scenario, as FCD is not equally important and might be dropped if the value is low. The importance (later referred to as impact) of a message depends on the type of contained information, and the context of the receiver.

Our contribution is the development of a hybrid communication approach, that offloads traffic from the cellular channel to the Wifi channel without forming explicit clusters and considering the impact of a message. In the following, the term *offloading* will be used to describe the load relief of the cellular channel.

To develop our offloading approach, we assume that we can rate the impact of a message for each vehicle. Based on this impact, we model the reception of messages as a non-cooperative game, in which each vehicle shares received messages on the Wifi channel. Other than that, we induce no management overhead on the Wifi communication channel except for Cooperative Awareness Messages (CAMs). The goal of our game is to maximize the aforementioned total impact of messages received by a vehicle.

As a solution for our game, we find a mixed strategy that maximizes the sum of impact values on a vehicle. With this strategy, most vehicles will receive a high-impact message via the cellular channel, as relying on neighbor vehicles may lead to not receiving the message, as the neighbors might not receive the message themselves. On the contrary, a low-impact message will be received by only a low percentage of vehicles, as a loss of this message impacts the system only slightly. Thus, our solution is very robust for high-impact messages, as the high-impact message is received via the cellular network by multiple vehicles. Additionally, our strategy depends only on the number of vehicles in proximity, which reduces the number of strategy updates drastically in urban environments.

The remainder of this paper structures as follows: In Section 2, we provide an overview of previous approaches for offloading the cellular connection. Next, we describe our scenario in Section 3. Based on this scenario, we describe our contribution, the modeling of the offloading as a non-cooperative game including the solution in Section 4, and the necessary adjustments to use this model in real-world scenarios in Section 5. In Section 6, we evaluate the performance of our offloading approach for different environmental settings. After that, we conclude this work with Section 7.

2 RELATED WORK

The collection and distribution of Floating Car Data (FCD) are important for future vehicular applications. FCD is information collected by the vehicles which are transmitted to a central backend. There they can be processed and distributed back to the vehicles.

In the next years, the load on the cellular network through FCD might increase to a level at which offloading is required to handle it [1]. The main challenge of offloading is the efficient combination of local Wifi-based communication with long-range cellular communication [5]. Due to its long-range, cellular communication is especially suitable to transfer information over large distances, while a significant advantage of Wifi-based communication is the locality. In the literature, the two communication technologies are often combined using clusters, i. e., organized groups of vehicles.

The main issue of a cluster is its stability under the high mobility of vehicular networks. Thus, much research has been performed to prolong the lifetime of a cluster. MOBIC [2], a clustering approach initially developed for Mobile Ad-hoc Networks (MANETs), has been extended by many researchers to match the requirements of vehicular networks [17]. Due to the complex cluster-management in case of multi-hop clusters, most clustering approaches require the Cluster Head (CH) to always be in communication range of the cluster members [21]. There are two main possibilities to form and manage clusters, decentralized [12, 21, 24] and centralized [4, 13]. While decentralized cluster management is more challenging regarding the coordination of nodes, centralized cluster management produces additional overhead on the cellular network. In [13], the authors managed the clusters at the eNodeB of the LTE network, which could significantly reduce the loss of information compared to a decentralized clustering approach. Additionally, transitions between centralized and decentralized coordination have been used to adapt to the requirements of the network [14].

While single-hop clusters simplify the management of the cluster under high topology changes, multi-hop-clusters aim to improve the performance of clustering further. In [15], the authors aim to find a suitable vehicle to aggregate and transmit information to a server. They use a distributed approach to select the vehicle to aggregate the collected FCD and transmit them to the server.

All the proposed clustering approaches face the issue of cluster stability under the high mobility of vehicular networks. Approaches in the literature aim to alleviate this issue by predicting the movement of the vehicles in proximity [7] or focus on highways [12], where the vehicle movement is much more predictable. In urban areas, however, these approaches tend to struggle due to the low predictability of vehicle movement. We resolve this issue by not forming clusters but determining the role of every vehicle probabilistically. This approach is less prone to topology changes, as the statistical role of every vehicle is similar.

In addition to that, the clustering approaches from the literature ignore the importance of distributed information. The importance of information has been investigated by Schroth et al. [16] and Meuser et al. [11]. In [6, 16], the authors combine several parameters like distance, the previous knowledge, and temporal aspects to rate the utility of information, which is normalized to a range between 0 and 1. This utility is used to optimize the performance of a Vehicular Ad-hoc Network (VANET). However, they do not provide a formula to calculate the impact, and an impact between 0 and 1 can hardly capture the difference in the impact that an event might have. In [11], the authors derive the relevance of information using knowledge about the road network and traffic flow. They improve communication using the probability of the vehicle to encounter a road event while it is active. However, they do not consider the different impact of different events, i. e., the type-dependent event costs.

In this work, we use the impact to restrict the used cellular bandwidth of each vehicle utilizing local Vehicle to Vehicle (V2V) communication. We model the transmission of messages using a non-cooperative game, which maximizes the impact of messages received by the vehicle. In the literature, game-theoretic modeling of networking aspects has also been investigated [3, 19]. Common aspects are network selection [3] and resource sharing [22]. In [22], the authors developed a game-theoretic approach to share bandwidth between users of VoIP applications. However, to the best of our knowledge, no work focuses on the impact of exchanged information and uses this meta-information to improve hybrid information exchange. In this work, we focus on the exchange of monitoring information in a vehicular network, in which we question the necessity to receive all FCD. Thus, we develop our game-theoretic approach such that each vehicle optimizes the total impact of messages received given a limited bandwidth.

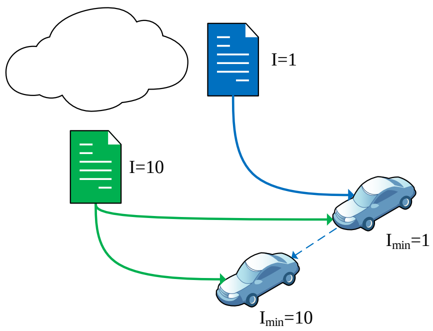


Figure 1: Visualization of the scenario.

3 SCENARIO OVERVIEW

In this chapter, we describe the components and assumptions of the considered scenario. We focus on a scenario in which a centralized backend provides Floating Car Data (FCD) to the vehicles using the cellular network. For this purpose, the backend might require the context, especially the position, of the vehicle. We assume that this context is available to the backend, either by the vehicle constantly updating its context using communication or monitoring strategies as presented in [25]. Based on the vehicle's context, the backend sends information to concerned vehicles. As services like Multimedia Broadcast/Multicast Service (MBMS) for cellular broadcasting/multicasting are not deployed widely, we assume that every vehicle is notified individually using a unicast message. Figure 1 showcases the scenario we are considering. In this scenario, the backend sends information with an impact I to vehicles that subscribed to an impact I_{min}. Once a message is received by a vehicle, the vehicle may distribute it further using Wifi-based communication.

The aim is to reduce the load on the cellular network to stick to certain bandwidth limitations. If the bandwidth consumed exceeds the predefined bandwidth limitations, the amount of transferred information needs to be reduced. In this work, we achieve this by both dropping low-impact information and distributing information locally. Compared to approaches of related work [15], we explicitly model the value of information in our networking system. In the following, we will provide a detailed description of the assessment of the impact of information, the components in the scenario, and their tasks in our offloading system.

3.1 Impact of Information

We assume that every transmitted FCD in the form of a message m can be assessed regarding its impact for any vehicle in the network. The impact $I_c(m)$ of a specific message m is influenced by the *type of information* and the *context of the vehicle* c. Regarding the *type of information*, an accident is generally more important than a speed sign. This impact needs to be predefined for our system by the automotive company and can be weighted by the accuracy of the provided information like in [10].

A standard method to consider the *context of the vehicle* is by defining an area around an event at which it is considered to be relevant. To capture this context-awareness in our impact function, we define the relevance to be 1 if the vehicle is inside the concerned area or 0 if the vehicle is not inside the concerned area. A more differentiated view on context can be achieved using the work of Meuser et al. [11]. In their work, the relevance of an event for a vehicle is estimated using the encounter probability of the vehicle and the event. Thus, the relevance considers knowledge about the road network in the relevance assessment.

In this work, we consider the expected impact of an event for a vehicle, i. e., the product of the type-specific impact and relevance. To this end, a vehicle aims to receive events with a high impact, while low-impact information might be dropped in case of a bandwidth shortage.

3.2 Exchange of Road Information

In our scenario, vehicles exchange FCD to improve driving comfort and safety. The FCD is detected by the onboard sensors of the vehicle which are limited by their sensor range. Once FCD is sensed, it is shared with other vehicles. While FCD is helpful around the event location, it often provides even more benefit if known at a different location from its sensing location. An example is the propagation of road-blockages or traffic jams which enables rerouting of vehicles.

We assume that every vehicle has cellular and Wifi communication technology available, i. e., it can send information via both interfaces. Each vehicle periodically broadcasts Cooperative Awareness Messages (CAMs) which include the location of the vehicle. The cellular network is mainly used to transmit the perceived FCD to the backend, as the Wifi-based local communication is very slow in propagating messages over large distances. In our model developed in Section 4, we assume that every message transmitted via the cellular network is successfully received.

The backend is responsible for the distribution of FCD to concerned vehicles. Once the backend receives FCD, it determines the concerned vehicles based on their context-aware impact function and pushes the FCD to the concerned vehicles. To realize the backend-triggered distribution of messages, we use the Publish/Subscribe (Pub/Sub) paradigm enhanced by context information. Notice, that the context of a vehicle is required to calculate the expected impact of an event for a specific vehicle.

Vehicles can restrict the amount of received information by announcing a minimum impact I_{min} of an event that they consider to be relevant to them. For Pub/Sub, we implemented this via content-based Pub/Sub which supports filtering based on the content of a notification. Once a vehicle has subscribed to a particular minimum impact, it only receives messages whose impact is at least equal to the announced impact. Similar to other works [11], we update the context separately from the subscription, as it has shown to be more effective. Without the cooperation presented in Section 4, the value of the impact in the subscription is chosen such that the predefined bandwidth requirements are met. To this end, the vehicle analyzes the received messages and chooses the bandwidth such that the average bandwidth matches the bandwidth requirements.

4 OFFLOADING AS A NON-COOPERATIVE GAME

In this section, we model the offloading process as a non-cooperative game, in which each vehicle individually decides on the impact it subscribes to. We assume this game is in the normal form, i. e., all players (vehicles) take their actions (subscriptions) simultaneously. Thus, they cannot consider the actions of the other players in their decision process. As possible actions for each vehicle, the vehicle can act as a receiver for messages with an impact I above a certain threshold I_i. The strategy, i. e., the action or combination of actions to be taken, is chosen such that it achieves optimal results for the vehicle, i. e., maximizes the sum of impact of the received messages $m \in M_{recv}$ while sticking to the bandwidth limitations.

We limit the number of possible actions in our modeling by assuming a fixed number $n_I + 2$ of possible actions. Each action is associated with an index $i \in \{0, \ldots, n_I + 1\}$. If $i = n_I + 1$, the action for the vehicle is to disable its cellular network interface and only receive information via Wifi. If $i \leq n_I$, the vehicle subscribes to a certain impact I_i which might include unsubscribing previous impacts. With this subscription, the vehicle v will receive all messages m with $I_v(m) \geq I_i$. The impact values I_i are ordered by their value, i. e., $I_i \leq I_{i+1}$. In this work, we use an exponentially distributed impact I_i as shown in Equation 1, as an exponential function can capture both very low and very high impact messages. The base of the exponential function $b > 1$ and the offset o are chosen to reasonably capture the impact of occurring messages in the system.

$$I_i = \frac{b^i}{o} \tag{1}$$

In our work, we assumed $b = 10$ and $o = 1$ with $n_I = 4$. This combination can capture an impact between 1 and 10000. However, the values of these variables are scenario dependent and need to be adjusted accordingly. Notice that the runtime performance of our approach decreases drastically for high values of n_I (roughly $n_I > 10$). We will discuss the runtime in detail later in Section 4.3.

Additionally to the consideration of impact levels described above, the vehicle needs to stick to predefined bandwidth restrictions. We assume that it is sufficient to set the available bandwidth (in bytes) A per vehicle and that this bandwidth is similar for all vehicles in the network. We assume that this available bandwidth is bounded, as monitoring applications should not reduce the bandwidth available to applications. Notice that we assume that the bandwidth of monitoring applications is generally not restricted by the cell tower, i. e., it is sufficient if the vehicle utilizes this bandwidth on average. However, if the available bandwidth of a cell tower is lower than the sum of the assumed available bandwidths of the vehicles in that cell, message drop would occur. In that case, every vehicle would need to decrease its allocated bandwidth to still stick to the requirements of the mobile network.

To select an appropriate impact given the current network conditions, each vehicle observes the incoming traffic and determines the currently utilized bandwidth. This process is described in more detail in Section 5.1. The output of this monitoring is a vector of bandwidth, for which each entry a_i describes the bandwidth amount used (in bytes) by messages with an impact between I_i and I_{i+1}. Based on this information, the vehicle can determine the impact it can subscribe to without violating its bandwidth restrictions. Although the vehicle subscribes to only one specific impact, it is still interested in other information if it can receive them without additional load on the cellular network.

We assume all subscription to be a probabilistic subscription, i. e., there is a probability p_i to subscribe to the impact I_i. Such a subscription will receive all information with an impact higher than I_i, i. e., the produced network traffic needs to consider all messages with an impact higher or equal to I_i. For a valid combination p_i, Equation 2 must hold on average.

$$\sum_{i=0}^{n_I} p_i \cdot \sum_{j=i}^{n_I} a_j \leq A \tag{2}$$

In the following, we describe how to find a strategy (a combination of p_i), that maximizes the total impact of messages received by the vehicle. We will solve this problem for two cases: (i) vehicles without any form of cooperation, and (ii) our contribution, in which implicit cooperation between vehicles is utilized.

4.1 Optimal Impact without Shared Bandwidth

In a system where vehicles must not share bandwidth (i. e., cannot receive messages via Wifi), each vehicle adjusts the impact such that the bandwidth requirements are met. Based on the bandwidth observations a_i and the impact of messages I_i, the vehicle starts aiming to receive all information of highest impact, i. e., set the corresponding probability p_i to 1. If all available messages of this event type are received, the vehicle chooses the state with the second highest impact-bandwidth ratio and aims to set the probability of that state to 1. Notice, that by increasing the probability of a state i will benefit the message reception of the state $j | j > i$, thus, p_j is reduced by the same amount that p_i is increased.

However, without cooperation, each vehicle will drop a large share of the available messages as the bandwidth reserved for this purpose is generally not sufficient. In this work, we aim to increase the number of received messages by coordinating vehicles implicitly. Thus, the vehicles cooperate and manage their subscriptions locally to lower the number of received events. Once a vehicle receives a new message from the backend, it broadcasts the message locally to notify nearby vehicles.

4.2 Optimal Impact with Shared Bandwidth

In this approach, the vehicles aim to cooperate to increase the total impact of received messages. As the cooperating vehicles are in Wifi communication range, we assume that the impact of a message m for them is similar, i. e., $I_v(m)$ will be denoted as $I(m)$ in the following. Section 5.2 describes how the difference in vehicle context can be considered. Based on the impact values of the received messages, the utility function u is shown in Equation 3 which equals the sum of the impact values of the received messages.

$$u = \sum_{m \in M_{recv}} I(m) \tag{3}$$

The vehicles again information via Wifi-based communication technology. Thus, not every vehicle needs to be subscribed to receive the necessary information.

One possibility, which has also been investigated in the literature, is the creation of communication clusters, in which one vehicle is responsible for the communication with the backend. The issue is the potential disconnects of cluster members from the cluster head and the dependency of all the vehicles from one vehicle. To circumvent this issue, we propose an approach to share the bandwidth between vehicles and reduce the consumed bandwidth without explicitly assigning roles to every vehicle. We model the sharing process of bandwidth as a non-cooperative game.

In this game, every vehicle has a set of $n_I + 2$ possible options, out of which it chooses the currently optimal strategy $\vec{p}$. Using explicit coordination, a vehicle could follow a pure strategy very efficiently, while vehicles in proximity can rely on that vehicle. As we do not want to utilize explicit coordination, we aim to find an optimal mixed strategy that can be derived using available knowledge. As there are potentially multiple mixed strategies fulfilling that requirement, we are searching for the strategy which maximizes the overall impact of messages received by the vehicles. To reduce the load on the local Wifi-based communication channel, we send no management messages on the Wifi channel.

As we do not exchange messages for explicit cooperation, each vehicle needs to estimate the strategies of the vehicles in its proximity. For this, we assume that the local environment of two nearby vehicles is comparable. The similarity of the environment decreases with increasing distance between the vehicles, but for vehicles in communication range the similarity is sufficient to achieve reliable results for the communication quality.

For our non-cooperative game, a vehicle will only stick to a particular strategy if this strategy is a Nash equilibrium, i. e., no change in the probabilities p_i will improve the utility of a vehicle. We will show that our proposed solution is a Nash equilibrium in Section 4.4.

In our game, we aim to maximize the utility shown in Equation 3, thus we derive the utility based on the strategy $\vec{p}$. As a message can be received via either Wifi or cellular communication, both channels need to be considered in the calculation. The first possibility is to receive the message via the cellular network. The probability p_i^c to receive a message with an impact I_i via the cellular channel is shown in Equation 4. This probability is calculated by summing all probabilities which refer to subscriptions with less or equal impact compared to I_i.

$$p_i^c = \sum_{j=0}^{i} p_j \tag{4}$$

The second possibility is to receive the message via Wifi, i. e., a vehicle in proximity has received the message via the cellular network and broadcasted it via Wifi. As stated above, we assume that each vehicle locally broadcasts messages which it receives via the cellular network. Additionally, we assume that the Wifi channel is sufficiently empty so that shared payload messages transmitted via Wifi can be received. The probability p_i^w to receive a message with impact I_i via Wifi is shown in Equation 5, where v is the number of vehicles in proximity. It is calculated as the probability that any of the nearby vehicles has received the message, i. e., *not* none of the nearby vehicles have received the message. As we assumed a similar environment for all vehicles, the probabilities for nearby vehicles can be assumed to be similar.

$$p_i^w = 1 - (1 - p_i^c)^v \tag{5}$$

Overall, a vehicle receives a message if the vehicle receives the message either via the cellular network or via Wifi. This is logically similar to the probability that the vehicle does *not* receive the message neither via the cellular network nor via Wifi. Based on this, the total probability p_i^t for a vehicle to receive a message via any network interface can be calculated according to Equation 6.

$$p_i^t = 1 - (1 - p_i^c) \cdot (1 - p_i^w) = 1 - (1 - p_i^c)^{v+1} \tag{6}$$

Based on this probability, the expected utility $\overline{u}(p_0, \ldots, p_{n_I})$ for a vehicle can be calculated according to Equation 7. In the following, we will refer to $\overline{u}(p_0, \ldots, p_{n_I})$ as $\overline{u}$ for readability purposes.

$$\overline{u}(p_0, \ldots, p_{n_I}) = \sum_{j=0}^{n_I} \left[a_j \cdot I_j \cdot p_j^t \right] \tag{7}$$

The challenge is to choose the values p_i for $i \in \{0, ..., n_I\}$ such that the expected utility $\overline{u}$ of messages received by a vehicle is maximized. To find the optimal solution, we partially derive $\overline{u}$ for all p_i and solve the resulting equations. The derivative is shown in Equation 8. This assumes that p_i is always non-zero because otherwise this derivative could not be calculated. As we cannot assume that p_i is always non-zero, we always consider the case $p_i = 0$ and $p_i \neq 0$ separately. In Section 4.3 we describe in detail how $p_i = 0$ is handled.

$$\frac{\delta \overline{u}}{\delta p_l} = -\sum_{j=0}^{n_I} \left[a_j \cdot I_j \cdot \left(-\frac{\delta p_j^c}{\delta p_l} \right) \cdot (v + 1) \cdot (1 - p_j^c)^v \right] = 0 \tag{8}$$

The individual values of p_i are not independent of each other, as Equation 2 limits the allowed values for p_i. Based on these limits, we derive the value of p_0 depending on the other values p_i for $i \in \{1, ..., n_I\}$ based on Equation 2 as shown in Equation 9. We assume that every vehicle will always use the maximum available bandwidth, as additional information can only increase the total impact of messages received by a vehicle.

$$p_0 = \frac{A - \sum_{i=1}^{n_I} p_i \cdot \sum_{j=i}^{n_I} a_j}{\sum_{j=0}^{n_I} a_j} \tag{9}$$

Additionally to this limitation, $p_i \geq 0$ and $\sum_{i=0}^{n_I} p_i \leq 1$ must hold. We ensure that by discarding every solution that does not match these requirements. Equation 8 can be further simplified by dividing the sum into two sums, the summands with $j < l$ and the summands with $j \geq l$. This is, as p_j^c in Equation 4 contains p_l for $j \geq l$ and, thus, the derivative differs from the case if $l < j$. However, as p_0 depends on all p_l according to Equation 9, the derivative of p_0 for p_l is always non-zero and needs to be considered separately. The calculation of the derivative of p_j^c is shown in Equation 10.

$$\frac{\delta p_j^c}{\delta p_l} = \begin{cases} \dfrac{\delta p_0}{\delta p_l} & \text{if } l < j \\ \dfrac{\delta p_0}{\delta p_l} + 1 & \text{if } l \geq j \end{cases} \tag{10}$$

For the calculation of p_0, we need to account for the dependency of p_0 from all $p_i|1 \leq i \leq n_I$. Thus, the derivative of p_0 based on Equation 9 is shown in Equation 11.

$$\frac{\delta p_0}{\delta p_l} = -\frac{\sum_{j=l}^{n_I} a_j}{\sum_{j=0}^{n_I} a_j} \tag{11}$$

Using the results from Equation 10 and from Equation 11, we can simplify Equation 8. The resulting equation is shown in Equation 12. The factors α_l, β_l, and B_j are defined in Table 1. α_l and β_l can be extracted from the respective sums as they are independent of j.

$$\frac{\delta \overline{u}}{\delta p_l} = \left[-\alpha_l \cdot \sum_{j=0}^{l-1} B_j - \beta_l \cdot \sum_{j=l}^{n_I} B_j\right] = 0 \tag{12}$$

To calculate the value for p_l given $p_i|i < l$ is known, we aim to set the derivatives for p_{l+1} and p_l to be equal, as both of them are 0. However, $B_i|i \geq l$ cannot be calculated, as $p_i|i \geq l$ is not known. Thus, we aim to eliminate all $B_i|i > l$ from our equations. For this purpose, we divide Equation 12 by $-\beta_l$ to obtain Equation 13. Notice that $-\beta_l$ is always non-zero for $l > 0$.

$$-\frac{\alpha_l}{\beta_l} \cdot \sum_{j=0}^{l-1} B_j + \sum_{j=l}^{n_I} B_j = 0 \tag{13}$$

Now, we use the derivative representation in Equation 13 to set the derivatives for p_{l+1} and p_l equal. After some transformations, we obtain Equation 14. As the sums for $j > l + 1$ are equal for both sides, we can remove them to calculate p_l.

$$-\frac{\alpha_l}{\beta_l} \cdot \sum_{j=0}^{l-1} B_j + B_l = -\frac{\alpha_{l+1}}{\beta_{l+1}} \cdot \sum_{j=0}^{l} B_j \tag{14}$$

Based on Equation 14, we need to extract B_l to calculate p_l. After some transforms, we obtain B_l as shown in Equation 15.

$$B_l = \frac{\left[\frac{\alpha_l}{\beta_l} - \frac{\alpha_{l+1}}{\beta_{l+1}}\right] \cdot \sum_{j=0}^{l-1} B_j}{\left[1 + \frac{\alpha_{l+1}}{\beta_{l+1}}\right]} \tag{15}$$

Equation 15 does only depend on $B_i \mid i < l$ which can be calculated using p_i. The values α_{l+1} and β_{l+1} can be calculated using the known number of received messages a_i. Notice that for $l = n + 1$, $\alpha_{l+1} = 0$ and $\beta_{l+1} = 1$. Using the definition of B_l and Equation 4, we can derive p_l from B_l as shown in Equation 16.

$$p_l = 1 - \sqrt[v]{\frac{B_l}{I_l * a_l}} - \sum_{j=0}^{l-1} p_j \tag{16}$$

Notice, that p_l might be lower than 0 or higher than 1, in this case, the optimal solution is not possible considering all possible actions are considered valid, i. e., $p_i \mid p_i \neq 0$. There is always at least one combination of $p_i \mid p_i \neq 0$, which provides a possible solution. As we require all $p_i \mid i < l$ to calculate p_l, we need to determine the very first p_0. Thus, p_0 is required to find the optimal strategy for our non-cooperative game. In the next chapter, we discuss how the optimal strategy is determined.

Variable	Description
i, j, k	Counter variables
I	Impact of a message
n_I	Number of possible actions in the subscription model
I_i	Impact associated with action of index i
p_i	Probability to subscribe to impact I_i
v	Number of vehicles in Wifi communication range
p_i^c	Probability to receive a message with impact I_i via the cellular network
p_i^w	Probability to receive a message with impact I_i via Wifi
p_i^t	Probability to receive a message with impact I_i via any network interface
B_i	$a_i \cdot I_i \cdot (1 - p_i^c)^v$
α_i	$\frac{\sum_{j=i}^{n_I} a_j}{\sum_{j=0}^{n_I} a_j}$
β_i	$1 - \frac{\sum_{j=i}^{n_I} a_j}{\sum_{j=0}^{n_I} a_j}$

Table 1: Used variables and their description.

4.3 Calculation of the Optimal Strategy

In the calculation process of the optimal strategy, we have two challenges to be solved: (i) the consideration of $p_i = 0$ for some i and (ii) the calculation of the initial probability p_0.

For the first challenge, we investigate all combinations of p_i with either $p_i = 0$ or $p_i \neq 0$. This leads to $2^{n_I+1} - 1$ possible combinations to investigate. As we cannot exclude any of these possible combinations, we calculate the probabilities for every possibility and select the solution with the highest utility. However, if n_I is very big, this process induces much computational overhead. Thus, n_I should generally be smaller or equal to 10. If $p_i = 0$, the action i has no impact on the system and can thus be removed from the action space. This increases both the amount a_{i-1} by a_i and the product of impact and amount $I_{i-1} \cdot a_{i-1}$ by $I_i \cdot a_i$, as the probability p_{i-1} captures the messages of state i. If $i = 0$, there is no possible action $i - 1$, thus, the action is discarded from the system.

For the second challenge, we need to determine p_0 based on the available actions $p_i \mid p_i \neq 0$ such that the resulting $\overline{u}$ is maximized. As stated in the previous chapter, p_0 cannot be easily calculated as it is only possible to calculate p_l based on p_{l-1}. However, we can determine the value for p_0 using a heuristic which doubles its accuracy every step. It starts with $p_0 = 0.5$ and a step-width of $s = 0.25$. Then the following process is executed until a sufficient accuracy is reached. Based on derivative of p_0, choose the next probability p_0^*: If the derivative is greater than 0, then $p_0^* = p_0 + s$, else $p_0^* = p_0 - s$. After that, the step-width s is halved.

To use our heuristic for determining p_0, we need to calculate the derivative of $\overline{u}$ for p_0 which is described in Equation 8. For this equation, we require the derivative of p_j^c for p_0, which is shown in Equation 17. Notice that the derivative of p_{n_I} for p_0 is determined with a similar idea as Equation 9 by expressing p_{n_I} as combination of the other probabilities.

$$\frac{\delta p_j^c}{\delta p_0} = \begin{cases} 1 & \text{if } j < n_I \\ 1 + \frac{\delta p_{n_I}}{\delta p_0} & \text{if } j = n_I \end{cases} \tag{17}$$

As the second derivative of $\overline{u}$ for p_0 is always negative (for $v > 1$), we assure that there is at maximum one solution. That is, as the derivative p_j^c for p_0 (the only factor which could be both positive and negative depending on j) is squared and thus always positive.

If the calculation of p_0 fails, we evaluate another combination of $p_i \mid p_i \neq 0$ is evaluated until we find a solution. We can always find at least one solution, as we can always fall back to the approach without shared bandwidth. If multiple valid combinations of p_i are found, we use the one with the highest utility $\overline{u}$.

4.4 Stability Considerations

Our approach relies on implicit cooperation between vehicles. However, an essential aspect of approaches of non-cooperative game theory is the stability of the found solution, i. e., if the found solution is a Nash-equilibrium. A Nash-equilibrium is achieved if no actor in the system can improve its outcome by solely changing its strategy.

As mentioned previously, the vehicle's strategy is a mixed strategy, i. e., it has a certain probability to follow the pure strategy to subscribe to a certain impact. To prove the stability of our system, we need to show that, given all other vehicles follow the proposed strategy, a single vehicle has no advantage of adapting its strategy. Thus, we show that the previously found solution is a maximum even if a single vehicle adapts its probability vector. We prove this using the partial derivative of a modified utility function.

In this utility function, we differentiate between the probabilities of the other vehicles p_j^c and the probabilities of the ego-vehicle q_j^c as shown in Equation 18.

$$\overline{u}_q(q_0, \ldots, q_{n_I}, p_0, \ldots, p_{n_I}) = \sum_{j=0}^{n_I} \left[a_j I_j \cdot (1 - (1 - q_j^c) \cdot (1 - p_j^c)^v) \right] \tag{18}$$

In the following, we refer to $\overline{u}_q(q_0, \ldots, q_{n_I}, p_0, \ldots, p_{n_I})$ as $\overline{u}_q$. If we derive the utility from Equation 18 partially for q_l, we get the result shown in Equation 19. If this derivative is 0 for all q_l and the second derivative is always smaller or equal 0, we are certain that the utility is maximized and the vehicle has no incentive to adapt its strategy.

$$\frac{\delta \overline{u}_q}{\delta q_l} = -\sum_{j=0}^{n_I} \left[a_j \cdot I_j \cdot \left(-\frac{\delta q_j^c}{\delta q_l} \right) \cdot (v+1) \cdot (1 - p_j^c)^v \right] \tag{19}$$

We observe that the equations Equation 8 and Equation 19 are quite similar, except for the fact that they contain different derivatives. As we already showed that Equation 8 is 0 for our developed solution, we need to show that the value for the derivative of q_j^c for q_l needs to be equal to the derivative p_j^c for p_l to maximize the utility for $p_i = q_i \forall i \in \{0, \ldots, n_I\}$. This is shown in Equation 20.

$$\frac{\delta q_j^c}{\delta q_l} = \frac{\delta p_j^c}{\delta p_l} \tag{20}$$

Equation 20 holds as long as the ego-vehicle utilizes its assigned bandwidth fully. It is evident, that a reduction of bandwidth for the ego-vehicle cannot increase the number of messages received; thus, no improvement can be gained from not utilizing the bandwidth.

Additionally, we observe that the derivative of Equation 19 is independent of q_l, i. e., the second derivative for q_l is always 0. That means that a single vehicle can neither improve nor reduce the utility of itself as long as it sticks to its assigned bandwidth.

Based on the same argument, we can also exclude any strategy for a different set of $p_i \mid p_i \neq 0$. As this different strategy has not been chosen initially, and no other strategy with the same $p_i \mid p_i \neq 0$ can outperform the initially found strategy, we can state that the found mixed strategy is a Nash equilibrium. Consequently, the found solution is stable and valid in a non-cooperative game.

5 REQUIRED ADAPTATIONS FOR REAL-WORLD APPLICATION

In the previous section, we modeled the sharing of bandwidth between vehicles as a non-cooperative game. In this section, we review the necessary assumptions and discuss the potentially required adaptations for real-world scenarios application. The reviewed assumptions are the estimation of the number of received messages, the locality of messages, and the fluctuation of subscriptions.

5.1 Estimation of the Number of Messages

In our model, the number of received messages of each state a_i is an essential meta-information required for our approach. We assumed that the number of messages received at the different impact levels is known, which cannot be assumed in real-world networks. If this number is not correct, our approach might not stick to the bandwidth requirements or even underestimate the impact of lost messages. This would drastically reduce the performance of our approach. To alleviate this issue, we propose a monitoring concept which estimates the number of messages per impact level.

The issue of the monitoring of received messages is the probabilistic aspect involved: As each vehicle only subscribes probabilistically, it is hard to monitor the actual number of transmitted messages. That is, a message might be received multiple times or dropped randomly. We account for the multiple receptions of messages, as we assume that duplicates can be detected by information-specific properties like the value, location, and detection date. A vehicle cannot directly detect the number of messages that it has not received. However, as stated in the previous section, each vehicle can estimate the strategy of the vehicles in its proximity. To account for messages that have not been received, we weight each received message based on the probability that it has been received via either channel. Based on Equation 6, we derive the weight w_i of a message which is between I_i and I_{i+1} as shown in Equation 21.

$$w_i = \frac{1}{p_i^t} = \frac{1}{1 - (1 - p_i^c)^{v+1}} \tag{21}$$

By setting the weight to this value, the vehicle monitors the number of received messages correctly, although the variation is higher due to the probabilistic behavior. However, the number of messages is determined over a larger period, as we do not expect much change in the rate of received messages. Due to this large monitoring periods, the fluctuation is expected to have a low impact on the system if p_i^c is high. For low p_i^c, we limit the weight of a message to 10, as the evaluation has shown that a single message received if p_i^c is low can heavily worsen the system performance.

Using this approach, the vehicle can only monitor messages which have a higher impact than the minimum impact it might subscribe. That is, the probability of subscribing to the state 0 might be $p_0 = 0$, thus, the vehicle will not receive any messages between I_0 and I_1 and, thus, cannot estimate the rate of received messages.

A possibility to solve this issue is to limit the minimum allowed p_0 to a certain value, which would slightly decrease the performance of our system but ensures that even this state can be monitored. In the remainder of this work, we will not set a minimum value for p_0, as the vehicle does generally not require the number of messages of p_0 if the probability for it to subscribe to it is 0, as it will not switch to that state even with cooperation.

5.2 Locality of Cellular Distributed Messages

As an input to our approach, we require the number of vehicles in proximity. Due to topological changes and context-awareness, the number of vehicles in communication range cannot be used directly. The locality of the distributed messages might impact the performance of our approach. The reason for that is the assumption that all vehicles in proximity of the ego-vehicle behave similarly to the ego-vehicle. However, if the messages received by a vehicle differs from the messages received by the ego-vehicle, the ego-vehicle cannot rely on this vehicle to provide these messages via Wifi. Thus, the number of vehicles usable for offloading is lower, which lowers the overall performance of our approach.

To account for this issue, the vehicles consider the dissemination approach used by the backend. If the backend uses a context-aware dissemination approach, the ego-vehicle may only cooperate with vehicles which share a similar context. This has no impact if a message is broadcasted in the system, while Geocast-based dissemination approaches are influenced. Next, we discuss the influence of the different dissemination strategies.

5.2.1 Broadcast. For the network-broadcast of messages, there is no impact of this issue as no context is used for the dissemination of messages. That is, as there are no vehicles to which a message is not transmitted. Thus, the assumption that each vehicle is similar holds for broadcasting messages in the systems and no adaptations are necessary. To reduce the impact of topology changes proactively, we still reduce the number of neighbors slightly such that the impact of a single vehicle is minimized.

5.2.2 Geocast. For the Geocast approach, the distance between the ego-vehicle and the vehicles in proximity in relation to the Geocast area is pivotal. That is, the area of the Geocast is essential for an ego-vehicle barely in range of the dissemination. While this vehicle relies on its neighbors to receive the message, some of the neighbors are not in dissemination range anymore. Thus, these vehicles do not receive the message and, thus, cannot forward it to the ego-vehicle. The ego-vehicle cannot decide if a vehicle in its neighborhood is in range of an event, as the locations of future events are unknown.

There are two possibilities to handle this issue: (i) artificially increase the dissemination range on the server side or (ii) account for this issue in our decision-making. The first alternative does not seem to be suitable for most use-cases, as it would increase the bandwidth consumption and force the vehicles to subscribe to higher impact levels, which would again lead to not receiving messages as the filter becomes more restrictive.

In the following, we assume that the backend Geocasts messages in a circle with radius r_m around the place of detection of the event. Based on r_m, we aim to find the maximum distance r_v of the ego-vehicle to a vehicle in proximity, which minimizes the impact of the missing of messages at the border of the Geocast area. Thus, we exclude vehicles in proximity of their current distance to the ego-vehicle r_c is higher than the maximum allowed distance. Remember that the distance r_c is known based on the exchanged Cooperative Awareness Messages (CAMs).

We now analyze the effects of Geocasting depending on the distance r_o of the ego-vehicle to the location of the message. If $r_o + r_v \leq r_m$, the Geocast dissemination does not impact our offloading approach. However, if this condition does not hold, i. e., $r_o + r_v > r_m$, while the ego-vehicle would receive the message, the effective number of neighbors is lower than the number anticipated by the ego-vehicle. The exact calculation of this area does not provide much benefit to our work, as we expect that the area of a Geocast r_m is generally much higher than r_v, in which the impact of this issue is small. However, if the Geocast area shall be decreased for further vehicular applications, the number of vehicles in proximity needs to reduced accordingly to account for the context-sensitivity.

5.3 Subscription Frequency

As we found a mixed strategy as a solution for our non-cooperative game in Section 4, the vehicles follow one pure strategy with a certain probability, i. e., subscribe to a certain minimum impact I_i with a certain probability. However, the probabilistic behavior of our approach might lead to frequent subscription updates, even if there is no change in environmental conditions. Especially for mixed strategies with low probabilities p_i, the fluctuation in subscription behavior is high, as the probability to subscribe to the same state twice is rather low. This is an issue, as updating the subscriptions induces load in the system, which reduces the available bandwidth for the actual payload.

We solve this issue by not performing an update of the subscription if no change in strategy has been performed. This includes, that the number of updated subscriptions required for two rather similar strategies, i. e., $p_i^* \approx p_i$, is lower compared to switching to a completely different strategy. We expect low change-rate of the parameters of our system, as both the rate of messages and the number of vehicles in proximity gradually change over time. Thus, the subscription strategies of the vehicles over time are expected to be rather similar.

To reduce the number of subscriptions, each vehicle only updates its subscription based on the difference between p_i and p_i^*. This includes the strategy to unsubscribe to everything, which it the difference between 1 and the sum of the probabilities p_i. If $p_i^* = p_i \forall i \in \{0, \ldots, n_I\}$, no update of subscriptions should be performed at all. Else, the vehicle calculates the difference in the strategies,

i. e., $\Delta p_i \forall i \in \{0, \ldots, n_I\}$. If the ego-vehicle has subscribed to a state for which $p_i^* > p_i$, then no change of subscription behavior is required, as the number of subscriptions in this state shall be increased. If the ego-vehicle has subscribed to a state for which $p_i^* < p_i$, a subscription change might be required. To reduce the number of subscriptions according to the new strategy, the vehicle unsubscribes with the probability p_i^*/p_i, which will lead to a share of p_i^* vehicles subscribing to state i. Additionally, the vehicles which unsubscribed need to choose the new subscription to perform. The new subscription is chosen randomly weighted by Δp_i of the states for which $p_i^* > p_i$. Using this approach, the percentage of adjusted subscriptions is limited to the change between p_i^* and p_i.

6 EVALUATION

In this section, we describe the evaluation setup and the results of this simulation. The goal of this simulation is to show the performance of our approach compared to an approach without cooperation between vehicles as a baseline and a clustering approach for comparison. In the following, we will first describe the setup of our simulation including a detailed description of the metrics and reference approaches. After that, we will provide a detailed analysis of the strengths and drawbacks of our approach compared to the reference approaches.

6.1 Evaluation Setup

For our evaluation, we use the event-based Simonstrator framework with the vehicular extension [9]. The Simonstrator simulates both cellular and Wifi-based communication. It uses the Simulation of Urban Mobility (SUMO) [8] and the TAPAS cologne dataset [20] for realistic vehicular movement, which is essential to compare the performance of our approach with clustering approaches.

To evaluate our game-theoretic approach (*GT*) under varying loads on the cellular network, we implemented a server which produces a constant rate of messages to each vehicle, as this is easier to control than sending the information from the vehicles. That neglects the possible influence of bandwidth changes, but we expect these changes to be rather slow. The adaptation to bandwidth change is an essential aspect of the Geocast-based dissemination we focus on later in this section. We added events of different event costs and event probabilities as shown in Table 2.

Evaluation Variable	Values
Event Costs (vector)	{(**1, 10, 100, 1000**)}
Event Probability (vector)	{(**90%, 9%, 0.9%, 0.1%**)}
Assigned Bandwidth	{0.1%, 1%, 5%, **10%**, 50%, 100%}
Message Load per Vehicle	{**10**, 50, 100}
Monitoring	{**Inactive**, Active}
Dissemination	{**Broadcast**, Geocast}
Message Size	$1000 Bytes$
Wifi bandwidth	$12 Mbps$
Wifi range	$150 m$
Cellular bandwidth	$50 Mbps$

Table 2: Parameters used for the evaluation. If more than one value is given, the bold value is used as default.

6.1.1 Baseline Approach. As a baseline, we use an approach which can use the impact of information similar to our approach but does not share information locally. We call this approach no-cooperation approach (*NC*). Thus, this approach still receives the most critical information first, but due to the lack of sharing, the low-impact messages will not be transmitted. Thus, the performance of this approach drops drastically when the bandwidth is exceeded.

6.1.2 Reference Approaches. We implement two clustering-based approaches to compare the performance of our approach, which we describe in the following.

ALM. As a reference, we use a clustering based on the approach presented in [17]. This approach aims to cluster vehicles with low variance in speed over time. Based on this metric, the vehicles perform clusters decentralized. In this work, we assume that the Cluster Head (CH) has access to the combined bandwidth of the members in the cluster. Thus, instead of choosing a minimal impact based on only its own bandwidth, the CH uses the combined bandwidth, which is more efficient in terms of bandwidth compared to our implicit cooperation approach. However, this approach relies on explicit management messages to detect disconnects of nodes, i. e., vehicles outside of the range of their cluster-head. To prevent frequent reclustering, a timeout before a reclustering is executed. During this timeout, the cluster members might not receive any information, which drastically decreases the performance of this approach. Thus, we expect this approach to perform poorly if the cluster lifetime is short.

Global Knowledge (GK). This approach uses global position and role knowledge to form clusters. These clusters are formed greedily, i. e., each node sequentially searches for a cluster-head in range. If the node is a cluster-head itself and detects another cluster-head, the node changes its role to be a cluster member. If the node is a cluster member and detects no cluster-head in range, it changes its role to be cluster head. As we derive this information from simulation knowledge, the role changes are immediate and, thus, this approach will not encounter similar problems as ALM. Although it is not realizable in practice, we use it as an upper baseline for comparison.

6.1.3 Parameters. We investigate the performance of our approach under varying conditions as shown in Table 2, i. e., the assigned bandwidth of a vehicle, the transmission rate of vehicles, and the dissemination strategy used by the backend. Additionally, we investigate the influence of monitoring on the system performance.

We expect the assigned bandwidth to have a high impact, as it drastically reduces the number of messages a vehicle can receive. For low bandwidths, this may lead to a vehicle missing important information. We expect that our approach and the cluster approach perform better than the baseline, as vehicle cooperatively share bandwidth. The values of the assigned bandwidth depend on the required bandwidth, i. e., an assigned bandwidth of 100% states that all monitoring information can be transmitted.

The dissemination strategy used by the backend is expected to have an impact on all approaches, as this strategy influences the required context-awareness of the cooperative approaches. For a message that is sent to all vehicles in the network, no context-awareness is required of the cooperation approaches. However,

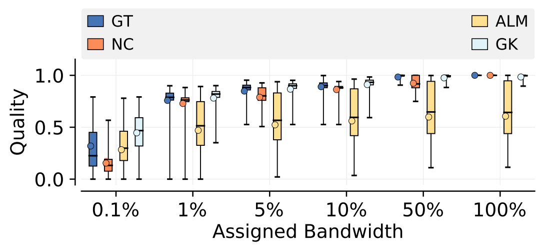


Figure 2: Achieved quality depending on the assigned bandwidth. Our approach outperforms the *NC* and the *ALM*-approach, and performs almost similar as the *GK*-approach.

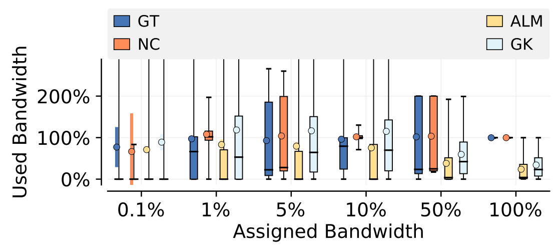


Figure 3: Received information per vehicle for the different approaches depending on the assigned bandwidth. All approaches stick to the predefined bandwidth requirements.

if messages are only sent to certain roads or areas, the vehicles need to consider the increasing level of context-awareness in their cooperation. As mentioned in Section 5.2, we do this by limiting the number of neighbors out of which the ego-vehicle might choose cooperation partners. Thus, the number of vehicles with which the ego-vehicle cooperates is reduced, which reduces the performance gain of our offloading approach.

6.1.4 Metrics. To evaluate the performance of our approach, we use two primary metrics: (i) bandwidth used by each vehicle, and (ii) the achieved communication quality.

The used bandwidth provides an insight on how the load is distributed in the network, i. e., if the load is distributed evenly or not. Additionally, we can verify if the bandwidth provided as input to our approach is achieved. This metric is defined based on the assigned bandwidth, i. e., a value of 100% means that all available resources are used.

The achieved communication quality per time interval captures the share of messages that each vehicle has received compared to the messages that have been provided by the backend. This metric provides insight into the performance of each approach and is generally expected to be as high as possible, as our optimization aims to maximize this metric.

6.1.5 Plots. In this work, we use box-plots, in which the metric values for each vehicle are displayed as the box. Thus, the variance between nodes in the achieved metric values can be observed. Additionally, we display the average performance including its variance over 5 simulation runs as a dot next to the boxes.

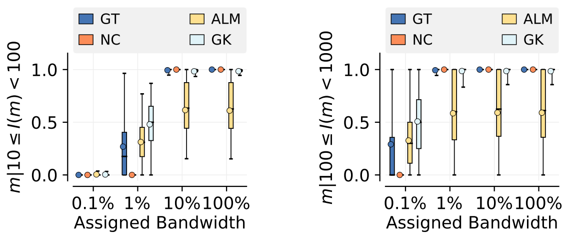
6.2 Evaluation Results

In the following, we investigate the performance of our approach under the varying conditions as described in Section 6.1.3.

6.2.1 Assigned Bandwidth. Figure 2 displays the achieved quality, i. e., the percentage of the impact of actually received messages compared to the impact of sent messages. The performance of our *GT*-approach is always higher as the baseline *NC*-approach. This improvement is expected, as vehicles can temporarily subscribe to lower impacts if they cooperate. For the assigned bandwidths 0.1%, 1%, 10%, and 100%, the improvement is lower compared to the assigned bandwidths 5% and 50%. That is, for the bandwidths 0.1%, ..., 100%, is chosen such that the *NC*-approach can subscribe deterministically to a particular state. Thus, our *GT*-approach needs to lower the probability for this state so that it can receive messages with lower impact. This leads to potential missing of high impact messages. Thus, many vehicles in proximity are required for this adaptation. For the assigned bandwidths 0.5 and 5, one state is partially available. Thus, the risk for our approach of losing high-impact messages is much lower. The cluster-based *ALM*-approach performs not as well as expected, as the topology seems to be changing too frequently to form stable clusters with this approach. During the time the vehicle does not detect that it disconnected from its cluster-head, the vehicle cannot receive any messages. As our *GT*-approach relies only on the number of vehicles in proximity, it is much less prone to these topology changes.

Figure 3 displays that our approach sticks to the bandwidth requirements. The variance of the number of received messages of the cooperation-based approaches (*GT*, *ALM*, *GK*) is much higher than the variance of the *NC*-approach for 0.1%, 1%, 10%, 100%. That is, as the *NC*-approach deterministically subscribes to a certain impact, while the other approaches aim to share bandwidth with their neighbors. For 5% and 50%, the variance of the *NC* is also very high, as the vehicles randomly subscribe to the higher or lower impact level. For 0.1%, we observe that the variance of the averages over multiple runs is high for *NC* and *GT*. This is justified to the randomness of message generation, which influences the number of receivable messages. However, this variance for our *GT*-approach is lower compared to the *NC*-approach, which states that our approach is less prone to fluctuations in the message generation.

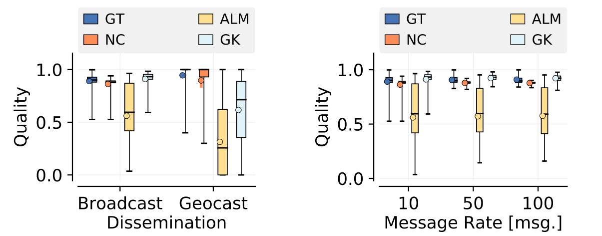
Figure 4 provides a detailed view of the performance of the approaches. There, we can use the *NC*-approach as a reference which messages would be received for certain bandwidths assigned. In both graphics, we omitted 5% and 50% to increase the readability of the results. Figure 4a shows that our *GT*-approach still receives around 25% on average of messages with an impact between 10 and 100 for an assigned bandwidth of 1%, which would normally not be received as showcased by the *NC*-approach. The results of the cluster-based approaches are slightly higher, but the *ALM*-approach lacks reliability for high-impact messages due to frequent disconnects. Our approach can receive low-impact messages, as the vehicles rely on each other to receive the high-impact messages and, thus, free bandwidth. For an assigned bandwidth of 10%, we can observe that our approach receives slightly fewer messages



(a) Share of received messages with an impact between 10 and 100.

(b) Share of received messages with an impact between 100 and 1000.

Figure 4: Share of received messages for certain impact levels. Our *GT*-approach cooperates to receive low-impact messages, which is not possible for the *NC*-approach.



(a) Influence of context-awareness on the approaches.

(b) Influence of the network load on the different approaches.

Figure 5: Achieved quality of the different approaches depending on different environmental properties. Our *GT*-approach handles context-awareness well.

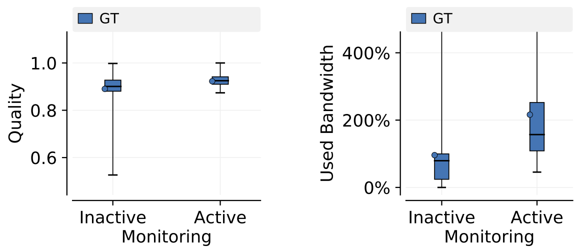
compared to the *NC*-approach, although the bandwidth would be sufficient to receive all messages. Due to the probabilistic behavior of our approach, there is no certainty that the neighbors will provide a message, but the minimal reduction of high-impact messages received leads to a significant increase of low-impact messages received. Thus, the overall impact is increased, even though a high-impact message might be missed.

Figure 4b displays the share of messages received with an impact between 100 and 1000. Comparing to Figure 4a, we can observe a higher share of messages received for all approaches, as the impact of the messages is higher. If the assigned bandwidth is above 1%, the bandwidth would be sufficient to receive all information provided by the backend. In this figure, we can observe the issues of the *ALM*-approach, as it never reaches a share of 1, even if the available bandwidth would be sufficient. Our *GT*-approach performs slightly worse compared to the *GK*-approach if the assigned bandwidth is 0.1%, but this is expected as our approach loses out on efficiency due to the additional robustness it provides. This robustness is also observable for assigned bandwidths above 1%, where our *GT*-approach performs slightly better than the *GK*-approach. That is, as not one but multiple vehicles vehicle provide the information in our approach. Thus, dropping a message on the Wifi channel has a lower influence on our system. At high loads on the Wifi channel, our approach might reduce in performance as the broadcasting might congest the channel. In this case, mechanisms, as proposed in [23], might be used to reduce the necessary number of broadcasts.

6.2.2 Server-Side Dissemination Mechanism. Depending on the server-side dissemination mechanism, different levels of context-awareness are required. As this influences our system, we compare the performance of the approaches for Geocast-dissemination with the performance of the Broadcast dissemination. The most-significant difference is noticeable for the cluster-based approaches (*ALM*, *GK*), as the vehicles in these approaches rely on exactly one cluster-head, but cannot check if this cluster-head always has the same context as the ego-vehicle. Thus, messages get lost, as the cluster-head does not receive the message itself and, thus, cannot forward the message to the ego-vehicle. The performance of the approaches without a cluster, our *GT*-approach, and the *NC*-approach, increases further for the Geocast approach. That is, as these approaches are only marginally influenced by the negative impacts of context-aware communication: For the *NC*-approach, the vehicle does not rely on any other vehicle. For our *GK*-approach, the ego-vehicle implicitly relies on multiple other vehicles for high-impact messages, due to the design of our offloading approach. The reason for the increase of both our *GK*-approach and the *NC*-approach is justified by the reduction of received messages by both approaches. The context of the vehicle filters some messages transmitted, thus, the overall load on the vehicle is lower, and the vehicle can receive a larger share of the interesting messages.

6.2.3 Network Load. To analyze the impact of network load on our approach, we varied the network load between 10 and 100 messages per second in Figure 5b. However, as shown in Figure 5b, the network load barely influence the performance of any of the approaches. The only visible change is the decreasing size of the 2.5% quantile for higher bandwidths. This gain of stability of the approaches is justified by the higher number of messages transmitted, which reduces the influences of the fluctuations in message generation. For sufficiently high network loads, we expect more frequent collisions on the Wifi channel and, thus, a decrease in performance of the cooperation-based approaches (*GT*, *ALM*, *GK*). In this case, approaches that reduce the load on the Wifi channel need to be utilized to alleviate the additional load.

6.2.4 Influence of Monitoring. The monitoring, as described in Section 5.1, adds additional uncertainty in the system and is shown in Figure 6. That is, that as the approaches cannot react proactively, but wait for monitoring information to decide their future strategies. We see this issue in Figure 6b, as our *GT*-approach exceeds the bandwidth limit if the monitoring is activated. This is due to the initial monitoring once a vehicle turns online. A short duration after the start, the vehicle receives all messages in the network to gain an overview of the system and exceeds its bandwidth restrictions. As the vehicles receive more messages than they would normally do, the quality of our approach also increases slightly as shown in Figure 6a. The more significant difference is the size of the outer quantiles, which reduces drastically if monitoring is activated. This



(a) Achieved Quality. **(b) Used Bandwidth.**

Figure 6: Influence of enabled monitoring on our developed *GT*-approach. As our approach adapts slower to bandwidth changes, it exceeds the assigned bandwidth slightly.

is also related to the initial monitoring. During this time, the vehicle shares all messages available in the network with its proximity and compensates for regions in which few vehicles are available. In future work, we want to analyze the impact of monitoring on our approach and implement proactive mechanisms to ensure that our approach sticks to its assigned bandwidth.

7 CONCLUSION

In this work, we propose an approach for the intelligent distribution of Floating Car Data (FCD) in a vehicular network using heterogeneous network interfaces. In this scenario, we assume that the available bandwidth for information-sharing is limited and that every FCD can be assigned an impact, which rates the importance of it. Compared to approaches proposed in related work, we do not organize vehicles in a cluster but rely on implicit cooperation. The basic idea of our approach is to stick to the predefined bandwidth requirements by (i) sharing received FCD with vehicles in proximity via Wifi and (ii) dropping low-impact information. We model this offloading as a non-cooperative game, in which the vehicles use a utility function that is based on the sum of impacts of the received messages. We derive a mixed strategy, which is maximizes the utility for the network and the vehicle itself, i. e., is a Nash equilibrium, in which a single vehicle has no incentive to deviate from this strategy. For the calculation of this strategy, the vehicle only requires the number of vehicles in their proximity. Thus, no management information needs to be exchanged.

In the evaluation, we show that our approach outperforms a clustering-based approach if the network topology changes frequently. That is, as our approach is more robust to topology changes and message drops than clustering approaches. Even compared to a clustering approach that can use simulation knowledge to detect topology changes, our approach performs only slightly worse. Additionally, we outperform an approach without cooperation though using shared bandwidth to receive lower-impact messages.

In future work, we aim to extend our work to analyze the impact of location-privacy on our approach and investigate the impact of monitoring on the performance of our approach. For the monitoring aspect, we aim to improve the proactiveness of our approach to account for bandwidth changes.

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REFERENCES

[1] S. Ancona, R. Stanica, and M. Fiore. 2014. Performance boundaries of massive Floating Car Data offloading. In *Prof. of WONS*. IEEE, 89–96.
[2] P. Basu, N. Khan, and T. D. C. Little. 2001. A mobility based metric for clustering in mobile ad hoc networks. In *Proc. of ICDCS Workshops*. 413–418.
[3] C.-J. Chang, T.-L. Tsai, and Y.-H. Chen. 2009. Utility and Game-Theory Based Network Selection Scheme in Heterogeneous Wireless Networks. In *Prof. of WCNC*. IEEE, 1–5.
[4] P. M. D'Orey, N. Maslekar, I. de la Iglesia, and N. K. Zahariev. 2015. NAVI: Neighbor-Aware Virtual Infrastructure for Information Collection and Dissemination in Vehicular Networks. In *Proc. of VTC Spring*. IEEE, 1–6.
[5] F. Dressler, H. Hartenstein, O. Altintas, and O. Tonguz. 2014. Inter-vehicle communication: Quo vadis. *IEEE Communications Magazine* 52, 6 (2014), 170–177.
[6] T. Kosch, C. Adler, S. Eichler, C. Schroth, and M. Strassberger. 2006. The scalability problem of vehicular ad hoc networks and how to solve it. *IEEE Wireless Communications* 13, 5 (2006), 22–28.
[7] S. Kuklinski and G. Wolny. 2009. Density based clustering algorithm for VANETs. In *Proc. of TRIDENTCOM*. IEEE, 1–6.
[8] P. A. Lopez, M. Behrisch, L. Bieker-Walz, J. Erdmann, Y. Flötteröd, R. Hilbrich, L. Lücken, J. Rummel, P. Wagner, and E. WieBner. 2018. Microscopic Traffic Simulation using SUMO. In *Proc. of ITSC*. 2575–2582.
[9] T. Meuser, D. Bischoff, R. Steinmetz, and B. Richerzhagen. 2019. Simulation Platform for Connected Heterogeneous Vehicles. In *Proc. of VEHITS*. SCITEPRESS.
[10] T. Meuser, P. Lieser, T. A. B. Nguyen, D. Böhnstedt, and R. Steinmetz. 2019. Lifetime-aware information aggregation under uncertainty for advanced driver assistance systems. *Ad Hoc Networks* 82 (2019), 56–67.
[11] T. Meuser, B. Richerzhagen, I. Stavrakakis, T. A. B. Nguyen, and R. Steinmetz. 2018. Relevance-Aware Information Dissemination in Vehicular Networks. In *Proc. of WoWMoM*. IEEE.
[12] Z. Y. Rawashdeh and S. M. Mahmud. 2012. A novel algorithm to form stable clusters in vehicular ad hoc networks on highways. *EURASIP Journal on Wireless Communications and Networking* 1 (2012), 15.
[13] G. Remy, S. Senouci, F. Jan, and Y. Gourhant. 2011. LTE4V2X: LTE for a Centralized VANET Organization. In *Proc. of GLOBECOM*. IEEE, 1–6.
[14] N. Richerzhagen, B. Richerzhagen, B. Koldehofe, and R. Steinmetz. 2017. Towards Transitions between Role Assignment Schemes: Enabling Adaptive Offloading in Challenged Networks. In *Proc. of CHANTS*. ACM, 1–6.
[15] P. Salvo, I. Turcanu, F. Cuomo, A. Baiocchi, and I. Rubin. 2017. Heterogeneous cellular and DSRC networking for Floating Car Data collection in urban areas. *Vehicular Communications* 8 (2017), 21–34.
[16] C. Schroth, R. Eigner, S. Eichler, and M. Strassberger. 2006. A Framework for Network Utility Maximization in VANETs. In *Proc. of VANET*. ACM, 86–87.
[17] E. Souza, I. Nikolaidis, and P. Gburzynski. 2010. A new Aggregate Local Mobility (ALM) clustering algorithm for VANETs. *Proc. of ICC* (2010), 1–5.
[18] A. Tigadi, R. Gujanatti, A. Gonchi, and B. Klemsscet. 2016. Advanced driver assistance systems. *iJERGS* 4, 3 (2016), 151–158.
[19] R. Trestian, O. Ormond, and G.-M. Muntean. 2012. Game Theory-Based Network Selection: Solutions and Challenges. *IEEE Communications Surveys & Tutorials* 14, 4 (2012), 1212–1231.
[20] S. Uppoor, O. Trullols-Cruces, M. Fiore, and J. M. Barcelo-Ordinas. 2014. Generation and analysis of a large-scale urban vehicular mobility dataset. *Transactions on Mobile Computing* 13, 5 (2014), 1061–1075.
[21] S. Vodopivec, J. Bester, and A. Kos. 2012. A survey on clustering algorithms for vehicular ad-hoc networks. In *Proc. of TSP*. IEEE, 52–56.
[22] E. H. Watanabe, D. S. Menasche, E. de Souza e Silva, and R. M. M. Leao. 2008. Modeling Resource Sharing Dynamics of VoIP Users over a WLAN Using a Game-Theoretic Approach. In *Proc. of INFOCOM*. IEEE, 915–923.
[23] N. Wisitpongphan, O. K. Tonguz, J. S. Parikh, P. Mudalige, F. Bai, and V. Sadekar. 2007. Broadcast storm mitigation techniques in vehicular ad hoc networks. *IEEE Wireless Communications* 14, 6 (2007), 84–94.
[24] G. Wolny. 2008. Modified DMAC Clustering Algorithm for VANETs. In *Proc. of COMSNETS*. IEEE, 268–273.
[25] Z. Xu, H. Gupta, and U. Ramachandran. 2018. STTR: A System for Tracking All Vehicles All the Time At the Edge of the Network. In *Proc. of DEBS*. ACM, 124–135.
[26] Q. Zheng, K. Zheng, L. Sun, and V. C. M. Leung. 2015. Dynamic Performance Analysis of Uplink Transmission in Cluster-Based Heterogeneous Vehicular Networks. *IEEE Transactions on Vehicular Technology* 64, 12 (2015), 5584–5595.