Population Protocols for Adaptive Event Dissemination with Autonomous Agents in Vehicular Networks

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Abstract: Recent advances in distributed vehicle-to-vehicle communication promise to transform the user's driving experience, providing new services capable of improving safety, efficiency and quality of travelling. Due to the large amount of information exchanged, a major challenge of Vehicular Networks is the adoption of appropriate data dissemination protocols that ensure good performance in real-time event detection, while guaranteeing low communication overhead. To this aim, this paper proposes an adaptive event dissemination algorithm which exploits Population Protocols (PPs) for modelling vehicle interactions as coordinated behaviors of autonomous agents in a distributed system. The experimental evaluation performed on realistic vehicle tracks over real-world maps demonstrates the system's ability to efficiently disseminate information in the network in order to support reliable and distributed event detection services.

1 INTRODUCTION AND RELATED WORKS

Nowadays, modern vehicles can increasingly be seen as smart entities capable of moving around in an *informed* manner, while collecting, processing and sharing data with their peers or other nodes in the network infrastructure. This leads to the concept of vehicular networks, where groups of entities (vehicles) act as autonomous agents that interact with each other to exchange relevant data, such as traffic information or events of interest, in the context of a temporal-spatial proximity. The increasing autonomy of vehicles opens up new opportunities to adopt agent-based models for distributed problem-solving in vehicular environments. For instance, each vehicle can be considered as an autonomous agent capable of making local decisions, while collaborating with others to achieve global goals such as efficient data dissemination. Given the large volumes of information exchanged, an important role in the vehicular network architecture is played by proper *data dissemination* protocols (Shahwani et al., 2022). In this perspective, several schemes have been proposed in the literature, distinguished by whether they rely on existing infrastructure or operate in a distributed way (Rashid et al., 2020). In the first case, several fixed units named Road Side Units (RSUs) are responsible for gathering/providing information from/to vehicles; conversely, a totally distributed approach consists only of vehicles that interact with each other based on their mutual physical distance.

The infrastructure-free approaches are preferable for real-word applications because they require a lower installation and maintenance cost than their counterparts; however, they poses severe challenges to be addressed (Rashid et al., 2020). For instance, message congestion can occur when the density of vehicles is high, or also the dissemination of an event may take a long time if there are few vehicles in the area of interest. Unfortunately, there are no standard approaches to deal with these issues and various solutions have been proposed in the literature, each of which is strongly dependent on the adopted routing strategies (Bouk et al., 2015).

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Some techniques exploit additional vehicle data (e.g., driving directions) to select one or more elite vehicles and create clusters through which information can be routed efficiently. In (Esmaeilyfard et al., 2017), the authors designed a middleware to be placed in a three-layered architecture that includes mechanisms to control the creation of dynamic groups based on characteristics of the agents. Within the cluster, one node is selected as the *group leader* to manage and supervise the group itself, and to be the one allowed to communicate with other road entities in order to reduce the network overload.

In general, the existing strategies add a significant processing and communication overhead to support reliable data dissemination to the vehicular network, thus causing link failures or degradation in network scalability in the worst case (Al-Rabayah and Malaney, 2012). This aspect negatively affects the detection of an event of interest to the driver community (Bouk et al., 2015). For example, in (Artimy et al., 2005) a scenario is described in which a vehicle detects an event in its surrounding and shares it with the rest of the network by adopting a predefined frequency for message broadcast. If every nearby vehicle receives the message and forwards it to its neighbors, the dissemination strategy that emerges inevitably causes several problems, e.g. network congestion, loss of messages, loss of signal, that impair the vehicle's ability to identify the event within its range of interest. Most of the works present in the literature achieve high performance in recognizing an event of interest, but do not address the method through which detected events are disseminated.

In order to design an efficient and effective solution for event dissemination in vehicular networks, we propose an adaptive communication scheme based on Population Protocols (PPs). Vehicular networks represent a natural application domain for multi-agent systems, where autonomous agents (vehicles) must collaborate to solve distributed problems in dynamic and resource-constrained environments. Leveraging agent-based frameworks, such as PPs, enables the design of scalable and adaptive solutions for communication and decision-making in these networks. Aim of the population protocols is to model the interactions between agents, allowing them to act as a distributed multi-agent system capable of collaborative decision-making and efficient data dissemination; as shown in our approach, PPs can be successfully adopted for handling both data dissemination and event detection tasks. This allows to meet the requirements described above while not requiring additional processing steps compared to state-of-the-art techniques. Early implementations of the PPs were focused on typical problems of distributed scenarios, from majority problems (Berenbrink et al., 2018) to leader election (Doty and Soloveichik, 2018). This approach has also found direct use in vehicular networks, where a simple counting problem can be used to validate a generic event that occurred in the vehicular network (Hsiao et al., 2011). The actual application of PPs to vehicle-to-vehicle communication poses several challenges, as their implementation depends on the specific scenario (Michail et al., 2011). Furthermore, it is worth noting that adapting the PP model to the vehicular context is not trivial as many theoretical assumptions may not be satisfied, such as vehicle speeds (Sadano et al., 2019) or transmission failures (Di Luna et al., 2019) .

The remainder of the paper is organized as follows. Section 2 describes the proposed adaptive event dissemination mechanism and details the underlying communication protocol. The results of the experimental assessment are discussed in Section 3, while Section 4 states our conclusions.

2 ADAPTIVE EVENT DISSEMINATION

The reference scenario for the proposed method involves the exchange of information in a vehicular network in which each node, modeled as an autonomous agent, is capable of acquiring data (*sensing layer*), transmitting it to other vehicles (*communication layer*), and processing information received in order to perform the actual event detection (*application layer*). The sensing layer may consist of either physical devices capable of capturing environmental data, or *humans-as-a-sensor* for reporting unexpected events such as road accidents, assemblies, strikes, traffic diversions. This paper focuses on the design of the communication layer, which implements all the required functionalities for communication between vehicles or with other entities available on the road. This layer models the interactions between agents in a population to enable all of them to converge on a common state, which in our case corresponds to a high-level view of monitored phenomena.The communication layer is composed of the two main modules illustrated in Fig. 1, namely the *Population Protocol Module* (PPM) and the *Adaptive Communication Module* (ACM).

2.1 Population Protocol Module

The PPM represents the core of the communication layer and implements the event dissemination al-

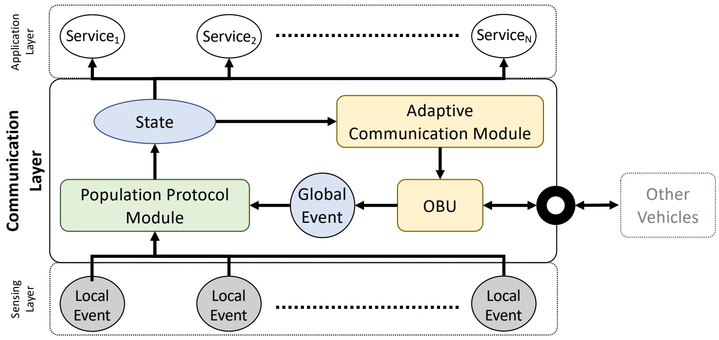


Figure 1: Principal components of the *Communication Layer.*

gorithm among the vehicles. Population Protocols (PPs) (Angluin et al., 2004) were originally conceived to describe a population of resource-constrained devices, named *agents*, characterized by random movements, which rely only on their random interactions in order to accomplish a distributed task. In this work, this theoretical model is adapted to handle vehicle interactions, while still guaranteeing its theoretical properties. Each population agent i is modeled as a finite-state automaton (see Fig. 2). It is initialized with an input value σ_i, from an alphabet Σ, that is used by an *input mapping function* $\lambda(\sigma_i)$ to set its initial state $s_i \in S$, where S is the *state space*. When two agents, i and j, interact with each other, their states are updated according to a *transition function* $\delta(s_i, s_j)$. PP agents are unable to determine whether the implemented algorithm has achieved convergence, but, at any time, they are able to return an output value that describes their perception of the surrounding environment. This information is generated through an *output mapping function* $\Omega(s_i)$, which maps the current state into a value $z \in Z$, where Z is the *output alphabet*. According to this theoretical model, the PP proposed here is defined by the following components.

2.1.1 Input Alphabet

The input alphabet Σ is defined as $\Sigma = \{id\}$, where id is an n-bit symbol that represents the vehicle identifier assigned during the initialization. A fully distributed way of assigning the id is for each vehicle to randomly choose its own; please note that since this identifier is not used for critical functions, id collisions are permitted.

2.1.2 State Space

The state of an agent should contain all the information needed during the execution of the algorithm. The state is encoded as $s = \{id,\ E,\ src\}$, where E is a vector containing all the events that the vehicle has collected, and src is a binary field which allows the source of the state to be distinguished. Specifically, $src = 1$ indicates that the state is generated by the vehicle's sensing layer, while $src = 0$ indicates that the state comes from other vehicles.

2.1.3 Event Encoding

Events, both physical measurements and other information, are stored in a list, $E = \{e_i\}_{i=1,M}$, that, for the sake of simplicity, can be assumed to be of unlimited length (this simple assumption avoids the implementation of a replacement strategy, e.g., remove the least recent or least relevant event). Each e_i consists of a set of fields, namely $e_i = \{Class, id, TTL, src, x, y, T\}$, where:

- *Class*: specifies the type of event. It is possible to define a specific event ontology depending on the specific considered scenario;
- *id*: identifier of the vehicle that detected the event;
- *TTL*: the *Time-To-Live* of the event. When GPS is not available, TTL can be used to estimate the proximity of the event;
- *src*: similarly to the state attribute *src*, it discriminates the events detected by the vehicle itself ($src = 1$) from those coming from the others ($src = 0$);
- x, y: spatial coordinates used only when GPS is available;
- T: timestamp indicating the time at which the event occurred (or was detected), e.g., 32-bit Unix Epoch Time.

2.1.4 Input and Output Mapping Functions

The input mapping function defines the initial state of a vehicle based on its input value. Since in our protocol, the input value is a random identifier, and initially each vehicle is not aware of any event, the input mapping function for the i-th vehicle sets its initial state as: $s_i = \{id_i, E = \emptyset, src = 1\}$. The output function Ω

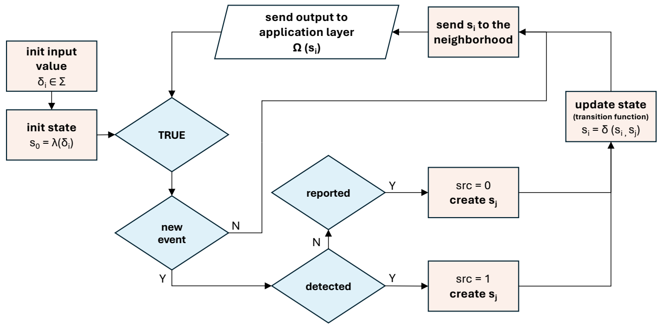


Figure 2: Population Protocol flow diagram for the *i*-th agent.

can be invoked by any service of the application layer and returns the value produced by the vehicle on the basis of its current state. In our model, it returns the current list of events of which the vehicle is aware: $\Omega(s_i) = \Omega(\{id_i, E, src\}) = E$.

2.1.5 Transition Function

The transition function represents the core of the entire PP model and defines the high-level logic of the event dissemination algorithm, whose goal is to propagate events between vehicles as efficiently as possible. In the theoretical model, the agents' interactions are considered (i) unpredictable because there is no knowledge about the order in which they occur, and (ii) asymmetric, i.e., one of the agents is the initiator of the interaction and another the responder. In order to adapt this model to the vehicular networks scenario, it is necessary to adopt a communication scheme that overcomes the communication issues that characterise real-world message exchange, while guaranteeing the main properties of PPs. In particular, we use the VPP communication scheme, presented in (Bordonaro et al., 2021), which guarantees that state updates are performed consistently. During VPP interactions it is possible to distinguish the transmitting and the receiving vehicles, thus allowing for an asymmetrical transition function, as envisaged by PP models. The receiving vehicle updates its state by incorporating into its event list the events contained in the received state. When the received state is *internal* (i.e., it comes from the transmitting vehicle's sensing layer), it is considered *recent* and is added to the event list by setting the maximum TTL value. If the event is already present, its TTL is simply updated to the maximum value. Conversely, if the received state is *external* (i.e., the transmitting vehicle is simply forwarding state information), the TTL of the events is decreased by one and the events are added to the event list only if $TTL > 0$. This aging mechanism prevents information that is no longer relevant (no longer directly detected by any vehicle in the area) from being propagated in the network.

Algorithm 1: Adaptive Communication Module - Sending Rate update function.

Input: *min_rcv_rate*, *max_rcv_rate*, *min_snd_rate*, *max_snd_rate*, *w*

$rcv\_rate = w.receivedMessages()/w.duration()$
if $rcv\_rate > max\_rcv\_rate$ **then**
    $snd\_rate = max(min\_snd\_rate, snd\_rate/2)$
else if $rcv\_rate < min\_rcv\_rate$ **then**
    $snd\_rate = min(max\_snd\_rate, snd\_rate * 2)$
end if

2.2 Adaptive Communication Module

The *Adaptive Communication Module (ACM)* operates in conjunction with the On-Board Unit (OBU), whose aim is to physically implement the communication protocols, such as WAVE, IEEE 802.11p, and the whole protocol stack adopted for VANETs. The ACM can be considered as a controller that ensures that all agents will adapt their individual behavior to the network conditions, with the side effect of improving them.

This control strategy makes each vehicle capable of regulating its sending rate according to its perceived receiving rate. Namely, a high receiving rate suggests that the vehicle is in a high-density area; in this case, in order to reduce the overload on the communication network, each vehicle decreases its own sending rate. Since all vehicles act in accordance with this strategy, such a reduction will result in a lower receiving rate over the whole area. On the contrary, a too-low receiving rate may negatively affect the timeliness of event detection; in this case, all vehicles in the area will increase their sending rate until the effect of this action will be perceived by the vehicles themselves. More specifically, the ACM tries to maintain the receiving rate between two acceptable thresholds, *min_rcv_rate* and *max_rcv_rate*, whose values can be chosen empirically. The updating rule follows a logic of multiplicative increase and decrease, so as to quickly adapt to fast-changing working conditions. The sending rate is doubled when the receiving rate is below the minimum threshold, and halved when the receiving rate is above the maximum threshold, as reported in Algorithm 1. Such analysis is performed by measuring the number of messages received within fixed-length sliding windows (indicated as w in Algorithm 1), whose size can be set empirically, e.g., in our system we considered windows of 10 seconds.

Fig. 3 shows an example of the effect of this adaptive strategy on the vehicle's sending rate. At time instant t_1, the vehicle detects that the receiving rate is within the correct range, so the sending rate is not changed. At instant t_2, the receiving rate goes above the maximum threshold and, as a consequence, the vehicle halves its sending rate. All vehicles act accordingly, so that after a few time steps every vehicle perceives a receiving rate that is in the safety range. A symmetrical effect is observed at time t_6, where an excessively low reception rate causes the sending rate to double.

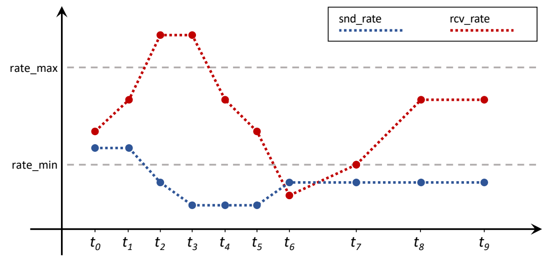


Figure 3: Example the changes in the receiving (`rcv_rate`) and sending rate (`snd_rate`) as a result of the ACM strategy.

3 EXPERIMENTAL EVALUATION

3.1 Experimental Settings and Metrics

The experimental evaluation was performed through the VEINS framework (Sommer et al., 2011), which is based on the SUMO traffic simulator (Lopez et al., 2018) and the OMNET++ event simulator (Varga, 2010). We considered different scenarios, defined by varying the following properties:

- **Map Size**: *Large Maps* (12 linear *km* of roads over an area of 1 km^2) and *Small Maps* (6 linear *km* of roads over an area of 0.25 km^2);
- **Vehicle density**: *High Density* (40 vehicles per linear kilometer) and *Low Density* (20 vehicles per linear kilometer);
- **GPS availability**: we assumed that in some circumstances vehicles are equipped with GPS sensors, while in others this information is not available;
- **Broadcasting Range**: when the adaptive communication strategy is used, the sending rate is the range $[5, 30]$ pkts/s; otherwise, the broadcasting rate is set to 1 pkts/s.

In all scenarios, the communication range of the vehicles is 70 m. The dissemination protocol is evaluated by considering the events detected by each vehicle in its Area of Interest (AoI), using the following metrics: *true positives* (relevant events within the AoI), *true negatives* (irrelevant events outside the AoI), *false negatives* (events within the AoI that the vehicle does not consider relevant), and *false positives* (events outside the AoI that the vehicle considers relevant). Based on these four basic metrics, also average *Precision*, *Accuracy*, *Recall*, and *F1-score* are computed over the n vehicles involved in the simulation.

Moreover, in order to quantitatively describe the impact of the adaptive communication strategy on the communication channel, the experiments report the sending and receiving rate at time t, averaged over all vehicles, and the number of messages sent from the beginning of the simulation until time t, averaged over all vehicles, i.e., $pkts(t)$.

3.2 Evaluation Results

In order to evaluate the advantages of our design choices, we compared three variants of the system proposed here. The first, called "GPS", requires vehicles to be equipped with GPS sensors that make them able to know their position and associate coordinates to the detected events. Preliminary experiments showed that when GPS is available, the event dissemination protocol achieves very good performance, regardless of the communication strategy chosen. Therefore, for the sake of brevity, in the scenario labeled as "GPS" a static sending rate is used. The second and third versions of the system cover the most challenging scenario where vehicles are not equipped with GPS sensors, and can therefore adopt either the "static" or the "adaptive" communication strategy.

Fig. 4 shows the performance evaluation of the proposed event dissemination protocol in *small* and *large* map scenarios, with *high density* and *low density* of vehicles. All plots indicate that GPS sensors allow to achieve the best performance, with values of accuracy, precision, recall and F1-score, averaged over all scenarios, equal to 0.99, 1.00, 0.98, and 0.98, respectively. It can also be observed that when vehicles are equipped with GPS sensors, the precision reaches the value 1, i.e., the system has no false positives. This is because the events detected by the ve-

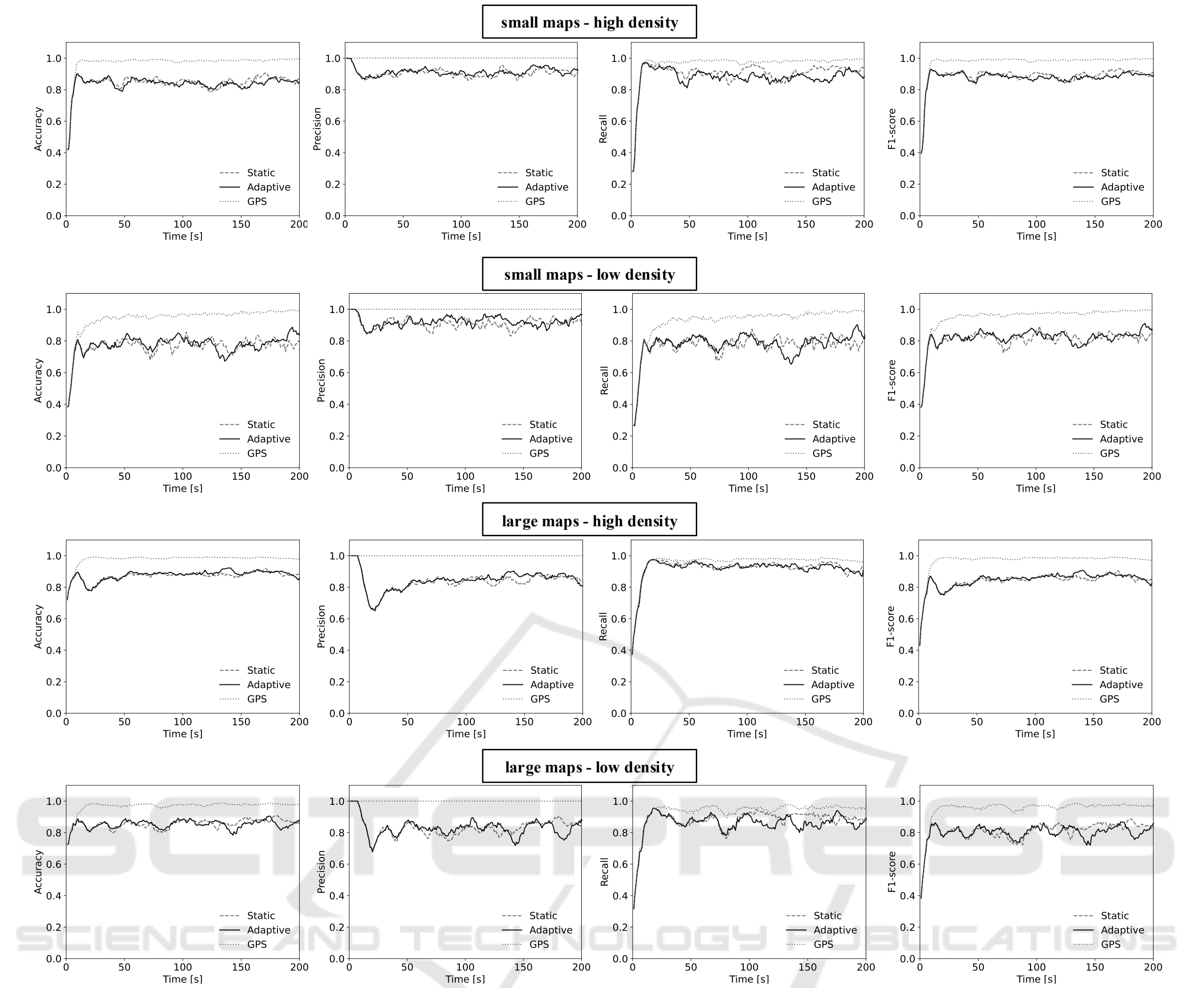
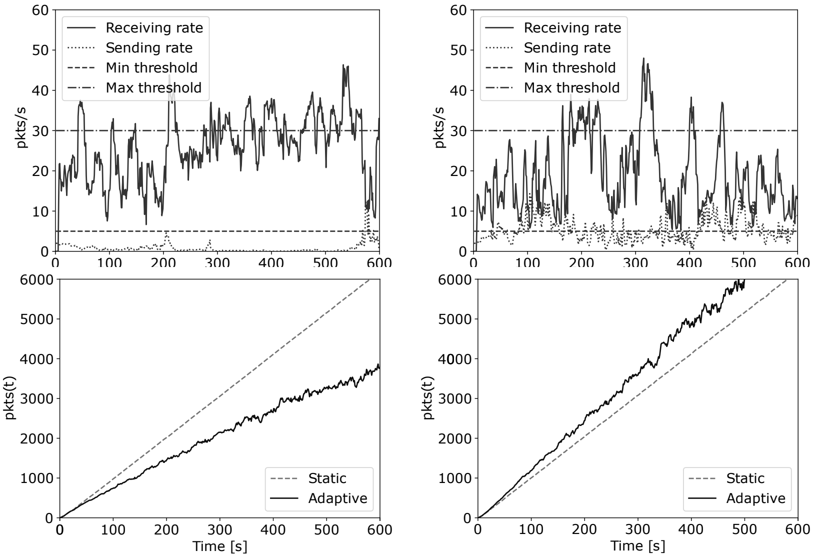


Figure 4: Comparison of Accuracy, Precision, Recall, and F1-Score in *small* and *large* map scenarios, with *high density* and *low density* of vehicles. In each plot three variants of the system are compared: with GPS sensors ("GPS"), without GPS with a static sending rate ("Static"), and without GPS with the adaptive communication strategy ("Adaptive").

hicles are georeferenced, which makes each node receiving a message able to correctly detect whether an event is in its AoI or not. Therefore, it never happens that an event outside the AoI is wrongly labelled as relevant. Without GPS data, in all the considered scenarios, the curves referring to the adaptive communication strategy exhibit essentially the same trend as those related to the static transmission rate. This indicates that adaptive transmission does not lead to a significant reduction in system performance, regardless of map size or density, but instead results in fewer packets being sent, as will be observed in the experiments below. To be more specific, the accuracy, precision, recall and F1-score values, averaged over all scenarios are 0.85, 0.88, 0.87, and 0.85, respectively. It is worth noting that under the high-density scenarios (see plots in the first and third rows), the values of all indicators, for all three system variants, are higher than those related to maps of the same size but with a lower density. This is mainly due the fact that in denser networks, vehicles exchange more information and, as a result, knowledge of detected events propagates more quickly.

The behavior of the adaptive strategy without GPS data was further analyzed by measuring the *sending* and the *receiving rates* and the cumulative *number of packets sent*, averaged over all vehicles. As mentioned above, a high transmission rate might cause excessive energy consumption, while lower values can lead vehicles to lose useful information, thus reducing detection accuracy. Results reported in Fig. 5 and Fig. 6 show that the adaptive mechanism is effective in maintaining the receiving rate between the min and max thresholds. This is achieved by adjusting the sending rate according to the perceived conditions. In high-density scenarios, both in small and



(a) (b)

Figure 5: Receiving and sending rates of the “adaptive” communication strategy (top row), and number of packets sent with “static” and “adaptive” strategies (bottom row) on *small* maps with *high density* (a) and *low density* (b) of vehicles.

large maps (top of Fig. 5.a and Fig. 6.a, respectively), the adaptive mechanism reacts to the perceived high receiving rate, which is interpreted as a symptom of high vehicle density, by reducing the sending rate. This behavior results in significantly fewer messages being sent than the static strategy (bottom of Fig. 5.a and Fig. 6.a), leading to reduce energy consumption, but without compromising event detection capability, as discussed previously. Conversely, it is possible to note that when low-density maps are considered (top of Fig. 5.b and Fig. 6.b), the adaptive strategy compensates for the presence of fewer vehicles in a given area by slightly increasing the sending rate to ensure that the event dissemination protocol is fed with an adequate amount of information. As expected, this results in a higher number of messages sent than the static strategy (bottom of Fig. 5.b and Fig. 6.b).

4 CONCLUSION

This paper proposes an adaptive event dissemination algorithm to support the development of efficient and reliable event-based cooperative services in in vehicular networks modeled as multi-agent systems. The proposed algorithm is based on the distributed model of population protocols, which allows the design of a lightweight and efficient way of disseminating events and information acquired by single vehicles, without imposing any communication burden to coordinate the interaction between peers, as required by other solutions proposed in the literature.

The fully distributed nature of the approach allows its adoption even in scenarios where external infrastructures are missing and thus cooperation between vehicles can only be supported by agents interactions, or even when vehicles are equipped with a reduced set of sensors. Furthermore, the adaptive nature of the proposed algorithm makes the system capable of reacting to rapidly changing network conditions by tuning its behavior. The experimental evaluation, which considered multiple scenarios characterized by different map sizes and network densities, showed that the proposed system achieves high performance in event dissemination while optimizing resource consumption according to network conditions. These results confirm the robustness of the multi-agent approach, demonstrating its ability to maintain efficiency and scalability across different scenarios.

As future work, we plan to extend the proposed system by dynamically adjusting the threshold with adaptive behavior modulated through a self-learning approach, thus eliminating any preliminary set-up and implementing true plug-and-play behavior.

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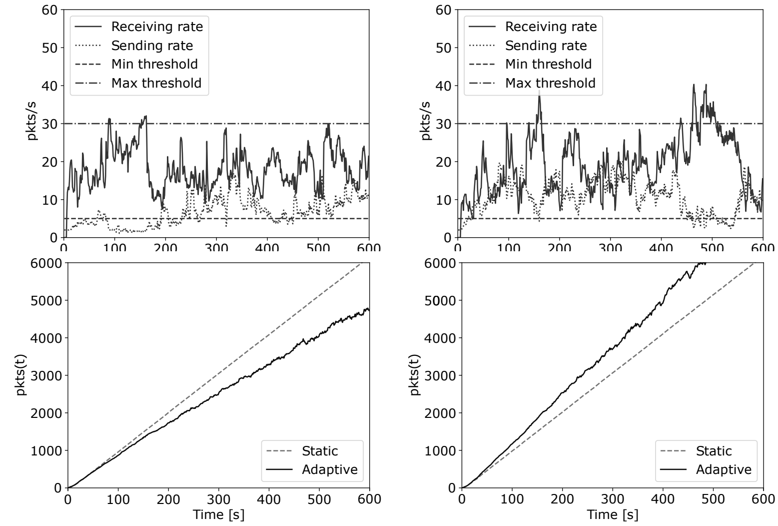

(a) (b)

Figure 6: Same settings of Fig. 5, in the case of *large* maps with *high density* (a) and *low density* (b) of vehicles.

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