MOVES: a MemOry-based VEhicular Social Forwarding Technique

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Abstract

Recently, the new paradigm of Vehicular Social Networks (VSNs) has stimulated a lot of interest in the research community. The rationale behind this interest relies on the integration of social relations in the Internet of Vehicles, taking into account of the human component –in terms of preferences and interests of individuals–, and then allowing to distinguish nodes based on social ties. This feature affects the content dissemination procedures in VSNs, so that the most social node within a transmission range is expected to be the most appropriate next-hop forwarder, for higher network performance achievement.

Leveraging on such premises, in this paper we propose a MemOry-based VEhicular Social forwarding approach, namely MOVES, that builds its packet forwarding logic by considering both the past and present "social" pattern of the nodes. MOVES is inspired by a previous forwarding mechanism, namely SCARF, that integrates the social components and physical features in its forwarding mechanism. MOVES has been compared to SCARF, and other existing forwarding approaches, in different scenarios and with real data in terms of delivery ratio, overhead and latency; results show its effectiveness of including the "social memory" in the selection of the next-hop forwarder.

Keywords: Vehicular social networks, packet forwarding probability, social features, next-hop forwarder selection.

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1. Introduction

The concept of social networking is largely applied to different contexts, ranging from crowd-sourcing data collection to dissemination and forwarding in information networks, as well as in information and coding theory. One of the main representations of social networking are the Online Social Networks (OSNs) [1], comprised of people with social interactions and relationships, that share common interests thus forming social communities. Platforms like Facebook, Twitter and LinkedIn are used everyday by users to be in contact with friends, colleagues, public celebrities, and so on.

OSNs have recently evolved towards the concept of mobile social networks, where users are in mobility in a very dynamic environment, such as the vehicular networks. This evolution has been driven by the observation of users' behavior in terms of (i) mobility pattern and (ii) social behavior. As known, due to the nature of vehicular networks, mobility and traffic patterns can provide social interactions among neighbors. As an instance, in heavy traffic scenarios, the vehicular density is very high and traffic pattern is relatively static. Such scenario becomes a popular social place for vehicles to connect to each other, and share information (*e.g.*, traffic information, weather news, points of interest, and so on) hop-by-hop.

This evolution has carried out the concept of Vehicular Social Networks (VSNs) that consists of groups of individuals that may share common interests, preferences and needs in the context of a temporal-spatial proximity on roads [2, 3]. VSNs are emerging as a novel communication paradigm that exploits opportunistic encounters among vehicles for mobile social networking and collaborative content dissemination. Vehicles are then members of a mobile social network, which is formed *on-the-fly* among neighbouring vehicles. Differently from traditional vehicular ad-hoc networks, data dissemination and routing in VSNs can exploit node social features.

The main motivations of this paper rely on the necessity to implement effective and efficient forwarding mechanisms able to account for the social fea-

tures [4]. In practice, in a VSN beyond the requirements and constraints typical of a high dynamic context as the vehicular networks, we can exploit the node social relations. Then, the main challenges for achieving effective forwarding mechanisms in VSNs are based not only on the social nature of the nodes, but also rely on the "correct" definition of sociality of the nodes. How to define their role in the network, to make the forwarding mechanisms more effective and to keep a certain fairness among the nodes, is also a topic to investigate.

In particular, one of the main challenges in VSNs is the identification of "the most social node" *i.e.*, the node that exhibits more social features and social behavior. The sociability of a node is a concept that needs definitions. Usually, centrality metrics are used to denote how "important" a node is inside a network [5, 6, 7], and in the context of VSNs, the importance of a node is referred to its sociability [8, 9]. Indeed, in a VSN a social node is usually referred also as *hub node*, *i.e.*, a node with the highest number of links in the whole network. Having many one-hop neighbors allows to reach many nodes in case of broadcast data dissemination, thus obtaining a more effective packet forwarding [10, 11].

A definition of *hub node* has been proposed in [12], through the concept of node degree of graph theory. A hub node is then a central node, and in case of social networks it can show social activity [13, 14, 15, 16, 17, 18]. Different definitions of social activity have been proposed. In [18], Aylani and Goyal introduce the Common Social Activity parameter, which exploits information about tags and comments sent by a user. A similar approach has been presented by Peleshchyshyn *et al.* in [17], where several indicators have been considered for user social activity, such as the average frequency of content and the socially relevant content. Finally, *Socialite* [16] is a social activity mining framework, able to achieve social group discovering by exploring users' interactions.

Information about node social activity results also as a criterion for next-hop forwarder selection. In [15], Li *et al.* consider a relay node as the one having more common interests with a destination node, and also having a higher local activity in the community, *i.e.*, it shows many interactions with other members

of the community. Similarly to previous works, in case of VSNs, the paper [12] defines the node social activity following a power-law distribution, depending on the number of messages sent by the node and the probability the node is "online" in the network. This latter aspect is typical of VSNs, where connections among nodes are built dynamically and last for a limited time period only [2].

In this paper, we aim to present a novel technique for next-hop forwarder selection in VSNs, based on a novel concept for node social degree. This parameter considers the amount of messages sent and the number of connectivity links formed by a node, both observed instantaneously and in a given time window. Indeed, we observe that the node social degree shows time dependence, as user's social behavior follows predefined patterns. For instance, a user that uses to send many messages in the community is expected to have this behavior in the future. The past and present observations of the node social activity (*i.e.*, number of messages sent and connectivity links) allow the estimation of the node social degree. As a result, the temporal dependence of social degree affects the decisions of next-hop forwarder selection.

This paper presents MOVES (MemOry-based VEhicular Social forwarding technique) *i.e.*, a probability-based approach for next-hop forwarder selection in VSNs, based on the concept of time-varying node social degree and physical parameters as typical of Dedicated Short Range Communications (DSRC) technology. MOVES refers to a previous approach, namely SCARF (SoCial-Aware Reliable Forwarding Technique for Vehicular Communications) [19, 12], which considers a next-hop forwarder as the farthest and most social node within a source node's transmission range. SCARF takes decision on next-hop forwarder at a given time instant, and the node social degree is computed hop-by-hop. SCARF does not consider the node social behavior from past observations, but it is limited to the present. Contrary, MOVES exploits information of social degree that the i-th node has exhibited in the past, and mixes with the social degree experienced by the i-th node in the present. As a result, the node social degree estimation is expected to be more accurate, resulting in a more effective next-hop forwarder selection.

MOVES comes from SCARF also due to dependence on physical parameters (*i.e.*, vehicles' inter-distance) that limit the next-hop selection. Specifically, MOVES splits (*i*) social features and (*ii*) physical parameters that exist in vehicular networks, as two independent events, and considers (*i*) the probability that the social degree of the i-th node is the highest in a given space, and (*ii*) the probability that the i-th node is the farthest from a source node, within a transmission range. The two events are statistically independent, and the MOVES probability assignment function can be expressed as simply the product of the two probabilities.

In details, the following contributions are addressed in this paper:

1. We introduce a new definition for node social degree, based on both present and past observations. Specifically, we consider the ability of a node to be in connectivity with neighbors (*i.e.*, number of connections) and the number of messages exchanged in a time window. These features allow to obtain an estimation of the node social degree, taking into account both its present and past social behavior. The rationale behind this approach is to observe how "social" a node is (and has been). Information about past and present estimations are accordingly weighted based on a given observation time period;
2. MOVES technique exploits (*i*) the proposed concept of node social degree, as well as (*ii*) physical features that need to be considered for an effective data transmission. Specifically, MOVES considers the probabilities that two events may occur *i.e.*, (*i*) the social degree of the i-th node is not lower than the social degrees of neighboring vehicles, and (*ii*) the i-th node is the farthest node within a given transmission range. The two events are statistically independent and take into account both the social aspects and the physical features, respectively. Furthermore, due to the time dependence of social degree, MOVES technique will be also dependent on the past and present estimation of social degree. Leveraging on such consideration, the proposed approach is a memory-based forwarding

technique *i.e.*, for each node, the information of past social behavior is taken into account;

3. MOVES has been assessed in real traffic scenarios and compared to other existing related approaches *i.e.*, Epidemic, SCARF and an optimal stopping-based technique [20]. Results are expressed in terms of (*i*) delivery ratio, (*ii*) overhead, (*iii*) latency, and (*iv*) computational cost (*i.e.*, number of hops). We observe that MOVES outperforms other techniques for what concerns the delivery ratio, the overhead and latency, but it needs a higher number of hops to reach a final destination.

This paper is organised as follows. Section 2 deals with current related works about data dissemination techniques in VSNs, with special highlights on social-based techniques. Specifically, more attention will be given to a previous technique *i.e.*, SCARF [19], that considers packet retransmissions based on both vehicles social degree and physical parameters. We then highlight the main differences that exist between our proposed MOVES approach and existing techniques. Section 3 presents MOVES forwarding technique via a mathematical model for next-hop forwarder selection, and presents the analysis on the average number of "social forwarder nodes". Simulation results are then carried out in Section 4, where real traffic traces have been considered for a more realistic performance assessment. A comparison to other forwarding approaches has been investigated as well. Finally, conclusions are drawn at the end of this paper.

2. Related works

Due to increasing popularity of OSNs and the increasing number of interconnected mobile devices by the means of the Internet of Things (IoT) paradigm, social relations and social ties have started to be studied and deeply analyzed into wireless networks. This paved the way for mobile social networks [21, 22] and opportunistic social networks [23, 24, 25]. The vehicular social network belong to the opportunistic social networks category.

We identify two main related topics for our approach MOVES *i.e.*, (*i*) how the **social ties** are established and used, and (*ii*) the **dissemination mechanisms**. Content dissemination techniques consider how to distribute contents to users or towards areas of interest. Different approaches are based on major social features, such as centrality metrics [4]. One of the initial contributions on the application of social relations in the vehicular context has been introduced in [26], where the authors analyze the centrality metrics in vehicular ad hoc networks. In particular, the authors motivate their research by considering the social networks analysis (SNA) and the social structures that are formed, and notice that there are similarities between sensors/vehicle networks and social networks. In [27], social metrics and SNA are exploited in order to improve the coverage of service channels (SCHs). It is investigated how the social metrics can be applied to improve the performance of the channel occupation, while SNA is considered for optimal deployment of RSUs (Road Side Units) and to improve data communication mechanisms. The use of RSUs along the roads can enhance the network performance through Vehicle-to-Infrastructure connectivity links, as presented by Bitaghsir *et al.* in [28], where the authors introduce a content distribution technique based on the idea of caching content to RSUs.

The importance on how the social relations are defined and their impact on the network performance, also in terms of radio coverage, have been addressed in [29], where the authors highlight how the weak ties are of paramount importance in order to maximize the probability of reaching more destinations. In [30], Pianese *et al.* consider temporal, spatial and activity profiles in order to characterize the social relations of the users. In [31], Gong *et al.* consider the social contribution of the relay node, expressed as the amount of (*i*) forwarding services each node has done to another, and viceversa, and (*ii*) forwarding services the node provides to other nodes within the community. Gai *et al.* [32] characterize the social relations based on reputation of a node rated by others during past transactions. A central server is considered to ensure the integrality of the trust information. A Ratee-based Trust Management is built in order to exploit the relationships between the nodes for increasing the trustworthiness

among the nodes. In [33], Basta *et al.* provide a novel definition of social tie strength that characterizes the meeting frequency of wireless nodes in a vehicular context. Finally, in [19], the authors introduce a new definition of social node to be integrated in a data forwarding mechanism in a vehicular context.

The main motivation behind this paper relies on the assumption that a social node is expected to frequently meets other nodes and then is a better candidate to disseminate messages. Similar considerations have been adopted by Yao *et al.* in [34], which propose a cooperative caching scheme based on social attributes and mobility prediction for Vehicular Content Centric Networks. The authors assume a caching node sharing more social attributes with the other nodes is more likely to be interested in the same contents and is willing to distribute the contents to other nodes with similar interests. Also, Ullah *et al.* [35] exploit the computation of tie strength based on social metrics, in order to estimate node's reputation. This aspect is then assumed as main criterion for message dissemination in 5G-based vehicular networks. All the approaches considered so far demonstrate the effectiveness of including the social components for improving the performance of vehicular networks.

Content dissemination is extremely important for mobile and opportunistic social networks. In [36], in the context of opportunistic social networks, three different categories of dissemination techniques have been considered, *i.e.*, (*i*) epidemic, (*ii*) probability-based, and (*iii*) interest community-based content dissemination. This classification matches also very well into VSNs. Different contributions belonging to the three different categories have been proposed recently. **Epidemic approaches** have been considered in [37], where the PeopleNet architecture relies on an already pre-existing infrastructure in order to "epidemically" send data in a mobile social network context. A hybrid approach, namely EpSoc, utilizes the Epidemic routing forwarding strategy together with social features, such as degree centrality [38]. In [39], Lee *et al.* propose a kind of virtual flea market based on users' interests, namely FleaNet, where the customers can express their requests and send their queries, as well as their offers, etc. Similarly, the Optimal Stopping (OS) approach [20] is a kind of message

broadcasting technique, where forwarding nodes are selected based on their (*i*) centrality, (*ii*) reliability, and (*iii*) similarity. The goal is to make the broadcast effective and pervasive all over the network.

In [40], Priority Based Efficient Information Dissemination Protocol (PBEID) has been proposed by combining **probability-based** and density-based information dissemination techniques with conventional broadcasting. In [41], Zhou *et al.* regard to the **interests matching** among vehicular users, and introduce the concept of *social relationship tightness* to realize the matches among users. Specifically, the authors a social big data-based content dissemination approach by relying on D2D (Device-to-Device) - V2V (Vehicle-to-Vehicle) connections.

A taxonomy for content dissemination in VSNs has been proposed in [42], where Mezghani *et al.* classify the dissemination approaches based on (*i*) information processing, (*ii*) content delivery, and (*iii*) performance. It is highlighted that the best approach in the context of social networks is represented by the class considering user preferences, even though this needs to exchange preferences before sending data. In particular, the authors also consider the *user satisfaction* as new feature to be considered in order to improve data dissemination. Finally, the results obtained by Li *et al.* in [36] have highlighted a deep analysis on the network topology, and it resulted that the temporal and spatial characteristics have to be analyzed and integrated in the content dissemination schemes, for the enhancement of network performance and effectiveness of the dissemination in opportunistic mobile social networks. Based on these results in the context of opportunistic social networks, in this paper we consider the sociality of a node as a prominent feature for being considered in a data forwarding process.

3. MOVES Forwarding Technique

MOVES technique exploits not only physical features of the communication environment, such as node inter-distance, channel estimation, vehicular density and so on, but also social features like node centrality, betweenness, degree,

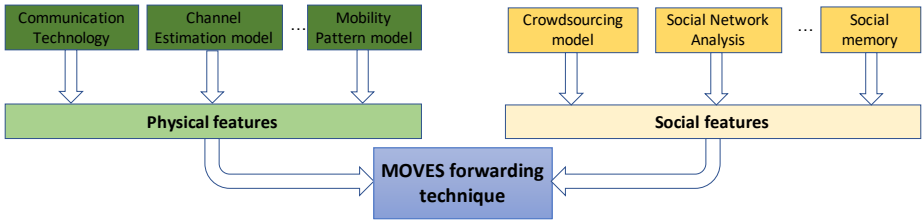


Figure 1: Main factors affecting MOVES forwarding technique.

etc. The joint combination of physical and social features allows to select the most social node within a given area as next-hop forwarder. Figure 1 depicts the main inputs affecting MOVES node selection. External factors coming from the network environment (*e.g.*, channel estimation, communication technology, mobility pattern model, etc.) represent the physical features, while social features identify how much nodes are social and depend on graph theory metrics like centrality, betweenness, etc. By varying physical and/or social features, we can obtain different MOVES forwarding probabilities that better fit in a given network scenario. For instance, changing the definition of social memory or the wireless carrier, the resulting forwarding probability will be different. This allows to extend MOVES approach according to different requirements and needs.

MOVES main goal is to identify which node in a VSN presents the highest degree of sociality *i.e.*, the node the most "social" in the network, since it is expected to be likely the most appropriate next-hop forwarder. As similar to SCARF [12], MOVES is applicable to main VSN applications, from security to entertainment-based ones, as it aims to select only those social vehicles likely to be the most suitable next-hop forwarders.

How sociality affects the message retransmission has been already addressed in previous works, but how to define the sociality degree of a node is a tricky issue that can be solved in several manners. In this paper, we consider the node sociality as the skill of a node of (*i*) connecting and (*ii*) communicating to neighboring nodes (*i.e.*, one-hop nodes). A node with a high node degree that communicates via broadcast is then expected to exhibit a good node sociality,

while a node with low degree and low number of packet transmissions has likely a bad sociality.

We can observe that a node is showing a good node sociality in a given time interval, and then represents a good candidate for next-hop forwarder, but this behavior is time-limited and may change quickly. For instance, let us consider a node is in contact and communicates with its neighbors for all the time interval the node is in mobility. However, due to quick variations of mobility pattern and connectivity that use to occur in vehicular environments, such node can show a totally different node sociality due to lack of neighbors and no packet to retransmit. It can be observed that the node sociality is time dependent according to both (i) present and (ii) past interactions with other nodes. For instance, a node that in the last n days has been connected with a high number of neighbors and has sent/received multiple messages, it is mostly likely to have a similar behavior in the future. In contrast, a node that in the last n days has being connected with a low number of nodes and also exchanged less messages, it is expected to have a poor skill of communicating and connecting with neighbors. It follows that its social skill is expected to be lower.

Leveraging the above considerations, we can define the social degree of the i-th node as:

$$s_i\left(t\right) = \mathcal{M}_i\left(t\right) + \mathcal{C}_i\left(t\right), \tag{1}$$

where $\mathcal{M}_i(t)$ and $\mathcal{C}_i(t)$ are the time-dependent message and connection coefficients associated to the i-th node, respectively. We observe that the social degree of the i-th node is the contribution of (i) the communication degree and (ii) the connectivity degree of the i-th node, obtained both from recent and past estimations. In Eq. (1), the first term on the right of *i.e.*, $\mathcal{M}_i$, represents the communication degree of the i-th node *i.e.*, how many messages a node has exchanged on average in the network, computed by weighting the average number of messages transmitted (i) in a given time interval *i.e.*, $t = \Delta T$, and (ii) in the whole time period [1], *i.e.*, $t = T$. Specifically, we pose $\bar{\mathcal{M}}_i$ as the average

[1]The parameter T represents the whole time period of mobility pattern of the i-th vehicle

number of messages that the i-th node has exchanged in the network in a given time window $t = \Delta T$, and $\bar{\mathcal{M}}_{i,h}$ as the average number of messages that the i-th node has used to exchange in the network in the whole time period, where the subscript h means a historical value. The message coefficient $\mathcal{M}_i$ in Eq. (1) can be then written as:

$$\mathcal{M}_i\left(t\right) = \begin{cases} \beta\bar{\mathcal{M}}_i\left(\Delta T\right) + \left(1-\beta\right)\bar{\mathcal{M}}_{i,h}, \\ \text{if } \bar{\mathcal{M}}_i\left(\Delta T\right) > \bar{\mathcal{M}}_{i,h} \\ \\ \left(1-\beta\right)\bar{\mathcal{M}}_i\left(\Delta T\right) + \beta\bar{\mathcal{M}}_{i,h}, \\ \text{if } \bar{\mathcal{M}}_i\left(\Delta T\right) \leqslant \bar{\mathcal{M}}_{i,h} \end{cases} \tag{2}$$

where β is a constant in the range $[0, 1]$ used to give different weights to the historical information and the new one. By mixing both historical and most recent message coefficients, the node's social attitude can be observed. For instance, a node that used to send messages in the past few days represents a very active node, as compared to a node with a lower average number of sent messages in the same time period. The introduction of historical data, which can be stored in a local node cache, allows to take into account the node's past interactions. Specifically, for $\bar{\mathcal{M}}_{i,h}$ we compute the average number of messages exchanged by the i-th node in the network in the past T period.

Similar considerations are applied to the second term on the right side of Eq. (1), *i.e.* $\mathcal{C}_i$, that represents the connectivity degree and can be expressed as:

$$\mathcal{C}_i\left(t\right) = \begin{cases} \beta\bar{\mathcal{C}}_i\left(\Delta T\right) + \left(1-\beta\right)\bar{\mathcal{C}}_{i,h}, & \text{if } \bar{\mathcal{C}}_i\left(\Delta T\right) > \bar{\mathcal{C}}_{i,h} \\ \left(1-\beta\right)\bar{\mathcal{C}}_i\left(\Delta T\right) + \beta\bar{\mathcal{C}}_{i,h}, & \text{if } \bar{\mathcal{C}}_i\left(\Delta T\right) \leqslant \bar{\mathcal{C}}_{i,h} \end{cases} \tag{3}$$

where $\bar{\mathcal{C}}_i$ and $\bar{\mathcal{C}}_{i,h}$ represent the average number of connections that the i-node has established with its neighboring nodes, respectively (i) in a given time window $t = \Delta T$, and (ii) in the whole time period *i.e.*, historical average. As

(*e.g.*, assumed as 24 hours). Notice that $\Delta T \leq T$ [s]. In the following, we consider the ratio $r = \Delta T/T$, which varies for different ΔT [s].

in the previous Eq. (2), the term β is a weight constant in the range $[0, 1]$.

From Eqs. (2) and (3), we observe that the meaning of $\bar{\mathcal{M}}_i$ ($\bar{\mathcal{C}}_i$) and $\bar{\mathcal{M}}_{i,h}$ ($\bar{\mathcal{C}}_{i,h}$) distinguishes according to the time window where exchanged messages (connections) are counted on average. In the first case, we consider the average number of messages exchanged by the i-th node in the time interval ΔT [s], while in the latter the average number of messages is computed in the overall time period. In Eq. (2) we observe a different expression for the message coefficient according to the condition that is satisfied. Indeed, by comparing the average number of messages that the i-th node has exchanged in ΔT [s] time interval and in the overall time period T [s], if the recent estimation is higher than the past one, then more weight is provided to the recent one. This means that, in the case $\bar{\mathcal{M}}_i(\Delta T) > \bar{\mathcal{M}}_{i,h}$, for $\beta > 0.5$, the average number of messages in the recent time window ΔT has higher weight than the average number of messages exchanged in the overall time period. Otherwise, in the case $\bar{\mathcal{M}}_i(\Delta T) \leq \bar{\mathcal{M}}_{i,h}$ and for the same values of β, less weight will be given to $\bar{\mathcal{M}}_i(\Delta T)$. Of course, the limit values *i.e.*, $\beta = 0$ and $\beta = 1$, allow to consider only one term between $\bar{\mathcal{M}}_i(\Delta T)$ and $\bar{\mathcal{M}}_{i,h}$. These cases are however not suitable to consider, as the estimation of the social degree would lack of a missing term. Similar considerations apply to Eq. (3). In Section 4, we will investigate the role of β in the social degree estimation in real traces.

Leveraging on previous considerations, the definition of social degree in Eq. (1) can be rewritten as

$$s_i(t) = \bar{s}_{i,h} + \bar{s}_i(\Delta T), \tag{4}$$

where the terms $\bar{s}_{i,h}$ and $\bar{s}_i(\Delta T)$ take into account both the average number of messages and the connections occurred for the i-th node in (i) the whole past time period, and (ii) the time window ΔT, respectively. The term $\bar{s}_{i,h}$ represents the "social memory" of the i-th node (*i.e.*, if a node has been social in the past) and depends on $\bar{\mathcal{M}}_{i,h}$ and $\bar{\mathcal{C}}_{i,h}$.

After introducing the social degree concept, we investigate how to consider this factor for data dissemination purpose in VSNs. Usually, message transmis-

sion techniques in vehicular networks are based on physical factors only, such as distance, vehicular density, power level and so on. When considering social features in vehicular scenarios, such as the ability of a node to form connections with neighboring nodes, then message transmission techniques should include also social aspects. As already highlighted in previous sections, it has been demonstrated that the next-hop forwarder selection based on social features of a node provides better performance, as a more social node is expected to reach more nodes in case of packet forwarding. In VSNs, the next-hop forwarder selection occurs on the highest value of social degree that a node in a given transmission range can experience. Basically, the node with the highest social degree is expected to be elected as next-hop forwarder. Finally, notice that data exchange and gathering of relevant information among vehicles is guaranteed by assuming an edge computing architecture, as already described in [12].

Let us consider a VSN community as comprised of a given number N of nodes. All the nodes are assumed to be forming a cluster of nodes, so that none of the N nodes has a null node degree *i.e.*, $\delta_i \neq 0$ with $i = \{1, 2, \ldots, N\}$. Figure 2 depicts a schematic of node degree in a vehicular network. Different clusters (*red rectangles*) are formed and comprised of nodes with non-null degrees *e.g.*, $\delta_1 = 3$, $\delta_2 = 2$, $\delta_3 = 3$, and $\delta_4 = 2$. Isolated nodes have a null degree and do not belong to any cluster *e.g.*, $\delta_5 = 0$. Similar considerations apply for the other cluster with node degrees $\delta_{6,7,8}$ respectively equal to 1, 2 and 1.

A source vehicle (*i.e.*, Tx node) has to forward a message towards a next-hop node within its transmission range *i.e.*, z [m]. The i-th vehicle within the transmission range z is at distance d_i (*i.e.*, $d_i \leq z$ [m]). As known, the nodes' positions can be generated according to a Poisson Point Process of parameter ρ, which is the vehicle linear spatial density [veh/m], and the inter-vehicle spacing is exponentially distributed with mean $1/\rho$. Then, we can assume X_i as an independent and identically distributed (*i.i.d.*) random variable denoting the space between the i-th and the $(i+1)$-th vehicle, with the exponentially-distributed Cumulative Distribution Function (CDF), expressed as $F_X(x)$.

The forwarding probability of the i-th vehicle should be proportional to (i)

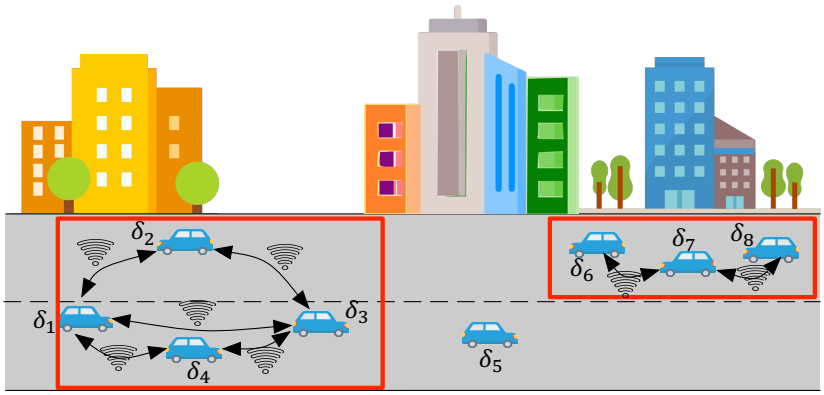


Figure 2: Schematic of node degree in a cluster (*red rectangles*), where nodes are in V2V communication and none of them has a null degree *i.e.*, $\delta_i \neq 0$, with $i = \{1, 2, 3, 4\}$. An isolated node is out of a cluster and has a null degree *e.g.*, $\delta_5 = 0$. Similar considerations apply for $i = \{6, 7, 8\}$.

the probability that there is no vehicle in the interval of length $(z - d_i)$ [m] able to re-forward, and (ii) the probability that there is no neighboring vehicle with a social degree higher than that of the i-th vehicle. The forwarding probability associated to the i-th node depends on two events that are independent from each other. The first event is represented by the probability that there is no other vehicle in the interval of length $(z - d_i)$ [m], and can be expressed as

$$p_{1,i} = 1 - F_X\left(z - d_i\right), \tag{5}$$

where $F_X(z - d_i)$ is the CDF of X_i, with $x = z - d_i$. On the other side, the probability that there is no neighboring vehicle with a social degree S higher than that of the i-th vehicle is

$$p_{2,i} = 1 - \Pr\left\{S > s_i\left(t\right)\right\}, \tag{6}$$

where the term on the right side represents the complementary cumulative distribution function in case of Pareto distribution [43], which is a viable assumption for the social degree distribution in vehicular scenarios [12].

We can observe that Eq. (5) represents SCARF forwarding probability assignment function in case of maximum value of social degree *i.e.*, $s_i = 1$, and

with $c_i \geq 1$ as a shape factor [12, 19], *i.e.*

$$p_{1,i} = \exp\left[-\rho \frac{z - d_i}{c_i}\right], \tag{7}$$

while $p_{2,i}$ in Eq. (6) represents the complementary CDF of a Pareto random variable with parameters α as the exponent of the power-law distribution *i.e.*, $\alpha = [2, 3]$ for small-world networks, and s_m is the minimum value of the social degree s_i, *i.e.*, [43]

$$p_{2,i} = 1 - \left(\frac{s_i\,(t)}{s_m}\right)^{(-\alpha+1)}. \tag{8}$$

Finally, since the two events described by Eq. (7) and (8) are statistically independent, the MOVES forwarding probability assignment function of the i-th vehicle can be expressed mathematically as:

$$\begin{aligned} p_{f,i}^{MOVES}(t) &= p_{1,i} \cdot p_{2,i} \\ &= \exp\left[-\rho \frac{z - d_i}{c_i}\right] \cdot \left[1 - \left(\frac{s_i\,(t)}{s_m}\right)^{(-\alpha+1)}\right]. \end{aligned} \tag{9}$$

In Eq. (9), the selection of the i-th vehicle as next-hop forwarder based on social features occurs if its social degree is at least higher than a given required minimum value *i.e.*, $s_i \geq s_m$, and no other neighboring vehicle exhibits a social degree higher *i.e.*, $1 - \Pr\{S > s_i(t)\}$. However, this condition is not enough to guarantee an optimal detection of a next-hop forwarder, since no information about the physical distance is considered. Indeed, in a transmission range, the farthest vehicle from a source vehicle should be the most likely next-hop forwarder of the packet as this will yield the highest forward progress. It follows that MOVES technique has to exploit (i) the physical dependence by preferring the farthest node, while guaranteeing (ii) the social degree. Finally, it is worth to notice that Eq. (9) shows the time dependence of MOVES forwarding probability assignment function, coming from the social degree $s_i(t)$. It is then expected to observe a variation of the forwarding probability assignment function based on the width of the time windows ΔT, which affects the social degree variability.

Figure 3 depicts the dependance of MOVES forwarding probability assignment function by both the distance from a Tx vehicle and the social degree

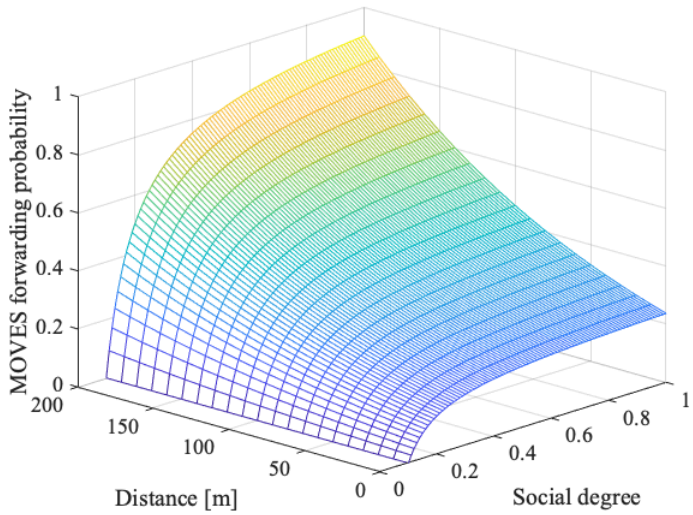
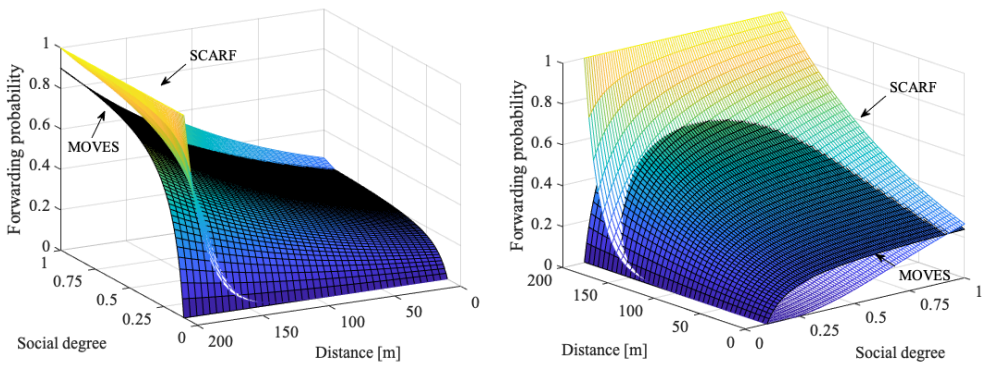


Figure 3: MOVES forwarding probability of the i-th vehicle at distance d_i [m] (*i.e.*, $d_i \leq z$ [m]) and social degree s_i (*i.e.*, $s_m \leq s \leq 1$, with $s_m = 0.1$). In particular, we assumed $z = 200$ [m], $\rho = 0.02$ [veh/m], $c = 3$, and $\alpha = 2$.

s_i. Here, we assume static values of the social degree, while in Section 4 we will present simulated results for different values of the time window ΔT. In Figure 3 we observe that MOVES forwarding probability exists for $s_i \geq s_m$, and is higher when $s_i \to 1$ and $d_i \to z$ [m]. In practice, MOVES takes into account both (i) the physical factor by means of inter-vehicle distance, then supporting the farthest vehicle, and (ii) the social aspect of vehicles. The farthest and most social vehicle is the preferable next-hop node. In conclusion, the selection of a next-hop forwarder occurs on the basis of the highest MOVES assignment function within a transmission range.

Differently from SCARF [12], MOVES considers the social aspect of the i-th vehicle as a single event *i.e.*, the probability that there is no other neighboring vehicle with a higher social degree, which is statistically independent from the event related to the physical factors. Indeed, MOVES forwarding probability assignment function considers two statistically independent events that are related to (i) physical factors, by means of the inter-vehicle distance and (ii)

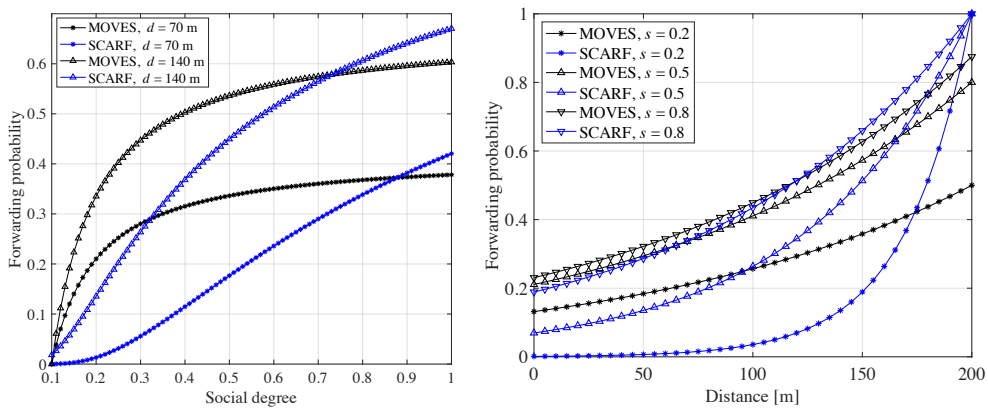


(a) (b)

Figure 4: Comparison of MOVES and SCARF forwarding probabilities versus the distance and the social degree. (a) MOVES shows lower probability than SCARF for high social degree and high distance, while (b) SCARF probability is lower when the social degree and the distance are lower.

social factors, by means of the social degree of the i-th node. On the other side, SCARF technique is based on a single event only *i.e.*, the probability that there is no neighboring vehicle at distance $(z - d_i)$ [m] with a social degree s_i. No comparison to other vehicles in terms of social aspect is provided.

To better understand the behavior of MOVES, as compared to SCARF, we observe the plots in Figure 4, where the two curves overlap to each other in particular areas. Specifically, for high social degree and high distance, MOVES forwarding probability results lower than SCARF (see Figure 4 (a)). Indeed, MOVES considers social aspects and physical ones associated to two separated events, and then cannot reach the maximum value of probability. For lower social degree and distance values, MOVES presents higher trend than SCARF, as depicted in Figure 4 (b). Again, this is due to the exponential nature of SCARF forwarding probability assignment function, which reaches high values only for higher social degree and distances. On the other side, MOVES essentially represents a power law with an exponential cutoff, where the exponential decay second term of Eq. (9) overwhelms the power-law behavior at very large

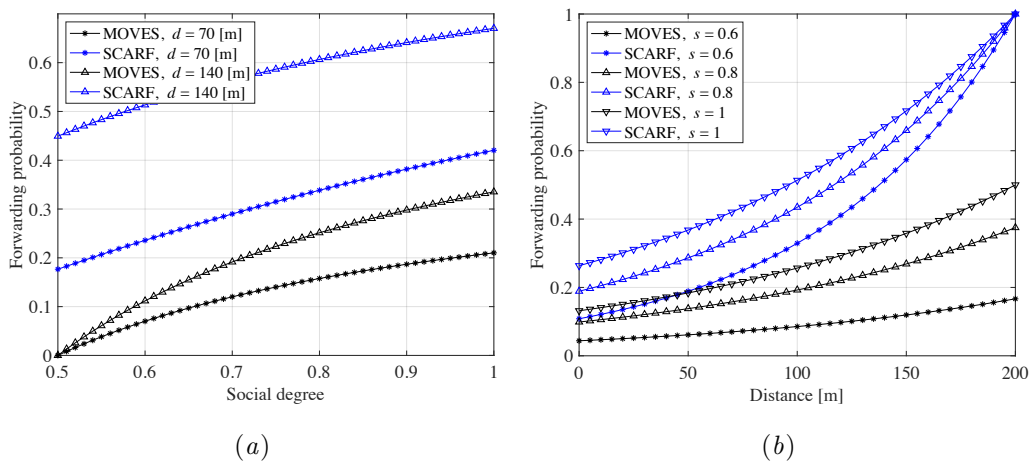


(a) (b)

Figure 5: Comparison of MOVES and SCARF forwarding probabilities (a) for different values of distance d_i [m] ($i.e.$, $d_i \leq z$ [m]), versus the social degree, and (b) for different values of social degree s_i, versus the distance. We assumed $z = 200$ [m], $\rho = 0.02$ [veh/m], $c = 3$, $s_m = 0.1$ and $\alpha = 2$.

values of the social degree.

Finally, we observe that SCARF and MOVES alternate their trends, so that the first looks more efficient in detecting those vehicles laying at long distances and with high social degree, while the latter assigns higher probability to those vehicles at lower distance and with lower social degree. MOVES shows a smooth trend for $s_i \to 1$ and $d_i \to z$, while SCARF forwarding probability reaches the maximum value very fast, due to the exponential factor of the inter-vehicle distance. For instance, for high values of distance ($e.g.$, $d_i = 190$ [m] with $z = 200$ [m]) and low social degree ($e.g.$, $s_i = 0.2$), SCARF forwarding probability is 0.716, while for MOVES it is 0.467. In general, for maximum distance and independently from the social degree, SCARF shows its maximum probability, while MOVES reaches its highest value only if the vehicle is the farthest and most social in the transmission range. For low distances and high social degree, both the approaches tend to assigning low probability values ($e.g.$, for $s_i = 1$ and $d_i = 10$ [m], SCARF probability is 0.281, while for MOVES it is



(a) (b)

Figure 6: Comparison of MOVES and SCARF forwarding probability in case of $s_m = 0.5$, versus (a) social degree, and (b) distance. We assumed $z = 200$ [m], $\rho = 0.02$ [veh/m], $c = 3$, and $\alpha = 2$.

0.253).

A more detailed description about the comparison between SCARF and MOVES is presented in Figure 5 (a), which depicts the two curves for fixed values of distance *i.e.*, $d_i = [70, 140]$ m, versus the social degree. We observe that MOVES curve starts with slightly higher probability values than SCARF, and then the trend varies slowly for increasing social degree. On the other side, SCARF assigns very low values of forwarding probability due to low social degree, but then increases fast till overcoming MOVES for very high social degree. MOVES trend is smoother, and looks like saturating for increasing social degree.

In Figure 5 (b), similar considerations can be applied by comparing MOVES and SCARF for fixed values of social degree *i.e.*, $s_i = [0.2, 0.5, 0.8]$, versus the distance. It is easy to observe that SCARF shows different curves that reach the maximum probability faster than MOVES, which in contrast shows a maximum probability that is always lower than SCARF. Again, we observe that MOVES overcomes SCARF in particular ranges due to its faster increase

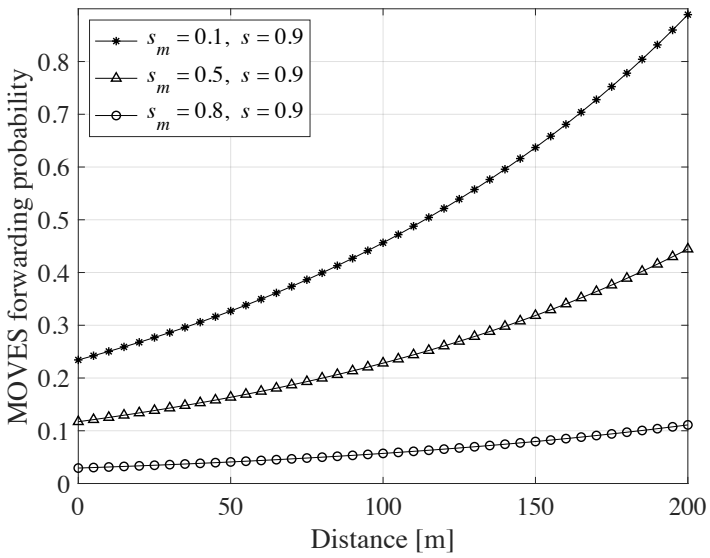
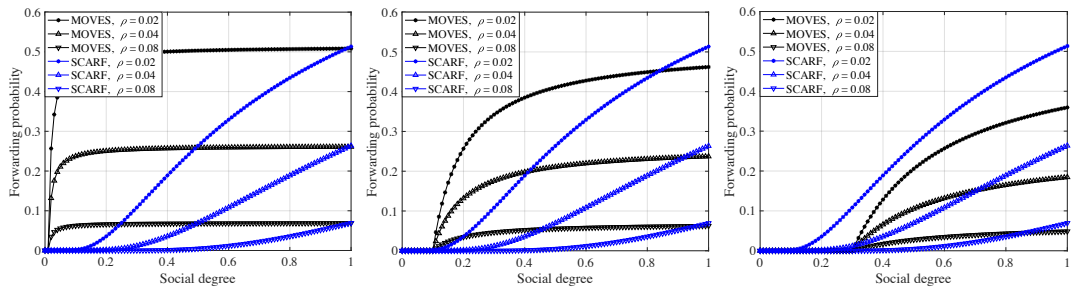


Figure 7: Dependence of MOVES forwarding probability on the minimum social degree parameter s_m.

at the beginning, followed by a slower trend for increasing distances. Finally, while SCARF presents different curves for different values of social degree, for increasing social degree MOVES shows very close probability values.

In all previous results, MOVES has been evaluated for $s_m = 0.1$. However, it is observed from Eq. (9) that MOVES forwarding probability strictly depends on the minimum value of social degree *i.e.*, s_m, as for $s_i < s_m$ the probability is null. In Figure 6 we depict MOVES trend in case of $s_m = 0.5$, as compared to SCARF. Notice that MOVES provides a forwarding probability only if $s_i \geq s_m$. This aspect represents a quality requirement since only those nodes exhibiting a social degree higher than a given threshold are eligible as potential next-hop forwarders. The minimum social degree value that a vehicle should exhibit limits the selection of potential forwarders *i.e.*, the higher (*lower*) the minimum social degree the lower (*higher*) the MOVES forwarding probability (see Figure 7). This allows the use of MOVES in applications needing higher quality requirements (*i.e.*, comfort and interactive entertainment), while SCARF does



(a) (b) (c)

Figure 8: MOVES forwarding probability versus the social degree, for different values of vehicular density ρ, in case of (a) $s_m = 0.01$, (b) $s_m = 0.1$ and (c) $s_m = 0.3$.

not introduce any constraint on the social degree *i.e.*, potentially all the vehicles have no social degree limitation and can become a next-hop forwarder.

Finally, Figure 8 depicts MOVES and SCARF forwarding probabilities behavior for different values of vehicular density *i.e.*, $\rho = [0.02, 0.04, 0.08]$ veh/m, computed for a vehicle at distance $d = 100$ m from a source node (again, $d < z$ and $z = 200$ m). Also, MOVES has been evaluated in case of different values of the minimum social degree s_m *i.e.*, $s_m = [0.01, 0.1, 0.3]$. It can be observed (see Figure 8 (c)) that for increasing s_m, the area of existence of the MOVES forwarding probability shifts to increasing social degree, with a reduced trend. Differently, in case of very low minimum value of social degree s_m as in Figure 8 (a), the behavior of MOVES forwarding probability saturates very quickly, with higher (*lower*) trend in case of low (*high*) vehicular density.

3.1. Average Number of Forwarders

In order to assess the propagation efficiency of MOVES forwarding technique, we are interested in the expected number of hops needed to transmit a packet from a source to a destination node. Let us consider the scenario where an information packet propagates from a source node to a destination one. We assume N_z as the number of potential forwarder vehicles in the transmission range $[0, z]$ [m] of a source vehicle; each of them can be elected as a social

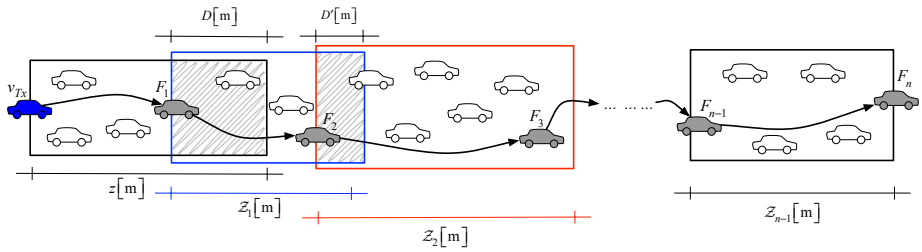


Figure 9: Schematic model of the propagation range in case of multi-hop scenario. A source vehicle (*blue vehicle*) will select the next-hop forwarder F_1 (*gray vehicle*) within its transmission range z [m]. Notice that the transmission ranges are randomly distributed in the range $[z/2, 3z/2]$ [m].

next-hop forwarder, according to Eq. (9).

As known [12, 44], the number of potential forwarders N_z within the source's transmission range can be assumed as a random variable, according to a Poisson-statistical distribution with parameter ρz, whose Probability Density Function (PDF) is:

$$f_{N_z}(n) = \Pr\{N_z = n\} = \frac{(\rho z)^n e^{-\rho z}}{n!}, \tag{10}$$

and then it follows that the expected value of N_z can be written as

$$\begin{aligned} \mathbb{E}\{N_z\} &= \int_1^{N_z} n f_{N_z}(n)\, dn \\ &= \int_1^{N_z} \frac{n(\rho z)^n e^{-\rho z}}{n!} dn \\ &= \int_1^{N_z} e^{-\rho z} \frac{(\rho z)^n}{\Gamma(n)} dn, \end{aligned} \tag{11}$$

where $\Gamma(n)$ is the Gamma function defined as

$$\Gamma(n) = \int_0^{\infty} e^{-t} t^{n-1} dt. \tag{12}$$

The solution of Eq. (11) can be computed numerically for different values of N_z, which correspond to different values of ρ, as $N_z = \rho z$. Eq. (11) considers the number of forwarders within one transmission range *i.e.*, z [m]. However, we are also interested in the average number of forwarders in a multi-hop propagation. For this aim, we consider the scenario as depicted in Figure 9, where

Algorithm 1 MOVES forwarding technique forwarding

INITIALIZATION:
v_{Tx} aims to transmit a message within its transmission range
if $i = 1$ **then** ▷ This is the first hop
    $z_i = z$ [m]
else ▷ Multi-hop message propagation
    z_i as in Eq. (13)
end if
v_{Tx} has information about its neighbors *i.e.*, $\mathcal{N} = \{n_1, n_2, \ldots, n_N\}$
procedure MOVES(n_ℓ) ▷ MOVES assignment function to $n_\ell \in \mathcal{N}$
    for $\ell \leq N$ **do**
        while $(v_{Tx}, n_\ell) \neq 0$ **do** ▷ Node v_{Tx} and n_ℓ are in connectivity
            Computation of Euclidean distance d_{n_ℓ} from v_{Tx}
            Gathering of social feature s_{n_ℓ}
            Computation of Eq. (9)
            if $p^{MOVES}_{f,n_\ell} = \max_{\mathcal{N}} p^{MOVES}_{f,\mathcal{N}}$ **then**
                $n_\ell \leftarrow F_i$
                v_{Tx} sends the message to F_i
            end if
            $(\ell + 1) \leftarrow \ell$
        end while
    end for
end procedure

we assume that the transmission ranges of the next-hop forwarders (*i.e.*, F_n vehicles, with $n \in \mathbb{Z}^+$ as the number of hops) are randomly distributed in the interval $[z/2, 3z/2]$ [m]. This assumption can represent a vehicular scenario with fading effect and noisy channel. Also, the inter-distance of vehicles within the transmission ranges is randomly distributed.

Algorithm 1 describes the main objective of MOVES technique. A source vehicle v_{Tx} (*i.e.*, *blue vehicle*) aims to send a message within its transmission range and selects the forwarder node (*i.e.*, F_1) from the set of all its neighbors $\mathcal{N} = \{n_1, n_2, \ldots, n_N\}$, showing the highest MOVES forwarding probability. The selection of node F_1 is based on both its physical distance and social feature. Such information is obtained by assuming an edge computing architecture, as already described in [12]. In the next-hop transmission, vehicle F_1 will select vehicle F_2 within the transmission range z' [m]. Notice that vehicle F_1 will seek for potential forwarders those vehicles that are in the area $(z' - D)$ [m], where D [m] is the overlapping area with the transmission range of previous hop. This is due in order to avoid the selection of next-hop forwarders that also belong to previous transmission range. Finally, in the next-hop transmission, vehicle F_2 will seek for potential forwarders in the area $(z'' - D')$, where z'' [m] is F_2 transmission range and D' [m] is the overlapping area with z' [m] transmission range. According to such criterium, F_3 will be selected as next-hop forwarder. In general, for a multi-hop propagation, the transmission range of the i-th node where the next-hop forwarder will be selected is computed as:

$$z_i = \mathcal{Z}_i - \mathcal{Z}_{i-1} + d_{i,i-1}, \tag{13}$$

where $\mathcal{Z}_i$ [m] is whole transmission range of the i-th forwarder and $d_{i,i-1}$ [m] is the inter-distance between two consecutive forwarders.

Figure 10 depicts the average number of forwarders for different values of vehicular density ρ, in case of single and multiple transmissions, *i.e.*, from one to four hops, respectively. Specifically, in Figure 10 we assume that the transmission range in one-hop scenario is $z = 200$ m, and then the number of nodes within this range is $N_z = \rho z$, with $\rho = [0.02, 0.17]$ [veh/m]. As expected, the

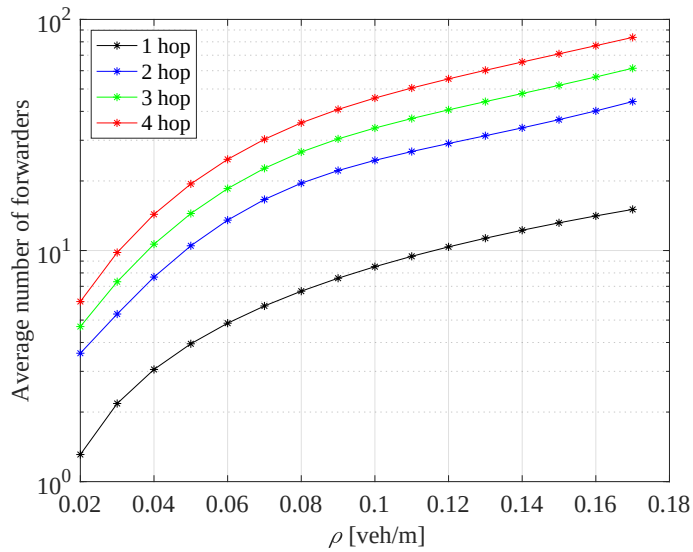


Figure 10: Average number of forwarders for different vehicular densities ρ and number of hops.

average number of forwarders increases with the number of transmissions, as well as with the vehicular density ρ.

Now, by considering the PDF of the social degree *i.e.*, $f_S(\cdot)$, is Pareto-distributed [45] with α as the exponent of the power law distribution and s_m as the minimum value of the social degree, we can compute the expected value of the social degree distribution as:

$$\begin{aligned} \mathbb{E}\{S\} &= \int_{s_m}^{s} s f_S(s)\, ds \\ &= \int_{s_m}^{s} s \frac{\alpha - 1}{s_m} \left(\frac{s}{s_m}\right)^{-\alpha} ds. \end{aligned} \tag{14}$$

Eq. (14) can be exploited in order to compute the expected value of the number of social forwarders in 1 hop transmission *i.e.*, SF_z, as

$$\mathbb{E}\{SF_z\} = \mathbb{E}\{N_z\} \cdot \mathbb{E}\{S\}, \tag{15}$$

with z [m] as the transmission range of first hop. In case of multi-hop propaga-

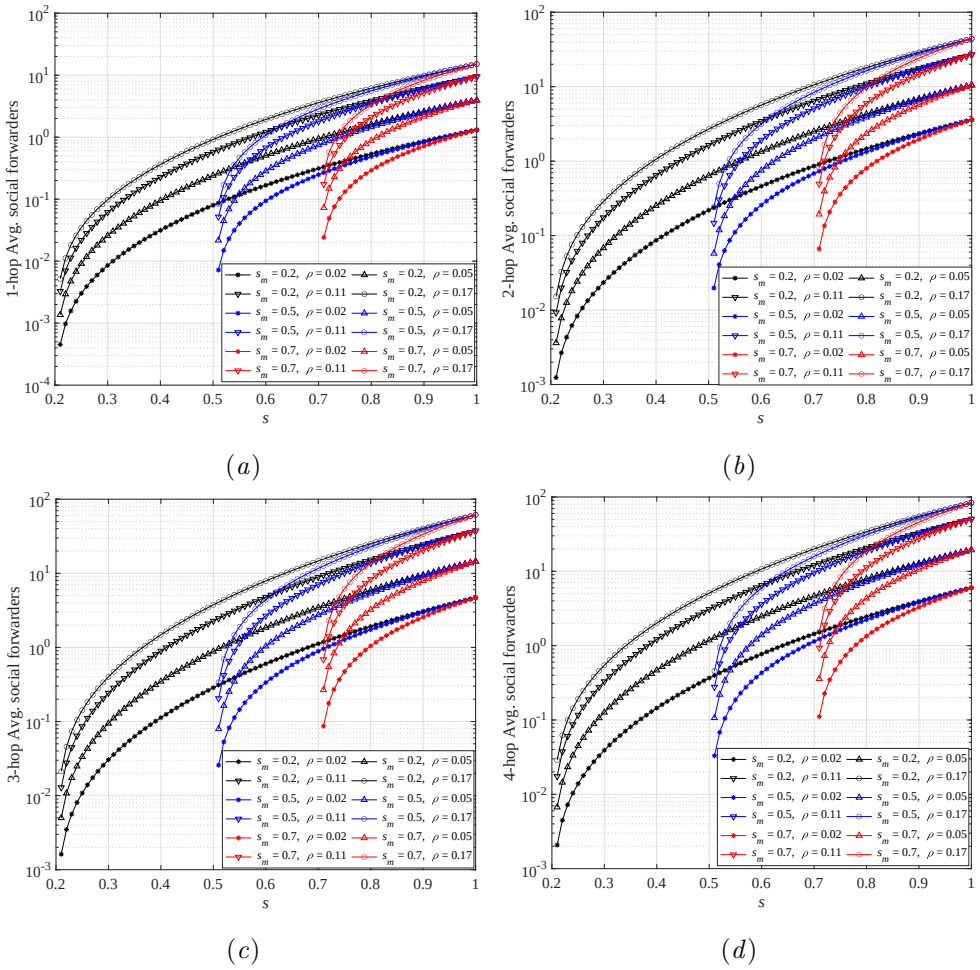


Figure 11: Average number of social forwarders vs the social degree, for different vehicular density ρ and minimum value of social degree s_m, in case of (a) 1 hop, (b) 2 hops, (c) 3 hops and (d) 4 hops. Here, we considered $\alpha = 2$.

tion, Eq. (15) becomes

$$\mathbb{E}\left\{SF_{z_i}\right\} = \mathbb{E}\left\{N_{z_i}\right\} \cdot \mathbb{E}\left\{S\right\}, \tag{16}$$

where z_i is defined in Eq. (13).

In Figure 11, the average number of potential social forwarders has been evaluated by considering the impact of (i) different vehicular densities ($i.e.$, ρ) and (ii) the minimum social degree ($i.e.$, s_m). We estimate the average number of potential social forwarders for different number of hops. Indeed, in order to the i-th node to be eligible as social forwarder within a transmission range, its corresponding social degree has to be higher than a given minimum social degree ($i.e.$, $s_i \geq s_m$). These figures give us important information on the average number of potential forwarders that we can find in subsequent hops, when we consider not only the purely physical conditions of the nodes, but also their social propensity to re-send data. As expected, the average number of potential forwarders increases with higher hops, since we consider "cumulative" forwarders. The interesting aspect of these curves is that even though the minimum social threshold value is different ($i.e.$, $s_m = [0.2, 0.5, 0.7]$), for the same density value, the curves converge towards the same value of forwarders for $s \to 1$. Finally, it is worth to highlight that MOVES, after detecting potential social forwarders within a transmission range, will select one of them based on a probabilistic comparison.

4. Simulation results

Performance of MOVES forwarding technique has been assessed via extended simulations, and also compared to other existing routing techniques. Two simulation scenarios have been considered $i.e.$, (i) San Francisco [46] and (ii) Rome taxies [47]. The first scenario is simulated by means of real taxi mobility traces from San Francisco, USA, where 533 taxis in the San Francisco Bay Area were monitored by recording their GPS positions over 30 days [46], moving along a grid topology. The second scenario was acquired by an extensive measurement campaign in the city of Rome (Italy), in which 370 taxi cabs working in

Table 1: Simulation parameters used in San Francisco [46] and Rome taxi [47] scenarios.

Parameter	**San Francisco**	**Rome taxi**
Number of nodes	533	370
Number of traces	11220492	449226
Complete trace duration [days]	30	30
Trace frequency monitoring [s]	10	7
Network range [m]	$[10, 50]$	$[10, 50]$
Bandwidth [MBps]	10	10
Buffer size [MB]	50	50
Message size [kB]	$[100, 1000]$	$[100, 1000]$

the center of Rome, characterized by high congestion streets and following a road topology, reported their positions at every 7 seconds for a period of six months [47]. Table 1 collects the main parameters assumed in the simulation results, which have been obtained in The One simulator [48].

In this experimentation, for both scenarios, we have simulated a group of different nodes forming a vehicular communication network. Specifically, we based our simulations on Active-DTN [49], *i.e.*, an Opportunistic Network solution that implements the Bundle Protocol and additionally extends it by allowing the messages being communicated to incorporate software and message state for forwarding, delivery, lifetime control and prioritization purposes. Then, we have adapted our enhanced version of The One simulator to include the proposed MOVES technique by implementing the social degree and the forwarding probability assignment function, as defined in Eq. (1) and Eq. (9), respectively.

We first aim to assess that the distribution of the node social degree in real vehicular trace scenarios shows a power-law trend. Figure 12 and 13 depict the percentage of social nodes in San Francisco and Rome taxi scenarios, respectively, computed for different values of r (*i.e.*, $r = \Delta T/T$, assuming values in

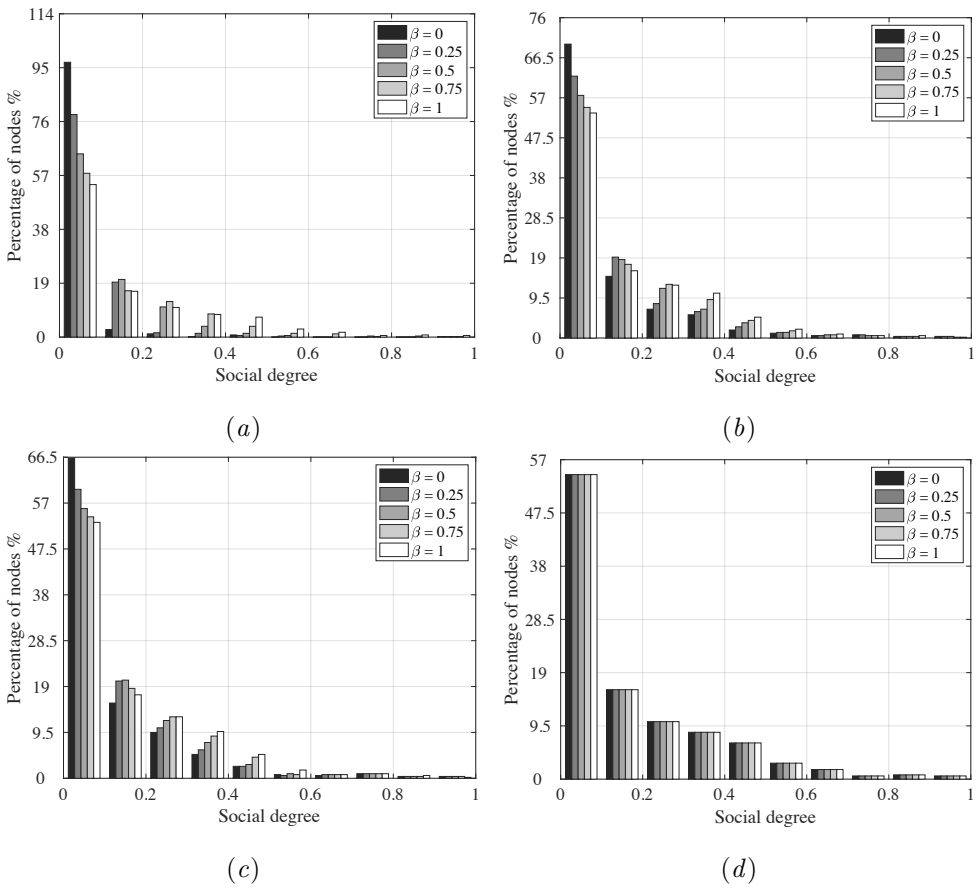


Figure 12: Percentage of nodes in San Francisco scenario, with a given social degree in the range $[0, 1]$, in case of (a) $r = \Delta T/T = 0.25$, (b) $r = 0.5$, (c) $r = 0.75$, and (d) $r = 1$.

the range $[0.25, 1]$), and parameter β (*i.e.*, $\beta = [0, 1]$). As expected, we notice that the social degree is Pareto-distributed, with a large percentage of nodes with a social degree lower than 0.2. The parameter β affects the social degree by opportunely weighting the message and connection coefficients, as expressed in Eq. (2) and (3), respectively. For low values of β (*i.e.*, $\beta < 0.5$), the frequency of nodes with the lowest social degree (*i.e.*, $s < 0.2$) is bigger when r is smaller or equal to 0.75. Also, for increasing r we can appreciate a decrease of the percentage of nodes with a given social degree. However, when r is equal to 1,

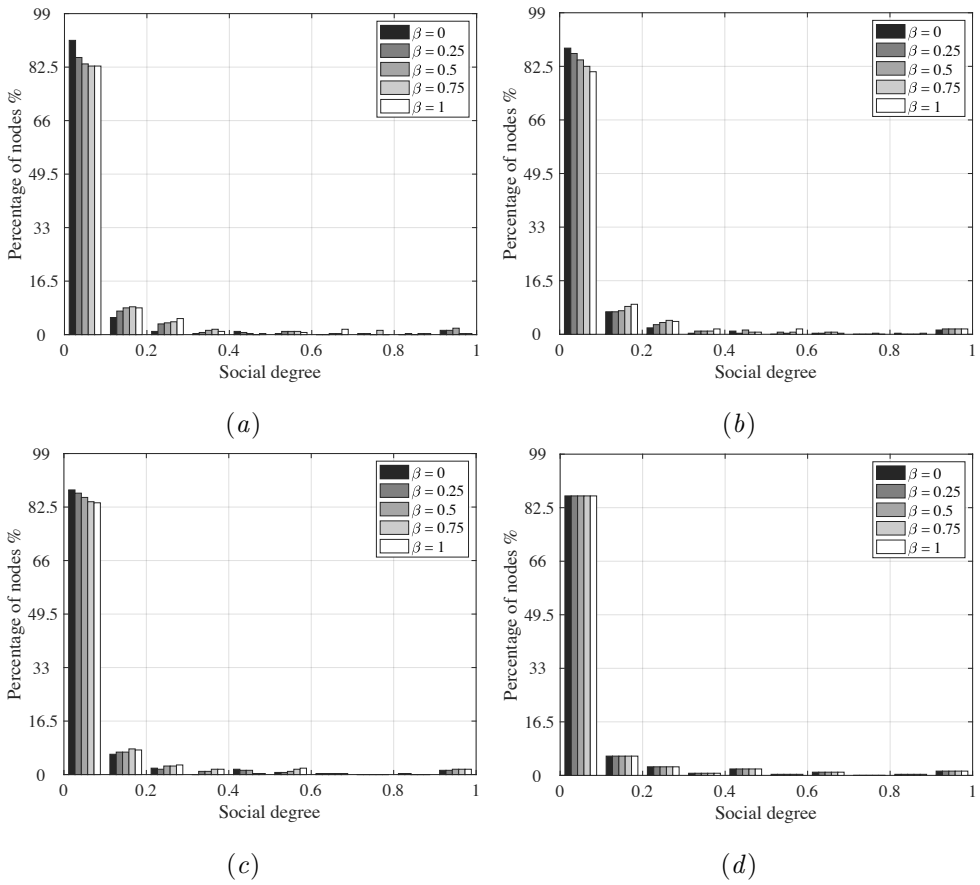


Figure 13: Percentage of nodes in Rome taxi scenario, with a given social degree in the range $[0, 1]$, in case of (a) $r = 0.25$, (b) $r = 0.5$, (c) $r = 0.75$, and (d) $r = 1$.

the social degree is equally distributed, no matter the value of β.

Next, we focus on the network performance of MOVES approach, as compared to three state-of-the-art approaches. Firstly, we compare MOVES with SCARF [19], that is the pillar approach from which MOVES derives. Secondly, we compare MOVES with Epidemic routing [50], where messages are always routed for every contacted node. Finally, we consider an optimal stopping-based approach [20], namely OS, that is a routing protocol where message custodian nodes are limited by carefully selecting their prospective forwarders in terms of

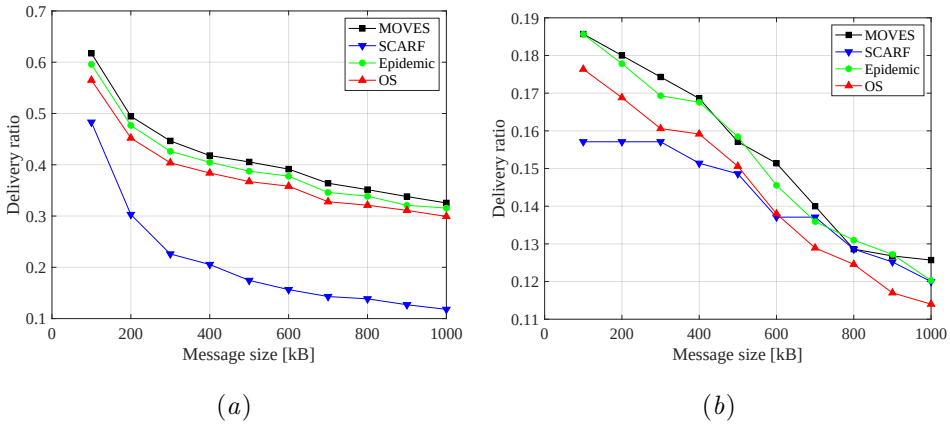
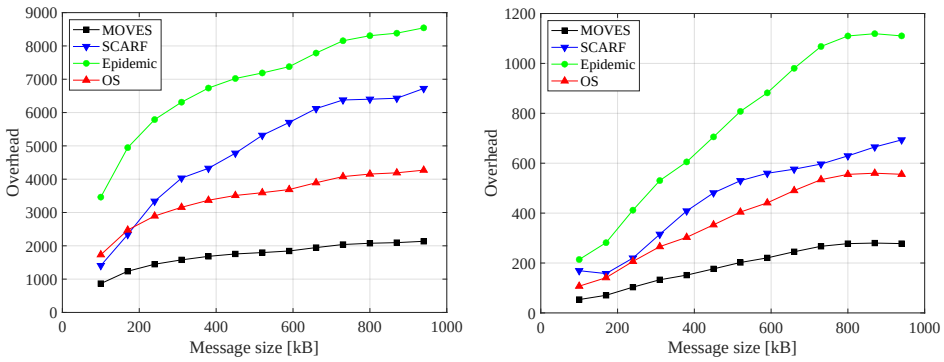


Figure 14: Comparison of MOVES delivery ratio w.r.t. Epidemic, OS and SCARF techniques, in (a) San Francisco and (b) Rome taxi scenario.

their reliability, network centrality and similarity. OS is based on the Optimal Stopping theory, which allows to select the best message storer, while holding back broad message dissemination until a relay node is met. Specifically, we will investigate (i) the packet delivery ratio, (ii) the overhead, (iii) the number of hops, and (iv) the latency time. As it will be clearer in the following, MOVES behaves better than these proposals, with a higher delivery ratio, lower overhead and latency, and similar number of hops.

Firstly, Figure 14 depicts the delivery ratio *i.e.*, $\mathcal{T}$, defined as the ratio of delivered messages to the number of created messages, for the four studied approaches in case of different scenarios, respectively. In both scenarios, we observe that MOVES shows higher delivery ratio, with a decreasing trend for increasing message sizes. In the best conditions (*i.e.*, a low message size), we get $\mathcal{T}_{MOVES} \approx 0.6$, while worst results are obtained for larger message sizes, although MOVES reaches always values higher than ≈ 0.35. We notice that MOVES shows values slightly higher than the Epidemic curve. As a matter, the high replication in Epidemic can flood buffer resources and can have an impact on the delivery ratio. On the other side, in the context of Rome taxi scenario, performance is worst for all four studied routing approaches, as depicted in



(a) (b)

Figure 15: Comparison of MOVES overhead w.r.t. Epidemic, OS and SCARF techniques in (a) San Francisco and (b) Rome taxi scenario.

Figure 14 (b). More in detail, we observe that MOVES cannot reach ≈ 0.2, as well as SCARF does not overcome ≈ 0.16. Interesting, SCARF slowly decreases for increasing message sizes, and outperforms OS for message size higher than 600 kB. This behavior is mainly due to the nature of the simulated scenario, where the percentage of nodes with a social degree higher than 0.2 is around 5%; on the other side, in San Francisco with a higher number of nodes the percentage of nodes with a social degree higher than 0.2 is around 10%, which is twice the value in Rome taxi scenario.

Figure 15 describes the overhead comparison *i.e.*, $\mathcal{O}$, in different scenarios. This is calculated by computing the ratio of the difference between the number of relayed messages *i.e.*, ℓ, and the number of delivered messages *i.e.*, $\mathcal{D}$, to the number of delivered ones, *i.e.*

$$\mathcal{O} = \frac{\ell - \mathcal{D}}{\mathcal{D}}, \tag{17}$$

with $\ell \geq \mathcal{D}$. We observe that MOVES always presents better performance than SCARF, Epidemic and optimal stopping-based approach, with a dynamic that increases slowly. Specifically, in Figure 15 (a) we have $\mathcal{O}_{MOVES} \approx [1000, 2000]$, while highest values are obtained with Epidemic ranging in $\approx [3200, 8500]$, with

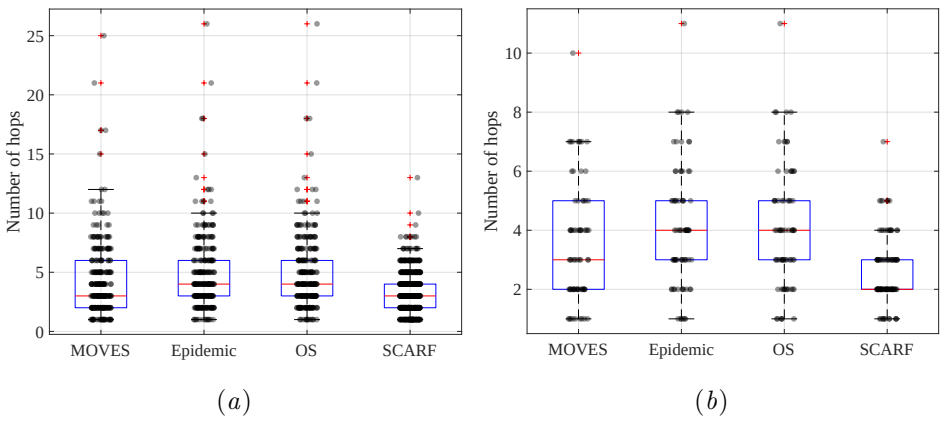


Figure 16: Comparison of MOVES number of hops w.r.t. Epidemic, OS and SCARF techniques in (a) San Francisco and (b) Rome taxi scenario.

message size of $\approx [100, 1000]$ kB, respectively. In case of small message size *i.e.*, 100 [kB], SCARF shows a value of overhead close to that of MOVES, but then we observe a fast increase of the overhead for increasing message size. Furthermore, in Figure 15 (b) the trends are similar to those in San Francisco scenario, but the values of overhead are lower of a ten multiplicative factor.

Figure 16 shows the average number of hops that the four approaches perform to disseminate messages in the whole network. This is calculated as the number of forwarders the messages are relayed to before arriving at destination. Due to the different features of San Francisco and Rome taxi scenarios, we observe a higher number of hops in the former scenario as compared to the latter. In case of San Francisco scenario depicted in Figure 16 (a), MOVES and SCARF exhibit similar results with a slightly increase experienced with Epidemic and OS. Similar considerations apply to the number of hops observed in Rome taxi scenario, as shown in Figure 16 (b).

Finally, in Figure 17, the latency time is analysed. This is calculated as the difference between the message delivery time and the message creation time. The plotbox depicts, for each message generated in the simulations, the average latency time and the interquartile range between a first quartile (*i.e.*, $Q1 = 25\%$)

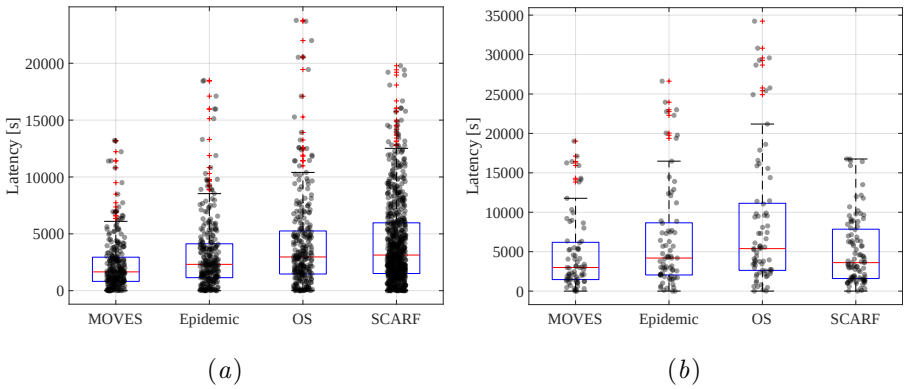


Figure 17: Comparison of MOVES latency time w.r.t. Epidemic, OS and SCARF techniques in (a) San Francisco and (b) Rome taxi scenario.

and the third quartile ($i.e.$, $Q3 = 75\%$). As it can be seen, our proposed MOVES technique performs better in terms of the latency time when comparing it to the other three techniques, for both two scenarios.

To summarize, we can conclude that MOVES shows better network performance as it achieves a higher delivery ratio, lower overhead and latency. This is due to the MOVES forwarding probability assignment function that relies on the selection of less social nodes as next-hop forwarders. This aspect does not represent a disadvantage of the proposed technique, but allows the enhancement of network performance, as compared to Epidemic, optimal stopping-based routing and SCARF approaches.

5. Conclusions

Social relations and ties in vehicular contexts have become very popular in the last few years and attracted the interest of the research community. It has been demonstrated that their integration in the forwarding mechanisms can highly impact on the performance of the network. This integration of social components in vehicular networks is certainly related to the enormous success of the online social networks, and new paradigms such as Vehicular Social Networks

have been introduced. VSNs are formed *on-the-fly* and normally social relations are considered ephemeral, but it has been also highlighted that specific patterns can emerge and would be important of considering them.

Based on this rationale, in this paper we have proposed a MemOry-based VEhicular Social (MOVES) forwarding approach. MOVES is based both on a time-varying social degree and physical parameters for the selection of the next-hop forwarder. The specific feature of MOVES resides into the evaluation of the social degree of a node in the past and in the present observations, by effectively exploiting the "social memory" of a node. In order to assess the behavior of MOVES, we have compared it to other existing related techniques *i.e.*, Epidemic, OS, and SCARF, by considering real vehicular data. The performance evaluation has been dealt in terms of delivery ratio, overhead, latency and computational cost, namely number of hops. We have observed that MOVES outperforms other approaches, in terms of delivery ratio, overhead and latency, by demonstrating the higher accuracy of the "social past" inclusion in the data forwarding. The computational cost is also comparable to that from SCARF, but MOVES exhibits higher performance. As next step for improving the effectiveness of the data forwarding, we aim to integrate a prediction algorithm in the MOVES mechanism, for taking into account the quality of a physical link.

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