



HAL
open science

MOVES: a MemOry-based VEhicular Social Forwarding Technique

Anna Maria Vegni, Carlos Borrego Iglesias, Valeria Loscri

► **To cite this version:**

Anna Maria Vegni, Carlos Borrego Iglesias, Valeria Loscri. MOVES: a MemOry-based VEhicular Social Forwarding Technique. *Computer Networks*, 2021, 197, 10.1016/j.comnet.2021.108324 . hal-03282823

HAL Id: hal-03282823

<https://hal.science/hal-03282823>

Submitted on 9 Jul 2021

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

MOVES: a MemOry-based VEhicular Social Forwarding Technique

Anna Maria Vegni^{a,*}, Carlos Borrego Iglesias^b, Valeria Loscri^c

^a*Department of Engineering, Roma Tre University, Italy*

^b*Department of Mathematics and Computer Science, University of Barcelona, Spain*

^c*INRIA Lille-Nord Europe, France*

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.

*Corresponding author

Email addresses: annamaria.vegni@uniroma3.it (Anna Maria Vegni),
carlos.borrego@ub.edu (Carlos Borrego Iglesias), valeria.loscri@inria.fr (Valeria Loscri)

Preprint submitted to Elsevier Computer Networks

July 9, 2021

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

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

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

17 This paper presents MOVES (MemOry-based VEhicular Social forwarding
18 technique) *i.e.*, a probability-based approach for next-hop forwarder selection
19 in VSNs, based on the concept of time-varying node social degree and physical
20 parameters as typical of Dedicated Short Range Communications (DSRC) tech-
21 nology. MOVES refers to a previous approach, namely SCARF (SoCial-Aware
22 Reliable Forwarding Technique for Vehicular Communications) [19, 12], which
23 considers a next-hop forwarder as the farthest and most social node within a
24 source node’s transmission range. SCARF takes decision on next-hop forwarder
25 at a given time instant, and the node social degree is computed hop-by-hop.
26 SCARF does not consider the node social behavior from past observations, but
27 it is limited to the present. Contrary, MOVES exploits information of social
28 degree that the i -th node has exhibited in the past, and mixes with the social
29 degree experienced by the i -th node in the present. As a result, the node social
30 degree estimation is expected to be more accurate, resulting in a more effective
31 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

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

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

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

22 **2. Related works**

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

We identify two main related topics for our approach MOVES *i.e.*, (*i*) how 1
the **social ties** are established and used, and (*ii*) the **dissemination mech-** 2
anisms. Content dissemination techniques consider how to distribute contents 3
to users or towards areas of interest. Different approaches are based on major 4
social features, such as centrality metrics [4]. One of the initial contributions on 5
the application of social relations in the vehicular context has been introduced 6
in [26], where the authors analyze the centrality metrics in vehicular ad hoc 7
networks. In particular, the authors motivate their research by considering the 8
social networks analysis (SNA) and the social structures that are formed, and 9
notice that there are similarities between sensors/vehicle networks and social 10
networks. In [27], social metrics and SNA are exploited in order to improve the 11
coverage of service channels (SCHs). It is investigated how the social metrics 12
can be applied to improve the performance of the channel occupation, while 13
SNA is considered for optimal deployment of RSUs (Road Side Units) and to 14
improve data communication mechanisms. The use of RSUs along the roads can 15
enhance the network performance through Vehicle-to-Infrastructure connectiv- 16
ity links, as presented by Bitaghsir *et al.* in [28], where the authors introduce a 17
content distribution technique based on the idea of caching content to RSUs. 18

The importance on how the social relations are defined and their impact on 19
the network performance, also in terms of radio coverage, have been addressed 20
in [29], where the authors highlight how the weak ties are of paramount im- 21
portance in order to maximize the probability of reaching more destinations. 22
In [30], Pianese *et al.* consider temporal, spatial and activity profiles in order to 23
characterize the social relations of the users. In [31], Gong *et al.* consider the 24
social contribution of the relay node, expressed as the amount of (*i*) forward- 25
ing services each node has done to another, and viceversa, and (*ii*) forwarding 26
services the node provides to other nodes within the community. Gai *et al.* [32] 27
characterize the social relations based on reputation of a node rated by others 28
during past transactions. A central server is considered to ensure the integrity 29
of the trust information. A Ratee-based Trust Management is built in order to 30
exploit the relationships between the nodes for increasing the trustworthiness 31

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

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

18 Content dissemination is extremely important for mobile and opportunistic
19 social networks. In [36], in the context of opportunistic social networks,
20 three different categories of dissemination techniques have been considered, *i.e.*,
21 (*i*) epidemic, (*ii*) probability-based, and (*iii*) interest community-based content
22 dissemination. This classification matches also very well into VSNs. Different
23 contributions belonging to the three different categories have been proposed
24 recently. **Epidemic approaches** have been considered in [37], where the Peo-
25 pleNet architecture relies on an already pre-existing infrastructure in order to
26 “epidemicly” send data in a mobile social network context. A hybrid approach,
27 namely EpSoc, utilizes the Epidemic routing forwarding strategy together with
28 social features, such as degree centrality [38]. In [39], Lee *et al.* propose a kind
29 of virtual flea market based on users’ interests, namely FleaNet, where the cus-
30 tomers can express their requests and send their queries, as well as their offers,
31 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,

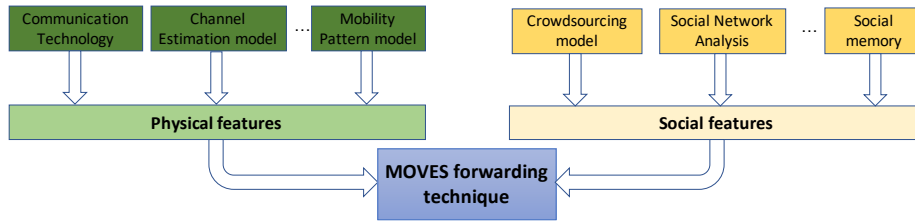


Figure 1: Main factors affecting MOVES forwarding technique.

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

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

18 How sociality affects the message retransmission has been already addressed
19 in previous works, but how to define the sociality degree of a node is a tricky
20 issue that can be solved in several manners. In this paper, we consider the
21 node sociality as the skill of a node of *(i)* connecting and *(ii)* communicating to
22 neighboring nodes (*i.e.*, one-hop nodes). A node with a high node degree that
23 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:

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

where $\mathcal{M}_i(t)$ and $\mathcal{C}_i(t)$ are the time-dependent message and connection coef-
ficients 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 num-
ber 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

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

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

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

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

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

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

18 where $\bar{\mathcal{C}}_i$ and $\bar{\mathcal{C}}_{i,h}$ represent the average number of connections that the i -node
 19 has established with its neighboring nodes, respectively (*i*) in a given time
 20 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 $[0, 1]$. 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. 2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20

Leveraging on previous considerations, the definition of social degree in Eq. (1) can be rewritten as 21
22

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

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 $\bar{\mathcal{C}}_{i,h}$. 23
24
25
26
27

After introducing the social degree concept, we investigate how to consider this factor for data dissemination purpose in VSNs. Usually, message transmis- 28
29

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

14 Let us consider a VSN community as comprised of a given number N of
 15 nodes. All the nodes are assumed to be forming a cluster of nodes, so that none
 16 of the N nodes has a null node degree *i.e.*, $\delta_i \neq 0$ with $i = \{1, 2, \dots, N\}$. Figure 2
 17 depicts a schematic of node degree in a vehicular network. Different clusters (*red*
 18 *rectangles*) are formed and comprised of nodes with non-null degrees *e.g.*, $\delta_1 = 3$,
 19 $\delta_2 = 2$, $\delta_3 = 3$, and $\delta_4 = 2$. Isolated nodes have a null degree and do not belong
 20 to any cluster *e.g.*, $\delta_5 = 0$. Similar considerations apply for the other cluster
 21 with node degrees $\delta_{6,7,8}$ respectively equal to 1, 2 and 1.

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

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

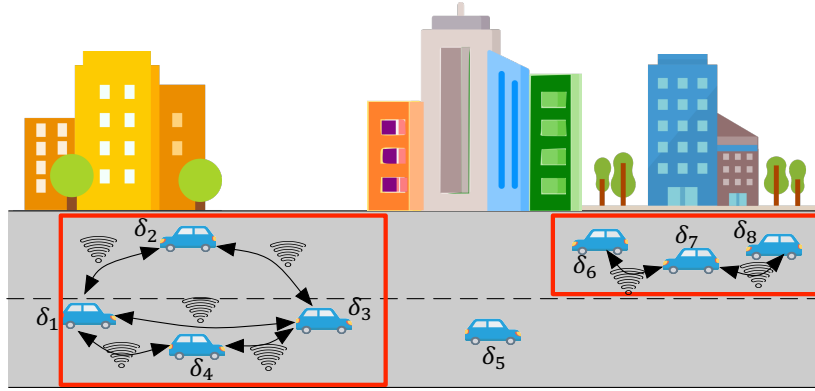


Figure 2: Schematic of node degree in a cluster (*red rectangles*), where nodes are in V2V communication and none of them has a null degree *i.e.*, $\delta_i \neq 0$, with $i = \{1, 2, 3, 4\}$. An isolated node is out of a cluster and has a null degree *e.g.*, $\delta_5 = 0$. Similar considerations apply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

the probability that there is no vehicle in the interval of length $(z - d_i)$ [m] able 1
to re-forward, and (*ii*) the probability that there is no neighboring vehicle with 2
a social degree higher than that of the i -th vehicle. The forwarding probability 3
associated to the i -th node depends on two events that are independent from 4
each other. The first event is represented by the probability that there is no 5
other vehicle in the interval of length $(z - d_i)$ [m], and can be expressed as 6

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

where $F_X(z - d_i)$ is the CDF of X_i , with $x = z - d_i$. On the other side, the 7
probability that there is no neighboring vehicle with a social degree S higher 8
than that of the i -th vehicle is 9

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

where the term on the right side represents the complementary cumulative distri- 10
bution function in case of Pareto distribution [43], which is a viable assumption 11
for the social degree distribution in vehicular scenarios [12]. 12

We can observe that Eq. (5) represents SCARF forwarding probability assign- 13
ment function in case of maximum value of social degree *i.e.*, $s_i = 1$, and 14

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

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

2 while $p_{2,i}$ in Eq. (6) represents the complementary CDF of a Pareto random
 3 variable with parameters α as the exponent of the power-law distribution *i.e.*,
 4 $\alpha = [2, 3]$ for small-world networks, and s_m is the minimum value of the social
 5 degree s_i , *i.e.*, [43]

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

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

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

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

23 Figure 3 depicts the dependance of MOVES forwarding probability assign-
 24 ment function by both the distance from a Tx vehicle and the social degree

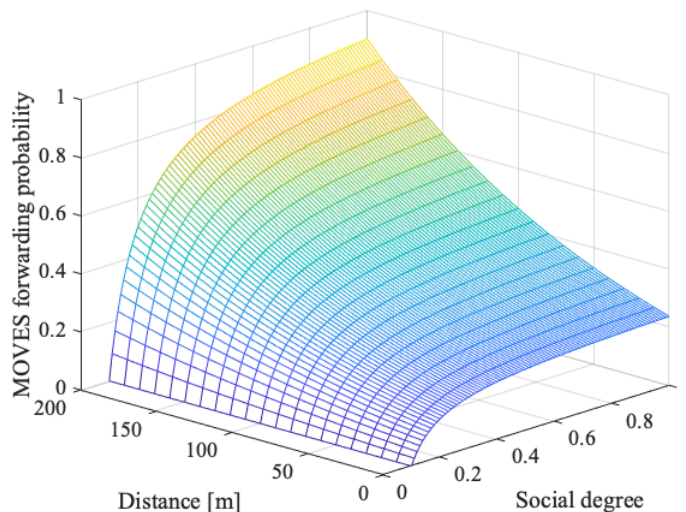


Figure 3: MOVES forwarding probability of the i -th vehicle at distance d_i [m] (*i.e.*, $d_i \leq z$ [m]) and social degree s_i (*i.e.*, $s_m \leq s \leq 1$, with $s_m = 0.1$). In particular, we assumed $z = 200$ [m], $\rho = 0.02$ [veh/m], $c = 3$, and $\alpha = 2$.

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 $s_i \rightarrow 1$ and $d_i \rightarrow z$ [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)

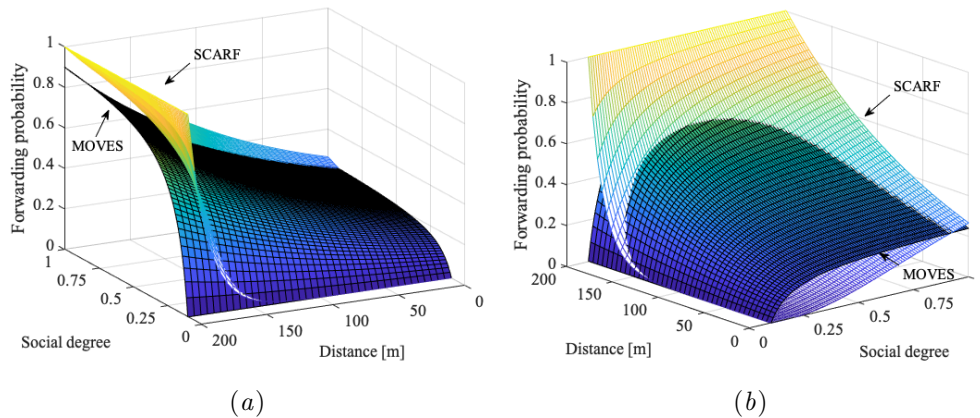


Figure 4: Comparison of MOVES and SCARF forwarding probabilities versus the distance and the social degree. (a) MOVES shows lower probability than SCARF for high social degree and high distance, while (b) SCARF probability is lower when the social degree and the distance are lower.

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

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

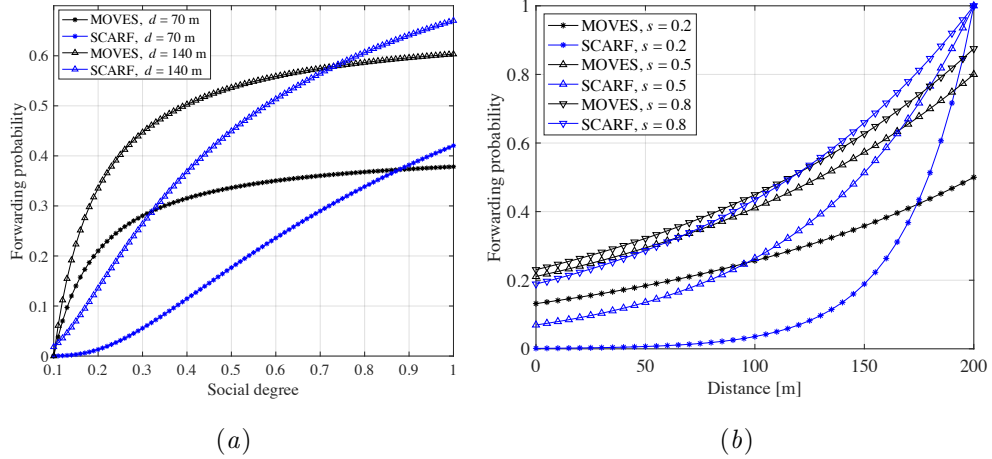


Figure 5: Comparison of MOVES and SCARF forwarding probabilities (a) for different values of distance d_i [m] (*i.e.*, $d_i \leq z$ [m]), versus the social degree, and (b) for different values of social degree s_i , versus the distance. We assumed $z = 200$ [m], $\rho = 0.02$ [veh/m], $c = 3$, $s_m = 0.1$ 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 $s_i \rightarrow 1$ and $d_i \rightarrow z$, 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

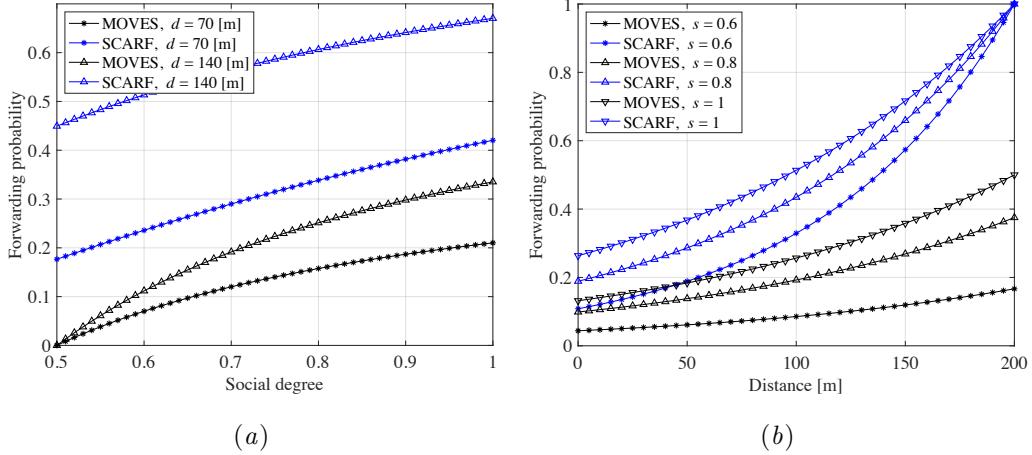


Figure 6: Comparison of MOVES and SCARF forwarding probability in case of $s_m = 0.5$, versus (a) social degree, and (b) distance. We assumed $z = 200$ [m], $\rho = 0.02$ [veh/m], $c = 3$, and $\alpha = 2$.

1 0.253).

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

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

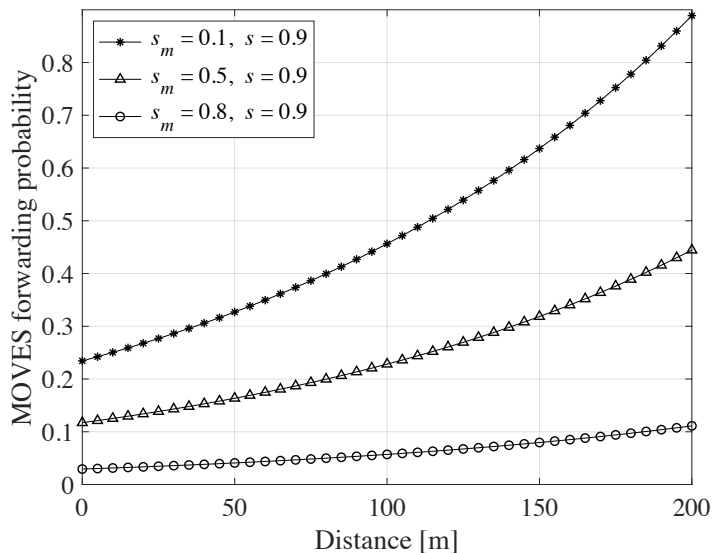


Figure 7: Dependence of MOVES forwarding probability on the minimum social degree parameter s_m .

at the beginning, followed by a slower trend for increasing distances. Finally, 1
while SCARF presents different curves for different values of social degree, for 2
increasing social degree MOVES shows very close probability values. 3

In all previous results, MOVES has been evaluated for $s_m = 0.1$. However, 4
it is observed from Eq. (9) that MOVES forwarding probability strictly depends 5
on the minimum value of social degree *i.e.*, s_m , as for $s_i < s_m$ the probability is 6
null. In Figure 6 we depict MOVES trend in case of $s_m = 0.5$, as compared to 7
SCARF. Notice that MOVES provides a forwarding probability only if $s_i \geq s_m$. 8
This aspect represents a quality requirement since only those nodes exhibiting 9
a social degree higher than a given threshold are eligible as potential next-hop 10
forwarders. The minimum social degree value that a vehicle should exhibit lim- 11
its the selection of potential forwarders *i.e.*, the higher (*lower*) the minimum 12
social degree the lower (*higher*) the MOVES forwarding probability (see Fig- 13
ure 7). This allows the use of MOVES in applications needing higher quality 14
requirements (*i.e.*, comfort and interactive entertainment), while SCARF does 15

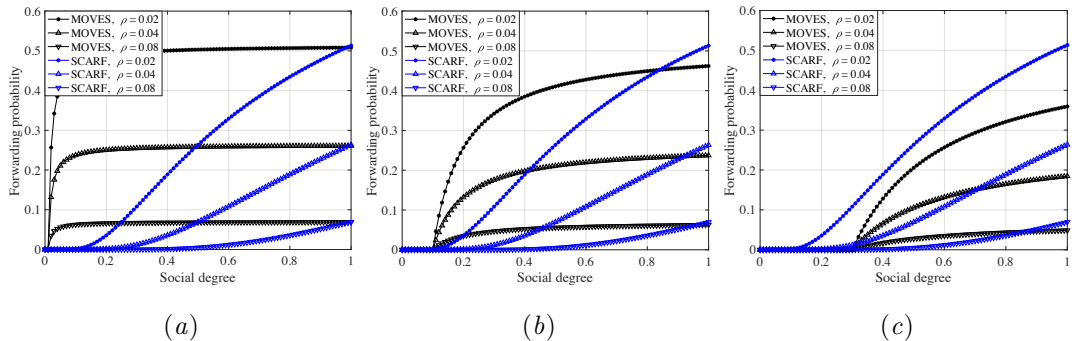


Figure 8: MOVES forwarding probability versus the social degree, for different values of vehicular density ρ , in case of (a) $s_m = 0.01$, (b) $s_m = 0.1$ and (c) $s_m = 0.3$.

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

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

13 3.1. Average Number of Forwarders

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

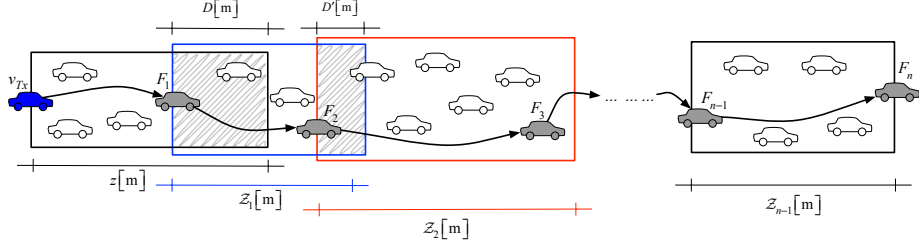


Figure 9: Schematic model of the propagation range in case of multi-hop scenario. A source vehicle (*blue vehicle*) will select the next-hop forwarder F_1 (*gray vehicle*) within its transmission range z [m]. Notice that the transmission ranges are randomly distributed in the range $[z/2, 3z/2]$ [m].

next-hop forwarder, according to Eq. (9). 1

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: 2
3
4
5

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

and then it follows that the expected value of N_z can be written as 6

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

where $\Gamma(n)$ is the Gamma function defined as 7

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

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 8
9
10
11
12

Algorithm 1 MOVES forwarding technique forwarding

```
1: INITIALIZATION:
2:  $v_{Tx}$  aims to transmit a message within its transmission range
3: if  $i = 1$  then                                     ▷ This is the first hop
4:    $z_i = z$  [m]
5: else                                               ▷ Multi-hop message propagation
6:    $z_i$  as in Eq. (13)
7: end if
8:  $v_{Tx}$  has information about its neighbors i.e.,  $\mathcal{N} = \{n_1, n_2, \dots, n_N\}$ 
9: procedure MOVES( $n_\ell$ )                               ▷ MOVES assignment function to  $n_\ell \in \mathcal{N}$ 
10:  for  $\ell \leq N$  do
11:    while  $(v_{Tx}, n_\ell) \neq 0$  do                 ▷ Node  $v_{Tx}$  and  $n_\ell$  are in connectivity
12:      Computation of Euclidean distance  $d_{n_\ell}$  from  $v_{Tx}$ 
13:      Gathering of social feature  $s_{n_\ell}$ 
14:      Computation of Eq. (9)
15:      if  $p_{f, n_\ell}^{MOVES} = \max_{\mathcal{N}} p_{f, \mathcal{N}}^{MOVES}$  then
16:         $n_\ell \leftarrow F_i$ 
17:         $v_{Tx}$  sends the message to  $F_i$ 
18:      end if
19:       $(\ell + 1) \leftarrow \ell$ 
20:    end while
21:  end for
22: 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 $\mathcal{N} = \{n_1, n_2, \dots, n_N\}$, 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:

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

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

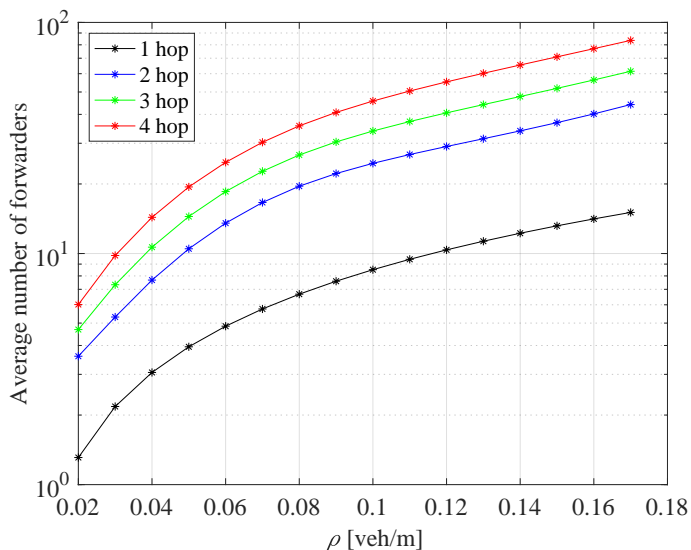


Figure 10: Average number of forwarders for different vehicular densities ρ and number of hops.

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

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

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

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

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

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

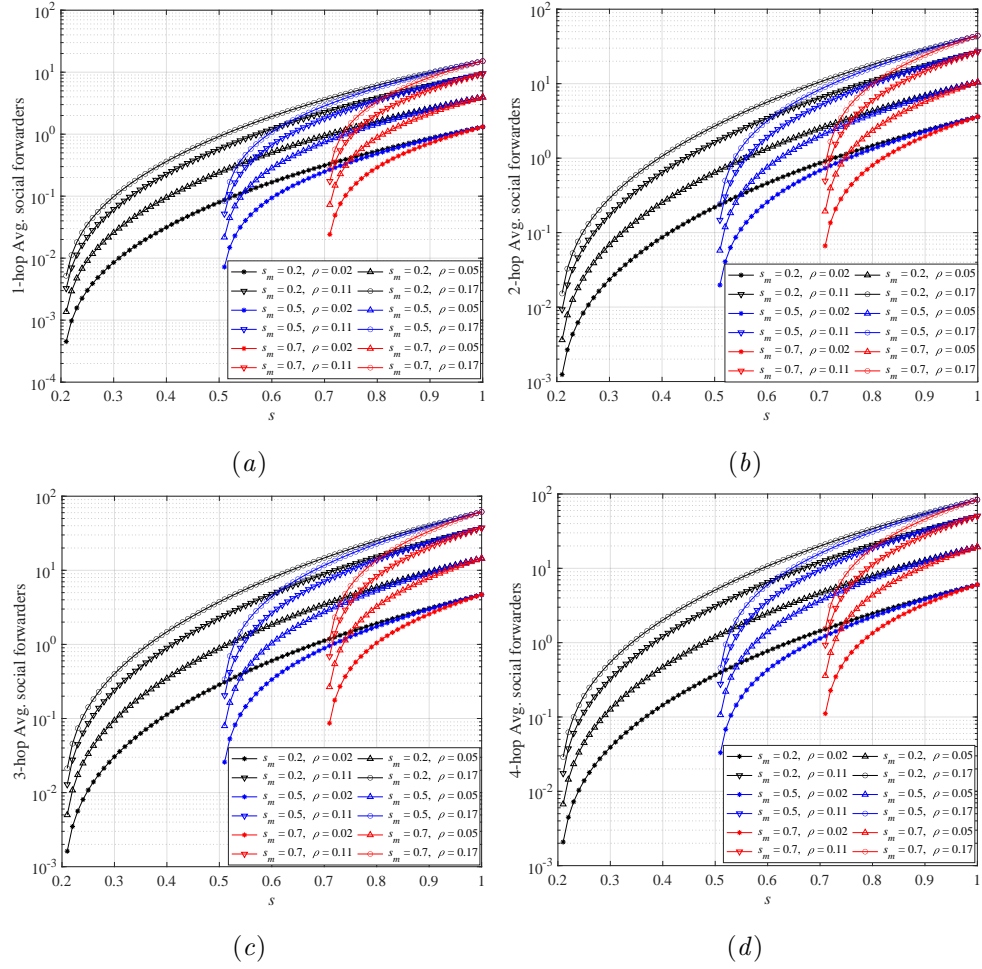


Figure 11: Average number of social forwarders vs the social degree, for different vehicular density ρ and minimum value of social degree s_m , in case of (a) 1 hop, (b) 2 hops, (c) 3 hops and (d) 4 hops. Here, we considered $\alpha = 2$.

1 tion, Eq. (15) becomes

$$\mathbb{E}\{SF_{z_i}\} = \mathbb{E}\{N_{z_i}\} \cdot \mathbb{E}\{S\}, \quad (16)$$

2 where z_i is defined in Eq. (13).

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

20 4. Simulation results

21 Performance of MOVES forwarding technique has been assessed via extended
22 simulations, and also compared to other existing routing techniques. Two simu-
23 lation scenarios have been considered *i.e.*, (i) San Francisco [46] and (ii) Rome
24 taxies [47]. The first scenario is simulated by means of real taxi mobility traces
25 from San Francisco, USA, where 533 taxis in the San Francisco Bay Area were
26 monitored by recording their GPS positions over 30 days [46], moving along
27 a grid topology. The second scenario was acquired by an extensive measure-
28 ment 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

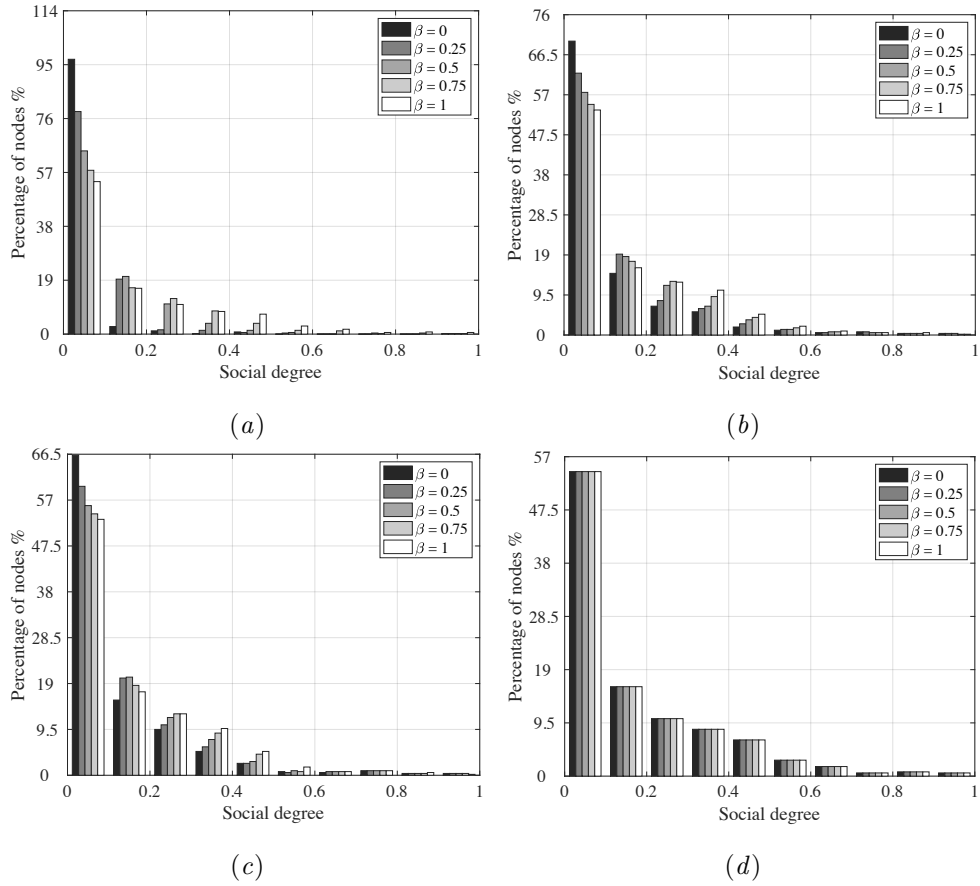


Figure 12: Percentage of nodes in San Francisco scenario, with a given social degree in the range $[0, 1]$, in case of (a) $r = \Delta T/T = 0.25$, (b) $r = 0.5$, (c) $r = 0.75$, and (d) $r = 1$.

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

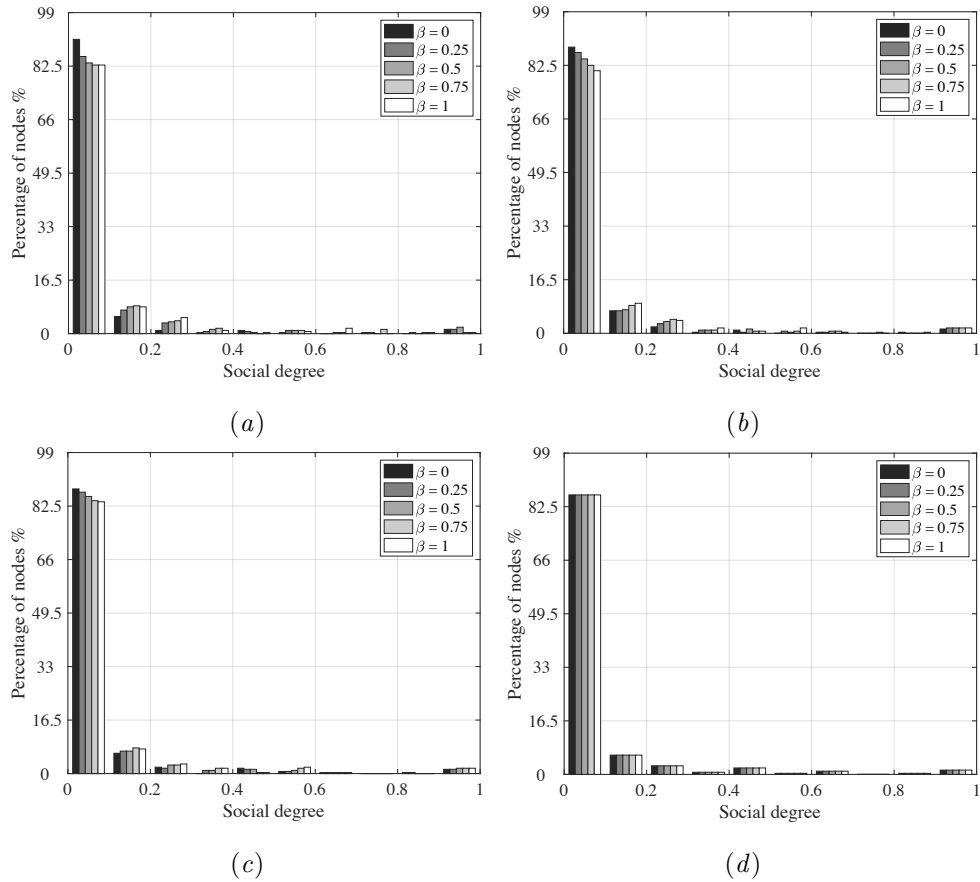


Figure 13: Percentage of nodes in Rome taxi scenario, with a given social degree in the range $[0, 1]$, in case of (a) $r = 0.25$, (b) $r = 0.5$, (c) $r = 0.75$, and (d) $r = 1$.

the social degree is equally distributed, no matter the value of β . 1

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 2
3
4
5
6
7
8

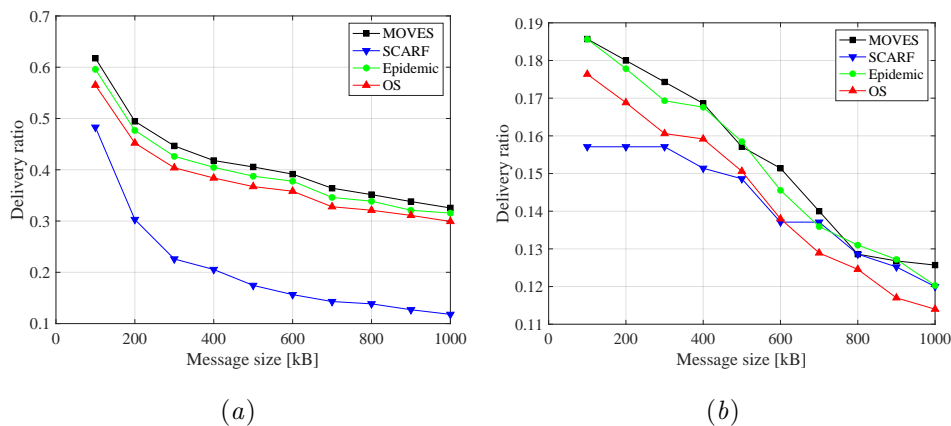


Figure 14: Comparison of MOVES delivery ratio w.r.t. Epidemic, OS and SCARF techniques, in (a) San Francisco and (b) Rome taxi scenario.

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

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

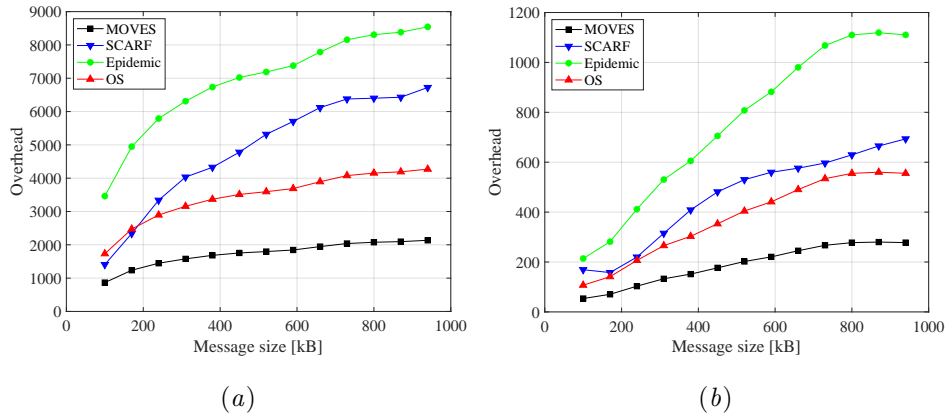


Figure 15: Comparison of MOVES overhead w.r.t. Epidemic, OS and SCARF techniques in (a) San Francisco and (b) Rome taxi scenario.

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.*

$$\mathcal{O} = \frac{\ell - \mathcal{D}}{\mathcal{D}}, \quad (17)$$

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

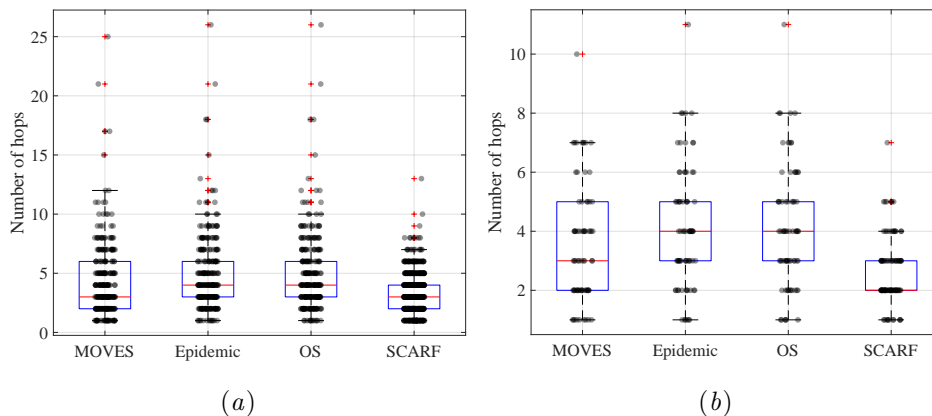


Figure 16: Comparison of MOVES number of hops w.r.t. Epidemic, OS and SCARF techniques in (a) San Francisco and (b) Rome taxi scenario.

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

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

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

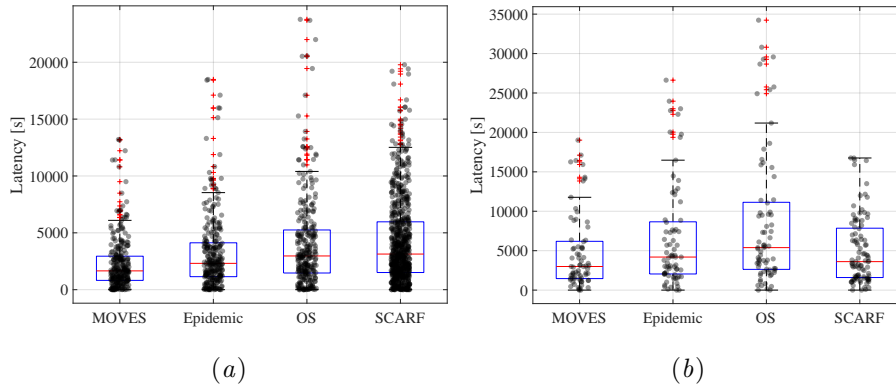


Figure 17: Comparison of MOVES latency time w.r.t. Epidemic, OS and SCARF techniques in (a) San Francisco and (b) Rome taxi scenario.

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

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

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

20 **References**

- 21 [1] V. Arnaboldi, A. Guazzini, A. Passarella, Egocentric Online So-
22 cial Networks: Analysis of Key Features and Prediction of Tie
23 Strength in Facebook, *Computer Communications* 36 (03 2013).
24 doi:10.1016/j.comcom.2013.03.003.
- 25 [2] A. M. Vegni, V. Loscrí, A Survey on Vehicular Social Networks, *IEEE*
26 *Comm. Surveys & Tutorials* 17 (4) (2015) 2397–2419.
- 27 [3] K. M. Alam, M. Saini, A. E. Saddik, Toward Social Internet of Vehicles:
28 Concept, Architecture, and Applications, *IEEE Access* 3 (2015) 343–357.
29 doi:10.1109/ACCESS.2015.2416657.

- [4] B. Zhang, R. Tian, C. Li, Content dissemination and routing for vehicular social networks: A networking perspective, *IEEE Wireless Communications* 27 (2) (2020) 118–126. doi:10.1109/MWC.001.1900225.
- [5] J. Niu, J. Fan, L. Wang, M. Stojinovic, K-hop Centrality Metric for Identifying Influential Spreaders in Dynamic Large-scale Social Networks, in: 2014 IEEE Global Communications Conference, 2014, pp. 2954–2959. doi:10.1109/GLOCOM.2014.7037257.
- [6] Y. Igarashi, T. Miyazaki, A DTN routing algorithm adopting the “Community” and “Centrality” parameters used in social networks, in: 2018 International Conference on Information Networking (ICOIN), 2018, pp. 211–216. doi:10.1109/ICOIN.2018.8343112.
- [7] H. Li, Centrality Analysis of Online Social Network Big Data, in: 2018 IEEE 3rd International Conference on Big Data Analysis (ICBDA), 2018, pp. 38–42. doi:10.1109/ICBDA.2018.8367648.
- [8] B. Zhang, R. Tian, C. Li, Content Dissemination and Routing for Vehicular Social Networks: A Networking Perspective, *IEEE Wireless Communications* (2019) 1–9doi:10.1109/MWC.001.1900225.
- [9] H. Zhou, M. Ruan, C. Zhu, V. C. M. Leung, S. Xu, C. Huang, A Time-Ordered Aggregation Model-Based Centrality Metric for Mobile Social Networks, *IEEE Access* 6 (2018) 25588–25599. doi:10.1109/ACCESS.2018.2831247.
- [10] A. Chakraborty, V. B. S., B. S. Manoj, Analytical Identification of Anchor Nodes in a Small-World Network, *IEEE Communications Letters* 20 (6) (2016) 1215–1218. doi:10.1109/LCOMM.2016.2554117.
- [11] Y. Guo, Z. Liu, Y. Zeng, R. Wang, J. Ma, Preserving Privacy for Hubs and Links in Social Networks, in: 2018 International Conference on Networking and Network Applications (NaNA), 2018, pp. 263–269. doi:10.1109/NANA.2018.8648740.

- 1 [12] A. M. Vegni, C. Souza, V. Loscrí, E. Hernández-Orallo, P. Manzoni, Data
2 Transmissions Using Hub Nodes in Vehicular Social Networks, *IEEE Trans-*
3 *actions on Mobile Computing* 19 (7) (2020) 1570–1585.
- 4 [13] V. Raghavan, G. Ver Steeg, A. Galstyan, A. G. Tartakovsky, Mod-
5 eling Temporal Activity Patterns in Dynamic Social Networks, *IEEE*
6 *Transactions on Computational Social Systems* 1 (1) (2014) 89–107.
7 doi:10.1109/TCSS.2014.2307453.
- 8 [14] S. Zeng, J. Zhang, Analyse Social Influence on Student Motivation based
9 on Social Activity Network, in: 2016 IEEE International Conference on
10 Service Operations and Logistics, and Informatics (SOLI), 2016, pp. 133–
11 138. doi:10.1109/SOLI.2016.7551675.
- 12 [15] Z. Li, C. Wang, S. Yang, C. Jiang, X. Li, LASS: Local-Activity and
13 Social-Similarity Based Data Forwarding in Mobile Social Networks, *IEEE*
14 *Transactions on Parallel and Distributed Systems* 26 (1) (2015) 174–184.
15 doi:10.1109/TPDS.2014.2308200.
- 16 [16] G. Wang, L. Zhang, Z. Yang, X. Li, Socialite: Social Activity Min-
17 ing and Friend Auto-labeling, in: 2018 IEEE 37th International Perform-
18 ance Computing and Communications Conference (IPCCC), 2018, pp.
19 1–8. doi:10.1109/IPCCC.2018.8710834.
- 20 [17] A. Peleshchyshyn, V. Vus, O. Markovets, S. Albota, Identifying Specific
21 Roles of Users of Social Networks and Their Influence Methods, in: 2018
22 IEEE 13th International Scientific and Technical Conference on Computer
23 Sciences and Information Technologies (CSIT), Vol. 2, 2018, pp. 39–42.
24 doi:10.1109/STC-CSIT.2018.8526635.
- 25 [18] A. Aylani, N. Goyal, Community detection in Social Network based on
26 Users Social Activities, in: 2017 International Conference on I-SMAC (IoT
27 in Social, Mobile, Analytics and Cloud) (I-SMAC), 2017, pp. 625–628.
28 doi:10.1109/I-SMAC.2017.8058254.

- [19] A. M. Vegni, V. Loscrí, R. Petrolo, SCARF: A SoCial-Aware Reliable Forwarding Technique for Vehicular Communications, in: Proceedings of the 3rd Workshop on Experiences with the Design and Implementation of Smart Objects, SMARTOBJECTS '17, ACM, Snowbird, Utah, USA, 2017, pp. 1–6. doi:10.1145/3127502.3127512.
URL <http://doi.acm.org/10.1145/3127502.3127512>
- [20] C. Borrego and J. Borrell and S. Robles, Efficient broadcast in opportunistic networks using optimal stopping theory, *Ad Hoc Networks* 88 (2019) 5–17.
- [21] N. Jabeur, S. Zeadally, B. Sayed, Mobile Social Networking Applications, *ACM Communications* 56 (3) (2013) 71–79.
- [22] X. Liang, R. Lu, X. Lin, X. Shen, Security and Privacy in Mobile Social Networks, Springer, 2013.
- [23] N. Montavont, S. Hachana, L. Loiseau, Opportunistic Social Network Experiments, in: 2009 International Conference on Advanced Information Networking and Applications Workshops, 2009, pp. 850–855. doi:10.1109/WAINA.2009.134.
- [24] A. Socievole, F. D. Rango, A. Caputo, Opportunistic Mobile Social Networks: From Mobility and Facebook friendships to structural analysis of user social behavior, *Elsevier Computer Communications* 87 (2016) 1 – 18. doi:<https://doi.org/10.1016/j.comcom.2016.04.025>.
URL <http://www.sciencedirect.com/science/article/pii/S0140366416301803>
- [25] L. Tang, Z. Duan, Y. Zhu, Data Dissemination in Service Discovery for Vehicular ad hoc Networks: a Survey, *IET Intelligent Transport Systems* 12 (10) (2018) 1189–1200.
- [26] A. Papadimitriou, D. Katsaros, Y. Manolopoulos, Social Network Analysis and its Applications in Wireless Sensor and Vehicular Networks, in: International Conference on e-Democracy, Springer, 2009, pp. 411–420.

- 1 [27] M. S. Frigau, Social-based forwarding in multi-channel vehicular networks,
2 in: 2015 IEEE Symposium on Computers and Communication (ISCC),
3 2015, pp. 166–173. doi:10.1109/ISCC.2015.7405511.
- 4 [28] S. A. Bitaghsir and S. Kashipazha and A. Dadlani and A. Khonsari, Social-
5 aware Mobile Road Side Unit for Content Distribution in Vehicular Social
6 Networks, in: 2019 IEEE Symposium on Computers and Communications
7 (ISCC), 2019, pp. 1–6. doi:10.1109/ISCC47284.2019.8969669.
- 8 [29] E. Pagani, L. Valerio, G. P. Rossi, Weak Social Ties improve Con-
9 tent Delivery in Behavior-aware Opportunistic Networks, Ad Hoc
10 Networks 25 (2015) 314 – 329, new Research Challenges in Mo-
11 bile, Opportunistic and Delay-Tolerant Networks Energy-Aware
12 Data Centers: Architecture, Infrastructure, and Communication.
13 doi:<https://doi.org/10.1016/j.adhoc.2014.07.005>.
14 URL [http://www.sciencedirect.com/science/article/pii/
15 S157087051400136X](http://www.sciencedirect.com/science/article/pii/S157087051400136X)
- 16 [30] F. Pianese, X. An, F. Kawsar, H. Ishizuka, Discovering and Predicting user
17 Routines by Differential Analysis of Social Network Traces, 2013 IEEE 14th
18 International Symposium on A World of Wireless, Mobile and Multimedia
19 Networks (WoWMoM) (2013) 1–9.
- 20 [31] H. Gong, L. Yu, X. Zhang, Social Contribution-Based Routing Protocol for
21 Vehicular Network with Selfish Nodes, International Journal of Distributed
22 Sensor Networks 10 (4) (2014) 753024. doi:10.1155/2014/753024.
- 23 [32] F. Gai, J. Zhang, P. Zhu, X. Jiang, Trust on the Ratee: A Trust Manage-
24 ment System for Social Internet of Vehicles, Wireless Communications and
25 Mobile Computing 2017 (2017).
- 26 [33] N. Basta, A. ElNahas, H. P. Grossmann, S. Abdennadher, A framework for
27 social tie strength inference in vehicular social networks, in: 2019 Wireless
28 Days (WD), 2019, pp. 1–8. doi:10.1109/WD.2019.8734218.

- [34] L. Yao and Y. Wang and X. Wang and G. WU, Cooperative Caching in Vehicular Content Centric Network Based on Social Attributes and Mobility, *IEEE Transactions on Mobile Computing* 20 (2) (2021) 391–402. doi:10.1109/TMC.2019.2944829.
- [35] N. Ullah and X. Kong and L. Lin and M. Alrashoud and A. Tolba and F. Xia, Real-time dissemination of emergency warning messages in 5G enabled selfish vehicular social networks, *Computer Networks* 182 (2020) 107482.
- [36] Z. Li, J. Bi, C. Borrego, Exploiting Temporal and Spatial Regularities for Content Dissemination in Opportunistic Social Network, *Hindawi, Wireless Communications and Mobile Computing* 2019 (2019) 1 – 16.
- [37] M. Motani, V. Srinivasan, P. S. Nuggehalli, PeopleNet: Engineering a Wireless Virtual Social Network, in: *Proceedings of the 11th Annual International Conference on Mobile Computing and Networking, MobiCom '05*, Association for Computing Machinery, New York, NY, USA, 2005, p. 243–257. doi:10.1145/1080829.1080855.
URL <https://doi.org/10.1145/1080829.1080855>
- [38] H. Lenando and M. Alrfaay , EpSoc: Social-Based Epidemic-Based Routing Protocol in Opportunistic Mobile Social Network, *Hindawi Mobile Information Systems* 2018 (2018). doi:10.1155/2018/6462826.
- [39] U. Lee, J. Lee, J. Park, M. Gerla, FleaNet: A Virtual Market Place on Vehicular Networks, *IEEE Transactions on Vehicular Technology* 59 (1) (2010) 344–355. doi:10.1109/TVT.2009.2030892.
- [40] R. Tomar, H. G. Sastry, M. Prateek, A Novel Protocol for Information Dissemination in Vehicular Networks, in: C.-H. Hsu, S. Kallel, K.-C. Lan, Z. Zheng (Eds.), *Internet of Vehicles. Technologies and Services Toward Smart Cities*, Springer International Publishing, Cham, 2020, pp. 1–14.
- [41] Z. Zhou, C. Gao, C. Xu, Y. Zhang, S. Mumtaz, J. Rodriguez, Social Big-

- 1 Data-Based Content Dissemination in Internet of Vehicles, *IEEE Transac-*
2 *tions on Industrial Informatics* 14 (2018) 768–777.
- 3 [42] F. Mezghani, R. Dhaou, M. N. Lima, A.-L. Beylot, Content Dissemina-
4 tion in Vehicular Social Networks: Taxonomy and User Satisfaction, *IEEE*
5 *Communications Magazine* 52 (2014) 34–40.
- 6 [43] M. Newman, Power laws, Pareto distributions and Zipf’s law, *Contempo-*
7 *rary Physics* 46 (5) (2005) 323–351. doi:10.1080/00107510500052444.
- 8 [44] S. Abuelenin, Moment Analysis of Highway-Traffic Clearance Distribution,
9 *IEEE Transactions on Intelligent Transportation Systems* 16 (2015) 2543 –
10 2550. doi:10.1109/TITS.2015.2412117.
- 11 [45] F. D. da Cunha, A. C. Viana, R. A. F. Mini, A. A. F. Loureiro, How
12 Effective is to Look at a Vehicular Network under a Social Perception?,
13 in: *Proc. of IEEE 9th International Conference on Wireless and Mobile*
14 *Computing, Networking and Communications (WiMob)*, 2013, pp. 154–
15 159.
- 16 [46] M. Piorkowski, N. Sarafijanovic-Djukic, M. Grossglauser, *Crowdad data*
17 *set epfl/mobility (v. 2009-02-24)* (2009).
- 18 [47] R. Amici, M. Bonola, L. Bracciale, A. Rabuffi, P. Loreti, G. Bianchi,
19 Performance Assessment of an Epidemic Protocol in VANET Using Real
20 Traces, in: *Proc. of International Conference on Selected Topics in Mo-*
21 *bile and Wireless Networking (MoWNeT)*, Vol. 40, 2014, pp. 92–99.
22 doi:10.1016/j.procs.2014.10.035.
- 23 [48] A. Keränen, J. Ott, T. Kärkkäinen, The ONE Simulator for DTN Protocol
24 Evaluation, in: *Proceedings of the 2nd International Conference on Simu-*
25 *lation Tools and Techniques, Simutools ’09, ICST (Institute for Computer*
26 *Sciences, Social-Informatics and Telecommunications Engineering)*, Brus-
27 sels, BEL, 2009. doi:10.4108/ICST.SIMUTOOLS2009.5674.
28 URL <https://doi.org/10.4108/ICST.SIMUTOOLS2009.5674>

- [49] C. Borrego, S. Robles, A. Fabregues, A. Sánchez-Carmona, A mobile code bundle extension for application-defined routing in delay and disruption tolerant networking, *Computer Networks* 87 (2015) 59–77.
- [50] X. Zhang, G. Neglia, J. Kurose, D. Towsley, Performance modeling of epidemic routing, *Computer Networks* 51 (10) (2007) 2867–2891.