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Improving Delivery Probability in Mobile Opportunistic Networks with Social-Based Routing

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Abstract: There are contexts where TCP/IP is not suitable for performing data transmission due to long delays, timeouts, network partitioning, and interruptions. In these scenarios, mobile opportunistic networks (MONs) are a valid option, providing asynchronous transmissions in dynamic topologies. These architectures exploit physical encounters and persistent storage to communicate nodes that lack a continuous end-to-end path. In recent years, many routing algorithms have been based on social interactions. Smartphones and wearables are in vogue, applying social information to optimize paths between nodes. This work proposes Refine Social Broadcast (RSB), a social routing algorithm. RSB uses social behavior and node interests to refine the message broadcast in the network, improving the delivery probability while reducing redundant data duplication. The proposal combines the identification of the most influential nodes to carry the information toward the destination with interest-based routing. To evaluate the performance, RSB is applied to a simulated case of use based on a realistic loneliness detection methodology in elderly adults. The obtained delivery probability, latency, overhead, and hops are compared with the most popular social-based routers, namely, EpSoc, SimBet, and BubbleRap. RSB manifests a successful delivery probability, exceeding the second-best result (SimBet) by 17% and reducing the highest overhead (EpSoc) by 97%.

Keywords: mobile opportunistic networks; routing algorithm; social-based routing; delay tolerant networks

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1. Introduction

The large spread of the Internet manifests how the TCP/IP network architecture [1] has become a reliable and successful communication mechanism for worldwide transmissions. The virtues of these networks are recognized, as well as their flexibility and adaptability; however, there are contexts where TCP/IP is not applicable. This is the case of networks where nodes are not able to keep a stable and continuous connection. These scenarios lead to dynamic topologies where nodes relapse on timeouts and interruptions [2,3]. Possible examples of these contexts are remote rural areas, interplanetary communications, or places devastated by natural disasters. Fortunately, the advances in mobile devices enable the appliance of mobile opportunistic networks (MONs) for these scenarios [4].

MONs [4,5] are a variant of delay tolerant networks (DTNs) [5] focused on providing communication in networks with an unstable dynamic topology shaped by mobile devices. The emerging works in computation have substantiated this discipline [6] and have enabled the viability of new disruptive applications for smartphones and wearables [7,8]. Moreover, these devices have been strongly sustained by the strides in energy consumption [9]. In this field, progresses, such as flexible solar cells as potential wearable electronics [10,11], enhance the possibilities that mobile devices can be used to face the challenges of MONs.

MONs can be used to face challenging conditions to communication devices. The unstable topology leads to a significant network partition with sparse deployment [12].

Continuous end-to-end paths may never exist, since nodes that form the network do not keep in touch continuously. Thus, communication opportunities are short and separated by long intervals of time; therefore, physical proximity and encounters become important to transmitting data. In an attempt to solve this issue, nodes perform the store–carry–forward strategy [13]: they receive the information through physical proximity, store the messages persistently, and forward the data to the next available hop to reach the destination. Since encounters become a relevant requirement for transmissions, MONs define routing algorithms that implement the way in which the information is sent [14].

Routing protocols specify the policies and requirements to forward the information from the sender entity to the destination [15]. Depending on the nature of the network, routing may pursue objectives, such as notifying all nodes or transmitting data from a specific node to a gateway node; therefore, routing algorithms can apply multiple factors to perform traffic control, such as contextual information or node data [15]. In recent years, many routing solutions have been focused on the social dimension of the nodes, applying data obtained from the node habits to choose hops and carriers [6,16].

Social-based routing [17] has motivated multiple works that incorporate interpreted social information about the nodes to optimize the traffic in opportunistic scenarios [18]. Aspects such as the social and contacts graph [19], the community concept [20], the centrality degree [21], and the common interests have become relevant for these algorithms [22]. Thus, this multi-hop routing seeks to benefit from real-world relations to achieve a better performance in the network [14].

In this article, Refined Social Broadcast (RSB) is introduced. This social-based routing algorithm seeks to improve data delivery benefiting from social behavior [14] using the social influence and the private interests of individuals. For this, the routing scheme makes use of context recognition to quantify encounters and identify the most potentially influential nodes. This concept refers to those network components that register a high number of encounters with other nodes. Transferring data to influential nodes then increases the probability of delivering a message to a destination and reaching more elements in the network. Furthermore, interests are considered using a virtual profile, an individual data store that enables the specification of data topics that the node is interested in carrying. With these main functions, the algorithm performs the selection of the most relevant nodes, maximizing the traffic sent to nodes that manifest the biggest influence while limiting content only to those interested in the data. This way, RSB aims to achieve a significant delivery probability while attempting to keep the overhead low—the metrics that become two of the most relevant in MONs [23].

The rest of the paper is organized as follows: Section 2 details the state of the art of social-based routing. Section 3 describes the proposed algorithm and its implementation. In Section 4, a performance evaluation of the proposed solution and comparison is provided against other state-of-the-art solutions. Finally, Section 5 draws conclusions and presents future work.

2. Related Work

Routing in challenging scenarios has attracted interest over time due to the key role it plays in opportunistic communication, including MONs [24,25]. Algorithms may implement different methods of communication, traditionally classified into two main categories [26]: (i) flooding strategies and (ii) forwarding strategies. The first one refers to solutions that aim to replicate data to the maximum number of nodes to improve the delivery probability of messages [27]. In the case of forwarding strategies, they apply techniques to optimize the hops and the copies, trying to define the most adequate path to the destination [26]; however, as far as we know, it is difficult to classify solutions into these two groups, since many current applications apply both philosophies [14]. This is the case of algorithms based on social information.

The use of social information for routing in MONs has motivated a large collection of works [6,14,28]. These solutions are mainly based on a set of properties and behaviors relevant for MONs. Some of the most significant characteristics used in social routing are the community concept [29], reflected in works such as [30,31], the spacial centrality [32], with popular contributions such as EpSoc [33], SimBet [21], and Bubble Rap [16,34], interest-based communication [35] and contact graphs of nodes [36], and even abstract notions such as friendship or affinity [22,37,38]. Among these different approaches, those based on degree centrality have achieved great recognition in the literature. This concept refers to the metric that indicates the popularity of a node in the network based on the number of encounters with the other elements. In this way, EpSoc, SimBet, and BubbleRap protocols apply these concepts in their approaches. Next, these proposals are detailed.

EpSoc [33] is a routing algorithm that aims to provide communication with an enhanced flooding philosophy that limits replication and overhead. For this, the solution proposes a hybrid protocol that makes use of an epidemic routing strategy [24] to forward information while applying degree centrality. This feature is used to dynamically adapt the time-to-live (TTL) of the messages, decreasing the value in the case that the next hop defines a higher centrality. If a message reaches a TTL of zero, incoming replicates of the message are refused. This solution has already demonstrated great performance in multiple contexts, contributing to the reduction in latency and overhead.

SimBet [21,39] presents an approach based on the concept of local influence. Using centrality and betweenness metrics, nodes are identified locally as bridges to forward information. The nodes identified as the most locally influential elements perform epidemic flooding, improved with the centrality characteristics. As a result, overhead is limited, and latency is enhanced even in contexts with a limited connectivity range.

BubbleRap was originally conceived in [30], but it has consolidated a solid work line with multiple contributions over time [16]. This solution applies the concepts of centrality and community to understand networks as a collection of individual groups with independent characteristics where the integration of the community members is irregular. As a consequence, in terms of connectivity, some people become more interesting than others. Considering this, the algorithm pretends to identify those nodes in OPPNets that provide a larger range of connections. Thus, BubbleRap has manifested good performance in multiple scenarios, becoming one of the most relevant solutions.

Considering these solutions, social metrics are features that have been explored in the literature; however, as far as we know, these mechanisms have not been combined with deeper parameters such as the node interests reflected with topics, with the purpose of enhancing delivery probability. The individual interests of the elements in OPPNets may become a relevant feature to consider at communications, becoming a resource to limit broadcasts to only specific sets of nodes. In the present work, interest-based routing is combined with an influence-based metric that values the presence of nodes through the number of encounters it has. Thus, every node is able to detect and store a set of potential influential nodes in the network. As a result, traffic flow is limited to those elements that provide more guarantees of delivery [29], disrupting the way data are forwarded. In the next section, the functioning of the algorithm is studied, analyzing the considered metrics and the interest-based routing.

Considering how these solutions work, they represent proposals that are close to that presented in this paper. However, our approach, RSB, combines the ideas of the social graph with the specification and matching of topic interests. These features have become a potential framework for multipurpose MONs. The objective is to maximize the delivery probability while overhead is also limited. This is especially relevant for contexts that may experience a high density of nodes, requiring limiting flooding to avoid buffer overflow and congestion. In this way, the proposal raises a solution to benefit from social interactions while optimizing the data flood when the node density is high. In the next section, the complete communication process of the proposal is detailed.

3. Refined Social Broadcast

RSB is a routing algorithm based on the social nature of the nodes in MONs to determine the best path between a pair of nodes. The solution is substantiated on the election of intermediate hops that manifest socially skilled behavior in the network and define interests on the transmitting information subject. These features are performed through the integration of two main elements in the network: (1) the historical encounters of the node and (2) the individual virtual profile of the node. Before detailing the working of the solution, these parameters are defined.

1. Historical encounters of the node. From a networking point of view, the socialization and collective influence of a specific node can be measured with the number of contacts it has encountered; therefore, this metric can used to identify, among a set of potential intermediate hops, a suitable candidate that can forward the information toward the destination. The consideration of historical encounters enables the social-based application to identify a set of the most influential nodes for forwarding the message.
2. Individual virtual profile of the node. This element is an individual dataset kept in every node in the network. This profile enables the storage and the definition of multiple pieces of information about the individual, including the set of interests of the node. This is suitable for marking the messages in the network with its topic, limiting its broadcasting to the set of nodes interested in that topic. As a result, information is restricted to those entities interested in the topic of the message. This functionality becomes interesting since it provides an abstract social dimension for routing with the consideration of the individual focus of nodes.

The historical encounters and individual interests are applied in the proposed routing algorithm to forward messages from a sender to a destination in MONs, using intermediate entities. The combination of these two metrics is disruptive, since the abstraction of individual interests is combined with the contrasted relevance of social influence; therefore, three main stages are involved in the complete transmission functioning of RSB. Figures 1–3 show the communication process and the way data are transferred among a specific set of nodes. Next, these stages are detailed.

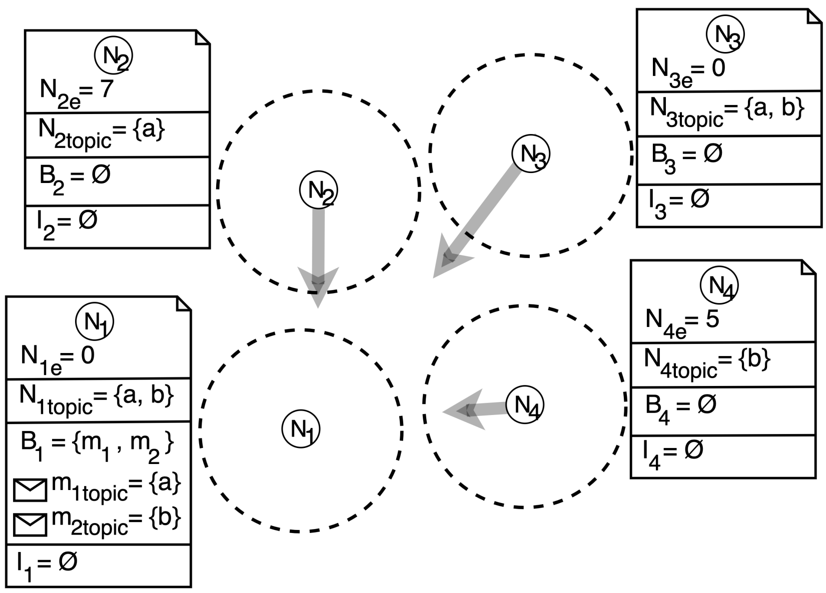

Figure 1. Scenario before the sender node transmits data.

Figure 1 depicts the initial scenario. There are four nodes, $N = \{N_1, N_2, N_3, N_4\}$, each one with an individual virtual profile that stores the number of historical encounters, the set of topics that it is interested in, the message buffer with the stored messages, and the set of nodes identified as influential. Messages stored in the buffer are also defined with numeric identification and with the message's topic. Regarding each node in the scenario, the virtual profile of N_1 describes a set of encounters $N_{1e} = 0$, a set of topics $N_{1\text{topics}} = \{a, b\}$, the buffer with two messages $B_1 = \{m_1, m_2\}$, and its empty set of nodes identified as influential $I_1 = \emptyset$. The two messages stored in the buffer describe different topics $m_{1\text{topic}} = a$ and $m_{2\text{topic}} = b$. In the node N_2, the number of encounters is $N_{2e} = 7$, the topic is $N_{2\text{topics}} = \{a\}$, the message buffer is empty $B_2 = \emptyset$, and the influential set is empty $I_2 = \emptyset$. In the case of N_3, the number of previous contacts is $N_{3e} = 0$, the topics are $N_{3\text{topics}} = \{a, b\}$, the message buffer is empty $B_3 = \emptyset$, and the influential set is empty $I_3 = \emptyset$. At last, the virtual profile of N_4 stores a number of encounters $N_{4e} = 5$, a set of topics $N_{4\text{topics}} = \{b\}$, an empty message buffer $B_4 = \emptyset$, and the influential set empty $I_4 = \emptyset$. As a result, in the moment described in Figure 1, nodes are not in contact with each other but may encounter each other later due to their movements in Figure 2.

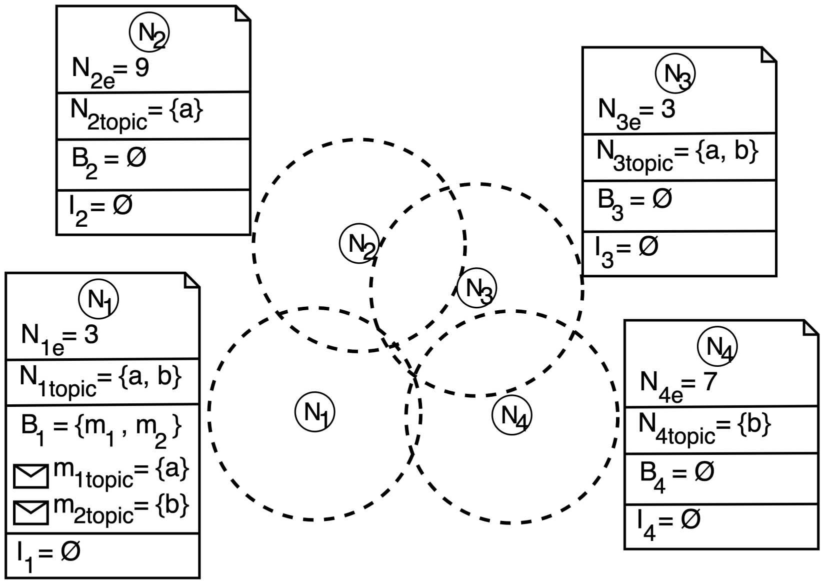

Figure 2. Encounter between nodes.

Figure 2 shows the encounter in the trajectory of the nodes detailed in Figure 1. This event increases the number of encounters of each node. Considering N_1 stores in its buffer two messages $B_1 = \{m_1, m_2\}$, this encounter produces a potential message interchange. For this, the proposed routing applies its metrics to broadcast the data to the most appropriate intermediate node in terms of interest matching and influence; therefore, N_1 performs two steps to achieve this: (i) identifying the nodes interested in the topic of the stored messages and (ii) selecting a candidate that keeps a higher number of encounters.

In the first step, N_1 identifies the nodes interested in the topics of the stored messages $m_{1\text{topic}} = \{a\}$ and $m_{2\text{topic}} = \{b\}$. Next, the process to transmit both messages is detailed. Beginning with m_1, N_1 aims to identify nodes interested in $m_{1\text{topic}}$. For this, all nodes in contact send their virtual profile to N_1, enabling the sender to recognize the surrounding entities. In this case, N_1 checks first that, for message $m_{1\text{topic}} = \{a\}$, Nodes N_2 and N_3 are compatible, since $N_{2\text{topics}} = \{a\}$ and $N_{3\text{topics}} = \{a\}$, respectively. As a result, both nodes are considered potential candidates for N_1. A node is considered a candidate because it is interested in the same topics of the messages stored by the sender. N_2 and N_3 are then added to the candidate set of N_1, $C_1 = \{N_2, N_3\}$. To perform this formally, Equation (1),

$$C_n = (N_{\text{itopics}} \cap m_{\text{ntopics}}) \forall N_i \in N, \forall m_n \in M_n \tag{1}$$

is used to match topics, where N_{itopics} is the set of topics in which N_i is interested, and m_{ntopics} is the topic of the message m_n, stored by Node n. In the case of N_i, it belongs to the set of nodes N that are encountered by Node n. Meanwhile, m_n belongs to the message buffer of the sender M_n. If the intersection between both interest declarations is not null, the encountered node becomes a candidate for node n C_n. As a result, nodes in C_n are considered for the second phase.

Considering the values in Figure 2, N_1 performs the second phase of the algorithm considering N_2 and N_3 as candidates. This stage aims to identify the node that will receive the message and will be saved as influential by the sender. This is achieved using the number of encounters. For this, the node that counts with a higher number of contacts among the candidates will receive the message from the sender. In this case, the number of encounters for N_2 is $N_{2e} = 9$ and for N_3, the other candidate in C_1, is $N_{3e} = 3$. Hence, N_2 is selected as the receiver of the message m_1, and it is recognized as influential by the sender $I_1 = \{N_2\}$. Formally, this process is specified in Equation (2),

$$I_n = \max(N_{\text{ie}}) \forall N_i \in C_n \tag{2}$$

where the identification of the most influential node in the candidates C_n of Node n is detailed. The highest N_{ie} receives the message and becomes part of the influential set of the sender, I_n in this case.

Considering the processing for m_1, the functions to transmit m_2 are the same but have a different topic, $m_{2\text{topic}} = \{b\}$. Thus, in the first stage, N_1 erases C_1 and identifies N_3 and N_4 as candidates $C_1 = \{N_2, N_3\}$. In the second stage, when N_1 compares its encounters, N_4 becomes the most suitable and a new influential node $I_1 = \{N_2, N_4\}$.

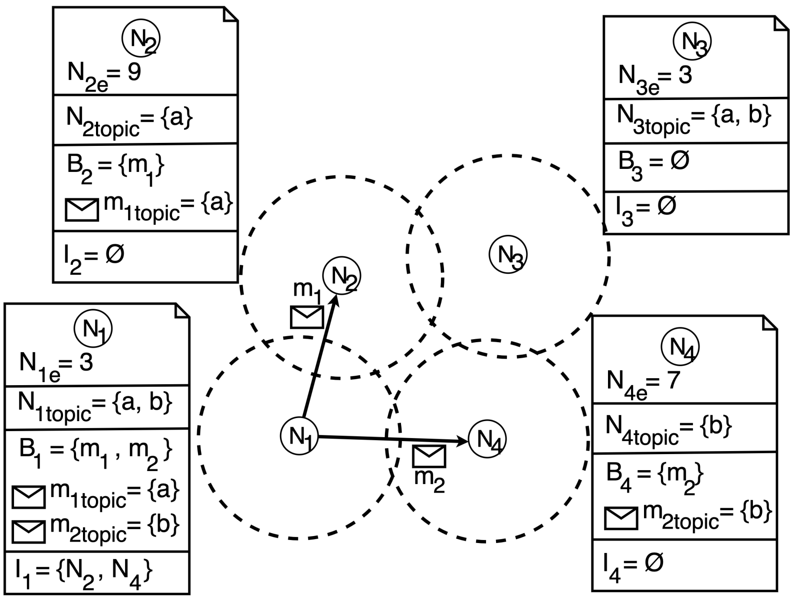

Figure 3. Broadcast based on interests and influence.

Figure 3 depicts the following situation for Figure 2. Previously, the most suitable node intermediates have been identified for each message. Thus, the messages are transferred: m_1 from N_1 to N_2; m_2 from N_2 to N_4. As a result, now N_1 stores both entities as influential. This means that the next time it encounters them, they will not be considered in the evaluation process again and will receive the stored messages that match their interests.

Considering the explained process, RSB applies individual properties in nodes to identify the optimal path in a network for achieving a high delivery probability. The raised approach enables the broadcast of information among a set of nodes that shares specific data topics. In order to do this, virtual profiles become useful entities in the routing that store the interests of the node; however, the topic idea can be applied as a contextual variable for node characteristics. For example, if the battery level in a specific node is low, the virtual profile subscribes the node to a topic that identifies it as a low energy relay; therefore, traffic will be restricted to it. In the same way, topics can be applied to dynamically identify nodes that lack the space needed to store more messages. Hence, a virtual profile and topic-based routing have become a potential framework to evolve MONs into interoperability, introducing changing behavior in the nodes and raising the network context as a tool to improve delivery.

With the objective of assessing the proposed algorithm, the next section proposes a realistic case of use that evaluates the performance of the proposal and compares it to state-of-the-art alternatives.

4. Experimental Results

In this section, RSB is evaluated in a realistic simulated scenario implemented with the ONE Simulator [40]. The simulation setup represents the case of use of the loneliness detection methodology proposed in [41]. This work applies technology to quantify loneliness in rural areas; therefore, a rural village is defined with sender, intermediate, and destination nodes.

4.1. Simulation Setup

The simulation setup was built following the directives of the proposal described in [41]. This paper, framed in the anthropology field, details a novel methodology to detect loneliness among aging people in rural areas. Thus, field work and semi-structured interviews are combined with a technological architecture based on the detection of encounters. Hence, the work of [41] proposes equipping aging people with smart bracelets that register the physical encounters they have along the day, using Bluetooth to detect the encounters with other bracelets or smartphones. It is then possible to track the companion patterns of aging people with neighbors, aiming to detect potential candidates that suffer from loneliness; therefore, the contacts data are stored in the bracelets and transmitted to beacons installed in representative popular places, such as medical centers, the town hall, or libraries. This information is processed to create a graph about the encounters, representing aging people as nodes and relations as links. This process is graphically represented in Figure 4, included in the original work, which shows an example of an encounter between an aging person and a neighbor and its later data transmission to a beacon. As can be seen, this communication process perfectly fits with the behavior of MONs. It can thus be successfully implemented with the proposed routing protocol.

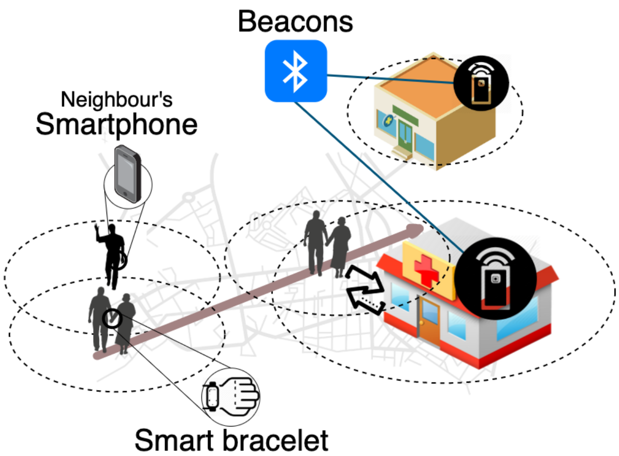

Figure 4. A technological solution proposed to detect loneliness [41].

To align the simulation setup with the loneliness detection proposal, it is required to provide a realistic context where nodes autonomously interact in a specific local area. For this, values were extracted from the Spanish Research Council (CSIC)'s annual reports about aging [42]. These studies manifest the rural depopulation and the current trends in the age distribution of population in small villages. Thus, for areas with less than 500 inhabitants, older adults have become almost the half of the population [42].

Following the directives of the study, a surface $s = 10,000 \times 10,000$ m^2 is considered, along with a total node number of $N = 110$. The simulation time is $T = 30,000$ s, aiming to recreate eight hours of a day. A distribution of 54.54% of aging people in the number of participants is defined. For this, three groups of nodes are described: (1) aging people in the scenario, N_e, (2) collaborative neighbors, N_i, and (3) a destination for the information, N_d. Next, each node group is detailed.

1. Aging people (N_e). These nodes represent the aging people equipped with smart bracelets in the village. They act as the information source and thus become senders in the MON. They then collect their encounters with other devices and forward this information among the network nodes, aiming to transmit it to destination. Following the functioning of RSB, the proposed router, they provide the information attached to the message topic, m_{topic}, "Elder's encounters". Thus, data are broadcast among the nodes interested in the information, N_i. The mobility of N_e represents the behavior of aging people in their living village. The mobility model, M, based on clusters then becomes a suitable choice to recreate the behavior of the aging population. This mechanism, integrated on the simulator [40], makes nodes move randomly around defined points, setting a maximum range of distance, M_r, and a center, M_c, with coordinates x and y. Thus, it is possible to simulate walks around points such as the main square, a district, the church, or leisure places. This feature is graphically detailed in Figure 5.

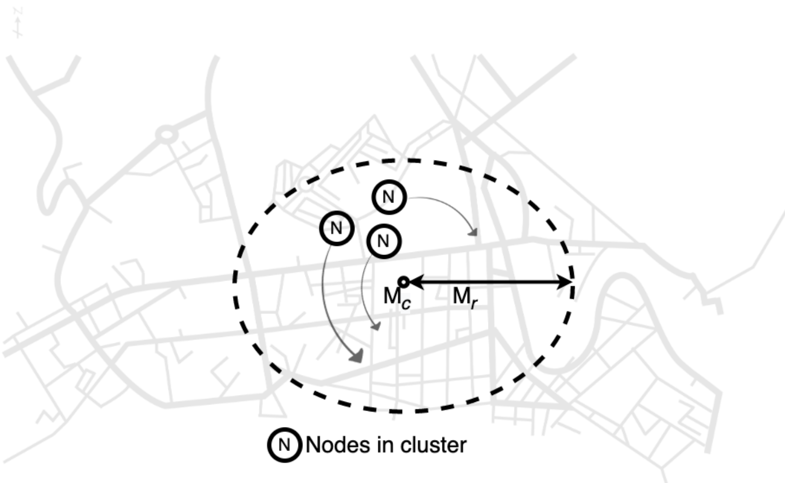

Figure 5. Cluster movement model integrated in the ONE Simulator.

2. Collaborative neighbors (N_i). The information generated by N_e finds the destination in N_d, which acts as a data sink; however, the physical distance between senders and the destination requires intermediate elements that serve as a mule for the information. For this, the smartphones of the neighbors in the village can act as intermediate nodes in the MON. Following the cluster movement model, these elements can provide communication in the scenario toward the data sink. Hence, they define as an interest the message topic $m_{\text{topic}} =$ "Elder's encounters", serving as a mule in the proposed routing system.
3. Destination (N_d). The destination node is the ultimate element in the network to which messages are forwarded. This entity is able to receive, process, and transmit to the Internet the incoming data about encounters. Because of this, it becomes a priority to communicate the data source with this element. Considering that the destination plays a passive role in the MON, it does not follow any movement model.

To perform communication between the devices in the MON, all of the nodes are simulated with the same interface, I, based on Bluetooth Low Energy (BLE) [43]. This technology can reach a range of several tens of meters [44]; therefore, a range of $I_{\text{range}} = 30$ m is considered. A transmission speed of $I_s = 1$ Mbps is also defined [44]. Furthermore, messages in the scenario are established with a size of $m_s = 300$ kb, which is an estimation of the size required to transmit a data relation between a specific anonymous elderly individual and their encounters. Meanwhile, considering the potential constraints of storage in previous research work in the literature [45,46], a buffer size of $N_{\text{buffer}} = 5$ Mb is included. A TTL of $m_{\text{ttl}} = 1800$ s is considered, reflecting the time lapsed before a message is discarded by the message carrier node. This selected value aims to avoid deprecated messages in the network. In addition, there are more elements that take part in the communication process.

The number of messages generated during simulation and the applied routing protocol are critical aspects in the success of communications in MONs. Both parameters are varied to study the impact in the results of the simulations. Firstly, in the case of the messages generated in the network, the parameter ω is defined with the message generation interval. This variable indicates the time lapsed between new messages sent in the network. To assess it, the values $\omega = \{1800, 3600, 7200\}$ are considered. Apart from RSB, three protocols are considered in the simulations: EpSoc [33], SimBet [21], and BubbleRap [16], all of which have been presented in the Related Work section.

Figure 6 depicts the node movement in the simulation. Six different clusters are considered in the scenario, aiming to distribute the nodes along the surface following a varied behavior. For this, three clusters are assigned to aging people, M_{e1}, M_{e2}, and M_{e3}. Meanwhile, the other three clusters are for collaborative neighbors, M_{i1}, M_{i2}, and M_{i3}. In the case of the first group, the distribution aims to require explicitly intermediate entities to connect the nodes of these clusters with destination. Except for M_{e1}, nodes in M_{e2} and M_{e3} never contact directly with the destination. As a consequence, intermediate nodes are highly required. Hence, the clusters that define the movements of the collaborative neighbors enclose the paths of older adults. This is the case of cluster M_{i1}, which encloses a large distance. Meanwhile, M_{i2} and M_{i3} serve as connection points between the different senders.

As a summary for all the assets and configurations included in the simulation, Table 1 resumes the values assigned to every variable in the scenario, including the node distribution, the mobility model, the cluster's range and center configuration, and the routing details. The performance analysis is explained in the next subsection.

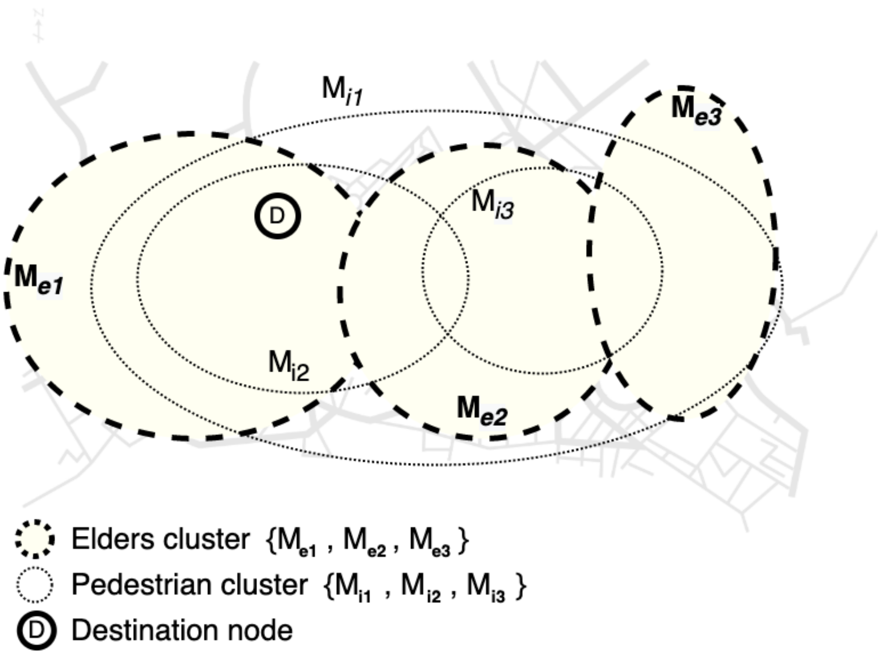

Figure 6. Mobility patterns (M) based on clusters in the simulated scenario.

Table 1. Variables and distribution in the simulated scenario.

Parameter	Value
s	10,000 × 10,000 [m^2]
T	30,000 [s]
ω	1800, 3600, 7200 [s]
N	110
N_{buffer}	5 Mb
N_e	60 (54.54%)
N_i	50 (45.45%)
N_d	1
M	ClusterMovement
M_{e1r}	1700 m
M_{e1c}	(x, y) = (3900, 2700)
M_{e2r}	1600 m
M_{e2c}	(x, y) = (5000, 2700)
M_{e3r}	1600 m
M_{e3c}	(x, y) = (5000, 2500)
M_{i1r}	2200 m
M_{i1c}	(x, y) = (4100, 2700)
M_{i2r}	900 m
M_{i2c}	(x, y) = (5400, 2700)
M_{i3r}	1600 m
M_{i3c}	(x, y) = (5000, 2500)
m_{topic}	Elder's encounters
m_{size}	300 kb
m_{ttl}	1800 [s]
I	BLE
I_{range}	30 m
I_{s}	1 Mbps
Algorithm	RSB, EpSoc, SimBet, BubbleRap

4.2. Performance Evaluation

In this section, the proposed algorithm is executed in the defined scenario, and the average obtained results are presented and discussed. For this purpose, 10 executions were run to determine the performance average of each solution. The performance is assessed accordingly to four considered variables: delivery probability, d_{prob} (%), which is the percentage of messages that successfully reached the destination node, latency, τ (s), which is the average time needed to receive a message, overhead, θ, which is the relation between duplicated messages and received ones, and hops average, σ, which represents the average number of nodes needed to reach the destination. In our case, the focus is on d_{prob}, since it is the main goal of the paper.

Figure 7 shows the delivery probability, d_{prob}, as a function of the message generation interval, ω. Generally, increasing the message generation interval, ω, leads to an improvement in the delivery probability, since the time elapsed without creating new messages is higher. In this case, a slight increase in d_{prob} is noticeable. However, there is not a significant difference between the different values, manifesting the considerable robustness of RSB even when the number of messages in the network increases. This fact becomes evidence of the potential of combining the historical encounters with the topics. Considering the node distribution defined for the simulation, reaching this volume of delivered data shows how the election of intermediate nodes has also been successful. It also implies that even the sender nodes that moved far from the destination were able to communicate. For this, the communication mechanism applied in the intermediate nodes appears to be effective. Regarding the comparison, the highest d_{prob} is reached with RSB at every value of ω. At $\omega = 3600$ s, RSB finds the best result of all simulations with $d_{\text{prob}} = 97.03\%$ of success at transmissions, over 17% more successful than SimBet, the second-best result.

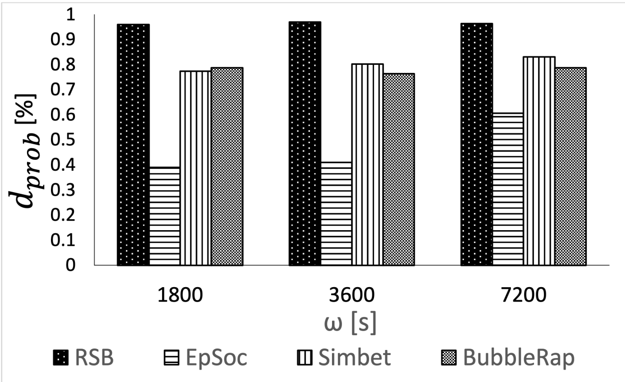

Figure 7. Delivery probability (d_{prob}) as a function of the message generation interval (ω).

Figure 8 shows the latency average of each solution (τ) as a function of the message generation interval (ω). Latency is one of the most affected parameters when the load in the network is varied. In this case, there is a clear inverse relation between the message generation interval and the average latency of the routing protocols. One of the main features in the solution to mitigate latency is saving the influential nodes when a new one is identified; however, this function is not very effective when there is a large number of messages. Moreover, the technique manifests a slightly improvement for $\omega = \{3600, 7200\}$. Compared with the other solutions, RSB manifests results that are close to the alternatives, requiring a reasonable time to deliver information to the destination.

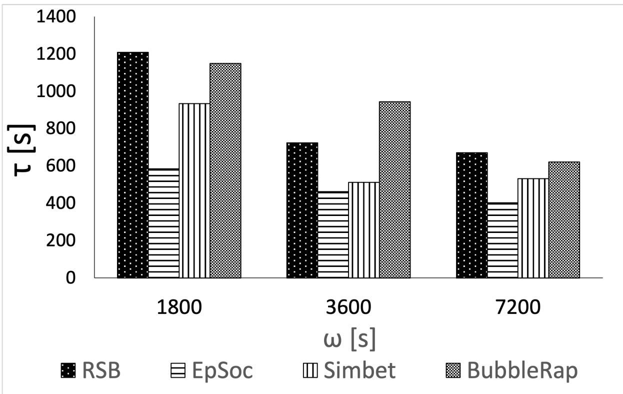

Figure 8. Latency average (τ) as a function of the message generation interval (ω).

Figure 9 shows the overhead, θ, as a function of ω. This metric reflects the relation between the number of message copies in the network and the number of received unique messages. This parameter is interesting because it measures the effectiveness of duplicity and copies introduced by the routing algorithm. In this case, RSB achieves very low values for $\omega = 3600$ s and $\omega = 7200$ s, manifesting the effectiveness at reducing the traffic flood among the nodes. Thus, the election of intermediate nodes can be interpreted as effective. Hence, the saving of nodes as influential and the interest-based constraints contribute to the reduction in message copies sent in the network. In the case of SimBet, considering that positioning and centrality play a significant role in the algorithm, we can deduce how cluster movement influences positively in the message replication.

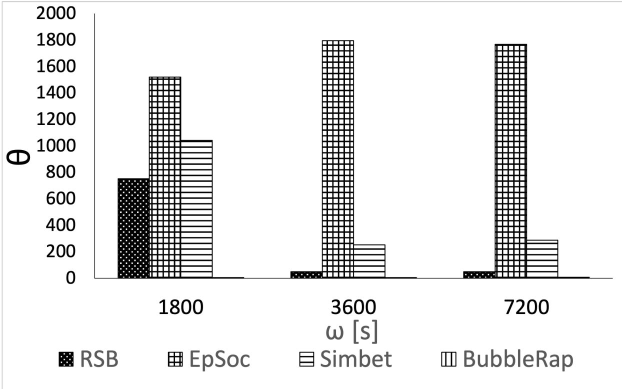

Figure 9. Overhead (θ) as a function of the message generation interval (ω).

Finally, in the case of Figure 10, the average number of hops required to reach the destination (σ) is shown as a function of ω. RSB registered similar values to EpSoc and SimBet, showing how a path of nodes between the source and the gateway is required. Thus, we can deduce how transmission becomes a success, especially if these values are considered with delivery probability. There is then a satisfactory relation between the nodes involved in the communication and the number of messages successfully delivered.

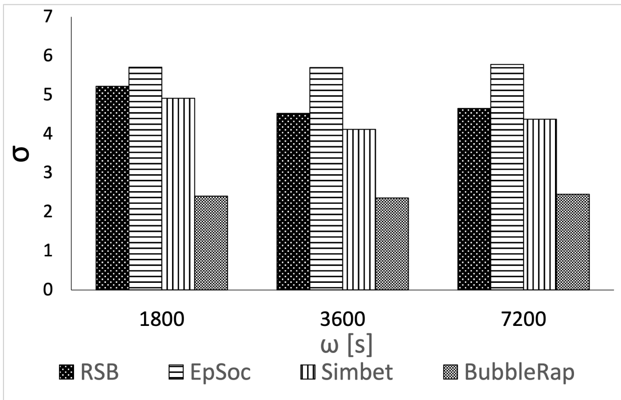

Figure 10. Hops average (σ) as a function of the message generation interval (ω).

An additional dimension to be considered in the result analysis is the energetic cost of the algorithm. In the case of use that illustrates the experimental results, the network architecture relies on autonomous independent devices for communication: smartphones and wearables. It is then crucial for a successful delivery to count with operative nodes. For this reason, energy consumption must be technically assumable by devices that may have to perform multiple tasks while satisfying the communication requirements of the network. Considering this, and based on the network load that reflects the overhead values, θ, the energetic cost of the routing solutions can be compared.

The energy consumption of the devices depends actively on the tasks that they perform in the network. The operations of sending, copying, and delivering messages then impact the battery lifetime. Considering that the executions have been performed under the same conditions for the four routing algorithms, the creation events are the same; therefore, only the metrics related to the overhead of the network, θ, are considered in the energetic cost comparison, since this value reflects the relation between delivered messages and copied messages. As a result, based on the overhead results, the sum of the energetic cost is estimated for each routing algorithm. For this, consumption metrics are obtained from [47], enabling the cost estimation for communications. In that work, the energy consumption of communication using BLE was measured, determining an estimation in milliamperes (mA) for each operation: sleeping, scanning, sending, and receiving. In our case, we simplify the assessment, assuming the estimation for sending and receiving messages with the values of overhead. In this way, the number of copies transmitted in the network is related using Equation (3):

$$E_g = \sum_{i=1}^{N} (m_{\text{isent}} \times c_{\text{sent}}) + (m_{\text{ireceived}} \times c_{\text{received}}) \tag{3}$$

obtaining a global consumption estimation (E_g) from the sum of the total number of messages sent by each node (m_{sent}) multiplied by the associated energy consumption (c_{sent}) and the total number of received messages (m_{received}) multiplied by the associated energy consumption (c_{received}).

As a result, Figure 11 shows the sum of energy consumption for each algorithm in the execution, manifesting how the consumption requirements of RSB are eminently lower than those of alternatives, in the case of the EpSoc and SimBet router, which reaches a higher value of overhead and, consequently, of energy cost. It is interesting to highlight that BubbleRap achieves lower values of energy consumption due to its low overhead; however, it is important to consider that, despite this, the delivery probability of BubbleRap is still lower than RSB.

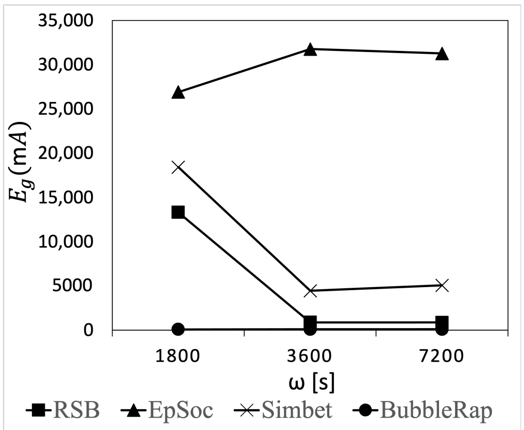

Figure 11. Energy cost (E_g) as a function of the message generation interval (ω).

After analyzing the four considered variables and the energetic cost for evaluating the proposed routing solution, the results obtained by RSB are promising. The solution behaves properly for the four dimensions, including d_{prob}. The obtained values show how RSB provides the best delivery probability, refining the outcomes obtained with alternative solutions. Considering that the focus of the algorithm achieves a high delivery probability, the implementation of the solution is proven to be effective; therefore, the combination of historical encounters and the interest-based routing enhances the delivery probability, compared with other popular routing alternatives.

5. Conclusions and Future Work

There are contexts where communication deals with long delays, timeouts, network partitioning, and connection interruptions, becoming a challenge for a traditional architecture. As a response to these challenging environments, mobile opportunistic networks (MONs) are a valid option for data delivery, providing decentralized asynchronous transmissions in dynamic topologies. These networks may exploit physical proximity and encounters to transmit data while storing the information during disconnected periods. Using intermediate nodes, an end-to-end path is then possible. To perform this, routing strategies are required, applying multiple variables to elect the best intermediate nodes.

In this paper, we introduced a novel social routing algorithm called Refine Social Broadcast (RSB). This algorithm applies the definition of individual interests and the relevance of social interactions to enhance the performance of MONs. The solution thus refines the traffic flooding among the nodes, aiming to improve delivery probability while reducing unnecessary data replication. RSB performs routing in two phases. First, it provides nodes with the possibility of subscribing to a specific information topic. Thus, intermediate nodes choose a topic, which is the subject of the information that they are interested in carrying. As a result, the algorithm filters the data replication of messages, considering only the nodes interested in the data topic. Then, in a second phase, RSB draws on social influence to choose the most suitable node to forward the information. For this, using contact registration, this approach identifies the most influential encounter and replicates the information to it. As a result, influential nodes are registered. Hence, the next time influential nodes are encountered, they are prioritized to receive data.

The proposal has been implemented, executed, and evaluated in a simulated scenario. This scenario represents the case of use of a methodology to detect loneliness among the elderly population in rural areas. The proposal applies technological devices to keep track of encounters that older people have in a day, aiming to detect those who lack contacts. For this, smart bracelets are used. Considering the challenges of many rural areas in the deployment of traditional transmission architectures, a MON is proposed. Hence, smart bracelets work as senders, transmitting its information about encounters. Collaborative neighbors then act as intermediate nodes, and a destination beacon acts as a receiver of the messages. This entity processes and transmits to the Internet the incoming data about the encounters, creating a relationship graph that enables the identification of potential candidates that suffer from loneliness in the population.

Considering the implementation in the simulation, the performance of the proposal was evaluated and compared with alternative routing strategies such as EpSoc, SimBet, and BubbleRap. The obtained results showed that RSB reached the highest delivery probability, exceeding the second best result (SimBet) by 17%. It also reduced the highest overhead value (EpSoc) by 97%. Nevertheless, latency values are improvable. For this, future work aims to improve the current version of the algorithm by reducing the time required to deliver information; therefore, the proposal will be extended following three main lines: (i) improving social-awareness routing with the consideration of additional metrics, (ii) calculating internal scores from the parameters of the virtual profile, and (iii) defining topics as affinity metrics inferred from the node's social characteristics. Thus, future work may further improve the performance of the routing algorithm solution.

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