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Social-Driven Information Dissemination for Mobile Wireless Sensor Networks

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Abstract: As we move into the so-called Internet of Things (IoT), the boundary between sensor networks and social networks is likely to disappear. Moreover, previous works argue that mobility in sensor networks may become a consequence of human movement making the understanding of human mobility crucial to the design of sensor networks. When people carry sensors, they become able to use concepts from social networks in the design of sensor network infrastructures. However, to this date, the utilization of social networks in designing protocols for wireless sensor networks has not received much attention. In this paper, we focus on the concept of information dissemination in a framework where sensors are carried by people who, like most of us, are part of a social network. We propose two social-based forwarding approaches for what has been called Social Network of Sensors (SNoS). To this end, we exploit two important characteristics of ties in social networks, namely *strong ties* and *weak ties*. The former is used to achieve rapid dissemination to nearby sensors while the latter aims at dissemination to faraway sensors. We compared our results against two well-known approaches in the literature: Epidemic and PRoPHET protocols. We evaluate our approaches according to four criteria: information-dissemination distance, information-dissemination coverage area, the number of messages exchanged, and information delivery time. We believe this is the first work that investigates the issues of information-dissemination distance and information-dissemination coverage area using an approach inspired on social network concepts. *Copyright © 2015 IFSA Publishing, S. L.*

Keywords: Social Networks, Social Network of Sensors, Human Mobility, Information Dissemination.

1. Introduction

Wireless Sensor Networks (WSNs) are an important area of research because they relate to many applications in the areas of communication, transportation, military and agriculture. A typical WSN consists of many small devices deployed over a geographical area, where each device is called a *Sensor* and can measure environmental or physical conditions (e.g., temperature, humidity). The structure of WSNs can be static or dynamic (mobile). In a static WSN, sensors are stationary. In a dynamic (mobile) WSN, sensors positions are subject to change over time. Traditionally, the design of Mobile Wireless Sensor Networks does not take into consideration complex human movements focusing instead on "artificial" (programed) mobility patterns [1-2]. However, with the advent of the so-called Internet of Things (IoT) [3], we have the possibility of sensors being carried by people (e.g., as part of smartphones). When considering this approach, the mobility of sensors is more complex but can be explained by what is called a *human mobility model* that describes the movement of mobile nodes and how their positions, directions, and velocity change over time [4-6]. These models describe human mobility characteristics. For instance, Song, *et al.* [5] proposed a model for individual mobility (IM) that is based on two social mechanisms:

- *Exploration*: Describes the tendency of individuals to explore new locations. In human mobility this tendency decreases over time.
- *Preferential Return*: In random walk, the probability of visiting a location is uniform and random. However, humans have the tendency to return to the locations visited frequently in the past (e.g., home and work).

The inclusion of mobility models, as part of the design of mobile sensor networks, has been studied in depth by Tomasini, *et al.* [7-8], who evaluated many mobility models and how they can be used in the design of what they called a Social Network of Sensors (SNoS).

A SNoS is central to the description of this work. Hence, to summarize, a SNoS is a dynamic WSN where each sensor (e.g., a smartphone) is assumed to be carried by an individual. Thus, all the movements in this environment reflect human dynamics. As such, a SNoS exhibits both the characteristics of WSNs and social networks because as people move they form connections to other people. Fig. 1 shows a view of a SNoS where people have "friendship" connections as well as connections related to their proximity to each other.

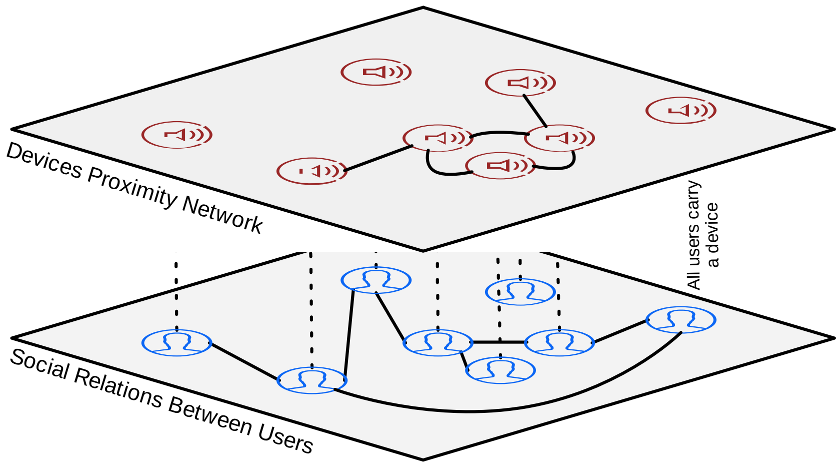

Fig. 1. The general structure of a SNoS. There are two levels of connectivity: social relations and proximity. Sensors can send messages to each other when they are in close proximity. So the top layer in the figure is more dynamic because users are mobile. The social relation layer is also mutable but the social relations do not tend to change as often as in the proximity network.

Humans evolved to live in social settings [9]. The collection of everyone's social contacts forms a social network; the set of relationships among a set of actors (i.e., individuals). The study of social networks can help us to understand the structure of people's relationships and their behavior. Furthermore, a social network structure contains different types of ties (relationships) among individuals that may support the understanding of how information flows within social settings. According to Granovetter [10], there are two types of ties in social networks: *Strong Ties* tend to form among family members, friends, and people we associate with frequently, while *Weak Ties* form among people we associate with rarely (less often).

In this work, we design social-based approaches for information dissemination in SNoS inspired by the concept of strong ties and weak ties. Following the definition and the hypothesis of Granovetter, we proposed information dissemination approaches to achieve nearby dissemination of information, called Strong-Ties-Based Forwarding (STBF) and to achieve faraway dissemination of information, called Weak-Ties-Based Forwarding (WTBF).

This paper is organized as follows: in Section 2 we describe some of the works related to our proposal; Section 3 explains the concept of strong and weak ties in SNoS; Section 4 discusses information dissemination in WSNs; we follow in Section 5 with the proposed approach for nearby and faraway information dissemination; Section 6 presents about the experimental results, Finally, we conclude the paper in Section 7 with suggestions for future research.

2. Related Works

The understanding of social interactions among people may be used in designing data forwarding protocols for sensor networks. A recent study by De Melo, *et al.* [11], proposed a strategy called RECAST to analyze individuals' interactions in a network. This strategy classifies individuals' interactions into four classes: *Friends*, *Acquaintance*, *Bridges*, and *Random*. Then, they involved these classes in designing a forwarding approach. Their findings showed that *Friends* were the most used to deliver messages, while the *Random* class was the least used.

Other social characteristics can be exploited in designing approaches for information dissemination in WSNs such as *Communities*. Li, *et al.* [12] proposed a social group-based forwarding approach that uses the history of encounters of individuals to select good relays for data delivery; the approach considers diverse social relationships among individuals. The experimental results showed that their approach outperforms Epidemic in terms of delivery ratio and number of messages exchanged.

The *Centrality* of nodes can also be utilized in WSNs. Mtibaa, *et al.* [13] proposed a new forwarding approach called *People-Rank.* This approach is based on the *PageRank* algorithm and the betweenness centrality of nodes. They rank nodes according to their social information; a node is given higher weight if it is socially connected to important nodes of a network (e.g., nodes with high degree centrality). The results showed that the People-Rank approach outperforms Epidemic in terms of the number of messages exchanged and delivery time.

The use of human mobility models has also been used to improve the performance of dynamic WSNs. Tomasini, *et al.* [7] showed that the WSNs with social mobility patterns could improve the performance of sensor networks in terms of the nodes' coverage as well as data delivery. In another study by the same authors [8], they evaluated which mobility models are more convenient for data delivery among different mobility models in SNoS. Their main observations were that: (a) there are small changes in the performance when using different mobility models in dense networks; (b) sensors' radius (communication range) plays a significant role in the performance (in terms of data delivery) and that (c) delivery rate is the real issue when using the individual mobility model [5] in WSN. Therefore, we focus our efforts on (c), more specifically trying to improve the process of forwarding information to other sensors in a network. In all the simulations used in this paper the human mobility model used is the one proposed by Song, *et al.* [5], as it is considered today one of the most accurate models of human mobility.

3. Tie Strength in SNoS

In Section 1, we described the concept of SNoS as proposed by Tomasini, *et al.* [7]. This concept depicts the integration of WSNs and social networks. Fig. 1 illustrates the general view of a SNoS in which each node represents an individual who carries a sensor in the form of a smartphone, a tablet, or a laptop; these devices' movements reflect the mobility behavior of the humans who carry the devices. Each sensor has a communication range that enables communication with other sensors forming a transient network topology. Sensors in a SNoS keep track of each other; the tracking process is performed at every time step, the tracking information is stored in a dynamic list for each sensor in the network. Each sensor then has a dynamic list, which contains the *history of encounters* with other sensors.

As mentioned, ties in social networks can be strong or weak [10]; these types can also be defined in the context of SNoS based on the frequency of encounters among sensors. That is, the strong ties of sensor *i* are the other sensors whose encounter frequency to *i* is high. By contrast, the weak ties are formed to those sensors that have low encounter frequencies with sensor *i*. Since we are dealing with a mobile network, extracting the strong and weak ties is performed at every time step for each sensor in the simulation environment. The purpose of focusing on the strong and weak ties in this work is that we believe using these ties may help to design efficient information dissemination approaches for sensor networks. More specifically, dissemination approaches to closed circles of friends (with strong ties), or dissemination to sensors located far away from the current sensor (with weak ties).

In this paper, we have not considered the issue of memory size of sensors to keep track of an encounter frequency list. Although important, this is left as future work. The focus on this paper is on the demonstration that if a sensor has full knowledge of encounter frequency, the framework can use this information to implement different strategies for information dissemination. As future work, we intend to tackle the issue of having only partial information (limited memory).

4. Information Dissemination in WSNs

Data forwarding is one of the crucial tasks to be efficiently implemented in WSNs. Moreover, it is quite a challenging undertaking because it directly affects the consumption of network resources (e.g., memory and battery) [14]. The main idea behind information dissemination in WSNs is to minimize the consumption of network resources by choosing appropriate receivers (relays) in the dissemination process [15]. In the network literature, several forwarding approaches have been described implementing different strategies in dealing with the consumption of network resources. Below we describe two of these approaches that later will be used to benchmark our proposed methods.

4.1. Epidemic Forwarding

Proposed by Vahdat and Becker [16], this approach is based on an Epidemic algorithm, where data messages are sent to all network nodes in the range of communication of a particular node leading to a scenario where all nodes are guaranteed to receive all data messages generated in the network. This is an analogous to a full broadcast. This approach has a high level of flooding due to the number of messages exchanged, which gradually leads to waste of network resources [17]. Yet, the Epidemic approach is widely used to benchmark other protocols.

4.2. PRoPHET Forwarding

PRoPHET stands for Probabilistic Routing Protocol using History of Encounters and Transitivity. This approach was proposed by Lindgren, *et al.* [18] and is based on a node's history of encounters. The assumption is that if a node *i* encounters another node *j* with high frequency, node *i* should be more likely to encounter node *j* again in the future. With the encounter ratios in place, the delivery predictability is calculated for each node destination, the value of delivery predictability represents the chance to deliver a message to a particular destination. When two nodes encounter, each one updates its delivery predictability. This value determines whether a particular message will be forwarded to a particular node. A node with higher value of delivery predictability is considered a good receiver for delivering a message [18]. Under this approach, as nodes encounter more nodes, they increase their delivery predictability value. We will also use PRoPHET in our results. The idea is to contrast what we proposed against a proposal that is not flood based.

5. The Model

This section describes the details of the proposed model. We tried to have realistic settings for our simulation environment. All the experiments were carried out on a simulator developed for evaluating models in sensor networks. The simulations were all implemented out using the NetLogo programming-modeling environment [19].

5.1. Model Initial Settings

We start with an environment representing a squared city of 6.2×6.2 sq. miles divided into squared blocks (100×100 total blocks). We deployed approximately 2000 mobile sensors in the simulation environment. These sensors are exponentially distributed from the center of the city (environment) because most metropolises follow this population distribution [20]. The event that is used in the measuring of the information dissemination is generated in a random location, which is then considered as the center of the dissemination (for the purposes of measuring distances). The communication type among sensors is peer-to-peer. The communication range of sensors (sensors' radius) is 55 yards (50 meters) simulating Wi-Fi technology. In the simulation environment, each sensor moves at a fixed velocity of 1 block per tick (a tick is equal to 1.2 minutes in real time considering a typical human walking speed of ≈ 3.1 miles/h (≈ 5 km/h) [21]. Sensors move according to the IM model [5] because this model has the ability to accurately describe the dynamics of human mobility. We provide the average of 100 runs for each approach. The simulations stop (*default stop condition*) when 90 % of the network knows about the event. For the sake of model evaluation, we later change the stop condition, as we will see in the results. Our model contains two proposed social-based approaches (STBF and WTBF) and two benchmarking approaches (Epidemic and PRoPHET).

5.2. Ties-Based Dissemination

We propose two novel approaches, namely: *Strong-Ties-Based Forwarding* (*STBF*) and *Weak-Ties-Based Forwarding* (*WTBF*). These approaches are used for information dissemination; the dissemination process is based on the type of relation between sender and receiver (strong or weak relation). We are inspired by the work of Granovetter [10] who argued that social relations come in two kinds: strong and weak ties. He also argued that in social networks, these ties are used for different purposes but mostly that weak ties are very important for individuals to receive information from faraway locations in their social network. Our proposal is that sensors can maintain the strength of ties and use this strength to achieve different dissemination patterns.

Each sensor in the simulation has to be able to keep track of encounters with other sensors. For each sensor, all encounters are memorized in a dynamic list T_i, where *i* represents a particular sensor in the environment. The items in this list represent the *IDs* (MAC addresses in a real system) of the encountered sensors. Each sensor has two other dynamic lists that are derived from the *Ti* list: the CST_i list (the list of cumulative strong ties) contains the sensors (candidates sensors) that have strong ties with sensor *i* while the CWT_i list (the list of cumulative weak ties) for each sensor *i* contains the sensors that have weak ties with sensor *i*. These derived lists are used respectively by the *STBF* and *WTBF* approaches in the dissemination process.

In *STBF*, we extract the strong ties from the T_i list for each sensor. As mentioned, the strong ties emerge with people we associate with frequently and frequency does not correlate with friendship; the strength of a tie does not represent affinity between two individuals. The friendship relation between two individuals may be derived from the strength of the relation, but the distribution of these encounters and their regularity also play a role [22-11-23]. For the purposes of this work, friendship definition is not important, but rather frequency; most of us meet many people frequently without considering them as friends (e.g., at work). In this approach, the strong ties of a sensor can be extracted by taking the higher frequency sensors in its history of encounters (the T_i list). This process can be performed based on the so-called "80/20 rule" [24]. This rule states that for many observations, 20 % of the individuals cause approximately 80 % of the effects. The "80/20" rule was introduced to the literature in 1969 [25], but it was proposed by Vilfredo Pareto in 1906, who noticed that 20 % of the population in Italy owned 80 % of the usable land. Moreover, this rule is common in economical and natural processes; for example, 80 % of a company's sales come from 20 % of its clients. Statistically, this rule is applicable to the applications that follow a power law distribution [24]. Given that our model produces such distribution, for each sensor *i* we take the higher 20 % frequencies items of the T_i list at time *t*, and insert the corresponding sensor IDs into the CST_i to represent the sensors with strong ties to *i*.

In *WTBF*, we insert the sensor ID of the lowest 80 % frequencies items of the T_i list into the CWT_i list (weak ties). Each sensor at every time step of the simulation performs this process. In order to have values that are statistically significant, *(i)* we employ a training procedure where we let all sensors freely move with the absence of any event in the environment for 100 time steps — this procedure represents a proactive step before executing any of the approaches we used in this work aiming to create a history of encounters and initializing the T_i list for each sensor; then *(ii)* we execute a checking procedure where at every time step *t* and for each sensor *i*, the decision of inserting an item(s) into the CST_i and CWT_i lists is based on Algorithm 1. In our algorithm, we take into consideration that a weak tie may, in the future, become a strong tie. In this case, we remove this item from CWT_i and insert it into the CST_i.

Algorithm 1 Algorithm for inserting a sensor ID into the CST_i and CWT_i.

```
for all ID ∈ higher 20% frequencies in the T_i(t) do
    if ID ∉ CST_i then
        add ID to CST_i
    end if
    if ID ∈ CWT_i then
        remove ID from CWT_i
    end if
end for
for all ID ∈ lower 80% frequencies in the T_i(t) do
    if ID ∉ CWT_i then
        add ID to CWT_i
    end if
end for
```

Once the sensors have their CST_i and CWT_i lists (candidates lists). These lists can basically be used in the dissemination process of *STBF* and *WTBF* respectively. This means a sensor disseminates information only to other sensors that are in their candidates list. Furthermore, to carry out the dissemination process, three conditions must be true:

1. Receivers must not have the event.
2. Forwarders and receivers must be in the communication range of each other.
3. Receivers must be in the candidates' list of forwarders.

The two approaches described (*STBF* and *WTBF*) are designed to work in two modes:

1) In the *Full Mode*, a sensor *i* disseminates information to all sensors in its candidates list (CST_i and CWT_i lists in *STBF* and *WTBF* respectively). This mode represents the default mode of these approaches.

2) In the *Partial Mode*, a sensor has a predefined number of sensors to disseminate information to (we used 1 to 5 receivers). These receivers must be selected from sensors candidates list. Fig. 2 illustrates the workflow of our model.

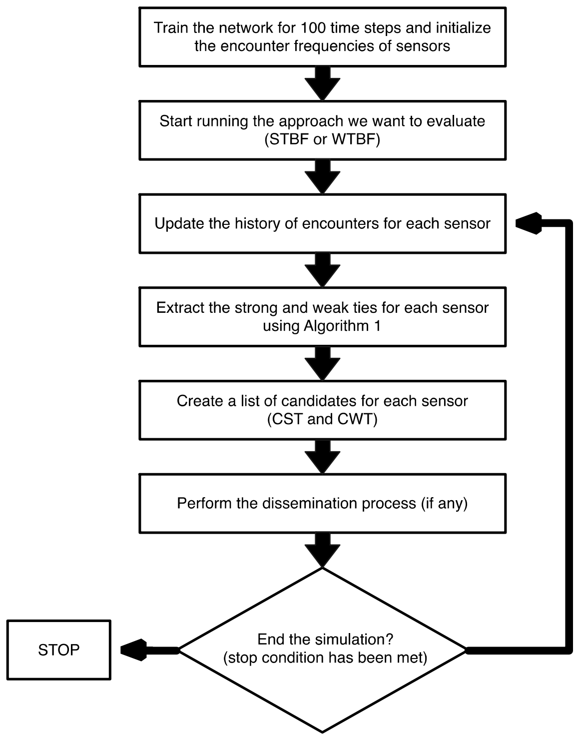

Fig. 2. Illustrates the workflow of our model (for both the proposed approaches).

6. Experimental Results

We benchmarked the proposed approaches by highlighting their behavior according to four criteria: information dissemination distance, information dissemination coverage area, number of messages exchanged, and delivery time. Moreover, for a deeper evaluation of the proposed approaches, we considered different scenarios for the Epidemic and PRoPHET approaches. In the Epidemic approach, we forced it to work in a multiple mode (in addition to its default working mode). In the default mode, a sensor spreads data randomly to all other sensors in its communication range, while in the multiple mode, we involve 1 to 5 receivers instead of considering all sensors as receivers. In PRoPHET, we involved 2 to 5 receivers rather than 1 (default working mode).

For example, if we involve 2 receivers, a sensor can forward data only to 2 receivers that are in its communication range and have highest delivery predictability.

6.1. Spreading Distance

The control of the spread distance is the main contribution of our approaches. We have proposed the two approaches aiming at having some control of the distance the event generated in a sensor will travel. The hypothesis that we adopted from social networks is that strong ties will restrict the dissemination to nearby sensors while the use of weak ties will disseminate the information to the farthest distances; spread to far distances may be useful to certain applications (e.g., emergency warnings).

In the simulations, we tested the full mode version of the proposed approaches and the default working mode of the benchmarking approaches. The findings show that the farthest possible distance from the center of the simulation environment can be obtained using the default mode of Epidemic (up to 2.85 miles), then the full mode of *WTBF* (up to 2.67 miles), followed by the full mode of *STBF* (up to 2.26 miles), and finally, the PRoPHET (up to 2.05 miles). This means that WTBF approach can disseminate information to locations as far as the ones done by a full Epidemic model.

For a detailed view to their behavior, we tested the partial mode of *STBF* and *WTBF*, and the multiple-message mode of the benchmarking approaches under different number of receivers. It should be clarified that in Epidemic, when spreading to 1 sensor, this sensor may have a strong tie to the forwarder because Epidemic discards the type of ties during the dissemination process. Therefore, this case may limit the forwarding process to include only the surrounded area (e.g., same group or community). Whereas in *WTBF*, when spreading to 1 receiver, the receiver will definitely have a weak tie to the forwarder. For this reason, the partial mode version of *WTBF* approach with 1 receiver outperforms Epidemic and the other approaches as shown in Fig. 3; this is a very interesting result because it demonstrates that if we want to maintain a low message overhead, *WTBF* can be a better alternative for message dissemination to far locations than even Epidemic. Moreover, being able to replicate such behavior in the context of mobile sensor networks (or SNoS) confirms the idea that a weak tie plays a significant role in data flowing to different social communities by acting as a bridge [10].

The results also show that the partial mode of *STBF* underperforms the multiple mode of Epidemic, and outperforms PRoPHET. Yet, the goal of *STBF* is to restrict the dissemination to nearby locations so the "underperforming" is actually the desired outcome for STBF. In more details, Fig. 3 exhibits the average spreading distance that can be obtained for each approach using different number of receivers. We noticed that each approach reaches the equilibrium when the number of receivers approximates 4 sensors; this can be interpreted as an indicator of the convergence between both modes of the proposed approaches at this level of receivers. However, this exact level may vary depending on sensor density within the simulation environment. In Fig. 4 we show the range of the distances that can be reached for each approach. This figure also shows the lowest and highest distances, the lower and upper quartiles, and the median for each approach.

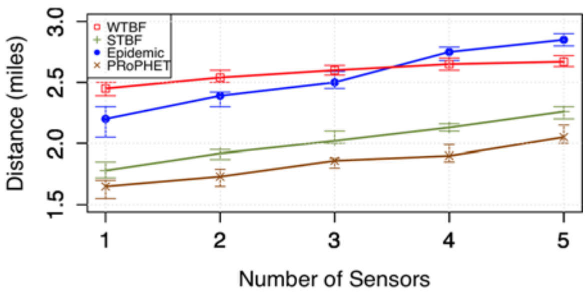

Fig. 3. The overall behavior in terms of information dissemination distance when varying the number of receivers in each approach.

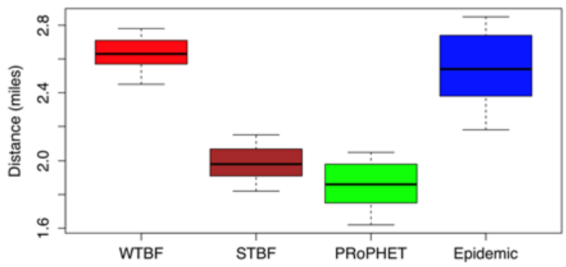

Fig. 4. The average distances and the variance of the full modes and partial modes of the proposed approaches, and the single modes and multiple modes of the benchmarking approaches.

Fig. 4 and Fig. 3 allow us to observe that the variations achieved in *WTBF* and *STBF* are smaller than the competition. *WTBF* can be said to be more reliable with the range of distance the event will reach than Epidemic because the variance is smaller. Conversely, although PRoPHET can limit the spread to very short distances, the variance is high when compared to *STBF*.

6.2. Coverage Area

Data forwarding approaches try to cover as much area in the network environment as possible. The efficiency of these approaches in terms of coverage area depends on the size of the area they cover which should be maximized, and the consumption of network resources, which should be minimized [26]. In this section, we evaluate the proposed approaches in terms of the coverage area of the dissemination process. Recall that in the simulation environment we have 38.44 sq. miles (or a square of 6.2×6.2 miles). In this evaluation, we calculate the minimum and the maximum areas that can be covered by the event during the dissemination process; these areas can be defined as follows:

- **Minimum Coverage Area**: A part of the area that is always under the coverage of data dissemination process. This can be seen as the intersection of the areas covered.
- **Maximum Coverage Area**: A part of the area, which is not always under the coverage of data dissemination process. This can be seen as the union of the areas covered.

As mentioned, we have 100 runs for each approach in our experiments; each run gives a particular coverage area. The intersection region of these areas represents the minimum coverage area, while the union of all the runs represents the maximum coverage area (as depicted in Fig. 5).

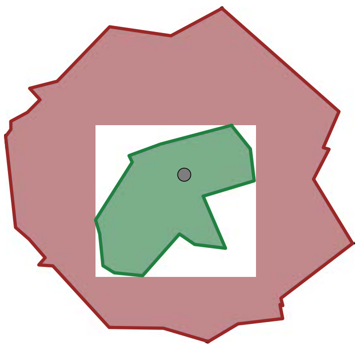

Fig. 5. The figure shows the minimum area marked close to the center of the environment (green). The maximum area is also marked by a dashed line (red) and includes all coverage runs, or the union of all coverage runs.

Fig. 6 shows the result of these areas for the proposed approaches and the benchmarking approaches. Clearly, we can see that the disparity in the areas between the minimum and the maximum is small. Tables 1 and 2 illustrate the obtained results and their proportion to the total environment area for each approach when using the default stop condition (as mentioned in Section 5.1.) of the simulations (Test 1).

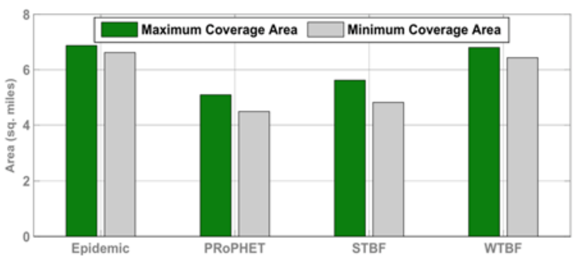

Fig. 6. Minimum and maximum coverage areas when using the simulator with a condition to stop based on 90 % of the sensors knowing about the event (Test 1).

Based on these results, we observe the following points:

- The minimum and the maximum areas that are covered using *WTBF* and Epidemic are similar.
- *WTBF* and Epidemic outperform PRoPHET and STBF in terms of minimum and maximum coverage area.
- The intensity (level or amount of data exchanged of information dissemination is extremely high in Epidemic and extremely low in WTBF.
- *STBF* covers more area than PRoPHET in both the maximum and the minimum coverage metrics. However, *STBF* has higher intensity in information dissemination than PRoPHET.

Given *STBF* is proposed to avoid the dissemination of information to faraway places, we had to investigate a little more what is happening, as the result above seems to negate our hypothesis of strong ties being useful for information dissemination to nearby locations. However, the results in Fig. 6 can be a side effect of the settings of our model that only stop when 90 % of the network knows about the event. This situation may give enough time for the event to cover more areas in the environment and hence making the performance of the approaches similar.

Table 1. Maximum coverage area of Test 1.

Approaches	Maximum Coverage Area	
	Covered Area (sq. mile)	**The proportion to the total area**
Epidemic	6.87	17.80 %
PRoPHET	5.06	13.20 %
STBF	5.62	14.55 %
WTBF	6.80	17.60 %

Table 2. Minimum coverage area of Test 1.

Approaches	Minimum Coverage Area	
	Covered Area (sq. mile)	**The proportion to the total area**
Epidemic	6.62	17.15%
PRoPHET	4.49	11.64%
STBF	4.82	12.50%
WTBF	6.43	16.65%

Hence, we changed the stop condition to be independent of the number of sensors knowing about the event. We provide two other tests (each of 100 runs) with different stop conditions. First, running the simulator for 100 time ticks (Test 2) and then for 50 ticks (Test 3). The goal of these tests is to come up with a more accurate evaluation of the proposed approaches. Fig. 7 and Fig. 8 show the minimum and the maximum coverage area for each approach. According to these results, we can observe that the disparity between the minimum and the maximum areas is more prominent than what we see in Fig. 6. These new results reflect better the behavior of both *WTBF* and *STBF* confirming the hypothesis that weak ties spread events farther than strong ties. Tables 3, 4 and 5, 6 show the results of 100 ticks and 50 ticks of running respectively, and their proportion to the total environment area. We finally measured the proportion of the minimum to the maximum coverage area of each approach for every test. Clearly, the proportions for Test 2 and Test 3 resemble the work of Granovetter better than Test 1 as shown in Table 7.

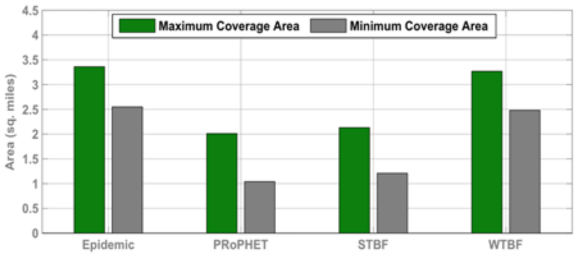

Fig. 7. Minimum and maximum coverage areas when using the setup of the experiment in which the sensors are allowed to work for 100 ticks of the simulation (Test 2).

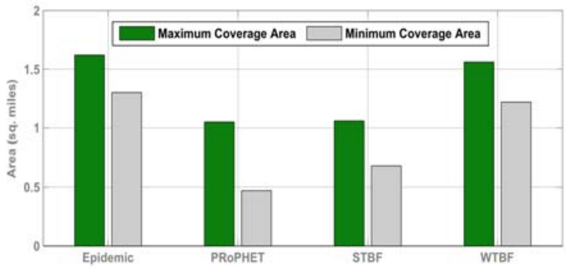

Fig. 8. Minimum and maximum coverage areas when using the setup of the experiment in which the sensors are allowed to work for 50 ticks of the simulation (Test 3).

Table 3. Maximum coverage area of Test 2.

Approaches	Maximum Coverage Area	
	Covered Area (sq. mile)	The proportion to the total area
Epidemic	3.36	8.72 %
PRoPHET	2.01	5.20 %
STBF	2.13	5.51 %
WTBF	3.27	8.47 %

Table 4. Minimum coverage area of Test 2.

Approaches	Minimum Coverage Area	
	Covered Area (sq. mile)	The proportion to the total area
Epidemic	2.55	6.60 %
PRoPHET	1.04	2.70 %
STBF	1.21	3.13 %
WTBF	2.48	6.42 %

Table 5. Maximum coverage area of Test 3.

Approaches	Maximum Coverage Area	
	Covered Area (sq. mile)	The proportion to the total area
Epidemic	1.62	4.21 %
PRoPHET	1.05	2.73 %
STBF	1.06	2.74 %
WTBF	1.56	4.04 %

Table 6. Minimum coverage area of Test 3.

Approaches	Minimum Coverage Area	
	Covered Area (sq. mile)	The proportion to the total area
Epidemic	1.30	3.37 %
PRoPHET	0.47	1.22 %
STBF	0.68	1.76 %
WTBF	1.22	3.15 %

Table 7. The proportion of the minimum to the maximum coverage area for all the approaches using the three tests we discussed (Test 1, Test 2, and Test 3).

Approaches	Test 1	Test 2	Test 3
Epidemic	96.3 %	75.8 %	80.2 %
PRoPHET	88.2 %	51.7 %	44.7 %
STBF	85.7 %	56.8 %	64.1 %
WTBF	94.5 %	75.8 %	78.2 %

6.3. Number of Messages Exchanged

The number of messages exchanged has a significant effect on the consumption of network resources (e.g., memory). Therefore, it is one of the important aspects when it comes to designing efficient sensor networks. In this section, we show the performance of all approaches in our model in terms of the number of messages exchanged. For this, we calculate this number for each approach considering all working modes of the approaches as shown in Table 8. This table also shows that the number of messages increases when increasing the number of receivers in each approach, which is expected.

As mentioned, using the weak ties of a sensor restricts the forwarding process to a few sensors compared to many sensors when using the strong ties of that sensor. For this reason, the experiments show that WTBF generates fewer messages than the other approaches because the sensors tend not to find others that do not already know about the event. This is confirmation that the message tends to stay within clusters of sensors (equivalent to a message staying within a group friends in social networks). In fact, these results agree with the RECAST approach in [11] and the results in [12] in terms of the most useful relations for data delivering.

Table 8. Performance in terms of the number of messages exchanged in our model. The columns show the approaches we use, and the rows show the working modes of each approach. The data in this table represents the number of messages exchanged per hour (msg\h). Note that forwarding to all means that a sensor forwards messages to all sensors that are in their candidates list (the equilibrium case we mentioned in Section 6.1). Also, it can be noticed that there is no forwarding to all in PRoPHET because it does not fit the approach.

	Epidemic	PRoPHET	STBF	WTBF
Forwarding to 1	509	490	418	**352**
Forwarding to 2	539	509	465	**384**
Forwarding to 3	573	539	490	**401**
Forwarding to all	622	-	504	**422**

6.4. Delivery Time

As mentioned in Section 5.1, we tried to use settings that are close to a real-world environment. In the simulation environment, each time step is called a tick, which is equal to 1.2 minute in real time. We deployed an event in the environment. The simulations stop when 90 % of the network knows about the event (default stop condition). The findings show that each approach in our model, the time needed for disseminating the event to 90 % of network sensors varies as follows (and as shown in Fig. 9 and Fig. 10): the full-mode versions of WTBF and STBF take approximately 4.2 and 3.58 hours respectively, while their partial mode versions (using 1 up to 5 receivers) take up to 5.11 hours, and up to 4.22 hours respectively. The default mode of Epidemic takes approximately 2.9 hours, and its multiple mode (using 1 up to 5 receivers) takes up to 3.7 hours. Finally, the default mode of PRoPHET takes approximately 3.85 hours, whereas its multiple mode (using 2 up to 5 receivers) takes up to 3.7 hours. In these results, we did not include the training time (100 ticks), because the event is not shown until the training time finished. This procedure makes the behavior of our model more accurate.

Based on these results, in our experiments, we can conclude the following:

- Epidemic is the fastest approach in disseminating events because a sensor forwards the event to all sensors in its communication range. However, it can also benefit from limiting the number of sensors it forwards the event to.
- The median time of STBF is close to the performance in PRoPHET.
- Minimizing the delivery time can be obtained by maximizing the number of receivers, but after a certain point the gains in delivery time are not noticeable.
- WTBF underperforms STBF, Epidemic, and PRoPHET approaches, because a sensor forwards the event less often. In contrast, strong ties are used to deliver data messages more than weak ties [24]; therefore STBF is faster than WTBF in delivering messages.

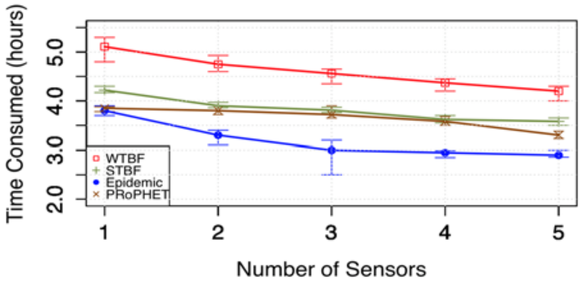

Fig. 9. The overall behavior in terms of time when varying the number of receivers in each approach. Note that there is very little gain from forwarding messages to more than 4 receivers in all approaches. This finding tells us that going beyond 4 receivers may only lead to more energy consumption without any gain in performance.

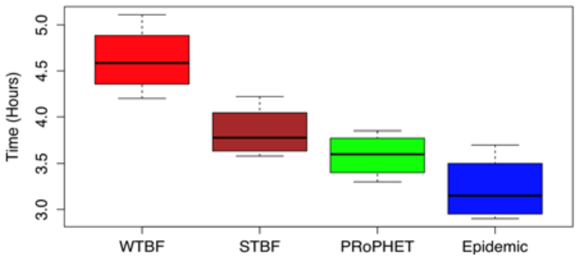

Fig. 10. The average time consumed for each approach including the full and partial modes of the proposed approaches, and the single and the multiple modes of the benchmarking approaches.

7. Conclusions and Future Works

We analyzed our results based on four criteria: information dissemination distance, information dissemination coverage area, the number of messages exchanged, and delivery time. Table 9 summarizes the approaches that have been involved in this work.

In addition, we can summarize *STBF* and *WTBF* approaches by giving some recommendations when designing a SNoS:

- If the goal is the dissemination of information to faraway distance, the best option is to use the partial mode of *WTBF*, because its results reflect a good performance in terms of distance and the number of messages exchanged. However, we should not discard the fact that *WTBF* approach spends more time than the other approaches.
- If we are looking to disseminate information to a wider coverage area with low spreading intensity we should choose *WTBF*.
- If the goal is reducing the number of messages exchanged within the network, we recommend the *WTBF* approach.

Table 9. A summary of the approaches discussed in this work.

Approach	Working Mode	Description
STBF	**Partial**	Spreading to 1-5 sensors from the candidates list of a forwarder (CST).
	Full	Spreading to all sensors from the candidates list of a forwarder (CST).
WTBF	**Partial**	Spreading to 1-5 sensors from the candidates list of a forwarder (CWT).
	Full	Spreading to all sensors from the candidates list of a forwarder (CWT).
Epidemic	**Default**	Spreading to all sensors that are in the communication range of a forwarder.
	Multiple	Spreading to 1-5 sensors that are in the communication range of a forwarder.
PRoPHET	**Default**	Spreading to one sensor according to the value of delivery predictability of a forwarder.
	Multiple	Spreading to 2-5 sensors according to the value of delivery predictability of a forwarder.

- If the time is an issue, the best option (after Epidemic) is to use the partial mode version of STBF, because it offers a reasonable performance in terms of distance and the number of messages exchanged.

As a future work, we are planning to investigate the issues of memory requirements and controlling the information dissemination direction.

Finally, the environment we currently use does not assume the existence of barriers or obstacles that may be common in urban environments. It may be interesting to investigate how the proposed forwarding mechanisms perform under configurations with obstacles (representing, for instance, buildings in a city). We believe the results will not change because the mobility model used has been shown to approximate human mobility in urban areas. The data used to evaluate the IM model comes from real cellular data in large cities.

References

[1]. G. Wang, G. Cao, T. La Porta, W. Zhang, Sensor relocation in mobile sensor networks, in *Proceedings of the 24th Annual Joint Conference of the IEEE Computer and Communications Societies (INFOCOM'05)*, Vol. 4, 2005, pp. 2302–2312.

[2]. P. Ogren, E. Fiorelli, N. E. Leonard, Cooperative control of mobile sensor networks: Adaptive gradient climbing in a distributed environment, *IEEE Transactions on Automatic Control*, 49, 8, 2004, pp. 1292–1302.

[3]. L. Atzori, A. Iera, G. Morabito, The internet of things: A survey, *Computer Networks*, 54, 15, 2010, pp. 2787–2805.

[4]. M. C. Gonzalez, C. A. Hidalgo, A.-L. Barabasi, Understanding individual human mobility patterns, *Nature*, 453, 7196, 2008, pp. 779–782.

[5]. C. Song, T. Koren, P. Wang, A.-L. Barabási, Modelling the scaling properties of human mobility, *Nature Physics*, 6, 10, 2010, pp. 818–823.

[6]. C. Song, Z. Qu, N. Blumm, A.-L. Barabási, Limits of predictability in human mobility, *Science*, 327, 5968, 2010, pp. 1018–1021.

[7]. M. Tomasini, F. Zambonelli, R. Menezes, Using patterns of social dynamics in the design of social networks of sensors, *IEEE and Internet of Things (iThings/CPSCom)*, 2013, pp. 685–692.

[8]. M. Tomasini, F. Zambonelli, A. Brayner, R. Menezes, Evaluating the performance of social networks of sensors under different mobility models, in *Proceedings of the IEEE International Conference on Social Computing (SocialCom)*, 2013, pp. 397–402.

[9]. R. A. Hill, R. I. Dunbar, Social network size in humans, *Human Nature*, 14, 1, 2003, pp. 53–72.

[10]. M. S. Granovetter, The strength of weak ties, *American Journal of Sociology*, 1973, pp. 1360–1380.

[11]. P. O. Vaz de Melo, A. C. Viana, M. Fiore, K. Jaffrès-Runser, F. Le Mouël, A. A. Loureiro, Recast: Telling apart social and random relationships in dynamic networks, in *Proceedings of the 16th ACM International Conference on Modeling, Analysis & Simulation of Wireless and Mobile Systems*, 2013, pp. 327–334.

[12]. F. Li, L. Zhao, C. Zhang, Z. Gao, Y. Wang, Routing with multi-level cross-community social groups in mobile opportunistic networks, *Personal Ubiquitous Computing*, 18, 2, Feb. 2014, pp. 385–396.

[13]. A. Mtibaa, M. May, C. Diot, M. Ammar, Peoplerank: Social opportunistic forwarding, in *Proceedings of the IEEE INFOCOM*, 2010, pp. 1–5.

[14]. K. Akkaya, M. Younis, A survey on routing protocols for wireless sensor networks, *Ad Hoc Networks*, 3, 3, 2005, pp. 325–349.

[15]. T. P. Lambrou, C. G. Panayiotou, A survey on routing techniques supporting mobility in sensor networks, in *Proceedings of the 5th International Conference on Mobile Ad-hoc and Sensor Networks (MSN'09)*, 2009, pp. 78–85.

[16]. A. Vahdat, D. Becker, *et al*., Epidemic routing for partially connected ad hoc networks, Technical Report CS-200006, *Duke University*, 2000.

[17]. C.-M. Huang, K.-C. Lan, C.-Z. Tsai, A survey of opportunistic networks, in *Proceedings of the IEEE 22nd International Conference on Advanced Information Networking and Applications*, 2008, pp. 1672–1677.

[18]. A. Lindgren, A. Doria, O. Schelén, Probabilistic routing in intermittently connected networks, *ACM SIGMOBILE Mobile Computing and Communications Review*, 7, 3, 2003, pp. 19–20.

[19]. U. Wilensky, NetLogo, Technical Report, *Center for Connected Learning and Computer-Based Modeling, Northwestern University,* Evanston, IL, 1999. http://ccl.northwestern.edu/netlogo/

[20]. S. Grossman-Clarke, J. A. Zehnder, W. L. Stefanov, Y. Liu, M. A. Zoldak, Urban modifications in a mesoscale meteorological model and the effects on near-surface variables in an arid metropolitan region, *Journal of Applied Meteorology*, 44, 9, 2005, pp. 1281–1297.

[21]. K. Fitzpatrick, M. A. Brewer, S. Turner, Another look at pedestrian walking speed, *Transportation Research Record: Journal of the Transportation Research Board*, 1982, 1, 2006, pp. 21–29.

[22]. E. Bulut, B. K. Szymanski, Friendship based routing in delay tolerant mobile social networks, in *Proceedings of the IEEE Global Telecommunications Conference (GLOBECOM'10)*, 2010, pp. 1–5.

[23]. F. Bai, A. Helmy, A survey of mobility models in Wireless Adhoc Networks, *University of Southern California*, USA, 206, 2004.

[24]. M. E. Newman, Power laws, pareto distributions and zipf's law, *Contemporary Physics*, 46, 5, 2005, pp. 323–351.

[25]. W. A. Britten, A use statistic for collection management: The 80/20 rule revisited, *Library Acquisitions: Practice and Theory*, 14, 2, 1990, pp. 183–189.

[26]. B. Gaudette, V. Hanumaiah, M. Krunz, S. Vrudhula, Maximizing quality of coverage under connectivity constraints in solar-powered active wireless sensor networks, *ACM Transactions on Sensor Networks (TOSN)*, 10, 4, June 2014, pp. 59:1–59:27.

[27]. B. Mahmood, M. Tomasini, R. Menezes, Social-Based Forwarding of Messages in Sensor Networks, in *Proceedings of the 4th International Conference on Sensor Networks (SENSORNETS'15)*, France, Feb. 2015, pp. 85-90.

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