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The Role of Human Relations and Interactions in Designing Memory-Related Models for Sensor Networks

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Abstract: Recently, the use of Wireless Sensor Networks has become substantial in most of our life aspects. These networks have many issues and challenges at the design phase (e.g., memory and power consumption). There exists a huge amount of works and studies that offer and provide solutions for many of these challenges. However, the issues of predicting memory requirements and memory management have not received enough attention in sensor networks literature. Yet, most of the studies in this field focus on issues related to power consumption and connectivity of sensor nodes. This paper has two main purposes: first, we propose a metric for measuring the strength of a relation between two sensors. In the proposed metric, we involve three important characteristics of human relations and interactions: encounter frequencies, duration of encounters, and regularities of encounters. We then exploit this metric in predicting memory requirements in a sensor network. Second, based on the estimated memory size, we propose an approach for memory management in a sensor network. The proposed approach is based on two concepts: social capital in sociology and preferential return in human mobility. The results show that our approach is effective in managing sensor memories comparing to other approaches in the literature. *Copyright © 2016 IFSA Publishing, S. L.*

Keywords: Wireless sensor networks, Social networks, Memory requirements, Mobility models, Social ties.

1. Introduction

Mobile Wireless devices such as smartphones, smart watches, tablets, and laptops have become substantial tools in our lives. Nowadays, with the widespread availability of the communication technologies (e.g., Wi-Fi), the number of these devices has significantly been increased. Yet, there exists an infrastructure formed from the mobile devices and the connections among them. Since people, who tend to be mobile, carry these devices the considered infrastructure represents a dynamic wireless sensor network in which “sensors” are the mobile devices and the connections among them are formed where these devices become in the communication range of each other. However, many issues have been introduced when designing applications on this infrastructure and many challenges have become apparent such as memory requirements, memory management, power consumption, connectivity, and security.

In the considered infrastructure, the connections among sensors are based on the social relations among people. Therefore, understanding the social networks of people supports the understanding of how information flows within the network, which may help the understanding of connectivity in these networks. Passing through the relations among network nodes performs the flow of information within a social network. The decision of transferring information from a node to other nodes is almost based on the strength of the relation to other network

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nodes. In social networks, a relation between two individuals can be *strong* or *weak* depending on the level of interactions between them [1].

As we can see from the above description, the coupling of sensor nodes to humans is interesting due to the fact that nodes would move as a consequence of human movement. In the context of human movements, one of the most accurate mobility models proposed that describes human dynamics is the work of Song, *et al.* [2], who proposed a model for describing individual mobility. This model can be incorporated into dynamic networks for simulation and evaluation purposes [3]. In the infrastructure we are dealing with, which is a peer-to-peer based, each sensor node should maintain a history of encounters with other sensors in the network for tracking purposes. Encountering more sensors within the network increases the size of the history of encounters, which is expected to gradually increase over time due to the large number of encounters. Yet, the size of the history of encounters of sensors might vary from a few items to thousands or more depending on factors such as sensor location, and network density. In many cases under the considered infrastructure, the size of sensors history of encounters cannot be handled due to memory size constraints. When a sensor's memory reaches the maximum capacity, no new encounters can be reported. Therefore, there is a need to use a predefined size for the history and then conveniently mange it, which is our purpose in this paper.

This paper has two goals as follows:

1) Proposing a metric for measuring the strength of relations among network sensors. We then involve three important characteristics of human relations and interactions: encounter frequencies, duration of encounters, and regularities of encounters. We then exploit this metric in predicting memory requirements for sensors in a network.

2) We suggest an approach for memory management, which is based on two social concepts: social capital in sociology and preferential return in human mobility.

This paper is organized as follows: the next section gives a background on this paper's area. Section 3 explores the literature and the related works. Section 4 describes our method in this paper and Section 5 presents the experimental results. Finally, we conclude our work in Section 6.

2. Background

2.1. Social Ties and Social Capital

In the social settings, people meet and encounter each other in different places, at different frequencies, and at different times. The number of encounters for people is mainly based on the features of their social relations and interactions. Every day we encounter people to whom we are familiar as well as strangers. In the context of social networks, there are two main types of ties: Strong Ties and Weak Ties [1]. Strong ties exist among family members, friends, and among people with whom we participate and associate frequently, while weak ties exist among people whom we participate and associate infrequently. Strong and weak ties play a significant role when it comes to information dissemination within a network. In the same context, the concept of social capital refers to the social benefits (economic, political, cultural, etc.) derived from the social relations and cooperation among social actors (e.g., groups or individuals) [4]. The social capital of an individual is the shared values of a relation with a particular individual [5-7]. In [8], the authors presented social capital as the total sum of the values and resources that an individual gains as a consequence of the interactions and relationships. The concept of social capital has been involved in many studies and areas such as information spreading in social networks [9]. It also can describe the characteristics of ties (e.g., the importance of a particular tie between two nodes). Moreover, social capital has many types such as public, private, formal, informal, bonding, bridging, and linking social capital. However, the main types in the literature are [10-11]: Bonding social capital exists among homogeneous actors (e.g., friends or family members) and this type is comprised primarily of strong ties. Bridging social capital exists among heterogeneous actors (e.g., across groups). This type incorporates mostly the weak ties of an individual. Linking social capital is also comprised of weak ties but only long-distance connections making linking social capital.

2.2. Homophily

In sociology, *Homophily* is the tendency of individuals to associate and connect with similar others [12-14]. According to [14], there are two main aspects of Homophily: *Status Homophily* referring to the fact that people with similar social status characteristics (e.g., race and gender) are almost tend to form ties, and *Value Homophily* which whereby individuals tend to associate with those who socially behave and think in similar ways regardless of differences in social status. However, Value Homophily has more significant impact on Homophily than Status Homophily as presented in [15]. Yet, in [16] the authors showed that Homophily could affect social capital. Borgatti, *et al.* in [17] and [18] found that Homophily, tie strength, and high rate of knowledge exchange (i.e., information flow) between two individuals have a significant impact on their social capital.

2.3. Human Mobility Model

The term "*Mobility*" in dynamic wireless sensor networks refers to the ability of sensor nodes to move in a particular pattern. A mobility model describes the movement of mobile nodes and how their positions, directions, and speed change over time [19-20]. Typically, to simulate and evaluate a dynamic network, a particular mobility model should be incorporated into the design of the network [21]. In the context of social movement, it is needed to involve models that have the ability to describe most of human mobility patterns. Song, *et al.* [2] proposed a mobility model for human dynamics that is able to precisely describe human movement. Song's model is based on two mechanisms: *Exploration*, meaning that the tendency to explore new locations decreases with time. *Preferential Return*, referring to the tendency to return to the most visited locations in the past (e.g., home or work).

3. Related Works

Measuring the strength of relations among people and predicting memory requirements in sensor networks have not received much attention by researchers. When predicting memory requirements in sensor networks, information is needed on the number of sensors that each sensor in the network should keep in memory. Therefore, it is needed to have knowledge on network pairs that are considered as friends. To this end, we require to measure the strength of relations among network sensors. The procedure of measuring the strength of ties is considered as a challenging task due to the need of involving many parameters (e.g., encounter frequency, duration of encounters, and regularity of encounters) [22-23]. Lavelle, *et al.* [24] suggested a metric to measure the strength of a tie between two individuals. They used the frequency of encounters at a predefined period of time between every two encounters. Their metric has the ability to determine whether a relation is strong or weak.

The concept of social capital has been used in different network applications such as information dissemination in social networks (e.g., knowledge transfer and exchange among network nodes). In [9], the authors explained the impact of social capital on knowledge transfer and knowledge creation in organizations. They studied the ability of organizations to use the existing resources (e.g., knowledge) and the external resources effectively for their success. In organizations, team inter- actions represent an important factor in knowledge acquisition and creation within the organization or among organizations. Another study [9] also showed that team social capital affects team knowledge transfer; when teams promote and develop their social capital using measures such as trust, they can transfer knowledge effectively. Moreover, Lin in [25] investigated the structural features (e.g., density) of people relations based on the resources that are embedded in them. He found that networks could provide the necessary conditions for accessing and using embedded resources (e.g., knowledge). In addition, he proposed a network theory of social capital that integrates network structural features such as density, reciprocity, openness, closeness, and Homophily.

Measuring the value of social capital can be performed in different methods based on network structure and available parameters. Burt in [5] showed that social component size, density, and hierarchy among individuals affect social capital. Larsen, *et al.* [11] proposed an approach to measure the value of social capital among neighbors in a particular environment. In [26], they proposed an approach to measure the value of social capital for individuals in online social networks. They used six indicators as follows: number of friends, number of community memberships, number of followers, number of posts written, number of comments made per day, and number of comments received per day. Abdel and Ali [27] measured the social capital in a network out of many networks by assuming three different variables for their networks: size, density, and transaction level (e.g., collaboration) that happened among network nodes. They found that social capital is mobilized to empowering communities to achieve collective telecommunication infrastructures. Sander, *et al.* [28] showed that social capital could be measured between two individuals based upon three main features: trust, reciprocity, and investment (e.g., information sharing).

4. Model Description

4.1. Measuring Ties Strength

Measuring the strength of a tie for a pair of sensors is one of our goals in the first part of this paper. The metric we suggest is called *Weighted Tie-Strength* or WTS, which is also the name of our dissemination approach (as we will see later in this paper). This novel metric is based on three main social features of human encounters as follows:

1. *Encounter Frequencies*: The encounter frequency of a pair of sensors represents how many times they are in the communication range of each other. In this work, each sensor *i* has a dynamic list $\varphi_{i,j}(t)$, in which the encounter frequencies of *i* with other sensors *j* at time *t* are reported.

2. *Duration of Encounters*: The duration of an encounter represents how long an encounter between two sensors lasts for. We calculate the duration rate of each pair starting from the first time they encounter as shown in Equation (1):

$$\delta i, j\ (t) = \sum_{t=tf}^{tc} DTi, j \frac{t}{\varphi i}, j\ (tc), \quad (1)$$

where $\delta_{i,j}(t)$ is the duration rate between sensors *i* and *j* at time *t*, $DT_{i,j}(t)$ is the duration time of every encounter, and *tf* is the time of the first encounter between sensors *i* and *j*, *tc* is the time of the current encounter. $\varphi_{i,j}(tc)$ is the frequency at the current time.

3. *Regularity of Encounters*: This feature reflects how regular two sensors are in their encounters. We calculate the regularity rate of each pair starting from the first time they encounter as shown in Equation (2):

$$\rho i,j\ (t) = \sum_{t=tf}^{tc} WTi,j \frac{t}{\varphi i},j\ (tc\ ), \qquad (2)$$

where $\rho_{i,j}(t)$ is the regularity rate between sensors *i* and *j* at time *t* and $WT_{i,j}(t)$ is the waiting time between every two encounters. $\varphi_{i,j}(tc)$ is the frequency at the current time.

After calculating $\varphi_{i,j}$, $\delta_{i,j}$, and $\rho_{i,j}$ lists, we normalize them to be in the range of [0, 1]. Now we move to next step, which is generating weights among network sensors. As mentioned above, we involved three main features of social encounters among people to generate the weights of network pairs. Socially, higher values of frequency (φ) and duration (δ), and lower value of regularity (ρ) between two sensors is considered an indicator that the two sensors are socially close and there exists a strong relation between them (i.e., same group members, family members, etc.). Thereafter, we calculate the weight of a relation between sensors *i* and *j* at time *t* as in Equation (3):

$$\omega_{i,j}\ (t) = \varphi_{i,j}\ (t) + \delta_{i,j}\ (t) + (1/\rho_{i,j}\ (t) \qquad (3)$$

4.2. Social Capital Calculations

Social capital is dynamic as shown by Burt in [6]. Therefore, we should consider indicators that also change over time for calculating social capital. Determining these indicators depends on the nature of the adopted infrastructure. In this work, social capital is calculated based on three indicators defined as follows:

a) Social Interactions (ι): this indicator represents the level of interactions among network sensors, which represent the weight we described above in Section 4.1 and shown in Equation (3).

b) Trust Level (τ): It expresses the amount of messages exchanged between two sensors. This indicator reflects how trustworthy two sensors are to exchange knowledge [9]. In this work, we measured the trust level of a pair of sensors by counting the number of messages they have exchanged.

c) Homophily Level (η): In Section 2.2, we described the concept of Homophily and showed its two aspects: Status and Value Homophily. However, using both aspects in calculating homophily makes our model to be overparameterized. Based on the study of Borgatti, *et al.* [18], which showed that Status Homophily on social capital is not significant, therefore, we decided to use only Value Homophily in this work. Its indicators are described as follows:

- Friends In Common (α): People have the tendency to consider their friends are like them. Yet, people tend to associate with those who have similar or close orientations [12].

- Locations In Common (β): Socially, structural positions of people can be utilized in referencing to other groups [30]. Moreover, people who are more structurally similar are most likely to have similar vies. They are more likely to associate, participate, and influence each other and eventually form social relations and connections.

- Distance In Between (γ): The distance between two individuals plays an important role given that the distance between individuals is a good measure of how strong the friendship may be as shown in [31].

According to the description above, the Homophily $\eta_{ij}(t)$ of a pair of devices *p(i, j)* at time *t* is shown in Equation (4):

$$\eta_{ij}(t) = \alpha_{ij}(t) + \beta_{ij}(t) + \gamma_{ij} \qquad (4)$$

Now, given the above three indicators the social capital (*SC*) of a pair of devices *p(i, j)* at time *t* can be calculated as in Equation (5):

$$SC_{ij}(t) = \iota_{ij}(t) + \tau_{ij}(t) + \eta_{ij}(t) \qquad (5)$$

4.3. Preferential Return Mechanism

This section describes a very important concept we adopted for the proposed memory management approach. In the human mobility model that was proposed by Song, *et al.*, in 2010, the movements of people are based on either exploring new locations (exploration) or return to the previously visited locations (preferential return). However, according to the study of Barbosa, *et al.* in 2015 [32], the concept of the second mechanism (preferential return) can be seen in two different points of view: return to frequently visited locations or return to recently visited locations. According to their findings, they observed that, in addition to the tendency to return to the most frequently visited locations, the recently visited locations have also a high visitation probability. Accordingly, we incorporated the idea of recently visited locations as an indicator in our replacement strategy for memory management (as we will see later in this paper). The reason of using this indicator in our proposed strategy is that when two individuals have recently visited the same location, the probability of both to visit this location is high. Therefore, it is more likely for them to become friends as explained by Burt [5-6].

5. Experimental Results

5.1. Predicting Memory Requirements

The settings of the simulation environment in terms of dimensions, sensor density, and the mobility model used are the same in our previous work [29].

Moreover, WTS approach (the proposed dissemination approach) has two phases: training phase for initializing the history of encounters of all sensors, and dissemination phase for information dissemination. Yet, WTS approach has two versions when it comes to the dissemination phase:

1) Default WTS, it limits the dissemination only to the highest weighted sensors that are in the communication range of the forwarder sensor.

2) Elite-WTS, it is based on the Elite Theory, it allows forwarders to disseminate information only to elite-sensors who have the highest weights with the forwarder.

Before performing the dissemination two conditions must hold true: the forwarder and the receiver must be in the communication range of each other; and the receiver must not have the event.

The main goal of this section is to predict and estimate memory requirements for network sensors. In other words, we are trying to predict memory size that each sensor should use for tracking other sensors in the environment. In sensor networks, a sensor may encounter many other sensors and if it tries to memorize all of them, it leads to a memory overflow. When overflow happens, it may prevent the new encounters to be reported into the history of encounters, which, in turn, leads undesired changes in the dissemination pattern. However, for avoid this, sensors should use a predefined size of memory, which represents the maximum allowable number of encounters that each sensor should memorize. Thereafter, it is needed to manage each sensor's memory under the predefined size by keeping the important items and remove the undesired sensors (the second purpose of this paper). By achieving these procedures, we will be able to avoid any change in the dissemination pattern.

In the experimental results, we provide the average of 100 runs for each approach and vary the number of receivers that are involved in the dissemination process for each approach. As proposed in [33] and demonstrated in [29], the use of strong ties can limit the dissemination of information to nearby locations. Therefore, the evaluation of the approaches is based on the distance that can be obtained from each approach; the more restricted the distance, the better the approach. We start the simulations with the training phase. Then, the simulations move to the second phase (dissemination phase). We benchmark our proposed approach WTS against two other approaches in the literature: STBF [29] and Lavelle's approaches [24]. Fig. 1 depicts the results of STBF, Lavelle's, and WTS (Default and Elite versions) approaches. From this figure it can be seen that when varying the number of sensors, Lavelle's approach limits the dissemination distance more than the default WTS, which in turn outperforms STBF.

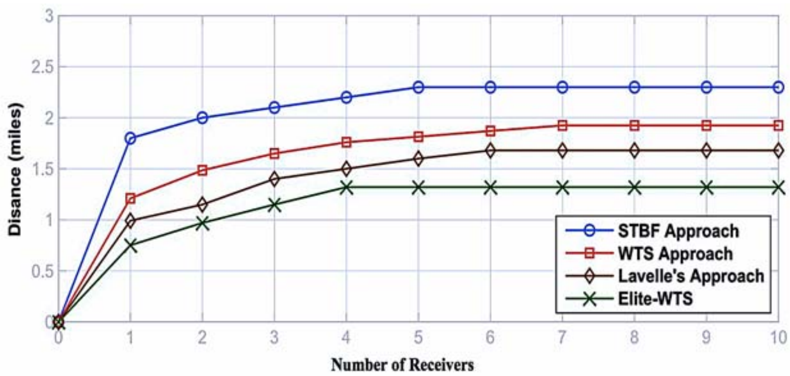

Fig. 1. Illustration of the behavior of the dissemination process when varying the approaches and the number of sensors that are involved in the dissemination process (receivers).

The reason why that STBF underperformed the other approaches is that, it does include only one feature out of many features of social encounters, which is the encounter frequency. This leads the process of determining tie strength to be inefficient.

Now, we involve the Elite-WTS version in the experiments (also shown in Fig. 1). However, before we run it, we need to define the number of sensors that should be considered as the elite-sensors.

To this end, it is required to determine the maximum number of neighbors that each sensor can have in the environment taking into consideration the given communication range (Wi-Fi). This determination leads us to know the maximum number of sensors that can be involved in the dissemination process and eventually determining the elite-sensors. As mentioned, we used the Song's model [2] as a mobility model in this work because it accurately describes human mobility patterns. Moreover, we performed a series of experiments, of which the goal is to define the number of elite-sensors. In these experiments, we use different sizes of the population as well as varying the mobility models used. We observe the number of neighbors (sensors who are in the communication range of each other) that sensors can have during each simulation separately. The results show that the maximum number of neighbors a sensor can have is ≈ 0.5 % of the population size as shown in Fig. 2. This figure also shows the stable behavior of Song's model compared to other mobility models such as Levy Flight, Cauchy Flight, and Brownian motion. The results in Fig. 2 lead to an important conclusion, which is the amount of elite-sensors is a function of the population size and is constant about ≈ 0.5 % of the total number of sensors. Therefore, we can interpret the behavior of not gaining more distance when the number of receivers is 5-6 in the dissemination process for all the modeled approaches. We also investigate the distribution of the relations' weights among network sensors. As shows in Fig. 3, the distribution follows a Gaussian distribution. Based on the characteristics of Gaussian distribution, 95 % of the observations (S) are within two standard deviations.

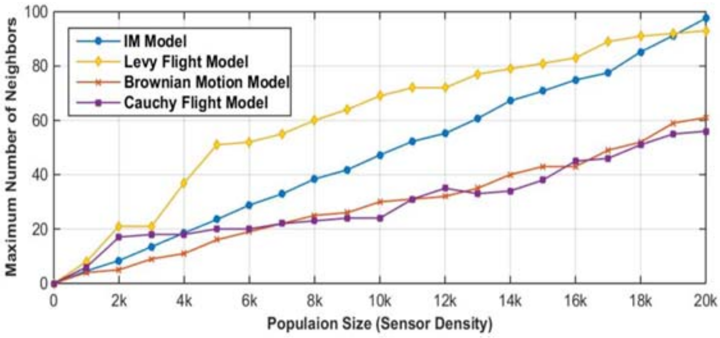

Fig. 2. Depiction of the maximum number of neighbors when varying population size and the mobility model used.

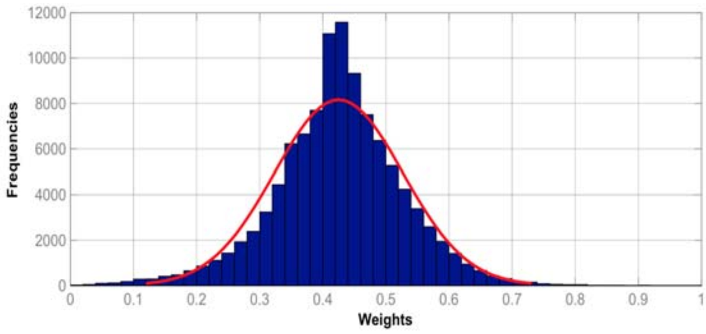

Fig. 3. The distribution of relations weights (Gaussian).

The other observations that are greater than $\mu + 2\sigma$ represents the highest 2.5 % of the total observations, while the lowest 2.5 % are smaller than $\mu - 2\sigma$, this means: $((\mu-2\sigma) < S < (\mu+2\sigma))$. Since the distribution of relations' weights using WTS approach follows a Gaussian, we are able to apply the above formula to the weights among sensors. Therefore, it is possible to inspire an indicator when defining memory limits for strong and weak ties. Based on the aforementioned description, we can better justify using the Elite-WTS version with maximum allowed number of elite sensors (≈ 0.5 % of the population size). In the simulations, for a better evaluation of our approach, we vary the number of elite-sensors to be from 1 sensor to the maximum allowed limit. The experimental results show that Elite-WTS reflects better performance than the other approaches (as shown in Fig. 1).

5.1.1. Statistical Analysis

For the sake of our proposed approach to be well evaluated, we performed statistical analysis for the obtained results. We compare the mean values of the distances that can be reached for each approach. Fig. 4 depicts that the mean distance value when using Elite-WTS is lower than the other approaches. However, the result in Fig. 4 is not sufficient because it visually does not tell much detail on the actual differences among the approaches. For this, we performed One-Way ANOVA for analyzing the variances of the modeled approaches in order to statistically prove that the mean values of our approaches are not equal.

The *null hypothesis* states that the mean values of the approaches are equal and the *alternative hypothesis* states that the means are not equal. Based on the output of the ANOVA table, we found that *F- statistic = 17.93* with a *p-value = 0.0002*. We, therefore, reject the null hypothesis of equal means for all model approaches. The ANOVA *F-test* tells whether there are differences in the mean values of the approaches. However, it does not provide information on the significance of the differences. Yet, when we rejected *the null hypothesis*, additional analysis is required to determine what is driving the difference in the mean values.

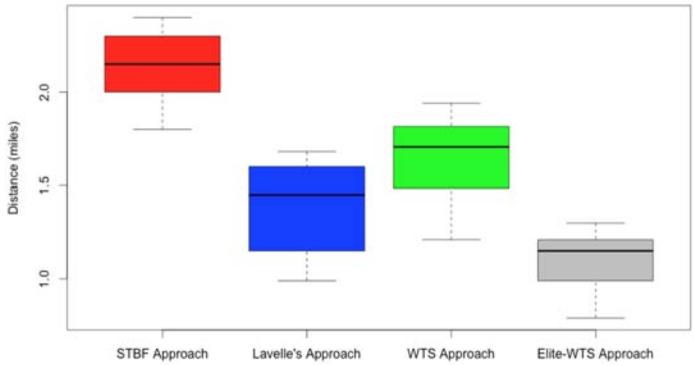

Fig. 4. Depicts the variance in the dissemination distance. It is clear that Elite-WTS outperforms the other approaches in terms of dissemination distance and variance.

Therefore, we use *Tukey's Honest Significance Test* or also known as *Tukey's Test* with 95 % of confidence level. It can be observed that there is a significant difference between Elite-WTS, and STBF and Lavelle's approaches (with *p-adjust = 0.000001* and *p-adjust = 0.02* respectively). We also observed that the difference between Elite-WTS and WTS is also significant (*p-adjust = 0.0006*), which accounts for the effect of using the Elite Theory. Based on these results, it is clear that Elite-WTS approach is more reliable for measuring ties strength than the other approaches.

Based on the aforementioned description, we can estimate memory requirements by estimating the number of strong and weak ties for each approach. In all model approaches, we varied the population size when estimating strong ties. We observed huge differences among them (see Table 1).

Table 1. The approximated number of strong ties when varying the size of population.

Sensor Density	STBF	Lavelle	WTS
1000	≈ 169	≈ 7.5	≈ 5
2500	≈ 420	≈ 20	≈ 12.5
5000	≈ 843	≈ 40	≈ 25
10000	≈ 1689	≈ 80	≈ 50
Percentage	≈ 17 %	≈ 0.8 %	≈ 0.5 %

Now, we are able to follow the results of Elite-WTS approach to measure the strength of ties among sensors. Finally, our estimation can be summarized as follows: the maximum number of strong ties ≈ 0.5 % of total population size, and the minimum number of weak ties ≈ 2.0 % of total population size.

5.2. Memory Management

5.2.1. Memory Anticipatory Strategy (MAS)

After estimating memory requirement as explained in details in the previous section, this section aims at proposing an approach for memory management. We call our proposed approach *Memory Anticipatory Strategy* (*MAS*) the reason behind this name is that our approach tries to anticipate whether a current encounter is important (the importance of a particular tie). MAS approach starts its work when sensor memory reaches the maximum allowable number of items. The MAS can remove one (or more) of the current items from sensor memory and replace it with one (or more) of the new incoming ones.

As described in the previous section, a sensor can keep track ≈2.5 % of devices in the environment as strong and weak ties (strong ties take about ≈0.5 % and ≈2.0 % for weak ties). Based on these results, we consider the maximum number of items that a sensor can store in its memory to be ≈2.5 % of the total number of sensors in the environment. During their movements in the simulation environment, sensors encounter each other; some of these encounters are important while others are not. A sensor memory that is limited in size may become full due to the large number of encounters in the environment. The MAS strategy starts when a device's memory contains the maximum allowable number of items. MAS performs two basic operations:

- Add Operation: A sensor adds an item into its memory if both the current encountered sensors have recently visited the same location – the most recent one according to [32] – this is also called the *adding condition*.

- Remove Operation: A sensor removes the item that has least value of social capital in its memory if the adding condition holds true.

To better understand MAS, we consider the following scenario: Consider A as a sensor with maximum allowable items in memory equal to 2. The current items in A's memory are X and Y with social capital values of 2.5 and 4.0 respectively, and the recent location of A is l_i. Furthermore, consider that A currently encountered two other sensors in the environment B and C and their recent locations l_i and l_j respectively. The status of A's memory is currently full. In such case, our model uses the MAS strategy to decide whether adding B, C, both, or neither is necessary. However, to add an item into A's memory, the recent location of B and/or C must be the same of A's recent location. In this scenario, B has the same recent location of A which is l_i. This means, B is a candidate to be added into A's memory. Now, the item that should be removed from A's memory must be chosen. MAS chooses the item that has least value of social capital among A's items: X in this case. Finally, MAS removes X then adds B. The reason of choosing B rather than C is the probability of B to encounter A is high in the future (more important). This means, the probability of them to be friends is also high. There are also some other cases that MAS strategy performs, such that, if two items D and E have the same recent location of A, MAS removes two items from A's memory that have least value of social capital among A's items and adds both D and E.

The MAS strategy can be characterize by the following:

- Only local information is used in the processes. This means a sensor does not request any external information (e.g., network level parameters) that cannot be accessed directly by the sensor.

- The MAS strategy always provides sensors with weak ties, and avoids keeping only strong ties in memory. More precisely, when adding an item to a device's memory, MAS does not take into consideration its social capital value. The item that is added may have a smaller value of social capital than the removed one.

- MAS calculations are dynamic and on-the-fly, this means at every time step a sensor uses the MAS strategy if an encounter occurs.

- MAS is socially inspired, in which two social concepts are involved; social capital and human mobility patterns.

For benchmarking purposes, we use two well-known approaches in memory management literature: FIFO and LRU:

5.2.2. FIFO Algorithm

The first-in-first-out is the most popular algorithm when it comes to memory management in operating systems. In this algorithm, an item that is added first will be removed first. It is widely used as a baseline by researchers to benchmark their approaches.

5.2.3. Marking-LRU Algorithm

In the context of operating systems, marking algorithms represent a general class of paging replacement algorithms that are based on the reference (e.g., reference bit) to recent use of a page. Least Recently Used (LRU) is a marking algorithm in which a page that is recently used is marked (e.g., reference bit is set). LRU is also used for benchmarking purposes. It has two main functions as follows; first, it memorizes the pages that have recently been involved in a process. Second, it replaces the pages that have not been used for longest time. In our model, we use LRU in our model as follows. For each sensor in the simulation environment, a list of recent encounters (recent-list) is generated. This list stores only the IDs of the recent encountered sensors without considering other encounter information. If sensor memory reaches the maximum allowed limit and a new encounter happens, LRU *removes* the least recent encounter from memory and *adds* an item from the recent-list of that sensor under the condition that there is at least one of the new encountered items in the recent-list (candidate item).

Our measurement in this part of our work is *Replacement Rate*, which represents the average replacements of all sensors over times. Assume that the number of replacements of sensor i at time t is $Ri(t)$, then:

$$Replacement\ Rate\ (t) = \frac{(\sum_{i=1}^{n} Ri(t)\ )}{n}, \qquad (6)$$

where n is the number of sensors deployed in the simulation environment. Fig. 5 depicts the cumulative replacement rate of the modeled approaches. According to Fig. 5, MAS gains lower rate comparing to the other approaches. The reason of gaining lower rate is that MAS infrequently replaces items in memory. This result reflects the fact that weak and strong ties do not tend to change frequently. Moreover, we evaluate the variances of all the modeled approaches (see Fig. 6). Clearly, MAS has a smaller variance than the benchmarking approaches. It should be mentioned that the above results are not reliable because they do not tell much detail on the differences among the modeled approaches. For this, it is needed to statistically approve these results. One- Way ANOVA is used to show whether the means μ of the approaches are similar. Our null hypothesis states that all the means are equal and the alternative hypothesis states that they are not equal. The output of ANOVA shows that *F-statistics = 11.26* and the *p-value = 0.001*. Given these results, we reject the null hypothesis. This confirms the differences in the mean. Now it is needed to verify if these differences are statistically significant. To this end, Tukey's Test with 95 % of confidence is used. It shows that the difference between the pair (MAS, FIFO) with a *p-value* of *0.004* is significant. Yet, the *p-value* of the pair (MAS, Marking-LRU) equals *0.003* is also significant. As a result, it can be said that our proposed approach (MAS) is efficient and it outperforms the benchmarking ones in terms of replacement rate and variance. Based on the framework considered in this work, the social relations and interactions of any given two sensors are symmetric. More precisely, assume that two sensors A and B encountered each other at a particular time, in this case, A and B are in each other's memory (history). During their movements, A may decide to remove B from its history, here, A still in B's memory. However, when A and B encounter again leading to A adding B back into its memory, it can retrieve from B all information about their history. This feature is important because it helps in keeping more historical tie strength. The results in this work show that the *Remove* operation in MAS prevents removing strong ties and in the same time the *Add* operation provides memory with weak ties. This means that MAS makes a balance between weak and strong ties.

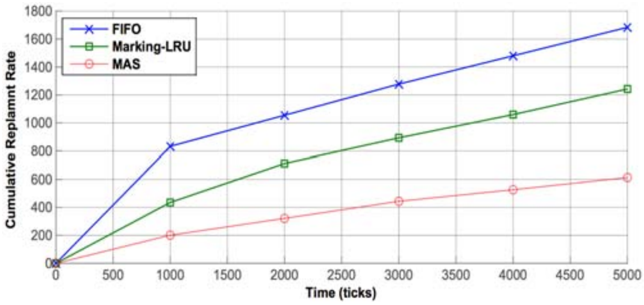

Fig. 5. Cumulative replacement rate for all the modeled approaches.

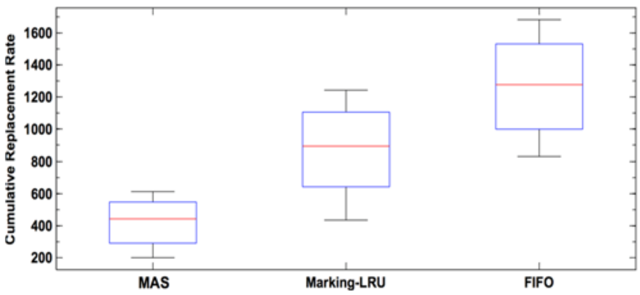

Fig. 6. Showing the variations (variance) in dissemination distance. The variance for each approach is obtained from all the runs (100 runs for each approach).

6. Conclusions

This paper dealt with two main issues in dynamic sensor networks: predicting memory requirements and memory management. The former is divided in to two parts:

1) Measuring the strength of ties among sensors. For this purpose, we proposed an approach for measuring the strength of a tie between two sensors based on three important characteristics of social encounters among people: encounter frequencies, duration of encounters, and regularity of encounters. We estimate the number of sensors that a sensor should keep memorize as strong and weak ties.

2) Predicting memory requirements by exploiting the proposed metric and define memory limit. The results show that each sensor needs to memorize about ≈ 0.5 % of population size as strong ties and about ≈ 2 % as weak ties.

The second main issue investigated in this paper is memory management; we proposed a social-inspired replacement approach (MAS) for memory management in sensor networks. This strategy is basically depends on two social concepts: social capital and preferential return mechanism in human mobility. We benchmarked MAS against two approaches; FIFO and Marking-LRU in the memory management literature. The results show that MAS is efficient comparing to the benchmarking approaches in two terms: replacement rate and variance. Also, MAS successfully prevent removing the strong ties of a sensor that are important to that sensor and provides memory with weak ties.

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