A Social-based Strategy for Memory Management in Sensor Networks

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Abstract: The technological structure of today's societies enables people to easily exchange and share their information. This structure contains many sophisticated technologies such as mobile wireless devices (e.g., smartphones and tablets). These devices are mainly used for connecting people with each other. As these devices grow in usability, many issues have become apparent such as memory management, security, and power consumption. In this paper, we propose a novel social-based strategy for memory management in mobile sensor networks. This strategy is inspired from two concepts, namely, *social capital* in sociology and *preferential return* mechanism in human mobility. The findings show that the proposed strategy is quite effective in keeping up-to-date information in each sensor/device about the sensor connections. We believe that this is the first work that investigates the issue of memory management in this type of networks using concepts form social networks and human mobility.

1 INTRODUCTION

Wireless devices (e.g., smartphones, tablets, laptops) have become important tools to many aspects of our lives. These devices support people in different tasks related to education, business, and social interactions. Recently, the use of wireless devices has significantly been increased, especially, with the widespread availability of the communication technologies (e.g., Wi-Fi). Therefore, an infrastructure that is formed from wireless devices and the connections among them already exists around us. Since these devices are carried by people who tend to be mobile, the considered infrastructure represents a Dynamic Wireless Sensor Network (DWSN) in which "sensors" are the mobile wireless 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 management, power consumption, connectivity, and security.

In the aforementioned DWSN, the connections among sensors depend on the social relations and interactions among people. Therefore, understanding the social networks helps the understanding of how information flows within the network which eventually may contribute in overcoming connectivity in these types of networks. The flow of information within a social network is performed by passing through the relations among network nodes. Moreover, the decision of passing information from a node to another one is more likely based on relation strength between the individuals. Yet, the strength of a relation between two individuals depends on the type of relation they maintain (Burt, 1982)(Borgatti et al., 1998)(Coleman, 1988). In social networks, the relations among individuals can be in two types: *strong* or *weak* depending on the behavior and the level of interactions (e.g., frequency of encounters between the individual) (Granovetter, 1973). Furthermore, *Social Capital* is another characteristic in social networks, by which the importance of a relation between two individuals can be quantified.

1.1 Social Capital and Homophily

In sociology, the concept of *Social Capital* refers to the benefits (economic, political, cultural, etc.) derived from the social relations and cooperation among social actors (e.g., groups or individuals) (Putnam, 2000). The social capital of an individual, in its simple case, is the shared norms and values of a connection with a particular individual (Burt, 1997)(Burt, 2001)(Coleman, 1988). Moreover, (Lin, 1999) defined social capital as *"resources embedded in an in-*

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dividual's social network, resources that can be accessed or mobilized through ties in the networks". Furthermore, social capital is not possessed by people themselves, but it is embedded in the social relationships among them (Wisconson Center for Education Research, 2006). (Ehrlich and Carboni, 2005) presented social capital as the total sum of the resources that an individual gains as a result of the interactions and relationships. (Licamele et al., 2005) also defined the social capital of an individual as the benefits that are given or received by this individual. Finally, (Johannessen, 2012) described social capital as the relations among individuals including the reciprocal trustworthiness which makes them more powerful in their social networks.

The concept of social capital has been used in different studies such as information dissemination in social networks (Bosen and Gang, 2010). It also describes many of social ties characteristics (e.g., cooperation among individuals, and the importance of a particular social tie), and among these characteristics one can include the classification of ties into weak and strong as defined by (Granovetter, 1973); clearly a high social capital needs to include some diversity between weak and strong tie.

Social Capital however is not a unified concept and the literature has introduced sub-classifications of the concept such as public, private, formal, informal, bonding, bridging, and linking social capital. However, the main types of social capital in social network literature are (Adhikari, 2008)(Larsen et al., 2004): 1) *Bonding* social capital exist among homogeneous actors (e.g., friends or family members) and this type is comprised primarily of strong ties. Hence, bonding social capital may be appropriate for internal information dissemination (e.g., among same group members). 2) *Bridging* social capital exists among heterogeneous actors (e.g., across groups). This type incorporates mostly the weak ties of an individual and can be useful in external information dissemination (e.g., among different groups). 3) *Linking* social capital is also comprised of weak ties but only long-distance connections making linking social capital also important for external information dissemination.

In social sciences and social networks, *Homophily* is the tendency of one to associate and connect with similar others (McPherson et al., 2001)(Ibarra, 1992)(Marsden, 1988). According to the seminal work of (McPherson et al., 2001), there are two main aspects of homophily, namely; *status homophily* which refers to the fact that individuals with similar social status features (e.g., race, gender, religion, and age) are more likely to form ties, and *value homophily* which whereby individuals tend to participate with those who 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 (Yuan and Gay, 2006). Moreover, there are many factors that lead to homophily such as geography (e.g., people's colocation), social ties (e.g., strong and weak ties), organizational foci (e.g., school or work), isomorphic sources (e.g., people who occupy equivalent roles), and cognitive processes (e.g., people who have demographic similarity) (McPherson et al., 2001). More importantly, (Lin, 1999) showed that homophily, as a social characteristic, can affect social capital. (Borgatti and Foster, 2003) and (Borgatti et al., 1998) found that homophily, tie strength, and high rate of knowledge transfer (i.e., information flow) between two individuals have a significant impact on their social capital.

1.2 Human Mobility

In DWSNs, the term *mobility* refers to the ability of nodes (sensors) to move in some way. One of the ways that sensors move is following a mobility model which describes the general spatio-temporal regularities of sensor node movements; more precisely, a mobility model describes the movement of mobile nodes and how their positions, directions, and speed change over time (Lin et al., 2004)(Kesidis et al., 2003). Typically, to simulate and evaluate a DWSN, a particular mobility model should be incorporated in the network (Musolesi and Mascolo, 2009). In the context of social movement, we need to use models that have the ability to describe most of human mobility characteristics. (Song et al., 2010) proposed a model for human mobility to that is able to precisely describe human movement. Their model is based on two mechanisms:

Exploration: The tendency to explore new locations decreases with time. This mechanism ensures that the next step of an individual can be completely independent of the previously visited locations.

Preferential Return: Humans behavior reflects an important property, which is the tendency to return to the most visited locations in the past (e.g., home or work).

(Song et al., 2010) represents the state of the art in modeling of human mobility. Recently other models have been proposed to focus on irregularities of human movement (e.g. (Barbosa et al., 2015)) but in the context of sensor networks, the regularities are more important because they represent the "normal" pattern of movement and hence can be exploited in information dissemination.

1.3 Problem Statement

In the beginning of Section 1, we described the framework we are working with. In this framework, wireless devices are carried by people who encounter each other as a part of their social activities. In the context of sensor networks, as people encounter each other, their devices also can establish connections each other by one of the communication technologies available (e.g., Bluetooth or Wi-Fi). These encounters should be stored in the devices' memories if one wants to make use of the regularities of encounters in information dissemination. The tracking of encounters requires these devices to remember their history of encounters. The ability to use this past information of encounters efficiently depends considerably on the size of devices' history. People however are likely to encounter many others as part of their daily activities and keeping track of all these encounters adds a burden to the sensors since it may not be able to store all the history due to strong memory constraints in the devices. In our previous work (Mahmood et al., 2015), we investigated the issue of memory requirements and predicted the size of memory that devices should use for tracking purposes. The findings showed that a device needs to be able to track $\approx$ 2.5% of the total number of devices in the environment ($\approx$0.5% is dedicated for strong ties and $\approx$2.0% for weak ties). Moreover, this approximation represents the maximum number of devices that can be tracked by a device. When one uses a pre-defined size of memory for tracking, it may become full and no space may be available for the new incoming encounters to be reported during people movement. This leads to loss some encounters that are perhaps important to devices and eventually affects, for example, data spreading pattern. This situation introduces the issue of *memory management* in sensor networks. To deal with this issue, a decision should be made to replace one (or more) of the existing item(s) in the list of encounters with the incoming (new) ones. This decision should avoid the loss the important encounters of devices. Therefore, in this work, *we propose a novel social-based approach for memory management in sensor networks inspired from two concepts, namely, social capital in sociology and preferential return mechanism in human mobility model*. In the former, we calculate the social capital among individuals based on three indicators: *Interaction Level*, *Trust Level*, and *Homophily Level*. For the latter, we involve the recent location of an individual as an indicator to also determine the importance of the current encounters. Our claim in this work is that using the aforementioned social concepts can efficiently contribute in managing a device's memory.

This paper is organized as follows: next section presents the related works, in Section 3 we describe the details of our memory management model, Section 4, we present the main results, and then we conclude our paper in Section 5.

2 RELATED WORKS

The concept of social capital has been used in different network applications such as information dissemination in social networks (e.g., knowledge transfer among network nodes). (Bosen and Gang, 2010) explained the effect 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 interactions represent an important factor in knowledge acquisition and creation within the organization or among organizations. The interactions among individuals as proposed in (Smith, 2008) and (Yao et al., 2014) can be incorporated to the formation social capital. Therefore, team social capital in an organization represents the intensity of the interactions within a team or among teams. (Bosen and Gang, 2010) 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. Furthermore, trust can help to decrease risks in the relationships among team's members and make them more likely to share their knowledge (Bosen and Gang, 2010)(Hsu et al., 2007).

(Lin, 1999) investigated the structural features (e.g., density) of people relations based on the resources that are embedded in them. He found that networks can 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. For instance, the density of a network may increase resource sharing among participant individuals or groups.

Measuring the value of social capital can be performed in different methods based on network structure and available parameters. (Burt, 1997) showed that social capital is affected by social component size, density, and hierarchy between individuals. (Larsen et al., 2004) measured the social capital among neighbors two neighbors interact and trust each other in the daily activities. (Licamele et al., 2005) proposed a friendship-event network which is a specific form of a social network capturing features of two inter-related networks (a friendship network and an event network). The event network describes events, event participants and organizers. Using these networks, they infer social capital based on the actor-organizer friendship relationship. Their dataset contains information from three scientific conferences for ten years. In the findings, they observed that having few powerful friends (e.g., high value of social capital) is more important than having many powerless friends (e.g., low value of social capital), and this power can be changed over time. In (Phung et al., 2013). They proposed an approach to calculate the social capital of an individual in online social networks which uses six indicators: 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. For each indicator, three values are defined: *low*, *medium*, and *high* based on the activity of an individual.

(Abdelaal and Ali, 2012) calculated the social capital in a network out of different wireless networks by considering three variables: *network size*, *network density*, and *the value of a transaction* (e.g., collaboration) that occur among actors. They found that social capital is mobilized to empowering communities to achieve collective telecommunication infrastructures. (Bosen and Gang, 2010) and (Zhao and Wang, 2009) showed how team social capital can support knowledge transfer more effectively. They used three social dimensions: *structural* (e.g., the intensity of social interactions among team members), *cognitive* (e.g., shared language, goals, and culture), and *relational* (e.g., trust). (Law and Chang, 2012) involved the same social capital factors used in Bosen and Gang's work—except the cognitive feature—to calculate one's social capital. They observed that these factors have a significant impact on knowledge transfer. (Smith, 2008) distinguished the connections among individuals as follows: *Explicit Social Networks* (ESNs) and *Implicit Affinity Networks* (IANs). ESNs connect actors together based on a well-defined relationship (e.g., many features in common). IANs connect actors based on loosely defined affinities (e.g., less features in common). Smith also mentioned that social capital is grounded on *relationships*, *individuals' attributes*, and *available social resources*. Based on the ESNs and IANs, they calculate two types of social capital; *bonding* and *bridging* social capital. (Subbian et al., 2013b)(Subbian et al., 2013a) calculated social capital based on the *closeness centrality* measurement in social networks. (Sander and Teh, 2014) showed that social capital can be determined between two individuals based on three main characteristics: *trust*, *reciprocity*, and *investment* (e.g., information sharing).

Overall, the descriptions of the works here tell us that social capital can be estimated. Despite the differences in the approaches above, what is important for our work is that the social capital of individuals can be extracted from their social network or network of encounters. Our approach is hence quite general because one may be able to change how the social capital is calculated and get different results. This may be useful in special-purpose scenarios in which social capital may be better defined according to one of the works above.

3 MODEL DESCRIPTION

As mentioned in Section 1.3, we propose a novel social-based replacement strategy for managing memory in sensor networks. This strategy is inspired from two social concepts: *social capital* and *preferential return*. The main idea behind our approach is to have a replacement mechanism, by which the importance of an encounter between two nodes can be determined and eventually helps the decision of replacing items in sensors' memories.

3.1 Calculating Social Capital

(Burt, 2000) pointed that social capital is dynamic and should consider indicators that also change of time. Determining these indicators is subject to the nature of the adopted infrastructure (see Section 2). In our work, social capital is calculated based on three indicators defined as follows (see also Figure 1):

Social Interactions (ι): This indicator expresses the level of interactions among network devices that contributes in measuring the strength of the relation between two devices. In this work, three aspects are used to measure this level:

- *Frequency of Encounters* (ϕ): The frequency of encounters of a pair of device represents how many times they encounter in a period of time.
- *Duration of Encounters* (δ): The duration of a particular encounter represents how long encounters tend to last for.
- *Regularity of Encounters* (ρ): Provides us with information about the regularity the encounters of a pair of devices. More precisely, it represents the time it generally takes until the pairs encounter each other again (waiting time).

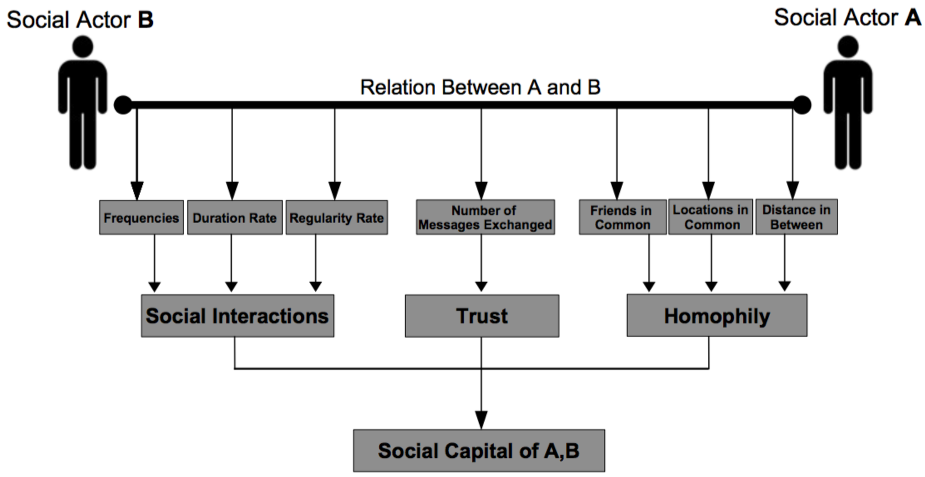

Figure 1: The definition of the social capital of a pair of social actors (individuals) A and B. It can be seen that many social characteristics are embedded in the relation between A and B and the collective value of these characteristics forms social capital of the pair A,B.

Based on the aforementioned aspects of social interactions, a relation between two devices is considered strong when they have high rates of frequency and duration, and low rate of regularity. Now, the interaction level ($\iota_{ij}(t)$) between a pair (i,j) can be calculated based on the following equation:

$$\iota_{ij}(t) = \phi_{ij}(t) + \delta_{ij}(t) + \frac{1}{\rho_{ij}(t)}. \quad (1)$$

Trust (τ)**:** This indicator reflects the amount of data exchanged between two devices. This means how trustworthy they are to share knowledge (Bosen and Gang, 2010)(Hsu et al., 2007). In our model, we measured trust of a pair by counting the number of messages that two devices have exchanged.

Homophily (η)**:** In Section 1.1, we described the concept of homophily and showed two aspects of it; status and value homophily. However, using both aspects in calculating homophily leads to our model to be over-parameterized. Based on the study of (Borgatti et al., 1998) on the factors that affect social capital, which stated that of status homophily on social capital is not significant , we decided to use only value homophily in our approach:

- *Friends In Common* (α): Individuals tend to consider that their friends are like them and also tend to participate with those who have similar orientations (McPherson et al., 2001). The effect of this feature can be on, for example, resource sharing among devices.
- *Locations In Common* (β): Structural positions of individuals can be used as a reference of other groups (Festinger, 1950). Yet, individuals who are more structurally similar are most likely to have similar vies. Also, they are more likely to communicate, influence each other (Burt, 1982)(Friedkin, 1993) and eventually form social connections (Cho et al., 2011).
- *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 (Preciado et al., 2012).

According to the description above, the homophily $\eta_{ij}(t)$ of a pair of devices $p(i, j)$ at time t is:

$$\eta_{ij}(t) = \alpha_{ij}(t) + \beta_{ij}(t) + \gamma_{ij} \quad (2)$$

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 follows:

$$SC_{ij}(t) = \iota_{ij}(t) + \tau_{ij}(t) + \eta_{ij}(t), \quad (3)$$

3.2 Preferential Return

In the human mobility model that was proposed by (Song et al., 2010), the movements of an individual 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., 2015), 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 in the next section). The reason of using this indicator in our proposed strategy is that when two individuals 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 (Burt, 1982)(Friedkin, 1993)(Preciado et al., 2012).

3.3 The Anticipatory Strategy

We named our approach *Memory Anticipatory Strategy* (MAS) because it tries to anticipate whether a current encounter is important and hence should be "remembered". The main goal of proposing MAS is to manage a device's memory when it reaches the maximum allowable number of items (device IDs) in memory. The MAS strategy aims to remove one (or more) of the current items from device's memory and replace it with one (or more) of the new incoming ones.

Determining the maximum number of items that a device can store in its memory is based on the number of devices that can be tracked by a particular device. In our previous work (Mahmood et al., 2015), we investigated the issue of memory requirements. We observed that a device can keep track ≈2.5% of devices in the environment (e.g., a city), we also observed that 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 device can store in its memory to be ≈2.5% of the total number of devices in the environment.

While devices move in the simulation environment, they encounter each other; some of these encounters are important while others are not. Ideally one would prefer to have a a full history of encounters in the devices' memories. However, a device's memory is limited may become full due to the large number of encounters. The MAS strategy starts when a device's memory contains the maximum allowable number of items. It performs two basic operations as follows:

Add Operation: A device adds an item into its memory if both the current encountered devices recently visited the same location—the most recent one according to (Barbosa et al., 2015)–this is also called the *adding condition*.

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

For a better understanding of how the MAS strategy works, a scenario is considered as follows: Consider A as a device 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 devices 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 (as explained in Section 3.2). 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.

Algorithm 1 shows the process of removing and adding item(s) into a device's memory. In this algorithm, A is a device in the environment. The maximum number of items that each device can store is Max_{limit}. A contains items that were previously added A_{items}. Also, E_{items} is a list that contains the devices that are currently near the device A (the list of devices encountered by A).

Algorithm 1: Illustrates the main steps of MAS strategy for managing the memory of a device.

INPUT: E_{items}, A_{items}, and Max_{limit}
for each item $\in (A_{items} \cap E_{items})$ **do**
  Update *SocialCapital* using **Equation 3**
end for
MinScItem = Minimum Social Capital $\in A_{items}$
if Length(A_{items}) $= Max_{limit}$ **then**
  for each item $\in E_{items}$ **do**
    if $RecentLocation(item) = RecentLocation(A)$ **then**
      remove MinScItem **from** A_{items}
      add item **into** A_{items}
      Initiate the social capital of *item*
    end if
  end for
end if

The MAS strategy can be summarized as follows:

- Only local information is used in the processes. This means a device does not request any external information (e.g., network level parameters) that cannot be accessed directly by the device.
- The MAS strategy always provides devices with weak ties, and avoid 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 social capital than the removed one.
- MAS calculations are dynamic and on-the-fly, this means at every time step a device uses the MAS strategy if an encounter occurs.
- MAS is a social-inspired approach, in which two social concepts are involved; social capital and the social behavior of human movements.

4 EXPERIMENTAL RESULTS

4.1 Simulation Environment

The simulation environment we designed is implemented as follows: a squared city of 10×10 km, the city consists of 100×100 squared blocks. About 2000 mobile nodes are exponentially distributed in the city because most metropolises follow this distribution (Grossman-Clarke et al., 2005). Each mobile node represents an individual who carries a wireless mobile device (e.g., smartphone, tablet, or laptop). Wi-Fi technology is used for connecting devices with range of $\approx$50 meters, the communication type is peer-to-peer based. In the environment, each node moves at a fixed velocity of 1 block per tick. Given the environment dimensions, a *tick* is equal to 1.2 minute in real time considering that each device is carried by humans who have an average walking speed is $\approx$5 km/h (Metta et al., 2006). Finally, the nodes move based on human mobility model (Song et al., 2010) (as described in Section 1.2).

4.2 Benchmarking Approaches

In this work, two well-known approaches (FIFO and LRU)[1]—that are used in page replacement algorithms in operating systems—were used to benchmark the our proposed approach (MAS):

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 (Hopcroft et al., 1983). It is widely used as a baseline by researchers to benchmark their approaches (Galvin et al., 2013).

Marking-LRU Algorithm: Marking algorithms represent a general class of replacement algorithms that are based on the reference (e.g., reference bit) to recent use of a page (O'neil et al., 1993). 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 other approaches. It works based on two mechanisms; 1) it memorizes the pages that has recently been used. 2) Replace the pages that have not been used for longest time. In our model, we implemented LRU by applying its mechanisms as follows. For each device, we use a list of recent encounters (recent-list), in which we store *only* the IDs of the recent encountered devices without considering other encounter information[2]. When device's memory reaches the maximum limit and a new encounter occur, LRU removes the least recent encounter from device's memory and adds an item from the recent-list of that device under the condition that there is at least one of the new encountered items in the recent-list (candidate item). Practically, this means that the candidate item is used more frequently than the one that is removed.

4.3 Experimental Results

We have implemented the proposed approach (MAS) plus two others used for comparison purposes: Marking-LRU and FIFO. The replacement rate is the metric used for benchmarking MAS. The replacement rate represents the average replacements of all sensors over times. Consider the number of replacements of sensor i at time t is $R_i(t)$, then:

$$ReplacementRate(t) = \frac{\sum_{i=1}^{n} R_i(t)}{n}, \qquad (4)$$

where n is the number of devices that are deployed in the environment.

Figure 2 depicts the cumulative replacement rate of the modeled approaches. Clearly, MAS reflects lower replacement rate because it infrequently replaces items in memory. This is a positive result because it reflects the known fact that our weak and

[1] We benchmark our approach against these two approaches because they fit the social framework we are dealing with.

[2] The recent-list is used only to support the decision of which item in this list will be stored in the memory of that device.

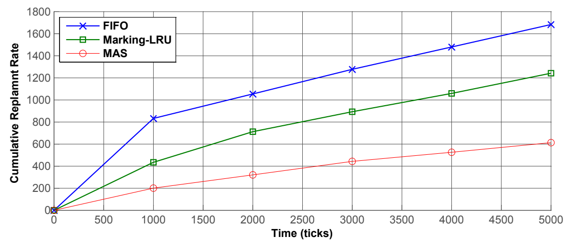

Figure 2: Cumulative replacement rate of MAS, Marking-LRU, and FIFO approaches.

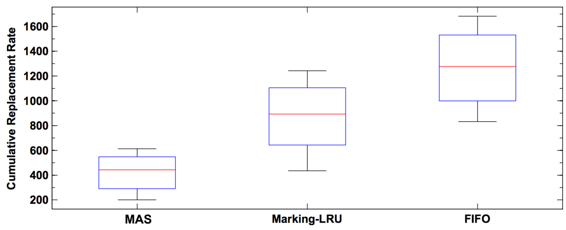

Figure 3: Showing the variations (variance) in dissemination distance for each of the modeled approaches. The variance for each approach is obtained from all the runs (100 runs for each approach).

strong ties do not to tend to change frequently. FIFO replaces an item at every new encounter and Marking-LRU is more likely to replace an item when encountering new devices leading to them displaying higher rate of replacements.

Furthermore, we investigate the behavior of the three approaches in terms of variance. Figure 3 shows the variance of each approach. Note that MAS has a smaller variance than the competitive ones.

However, the above findings are not significant because they do not provide details on the differences among the approaches. Therefore, we decide to statistically confirm 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 while the *alternative hypothesis* states that they are are not equal as follows:

$H_0 : \mu_{(\text{MAS})} = \mu_{(\text{Marking-LRU})} = \mu_{(\text{FIFO})}$
$H_a : \mu_{(\text{MAS})} \neq \mu_{(\text{Marking-LRU})} \neq \mu_{(\text{FIFO})}$

The output of ANOVA shows that *F-statistics* = 11.26 and the *p-value* = 0.001. Given these results, we cannot accept the null hypothesis which confirms that there is a difference in the means of the approaches.

Now, we need to verify if these differences are statistically significant. To this end, we compute a pairwise multiple comparisons among the modeled approaches using *Bonferroni's Test* (Bonferroni, 1936) with 95% of confidence. It can be observed that the difference between the pair (MAS, FIFO) with a *p-value* of 0.004 is significant. Besides that, the *p-value* of the pair (MAS, Marking-LRU) equals 0.003

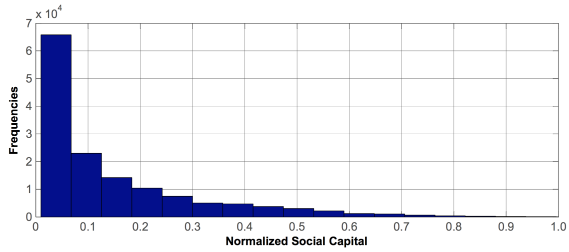

Figure 4: The distribution of social capital among devices follows a *power-law* distribution.

which is also significant. Therefore, it can be inferred that our proposed approach (MAS) outperforms the benchmarking approaches in terms of replacement rate and variance.

Figure 4 shows the distribution of social capital among devices in the environment. Clearly, it follows a power-law distribution. Based on the framework we are working on, the *social interactions* of a pair of devices is symmetric (see Section 3.1). For example, consider two devices A and B, and also that they are in each other's memory. After a while, A removed B from its memory (A still in B's memory) due to an important encounter that causes B to be removed. 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 characteristic is important insofar as it contributes in keeping a more historical tie strength.

In our previous work (Mahmood et al., 2015), we involved the interactions among nodes (e.g., frequencies, duration, and regularities of encounters) in order to measure the strength of relations among nodes. In this work, the calculations of social capital also include the interactions among network nodes—the strength of a tie is embedded in the social capital of the relation itself (Lin, 1999)(Borgatti et al., 1998). This work then builds from our previous results to generalize the concepts of interactions into the concept of social capital value.

Our findings show that the *Remove Operation* in the MAS approach avoids losing strong ties from memory while the *Add Operation* provides memory with weak ties in the same time. The overall outcome is a good balance between weak and strong ties as shown in Figure 4. The distribution shows few sensors with high social capital (strong ties) and many values with low social capital (weak ties).

5 CONCLUSIONS

In this work, we proposed a novel social-based replacement strategy (Memory Anticipatory Strategy) for memory management in sensor networks. This strategy is based on two social concepts: the idea of *Social Capital* in sociology and the *Preferential Return* mechanism in human mobility modeling. The proposed strategy is benchmarked with two well-known approaches (FIFO and Marking-LRU) in memory management literature. The findings show that our approach outperforms the comparative approaches in terms of replacement rate and variations and that it can successfully maintain a 80-20 ratio between weak and strong ties. Our approach avoids losing strong ties that are important to a particular device and provides memory with weak ties.

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REFERENCES

Abdelaal, A. and Ali, H. (2012). Measuring social capital in the domain of community wireless networks. In *System Science (HICSS), 2012 45th Hawaii International Conference on*, pages 4850–4859.

Adhikari, K. P. (May 2008). Bridging, linking, and bonding social capital in collective action. *Collective Action and property rights CAPRi*.

Barbosa, H., de Lima Neto, F. B., Evsukoff, A., and Menezes, R. (2015). The effect of recency to human mobility. *European Physical Journal Data Science (in press)*.

Bonferroni, C. E. (1936). *Teoria statistica delle classi e calcolo delle probabilita*. Libreria internazionale Seeber.

Borgatti, S. P. and Foster, P. C. (2003). The network paradigm in organizational research: A review and typology. *Journal of management*, 29(6):991–1013.

Borgatti, S. P., Jones, C., and Everett, M. G. (1998). Network measures of social capital. *Connections*, 21(2):27–36.

Bosen, L. and Gang, Q. (2010). Relationship between team social capital and knowledge transfer: The mediated effect of tms. In *E-Product E-Service and E-Entertainment (ICEEE), 2010 International Conference on*, pages 1–4.

Burt, R. S. (1982). *Toward a structural theory of action: network models of social Structure, Perception, and Action*. Academic Press.

Burt, R. S. (1997). The contingent value of social capital. *Administrative science quarterly*, pages 339–365.

Burt, R. S. (2000). Decay functions. *Social networks*, 22(1):1–28.

Burt, R. S. (2001). Structural holes versus network closure as social capital. *Social capital: Theory and research*, pages 31–56.

Cho, E., Myers, S., and Leskovec, J. (2011). Friendship and mobility: user movement in location-based social networks. In *KDD '11 Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 1082–1090, New York. ACM.

Coleman, J. S. (1988). Social capital in the creation of human capital. *American journal of sociology*, pages S95–S120.

Ehrlich, K. and Carboni, I. (2005). Inside social network analysis. *Boston College*.

Festinger, L. (1950). Informal social communication. *Psychological review*, 57(5):271.

Friedkin, N. E. (1993). Structural bases of interpersonal influence in groups: A longitudinal case study. *American Sociological Review*, pages 861–872.

Galvin, P. B., Gagne, G., and Silberschatz, A. (2013). *Operating system concepts*. John Wiley & Sons, Inc.

Granovetter, M. S. (1973). The strength of weak ties. *American journal of sociology*, pages 1360–1380.

Grossman-Clarke, S., Zehnder, J. A., Stefanov, W. L., Liu, Y., and Zoldak, M. A. (2005). 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):1281–1297.

Hopcroft, J. E., Ullman, J. D., and Aho, A. V. (1983). *Data structures and algorithms*. Addison-Wesley Boston, MA, USA:.

Hsu, M.-H., Ju, T. L., Yen, C.-H., and Chang, C.-M. (2007). Knowledge sharing behavior in virtual communities: The relationship between trust, self-efficacy, and outcome expectations. *International Journal of Human-Computer Studies*, 65(2):153–169.

Ibarra, H. (1992). Homophily and differential returns: Sex differences in network structure and access in an advertising firm. *Administrative science quarterly*, pages 422–447.

Johannessen, M. (2012). Social capital and the networked public sphere: Implications for political social media sites. In *System Science (HICSS), 2012 45th Hawaii International Conference on*, pages 2573–2582.

Kesidis, G., Konstantopoulos, T., and Phoha, S. (2003). Surveillance coverage of sensor networks under a random mobility strategy. In *Sensors, Proceedings*, volume 2, pages 961–965. IEEE.

Larsen, L., Harlan, S. L., Bolin, B., Hackett, E. J., Hope, D., Kirby, A., Nelson, A., Rex, T. R., and Wolf, S. (2004). Bonding and bridging understanding the relationship between social capital and civic action. *Journal of Planning Education and Research*, 24(1):64–77.

Law, S. and Chang, M.-K. (2012). Social capital and knowledge sharing in online communities: A mediation model. In *System Science (HICSS), 2012 45th Hawaii International Conference on*, pages 3530–3539.

Licamele, L., Bilgic, M., Getoor, L., and Roussopoulos, N. (2005). Capital and benefit in social networks. In *Proceedings of the 3rd International Workshop on Link*

Discovery, LinkKDD '05, pages 44–51, New York, NY, USA. ACM.

Lin, G., Noubir, G., and Rajaraman, R. (2004). Mobility models for ad hoc network simulation. In *INFOCOM 2004. Twenty-third AnnualJoint Conference of the IEEE Computer and Communications Societies*, volume 1. IEEE.

Lin, N. (1999). Building a network theory of social capital. *Connections*, 22(1):28–51.

Mahmood, B., Tomasini, M., and Menezes, R. (2015). Estimating memory requirements in wireless sensor networks using social tie strengths. In *Local Computer Networks Workshops (LCN Workshops), (SenseApp) 2015 IEEE 40th Conference on*. IEEE.

Marsden, P. V. (1988). Homogeneity in confiding relations. *Social networks*, 10(1):57–76.

McPherson, M., Smith-Lovin, L., and Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual review of sociology*, pages 415–444.

Metta, G., Fitzpatrick, P., and Natale, L. (2006). Yarp: yet another robot platform. *International Journal on Advanced Robotics Systems*, 3(1):43–48.

Musolesi, M. and Mascolo, C. (2009). Mobility models for systems evaluation. In *Middleware for Network Eccentric and Mobile Applications*, pages 43–62. Springer.

O'neil, E. J., O'neil, P. E., and Weikum, G. (1993). The lru-k page replacement algorithm for database disk buffering. *ACM SIGMOD Record*, 22(2):297–306.

Phung, D., Gupta, S., Nguyen, T., and Venkatesh, S. (2013). Connectivity, online social capital, and mood: A bayesian nonparametric analysis. *Multimedia, IEEE Transactions on*, 15(6):1316–1325.

Preciado, P., Snijders, T. A., Burk, W. J., Stattin, H., and Kerr, M. (2012). Does proximity matter? distance dependence of adolescent friendships. *Social networks*, 34(1):18–31.

Putnam, R. D. (2000). Bowling alone: The collapse and revival of american community. In *Proceedings of the 2000 ACM Conference on Computer Supported Cooperative Work*, CSCW '00, pages 357–, New York, NY, USA. ACM.

Sander, T. and Teh, P.-L. (2014). Determining the indicators of social capital theory to social network sites. In *User Science and Engineering (i-USEr), 2014 3rd International Conference on*, pages 264–268.

Smith, M. S. (2008). Social capital in online communities. In *Proceedings of the 2Nd PhD Workshop on Information and Knowledge Management*, PIKM '08, pages 17–24, New York, NY, USA. ACM.

Song, C., Koren, T., Wang, P., and Barabási, A.-L. (2010). Modelling the scaling properties of human mobility. *Nature Physics*, 6(10):818–823.

Subbian, K., Sharma, D., Wen, Z., and Srivastava, J. (2013a). Finding influencers in networks using social capital. In *Advances in Social Networks Analysis and Mining (ASONAM), 2013 IEEE/ACM International Conference on*, pages 592–599.

Subbian, K., Sharma, D., Wen, Z., and Srivastava, J. (2013b). Social capital: The power of influencers in networks. In *Proceedings of the 2013 International Conference on Autonomous Agents and Multi-agent Systems*, AAMAS '13, pages 1243–1244, Richland, SC. International Foundation for Autonomous Agents and Multiagent Systems.

Wisconson Center for Education Research (2006). Families and school together. social capital: social capital as a theoretical construct. Technical report, University of Wisconsin-Madison.

Yao, C.-Y., Tsai, C.-C., and Fang, Y.-C. (2014). Understanding social capital, team learning, members' e-loyalty and knowledge sharing in virtual communities. *Total Quality Management and Business Excellence*, pages 1–13.

Yuan, Y. C. and Gay, G. (2006). Homophily of network ties and bonding and bridging social capital in computer-mediated distributed teams. *Journal of Computer-Mediated Communication*, 11(4):1062–1084.

Zhao, Y. and Wang, Y. (2009). Research on the knowledge transfer among enterprise network: A perspective from social capital. In *Knowledge Acquisition and Modeling, 2009. KAM '09. Second International Symposium on*, volume 2, pages 379–382.