Energy Consumption Optimization using Social Interaction in the Mobile Cloud

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Abstract. This paper addresses the issue of resource offloading for energy usage optimization in the cloud, using the centrality principle of social networks. Mobile users take advantage of the mobile opportunistic cloud, in order to increase their reliability in service provision by guaranteeing sufficient resources for the execution of mobile applications. This work elaborates on the improvement of the energy consumption for each mobile device, by using a social collaboration model that allows for a cooperative partial process offloading scheme. The proposed scheme uses social centrality as the underlying mobility and connectivity model for process offloading within the connected devices to maximize the energy usage efficiency, node availability and process execution reliability. Furthermore, this work considers the impact of mobility on the social-oriented offloading, by allowing partitionable resources to be executed according to the social interactions and the associated mobility of each user during the offloading process. The proposed framework is thoroughly evaluated through event driven simulations, towards defining the validity and offered efficiency of the proposed offloading policy in conjunction to the energy consumption of the wireless devices.

Keywords: Resource sharing, centrality, social collaboration, energy conservation, dynamic resource migration, dependable mobile computing, temporal execution-oriented metrics.

1 Introduction

As social networking is experiencing an exponential growth and is becoming part of our daily routines, the communications overlay it creates can be exploited, by a number of applications and services [1]. Users are connecting to social networks by using small mobile devices, such as smart phones and tablets that are able to form opportunistic networks. Such networks form a potential infrastructure for increased resource availability to all users in the network, especially to those that face reduced resource availability (e.g. energy, memory, processing resources etc.). Opportunistic wireless networks exhibit unique properties, as they depend on users' behavior and movement, as well as on users' local concentration. Predicting and modeling their behavior is a difficult task but the association of the social interconnectivity factor may prove part of the solution, by successfully tapping into the resources they are offering. Resource sharing in the wireless and mobile environment is even more demanding as applications require the resource sharing to happen in a seamless and unobtrusive to the user manner, with minimal delays in an unstructured and ad-hoc changing system without affecting the user's Quality of Experience (QoE) [2]. This forms a highly ambitious objective as on one hand wireless environments cannot reliably commit to sharing resources for establishing reliable communication among users since there is no way of guaranteeing resource allocation and on the other hand, if that was to be overcome their limited capabilities exacerbate further the problem. The mobility factor imposes additional constraints as network topology is constantly producing fluctuation in bandwidth usage and resource availability. The dependency on device capabilities restricts solutions to particular devices, lacking generality in its applicability. In this context and by considering all the above-mentioned issues, this work uses social interactivity as a method for modeling and achieving resource sharing in the wireless mobile environment.

As social platforms are used by a staggering majority of 87% of mobile users for communication and message exchange, they form an underlying web interconnecting mobile users and possibly enabling reliable resource sharing [3]. Using social connectivity and interactivity patterns, we should be able to provide adaptability to device capabilities and operating environment, enabling devices to adapt to frequent changes in location and context. One of the ever lacking resources in the wireless mobile environment is that of energy. As energy is stored in batteries, it forms the only source for mobile device operation and as new and more power demanding applications are created every day, energy usage optimization forms a challenging field, approached by both hardware and software solutions.

This work proposes a model of energy usage optimization for mobile devices in an opportunistic wireless environment, using the social interaction model. The social interaction model is based on the social centrality principle. With the social centrality principle users are able to share resources when a shared contact threshold is satisfied. Energy intense processing and other actions are disseminated using the proposed model enabling nodes running low on energy resources to extend or alleviate their energy demands and thus extend their life and availability. In the proposed model, the centrality principle and the "ageing" timing rule are applied, in order produce a more efficient use of the available energy. Thus, opportunistic energy conservation takes place enabling efficient management of the energy available to other wireless peer users, and guaranteeing end-to-end availability for the longest time possible, in a wireless mobile environment.

This introduction of the social interaction model for achieving optimum resource usage forms the key innovation of the proposed framework. The framework evaluates the energy state of each node, according to its type, energy demands and usage combines this with its social centrality, determining if the node is to receive or provide energy to the network. Through the proposed framework, the ability to adaptively perform tasks for another node increases and depends on the node's current energy state, as well as on its "friendship" degree. Furthermore, the proposed framework strengthens or relaxes the energy usage and the task allocation scheme, according to the social contacts and the user's interaction parameters. In section 2, we describe the related work, while section 3 elaborates on presenting the proposed social-enabled mechanism for opportunistic and socially oriented energy sharing and process off-loading. Section 4 presents the performance evaluation of the proposed scheme through the experimental evaluation and section 5 concludes this paper, by proposing future potential directions for further research.

2 Related work

Social networking started as an online tool for forming connections and information sharing. Its appeal and huge popularity primarily came from the fact that the social activity was enhanced in the online line environment with the use of multimedia, giving users instant access to information. Another aspect of the online environment was the ability of the social network users to share their location with others, instantly advertising their present coordinates either using programs such as FourSquare or having automatic tracking, by exploiting the mobile devices GPS capabilities. The use of user mobility in opportunistic networks will help to realize the next generation of applications based on the adaptive behavior of the devices for resource exchange. The problem of energy usage optimization that considers energy as a finite resource that needs to be shared among users, providing most processing power whilst maintaining group connectivity, will greatly benefit by using the social centrality model. Opportunistic networks will greatly benefit from the capability of the mobile devices to gather information from any hosted application, in order to better utilize network resources. The task allocation and load balancing can be strictly or voluntarily associated with the social communication. Works such as [4] propose architectures, which rely on the local information derived by the devices and their local views, in optimizing load balancing and energy management, as well as even some self-behaving properties, like self-organization. In [4] resource manipulation optimization is offered. However, this occurs without considering social parameters, such as friendship, contact rate or the temporal parameters (i.e. users' location).

The contribution of this work is to combine the energy management scheme with the proposed social parameters and model for each node, in order to optimize the energy management and load sharing process. In the game theoretic approach [5], the energy usage optimization problem is translated to a contention game, where the nodes compete to access the energy resources, reaching to the Nash equilibrium; an approach that improves on the random and individualized approach. In [5] the proposed system supports fine grained offload to minimize energy savings with minimal burden on the programmer. The model decides at runtime which methods should be remotely executed driven by an optimization engine that achieves the best energy savings possible under the mobile devices current connectivity constraints. In [7] energy offloading is viewed as potentially energy saving but the overheads of privacy, security and reliability need to be added as well. The integration of social connectivity into the process is an unexplored area. Social connectivity takes into consideration users associations, location profiles and social interactions as a basis for creating an index for users' resources over time for subsequent resource offloading.

In this work, a social-oriented methodology is used for minimizing energy consumption for highly demanding applications with high memory/processing requirements. The social-oriented model with the associated friendships as the basis for social mobility, utilizes the introduced social-centrality, for selecting and offloading energy hungry partitionable tasks (parts of executable applications and processes) under the availability optimization objective. In addition, this work considers the motion coefficients for each user (using normalized [0…1] parameter) and encompasses these characteristics into the proposed energy utilization scheme for enabling maximum temporal node availability without reducing the processing capabilities of the system as a whole. The proposed scheme uses both the pre-scheduled opportunistic offloading [6] and the social interactions that take place among the collaborative users and their associated strength of friendship. The scheme improves on predicting user mobility under the end-to-end availability. In order to assess the effectiveness of the proposed scheme, exhaustive simulations take place considering the offered energy by the social-collaborative network within the mobility context. The results of these lead to thorough measurements of the energy consumption optimization for mobile nodes/users.

3 Probabilistic motion and social oriented methodology for efficient energy consumption

Wireless mobile networks allow unrestricted access to mobile users under a changing topology. The implications of mobility cannot be determined over time as the network topology is dynamically changing. In our work, the mobility model used is based on the probabilistic Fraction Brownian Motion (FBM) where nodal motion is done according to certain probabilities in accordance with location and time. Assume that we need to support a mobile node that is low on energy reserves and requires an energy heavy application to run. This implies that in a non-static, multi-hop environment, there is a need to model the motion of the participating nodes in the end-to-end path such that the requesting nodes can move through the network and conserve its resources. We also assume a clustered-mobility configuration scenario presented in [2], where each node has its own likelihood for the motion it follows. To predict whether a node will remain within the cluster, we aggregate these probabilities. This also shows the probabilities for the other nodes remaining in the cluster. The mobility scenario used in this work is modelled and hosted in a scheme that enables the utilization of social feedback into the model. Unlike the predetermined relay path in [7] and the known location/region, the mobility scenario used in this work is a memoryless FBM [8], with no stationary correlation among users' movements. FBM can be derived probabilistically from the random walk mobility model and can be expressed as a stochastic process that models the random continuous motion. The mobile node moves from its current location with a randomly selected speed, in a randomly selected direction in real time as users interact. However, in real life the real time mobility that the users exhibit, can be expressed as an ordinary walk, where the users spot-out some environmental stimuli and are attracted to them. Their decisions may be relayed to their respective social communication. In the proposed scenario, the walking speed and direction are set for the mobile users and are both chosen from predefined ranges, $[v_{min}, v_{max}]$ and $[0, 2\pi)$, respectively [10]. The new speed and directions are maintained for an arbitrary length of time randomly chosen from $(0, t_{max}]$. The node makes a memoryless decision for new speed and direction when the chosen time period elapses. The movements can be described as a Fractional Random Walk on a weighted graph [1], with the total likelihood $P_{i,j}^{L}$ in L^n.

We model the movement of each device using a graph theoretical model, in which a device can move randomly according to a topological graph *G=(V,E),* that comprises of pair of sets *V(or V(G))* and *E (or E(G))* called edges. The edges join different pairs of vertices. This walk considers a connected graph with *n* nodes labeled *{1, 2, 3, … ,n}* in a cluster L^n with weight $w_{ij} \geq 0$ on the edge *(i,j)*. If edge *(i,j)* does not exist, we set $w_{ij} = 0$. We assume that the graph is undirected so that $w_{ij} = w_{ji}$. A node walks from a location to another location in the graph in the following random walk manner. Given that node *i is in reference*, the next location *j* is chosen from among the neighbors of *i* with probability:

$$p_{ij}^{L} = \frac{w_{ij}}{\sum_k w_{ik}} \qquad (1)$$

where in (1) above the p_{ij} is proportional to the weight of the edge *(i, j),* then the sum of the weights of all edges in the cluster *L* is:

$$w_{ij}^{L} = \sum_{i,j:j>1} w_{ij} \qquad \textbf{(2)}$$

Then the stationary distribution according to [1] is given by

$$\pi_i^{L} = \frac{w_i^{L}}{2w} \qquad \textbf{(3)}$$

where, it can be seen that the preceding distribution satisfies the relationship $\pi P = \pi$, when the movement is performed for a node/device *i* to location *j* (stationary distribution of the Markov chain as each movement of the users usually has a selected predetermined path (i e. corridor etc.)) associated as follows:

$$\sum_i \pi_i P_{ij} = \sum_i \left\{\frac{w_i}{2w} \times \frac{w_{ij}}{w_i}\right\} = \sum_i \left\{\frac{1}{2w} w_{ij}\right\} = \frac{1}{2w} \sum_i \{w_{ij}\} = \frac{w_j}{2w} = \pi_j \qquad \textbf{(4)}$$

Equation 4 above denotes that the stationary probability of state of *i* is proportional to the weight of the edges emanating from node *i.* By using the motion notation we can express the track of requests as a function of the location (i.e. movements and updates p_{ij}^{L}) as: $R_i(I_{ij}, p_{ij}^{L})$ *where* R_i is the request from node *i,* I_{ij} is the interaction coefficient measured in equation 2. We use the representation of the interactions by utilizing notations of weighted graphs (Eq. 1).

Different types of links or involvements are expressed in different ways in social connectivity modeling. Consequently, several types of centralities are defined in the directed or undirected graphs [1]. Users may have or not a certain type of association with any other user in the global network and this is modelled with the concept of the social network. Nodes carry weights that represent the degree of associativity with other nodes. These weights are associated with each edge linking two nodes and are used to model the interaction strength between nodes [10]. This models the degree of friendship that each node has with the other nodes in the network. The weights are assigned and used to measure the degree of the strength of the association of the connecting parts. Consequently the degree of social interaction between two devices can be expressed as a value in the range of [0, 1]. A degree of 0 signifies that the two nodes/devices are not socially connected and therefore no social interaction exists between them. As social interaction increases so does the weight reaching 1 indicating very strong social interaction. The strength of the social interaction and the energy state of each node will form the basis for offloading processes to other nodes in the network. In this work, we propose such a model for efficient energy management prolonging node lifetime based on the social association scheme.

We propose that the strength of social interaction will also affect the offloading process, which as next sections show will affect the energy conservation mechanism. The social interaction can be represented by the 5×5 symmetric matrix (eq. 2 matrix is based on the social population in the network), the names of nodes correspond to both rows and columns and are based on the interaction and connectivity. The latter matrix, forms the Interaction Matrix which represents the social relationships between nodes. The generic element *i,j* represents the interaction between two individual elements *i* and *j*, the diagonal elements represent the relationship an individual has with itself and are set to 1. In (5), the I_{ij} represents all the links associated to a weight before applying the threshold values which will indicate the stronger association between two nodes.

$$I_{ij} = \begin{bmatrix} 1 & 0.766 & 0.113 & 0.827 & 0 \\ 0.132 & 1 & 0.199 & 1 & 0.321 \\ 0 & 0.231 & 1 & 0.542 & 0.635 \\ 0.213 & 0 & 0 & 1 & 0.854 \\ 0 & 0 & 0.925 & 0.092 & 1 \end{bmatrix} \quad \textbf{(5)}$$

3.1 The use of the "friendship" for process execution memory-oriented offloading

The elements of the Matrix I_{ij} (5) represent the measure of the social relationship "friendship" between the users. This is determined by the amount of direct or indirect social interaction among the different users belonging to the network as follows:

$$f_{i \to j}^{d} = norm\left[c(t) \cdot P(t)\right]^{0..1} \forall i, j \quad \textbf{(6)}$$

Where $f_{i \to j}^{d}$ is defined as the direct friendship evaluation from node *i* to node *j*, $P(k_t)$ is the probability *P(k)* of a node being connected to *k* other nodes at time *t* in the network decays as a power law, given by: $P(k) = k^{-\gamma}$ where for the value of the power γ is estimated as follows $2 < \gamma < 3$ as explored in various real networks [13]. This results in a large number of nodes having a small node degree and therefore very few neighbors, but a very small number of nodes having a large node degree and therefore becoming hubs in the system. *c(t)* consists of the duration of the communication among "friends", and is determined as a function of the communication frequency and the number of roundtrip "friendships". The roundtrip "friendships" are determined by the "hop-friendships" of the node *i* to a node *k,* as figure 1 presents. These are the "friends-of-friends" where according to the node *i* any "friend-of-friend" can reach –on a roundtrip basis- the node *i* again.

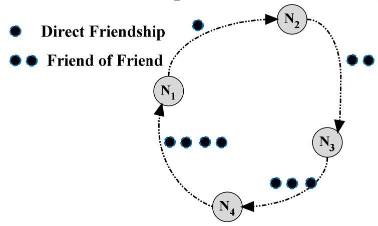

Fig. 1. Roundtrip "friendship" of a node i via other peers, and the "reach-back" notation to the node via the intermediate peers.

Then, the $c(t)$ of any of the "friendship" peers can be evaluated as the: $c(t) = \frac{1}{N} f^{d}_{i \to j}$, where N is the number of peers away from *i*, for reaching a friendship within $f^{d}_{i \to k}$ for a specified time slot *t*. Each element in the I_{ij} is re-estimated and varies through time according to the enhancement of the relation of the individuals as follows:

$$I_{ij} = \frac{I_{ij} + \Delta I_{ij}}{1 + \Delta I_{ij}} \tag{7}$$

Where I_{ij} is the association between two individuals that is strengthened or weakened (if less than $\nabla I_{ij} = I_{ij_{(\tau)}} - I_{ij_{(\tau-1)}}$) and ∇I represents the difference from the previous I_{ij} association between *i,j*. As associations and friendships vary over-time resulting in the strengthening or weakening of different links we incorporate this element by adding a time-varying parameter enabling an association to fade if two individuals are not in contact for a prolonged time period. This is expressed using the flowing equation:

$$\Delta I_{ij} = \frac{a}{t_{age}} + b, \forall t_{age} < T_{R_L} \tag{8}$$

where t_{age} is the time that has passed since last contact and is measured until the individuals abandon the clustered plane *L*. The empirical constants *a* and *b* are chosen be the network designer [15] with typical values of 0.08 and 0.005 respectively. The proposed model encompasses the impact of the mobility on the interaction elements I_{ij} as the derived matrix consisting of the elements of w^{L}_{ij} and I_{ij} as follows:

$$M_{ij} = I_{ij} \cdot p_{ij}^{L} \quad (9)$$

where the element w_{ij} derived from the p_{ij}^{L} matrix of the plane area L, is the likelihood of an individual to move from i to a certain direction to j, as Figure 1 shows.

3.2 Cloud offloading model using social centrality

The determination of the importance of each node in a wireless mobile network is a very important task. This importance is based on the node's position, connectivity and interactivity patterns, as well as on motion thought time. A large number of connections and interactions signify an important and social central node. The term of centrality that has been introduced in [1] combines user behavior of each individual device with respect to its placement and behavior with the other devices within the cluster [2]. From a group of nodes a subset of the individuals is sampled and used to produce a subgraph, consisting only of those individuals and the links among them. The subgraph produced is used for performing the centrality approximation with the centrality scores of the sample being used as approximations. In social networks the high connectivity degree nodes serve as bridges in order to provide connectivity to lower degree nodes. A node's degree can be measured by $D_c(aj) = \sum_{i=1}^{n} d(ai, aj)$, where $d(ai, aj) = \begin{cases} 1 \forall ai, aj \in D \\ 0 \forall ai, aj \notin D \end{cases}$, D denotes the direct connectivity. As the maximum number of connected nodes for any graph is *n-1,* the formula to calculate the centrality of the node by using the proportion of the number of adjacent nodes to the maximum number *(n-1)* is as follows:

$$D'_c(aj) = \frac{\sum_{i=1}^{n} d(ai, aj)}{n-1} \quad \textbf{(10)}$$

Centrality is used to indicate the relative importance of a node in a network of nodes [17] and its relative contribution to the communication process as derived by the duration and distance covered with the frequency and parameterized in the context of avoiding network communication partitioning. Adding to this, social centrality measures the social closeness of two or more nodes. With social centrality we measure the number of times a node is chosen to host the "best-effort" parameters, process offloading in our case, for time t in L. A node with high social betweenness centrality β_{ai} will have to strongly interact with the other nodes belonging to social cluster L, measured as:

$$\beta_{ai} = \frac{\sum_{1}^{j} P_{aj \to ak}}{\sum_{1}^{k} P_{ij} \forall P \in ai} \quad \textbf{(11)}$$

with $P_{aj \to ak}$ representing the number of paths in the cluster via which the requested memory/capacity resources can be served between nodes *aj* and *ak* and P_{ij} represents the number of paths in the social cluster that include ai, $\forall P \in ai$. Based on the latter, we introduce the social-oriented stability parameter $\sigma_{c(t)}$ for a specified time t, as:

$$\sigma_C(t) = \left[\frac{R_{ij|t} \cdot (1 - norm(\beta_{ai})) \cdot N_{C(i \to j|t)}}{\inf(C_r) \cdot R_{C(t)}} \right] m_{ij}(t) \quad \textbf{(12)}$$

where R_{ij} is the normalized communication ping delays between i and j nodes at time t, β_{ai} is the normalized [0..1] social betweenness centrality showing the strong ability to interact with other nodes in the cluster L, $N_{C(i \to j|t)}$ is the successfully offloaded capacity/memory units over the total allowed capacity, C_r is the multi-hop channel's available capacity, $m_{ij}(t)$ is the interaction measures derived from equation (8) at the time interval t, and $R_{C(t)}$is the end-to-end delay in the cluster's pathway. The social-oriented stability parameter $\sigma_c(t)$ indicates the capability and transmitability of the node i to offload a certain process according to the ranked criteria of each process in L for time t.

3.3 Energy-consumption model using social-oriented capacity measurement

Energy consumption is important for wireless nodes as non-optimized energy usage can lead to uncertainty in availability and reliability for each node and consequently the whole of the network. In this work, we use the social centrality aspect of the network as the substrate for efficient energy conservation. As the social centrality degree differs per node, processes are offloaded so as to minimize the total energy consumption and provide a total higher node availability for the most popular nodes, thus maintaining network connectivity. The system will decide when and where to offload processes, according the current energy state of each device. The degree of social centrality allows the node to offload resources according to the social model and the estimation of the each node's energy consumption as in equation (14). So ultimately, in order to achieve energy conservation, resources may be offloaded to the cloud or any other peer-neighboring device (so that the device that needs to run the executable resource will potentially conserve energy). Thus, the measurable energy consumption can be evaluated according to the:

$$E_{r(a_j)} = E_C(a_j) \cdot \frac{C}{S_{a_j}} \quad \textbf{(13)}$$

where C is the parameter indicating the number of instructions that can be processed within T_t, S_{a_j}represents the processing time at the server-device and $E_C(a_j)$ represents the relative energy consumption which is expressed as:

$$E_C(r_i) = \frac{Cost_{C(r_i)}}{s_{C(r_i)}} W_C \quad \textbf{(14)}$$

where S_C is the server instruction processing speed for the computation resources, $Cost_C$ the resources instruction processing cost for the computation resources and W_c signifies the energy consumption of the device in mW.

Each mobile device should satisfy an energy threshold level and a specified centrality degree in the system in order to proceed with process execution offloading. By using N devices within *2-hops vicinity coverage* which is evaluated based on the measurements regarding the maximum signal strength and data rate model [13]) the following should be satisfied:

$$\frac{Cost_{c(r_i)}}{S_{c(r_i)}} \cdot W_c \Big|^{r_i} > \frac{Cost_{c(r_i)}}{S_{c(r_i)}} \cdot W_c \Big|^{1,2..N} \tag{15}$$

$$W_{r_i} > W_c \forall f^d_{i \to j} \text{ devices} \tag{16}$$

The energy consumption of each device should satisfy the (15)-(16) for each of the resources (executable processes) running onto the device MN_{m-1} hosting the r_i resource. The $r_{1,} r_2, r_3, ..r_i$ parameters represent the resources that can be offloaded to run onto another device based on the resources' availability as in [15]. In this respect, the r_i with the maximum energy consumption is running in a partitionable manner to minimize the energy consumed by other peer-devices. These actions are shown in the steps of the proposed algorithm in table I.

Table 1. Centrality-based offloading scheme

1: **Inputs:** MN_m, Location, resources $r_{1,} r_2, r_3, ..r_i \forall MN_m$ with certain mobility direction w^L_{ij}

2: for all Cloud devices that have association of $f^d_{i \to j}$ and satisfy $c(t) = \frac{1}{N} f^d_{i \to j}$

3: find from $r_{1,} r_2, r_3, ..r_i$ the r_i that can be offloaded to run onto another device

4: for all MN_{m-1} do{

5: Estimate $\sigma_C(t) = \left[\frac{R_{ij|t} \cdot (1 - norm(\beta_{ai})) \cdot N_{C(i \to j|t)}}{\inf(C_r) \cdot R_{C(t)}} \right] m_{ij}(t)$

6: if ($\sigma_C(t)$ is valid and above a threshold){

7: search for MN_{m-1} device that satisfies

$$\frac{Cost_{c(r_i)}}{S_{c(r_i)}} \cdot W_c \Big|^{r_i} > \frac{Cost_{c(r_i)}}{S_{c(r_i)}} \cdot W_c \Big|^{1,2..N}, \; W_{r_i} > W_c \forall 1,2,3,...N$$

8: offload ($r_i, MN_{k(i)}$) //to $MN_{k(i)}$ to execute resource *(i)* onto *k* node

9: end **if**

10: end **for**

11: end **for**

The resource allocation will take place, towards responding to the performance requirements as in [2] and [15]. A significant measure in the system is the availability of memory and the processing power of the mobile cloud devices, as well as the server-based terminals. The processing power metric is designed and used to measure the processing losses for the terminals that the r_i will be offloaded, as in (18), where a_j is an application and T^j_k is the number of terminals in forming the cloud (mobile and static) rack that are hosting application a_j and $T_{a_j}(r)$ is the number of mobile terminals hosting process of the application across all different cloud-terminals (racks).

$$C_{a_j} = \frac{T_k^j}{\sum_k T_{a_j}(r)} \forall \min(E_c(r_i)) \in f_{i \to j}^d \tag{17}$$

Equation (17) shows that if there is minimal loss in the capacity utilization i.e. $C_{a_j} \cong 1$ then the sequence of racks $T_{a_j}(r)$ are optimally utilized. The latter is shown through the conducted simulation experiments in the next section. The dynamic resource migration algorithm is shown in Table I with the basic steps for obtaining an efficient execution for a partitionable resource that cannot be handled by the mobile device in reference and therefore the offloading policy is used to ensure execution continuation. The entire scheme is shown in Table I, with all the primary steps for offloading the resources onto either MN_{m-1} neighbouring nodes (or –as called- server nodes (as in [15])) based on the delay and temporal criteria of the collaborating nodes.

4 Performance Evaluation Analysis, Experimental Results and Discussion

Performance evaluation results encompass comparisons with other existing schemes for offered reliability degree, in contrast to the energy conservation efficiency. The mobility model used in this work is based on the probabilistic Fraction Brownian Motion (FBM) adopted in [15], where nodes are moving, according to certain probabilities, location and time. The simulated scenario uses 80 nodes that are randomly initialized with social parameter and through the transient state during simulation the system estimates the social betweenness centrality in regards to the ability to interact with other nodes in *L,* and successfully offload memory or processing intense processes to be partially executed onto socially-collaborating peers based on the criteria depicted in Table 1 pseudocode.

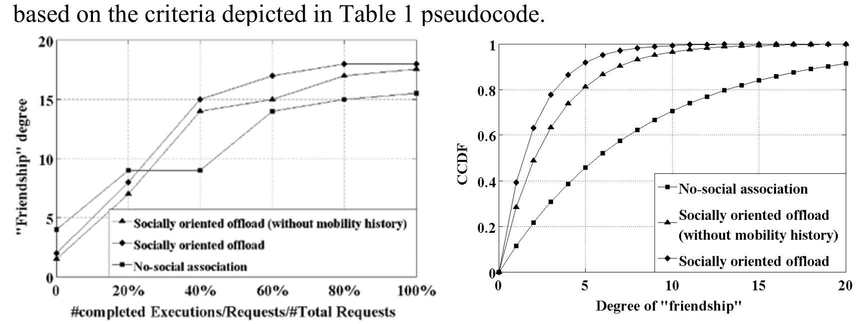

Fig. 2 (a) and (b). Friendship degree with the completed requested offloads and the CCDF with the degree of friendship.

"Friendship" degree with the completed requested offloads is shown in Figure 2 (a) for three different schemes. It is important to mark out that by using the social interactions the number of completed offloading processes are greater and outperforms the applied scheme with no social interactions at all. In Figure 2 (b) the Complementary Cumulative Distribution Function (CCDF or tail distribution) with the degree of “friendship” is shown within the respective values of ageing factor (Equation 8). The proposed social-enabled scheme allows the distribution of partitionable resources to be offloaded to “friendship” peers, whereas the degree of the “friendship” among peers plays a catalytic role for offloading executable resources in respect to the location of each user. These measures were extracted for social centrality parameter >0.6. In addition, when resources are offloaded, a critical parameter is the execution time, while nodes are moving from one location to another. Figure 3(a) shows the execution time during simulation for mobile nodes with different mobility patterns and it is evaluated for GSM/GPRS, Wi-Fi/WLAN and for communication within a certain Wi-Fi/WLAN to another Wi-Fi/WLAN remotely hosted. The latter scenario -from a Wi-Fi/WLAN to another Wi-Fi/WLAN- shows to exhibit significant reduction, in terms of the execution time duration, whereas it hosts the minimum execution time through the FBM with distance broadcast mobility pattern. Figure 3(b) shows the Successful Delivery Rate (SDR) with the End-to-End resource offloading capacity based on the “friendship” model whereas in Figure 3(c) shows that the proposed scheme extends the average node’s lifetime significantly when the number of mobile devices increases.

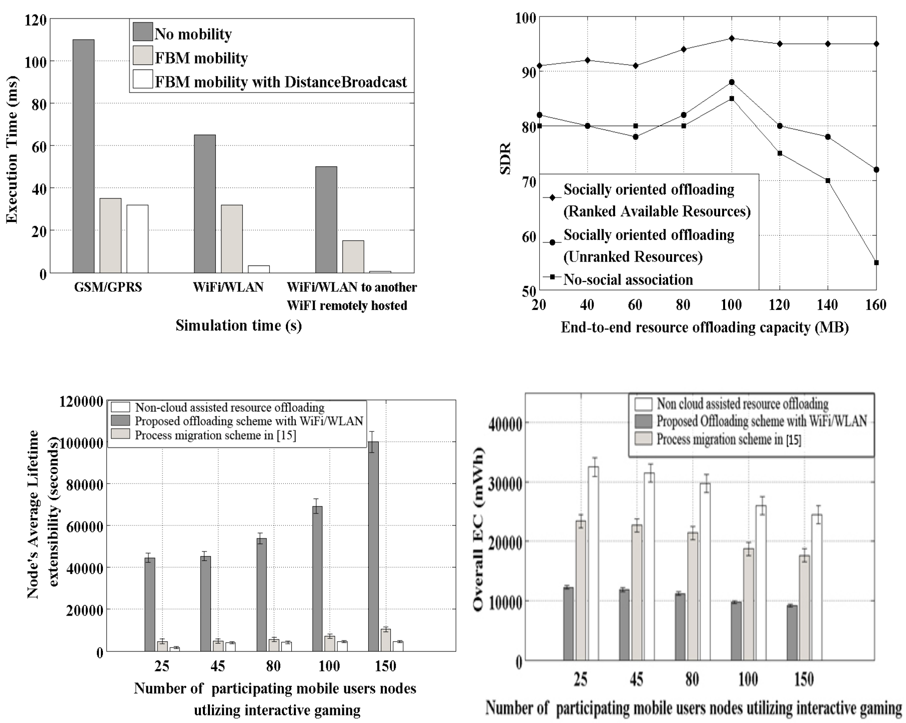

Fig. 3 (a)-(d). Comparative evaluations and results obtained for the social offloading regarding the (a) Execution time through simulation; (b) Successful delivery rate with the End-to-End resource offloading capacity based on the “friendship” model; (c) Average node’s lifetime extensibility with the number of mobile devices for three different schemes in the evaluated area (evaluated for the most energy draining resources); and (d) Energy Consumption (EC) with the number of mobile users participating during an interactive game.

As interactive game playing requires resources in GPU/CPU-level, the lifetime is an important metric for the evaluation of the overall performance of the scheme and the impact on nodes lifetime. Measurements in Figure 3(c) were extracted for the total number of 150 mobile terminals that are configured to host interactive gaming applications, using Wi-Fi/WLAN access technology. The proposed scheme outperforms the other compared schemes, by significantly extending the lifetime of each node. This is as a result of the offloading procedure incorporated into a social centrality framework that takes place on each node, which evaluates the energy consumption of each device according to the Equations (15-18) for the associated cost for each one of the executable processes. It is also worthy to mention that the proposed scheme outperforms the scheme in [15] by 11-48%, extending the lifetime of the mobile devices, when devices reach 150 by a maximum of 48%. The Energy Consumption (EC) with the number of mobile users participating during an interactive game (demanding in GPU/CPU processing) is shown in Figure 3 (d). During the interactive game-playing process, the processing requirements of each device dramatically increase. Figure 3 presents the evaluation for the energy consumed (EC) for three schemes, including a non-Cloud oriented method for 150 mobile terminals. The proposed scheme outperforms the other compared schemes, with the associated EC to be kept in relatively low levels.

5 Conclusions

This paper proposes a resource manipulation method comprising of an executable resource offloading scheme, incorporated into a social-aware mechanism. The proposed scheme allows partitionable resources to be offloaded, in order to be executed according to the social centrality of the node (“friendship” list). According to the model, which targets the minimization of the energy consumption and the maximization of the lifetime, each mobile device can offload resources in order to conserve energy. The scheme is thoroughly evaluated through simulation, in order to validate the efficiency of the offloading policy, in contrast to the energy conservation of the mobile devices. Future directions in our on-going research encompass the improvement of an opportunistically formed mobile cloud, which will allow delay-sensitive resources to be offloaded, using the mobile peer-to-peer (MP2P) technology.

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