# Optimizing the End-to-End Opportunistic Resource Sharing using Social Mobility

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***Abstract*—Opportunistic resource sharing, and contacts' interaction in opportunistic networks, faces several resource challenges that need to be faced via intelligent combinatorial practices. This work proposes a scheme which takes into account the non-synchronized motion of the devices in an urban area where an intelligent opportunistic socially oriented caching scheme is presented. The concept of social centrality is being introduced and modeled, which takes into consideration interactions among users. Through the proposed model the users' interactions can be exploited through time according to the contact frequency, in order to enable in an efficient way opportunistic resource sharing among mobile peers. The collaborative opportunistic communication with the proposed combined social-oriented model and the gossip-based replication scheme is thoroughly evaluated through experimental simulation, which takes measures for the end-to-end reliability of the resource sharing scheme. The proposed scheme enables efficient resource sharing via the social model and the evaluated interactions, minimizing at the same time, the delay variations between packets and maximizing the efficiency of resource exchange between mobile peers.**

***Keywords-Temporal Social Metrics; Resource Exchange Scheme; Social Interaction Metrics; Opportunistic Communication Performance; Opportunistic Optimistic Replication.***

## I. INTRODUCTION

Today, wireless networks are used in many real-time applications that offer specialized services 'on-the-move', where these services require reliable communication and continuous end-to-end connectivity. When dealing with resource sharing applications, low latency and high responsiveness should be supported by the device in a decentralized way, whereas the ease of interaction, and the "always-on" connectivity should be engaged with users' demands and their requested data [1]. Current devices' limitations host many problems in the end-to-end communication, and therefore, are unable to handle resource sharing in a reliable manner. The challenging problems expressed by these devices are considered very disastrous and impair significantly the high responsiveness when devices face temporary and unannounced loss of network connectivity while they move, whereas they are usually engaged in rather short connection sessions since they need to discover other hosts in an ad-hoc manner where, then, the requested resources may not be available. Therefore, a mechanism that faces the intermittent connectivity problem and enables the devices to react to frequent changes in the environment, such as change of location or the context conditions, the variability of network connectivity, will affect significantly the end-to-end reliability and will face the unavailability and the scarceness of wireless resources. This work proposes a model for combining the resource sharing characteristics with the opportunistic content sharing procedure in order to offer higher reliability and availability of the requested resources. The interaction model that is introduced, and the social centrality principle [1] allow the users to share resources among devices when a shared contact rate threshold is satisfied, and devices follow a stationary non-synchronized motion while the connectivity is maintained. Social centrality is evaluated according to the usefulness of the location of a node in public areas. Usefulness is formed within a context of the connections allowed and the bandwidth served for a certain location. Opportunistic object/resource sharing [2] takes place in order to enable efficient dissemination of files chunks [3] whereas, the designed model guarantees the end-to-end connectivity maintenance, in a mobility-enabled cluster-based communication.

In this work, the proposed socially-oriented model for storing-and-forwarding for a certain time-cycle requested objects, utilizes the network resources (capacity and temporal connectivity) and enables high resource exchange. The high resource availability is as a result of the utilization of the social centrality principle as simulation results show. This work primarily addresses the problem of resource sharing in opportunistic systems and uses a constrained social caching mechanism. Through the proposed model the ability to accommodate in an adaptive way the requested data increases, whereas it enables a specified maximum number of concurrent users to share resources in a cluster according to social-interaction parameters of the users who are interacting. The model strengthens or weakens the resource exchange scheme according to the social contacts and the replication scheme exploited by the user's interaction parameters. In addition, different types of traffic can be supported where the adaptability and the robustness is shown by the proposed scheme.

The structure of this work is as follows: Section II describes the related work done and Section III follows presenting the proposed social-enabled mechanism for opportunistic resource sharing. Section IV presents the performance evaluation of the proposed scheme through simulation followed by Section V with the conclusions and foundations as well as potential future directions.

## II. RELATED WORK

As location-based social networks have already appeared (i.e., Foursquare [3]) with great acceptance from the social community, different models were extracted in order to link

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communicational problems and connectivity maintenance during a communication among peers. Mobility in autonomic communication is considered an essential parameter, where, along with the user's demands, they pose the vision of what self-behaving flexibility should encompass in next-generation self-tuning behavior of the devices[4]. The opportunistic communication aggravates the capacity of the nodes [2][5], where the requested information is being forwarded. Obviously, the need of modeling the social contacts behavior becomes timely nowadays since smartphones are now capable to process efficiently any requested information, whereas at the same time they can gather information from any hosted application (i.e., location aware or social contacts) in order to better utilize the network resources.

From the object sharing perspective, research has extensively proposed efficient architectures [6] [7] [8], which rely on local information and local devices' views, without considering the global networking context or views, which may be very useful for optimizing load balancing, enable adaptive routing, energy management, and even some self-behaving properties like self-organization. Mavromoustakis and Karatza in [9] propose the HyMIS scheme, which extends the advantages offered by the Hybrid Mobile Infostation System architecture, where the Primary Infostation (PI) is not static but can move according to the pathway(s) of the roadmaps. However, the HyMIS does not consider the social parameters-like the history contract rate and the temporal parameters of the users.

This work's contribution is to link the file sharing scheme with the underlying social parameters in order to optimize the efficiency of the resource sharing process. Event dissemination protocols use gossip to carry out multicasts. These gossips may be even more efficient in broadcasting information, if social parameters can be hosted and evaluated in a way that they affect the end-to-end resource sharing. Different caching approaches were used in the past, for enabling the requested data content to be available and discoverable [10] [11] at any time such that content can be discovered in a peer-to-peer manner without having network partitioning problems. Additionally if requested data was at some time window back available then through the proposed scheme we can keep an adaptive track of the resources and their availability. Mavromoustakis and Karatza in [12] consider the impact of impatience on optimal content dissemination scheme and a general model to capture this impact and show that under very general assumptions, the impatience function. However the contact relation and the history of the mobile peers is not yet explored due to the complexity and the dynamic nature that these environments impose. However selective and criteria-based dissemination procedures that take into consideration the social mobility and the social interactions in order to gather an allocation index for each ranked request by each peer, based on mobile nodes' content requirements is still a relatively unexplored area.

This work proposes an efficient way to optimize the end-to-end resource sharing reliability by enhancing the replications of the high ranked requested objects by users using a social-oriented methodology. The social-oriented model introduces the social centrality, and is utilized for selectively storing -for a certain time-cycle- the requested objects, whereas it considers the motion and movement characteristic of the devices for enabling optimized reliability, reduced traffic and generated overhead. The proposed scheme combines the strengths of both selective replication in opportunistic communication systems utilizing the outsourcing concept and attempts to fill the trade-offs between user's mobility, reliable file sharing and on-demand requested file availability limitation in the end-to-end path. Examination for the effectiveness of the proposed scheme is performed through simulation taking into consideration the offered reliability by the collaborative-social caching replication scheme within the mobility context. Thorough evaluations have been performed for the throughput optimization and the variation in the grade of robustness during the file sharing process among mobile peers, as well as for the throughput response.

## III. PROBABILISTIC RANDOM WALK MOTION FOR EFFICIENT END-TO-END RESOURCE SHARING USING OPPORTUNISTIC SOCIALLY ORIENTED CACHING

Assuming that a source needs to send requested packets or stream of packets (file) to a destination where the destination moves from one location to another. This implies that, in a non-static multi-hop environment, there is a need to model the motion and the requested resources in the end-to-end path such that the resources can be efficiently shared among users, whereas any redundant transmissions and retransmissions are avoided. This work proposes a clustered-based mobility configuration scenario, which is set in Figure 1. Clusters enable the connectivity between nodes and the local (within a cluster) control of a specified area. On the contrary with [12][13] in this work a different mobility scenario is modeled and hosted in the scheme, which enables a parameterized feedback provision through the modeled scheme. Unlike the predetermined Landscape in [12], in this work, the mobility scenario used is Fractional Random Walk. The random walk mobility model was derived from the Brownian motion, which is a stochastic process that models random continuous motion [14]. In this model, a mobile node moves from its current location with a randomly selected speed in a randomly selected direction as real time mobile users act. However the real time mobility that the users express, can be defined by spotting out some environmental stimulating elements (adverts, cinema, shopping mall et.c) where users' decisions may be affected. In the proposed scenario the new speed and direction are both chosen from predefined ranges, $[v_{min}, v_{max}]$ and $[0, 2\pi)$, respectively [15]. The new speed and direction are maintained for an arbitrary length of time randomly chosen from$(0, t_{max}]$. At the end of the chosen time, the node makes a memoryless decision of a new random speed and direction. Figure 1(a) shows the scenario where the associations and the potential coverage area of a node is depicted. The movements are shown as a Fractional Random Walk (FRW) on a Weighted Graph.

Taking into consideration the movement of each device and by using the graph theoretical model, a device can perform random movements according to the topological graph $G = (V,E)$ where it comprises of a pair of sets $V$ (or $V(G)$) and $E$ (or $E(G)$) called vertices (or nodes) and edges (or arcs), respectively, where the edges join different pairs of vertices. This work considers a connected graph with $n$ nodes labeled $\{1, 2, . . . , n\}$ 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

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that $w_{ij} = w_{ji}$. A particle walks from node to node in the graph in the following random walk/movement manner. Given that the device/particle is currently at node *i*, the next node *j* is chosen from among the neighbors of *i* with probability:

$$p_{ij}^{L} = \frac{w_{ij}}{\sum_{k} w_{ik}} \tag{1}$$

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:

$$w^{L}{}_{ij} = \sum_{i,j:j>1} w_{ij} \tag{1.1}$$

By using the motion notation, we can express the track of the 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 as in eq. 2. This work uses the representation of the interactions by utilizing notations of weighted graphs (equation 1). An example of social network is represented in Figure 1(a) where each node represents one person. The weights associated with each edge linking two persons (two devices) of the network are used to model the strength of the interactions between individuals [16]. The assumption made lays within the context that these weights are expressed as a measure of the strength of the social relations of the linking parts. Then the degree of social interaction between two people/devices can be expressed as a value in the range [0, 1]. These social interaction coefficients have a simplistic mean that, when 0 is expressed, it indicates that there is no interaction; whereas when 1 is expressed, it indicates that there is a strong social interaction. This aspect will affect the outsourcing degree of the requests in order to be available by other users in any cluster as 3.A's section show. Therefore, the connectivity of interactions in the network of Figure 1 can be represented by the 5×5 symmetric matrix (matrix is based on the population in the network and the hosted clusters), where the names of nodes correspond to both rows and columns and are ordered based on the interaction and connectivity. Matrix $I_{ij}$ is referred to, as the Interaction Matrix. The generic element *i,j* represents the interaction between two individuals *i* and *j* where the diagonal elements represent the relationships that an individual has with himself and are set, conventionally, to 1. In (2), the $I_{ij}$ represents all the links associated to a weight before applying the threshold values, which will indicate the stronger association between two individuals.

$$I_{ij} = \begin{bmatrix} 1 & 0.66 & 0.13 & 0.87 & 0 \\ 0.12 & 1 & 0.99 & 1 & 0.31 \\ 0 & 0.21 & 1 & 0.54 & 0.65 \\ 0.21 & 0 & 0 & 1 & 0.84 \\ 0 & 0 & 0.95 & 0.09 & 1 \end{bmatrix} \tag{2}$$

The threshold value is estimated according to the enhancement of the relation of the individuals as follows:

$$I_{ij} = \frac{I_{ij} + \Delta I}{1 + \Delta I} \tag{2.1}$$

where $I_{ij}$ is the enhanced or weakened (if less than $\nabla I_{ij} = I_{ij(\tau)} - I_{ij(\tau-1)}$) association between two individuals and $\Delta I$ is the difference according to the previous $I_{ij}$ association between *i* and *j*. Since while sharing resources time plays a major role, this work models a time-oriented enforcement of enabling an association to fade, i.e. if two individuals are not in contact for a prolonged time period. This association increases or reduces progressively with the time using the equation:

$$\Delta I_{ij} = \frac{a}{t_{age}} + b, \forall t_{age} < T_{R_L} \tag{2.2}$$

where $t_{age}$ is the time that has passed since last contact and is measured until the individuals abandon the clustered plane L. *a* and *b* are proper constants[1] chosen by the designer of the network (*a*= 0.08, *b*=0.005). 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:

$$M_{ij} = I_{ij} \cdot p_{ij}^{L} \tag{2.3}$$

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.

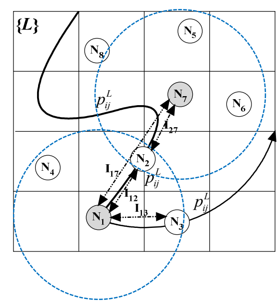


Figure 1. Inter-cluster communication and connectivity between nodes (within a cluster) with FRW model and social interactions (I).

### A. *Using social centrality for replicated object policy*

One of the key tasks in wireless network analysis is determining the relative importance of individuals based on their positions, connectivity structure and motion through time. One concept in measuring and combining these aspects of the behavior of wireless networks is referred to as the centrality of individual devices with respect to the placement and behavior of each individual device in the cluster. Thus by using centrality approximation, a subset of the individuals in the network is sampled, and an induced subgraph consisting only of these individuals, and the links among them is produced, as a representative sample at time t. The centrality computation, then, is performed on this induced subgraph instead of the entire network, with the centrality scores of the sample being used as approximations. This work uses the social centrality as a measure

[1] Constant values for *a*= 0.08, *b*=0.005 are design parameters and were found to consist a suitable set (see [16] for more calculations on these estimations), based on the network's dimension at a certain time.

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of the generic centrality of the system and the relative associations. Thus in the system with moving devices, a node that is directly connected with many nodes and has high $I_{ij}$ can be considered as a high degree node. In other words, the lower degree nodes need the high degree nodes to serve as a bridge in order to connect with other lower degree nodes. According to the high degree nodes, the degree or centrality $D_c(aj)$ 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. A maximum number of connected nodes for a certain graph is $n-1$. Therefore, 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:

$$D'_c(aj) = \frac{\sum_{i=1}^{n} d(ai,aj)}{n-1} \qquad (3.1)$$

Centrality indicates the relative importance of a node in a network [17] and the relative contribution of this node to the communication process (in terms of duration and distance covered with the frequency, and parameterized in the context of avoiding communication partitioning problems). The social centrality is a relative measure of the betweenness centrality of two or more nodes. Social centrality is a type of centrality, that measures the number of times a node is chosen to host the 'best effort' parameters (in terms of storage, capacity and betweeness location) for time $t$ in L, for, which requested data can be outsourced to this node. Therefore, a node with high social betweenness centrality $\beta_{ai}$ can have a strong ability to interact with other nodes in the cluster $L$, and can be measured as:

$$\beta_{ai} = \frac{\sum_{1}^{j} P_{aj \to ak}}{\sum_{1}^{k} P_{ij} \forall P \in ai} \qquad (3.2)$$

where $P_{aj \to ak}$ is the number of paths in the cluster via, which a requested object can be retrieved between the $aj$ and $ak$, and $P_{ij}$ is the number of paths in the cluster that include ai, $\forall P \in ai$. We introduce the social-oriented stability parameter $\sigma_C(t)$ for a time t, and is estimated as:

$$\sigma_C(t) = \left[ \frac{R_{ij|t} \cdot (1 - norm(\beta_{ai})) \cdot N_{C(i \to j|t)}}{\inf(C_r) \cdot R_{C(t)}} \right] m_{ij}(t) \qquad (3.3)$$

where $R_{ij}$ is the normalized communication ping delays between $i$ and $j$ nodes at time t, $\beta_{ai}$ 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 downloaded chunk capacity files over the total file capacity, $C_r$ is the multi-hop channel's available capacity, $m_{ij}(t)$ is the interaction measures derived from eq. 2.3 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 diffuse a certain requested object according to the ranked criteria of each requested object in $L$ for a time $t$.

*1) Ranking requested resources according to users' demands*

In order to define which requested objects should be outsourced for being available for future requests, a ranking model has been applied as follows: To find the rank of an object $a1\ a2 \ldots a_m$, one should find the number of objects preceding it. It can be found by the following function:

function rank($a_1, a_2, \ldots, a_m$ $|L$)// ranking the $a_1$, $a_2$, .. in L cluster
*rank*← 1 ;
**for** $i \leftarrow 1$ **to** $m$ **do**
**while** (*k has any neighbor with* $a_i$) ***do***
$rank \leftarrow rank + N(a_1, a_2, \ldots, a_{i-1})$

where the function above indicates which resources are highly demanded and are ranked according to these demands for the first *k-hop* nodes in the path.

*2) Cluster merging and transfers' minimization*

This work has utilized a cluster merging notation, where, if a resource is available from a nearby user in another Cluster accessible in a specified number of hops, a virtual merging mechanism has been enabled similar with the cluster merging in [18]. This means that by the utilization of the MinMax Cut algorithm proposed in [18], the cluster is partitioned in a way to make a distinction between pair-wise similarities with regards to the requested objects.

*B. Optimistic intracluster outsourcing scheme using social interactions*

In order to enable the proposed combination of the weights of the motion, with the interaction matrix and its elements of the matrix denoted as the interaction indicators we have modeled a mechanism for diffusing the requested high ranked resources to be outsourced. The diffusion policy used is using a resource sharing model, which reflects the impact of the mobility and the impact of the interaction indicators onto the proposed diffusion mechanism. Equation 4 shows the quantitative resource sharing approach by using the $M_{ij}$ as a function of the contact rate and the number of users that are interacting (or not) in the cluster. The model is similar with the [12] in the sense that, the epidemiological model that is used in [12] is being replaced by the social interactions and the elements of the interaction indicators. We assume that a common lookup service is followed by all devices in the network cooperating via a shared platform. This model is providing feedback via the interactions performed $M_{ij}$ and the number of users that are not interacting within time frame $t$. Suppose there are $u$ hosts in the system, then a host is sharing a resource with $\beta(u-1)$ other hosts per unit time. $\tilde{I}$ $(k-1)$ are the number of users that are not interacting with (i,j) taking into account the threshold values, and/or are newly entered users in the cluster and have no relation/interaction with i,j. Therefore,

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the diffusion transition rate for the resource sharing process taking into consideration the above, becomes:

$$\Phi_{ij} = M_{ij} \cdot \beta(u-1) \cdot \widetilde{I}_L \qquad \widetilde{I}_L = \frac{\overline{I}}{(u-1)} \tag{4}$$

where $\Phi_{ij}$ is the resource sharing from *i* to *j*, $\beta$ is the contact rate, *u* are the hosts in the cluster as in [12]. It stands that all $u \in L$. The download rate can be measured as $\delta = M_{ij} \cdot \gamma \forall i, j \in L$, where $\gamma$ is the supported transmission rate by the channels for downloading resources from *j* to *i* for time t. In order to avoid caching saturation [4] onto nodes, which are hosting the requested cached resources, this work uses a countermeasure to delete the requested resources from any node after time t. This is to clean up with redundant files the devices' storage units and memories. The delete or Purging Enforcement policy encompasses the Time-To-Leave duration of a node in the cluster, which is enforced by the motion weight $w^L_{ij}$ as follows:

$$d_{TTL} = \frac{m_{ij}\tau}{C_{ij}} \cdot C_{ij}(\tau) \tag{4.1}$$

where $m_{ij}$ is the *i,j* element of the matrix of eq. 2.3, $\tau$ is the duration since last claim of the file from destination *j*, $C_{ij}(\tau)$ is the relative reserved capacity according to the channel's available capacity from *i* node to *j*, and $C_{ij}$ is the total channel's capacity from node *i* to node *j* within the time duration $\tau$ .

## IV. PERFORMANCE ANALYSIS THROUGH SIMULATION AND DISCUSSION

In the implementation-simulation of the proposed scenario, C/Objective programming language libraries were used as in [2]. The movement patterns generator was implemented to produce primarily traces for the ns-2 simulator [19]. All mobile nodes collaborate via a shared application that uses a distributed look-up service. Radio coverage is small compared to the area covered by all nodes, so that most nodes cannot contact each other directly. Additionally, we assume IEEE 802.11x as the underlying radio technology supporting the Cluster-based Routing Protocol (CRP). Queries regarding the resources that are available by peers for sharing, are generated dynamically and are selectively cached onto nodes according to Section III.A (eq. 3.4), where requested resources are ranked according to users' demands. The community is following the FRW on a Weighted Graph and consists of 250 users diffused in a landscape. The interaction of a particular user affects the contact rate and the interaction matrix entries of the next moment as real time users do and follows the measure of the equation 2.2. This association increases or reduces progressively with the time. Figure 2(a) shows the distribution of contacts' duration in *msec* with the Successful packet Delivery Ratio (SDR), whereas Figure 2(b) shows the SDR with the speed of each device comparing three different schemes.

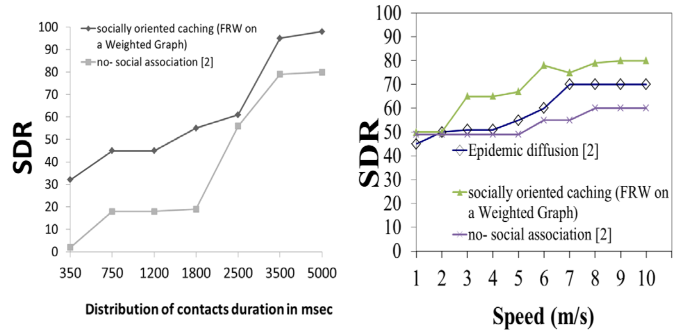


Figure 2(a). The Successful packet Delivery Ratio (SDR) with the distribution of contacts' duration in msec. Figure 2(b). The SDR with the speed of each device comparing three different schemes.

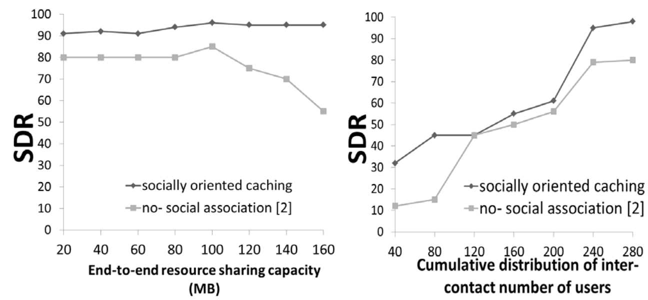


Figure 3(a)-(b). The Successful packet Delivery Ratio (SDR) with the End-to-end resource sharing capacity (MB) and Cumulative distribution of the number of users that are experiencing inter-contact.

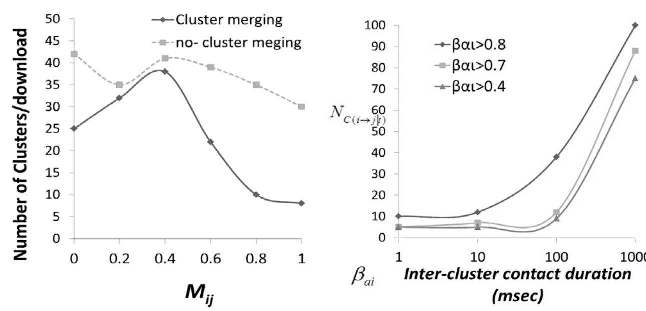


Figure 4(a)-(b). Number of Clusters/download with the Interaction-Mobility estimation of the $M_{ij}$ between peers, and the social centrality values with the successfully downloaded chunk capacity files over the total file capacity with respect to the inter-cluster duration.

Figures 3(a) and (b) show the Successful packet Delivery Ratio (SDR) with the End-to-end resource sharing capacity (MB) and Cumulative distribution of the number of users that are experiencing inter-contact. Figure 3(b) shows that if users will outsource the requested resources using the interaction model, then the associated SDR increases significantly and the number of completed files are also increasing. Figure 4 shows the number of Clusters/download with the Interaction-Mobility estimation of the $M_{ij}$ between peers. If the social centrality of the node increases, which means that the node has greater likelihood of its spatial and temporal location then the SDR increases and the inter-cluster contact time is reduced. Figures 5(a) and (b) show the total download time with the contact duration for complete downloads and the volume of the outsourced capacity with the contact duration for complete downloads. In Figure 6, the SDR with the number of delay-deadlined transmissions when a node requests resources is shown. By using socially-oriented caching the

 

SDR is kept high when the associated interaction parameters are greater than >0.4 and the social centrality parameter is >0.6.

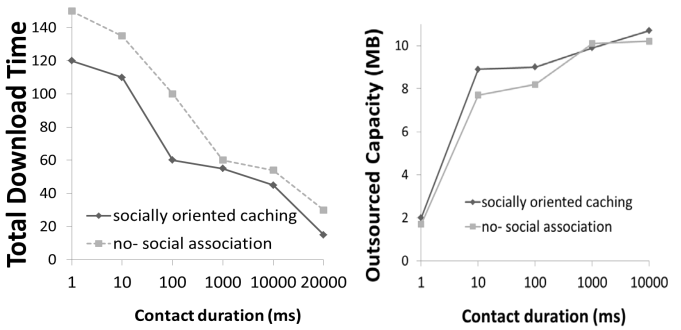


Figure 5(a)-(b). Total download time with the contact duration for complete downloads and the volume of the outsourced capacity with the contact duration for complete downloads.

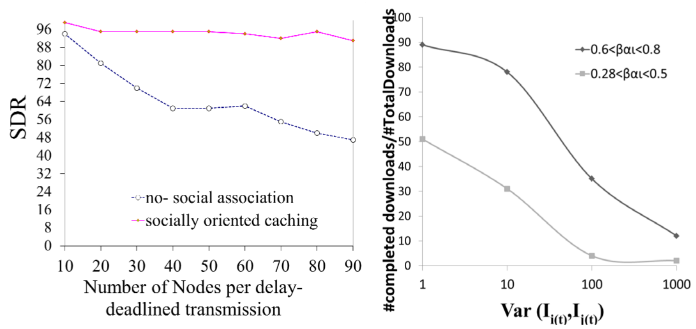


Figure 6(a). SDR with the number of nodes per transmissions with delay-deadlines. Figure 6(b). Successfully completed downloads with the interaction parameters and the social centrality measures.

## V. CONCLUSIONS AND FURTHER RESEARCH

This work considers the probabilistic social interactions in order to assign available resources to communicating nodes according to a combined mobility model and the users' social relations. The collaborative resource sharing is achieved through the opportunistic socially-oriented caching model. Based on users' mobility and the associated probabilistic variation based on time and location, the social-based selective replication enables the cache-and-forward outsourcing model to fill the trade-offs between user's mobility, and reliable file sharing. The scheme outperforms from other existing schemes due to the social model which enables on-demand requested file availability. Examination for the effectiveness of the proposed scheme is performed through simulation taking into consideration the offered reliability by the collaborative-social caching replication scheme within the mobility context. Experimental results show that by introducing interaction parameters to mobile users while sharing resources on-the-move, the reliability increases significantly. Next steps and on-going work within the current research context will be the expansion of this model into a file sharing platform where on-the-move the users can share resources in real-time.

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