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Content replication and placement in mobile networks

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Abstract

Performance and reliability of content access in mobile networks is conditioned by the number and location of content replicas deployed at the network nodes. Location theory has been the traditional, *centralized* approach to study content replication: computing the number and placement of replicas in a *static* network can be cast as a facility location problem. The endeavor of this work is to design a practical solution to the above joint optimization problem that is suitable for mobile wireless environments. We thus seek a replication algorithm that is *lightweight*, *distributed*, and *reactive to network dynamics*.

We devise a solution that lets nodes (i) share the burden of storing and providing content, so as to achieve load balancing, and (ii) autonomously decide whether to replicate or drop the information, so as to adapt the content availability to dynamic demands and time-varying network topologies. We evaluate our mechanism through simulation, by exploring a wide range of settings, including different node mobility models, content characteristics and system scales. Furthermore, we compare our mechanism to state-of-the-art approaches to content delivery in static and mobile networks.

Results show that our mechanism, which uses *local measurements only*, is: (i) extremely precise in approximating an optimal solution to content placement and replication; (ii) robust against network mobility; (iii) flexible in accommodating various content access patterns. Moreover, our scheme outperforms alternative approaches to content dissemination both in terms of content access delay and access congestion.

Index Terms

content replication, mobile networks, facility location theory, distributed algorithms

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1 Introduction

Academic and industrial research in the networking field is pursuing the idea that networks should provide access to contents, rather than to hosts. Recently, this goal has been extended to wireless networks as well, as witnessed by the tremendous growth of services and applications offered to users equipped with advanced mobile terminals.

The inexorable consequence of a steady increase in data traffic exerted by mobile devices fetching content from the Internet is a drainage of network resources of mobile operators [1–3]. A promising approach to solve this problem is *content replication*, i.e., to create copies of information content at user devices so as to exploit device-to-device communication for content delivery. This approach has been shown to be effective especially in wireless networks with medium-high node density, where *access congestion* is the main limiting factor that determines the performance of content delivery (see, e.g., [4] for a survey on the topic).

been extensively side, and delay replication mechanisms paths with the

In this paper, we consider such a wireless network scenario and explore the concept of content replication in a cooperative environment, when the content demand and network topology dynamically change in time. In this context, nodes can fetch content from the Internet using a cellular network, store it, and possibly serve other users through device-to-device communication (e.g., using IEEE 802.11 or Bluetooth). Our scenario also accommodates the possibility for content to exhibit variegated popularity patterns, as well as to be updated upon expiration of a validity-time tag, so as to maintain consistency with copies stored by servers in the Internet.

according to an epidemic approach the content to all users, might not be

The application scenario we target in this work introduces several problems related to content replication. *Optimal replica placement* is one of those: selecting the location that is better suited to store content is difficult, especially when the network is dynamic. Another prominent issue is *how many content replicas* should be made available to mobile nodes. Clearly, decisions on the placement and number of replicas to be deployed in the network are tightly related problems: intuitively, the latter introduces a feedback loop to the former as every content replication triggers a new instance of the placement problem.

studied through the lenses of classic Location [5]. Our endeavor is to build upon the theoretic works that have flourished in the facility location theory literature, and address the above *joint problems*, with the ultimate goal of designing a lightweight, distributed mechanism to achieve content replication in mobile wireless networks. Thus, our work departs from previous approaches that either require global (or extended) knowledge of the network [6, 7] or are unpractical [8]. In particular, study realistic scenarios in simultaneously consumed by mobile nodes have capacity constraints for the amount other nodes. we design a content replication scheme that requires *local measurements* only and that aims at evenly distributing among nodes the demanding task of hosting a content replica and serve others.

We show that optimality in both placement and replication can be approximated through our simple practical solution.

The contributions of this paper are summarized as follows:

- we revisit traditional facility location theory in the light of the extremely challenging settings that mobile wireless networks introduce. Leveraging the insights provided by capacitated facility location approaches to content replication, we propose a distributed mechanism inspired by local search approximation algorithms. Our solution exploits a particular formulation of a multi-commodity capacitated facility location problem to compute an approximate solution based on local measurements only;
- we perform an extensive simulation study where we dissect the properties of our distributed mechanism. As a result, we show that content placement and replication achieved through our scheme well approximate an optimal solution when both network and content dynamics are considered. Furthermore, our results prove that our mechanism (i) achieves load balancing among the network nodes, in terms of both amount of served requests and storage capacity required at each mobile user, and (ii) scales very well with the network size and density, making it suitable for those scenarios in which access congestion may appear;
- we compare through simulation our content replication scheme with existing mechanisms, considering the realistic case where not all users are interested in the available information items.

The remainder of the paper is organized as follows. In Sec. 2, we give a detailed overview of the system model and we introduce the content replication problem, pointing at the new problems introduced by the dynamic nature of wireless networks. In Sec. 3, we revisit traditional location theory and extend it to accommodate the constraints and requirements of our system. Based on the insights gained from a theoretical ground, we move on to the design of our distributed mechanism for content replication and replica placement in Sec. 4. In Secs. 5 and 6 we describe the simulation settings and methodology and present a thorough discussion on the results. We review prior works in the domain of content dissemination in mobile networks in Sec. 8, and finally draw our conclusions in Sec. 9.

2 Network scenario and problem statement

Here, we first detail the system model we refer to, then we define the problem of content replication and placement in mobile networks. In particular, we inherit the problem of replication typical of the wired Internet and we discuss the new challenges introduced by the dynamic nature of wireless networks with respect to their wireline counterpart. At last, we describe the steps we take in order to address content replication and placement in our setting.

2.1 System model

We investigate a scenario including mobile users (i.e., mobile nodes), equipped with devices offering 3G/4G Internet connectivity as well as device-to-device communication capabilities (e.g., through IEEE 802.11). Although we do not concern ourselves with the provision of Internet access in ad hoc wireless networks, we remark that broadband connectivity allows new content to be fetched and, possibly, updated.

We denote the set of mobile nodes by \mathcal{V} , with $V = |\mathcal{V}|$, and we consider that they may be interested in a set of information items. We refer to such a set as \mathcal{I} and to its cardinality as I . Each item $i \in \mathcal{I}$, of size $s(i)$, is tagged with a validity time, and originally hosted on a server in the Internet, which can be accessed by mobile users through the broadband access we hinted at. We define as $p(i)$ the content popularity level of the generic item i , i.e., the fraction of nodes interested in such an item. Thus, we have $0 \leq p(i) \leq 1$, with $p(i) = 1$ corresponding to the highest popularity level, i.e., when all nodes in the system are interested in content i .

We focus on a *cooperative environment* where a node $j \in \mathcal{V}$ wishing to access the content first tries to retrieve it from other devices. If its search fails, the node downloads a fresh content replica from the Internet server and temporarily stores it for a period of time τ_j , termed *storage time*. For simplicity of presentation, in the following we assume $\tau_j = \tau, \forall j \in \mathcal{V}$. During the storage period, j serves the content to other nodes upon receiving a request for it and, possibly, downloads from the Internet server a fresh copy of the content if its validity time has expired. We refer to the nodes hosting an information copy at a given time instant as *replica nodes*. We denote the set of nodes storing a copy of item i at time t by $\mathcal{R}_i(t)$, and define $\mathcal{R}(t) = \cup_{i \in \mathcal{I}} \mathcal{R}_i(t)$, with $R = |\mathcal{R}|$. Also, we associate to each replica node j a capacity value c_j , which, as we shall see later, relates to the capability of the node to serve content requests.

A node, which is interested in a generic information item i and does not store any copy of it, issues queries for such an item at a rate λ . Replica nodes, which receive a query for an information item they currently store, will reply with a message including the requested content.

Finally, in order to clearly define the problem we address, in the following we model the network topology at a given time instant t through a graph $G(t) = (\mathcal{V}, \mathcal{E}(t))$, whose set of vertices coincides with the set of network nodes \mathcal{V} and the set of edges $\mathcal{E}(t)$ represents the set of links existing between the network nodes at time t .

2.2 Problem statement

Both content replication and caching have received significant attention in the literature, due to their importance in enhancing performance, availability and reliability of content access for Web-based applications. The two problems, however, differ since content replication is an independent process aimed at creating copies

of a content at the network nodes, regardless of whether they asked for it or not. Caching, instead, is a by-product of the content query mechanism as only nodes that retrieved the content have the possibility to cache it [4].

Our claim (confirmed by simulation results) is that, in a network scenario as the one we address in this work, content replication is to be preferred to caching. Indeed, caching may lead to the creation of a large number of copies in the network, especially for highly-popular content. In medium-high dense networks, this raises the problems of (i) large overhead due to multiple replies to a single query, (ii) energy depletion of a large fraction of nodes acting as content providers, (iii) congestion in accessing the cellular network for fresher versions of the content in order to avoid inconsistencies. We therefore deal with content replication, that is, we design a mechanism to determine how many replicas should be created in the network and where, under dynamic, realistic conditions.

Traditionally, a similar problem has been studied through the lenses of classic Facility Location Theory [5], by considering replicas to be created in the network as facilities to open. Which new problems are then introduced in our work?

i) Content replication and placement can be cast as an optimization problem in presence of static network conditions. However, node mobility leads to a dynamic graph $G(t)$, which would require the problem to be solved upon every network topology or demand rate change.

ii) While addressing content replication, we also target load balancing among the nodes. Even under static topology and constant demand, solving the facility location problem does not yield load balancing.

iii) The input to the facility location problem is the content demand workload generated by users: both replica locations and the number of replicas to deploy in a network depend on content consumption patterns. While the approach traditionally adopted is to assume content demand to be directed to the closest facility, the wireless nature of our system yields unpredictable propagation paths for content requests, potentially reaching multiple facilities (replica nodes).

iv) The traditional approach defines two separate sets, one for facilities (replica nodes) and one for the users. In our context, instead, any node may store an information replica as well as request an item which it does not currently own.

As a first step to address all of the above issues, in Sec. 3 we restrict our attention to a simplified network setting and revisit a centralized approach for facility location problems. Our goal is to gain sufficient insights from such a problem formulation, as well as from solutions to it proposed in the literature, to build a distributed approach that closely approximates the optimal solution to the problem. Then, in Sec. 4 we consider a dynamic scenario (i.e., mobile nodes and time-varying demand) and seek an algorithm that only requires local knowledge and a distributed implementation.

3 Getting insights: A centralized approach

The simplified network scenario we address here is characterized by static nodes and constant demand; furthermore, we drop the load balancing requirement we previously outlined and assume that content queries are directed to the closest replica node. For simplicity, let us fix the time instant and drop the time dependency from our notation; also, let all users be interested in every content i ($i = 1, \dots, I$) and request it at the same constant rate.

Given such a scenario, we formulate our replication problem as a *capacitated* facility location problem where the set of replica nodes $\mathcal{R} = \cup_i \mathcal{R}_i$ corresponds to the set of facilities that are required to be opened, nodes requesting a content are referred to as clients and information items correspond to the commodities that are available at each facility. We model the capacity of a replica node as the number of clients that a facility can serve. The goal is to identify the *subset* of facilities that, at a given time instant, can serve the clients so as to minimize some global cost function while satisfying the facility capacity constraints.

We point out that, with respect to traditional formulations of the capacitated facility location problem, we need to take into account the following aspects. Both clients and facilities lay on the same network graph $G = (\mathcal{V}, \mathcal{E})$. As such, any vertex of the graph can be a client or a facility: all vertexes that are not selected as facilities will be treated as clients.

In the location theory literature, two copies of the same facility can be opened at the same location, in order to increase the capacity of a site. Instead, in our work a vertex of the graph can host only one copy of the same facility: indeed, it is reasonable to assume that a node stores only one copy of the same information item.

For the sake of clarity, we first define a *single-commodity* capacitated facility location problem, where we delve into the details of local search techniques that have been applied in the literature to solve such problems. We then move to a *multi-commodity* version of the problem and discuss the issues related to the capacity constraints we are required to satisfy in this case.

3.1 The single commodity problem

Let us consider one information item only (i.e., $I = 1$). Then, we can define the single commodity capacitated facility location problem as follows.

Definition 1 *Given the set \mathcal{V} of nodes (which can act as both clients and facility nodes) and cost f_j of opening a facility at $j \in \mathcal{V}$, select a subset of nodes as facilities, $\mathcal{R} \subseteq \mathcal{V}$, so as to minimize the joint cost $C(\mathcal{V}, f)$ of opening the facilities and serving the demand while ensuring that each facility j can only serve at most c_j clients:*

$$C(\mathcal{V}, f) = \sum_{j \in \mathcal{R}} f_j + \sum_{h \in \mathcal{V}} d(h, m_h). \quad (1)$$

In (1), $m_h \in \mathcal{R}$ is the facility j closest to h , and $d(h, m_h)$ is the cost attributable to facility m_h for serving client h (in the literature, this is typically modelled as a pair-wise distance function between client and facility). Also, the number of clients attached to facility $j \in \mathcal{R}$, i.e.,

$$u_j = |\{h \in \mathcal{V}, \text{ s.t. } m_h = j\}|,$$

must be such that $u_j \leq c_j$.

In words, the above problem amounts to finding how many facilities should be open, and at which nodes, so as to minimize the average distance to access a facility from a client location, while satisfying the capacity constraints of each opened facility. This problem nicely translates into our setting, where we need to establish the number of replicas to be created for an information item and find the best nodes to store them so as to minimize the distance (hence the delay) to access the information. We also point out that the facility location problem in Def. 1 reduces to a k -median problem if the number of facilities is given, i.e., $R = k$, and we drop the capacity constraints. The solution to such a special case maps to finding the best location for k facilities to be opened.

It is well known that, for general graphs, the above problems are NP-hard [9] and a variety of approximation algorithms have been developed and analyzed to solve them. Among these algorithms, the ones based on local search are the most versatile [6]. In a general form, a local search algorithm to solve capacitated facility location problems consists of an iterative procedure in which, at every step, a variation is applied to the current solution of the problem. If the *global* cost decreases, the variation is accepted as a new solution to the problem. The algorithm stops when no more improvements can be obtained. Three variations are possible: to *swap* the location of a currently opened facility, to *drop* a currently opened facility, and to *add* a facility to the current solution. Note that the local search algorithm to the capacitated version of the facility location problem is fairly complex: indeed, it involves the computation of a minimum cost flow problem in order to verify the capacity constraints [6].

Such local search procedures will inspire our distributed mechanism described in Sec. 4, where we introduce three basic operations that iteratively, albeit *asynchronously*, yield the solution to the content replication problem. However, there are some important remarks to make. The key point in our solution is the definition of the opening costs f_j 's, which allows us to move from a centralized to a distributed implementation as well as provide load balancing. Moreover, the particular operation that each node executes to solve the replica placement problem is performed irrespectively of the number of replicas in the network. As such, content placement and replication are effectively de-coupled. Finally, in our network system adding and swapping are constrained operations: only vertexes that are connected by an edge to the current vertex hosting a content replica can be selected as possible replica locations. Thus, our operations are *local* and information item replicas can only move by one hop at the time in the underlying network graph.

3.2 The Multi-commodity problem

We now consider the more general setting in which multiple commodities (i.e., information items) may be available at each facility (i.e., replica node).

While the problem can be defined similarly to Def. 1, the cost function that we need to minimize, formerly defined in (1), has to be rewritten as follows:

$$C(\mathcal{V}, f) = \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{R}_i} f_j(i) + \sum_{i \in \mathcal{I}} \sum_{h \in \mathcal{V}} d(h, m_h(i)) \quad (2)$$

where $f_j(i)$ is the cost to open a facility for commodity i , $\mathcal{R}_i \subseteq \mathcal{V}$ is the subset of nodes acting as facilities for commodity i , $m_h(i) \in \mathcal{R}_i$ is the facility holding item i that is the closest to h , and the number $u_j(i)$ ¹ of clients requesting any content i attached to facility $j \in \mathcal{R}_i$, i.e., $u_j(i) = |\{h \in \mathcal{V} \text{ s.t. } m_h(i) = j\}|$, is such that $\sum_{i \in \mathcal{I}} u_j(i) \leq c_j$.

In the traditional formulation of such problem, with distinct sets of facilities and clients, a solution amounts to finding the location and the number of facilities to open so that the overall client requests are satisfied. In our setting, however, the problem is more complex: since any vertex of the graph G can host a facility or can be a client, it is possible for a vertex to assume both roles. Indeed, a vertex can be a replica node for one or more information items, and, at the same time, a client requesting information items that are not currently hosted at the vertex.

Finding approximate solutions to the multi-commodity capacitated facility locations is still an open issue and little is known concerning local search heuristics that can be effectively implemented in practice. In this work, we take a simple approach that has been also discussed in [10]: a solution to the multi-commodity problem is built from the union of the solutions to individual single-commodity facility location problems. Therefore, we transform the formulation from multi-commodity to single-commodity by solving the above problem for each item i ($i = 1, \dots, I$) separately.

Then, for each item i , (2) becomes:

$$C(\mathcal{V}, f(i)) = \sum_{j \in \mathcal{R}_i} f_j(i) + \sum_{h \in \mathcal{V}} d(h, m_h(i)) \quad (3)$$

where $m_h(i) \in \mathcal{R}_i$ is the facility closest to h and the number of clients attached to facility $j \in \mathcal{R}_i$ is such that the capacity constraints are satisfied.

Despite the apparent simplicity of such an approach, how the capacity constraints are verified remains an issue to be discussed. In our work, we adopt the two techniques presented below, where we denote the subset of commodities hosted at j by \mathcal{I}_j and its cardinality by I_j :

1. Each opened facility has a capacity that is allocated to each commodity individually. In practice, this translates into having a separate budget allocated

¹Clearly, we have $u_j(i) = 0$ if j does not own i .

to each information item that is currently replicated at a node in the network. Formally, the capacity constraints can be written as $u_j(i) \leq c_j/I_j, \forall i \in \mathcal{I}_j$, where we equally split the budget c_j available to facility j over all the commodities it hosts. In the following, we name such a technique *split capacity budget*.

2. We consider a facility to have a capacity that is shared among the commodities currently hosted by the facility. This case appears to be more realistic for our application scenario: each node hosting replicas of information items allocates a preset budget that is used to serve all the contents requested by other nodes. Formally, we define the capacity constraints for this case as follows: $\sum_{i \in \mathcal{I}_j} u_j(i) \leq c_j$, and we refer to such a technique as *shared capacity budget*.

In conclusion, the approach we take in this work is to break the joint optimization problem of the capacitated multi-commodity facility location into a number of single-commodity location problems, as from (3), for which we use the local search techniques outlined above with the additional considerations we made in this section concerning the capacity constraints.

To the best of our knowledge, there is no known practical, distributed algorithm to obtain approximate solutions to the capacitated version of the multi-commodity facility location problem either. In the next section, we therefore propose a new approach that only requires local knowledge, which is acquired with simple measurements, and also provides load-balancing. It follows that, even in a static scenario, our distributed algorithm does not converge to a static configuration in which a fixed set of nodes is selected to host content replicas. As such, the traditional methods that are used in the literature to study the convergence properties and the locality gap of local search algorithms cannot be directly applied, which is the main reason for us to take an experimental perspective and validate our work through simulations.

4 Distributed mechanism for content replication

We now describe our distributed replication mechanism. Armed with the insights on the problem formulation discussed in Sec. 3, our mechanism mimics a local search procedure, by allowing replica nodes to execute one of the following three operations on the content: (1) handover, (2) replicate or (3) drop. For clarity of presentation, in the following we describe our mechanism in terms of two objectives: content replication (Sec. 4.1) and replica placement (Sec. 4.2). Indeed, the handover operation amounts to solving the optimal placement of content replicas, whose number is determined through the add and drop operations.

For simplicity, we consider again that all users are interested in every content i ($i = 1, \dots, I$) and request it at the same constant rate. Also, we fix the time instant and drop the time dependency from our notation.

4.1 Content replication

Let us define the workload of the generic replica node j for content i , $w_j(i)$, as the number of requests for content i served by j during its storage time. Also, recall that we introduced the value c_j as the capacity value of node j and we provided a definition that suited the simplified, static scenario described in Sec. 3. We now adapt the definition of c_j to the dynamic scenario at hand, as the reference volume of data that replica node j is willing to provide during the time it acts as a replica node, i.e., in a storage time τ . Then, with reference to Eq. 1, we denote by $f_j = \sum_{i \in \mathcal{I}_j} f_j(i)$ the cost associated with replicas at node j .

Given the load balance we wish to achieve across all replica nodes and the node capacity constraint, the total workload for replica node j should equal c_j . Thus, we write f_j as:

$$f_j = c_j - \sum_{i \in \mathcal{I}_j} s(i)w_j(i) \quad (4)$$

where we recall that $s(i)$ denotes the size of content i . In other words, we let the cost associated with replica node j grow with the gap between the workload experienced by j and its capacity c_j .

Then, during storage time τ , the generic replica node $j \in \mathcal{R}$ measures the number of queries that it serves, i.e., $w_j(i) \forall i \in \mathcal{I}_j$. When its storage time expires, the replica node j computes f_j and takes the following decisions: if $f_j > \epsilon$ the content is *dropped*, if $f_j < -\epsilon$ the content is *replicated*, otherwise the hand-over operation is executed (see Sec. 4.2). Here, ϵ is a tolerance value to avoid replication/drop decisions in case of small changes in the node workload.

The rationale of our mechanism is the following. If $f_j < -\epsilon$, replica node j presumes that the current number of content replicas in the area is insufficient to guarantee the desired volume of data, hence the node replicates the content and hands the copies over to two of its neighbors (one each), following the placement mechanism described below in Sec. 4.2. The two selected neighbors will act as replica nodes for the subsequent storage time. Instead, if $f_j > \epsilon$, node j estimates that the workload the current number of replicas can provide is exceeding the total demand, thus it just drops the content copy. Finally, if the experienced workload is (about) the same as the reference value, replica node j selects one of its neighbors to which to hand over the current copy, again according to the mechanism detailed next.

4.2 Replica placement

As noted in Sec. 3, given the graph representing the network topology at a fixed time instant, the placement of $R = k$ replicas can be cast as a k -median problem. By applying the approximation algorithm in [6], we observed that the solution of such a problem for different instances of the topology graph yields replica placements that are instances of a random variable uniformly distributed over the graph. As a consequence, in a dynamic environment our target is to design

a distributed, lightweight solution that closely approximates a uniform distribution of the replicas over the network nodes while ensuring load balancing among them. To this end, we leverage some properties of random walk and devise a mechanism, called *Random-Walk Diffusion (RWD)*, that drives the “movement” of replicas over the network according to a random walk mobility model.

According to RWD, at the end of its storage time τ , a replica node j randomly selects another node l to store the content for the following storage period, with probability $p_{j,l} = \frac{1}{d_j}$ if l is a neighbor of j , and 0 otherwise, where d_j is the current number of neighbors of node j . In this way, each replica performs a random walk over the network, by moving from one node to another at each time step τ . Thus, we can apply the result stating that in a connected, non-bipartite graph, the probability of being at a particular node j converges with time to $d_j/(2|\mathcal{E}|)$ [11]. In other words, if the network topology can be modeled by a regular graph² with the above characteristics, the distribution of replicas moving according to a random walk converges to a stationary distribution, which is uniform over the nodes.

In general, real-world networks yield non-regular graphs. However, when V nodes are uniformly deployed over the network area and have the same radio range, the node degree likely has a binomial distribution with parameters $(V - 1)$ and p , with p being the probability that a link exists between any two nodes [12, 13].

For practical values of p and V in the scenarios under study, we verified that the node degree distribution is indeed binomial with low variance, i.e., all nodes have similar degree. It follows that a random walk provides an acceptable uniform sampling of the network nodes, hence the replica placement distribution well approximates the uniform distribution.

A similar result can be obtained also for clustered network topologies, where each cluster core results to be an expander graph [14]. In this case, a uniform replica placement over the nodes can be achieved within each of the network clusters, thus ensuring the desired placement in all areas where the user demand is not negligible.

Finally, we stress that the presence of R replicas in the network corresponds to R parallel random walks. As observed in [15], this reduces by almost a factor R the expected time to sample all nodes in the network, which is closely related to the time needed to approximate the stationary distribution by a constant factor [16]. It follows that, given a generic initial distribution of the replicas in the network, the higher the R , the more quickly the replica placement approximates a uniform distribution.

5 Simulation scenario

We implemented our mechanism in the *ns - 2* simulator. We consider a wireless network with high node density, namely $3.2 \cdot 10^{-4}$ nodes/m², on a square area of 1 km², which results in $V = 320$ and an average node degree of 9.6 neighbors.

²A graph is regular if each of its vertices has the same number of neighbors.

By default, nodes move according to the stationary random waypoint model [17] with an average node speed of 1 m/s and a mean pause time of 100 s, a setting that is representative, for example, of customer mobility within a mall. We also explored the performance of our mechanism in presence of outdoor pedestrian mobility.

We assume nodes to be equipped with a standard 802.11 interface, with a 54 Mbps fixed data transmission rate and a radio transmission range of 100 m. As our focus is on the placement and replication of items within the ad-hoc network, we do not simulate cellular access. However, we account for the delay associated with the download of information items from the cellular network, by assuming a throughput of 384 kbps, matching that typically provided by 3G technologies to outdoor mobile users.

The rate at which a node interested in a content generates queries for that item is set to $\lambda = 0.01$ requests/s. As for the propagation of the queries in the ad hoc network, we assume the presence of a content-location service that nodes can access to obtain the identity of the closest content replica³. A query for the closest replica node is then propagated using sequence numbers to detect and discard duplicate queries, as well as an application-driven broadcast that optimally selects the forwarding nodes by leveraging the Preferred Group Broadcast (PGB) technique [19]. Also, a TTL is included into queries, allowing them to travel 5 hops at most so as to prevent network flooding. Once reached by the request, the intended destination serves it, while other replica nodes ignore the query.

As far as the content return path is concerned, we assume that, at each hop, the identity of the last node that relayed the query is included in the message and recorded at the following forwarder. Thus, the path from the target replica node to the query source is backtracked at the application layer without resorting to ad hoc routing protocols, which would induce overhead or delay in the process.

Since all standard MAC-layer operations are simulated, both queries and replies may be lost due to typical problems encountered in 802.11-based ad hoc networks (e.g., collisions, hidden terminals): if a query fails (i.e., no answer is received after 2 s), a new request is issued, up to a total of 5 times⁴.

Finally, concerning the replication/drop parameters, the tolerance value ϵ used in the replication/drop algorithm is set to 5% of the node capacity budget, while the storage time τ is set to 100 s.

For each experiment described in the following, results are averaged over 10 simulation runs, each lasting around 3 hours of simulated time after a warm-up period of 500 s.

³Since query propagation is not the focus of our work, we do not further address how such a service is maintained; for details, we refer the reader to the vast literature on the topic, e.g., [18] and references therein.

⁴According to extensive calibration tests, omitted due to space limitations, these parameters provide the best results in terms of content access performance.

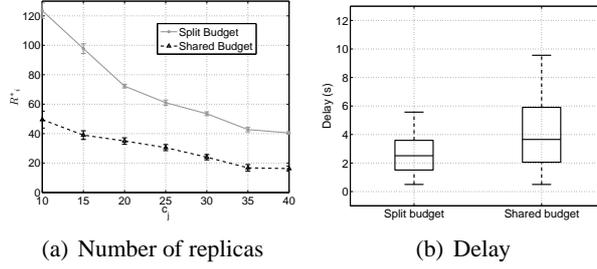


Figure 1: Numerical solutions of the optimization problems in terms of number of replicas (a) and query solving delay (b)

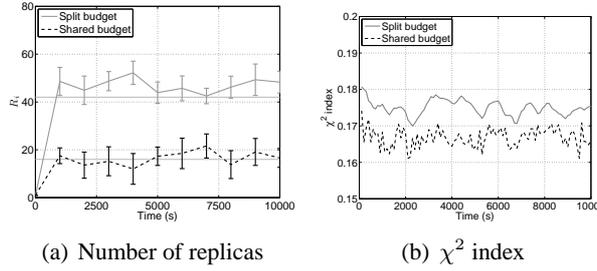


Figure 2: Numerical solutions of the optimization problems, and comparison against our replication scheme: temporal evolution of the number of replicas (a), and of the χ^2 index (b)

6 Results

We present the main results of our work organized in a series of questions. Furthermore, in order to benchmark the distributed mechanism proposed in Sec. 4 against the centralized approach discussed in Sec. 3, we implement the latter as follows. Given the network time evolution, we take a snapshot of the network topology every τ s. For every snapshot, we solve I separate single-commodity problems as in (3), under both split and shared capacity budgets. To do so, we set $f_j(i) = c_j/I_j - u_j(i)$ and $f_j = c_j - \sum_{i \in \mathcal{I}_j} u_j(i)$ in the case of split and shared capacity budget respectively, with $u_j(i) = s(i)w_j(i)$. As a result, load balancing is achieved under the assumption that each content query reaches one replica node only.

6.1 Benchmarking the replication scheme

Here, we provide baseline results on the performance of our replication scheme with respect to the multi commodity problem presented in Sec. 3.2, and discuss its fairness.

What is the impact of the capacity budget on the replication scheme?

To answer this first question, we run the CFL centralized algorithm in a snapshot of the mobile network topology, in presence of 4 items of 1 Mbytes each. We vary the value of c_j from 10 Mbytes to 40 Mbytes, which, in the case of optimization with split capacity budget, means that each content is assigned a budget $c_j/4$.

The optimal number of replicas per information item, denoted by R_i^* , is obtained by numerically solving the optimization problem in (3), in both its split and shared capacity budget versions, and is shown in Fig. 1(a)⁵. The plot clearly shows that, as higher budgets allow replica nodes to satisfy larger amounts of requests, increasing c_j reduces the need for replication, with the result that a lower number of replicas is present in the network.

It is interesting to observe that a significantly higher number of replicas is required by an optimization with split capacity budget with respect to that needed by an optimization with shared capacity budget. The reason is that the latter, using a common budget for all items, forces replications only when the total workload for all items exceeds the budget. Conversely, optimization with split capacity budget uses separate budgets for each content and, thus, results in more frequent violations of such constraints.

Now, intuitively, a large number of replicas may have a beneficial effect on content access performance: more replicas should imply higher chances for queries to be satisfied through device-to-device communication. In Fig. 1(b) we show the most important percentiles (5%, 25%, 50%, 75%, 95%) of content access delay with split and shared capacity constraints, for $c_j = 40$ Mbytes. Contrary to the intuition, our results indicate that the advantage granted by a high number of replicas under the split capacity is quite negligible, and this is mainly due to the congestion that arises in the wireless network.

In summary, our findings pinpoint that the replication mechanism with shared capacity constraints is a suitable approach. Beside experimental results, there are also practical reasons to opt for shared capacity constraints. Indeed, in the split capacity case, a budget has to be assigned to each item currently stored by a replica node, which is a quantity that may vary over time. As a consequence, content replicas may not be suitably handled if the remaining capacity available to a node is not appropriately re-distributed. Furthermore, usability aspects also play a role in favor of a shared capacity approach: it would be unfeasible to ask a user to select a service budget to allocate to every possible item she will ever replicate.

⁵Here and in the following, unless stated otherwise, the results refer to one of the four items since similar results were obtained for each of them.

How does our replication scheme perform with respect to the CFL centralized algorithm?

In order to provide an answer, we simulate our replication scheme and we focus on the case where $c_j = 40$ Mbytes. As shown in Fig. 2(a), our replication scheme can well approximate the results obtained by solving the optimization problems: indeed, the number of replicas R_i generated by our scheme is very close to the optimal value R_i^* , in both the cases of split and shared capacity budget. Moreover, the number of replicas in the system appears quite stable over time, which is obviously a desirable feature.

Not only the number, but also the placement of replicas itself is important when comparing our scheme against a centralized solution. Thus, we now investigate the similarity between the replica placement achieved by our technique and that obtained with the CFL centralized algorithm over the different snapshots representing the network evolution. To do so, we employ the well-known χ^2 goodness-of-fit test on the inter-distance between content replicas⁶. As depicted in Fig. 2(b), the χ^2 error obtained comparing the distributions we achieve with the optimal ones is extremely low in all cases; indeed, the χ^2 error we obtain is well below the value⁷ needed to accept the null hypothesis that the two distributions are the same at a 95% confidence level.

How fair is our replication scheme?

The scheme we propose is fair in terms of resources demanded from nodes in the network. On the one hand, in Fig. 3(a), we show the distribution of the number of items stored by a node at the same time: a node seldom stores more than one replica, which implies that node memory utilization is similar across the network. Indeed, our scheme successfully avoids the risk of replica stacking at some good candidates thanks to the enforced periodic swapping of the replica role among nodes. On the other hand, Fig. 3(b) depicts the cumulative distribution function (CDF) of the percentage of total network workload handled by each node, in terms of answered queries: the curve is quite steep around the ideal value $\frac{1}{V} = 0.3\%$, corresponding to a perfectly fair workload distribution among nodes.

6.2 Impact of the content characteristics

We now vary the popularity and size of content items, and observe their impact on the performance of our replication scheme.

⁶Note that using inter-distances instead of actual coordinates allows us to handle a much larger number of samples (e.g., $V \cdot (V - 1)$ instead of just V samples) thus making the computation of the χ^2 index more accurate.

⁷With 14 degrees of freedom as in our case, such value is 23.685.

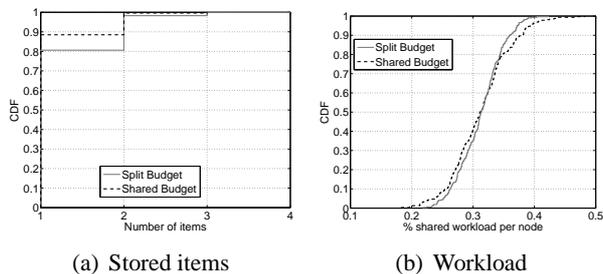


Figure 3: CDFs of the stored items and of the workload at each network node

Table 1: R_i^* computed by the centralized CFL algorithm in presence of different content popularity

Item id	Interested	Opt. with split budget	Opt. with shared budget
1	100%	39	42
2	75%	30	29
3	50%	19	18
4	25%	14	15

How does our replication scheme perform in presence of items with different popularity?

We study now the scenario when not all nodes are interested in a content. In such a situation, a node stores a replica of the content only if it is interested. If a node attempts to hand over the content to an uninterested node (by random selection), the request will be denied and a different node will have to be selected.

In Table 1, we report the results of the CFL algorithm when the percentage of interested nodes, $p(i)$, $i = 1, \dots, 4$, varies from 25% to 100%. We also set $c_j = 40$ Mbytes for the optimization with shared capacity budget and $c_j = 60$ Mbytes for the optimization with split capacity budget. Interestingly, Table 1 indicates that, in order for the replication mechanisms to yield roughly the same replication factor, the capacity budget that is required for the shared capacity approach is substantially lower than that required for the split capacity case.

As far as the optimization with shared capacity budget is concerned, Fig. 4(a) shows that the average number of replicas for item i , \bar{R}_i , generated by our scheme oscillates around the optimal value determined by the CFL algorithm for the same item, R_i^* , even when i is characterized by low popularity. Moreover, the workload remains evenly shared among replica nodes: Fig. 4(b) shows that each node serves at least 0.2% of the total workload and 98% of nodes serve less than 0.4% of the total workload. The load distribution is thus quite dense around 0.3%, i.e., $\frac{1}{V}$ that is the ideal mean workload. Finally, the results in Fig. 4(c) underline the fairness of our replication scheme also from a memory utilization point of view, with nodes caching with high probability at most one content at a time. We observe similar

Table 2: R_i^* computed by the centralized CFL algorithm in presence of different content sizes

Item id	Item size	Opt. with split budget	Opt. with shared budget
1	1 Mbytes	39	42
2	2 Mbytes	62	67
3	3 Mbytes	87	91
4	4 Mbytes	115	117

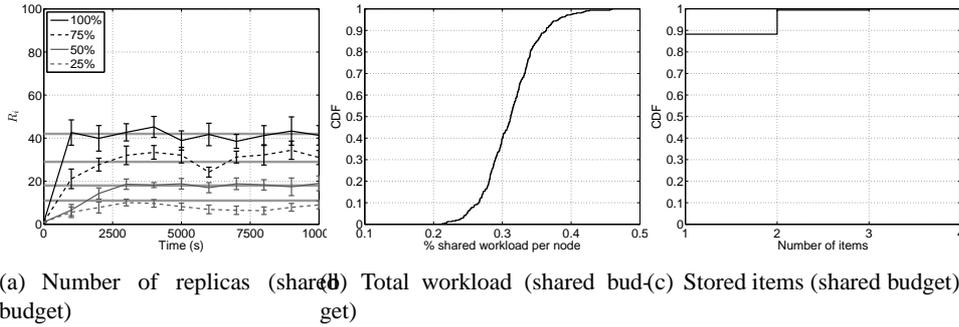


Figure 4: Impact of content popularity on the replication with shared capacity, in terms of number replicas, workload distribution, and memory utilization

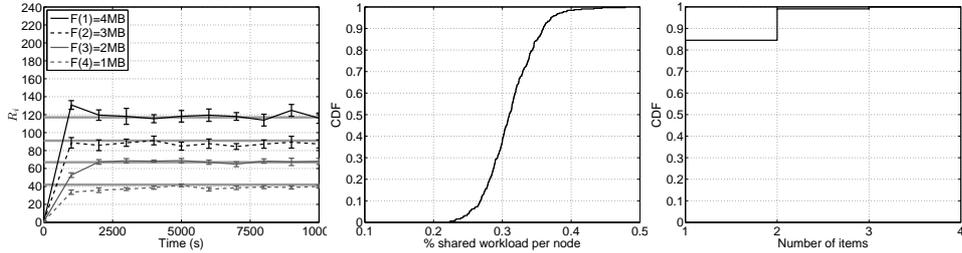
results⁸ when the split capacity approach is used, although this requires a larger budget to be allocated to the replication process.

How does our replication scheme perform with different content sizes?

Let us focus on a scenario where the four items have identical popularity but different sizes ($s(i)$, $i = 1, \dots, 4$). The considered values are detailed in Table 2, along with the optimal number of replicas R_i^* computed, for each item, by the centralized CFL algorithm under the split and shared capacity budget constraints.

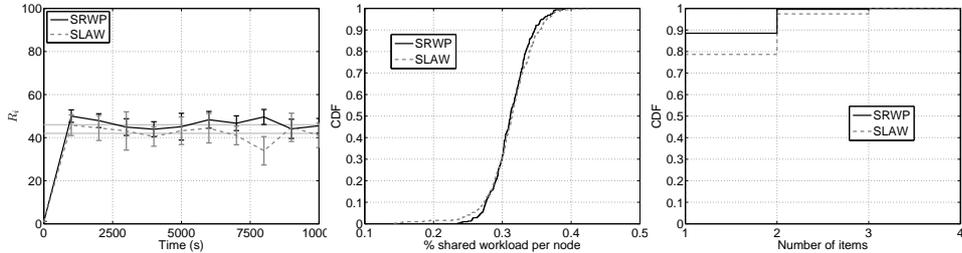
Focusing on the optimization problem with shared capacity budget, Fig. 5(a) shows a good matching between \bar{R}_i and the optimal value R_i^* , for any item i . The workload exacted from the nodes by our scheme is shown in Fig. 5(b), and the number of information items stored by each node is depicted in Fig. 5(c). Very similar considerations apply to the case of optimization with split capacity budget, although comparable performance can only be attained if the capacity budget allocated by each node largely exceeds that in the shared capacity approach.

⁸For the sake of brevity, we omit these results in this work.



(a) Number of replicas (shared budget) (b) Total workload (shared budget) (c) Stored items (shared budget)

Figure 5: Impact of content size on the replication with shared capacity, in terms of number of replicas, workload distribution, and memory utilization



(a) Number of replicas (shared budget) (b) Total workload (shared budget) (c) Stored items (shared budget)

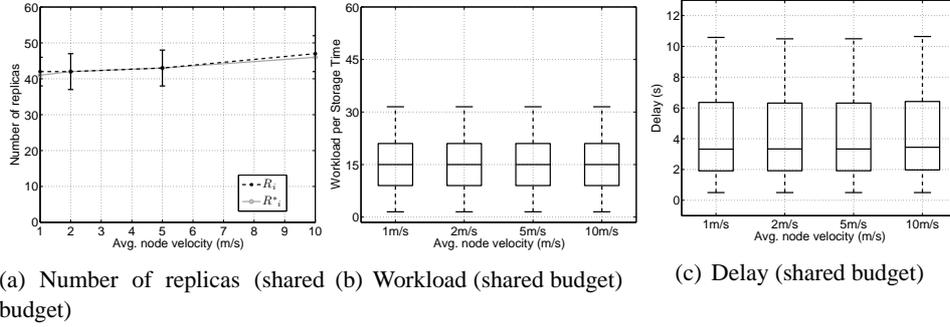
Figure 6: Impact of user mobility on the replication with shared capacity, in terms of number of replicas, workload distribution, and memory utilization

6.3 Impact of mobility

What is the impact of a more accurate human mobility model on our scheme?

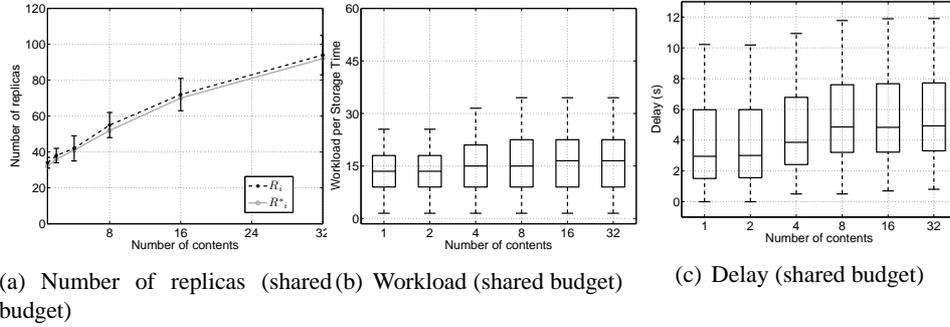
We now study the performance of our scheme in presence of non-random clustered mobility, which has been shown to characterize human movements in outdoor environments. More precisely, we employed the SLAW model [20] to generate a synthetic trace representing the movements of 320 outdoor users within an area of 1 km², during 3 hours. The SLAW settings included 600 waypoints, Pareto-distributed with Hurst parameter equal to 0.75, a flight speed of 1 m/s, and pause times that obey a Levy distribution with coefficient equal to 1 and minimum and maximum values equal to 100 s and 1000 s, respectively. The distance weight, which determines the priority that nodes give to nearby locations before traveling to farther locations, is set to 3. All results refer to the case of the optimization with shared capacity budget: those for the optimization problem with split capacity budget are very similar and are omitted for sake of brevity.

Fig. 6(a) shows the evolution of the number of replicas per information item over the simulation time, for SLAW and the stationary RWP previously employed.



(a) Number of replicas (shared budget) (b) Workload (shared budget) (c) Delay (shared budget)

Figure 7: Impact of node speed on the replication with shared capacity, in terms of number of replicas, workload distribution, and memory utilization



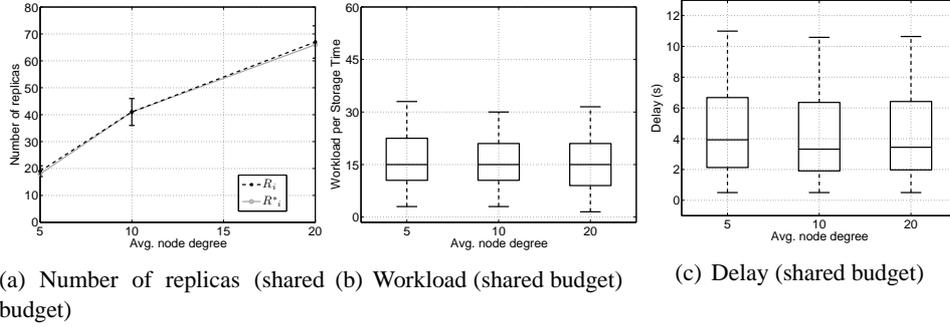
(a) Number of replicas (shared budget) (b) Workload (shared budget) (c) Delay (shared budget)

Figure 8: Impact of content set cardinality on the replication with shared capacity, in terms of number of replicas, workload distribution, and delay

In both cases, the number of replicas per item roughly matches the optimal value. In the SLAW scenario, the presence of a small number of dense clusters implies that content queries will be originating from within each cluster: this explains the (almost negligible) difference in the number of replicas and workload with respect to the RWP model. It also follows that the different mobility does not result in significant differences in the total load distribution, as shown by the plot in Fig. 6(b). As far as memory utilization is concerned, in Fig. 6(c) SLAW forces a slightly more unbalanced CDF, as nodes group into denser clusters than under RWP mobility. Specifically, under SLAW, 80% of nodes hold two or more items versus the 90% measured under the RWP model.

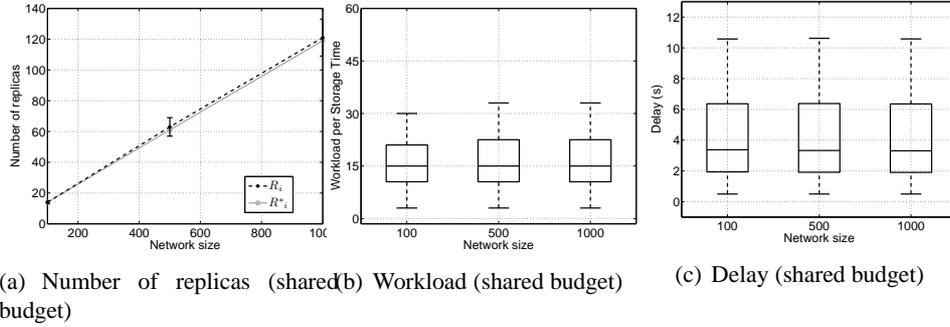
How does our mechanism work as the node speed varies?

Invariance of the performance of our replication scheme to the node speed is demonstrated by Fig. 7(a), Fig. 7(b) and Fig. 7(c). There, we can notice how the different velocity of nodes during their movement does not lead to significant variations in the number of replicas, per-node workload and delay, respectively.



(a) Number of replicas (shared budget) (b) Workload (shared budget) (c) Delay (shared budget)

Figure 9: Impact of network density on the replication with shared capacity, in terms of number of replicas, workload distribution, and delay



(a) Number of replicas (shared budget) (b) Workload (shared budget) (c) Delay (shared budget)

Figure 10: Impact of network size on the replication with shared capacity, in terms of number of replicas, workload distribution, and delay

6.4 Scalability

In order to determine the scalability properties of the proposed replication scheme, we study the impact that the number of items, network density, and network size have on the system performance. Again, all results refer to the case of optimization with shared capacity budget, since those obtained under optimization with split capacity budget are similar, but require a significantly higher budget to be allocated at nodes.

We first evaluate the performance when the cardinality of the information item set varies between 1 and 32. More precisely, Fig. 8(a) shows the number of replicas per item generated in the system, which grows as the size of the information set increases. Indeed, a larger content set implies that nodes tend to store more items on average; however, their capacity budget c_j remains constant, and is shared among all items they store. As a result, focusing on one single content, each replica node for that content will be able to serve fewer and fewer queries as the number of available items increases. As a consequence, more replicas for the same content are needed in order to meet the constraint on the capacity budget, hence to keep the workload constant, as depicted in Fig. 8(b).

Fig. 8(c) shows the effect that the number of information item has on the service provisioning delay. The increase of the delays is imputable to the heavier traffic on the channel, that results in collisions and retransmissions of the information replies.

We then study the effect of the network density, measured as the average node degree, which is increased up to a mean number of neighbors per node equal to 20 in Fig. 9. Fig. 9(a) shows that the number of replicas increases according to the optimal number of facilities computed by the CFL local search algorithm. Indeed, the increased presence of neighbors induces a higher load in the network, in terms of queries: in order to satisfy the new demand, and yet fulfill the per-node workload constraint, additional nodes must become providers for each content. The availability of additional facility nodes allows them to experience a practically unchanged per-storage time workload, in Fig. 9(b), as well as a similar delay for successful content requests, in Fig. 9(c).

Finally, in Fig. 10, we assess the performance of the replication system versus the size of the network: that is, we maintain the network density constant but we consider a number of nodes ranging between 100 and 1000. As one could expect, the number of replicas grows linearly with the network size, in Fig. 10(a), while Fig. 10(b) and Fig. 10(c) show that the network size has virtually no impact on the average workload at replica nodes and on the delay, respectively.

Overall, our replication scheme shows excellent scalability properties, since it can dynamically adapt the number and placement of replicas to the network settings, so as to maintain a constant utilization of communication and memory resources at each node. Moreover, we recall that such result is obtained with local measurements only, and thus the cost of the process does not change with the number of items or the size and density of the network.

7 Benchmarking our replication scheme to other approaches

We now turn our attention to a network system where information items are associated to different query rates, and we evaluate the allocation of replicas for each content. In this case, we compare the performance of our replication scheme with that of the so-called square-root replication strategy [21]. According to such a strategy, the allocation percentage $\alpha(i)$ for a content i is proportional to the square root of the total demand per second for that content, i.e.,

$$\alpha(i) = \frac{\sqrt{p(i)}}{\sum_{i=1}^I \sqrt{p(i)}}.$$

In [21], it has been proved that square-root replication is optimal in terms of number of solved queries. Although initially introduced for wired, unstructured, peer-to-peer networks, the square-root rule has since been applied to wireless networks as well [22].

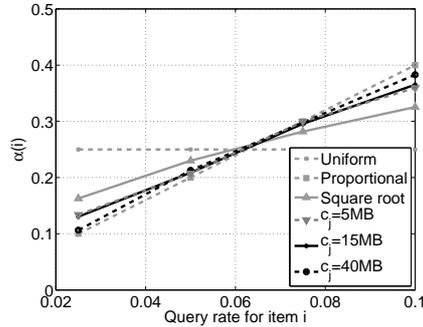


Figure 11: Fraction of replicas for each of the four items, in comparison with uniform, proportional and square-root allocation

We derive our simulation results in the case of $I = 4$ items with different popularity, and $c_j = \{5, 15, 40\}$ Mbytes. Fig. 11 shows the fraction of the total number of replicas of item i , versus the associated query rate $p(i)V\lambda$. The plot compares our scheme with: (i) the square-root strategy, (ii) a uniform strategy, which allocates the same number of replicas per item, and (iii) a proportional strategy, where the number of replicas is proportional to the content popularity. We observe that our scheme achieves an allocation in between the square-root and proportional distributions, while it is far from that obtained under the uniform strategy. This suggests that our replication scheme well approximates the optimal replication strategy. In particular, we can observe that, when c_j is higher, i.e., replica nodes are more generous in reserving resources to serve requests, the allocation tends to follow a proportional distribution. Conversely, in presence of lower values of c_j , i.e., when the budget is limited, the allocation better fits the square root rule. In other words, a “strict” budget sacrifices content replicas that play a marginal role in achieving low access cost: such replicas are dropped and the overall shape of the distribution drifts from proportional to square root.

Before we move on, a further observation is required. Since our replication scheme roughly achieves the result obtained by a square-root allocation, it is reasonable to wonder why a different approach to content replication is required. First of all, in this work we have different objectives than that of [21]: load-balancing, for example, requires an additional layer to complement the square root allocation scheme, which instead we achieve as part of our design. Furthermore, the distributed version of the replication algorithms proposed in [21] has some limitations that renders them less suitable to be deployed in a mobile, wireless environment. The simple path replication scheme catering to low storage requirements, just like our scheme, substantially over/undershoots the optimal number of replicas. The other approaches discussed in [21] are better at converging to an optimal number of replicas but require the bookkeeping of large amounts of information. Finally, the design and the evaluation of such algorithms in [21] do not take into account the dynamic nature that is typical of a mobile network.

As a second step in our comparative evaluation, we benchmark our replication mechanism with a simple caching scheme. In particular, we consider a *pull-based*⁹ caching mechanism: a node issues a query for an information item of interest to other nodes in its vicinity. Such a request can travel up to h hops away from the node that issued the request. If a request is not satisfied within a timeout, the content is fetched directly from the cellular network. After having successfully downloaded the content, the node stores it until the corresponding validity time expires. In case a node receives a query for the stored content, it will serve it through device-to-device communication. Note that, if a node is not interested in an information item, it will not participate to the caching process, including content transfer and storage.

In summary, with the mechanism outlined above, information items spread from one node to another in the network in a manner that loosely resembles an epidemic diffusion process. However, when this content propagation is hindered by availability problems, the cellular network is used to create new content sources and avoid starvation.

With respect to the replication scheme we propose, the pull-based caching approach analyzed here differs in many aspects. First, such a caching scheme eventually achieves full content replication, in that all nodes, at the end of the diffusion process, hold a copy of the content and can serve requests from neighbors. Instead, the goal of our replication mechanism is to find the optimal number of replicas that minimize content access costs, while guaranteeing load balancing. Additionally, in the caching scheme, nodes simply discard expired content, while, in our scheme, replica nodes are in charge of downloading up-to-date versions of the content. Since in our simulations nodes are loosely synchronized, the former behavior implies that, at regular intervals corresponding to the content version expiration times, the whole content diffusion process restarts from scratch.

In order to better understand our results, we now proceed with some key intuitions that follow from the differences between caching and replication schemes outlined above. It is well known that pull-based caching approaches are sub-optimal during the bootstrap phase of the content delivery process: the few nodes storing a copy of the content are overwhelmed by queries originating from nearby nodes, while the vast majority of the other nodes remain idle and wait for the content to propagate towards them. The caching scheme we evaluate here partially overcomes this problem by allowing nodes to fetch content through the cellular network. However, it is reasonable to expect a large number of “external” data transfers: as a consequence, access congestion may arise also at the cellular level. Finally, we note that when the content is unpopular, the diffusion process is even slower and the above negative effects are amplified.

In the following, we test the performance of the replication and caching approaches in presence of two content discovery mechanism: the one presented in

⁹It is not the focus of this work to explore push-based mechanisms, nor more advanced approaches such as interleaving of push/pull phases.

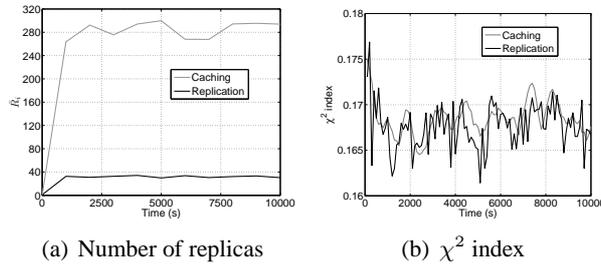


Figure 12: Performance of caching and replication mechanisms in terms of (a) number of replicas and (b) χ^2 index, for 100% content popularity and 100 s content validity time

Sec. 5 and employed in the previous sections, which is based on a content location service, and a flooding-based approach. The latter mechanism lacks the knowledge of replica node identities, and thus floods the network with queries for the desired content, although the overhead is reduced by means of a PGB-based, TTL-bounded forwarding. The presence of two discovery techniques allows us to comment on the impact that an optimized, yet complex solution (as the one based on the use of a content location service) and a simple, yet sub-optimal one (flooding) have on the overall system performance.

We first focus on the behavior of the replication and caching schemes over time. We run the two solutions in the identical standard settings outlined in Sec. 5, assuming a content validity time of 100 s and injecting one replica in the network at the beginning of the simulation. The number of replicas present in the system over time is depicted in Fig. 12(a). We observe that, while our replication scheme controls the number of replica nodes and keeps it relatively small, the caching solution leads to a rapid growth of users caching the content. As expected, by achieving full replication, the caching strategy is more expensive than the replication scheme for the mobile nodes, in terms of storage requirements.

One may argue that fewer content replicas may lead to a suboptimal placement: full replication ensures that the content resides where the demand is. The results illustrated in Fig. 12(b), however, show that such additional storage space usage does not lead to any significant advantage in terms of the quality of replica placement. The χ^2 index obtained by comparing the geographical distribution of replicas under the two schemes with that computed by the centralized solution is essentially equivalent.

We now compare the performance of the caching approach with that of our replication scheme, when considering the following metrics that complement those previously employed:

- query solving delay, intended as the time elapsed from the instant when a node sends the first query until the request is fulfilled, by either a replica node or the cellular network;

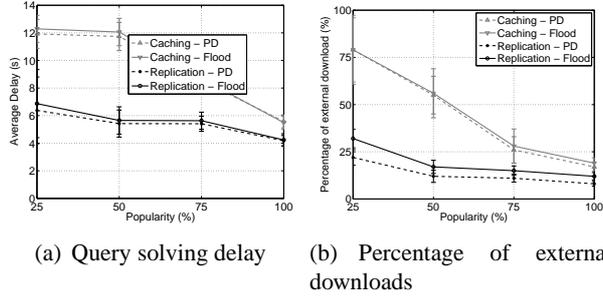


Figure 13: Performance of caching and replication mechanisms in terms of ratio of cellular downloads (a) and query solving delay (b) for content popularity of 25-100%

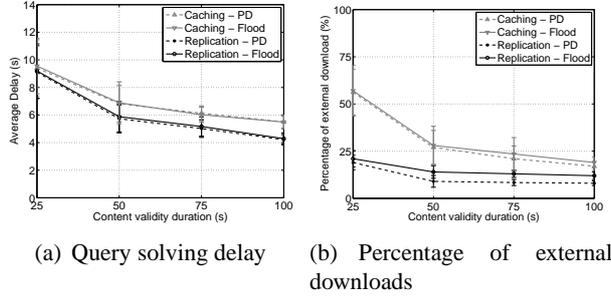


Figure 14: Performance of caching and replication mechanisms in terms of ratio of cellular downloads (a) and query solving delay (b) for different content validity periods [25,50,75,100] s

- percentage of external downloads, i.e., queries that resulted in an external download, with respect to the overall requests generated in the network.

Assume the content update period to be fixed at 100 s. Fig. 13(a) shows the average delay (along with the 95% confidence interval) for the replication and caching scheme as the content popularity varies. As hinted at above, the replication scheme outperforms the caching mechanism, and the difference in the relative performance is amplified (in favor of replication), as the content popularity decreases. Indeed, as content popularity decreases, fewer nodes participate in the diffusion process that underlies the caching scheme. As such, nodes have to wait longer for their queries to be satisfied and, in general, they end up downloading the content from the cellular network. Instead, when the content popularity is high, the epidemic-style diffusion process performs better, and the delay decreases. Fig. 13(b) reinforces the key intuitions we discussed in this section: when the content diffusion process is hindered by content popularity, mobile nodes resort to the cellular network to compensate for the delays of device-to-device communication. Our replication scheme outperforms the caching approach also in this aspect: by approximating optimal content replication and placement, our mechanism reduces the content access costs, in terms of congestion. Instead, the caching mechanism

does not alleviate access congestion: i) nodes in the vicinity of a content replica will “collide” to obtain the content through device-to-device communication, and ii) nodes resorting to the cellular infrastructure because of query timeout expiration also compete for bandwidth. These intertwined aspects are exacerbated when the content becomes stale: with our approach, few replica nodes take care of the update process, while, with the caching scheme we study here, the whole content diffusion process has to start over.

Next, we delve into the impact of the content update frequency, and compare the replication and caching scheme when the content validity time is in the interval $[25, 100]$ s. Here the content popularity is set to 100%. Fig. 14(a) shows the delay for the replication and caching scheme as the update frequency decreases (i.e., larger update times). When the update frequency is high, both caching and replication suffer in terms of access delay. Requests for an updated version of the content put under stress the replication scheme, because few replica nodes are in charge of the content update, and consumer nodes have to wait for the update process to finish. Instead, as we argued above, the caching scheme has to restart at every content update, and this is suboptimal. Fig. 14(b) reinforces the intuition that the caching scheme, in order to mitigate a slow diffusion process, heavily relies on cellular communications, a phenomenon that is exacerbated when the update frequency is high. Instead, the replication scheme is essentially unaffected by the update frequency with respect to the number of external downloads.

As described earlier in this section, we carried out our comparative analysis using different content access mechanisms. As reported in our results, there is no noticeable impact of using a simple flooding technique versus a more sophisticated one based on content location service. However, although we do not report the results here for sake of conciseness, the workload payed by each node because of queries being flooded in the network is larger than with an auxiliary service helping nodes to target the closest replica.

In light of the results discussed above, our content replication scheme clearly emerges as a simple, efficient and performing alternative to traditional mechanisms that distribute the content through opportunistic communications among the nodes. By controlling the number and the placement of content replicas, our mechanism appears to be suitable especially when content popularity is not 100%, both for performance and cost-related reasons.

8 Related work

Simple, widely used techniques for replication are gossiping and epidemic dissemination [23, 24], where the information is forwarded to a randomly selected subset of neighbors. Although our RWD scheme may resemble this approach in that a replica node hands over the content to a randomly chosen neighbor, the mechanism we propose and the goals it achieves (i.e., approximation of optimal number of replicas) are significantly different.

Another viable approach to replication is represented by quorum-based [25] and cluster-based protocols [26]. Both methods, although different, are based on the maintenance of quorum systems or clusters, which in mobile network are likely to cause an exceedingly high overhead. Node grouping is also exploited in [27,28], where groups of nodes with stable links are used to cooperatively store contents and share information. The schemes in [27,28], however, require an a-priori knowledge of the query rate, which is assumed to be constant in time. Note that, on the contrary, our lightweight solution can cope with a dynamic demand, whose estimate by the replica nodes is used to trigger replication. We point out that achieving content diversity is the goal of [29] too, where, however, cooperation is exploited among one-hop neighboring nodes only.

Threshold-based mechanisms for content replication are proposed in [30,31]. In particular, in [30] it is the original server that decides whether to replicate content or not, and where. In [31], nodes have limited storage capabilities: if a node does not have enough free memory, it will replace a previously received content with a new one, only if it is going to access that piece of information more frequently than its neighbors up to h -hops. Our scheme significantly differs from these works, since it is a totally distributed, extremely lightweight mechanism, which accounts for the content demand by other nodes and ensures a replica density that autonomously adapts to the network dynamics.

Finally, relevant to our study are the numerous schemes proposed for handling query/reply messages; examples are [32], which resembles the perfect-discovery mechanism, and [33,34] where queries are propagated along trajectories so as to meet the requested information. Also, we point out that the RWD scheme was first proposed in our work [35]. That paper, however, besides being a preliminary study, focused on mechanisms for content handover only: no replication or content access were addressed.

9 Conclusions

We focused on content replication in mobile networks and we addressed the joint problem of (i) establishing the number of content replicas to deploy in the network, (ii) finding their most suitable location, and (iii) letting users efficiently access content through device-to-device communication.

We studied the above problems through the lenses of facility location theory and proposed a distributed, lightweight scheme that builds on (i) local search approximations of the multi-commodity capacitated facility location problem and (ii) parallel random walk diffusion in non-regular graphs. We showed that, despite its simplicity and the fact that it only leverages local measurements, our replication solution can approximate with high accuracy the solution attained by optimal centralized algorithms, while also guaranteeing a fair balancing of the communication and memory resources demanded of nodes. Additionally, the scheme we propose

adapts to network dynamics, in terms of content popularity, size and set cardinality, as well as user number, density and mobility.

When compared to different approaches to content replication and caching, our approach performs closely to square-root-based replication, while it outperforms traditional caching techniques that mimic an epidemic diffusion of the content, especially in the more challenging settings of low content popularity and high frequency of content updates.

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