Distributed Proactive Caching in a Group of Selfish Nodes

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Abstract—**The paper considers the problem of proactive caching (or replication) of content in a collection of caches which can form a group and collectively satisfy content requests of their users (clientele); such caches can be the ones associated with close-by base stations. Under significant user similarity, avoiding caching the same content in multiple locations within the group and leaving room for more content to be cached within the group, can yield significant performance improvement compared to the case of isolated, greedy local, caching behavior by the nodes. The work considers a generic content-provisioning cost structure that jointly incorporates objective (i.e., distance-based) and subjective (social/behavioral-based) cost elements and studies the resulting non-cooperative game, proposes a simple content placement implementation, presents results and discusses the impact of the subjective cost element.**

I. Introduction

A rapid increase of transferred and stored content has been observed over the last years, a good part of which is due to the proliferation and enhanced capabilities of smart mobile devices. A recent report by CISCO, [1], predicts a massive increase of the wireless Internet devices that is bound to further increase the demand for content. Consequently, the ever increasing content traffic becomes a major challenge for the upcoming Fifth Generation (5G) wireless networks under development. Not only bandwidth and storage resource demand will increase significantly, but also the user Quality of Experience (QoE) may suffer, primarily due to a potentially high delay induced by congested links or/and fetching content from far away locations.

One potentially efficient approach for addressing the aforementioned challenge and reducing the content retrieval latency of popular objects, [2], would be by caching content at the network edges, such as the Base Stations (BSs). The number of base stations is expected to explode in 5G in order to meet the anticipated high bandwidth capacity requirements and deliver the required user QoE, [3]. Not only the bandwidth capacity of the wireless network will increase as the density of these BSs would increase, but also their distance from the users would decrease, further reducing the content retrieval latency from the BS. Unless some caching at the BSs is implemented though, the aggregate content requests from these BSs would congest the backhaul network, [3].

Caching efficiency can be further improved by pre-downloading popular contents during low traffic periods. The content popularity can be predicted from recent data and by tracking users' content requesting activity, [4]. This technique is referred to as proactive caching, or content replication. Proactive caching is able not only to reduce heavy traffic load during peak hours, but also to decrease content retrieval latency more effectively and improve user experience, [5].

The content to be proactively cached at a BS would depend on the content popularity profiles of the users accessing the Internet through the particular BS. As the density of (distance between) the BSs increases (decreases) two implications are worth noting. The first is that the closer distance between BSs in conjunction with the user mobility would tend to increase the similarity of the aggregate content profiles of the users supported by neighboring BSs; in the extreme case in which users may be supported with equal probability by any of two neighboring BSs, these profiles would be identical. The second implication is that since the distance between neighboring BSs decreases and is expected to be small, fetching content cached in a neighboring BS would incur a small QoE reduction compared to fetching it locally (i.e., from the supporting BS). On the other hand, fetching content from outside the group of neighboring BSs would incur a high QoE reduction (for example, due to the backhaul congestion and/or distance from the content hosting server). The aforementioned two implications suggest that a group of neighboring BSs could cooperate to collectively decide what to proactively cache locally, so as to avoid caching similar content (as a result of the associated user profile similarities) and bring closer content unrepresented in the neighbors' caches, instead, increasing content availability within the group and ultimately enhancing the delivered QoE.

A commonly employed abstraction for studying such groups of caches is that of the distributed replication group, [6]. Under this abstraction, nodes utilize their storage capacity to replicate information objects (proactively cache content) and make them available to local and remote (elsewhere within the group) users. A user's request can be first served by the local node, if the requested object is available, incurring a minimal access cost. Otherwise, the requested object is searched and fetched from other nodes within the group, at a potentially higher cost. If the object cannot be located anywhere in the group, it is retrieved from a node which is located outside the group (maximum access cost), [6].

Generally, nodes tend to behave selfishly in the sense that they prefer to store the most popular for them objects in order to get the maximum gain by taking fully advantage of the cache, [7]. Such a proactive content caching or content

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placement strategy can be referred as Greedy Local (GL). When the similarity of the participating nodes is high and their distance small, replicating multiple times the same most popular objects is ineffective and all the nodes may gain substantially and improve their access costs if they cooperate and replicate different objects, [6].

Several proactive content caching or content placement strategies have been proposed in order to determine the content distribution within a replication group. Earlier works, [8-11], have focused on the derivation of placements that optimize the social utility (sum of the individual utilities capturing delay and bandwidth gains), referred to as socially optimal (SO) strategies. SO strategies are expected to require some nodes to host less popular objects than they would had they acted in isolation under a Greedy Local (GL) strategy, which may lead to experiencing a worse performance compared to that under the GL strategy. Practically, SO placement strategies can be applied in environments where all node-caches are under a single central authority which dictates its replication decisions to the nodes, [6], aiming at maximizing the average benefit for this authority.

In case of a distributed environment with node-caches under different ownership/administration, SO strategies would not be acceptable since a node could be mistreated; i.e., its local utility may turn out to be less than that under the GL strategy. In this case, the distributed selfish replication group abstraction is employed and a placement strategy is sought that is mistreatment-free, to ensure the sustainability of the group. Such a strategy was first introduced in [6] under a simple content serving cost structure that accounted only for the physical distance between the requesting node and the content hosting/serving node.

In this paper a distributed proactive caching strategy is derived for an environment where the user QoE has subjective and objective factors: the subjective QoE factor is shaped jointly by the user and the requested object, while the objective QoE factor is determined by the distance between the user and the location of the requested object. The subjective QoE factor allows for capturing the human-driven diverse desirability or perception of quality of different nodes for different objects, which maybe completely decoupled from the object popularity (frequency of use). Besides the human-driven factors, users may be equipped with different hardware and software capabilities (high-end, low-end users). As a result, network-induced content delivery impairments could possibly be largely fixed by high-end users. Thus, the high-end users experience better quality compared to low-end users; for the same network-level quality of service a high-end user may experience a lower cost (impact on its QoE) compared to a low-end one. Thus, the subjective QoE factor introduces another significant dimension to the resulting QoE besides the object popularity and the objective QoE factor that have typically been incorporated in similar environments in the past. The proactive content caching strategy is derived through a formulation of a non-cooperative game and it is shown to be mistreatment-free and yield a Nash Equilibrium (NE) under certain broad conditions on the cost structure. Examples of subjective QoE factors are provided and shown to yield significantly different content placement compared to that when only the objective QoE factor is considered.

II. Definitions and Preliminaries

Consider a group of connected nodes each equipped with a cache of size W objects and capable of accessing content from and distributing content to other nodes within the group. Such a group of nodes is referred to as a distributed replication group. As already discussed, the main driver for formulating such a group is the similarity among participating nodes. Similarity refers to nodes' attributes, such as locality or content preferences, that shape the benefits of cooperation, [7].

Under cooperation, nodes have access to content replicated anywhere within the group. A participating node will access content from its local memory (access location l) if available; otherwise, from the local memory of a remote node within the group (access location r) or from a further away source if the object is not found within the group (access location s).

Let $V = \{1, ..., N\}$ denote the set of nodes in a distributed replication group and let $O = \{1, ..., M\}$ denote the set of all objects (assumed to be of uniform size). Let n and m denote a node in V and an object in O, respectively. Let F_m^n denote the popularity (request probability) of object m for node n and let $F^n = \{F_1^n, F_2^n, ..., F_M^n\}$ denote the popularity distribution for node n over all objects.

All participating nodes take fully advantage of their local cache and select objects for local placement according to a proactive caching strategy. Let P_n denote the placement of objects in the local memory of node n. Let $P = \{P_1, P_2, ..., P_N\}$ denote the group's placement and $P_{-n} = P \backslash P_n$ denote the set of placements for all nodes of the group except from n. Finally, let L_n, R_n and S_n denote the sets of objects that are retrieved by node n from respective access locations l, r and s; that is, $L_n = \{m \in O : m \in P_n\}$, $R_n = \{m \in O : m \notin P_n \cap m \in P_{-n}\}$ and $S_n = \{m \in O : m \notin P_n \cap m \notin P_{-n}\}$.

The cost for accessing content from the three potential locations l, r and s is typically distinct and is shaped by the associated distance, access delay, connectivity, level of trust, etc. Typically, the access location l provides the best QoE to all users due to the minimal access delay incurred; access from location r should provide lesser QoE compared to location l, but much greater compared to location s. Under such location-shaped QoE it is reasonable to associated a certain cost with each location hosting the content, that would be considered to be fixed for all requesting nodes and requested objects, as in [6,7]. However, this location-shaped only QoE may be a grossly oversimplifying assumption for today's user/content-centric environments, as it assumes a highly homogeneous environment, ignoring potential dependence of the QoE from the specific requesting node and the requested object, as well.

This paper departs from the previously considered location-shaped only QoE by considering an enhanced content access cost structure which is capable of capturing QoE factors associated with the specific requesting node n and the specific requested object m, besides that associated with the traditional factor of distance from the access location. Let $t_m^n(X)$ denote the actual cost incurred for accessing object m by node n from an access location X, $X \in \{l, r, s\}$. The broader dependence of cost from n and m allows for capturing more realistic, human-driven distributed selfish proactive caching (or replication) environments. Dependence on node n is anticipated in human-driven environments, as different nodes may have different level of satisfaction (QoE) associated with some content access; for instance, two distinct nodes may have a different level of satisfaction (QoE) regarding the delivery of the same content with the same latency. Similarly, dependence on object m is also anticipated in human-driven environments; for instance, a given node maybe unequally satisfied regarding the delivery of two distinct objects with the same latency.

In view of the above discussion, the distance from the access location is considered to be the objective QoE factor captured in the proposed cost function $t_m^n(X)$, as it is the basic common factor associated with any node's QoE for any content retrieval. The cost dependence on the perception associated with the specific node and the specific content is considered as the subjective QoE factor. Generally, high cost values should be assigned for users with increased QoE requirements for certain types of content or applications. Even if such high costs are not frequently incurred when the associated object popularity is low, they can contribute significantly in shaping the content placement under an efficient proactive caching. In view of the discussion above, $t_m^n(X)$ may be expressed in terms of the subjective (Q_m^n) and the objective (distance from the access location X dependent, $b(X)$) QoE factors, as

$$t_m^n(X) = f(Q_m^n, b(X)) \tag{1}$$

Intuitively, we expect that in case of accessing objects from the same access location (same objective QoE factor), their costs would be differentiated by the subjective QoE factor only. Thus, the more desirable objects (higher value of the subjective QoE factor Q_m^n) would yield a higher access cost $t_m^n(X)$ than the less desirable objects that are located in the same access location. Thus, the cost ranking among a set of objects is invariant to the access location. On the other side, for any two equally desired objects (same subjective QoE factor) located in different access locations, only the objective factor differentiates their costs that typically assigns lower access cost to the nearest objects.

It is worth noting that the proposed cost structure allows for breaking the strong dependence of the induced mean access cost from the object popularity, that traditionally shapes the resulting placement by favoring the most popular objects. If the subjective QoE factor is low, an otherwise very popular object may not be selected for placement in locations associated with a low objective QoE factor.

When the subjective QoE factor Q_m^n is fixed for all n and m it is in essence neglected and the access cost is shaped entirely by its objective QoE factor (access location), similarly to the approach considered in [6,7]. In this case, (1) is reduced to

$$t_m^n(X) = f(b(X)) = t(X), X \in \{l, r, s\} \tag{2}$$

For a given node n, the mean access cost $C_n(P)$ per unit time under a content placement P is given in (3) and consists of three parts (each part capturing the mean cost of accessing objects from each access location). The cost associated with the entire group $C(P)$ is derived by summing $C_n(P)$ over all $n \in [1, N]$.

$$\begin{aligned} C_n(P) &= \sum_{m=1}^{M} F_m^n t_m^n = \\ &= \sum_{m \in L_n} F_m^n t_m^n(l) + \sum_{m \in R_n} F_m^n t_m^n(r) + \sum_{m \in S_n} F_m^n t_m^n(s) \end{aligned} \tag{3}$$

III. TSLS STRATEGY UNDER THE PROPOSED COST STRUCTURE

In this section a content placement strategy is derived for the group based on a non-cooperative distributed game of N players. A two-step local search (TSLS) algorithm is employed following the methodology presented in [6] under the cost structure introduced in the previous section. The local search algorithm is shown to have the important property of mistreatment-free; that is, no node within the group will experience an access cost that is higher than the one that would be incurred if the node was not part of the group. Additionally, the conditions under which it yields a Nash-Equilibrium are derived. The Nash-Equilibrium property amounts to yielding a group placement P under which no node n in the group has motivation to unilaterally modify its local placement P_n for higher gain.

The local search algorithm operates in two rounds. In the first round (step 0) each node n establishes its initial content placement P_n^0 by selecting the W most popular objects, similarly to the GL strategy. The initial step 0 amounts to calculating the excess gains $g_{n,m}^0 = F_m^n(t_m^n(s) - t_m^n(l))$ for all objects m, ranking the resulting gains and selecting the W objects yielding the top W values of these gains. The excess gain expresses the mean access cost reduction that incurs if object m is replicated locally and is not accessed from a server. The procedure that yields the W most valuable objects for replication under any definition of excess gains $g_{n,m}^*$ may be referred to as the application of the GreedyLocal Operator. The GreedyLocal operator is equivalent to solving a 0/1 Knapsack problem where object values are the excess gains $g_{n,m}^*$, the object weights are unit and the Knapsack capacity is W.

In the second round (step 1) the nodes take turns (in some order) in improving their placements by taking into consideration also the placements (by that time) of all the other nodes in the group. Then a new placement P_n^1 for node n is derived in a similar way as P_n^0, by applying the GreedyLocal Operator on the excess gains $g_{n,m}^1$ that are now given by (4); $P_{-n}^{1-} = P_1^1 \cup ... P_{n-1}^1 \cup P_{n+1}^0 \cup ... P_N^0$ denotes the placement of all nodes except node n before the execution of node's n step 1 (improvement step). During this second round a node has the chance to replace some or even all its items in order to come up with the most cost-effective placement given the placements of other nodes. Thus, a node may decide to evict one of its objects that is also stored somewhere else inside the group and insert a new one, if this reduces its access cost. As the nodes amend their placements sequentially, each replacement made by one node affects both the access cost of nodes that have already made their adjustments and the choices made by nodes that follow. A comparison of P_n^0 and P_n^1 reveals which objects are inserted and evicted in step 1.

$$g_{n,m}^1 = \begin{cases} F_m^n(t_m^n(s) - t_m^n(l)), \text{if } m \notin P_{-n}^{1-} \\ F_m^n(t_m^n(r) - t_m^n(l)), \text{if } m \in P_{-n}^{1-} \end{cases} \quad (4)$$

The nodes in the group may experience a cost reduction due to accessing some objects locally or from a node within the group instead of a server outside the group. Let $G_n(P)$ denote the total resulting gain experienced by node n, due to the cooperation and participation in the distributed replication group, given by (5).

$$\begin{aligned} G_n(P) = &\sum_{m \in L_n} F_m^n(t_m^n(s) - t_m^n(l)) \\ &+ \sum_{m \in R_n} F_m^n(t_m^n(s) - t_m^n(r)) \end{aligned} \quad (5)$$

In the sequel, the TSLS strategy is studied under the proposed cost structure incorporating both the objective and subjective QoE factors. The mistreatment-free property of the placement induced by the TSLS strategy outlined above is established, followed by the derivation of the conditions under which the TSLS yields a placement that is a NE. Initially, Proposition 1 proves that after the execution of the improvement step for any node n its gain is not downgraded. This statement precludes any mistreatment phenomena. Thus, determining the final placement P_n^1 for a node n by solving the 0/1 Knapsack problem under gains $g_{n,m}^k$, $k \in \{0, 1\}$, is equivalent to maximizing $G_n(\cdot)$ given the current placements of the nodes other than n.

Proposition 1. *Following the TSLS strategy under the cost structure $t_m^n(X)$ dependent on the subjective QoE factor Q_m^n and the objective QoE factor $b(X)$, the produced placement P_n^1 for node n, $1 \leq n \leq N$, satisfies for all $P_n \in \{P_n\}$:*

$$\begin{aligned} G_n(P_1^1, ..., P_{n-1}^1, P_n^1, P_{n+1}^0, ...P_N^0) \geq \\ G_n(P_1^1, ..., P_{n-1}^1, P_n, P_{n+1}^0, ...P_N^0) \end{aligned} \quad (6)$$

Proof. Rewrite $G_n(P)$ from eq.(5) as follows:

$$\begin{aligned} G_n(P) = &\sum_{m \in P_{-n}} F_m^n(t_m^n(s) - t_m^n(r)) \\ &+ \Bigg(\sum_{\substack{m \in P_n \\ m \notin P_{-n}}} F_m^n(t_m^n(s) - t_m^n(l)) \\ &+ \sum_{\substack{m \in P_n \\ m \in P_{-n}}} F_m^n(t_m^n(r) - t_m^n(l)) \Bigg) \end{aligned} \quad (7)$$

The new expression is derived by considering objects that are replicated at node n and again elsewhere in the group and re-expressing their gain by splitting it into two parts through $F_m^n(t_m^n(s) - t_m^n(l)) = F_m^n(t_m^n(s) - t_m^n(r)) + F_m^n(t_m^n(r) - t_m^n(l))$. Given P_{-n}, the quantity outside the parenthesis of eq.(7) is independent of the objects selected for replication at n and can be considered as constant. Thus, to maximize $G_n(P)$ amounts to maximizing the quantity inside the parenthesis, which depends on both the objects replicated at other nodes and locally at n. This is the exact quantity that is maximized by solving the aforementioned 0/1 Knapsack problem with weights $g_{n,m}^1$, which compose eq.(7). □

In the sequel, we derive the conditions under which the produced global placement is a pure Nash-Equilibrium. The establishment of the NE property requires that under the final placement $P^1 = (P_1^1, P_2^1, ..., P_N^1)$ produced by the execution of the improvement steps for all nodes, no node n may increase its gain by modifying its placement. This means that under this placement where evictions and insertions have been performed by the nodes after n's turn, the TSLS strategy could not yield a local placement P_n^*, other than P_n^1, with improved gain. Propositions 2 and 3 define the properties of the evicted and the inserted objects that can be combined and lead to the NE property in Proposition 4. Basically, Proposition 2 guarantees that only duplicate objects (within the group) are evicted, while Proposition 3 identifies the cases where only unrepresented objects (within the group) are inserted. Before proceeding with the propositions, the sets of evicted and inserted objects during the execution of improvement step for node n are defined. Let $E_n^1 = \{m \in O : m \notin P_n^1, m \in P_n^0\}$ denote the eviction set of objects for node n after its improvement step and let $I_n^1 = \{m \in O : m \in P_n^1, m \notin P_n^0\}$ denote the set of inserted objects which replace the objects belonged in E_n^1.

Proposition 2. *The TSLS strategy, under the cost structure $t_m^n(X)$ dependent on the subjective QoE factor Q_m^n and the objective QoE factor $b(X)$, guarantees that the eviction set of n is such that only duplicate objects are evicted. This amounts to $E_n^1 \subseteq P_n^0 \cap P_{-n}^{1-}$.*

Proof. Consider two objects $m_e \in E_n^1$ and $m_i \in I_n^1$. Thus, node n selected m_e for local storage during step 0, while m_i was preferred at step 1 since it was considered to increase the n' gain. By their definition, it holds for gains g_{n,m_e}^0,g_{n,m_i}^0 and g_{n,m_e}^1,g_{n,m_i}^1 that:

$$g_{n,m_e}^0 \geq g_{n,m_i}^0 \quad (8)$$

$$g_{n,m_i}^1 > g_{n,m_e}^1 \quad (9)$$

Suppose now that contrary to the claim of the proposition $m_e \notin P_n^0 \cap P_{-n}^{1-}$ which translates to $m_e \notin P_{-n}^{1-}$ since $m_e \in P_n^0$. Due to $m_e \notin P_{-n}^{1-}$, m_e retains its step 0 gain (by definition of $g_{n,m}^1$), hence

$$g_{n,m_e}^1 = g_{n,m_e}^0 \quad (10)$$

For all objects and nodes it holds that $t_m^n(s) > t_m^n(r)$. Hence by the definition of gain function (4) it is valid that:

$$g_{n,m_i}^1 \leq g_{n,m_i}^0 \tag{11}$$

Combining (9) and (10) gives:

$$g_{n,m_i}^1 > g_{n,m_e}^0 \tag{12}$$

Multiplying (11) by (-1) and adding side-by-side (12) leads to $g_{n,m_i}^0 > g_{n,m_e}^0$ which is false as it contradicts with (8). Thus it must be that $m_e \in P_{-n}^{1-}$. □

Proposition 3. *The TSLS strategy, under the cost structure $t_m^n(X)$ dependent on the subjective QoE factor Q_m^n and the objective QoE factor $b(X)$, guarantees that the insertion set of node n is such that includes only unrepresented objects (within the group) under the cases (A) and (B) shown below. This amounts to $I_n^1 \subseteq ([1, M] \setminus (P_n^0 \cup P_{-n}^{1-}))$.*

Case (A): Without loss of generality, the cost associated with access location l can be ignored and considered to be zero for all nodes and objects, $t_m^n(l) = 0$. If it holds that the ranking of popularity-cost products is location shift invariant, then Proposition 3 holds.

Case (B): If the cost associated with accessing object m from location X by node n is $t_m^n(X) = Q_m^n b(X)$ then the stipulation under case (A) holds and, thus, Proposition 3 holds.

Proof. Consider two objects $m_e \in E_n^1$ and $m_i \in I_n^1$. By their definition $m_e \in P_n^0$ and $m_i \notin P_n^0$ which implies that n benefits more by replicating m_e locally during the step 0:

$$g_{n,m_e}^0 \geq g_{n,m_i}^0, \text{ or} \tag{13}$$

$$F_{m_e}^n(t_{m_e}^n(s) - t_{m_e}^n(l)) \geq F_{m_i}^n(t_{m_i}^n(s) - t_{m_i}^n(l)) \tag{14}$$

Since m_i is inserted in place of the evicted m_e during the improvement step, it should hold that n benefits more by replicating m_i locally compared to the penalty of the remote access cost for m_e at step 1:

$$g_{n,m_i}^1 > g_{n,m_e}^1 \tag{15}$$

Suppose now that contrary to the claim of the proposition $m_i \in P_n^0 \cup P_{-n}^{1-}$, which translates to $m_i \in P_{-n}^{1-}$ since $m_i \notin P_n^0$. Proposition 2 also guarantees that m_e is a duplicate which translates to $m_e \in P_{-n}^{1-}$. Thus, both objects are retrieved from the same access location r. According to the gain definition in step 1 given in (4), (15) leads to:

$$F_{m_i}^n(t_{m_i}^n(r) - t_{m_i}^n(l)) > F_{m_e}^n(t_{m_e}^n(r) - t_{m_e}^n(l)) \tag{16}$$

Let now consider separately the cases (A) and (B).

Case (A):

Since it is considered that $t_m^n(l) = 0$ for all objects and nodes, (14) leads to (17) and (16) leads to (18).

$$F_{m_e}^n t_{m_e}^n(s) \geq F_{m_i}^n t_{m_i}^n(s) \tag{17}$$

$$F_{m_i}^n t_{m_i}^n(r) > F_{m_e}^n t_{m_e}^n(r) \tag{18}$$

Thus, the popularity-cost product under access location r is higher for object m_i. By definition, the popularity and the subjective factor are not dependent on the access location. Taking into consideration the property under which the ranking of the popularity-cost products is location shift invariant, we can conclude that the popularity-cost product under the access location s is also higher for object m_i. Hence (18) leads to:

$$F_{m_i}^n t_{m_i}^n(s) > F_{m_e}^n t_{m_e}^n(s) \tag{19}$$

However, (19) is clearly false as it contradicts with (17). Thus it must be $m_i \notin P_n^0 \cup P_{-n}^{1-}$ which proves the claim of the proposition for case (A).

Case (B):

Let now consider the case where the access cost $t_m^n(X)$ is given by (20).

$$t_m^n(X) = Q_m^n b(X) \tag{20}$$

Thus, taking into consideration the specific cost $t_m^n(X)$ defined in (20), (14) can be rewritten as:

$$F_{m_e}^n Q_{m_e}^n (b(s) - b(l)) \geq F_{m_i}^n Q_{m_i}^n (b(s) - b(l)) \tag{21}$$

Also (16) can be rewritten as:

$$F_{m_i}^n Q_{m_i}^n (b(r) - b(l)) > F_{m_e}^n Q_{m_e}^n (b(r) - b(l)) \tag{22}$$

Clearly, the factor $b(r) - b(l)$ in (22) is common for all nodes and objects retrieved from location r and can be ignored. Multiplying (22) by $\frac{b(s)-b(l)}{b(r)-b(l)}$ leads to:

$$F_{m_i}^n Q_{m_i}^n (b(s) - b(l)) > F_{m_e}^n Q_{m_e}^n (b(s) - b(l)) \tag{23}$$

However, (23) is clearly false as it contradicts with (21). Thus, it must be $m_i \notin P_n^0 \cup P_{-n}^{1-}$ which proves the claim of the proposition for case (B).

Notice also that the specific cost function $t_m^n(X)$ given in (20) satisfies the property that the ranking of popularity-cost product is location shift invariant and can be considered as a specific scenario of case (A). □

Proposition 4. *The group (global) placement $P^1 = (P_1^1, P_2^1, ..., P_N^1)$ at the end of the TSLS strategy under the cost structure $t_m^n(X)$ dependent on the subjective QoE factor Q_m^n and the objective QoE factor $b(X)$ is a pure Nash Equilibrium in case that only duplicates are evicted (guaranteed by the Proposition 2) and only unrepresented objects are inserted (under the conditions of Proposition 3).*

Proof. Let $P_{-n}^1 = P_1^1 \cup ... \cup P_{n-1}^1 \cup P_{n+1}^1 \cup ... \cup P_N^1$ denote the final set of objects collectively held by nodes other than n. Notice generally that $P_{-n}^1 \neq P_{-n}^{1-}$. To prove the claim of the proposition it suffices to show that for every $n \in [1, N]$ and for all P_n:

$$G_n(P^1) \geq G_n(P_1^1, ..., P_{n-1}^1, P_n, P_{n+1}^1, ..., P_N^1) \tag{24}$$

Since, as stated in Proposition 1, solving the 0/1 Knapsack problem under P_{-n}^{1-} maximizes n's gain, we need to show that solving the Knapsack under P_{-n}^1, instead of P_{-n}^{1-}, leads to the same placement P_n^1 for every node n.

The differences between the global placement at n's turn at the end of strategy are determined by the duplicates m_e, $m_e \in E_j^1$ that were evicted and the objects m_i, $m_i \in I_j^1$ that were inserted, where $n+1 \leq j \leq N$. We will show that these changes do not affect the optimality of P_n^1 in case that only unrepresented objects m_i are inserted under the conditions clarified in the Proposition 3.

Consider an object m_e that belonged to P_{-n}^{1-} but was later evicted by some of the nodes that were holding it during n's turn. Proposition 2 guarantees that finally at least one node will be replicating m_e, $m_e \in P_n^1$. This precludes the case that n would decide to modify P_n^1 in order to include m_e. Similarly, if $m_e \in P_n^1$ then again the evictions of some remote copies cannot trigger changes to P_n^1.

Consider m_i, an object that was inserted by a node following n's turn. Proposition 3 specifies the conditions under which the m_i is an unrepresented object, that is, that $m_i \notin P_n^1$. The insertion of an unrepresented object m_i cannot cause the reduction of $g_{n,m}^1$ of any $m \in P_n^1$, since the only such object would be m_i which does not belong to P_n^1. On the contrary, if m_i is already represented within the group, node's n gain g_{n,m_i}^1 would be reduced. Potentially this could cause a different ranking of gains for n resulting in placement P_n other than P_n^1 of higher gain.

The previous two arguments regarding m_e and m_i guarantee that no node n has a reason to modify P_n^1 as a result of transition from P_{-n}^{1-} to P_{-n}^1 if the conditions of Proposition 3 are fulfilled. Combining the previous with the fact that P_n^1 maximizes G_n given P_{-n}^1, based on Proposition 1, establishes that P^1 is a pure NE. □

The above investigation shows that the TSLS strategy under the cost structure dependent on the QoE derives stable NE placements under the cases clarified in Proposition 3. More specifically, the yielded placements under the TSLS strategy are NE in case that (a) the popularity-cost product ranking is location shift invariant and (b) the local access costs are considered to be zero. Generally, the local access cost may practically be considered to be negligible for all users and objects, as the induced latency would typically not be perceptible to the users. Consequently, the local access cost may be ignored without loss of generality. Regarding the location shift invariance of the ranking of the popularity-cost product, it is noted that this is a property intuitively expected to hold in practice. For example, it clearly holds under the simple cost case in (20) or when the subjective QoE factor is absent.

Although the TSLS strategy may not yield the optimal gain for the group, the access cost for each user will be at most equal to cost incurred under the isolated GL behavior and possibly even better. Even if the final placements produced by the TSLS strategy under some content-provisioning cost structure may not yield a NE, the participation and sustainability of the distributed replication group is ensured due to the performance improvement over that under the GL strategy in isolation.

IV. NUMERICAL EXAMPLES

In this section the groups' access costs associated with content placements derived by the TSLS strategy have been presented for distributed proactive caching groups of $N = 5$ selfish nodes, a content population of $M = 50$ objects and a node cache capacity of $W = 8$ objects. The popularity profiles F_m^n are considered to be dissimilar or identical for all nodes. We emphasize the case of identical popularity distributions, because such environment maximizes the benefits of forming a distributed proactive caching group. For all the environments, the content placements are derived under two cost types: (a) a cost $t_m^n(X)$ dependent on the subjective and the objective QoE factors, given by (25) because of its simplicity and satisfying the NE property as proven in Section III and (b) an equivalent cost $t(X)$ dependent on the objective QoE factor only.

$$t_m^n(X) = b(X)Q_m^n \tag{25}$$

In general, the content popularity indicates the possibility that a random request addresses a specific object. It has been proved empirically that the content popularity over a time period follows a Zipf distribution, which assigns high popularity to a few objects and low popularity to the majority of objects, [13]. The popularity of the i^{th} popular object is equal to $(1/i^a)/\sum_{l=1}^{M}(1/l^a)$, where a is the Zipf parameter and assumes a positive value, typically from 0.8 to 1.7. In order to generate dissimilar groups, the Zipf parameter a_n for each node n is given in (26), where the parameters of any two subsequent nodes differ by p, $p \in \{0, 0.1, 0.2\}$. The distribution of a node n is also shifted to the right by k positions with respect to the distribution of node $n-1$, $k \in [0, 3]$, in order to yield groups where the set of popular objects may differ for each node. Identical popularity distributions for all nodes are derived in case that : (a) the same Zipf parameter ($p = 0$ leading to $a_n = 1$) is assigned to each node; (b) the popularity ranking of the objects is the same for all nodes ($k = 0$).

$$a_n = \begin{cases} a_{n+1} - p, & \text{if } 1 \leq n < N/2 \\ 1, & \text{if } n = N/2 \\ a_{n-1} + p, & \text{if } N/2 < n \leq N \end{cases} \tag{26}$$

Concerning the objective QoE factor, $b(X)$, we assume values $b(s)$, $b(r)$ such that $b(s) = db(r)$ with $d > 1$ leading also to $t_m^n(s) = dt_m^n(r)$). After some experimentation over various values $b(s)$ and $b(r)$, we have selected $b(s) = 20$, $b(r) = 5$ and $d = 4$ to emphasize the cost distance between accessing from the group (access location r) and accessing from a source outside the group (access location s). Regarding the local access, there is practically no room for differentiation through a subjective QoE factor, due to the high benefits associated with local access for all users and objects. Thus, without loss of generality, we have considered that $b(l) = 0$.

The selected function for $t_m^n(X)$ guarantees that the cost is an increasing function of Q_m^n and $b(X)$. More desirable objects (higher value of Q_m^n) would yield a higher access cost $t_m^n(X)$ than less desirable objects that have the same access location. Also $b(X)$ ensures that for any object m and node n the costs associated with access locations l,r and s satisfy $t_m^n(l) < t_m^n(r) < t_m^n(s)$ due to $b(l) < b(r) < b(s)$.

Regarding the subjective QoE factor, as already indicated, function Q_m^n reflects the quality expectations of node n for content m retrieval. Since the environment that ignores the subjective QoE factor would place the most popular objects in each node at step 0, to emphasize the potential impact of the subjective QoE factor, we select such factors Q_m^n which would not be in line with the popularity of the objects. That is, we consider low popularity objects that have high subjective QoE expectations, as shown in the factor Q_m^n given by (27), where the same set of r, $r < M$, unpopular objects for all nodes n has been also selected as objects of high QoE expectations. The parameter q in (27) manipulates the importance of the subjective QoE factor in the cost values $t_m^n(X)$. The values $q = 10$ and $r = 5$ have been selected for our results.

$$Q_m^n = \begin{cases} qF_m^n & \text{, if } 1 \leq m \leq M - r \\ qF_{M+1-m}^n & \text{, if } M - r < m \leq M \end{cases} \tag{27}$$

For comparison reasons, we have also considered an equivalent distributed replication group under a cost structure that ignores the subjective QoE factor. This cost depends only on the objective QoE factor and is equivalent to the simple cost scheme described in the previous works [6,7]. In order for the comparison to be meaningful, an average subjective QoE factor $\overline{Q}$ is computed as the mean of the subjective factors Q_m^n over all objects and nodes (given by (28)) and the access cost in the equivalent group that ignores the subjective QoE factor is given by (29) for all access locations $X \in \{l, r, s\}$:

$$\overline{Q} = \frac{1}{M}\frac{1}{N}\sum_{m=1}^{M}\sum_{n=1}^{N} Q_m^n \tag{28}$$

$$t_m^n(X) = t(X) = \overline{Q}b(X) \tag{29}$$

Let also $\overline{P}$, $\overline{P^1}$, $\overline{P_n}$, $\overline{P_{-n}}$, $\overline{P_n^0}$, $\overline{P_n^1}$ and $\overline{P_{-n}^{1-}}$ denote the corresponding placements of the TSLS strategy produced under the use of costs $t(X)$ agnostic to the subjective QoE factors Q_m^n. Let $\overline{L_n} = \{m \in O : m \in \overline{P_n}\}$, $\overline{R_n} = \{m \in O : m \notin \overline{P_n} \cap m \in \overline{P_{-n}}\}$, $\overline{S_n} = \{m \in O : m \notin \overline{P_n} \cap m \notin \overline{P_{-n}}\}$ denote the sets of objects retrieved from access locations l, r and s, respectively. The cost reduction $\overline{g_{n,m}^0}$ and $\overline{g_{n,m}^1}$ incurred for each node n, given by (30) and (31), determine the respective placements $\overline{P^0}$ and $\overline{P^1}$. The cost of each node n, $\overline{C_n}(\overline{P})$, and the associated gain $\overline{G_n}(\overline{P})$ are given by (32) and (33), respectively, ignoring the subjective QoE factor.

$$\overline{g_{n,m}^0} = F_m^n(t(s) - t(l)) \tag{30}$$

$$\overline{g_{n,m}^1} = \begin{cases} F_m^n(t(s) - t(l)), \text{if } m \notin \overline{P_{-n}^{1-}} \\ F_m^n(t(r) - t(l)), \text{if } m \in \overline{P_{-n}^{1-}} \end{cases} \tag{31}$$

$$\overline{C_n}(\overline{P}) = \sum_{m=1}^{M} F_m^n t(X)$$
$$= \left[b(l) \sum_{m \in \overline{L_n}} F_m^n + b(r) \sum_{m \in \overline{R_n}} F_m^n + b(s) \sum_{m \in \overline{S_n}} F_m^n \right] \overline{Q} \tag{32}$$

TABLE I

SET OF OBJECTS LOCALLY REPLICATED PER NODE ACCORDING TO THE TSLS STRATEGY FOR THE SYMMETRIC ENVIRONMENT

	Subjective and Objective Costs $t_m^n(X)$	**Objective Costs** $t(X)$
Node 1	$\{1:5\} \cup \{8, 9, 49\}$	$\{1:3\} \cup \{8:12\}$
Node 2	$\{1:6\} \cup \{10, 11\}$	$\{1:4\} \cup \{13:16\}$
Node 3	$\{1:6\} \cup \{12, 48\}$	$\{1:5\} \cup \{17:19\}$
Node 4	$\{1:6\} \cup \{13, 47\}$	$\{1:5\} \cup \{20:22\}$
Node 5	$\{1:7\} \cup \{50\}$	$\{1:7\} \cup \{23\}$

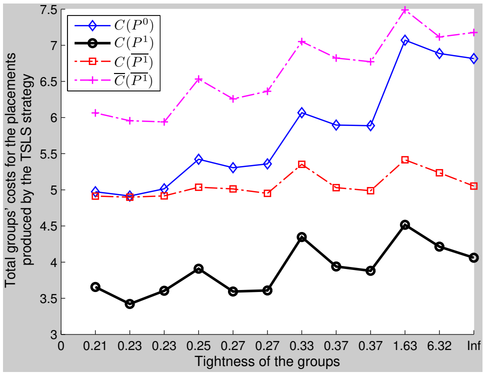

Fig. 1. Total access costs for the groups under both the proposed cost structure and the equivalent ignoring the objective QoE factor.

$$\overline{G_n}(\overline{P}) = \sum_{m \in \overline{L_n}} F_m^n(t(s) - t(l)) + \sum_{m \in \overline{R_n}} F_m^n(t(s) - t(r)) \tag{33}$$

In Table I, the set of objects locally replicated have been presented for all nodes under the execution of the TSLS strategy in our symmetric environment, where all nodes have identical popularity distributions. As expected, each node replicates a different set of objects according to the group 's current placement and the selected cost functions, which can be dependent on either both the subjective and the objective QoE factors or the objective QoE factor only. We can observe that the costs associated with the objective QoE factor only give an advantage to the popular objects for local storage due to their frequently incurred costs, while all the unpopular objects have been ignored although associated with a high QoE factor and their contribution to the mean cost is relatively high. On the contrary, this behavior is modified when the cost captures also the subjective QoE factor. Under this case, the local caches include also the least popular objects due to their impact on the QoE. *Therefore, the proposed cost structure allows for breaking the strong dependence of the induced mean access cost from the object popularity, that traditionally shapes the resulting placement and favors the most popular objects.* If the subjective QoE factor is low, an otherwise very popular object may not be included in the local placement.

To investigate the achieved total cost collectively for the group, we have also considered the various environments of variant similarity, described above, by modifying the Zipf

TABLE II
ACCESS COSTS INDUCED PER NODE IN CASE THAT THE SUBJECTIVE AND OBJECTIVE QOE FACTORS ARE CONSIDERED FOR THE SYMMETRIC ENVIRONMENT

	Cost $C_n(P^0)$	**Cost** $C_n(P^1)$
Node 1	1.3632	0.8329
Node 2	1.3632	0.8135
Node 3	1.3632	0.8243
Node 4	1.3632	0.8309
Node 5	1.3632	0.7588

parameters and by shifting the popularity distributions for all considered values of p and k, respectively. The similarity of the yielded groups has been measured through the tightness metric T, introduced in [7]. For each group, the initial (P^0) and the final (P^1) placements have been derived under the same cost functions where both the subjective and the objective QoE factors have been taken into consideration. The resulting costs $C(P^0)$ and $C(P^1)$ are depicted in Fig. 1. The placement $\overline{P^1}$ has also been derived by considering a fixed subjective QoE factor (i.e., in essence ignoring it) which is the average $\overline{Q}$ (see earlier); i.e., $\overline{P^1}$ is shaped by the objective QoE factor only. The induced cost $\overline{C}(\overline{P^1})$ is also shown in Fig. 1, it is shaped by $b(X)$ and $\overline{Q}$ and observed to be higher than $C(P^1)$. Finally, the cost produced under placement $\overline{P^1}$ but considering the real cost $t^n_m(X)$ (25) is also shown in Fig. 1 and is given by (34).

$$C_n(\overline{P}) = \sum_{m=1}^{M} F^n_m t^n_m(X)$$
$$= \sum_{m\in\overline{L_n}} F^n_m Q^n_m b(l) + \sum_{m\in\overline{R_n}} F^n_m Q^n_m b(r) + \sum_{m\in\overline{S_n}} F^n_m Q^n_m b(s) \quad (34)$$

Fig.1 shows that ignoring the subjective cost Q^n_m when it is present leads to a placement $\overline{P^1}$ of higher cost ($C(\overline{P^1})$ and $\overline{C}(\overline{P^1})$ are higher than $C(P^1)$). Notice also that the GL strategy induces average costs $C(P^0)$ that are higher than those under the proposed strategy, as expected, since all nodes will perform under the proposed strategy at least as well as under the GL (mistreatment-free property). In fact, the calculation of all costs $C_n(P^1)$ reveals that no node n induces a higher cost than the respective GL cost $C_n(P^0)$, as observed in Table II under the symmetric environment.

V. CONCLUSION

In this work we have considered the problem of proactive caching (or replication) of content in a group of caches. Since this problem refers to node and content centric environments, we have introduced a generic content-provisioning cost structure that incorporates an objective QoE cost factor (the distance from the access location) and a subjective QoE cost factor (social/behavioral-based). Such cost structure enables us to take into consideration the specific nodes' preferences and the content's characteristics in order to enhance QoE for all users.

We have employed a distributed two-step local search strategy that determines the proactive distribution of content in the group of caches under the proposed generic content-provisioning cost structure. We have established for the proposed strategy two important properties. These are that (a) the strategy is mistreatment-free since no node belonging in the group will experience a deterioration of access cost compared to the access cost that would be incurred if the node was not part of the group; (b) the strategy yields a Nash-Equilibrium under logical conditions for the cost structure. Therefore, stable NE placements can be derived, performance is improved collectively and for each node, while the sustainability of the group is ensured.

Additionally, we have presented numerical results that demonstrate *the decoupling of QoE and popularity achieved by the proposed generic content-provisioning cost structure*. As observed the unpopular objects of high importance for QoE are selected for proactive caching within the group. The generic cost structure also achieves improved access cost for the entire group compared to the total cost incurred in case of ignoring the subjective QoE cost element.

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