APRE: A Replication Method for Unstructured P2P Networks

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Abstract

We present *APRE*, a replication method for structureless Peer-to-Peer overlays. The goal of our method is to achieve real-time replication of even the most sparsely located content relative to demand. *APRE* adaptively *expands* or *contracts* the replica set of an object in order to improve the sharing process and achieve a low load distribution among the providers. To achieve that, it utilizes search knowledge to identify possible replication targets inside query-intensive areas of the overlay. We present detailed simulation results where *APRE* exhibits both efficiency and robustness relative to the number of requesters and the respective request rates. The scheme proves particularly useful in the event of flash crowds, managing to quickly adapt to sudden surges in load.

I. Introduction

Peer-to-Peer (hence P2P) computing represents the notion of sharing resources available at the edges of the Internet [32]. Its success can still be largely attributed to file-sharing applications (e.g., [11], [13], [14], [19]) which enable users worldwide to exchange locally maintained content. Nevertheless, an increasing number of diverse applications that utilize this technology have emerged. P2P has been proposed to assist in web caching [16], instant messaging [15], e-mails [18], update propagation [8], conferencing [3], etc.

A basic requirement for every P2P system is fault-tolerance. Since the primary objective is resource location and sharing, we require that this basic operation takes place in an reliable manner. In a variety of circumstances, the distributed and dynamic nature of the target environments stress the system's ability to operate as desired. Therefore, in many scenarios (routes to) recourses become scarce, servers get overloaded and throughput can diminish due to high workloads.

Data replication techniques are commonly utilized in order to avoid such instances. System resources (content and its location, routing indices, topology information, etc) are cached/replicated by more than a single node in the network, alleviating single points of contact in both routing

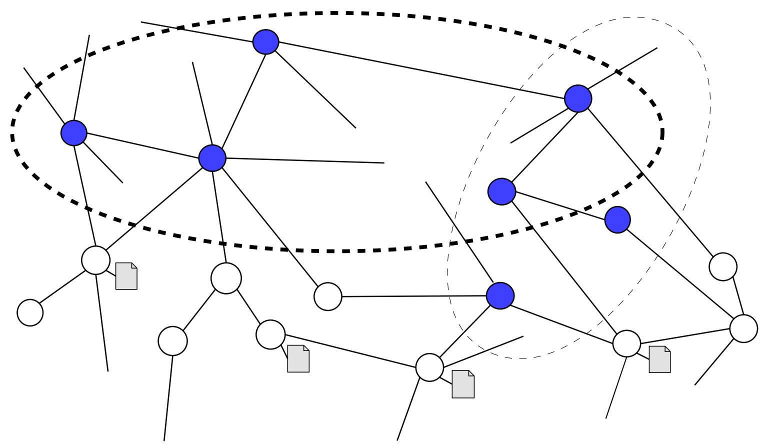


Fig. 1. Part of the overlay network of our model. Shaded peers inside the bold dotted line represent $\mathcal{M}_i$, while those inside the thin dotted eclipse represent $\mathcal{M}_j$. Other peers (those with a file connected to them) also serve objects i or j

and data exchange and reducing the average distance to the objects. Replication can be performed in a variety of manners: Mirroring (Akamai), caching (web servers), CDNs, etc. In large scale unstructured P2P networks, peers usually operate on local knowledge, with variable up-times and no control over the induced topology or workload. Data availability and efficient data sharing dictate replication in this challenging environment. P2P file-sharing applications implicitly handle replication through object sharing. Some systems force users to maintain the new replicas for the benefit of other users. However, this does not tackle the issue of real-time replication adaptive to the current workload.

In this work, we present *APRE* (Adaptive Probabilistic REplication), a replication method based on soft-state probabilistic routing indices. Our approach focuses on providing an adaptive solution to the problem of availability together with minimizing the instances of server overloads and serious service degradation. We intend for our system to "expand" and "contract" its resources according to the workload as perceived locally. New replicas are created in areas of high demand in the overlay, thus disposing of the need of advertising them. Moreover, this will be done in a completely decentralized manner, with minimal communication overhead and using absolutely affordable memory space per node.

A. Our Framework

First, we describe our framework for resource-sharing in an unstructured P2P network. We intend to present a model as general and realistic as possible, avoiding many unnecessary assumptions.

We assume a *pure* Peer-to-Peer model, with no imposed hierarchy over the set of participating peers. All of them may serve and request various objects. Each peer locally maintains its own collection of objects, as well as a local view of the system. Ignoring physical connectivity and topology from our talk, we generally expect peers to be aware of their one-hop neighbors in the overlay, while maintaining any other protocol-specific information (e.g., search indices, routing tables, etc). The system is expected to exhibit a dynamic behavior, with peers entering and leaving at will and also inserting/removing objects from their repositories. The overlay structure will also be affected, since nodes are not guaranteed to connect to the same neighbors each time.

As a motivating example, assume an unstructured P2P system, where peers share and request replicated resources. Objects are assumed to be requested regularly, e.g., results of a live sports meeting, weather maps, security updates, real time aggregated statistics, software, etc. There exist some nodes (similar to the web servers or mirror sites in the Internet) that provide with fresh content, but their connectivity or availability varies, as happens with all other network nodes. Peers that are interested in retrieving the newest version of the content conduct searches for it in order to locate a fresh or closer replica.

Figure 1 gives a graphic representation of our system. For each object i, there exists a set of peers called the *server set* $\mathcal{S}_i = \{s_{i_1}, s_{i_2}, \ldots, s_{i_k}\}$ that serve the specific object. These are the nodes that, at a given time, are online, store object i and are willing to share it. A subset of $\mathcal{S}_i$, the *mirror set* $\mathcal{M}_i \subseteq \mathcal{S}_i$ (the shaded peers) represents the set of peers that, if online, *always* serve i. This does not imply that all peers in $\mathcal{M}_i$ will always be online, their connectivity in the overlay will remain the same, or that they will never refuse connections. But we can assume, without loss of generality, that these nodes will be mostly available. Our assumption is not unrealistic: Imagine that these servers can represent mirror sites/authority nodes that provide with up-to-date content. Nevertheless, they are not guaranteed to be always on-line, nor do they provide similar services. Apart from the mirror set, other peers that already host or have recently retrieved an object can serve requests for it (nodes with files attached to them in Figure 1). A server set comprises of these nodes plus the corresponding mirror set.

Naturally, peers may belong to server or mirror sets for multiple objects. While this is a symmetric environment, it is clear that nodes will exhibit different sharing abilities. A variety of parameters, including available storage, CPU power, popularity of stored objects, system workload, connectivity, etc, contribute to this fact. Some of these factors remain more or less static over time (e.g., processing power or the maximum available bandwidth of a host), while others change dynamically.

Whichever the case, it is safe to assume that each peer in such a system will impose a limit on the services it can provide to other peers. This is something that is already utilized by several file-sharing applications (e.g., Kazaa [19]), FTP servers, etc. There exist a variety of metrics that can be used to realize those limits, for example the maximum number of concurrent connections, upload bandwidth, number of shared files, rate of received requests, etc. In this work, we focus on two of these parameters, namely workload and object popularity as they are manifested through a single observable quantity, the request rate λ. It is obvious that servers of popular (or temporally popular) items receive a larger number of requests, which can possibly affect their sharing ability as well as the system's behavior.

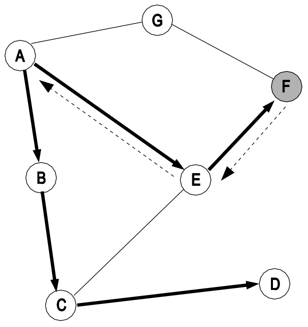
Given this general framework, our goal is to design and implement a replication protocol that will provide efficient sharing of objects (in terms of providing low load operation), scalability and bandwidth-efficiency. *APRE* is a distributed protocol that automatically adjusts the replication ratio of every shared item according to the current demand for it. By utilizing inexpensive routing indices during searches, loaded servers are able to identify "hot" areas inside the unstructured overlay with a customizable push phase. Selected nodes create replicas, sharing part of the load. Under-utilized servers are able to host different content. The rationale behind *APRE* is the tight coupling between replication and the lookup protocol which controls how searches get disseminated in the overlay. By combining the Adaptive Probabilistic Search (*APS*) state with *APRE*, we are able to identify (in real-time) "hot" or "cold" lookup paths and avoid the need of advertising new replicas. We show that this method proves very efficient in a variety of metrics and environments and is fully customizable.

The rest of this report is organized as follows: Section II summarizes our work in probabilistic searching and content dissemination which is the basis of *APRE*. In Section III we describe our protocol in detail and extensive results are presented in Section IV. Finally, Sections V and VI contain our related work and conclusions respectively.

II. Probabilistic Resource Location

A. Probabilistic Search

We now briefly describe the *APS* [37] search method, upon which our replication scheme is based. In *APS*, each node keeps a local index consisting of one entry for each object it has requested per neighbor. The value of this entry reflects the relative probability of this node's neighbor to



Indices	Initially	After walkers finish	After the updates
A→B	30	20	20
B→C	30	20	20
C→D	30	20	20
A→E	30	20	40
E→F	30	20	40
A→G	30	30	30

Fig. 2. Node A searches for an object stored at node F using APS (pessimistic) with two walkers. The table shows how index values change. X→Y denotes the index value stored at node X for neighbor Y relative to the requested object.

be chosen as the next hop in a future request for the specific object. Searching is based on the deployment of *k* independent walkers and probabilistic forwarding. Each intermediate node forwards the query to one of its neighbors with probability given by its local index. Index values are updated using feedback from the walkers. If a walker succeeds (fails), the relative probabilities of the nodes on the walker's path are increased (decreased). The update procedure takes the reverse path back to the requester and can take place either after a walker miss (*optimistic* update approach), or after a hit (*pessimistic* update approach). Figure 2 shows an example.

APS exhibits many plausible characteristics as a result of its *learning* feature. Every node on the deployed walkers updates its indices according to search results, so peers eventually share, refine and adjust their search knowledge with time. Walkers are directed towards objects or redirected if a miss or an object deletion occurs. *APS* is also bandwidth-efficient: It induces zero overhead over the network at join/leave/update operations and displays a high degree of robustness in topology changes.

III. Our "Expand-Contract" Technique

APRE is based on two basic operations: *Expansion* and *Contraction*. These are shown pictorially in Figures 4 and 5 respectively. Our main goal is to provide a completely decentralized mechanism through which the system will adaptively expand its replica size when demand is increased and will shrink when demand will fall.

The high-level behavior of our system can be described using a simple model (Figure 3): In normal mode, nodes can adequately serve requests and also retrieve objects. As load increases, some may reach their self-imposed limits. By invoking the *Expand* process, we aim at bringing the node status back to normal and lower the average load for a specific object inside an area.

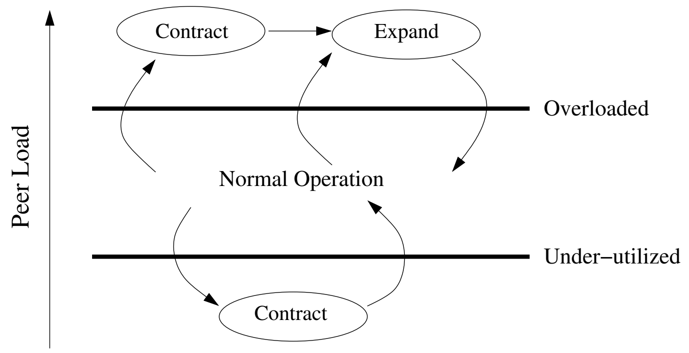


Fig. 3. State transitions in our system

Normal operation and load balancing will not be necessarily achieved simultaneously. Consider, for example, that a peer initiating *Expand* may receive requests for multiple objects. Expanding in respect to one of them will probably lower its load, but will not necessarily bring its level back to normal. As load decreases, nodes can free up space (and the respective resources) and thus share a bigger portion of the available workload.

Let us now discuss why the system would benefit from those two operations. When parts of the server set $\mathcal{S}_i$ receive too many requests, the following may occur: Clients' connections get refused, while servers receive an increasing amount of requests and their performance deteriorates. Both groups would benefit from an increase in the number of replicas available, especially if those replicas were placed inside the areas of high demand in the overlay.

Conversely, consider that one or more subsets of $\mathcal{S}_i$ have recently received very few requests for object i. This practically means that a potentially large amount of their storage space is under-utilized. They could remove the document to free up space or replace it with another document of high demand. We have to stress here the point that the system will not force any peer to store or serve an object until this becomes necessary; Only peers that have already retrieved the document, or have available storage can play that role. *Contract* will also be invoked when a peer is called to join $\mathcal{S}_i$ but cannot do so without exceeding its limits (e.g., maximum sharing capacity). Note that peers can still choose to reject a certain action, for example refuse to deactivate an object in order to serve a new one.

Figure 4 shows an example of our system expanding in response to increased demand for a specific object. On the left we see some initial server set (gray oval) and the demand for i (arrows from various parts of the network). Servers in two areas are overloaded with requests, thus forcing extra replicas in those two areas to be activated for sharing. $\mathcal{S}_i$ expands, as we see on the right

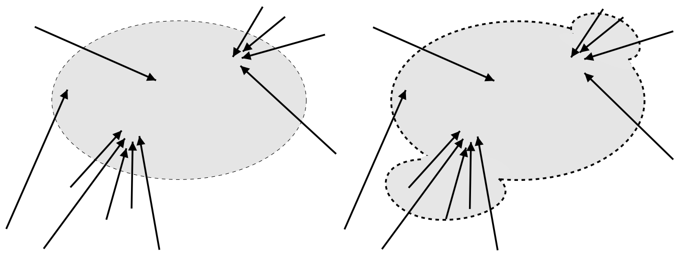


Fig. 4. Expansion

Algorithm 1 *Expand*

```
1: if Replica i at node x reaches its limit then
2:     $P \leftarrow FindPossibleServers(i)$; $\{P \cap \mathcal{S}_i = \emptyset\}$
3:     Activate $i$ at $Y \subseteq P$
4: end if
```

part of the picture, in response to the demand and replication status for object i. Similarly, Figure 5 shows that the two white areas of the server set (the area inside the dotted line) do not receive requests for object i. This leads to the contraction of $\mathcal{S}_i$ which is now the gray oval on the right part of the figure. Algorithms 1 and 2 presents a high-level description of how these two methods would work. Our goal is to achieve a system behavior that resembles the buffer management techniques in databases: Viewing the P2P network as a large buffer, we want to decide (in a distributed manner) the ratio of object presence in the buffer according to user-specified queries (i.e., workload).

A. Protocol Implementation

In this section we describe the actual implementation of the *APRE* protocol as described by the expand-contract algorithms. We assume that servers measure load and perform replication on a per object basis (similar to lookup and reverse indices).

Vital to the success of our scheme are the following points:

1) Mechanism to identify when an object is “hot” (many requests) or “cold”
2) Mechanism to create replicas inside high-demand areas
3) Minimization of communication inside $\mathcal{S}_i$

The conditions of line 1 in Algorithms 1, 2 describe when *Expand* or *Contract* are initiated. We believe that each peer can independently choose when to initiate an expansion or when to deactivate a replica. Therefore, there is no need for any message exchange between peers inside $\mathcal{S}_i$.

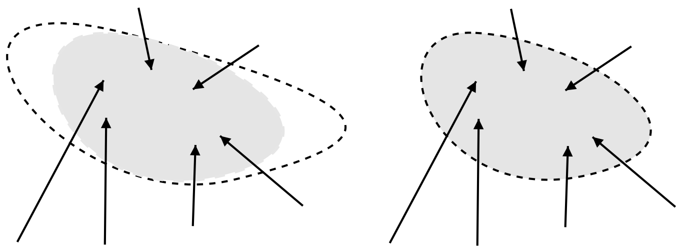


Fig. 5. Contraction

Algorithm 2 *Contract*

```
1: if (Replica i at node x is under-utilized) or
   (x receives $Activate(x, j)$) then
2:   $i \leftarrow ChooseObject()$; {$i$ is among the candidates for eviction}
3:   $DeactivateReplica(i)$;
4:   if (x received an $Activate(x, j)$) then
5:     $ActivateReplica(j)$;
6:   end if
7: end if
```

We assume that each server s advertises the maximum number of requests that replica i can accept per time unit $Limit_{s,i}^{up}$. If it receives less than $Limit_{s,i}^{down}$ requests for object i, this replica is deactivated/deleted from the node's cache without any further communication. Alternative measures such as the maximum number of allowed connections can be used. If the replica cannot sustain its advertised rate, then it may choose to advertise a new maximum capacity. Obviously, the total maximum capacity for server s is equal to $\sum_{i \in s} Limit_{s,i}^{up}$. Function *ChooseObject* decides at each point which object should be evicted at nodes that have reached their storage capacities. Natural choices are to have the new replica replace the least recently used one or the least popular one.

In order to identify "hot" areas inside the overlay, we utilize part of the state that *AGNO* [9] builds during searches: After some queries take place, paths with large index values connect the requesters to the content providers (see Fig. 6). In *AGNO*, we use these paths (plus some extra state) to relay messages from content-holders directly to interested peers. In this problem, paths with high index values are used to identify "hot" areas inside the overlay (i.e. locate subset Y).

In short, peers store *reverse index* values for each of their neighbors. These represent the *APS* index values that their neighbors hold relative for them and are piggybacked during searches (see Figure 7). Reverse indices can be used to contact nodes inside query-intensive areas in an unstructured overlay. They represent a measure of how useful a peer is for finding an object according to its neighbors. Overloaded servers issue a special message which is forwarded either

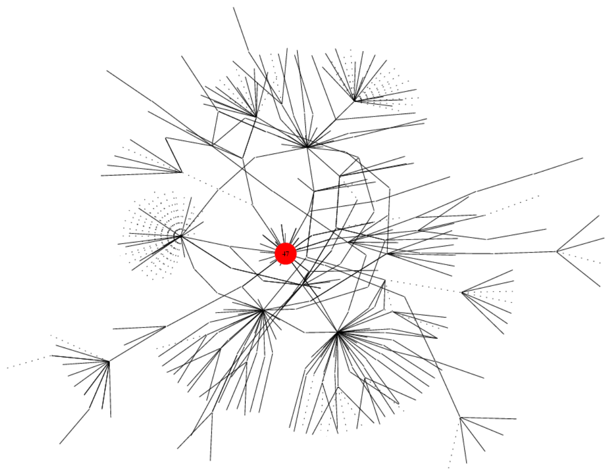


Fig. 6. Visual representation of a sample power-law graph, after several searches for a single object using the APS method. Solid line arcs show high index value links between nodes

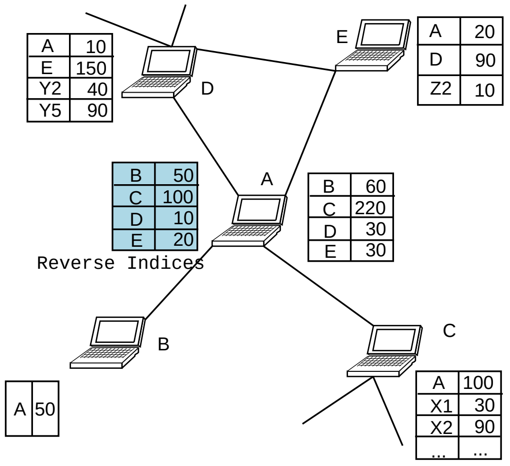


Fig. 7. Node A has four neighbors who obtain index values as the white tables show. The blue table depicts the reverse index values stored at node A

probabilistically or to the top-k neighbors according to the stored reverse index values. Each node on the path independently decides whether it will join S_i according to the implemented replication policy. This phase continues with nodes passing this message over in a similar fashion, until either their TTL value reaches zero or a duplicate reception (due to a cycle) occurs. Figure 8 shows an example of our scheme at work: Black nodes represent requesters of the item held at the middle node. Directed APS searches are depicted by arrows. In the push phase, paths with high index values are visited (links with dotted lines). The new shaded nodes with bold outline represent possible replicas created.

Reverse indices get updated during searches, but this is not enough: There may be peers that have searched for an object and built large index values in the past, but are no longer interested in it. If searches are no longer routed through those peers, the respective reverse index values will not be updated and will remain high. Thus, our scheme could erroneously consider such nodes as candidates for replication. To correct this situation, we add an *aging* factor to the reverse indices, which forces their values to decrease with time. Peers now keep track of the time that a reverse index was last updated in order to acquire its correct value before using it. When a peer receives a search message, it sets the corresponding reverse index to the piggybacked value and its last modified field to the time of receipt. We describe this process in Figure 9. The value of the index decreases exponentially, while two searches at times t_1, t_2 reset its value. A push message received at time t_3 will use the value as shown in the figure. The last modified value is also reset when a reverse index is used, since a peer computes its current value before using it.

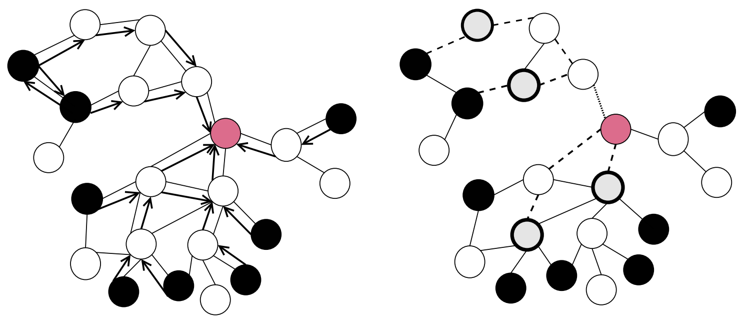


Fig. 8. After searches take place, reverse index values are updated and new replicas can be created inside areas of high demand

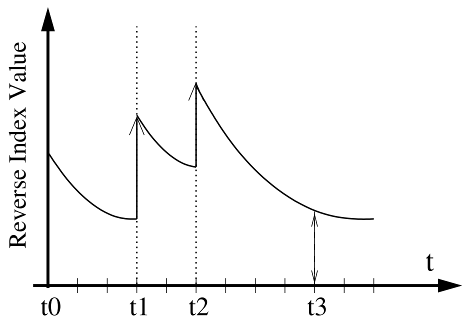


Fig. 9. Example of exponential decay in the reverse index values

Each node on the path independently decides whether it will join S_i according to our replication policy. Currently, we have implemented three: *FurthestFirst*, *ClosestFirst* and *Uniform*. In the first policy, the probability of a node joining S_i increases with the message distance, while the opposite occurs in *ClosestFirst*. All nodes are given the same chance in *Uniform*. After Y has been identified, replicas are transmitted and activated.

In order for *APRE* to adapt to various workloads and avoid system oscillation due to replicas with perceived load a little above or below the limits frequently entering and leaving $\mathcal{S}_i$ [29], we introduce a *scaled* replication policy. In effect, we define 3 different intervals that relate to the amount of overloading $D = \lambda_i - Limit_i^{up}$. Servers individually estimate λ_i, the rate of requests for object i measured locally. Each interval has TTL probability values associated with it, one for each hop distance. These values increase as D falls into higher number intervals. Thus, a heavily overloaded server will create more replicas than a less overloaded one and marginally overloaded peers will not alter $\mathcal{S}_i$ significantly.

IV. Results

We test the effectiveness of *APRE* using a message-level simulator written in C. Object requests occur at rate λ_r with exponentially distributed inter-arrival times. At each run, we randomly choose a *single* node that plays the role of the initial $\mathcal{M}_i \equiv \mathcal{S}_i$ set and a number of requesters, also uniformly at random. The requester set is periodically altered by 10%. Results are averaged over several tens of runs. We utilize 10,000-node *random* and *power-law* graphs with average node degrees around 4 (similar to gnutella snapshots [27]) created with the *BRITE* [22] and *Inet-3.0* [17] topology generators.

To evaluate the replication scheme, we utilize the following metrics: The average load Λ which is the number of received requests per second for $\mathcal{S}_i$. Obviously, regarding our load-balancing

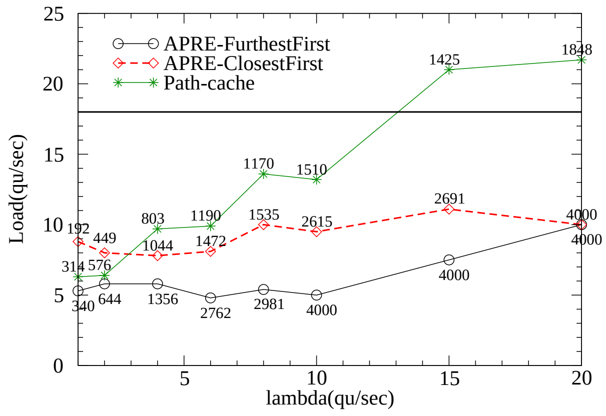


Fig. 10. Variation in Λ and $|\mathcal{S}_i|$ over increasing λ_r values

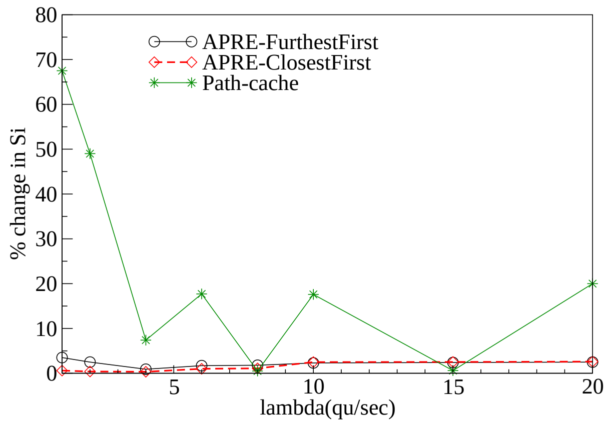


Fig. 11. Percentage of change in $\mathcal{S}_i$ per replication phase

requirement, we also need to measure its standard deviation σ_Λ. A high value for σ_Λ indicates that load is very unevenly balanced across $\mathcal{S}_i$. Besides the size of the server set, we also keep track of the number of replica activations/de-activations. Regardless of how low Λ and σ_Λ may be, frequent changes in $\mathcal{S}_i$ incur huge overheads in terms of messages and bytes transferred.

APRE Parameters: We assume that $(Limit_{s,i}^{up}, Limit_{s,i}^{down}) = (18,3)$ for all nodes and objects. During each time step, server nodes estimate λ_r (within $\varepsilon = 0.1$) by counting the number of requests and estimating the number of different requesters involved. This value will be used to calculate the decay of the reverse indices (as described in [9]). During the *Expand* push phase, peers forward to the two neighbors with the largest reverse index values. We utilize a scheme with 3 distinct intervals for values of D: $[0-5], (5-20], (20-\infty)$. While we experimented with more fine-grained granularities, the results did not vary considerably. Finally, we assume no item can be replicated at more than 40% of the network nodes (maximum replication ratio). This external condition simulates the natural limitations in storage that exist in most systems.

We compare our method against a random replication scheme as well as path-replication as applied by Freenet [4] and in effect by *lar* [12]. In the first case, we randomly create the same number of replicas as our method. In path replication (hence *path-cache*), each time a server is overloaded we replicate the object along the reverse path to the requester. In both cases, the *APS* method is used for lookups, while in *path-cache* replicas are also deactivated using our *Contract* scheme. Obviously, by varying the push method and the replication probabilities, *APRE* can behave either as *path-cache*, random, or in between with a variable rate of replica creation per workload. This allows for full customization according to the system's primary objects, namely low load (more replicas) or space (replicas only where necessary).

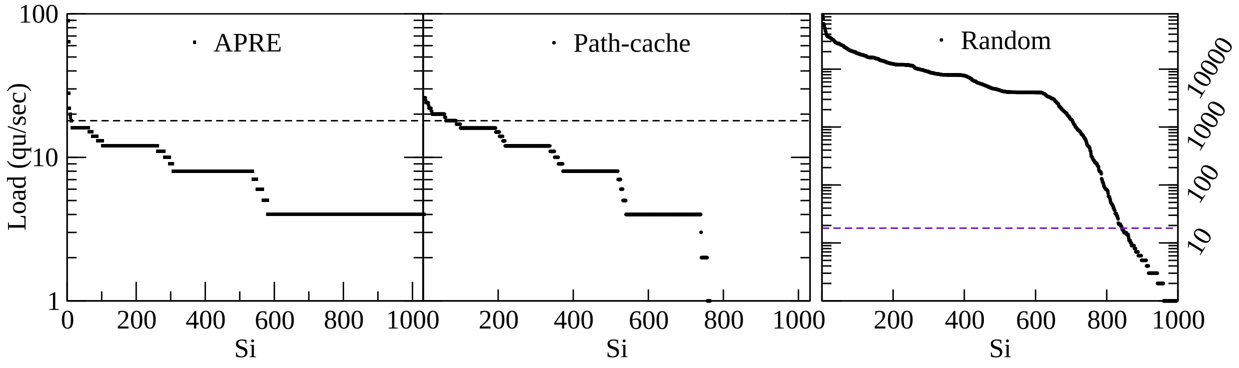


Fig. 12. $\mathcal{S}_i$ load distribution for $\lambda_r = 4/sec$

A. Basic Performance Comparison

For our default setting, we assume 2000 random requesters, with initial $|\mathcal{S}_i| = 1$ as we vary their λ_r. The results are presented in figures 10, 11. At each point in Figure 10, we annotate the respective $|\mathcal{S}_i|$ value.

APRE effectively expands $\mathcal{S}_i$ in order to accommodate increased demand and manages to keep all servers into the Normal Operation zone, well below $Limit^{up}$ (identified by the bold horizontal line). Our first observation is that *FurthestFirst* achieves lower Λ values by creating more replicas than *ClosestFirst*. Downstream paths during the "push" phase contact an increasing number of nodes as their distance from the initiator increases, thus giving *FurthestFirst* an increased probability of replication. *Path-cache* exhibits a steeper increase in Λ and fails to keep its value within the acceptable region for large λ_r. Choosing only successful walks to replicate along, quickly "saturates" the frequently used paths with replicas. Increased demand merely forces the algorithm to utilize a few more paths, which is the reason why this method fails to increase the replica set to meet the limits.

It is interesting to note that *APRE* exhibits small σ_Λ values, ranging from 3.9 to 16 only in the highest λ_r setting. These values are either smaller or at most comparable to Λ, a good indication of load balancing. On the other hand, randomly placing the same number of replicas yields a very poor load-balancing result, with σ_Λ values 2 orders of magnitude higher. This is also a clear indication of the need for correct placement inside structureless multi-path overlays.

While a low deviation from the mean value is desired, it is also important that only few peers are documented as operating above their limits. Figure 12 shows the load distribution of every server s at a random point in time ($\lambda_r = 4/sec$). Servers are sorted in decreasing order of load. While *APRE, path-cache* have similar Λ, σ_Λ values, our method exhibits a less steep curve and, more

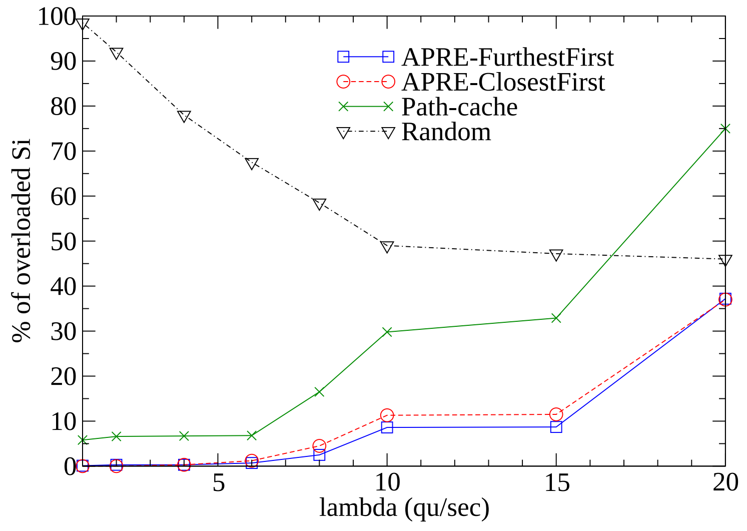


Fig. 13. Ratio of overloaded servers

importantly, has only 3 servers above *Limit*^{up}, compared to 54 for *path-cache*. Random replication causes extremely unbalanced load. Figure 13 displays the average percentage of overloaded servers at any time for all three methods. Our technique clearly outperforms the two competing methods by having 2-6 times fewer overloaded servers than *path-cache*. Replicating closer to requesters creates, as we saw, more service points, thus marginally reducing the number of overloaded instances for *FurthestFirst*. *Random* exhibits very poor performance which is partly undone as demand increases. This is exclusively due to the learning feature of *APS*.

Moreover, we show that *APRE* achieves a much more robust replication. The stability of the server population constitutes an important metric to the evaluation of a replication scheme. This is measured by the average ratio of new replicas entering $\mathcal{S}_i$ per replication phase over the size of $\mathcal{S}_i$. Obviously, a large percentage of new content creation is highly undesirable, as it burdens network and local resources. Figure 11 shows that *APRE* is particularly robust, altering at most 3% of $\mathcal{S}_i$ per push phase, while *Path-cache* oscillates and performs poorly in most runs.

The same experiment is repeated with 5,000 requesters, which constitute 50% of the overlay (see Figures 14 and 15). *APRE* again keeps the system within its limits, except for the two cases where even the largest replica set cannot achieve that (75k and 100k total queries per second). Figure 15 exhibits why *ClosestFirst* is a preferred strategy over *FurthestFirst* in these settings: Besides creating more replicas, in conditions of very high demand load is less evenly distributed among the server set (see the embedded graph in Figure 15). Still, our method shows remarkable stability in the $\mathcal{S}_i$ population for both strategies, while *Path-cache* exhibits even worse performance

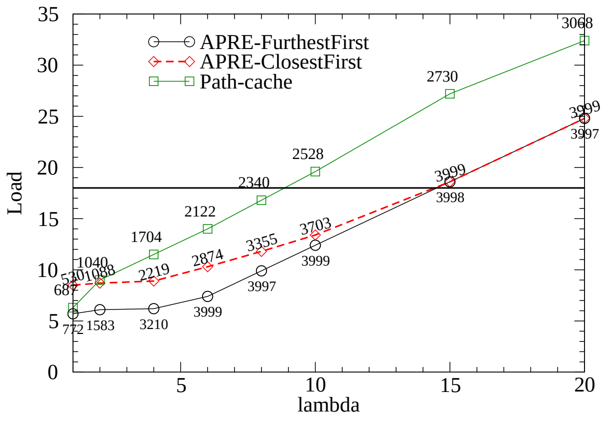


Fig. 14. Variation in the average load vs. variable λ_r (5000 requesters)

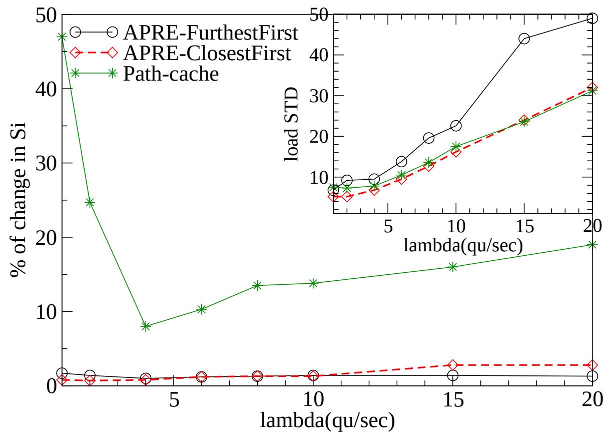


Fig. 15. Percentage of change in $\mathcal{S}_i$ and σ_Λ vs. variable λ_r (5000 requesters)

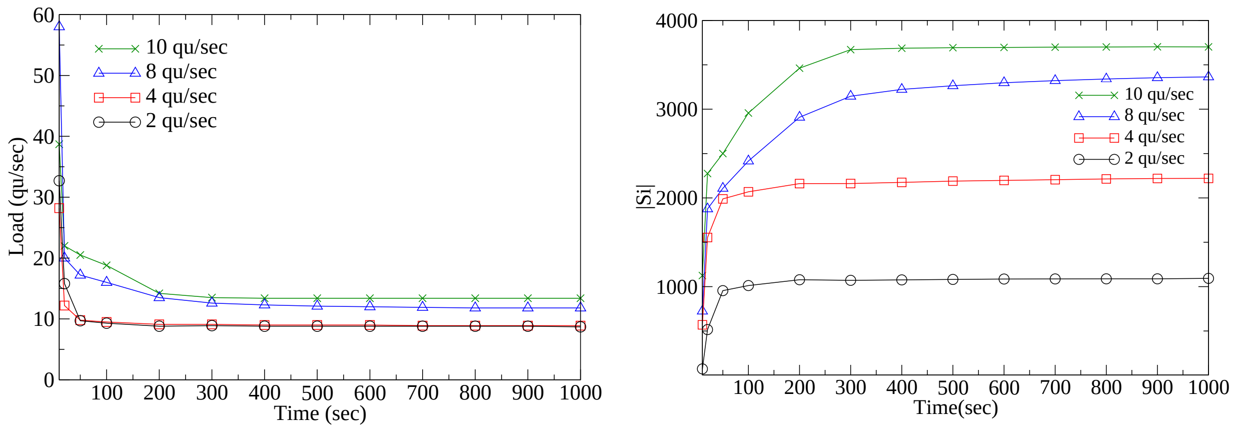


Fig. 16. Λ and $|\mathcal{S}_i|$ over time for 5000 requesters and multiple λ_r values

than before.

Finally, Figure 16 shows how Λ and $|\mathcal{S}_i|$ vary with time, using *ClosestFirst*. For all values of λ_r, *APRE* manages to bring Λ to a steady state in few time steps, a state which is hence maintained with almost no deviation. The same is true for the size of $\mathcal{S}_i$, with the exception that for high total demand, it takes longer to reach the steady state. This is due to the fact that even more paths are now utilized, with reverse index values increasing besides the originally “hot” ones.

Table I summarizes our observations for this setup by showing the performance of the two schemes for the remainder of our metrics. *APRE* achieves very high success rates in lookups keeping bandwidth consumption steadily low in all runs. The same holds for the messages produced during Expand. Finally, replicating inside query-intensive areas allows for an active reduction to the average hop-distance from requesters to servers.

TABLE I

PERFORMANCE COMPARISON UNDER A VARIETY OF METRICS (5000 REQUESTERS)

Method		$\lambda_r = 1/sec$	$\lambda_r = 4/sec$	$\lambda_r = 8/sec$	$\lambda_r = 15/sec$	$\lambda_r = 20/sec$
Closest-First	Success(%)	90.2	95.8	98.4	99.0	99.9
	SearchMesg	9.6	7.8	7.8	7.9	7.8
	ReplMesg	41.7	39.7	39.2	39.3	39.4
	PathLength	3.4	2.2	2.0	2.0	1.9
Furthest-First	Success(%)	91.6	99.0	99.4	99.9	99.9
	SearchMesg	9.6	8.1	8.0	8.1	8.0
	ReplMesg	40.4	38.4	38.4	38.3	38.2
	PathLength	3.2	2.0	1.9	1.9	1.8
Path-cache	Success(%)	87.8	97.8	98.6	99.0	99.0
	SearchMesg	10.2	8.4	7.9	7.6	7.7
	PathLength	3.6	2.5	2.2	2.1	2.0

B. Flash Crowds

In the previous section we established our basic premise, replication along high demand paths in the overlay proves an effective and highly robust solution in a variety of metrics and workloads. Although our method does not explicitly offer load-balancing, it achieves a well-proportionate load distribution. We also showed that our method is advantageous to randomly replicating inside the network or merely choosing a single path and fully replicate along it. In the first case, few replicas receive the majority of requests, while in the second case, a large amount of replicas get deactivated and re-activated each time.

In the next experiment, we examine the behavior of our method when we experience a sudden surge in the workload. This is often referred to as a *flash crowd*, an unexpected rise in requests towards specific item(s), typically due to some newsworthy event that just took place. Flash crowds have been regularly documented in web traffic history (e.g., September 11th) and are known to cause severe congestion at the network layer. Requests may never reach content servers while others do so with significant delays, caused by packet loss and retransmission attempts. Content holders are unable to handle the volume of requests while end-users experience long delays and failures in their queries.

To simulate a similar situation, we start our system with 500 requesters querying at rate $\lambda_r = 2/sec$. At time t=401sec, 10 times as many requesters start querying for this item at rate $\lambda_r = 12/sec$. The parameters return to their initial values at time t=601sec. On average, the total demand during the flash-crowd period increases by a factor of over 70. Note that this is the worst case scenario, when simultaneously both requesters and rates increase. We present the variations in Λ

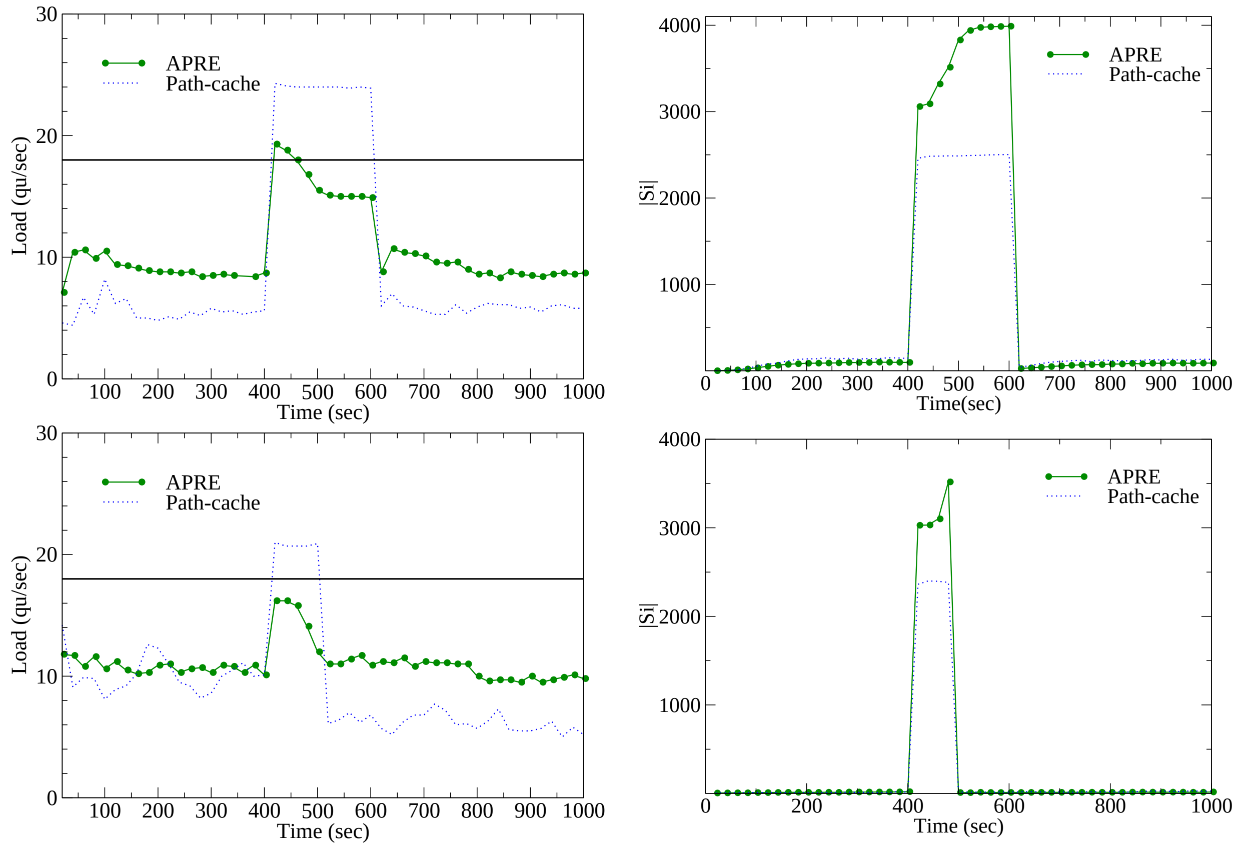


Fig. 17. Effect of flash crowds in Λ and $\mathcal{S}_i$ in two different settings

and $|\mathcal{S}_i|$ in the first 2 graphs of Figure 17.

APRE promptly manages to meet the surge in requests by increasing the replication ratio by a factor of 30. Excluding a very short window due to our mechanism's response, our method succeeds in keeping the load factor below the limit (with $\sigma_\Lambda < 10$) and steady through time. At both moments of load change, replicas are activated and de-activated rapidly to meet the extra requests or reduced traffic. While *path-cache* shows similar response speed, it creates more servers in the low-workload period and less than the minimum number required to keep content providers from overloading during the surge.

The next two figures show how the same two metrics vary in a more challenging flash-crowd setting. Here, we initially set $|\mathcal{S}_i| = 500, \lambda_r = 1/sec$, while for time $t \in (400, 480]$ we set $|\mathcal{S}_i| = 5000, \lambda_r = 10/sec$. On average, the workload inside the overlay increases by a factor of 120. Our results show that, even for shorter and steeper changes, *APRE* very successfully adapts to the surge in requests. On average, $\mathcal{S}_i$ is expanded by a factor of 175 in order to reduce and balance load (our results document an average $\sigma_\Lambda \simeq 8.6$).

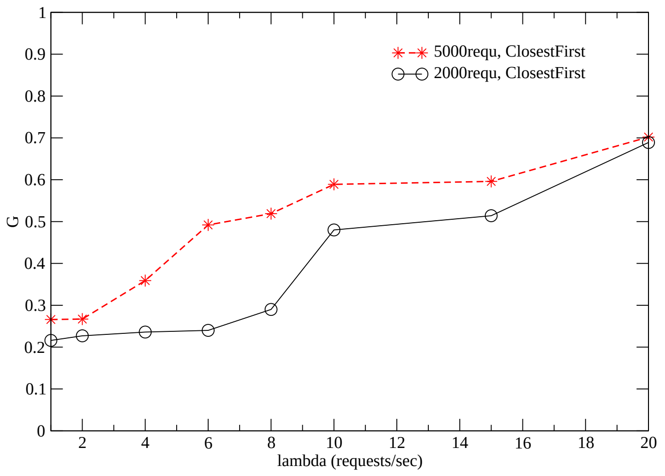


Fig. 18. Average value of the gini coefficient $\mathcal{G}$ as a function of λ_r for the ClosestFirst strategy

C. *Measuring the Degree of Load-Balancing*

The *Gini coefficient* (or Gini ratio) $\mathcal{G}$ is a summary statistic that serves as a measure of inequality in a population [7]. The Gini coefficient is calculated as the sum of the differences between every possible pair of individuals, divided by the mean size:

$$\mathcal{G} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}|x_i - x_j|}{2n^2\mu},$$

where n is the number of observations, whose values are given by x_i, and $\mu = \frac{\sum_{i=1}^{n} x_i}{n}$ is their mean. The Gini coefficient has been used as a measure of inequality in size and fecundity in plant populations in numerous studies (e.g., Weiner 1985, Geber 1989, Knox et al. 1989, Preston 1998). Recent work [36] proposed its use as a load-balancing metric. Assuming our population comprises of the number of received requests for each replica, we calculate the value of $\mathcal{G}$ as an additional index of load distribution among servers. Note here that a low value of $\mathcal{G}$ is a strong indication that load is equally distributed among them, but it does not necessarily mean that this load is low.

Figure 18 shows the average values of $\mathcal{G}$ for all different values of request rates and both numbers of requesters (2k and 5k). In low-load runs servers show very similar loads. As the total load increases (either through an increase in λ_r or $|\mathcal{S}_i|$), so does the inequality between the received requests. The authors in [36] identify that $\mathcal{G} < 0.5$ presents very well-balanced configurations, while when $\mathcal{G}$ is approximately between 0.5 and 0.65, relatively fair distributions are achieved. Our scheme, while not explicitly providing any mechanism to balance load inside $\mathcal{S}_i$, manages to provide very well-balanced configurations for medium to low loads and fair ones for medium to high loads.

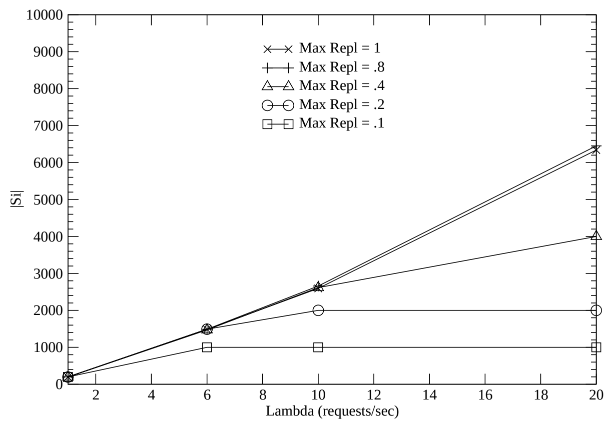


Fig. 19. $|\mathcal{S}_i|$ variation for different maximum allowed replication ratio

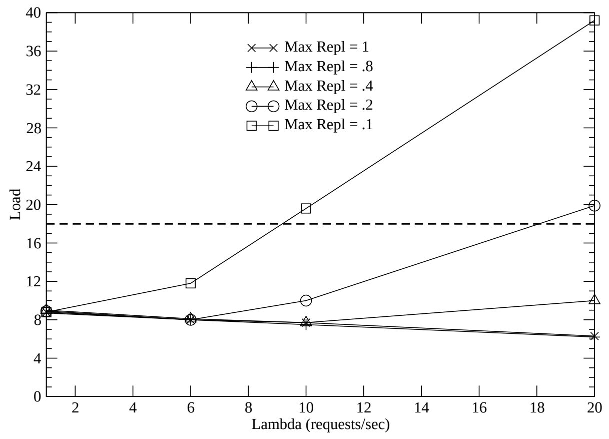


Fig. 20. Λ variation for different maximum allowed replication ratio

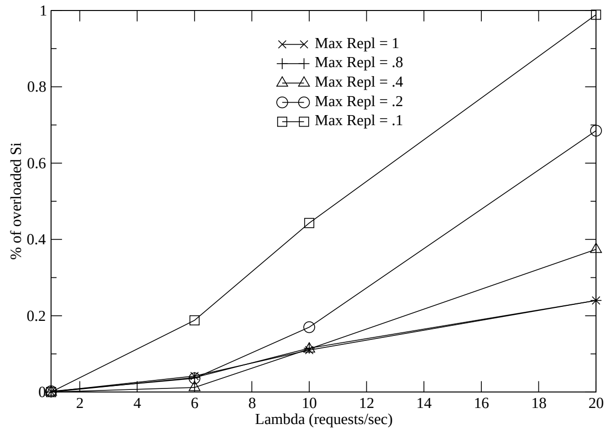


Fig. 21. Percentage of overloaded nodes for different maximum allowed replication ratio

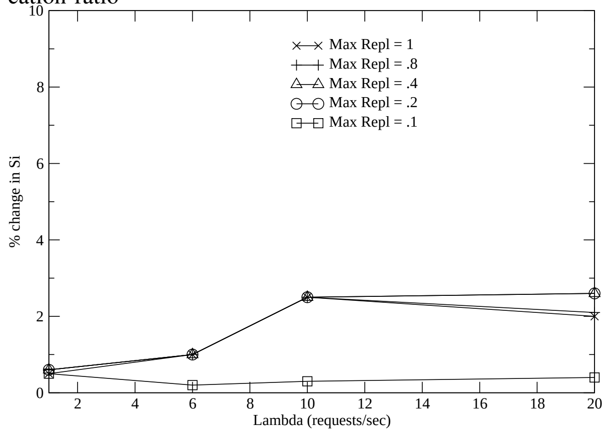


Fig. 22. Percentage of change in $\mathcal{S}_i$ for different maximum allowed replication ratio

The reason for that is because the push phase (thus, by extension, the creation of new replicas) operates symmetrically on multiple (k) high-quality paths. So, neither the originating server gets starved of requests, nor the newly established ones differ substantially in their positioning. Only when $|\mathcal{S}_i|$ reaches our artificial limit of 4000 peers we notice that load allotment gets uneven.

D. Effect of the Maximum Replication Ratio and $Limit_{s,i}^{up}$

Our default scenarios assumed a set value of $0.4 \times N$ for the maximum allowed $|\mathcal{S}_i|$ (where $N = 10k =$ size of our overlay). In the next figures, we show how the performance of *APRE* using *ClosestFirst* varies while we vary the maximum allowed ratio from 0.1 to 1.0. Too small values should force the system to quickly saturate while complete freedom to replicate should exhibit the best behavior. The results are presented in Figures 19, 20, 21 and 22

When the ratio is too small (at most 1000 nodes are allowed to host the object), $\mathcal{S}_i$ quickly

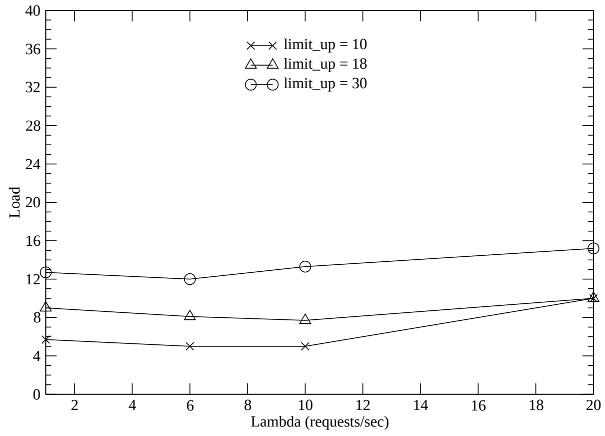


Fig. 23. Λ variation for different values of $Limit_{s,i}^{up}$

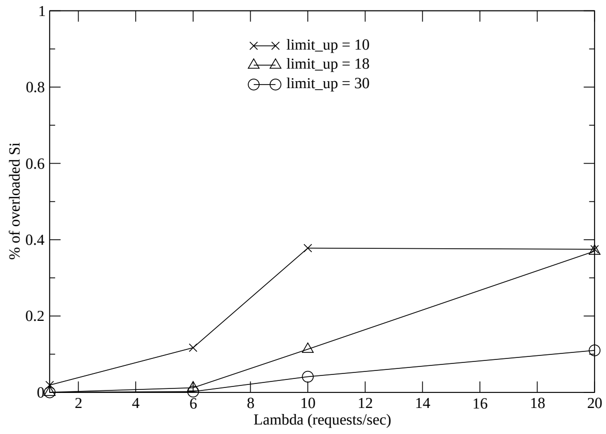


Fig. 24. Percentage of overloaded nodes for different values of $Limit_{s,i}^{up}$

reaches this limit. This affects the values of Λ as well as the number of servers over $Limit_{s,i}^{up}$, which rapidly increase. As more peers are allowed to become servers, $|\mathcal{S}_i|$ increases and so does the percentage of servers above the limit. The interesting observation here is that even for the most optimistic case (no replication restriction), *APRE* manages to keep the ratio of change in the server-set below 3%.

In the next experiment, we vary the maximum advertised capacity $Limit_{s,i}^{up}$ uniformly. Sample results are presented in Figures 23 and 24.

As we would expect, the smaller the upper limit gets, the faster our algorithm reacts to load, thus creating replicas sooner. Obviously, given some storage restriction (such as a maximum allowed number of peers able to enter $\mathcal{S}_i$), small $Limit_{s,i}^{up}$ values cause system saturation and more overloaded instances. On the other hand, for larger upper limits, the server-set increases more gracefully and significantly fewer server overloads are observed.

E. Other Experiments

We test our method on a set of 4,000-node power-law graphs created with Inet-3.0 generator [17]. These graphs have an average degree of $d = 4.3$ (maximum degree equals to 855), while over 30% of the nodes have only one neighbor. Figure 25 shows how Λ varies with time for both replication strategies used in *APRE* using 1000 or 2000 nodes as requesters.

These topologies noticeably affect performance compared to our previous tests. Even for average-range λ_r values, Λ moves close to the overload line, while expansion shows diminished ability to extend $\mathcal{S}_i$. This is consistent with results documented in previous work [37]. The tested topologies

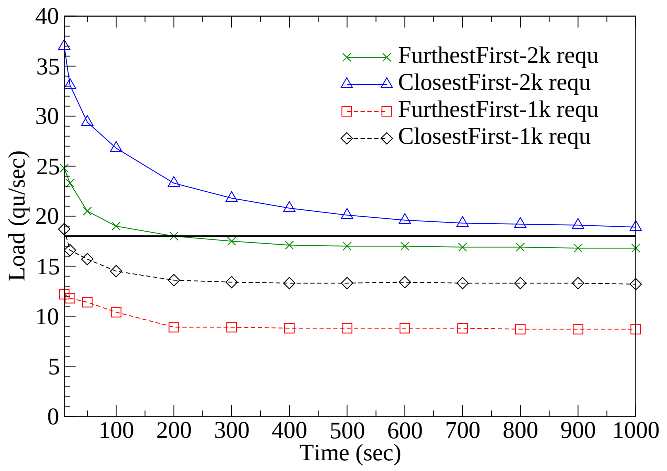


Fig. 25. Average load for 1k and 2k requesters in power-law topologies ($\lambda_r = 6/sec$)

offer fewer paths between servers and clients, while a large percentage of the nodes only have one neighbor. This also explains why *FurthestFirst* outperforms *ClosestFirst*. Favoring replication close to the requesters quickly saturates available nodes due to lack of alternate paths. Nevertheless, its is worth to notice that our method still manages to keep Λ at lower levels. Even at the 2k-*ClosestFirst* run, where $\Lambda > Limit^{up}$, 14% of the servers are overloaded compared to 20% by *path-cache*.

We must note here that the replication protocol is not always responsible for overloaded servers. In many occasions, the amount of demand (query-intensive areas have been saturated) or the overlay connectivity (e.g. power-law overlays) cannot allow for more extensive or balanced replication. As we experiment with more densely connected graphs, *APRE* performs inside the load limits where it failed to do so over more sparse overlays. Moreover, with biased forwarding, as happens with most informed approaches, certain nodes will unavoidably receive a bulk of requests. This situation can only be corrected through maintaining additional state at each peer (such as the location of other servers) and changing the forwarding scheme. In an environment with rapid changes in both workload and $\mathcal{S}_i$, this locally maintained metadata can become frequently stale, thus incurring larger communication (besides the local storage) overhead. Our approach, on the other hand, does not require a change in *APS*, but relies on its ability to independently create and store that state through new object discoveries and reverse index built-up.

V. Related Work

Replication is a well-known technique utilized to achieve high availability and fault-tolerance in large-scale systems. While applied to a variety of contexts, we focus in the area of distributed

(P2P) systems.

Structured overlays (DHTs) balance routing between network nodes, due to the nature of the hashing functions used. Moreover, in systems like CFS [6] and PAST [30], each item (or chunk of it) is replicated on a set number of network nodes. DHTs take advantage of the routing structure, which in effect allows for almost-deterministic paths between two nodes, thus identifying "hot" areas easily. Nevertheless, DHTs are not optimized for skewed access patterns and direct such traffic to few nodes responsible for popular content.

DHash [2] is a replication method applied on Chord [35]. The protocol allows for r copies to be stored at the r immediate successors of the initial copy's home. In [38], the authors propose the storage of at most R replicas for an object. Their location is determined by a hash function, allowing requesters to pro-actively redirect their queries. The work in [33] proposes replicating one hop closer to requester nodes as soon as peers are overloaded.

Lar [12] is a DHT-based approach similar to *APRE*, in that it adapts in response to current workload. Overloaded peers replicate at the query initiator and create routing hints on the reverse path. Hints contain some other locations that the content has been previously replicated, so queries are randomly redirected during routing. The method takes advantage of the DHT substrate in order to place the hints. Our scheme does not attempt to re-route queries or shed load to the initiator, but rather places replicas inside forwarding-intensive areas using multiple paths. Moreover, the state kept is accessible at any time, not only at the time of the query arrival.

HotRoD [36] presents a load-balancing approach for DHTs handling range queries in RDBMSs. It is based on a locality-preserving DHT and replication of overloaded arcs (consecutive modes on the DHT ring). [25] employes minimization function that combined high availability and low load to replicate video content inside a DHT. The approach requires knowledge of peer availabilities, workload and data popularity. In [29], the authors show that load-balancing based on periodic load statistics suffer from oscillation. By directing queries towards the the maximum capacity replica store, they show that both heterogeneity and oscillation issues are tackled. This method, nevertheless, assumes prior contact of an authority server which provides with a list of existing replicas. Moreover, replicas regularly advertise their maximum capacities to the network.

In most P2P file-sharing applications, replication is naturally handled through content sharing among users. In general, the following two approaches exist: Files comprise of equal size chunks and are individually indexed, or peers dynamically decide the portion that is retrieved from each source peer. The first approach is utilized by Overnet [24], BitTorrent [5] and Slurpie [31]. Each file is divided into a number of standard-size fragments (9500KB, 256KB, 256KB for those systems respectively). A peer may then download different fragments from various sources. Upon completion, each fragment becomes available for sharing with other nodes.

The second approach [28] (or modifications of it [1]) is currently used by other P2P applications (e.g., Morpheus [23]). A requester contacts many source peers and retrieves small portions of the file from each of them. When each small chunk is retrieved, more is asked from that specific source. There also exist several schemes (e.g. [20], [26]) which allow for increased robustness in reconstructing a file by receiving a few extra parts of it.

There has also been considerable amount of work on flash crowd avoidance. In [10], overloaded servers redirect future requests to mirror nodes to which content has been pushed. This approach does not tackle the issue of which node to replicate to. PROOFS [34] explicitly constructs a randomized overlay to locate content under heavy load conditions or unwilling participants. In effect, the method relies on the combination of custom overlay creation and a gossiping lookup scheme to locate objects and does not involve replication. Finally, the work in [21] discusses static replication in unstructured networks, given content popularity and random walks as a lookup method.

VI. Conclusions

In this report we presented our adaptive replication scheme for unstructured Peer-to-Peer systems based on probabilistic soft state. *APRE* aims at providing a direct response to workload changes, by creating server points in needy areas or releasing redundant replicas in areas of low demand. Our approach couples lookup indices together with an aging mechanism in order to identify, in real time, query intensive areas inside the overlay. Peers then individually decide on the time and extent of replication, based on local workload computation.

Our work shows that it is important to couple replication with the search protocol in unstructured systems. Random replication performs poorly with informed lookup schemes, unless extra state is added to enhance searches. Applying *APRE* over a scheme such as *APS* mitigates this problem. *APS*-indices store local, per-object state to direct queries to objects. While peers only keep metadata about their neighbors, this information can be used to identify, hop-by-hop, where the queries are coming from. Moreover, our scheme is highly customizable allowing control of both the size and the location (as defined through reverse-indices) of replication.

Through thorough simulations, we show that *APRE* is extremely robust in eliminating server overloads while minimizing the communication overhead and balancing the load. Specifically, we show that replicating along the reverse path is an extreme case of our protocol. By effectively discovering all reverse paths, *APRE* manages to distribute content proportional to demand in a variety of overlays and workloads. Finally, we show that our method succeeds in creating a very stable server set with minimal amount of oscillation.

VII. Acknowledgments

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