Distributing Content Simplifies ISP Traffic Engineering

ABSTRACT

Several major Internet service providers (e.g., Level-3, AT&T, Verizon) today also offer content distribution services. The emergence of such "network-CDNs" (NCDNs) is driven both by market forces as well as the cost of carrying ever-increasing volumes of traffic across their backbones. An NCDN has the flexibility to determine both where content is placed and how traffic is routed within the network. However NCDNs today continue to treat traffic engineering independently from content placement and request redirection decisions. In this paper, we investigate the interplay between content distribution strategies and traffic engineering and ask whether or how an NCDN should address these concerns in a joint manner. Our experimental analysis, based on traces from a large content distribution network and real ISP topologies, shows that realistic (i.e., history-based) joint optimization strategies offer little benefit (and often significantly underperform) compared to simple and "unplanned" strategies for routing and placement such as InverseCap and LRU. We also find that the simpler strategies suffice to achieve network cost and user-perceived latencies close to those of a joint-optimal strategy with future knowledge.

1. INTRODUCTION

Content delivery networks (CDNs) today provide a core service that enterprises use to deliver web content, downloads, streaming media, etc. to a global audience of their end-users. The traditional and somewhat simplified, tripartite view of content delivery involves three sets of entities as shown in Figure 1. The *content providers* (e.g., media companies, news channels, e-commerce sites, software distributors, enterprise portals, etc.) produce the content and wish to provide a high-quality experience to their end-users. The *networks* (e.g., telcos such as AT&T, multi-system operators such as Comcast, and ISPs) own the underlying network infrastructure and are responsible for provisioning capacity and routing traffic demand. Finally, the *CDNs* (e.g., Akamai, Limelight) are responsible for optimizing content delivery to end-users on behalf of the content providers, residing as a global, distributed overlay service.

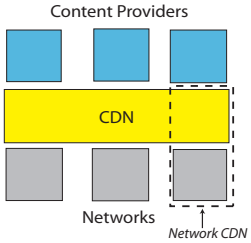


Figure 1: A tripartite view of content delivery.

Recent powerful trends are reshaping the simplified tripartite view of content delivery. A primary driver is the torrid growth of video [22, 7] and downloads traffic on the Internet. For example, a single, popular TV show with 50 million viewers, with each viewer watching an HD-quality stream of 10 Mbps, generates 500 Tbps of network traffic! The increasing migration of traditional media content to the Internet and the consequent challenges of scaling the network backbone to accommodate that traffic has necessitated the evolution of *network CDNs* (or NCDNs)[1] that vertically integrate CDN functionality such as content caching and redirection with traditional network operations [14, 21, 20, 4, 28] (refer Figure 1). A second economic driver of NCDNs is the desire of networks to further monetize the "bits" that flow on their infrastructure by contracting directly with content providers, or to offer value-added service packages to their own end-user subscribers (e.g., Verizon's recent offering that delivers HBO's content to FIOS subscribers [27].

As NCDNs control both the content distribution and network infrastructure, the costs and objectives of their interest are different both from a traditional CDN and a traditional ISP. In particular, an NCDN is in a powerful position to place content in a manner that "shapes" the traffic demand so as to optimize both network cost and user-perceived latency. Indeed, several recent works have alluded to the benefits of such joint optimization strategies in the context of cooperative or competitive interaction between ISPs and content providers [30, 9, 18, 13]. On the surface, an NCDN would appear to be the perfect setting for fielding joint optimization strategies as it eliminates potentially conflicting competitive interests. Nevertheless, NCDNs today continue to treat content distribution and traffic engineering concerns

[1]NCDNs are sometimes referred to as Telco CDNs, or Carrier CDNs. Further, they are referred to as a Licensed CDN when a pure-play CDN such as Edgecast[6] licenses the CDN software to a network to create an NCDN.

separately, operating the former simply as an overlay.

This disparity raises several research questions that form the focus of this paper. How should an NCDN determine content placement, network routing, and request redirection decisions so as to optimize network cost and user-perceived latency? How much benefit do joint optimization strategies yield over simpler strategies as practiced today, and does the benefit warrant the added complexity? How do content demand patterns and placement strategies impact network cost? How do planned strategies (i.e., using knowledge of recently observed demand patterns or hints about anticipated future demands) for placement and routing compare against simpler, unplanned strategies?

Our primary contribution is to empirically analyze the above questions for realistic content demand workloads and ISP topologies. To this end, we collect content request traces from Akamai, the world's largest CDN today. We focus specifically on on-demand video and large-file downloads traffic as they are two categories that dominate overall CDN traffic and are significantly influenced by content placement strategies. Our combined traces consist of a total of 28.2 million requests from 7.79 million unique users who downloaded a total of 1455 Terabytes of content across the US over multiple days. Our main finding based on trace-driven experiments using these logs and realistic ISP topologies is that *simple, unplanned strategies for placement, routing, and redirection of NCDN content are better than sophisticated joint-optimization approaches.* Specifically,

- For NCDN traffic, simple unplanned schemes for placement and routing (such as least-recently-used and InverseCap) yield significantly lower (2.2–17×) network cost and user-perceived latency than a joint-optimal scheme with knowledge of the previous day's demand[2].
- NCDN traffic demand can be "shaped" by simple placement strategies so that traffic engineering, i.e., optimizing routes with knowledge of recent traffic matrices, hardly improves network cost or user-perceived latency over unplanned routing (InverseCap).
- For NCDN traffic, unplanned placement and routing is just 1%-18% sub-optimal compared to a joint-optimal placement and routing with perfect knowledge of the next day's demand at modest storage ratios (≈ 4).
- With a mix of NCDN and transit traffic, traffic engineering does lower network cost (consistent with previous studies), but the value of traffic engineering substantially diminishes as the relative volume of NCDN traffic begins to dominate that of transit traffic.

In the rest of this paper, we first overview the NCDN architecture highlighting why it changes traditional ISP and CDN concerns (§2). Next, we formalize algorithms that jointly optimize content placement and routing in an NCDN (§3). We then describe how we collected real CDN traces (§4) and evaluate our algorithms using these traces and real ISP topologies (§5). Finally, we present related work (§6) and conclusions (§7).

[2]We use the term "optimal" when placement or routing is the solution of an optimization problem, but the solution may not have the lowest cost (for reasons detailed in §5.3.1)

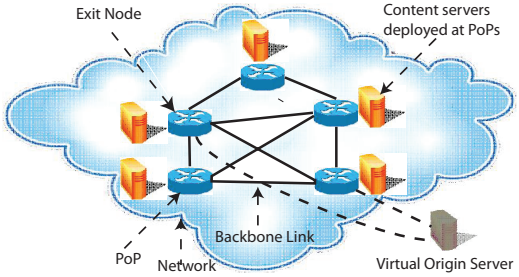


Figure 2: NCDN Architecture

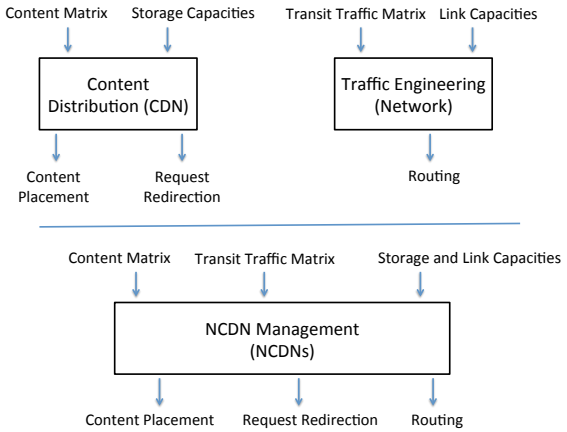


Figure 3: (Top) Traditional formulation with content distribution and traffic engineering optimized separately. (Bottom) Our new formulation of NCDN magamenent as a joint optimization.

2. BACKGROUND AND MOTIVATION

A typical NCDN architecture, as shown in Figure 2, resembles the architecture of a global CDN but with some important differences. First, the content servers are deployed at points-of-presence (PoPs) within the network rather than globally across the Internet as the NCDN is primarily interested in optimizing content delivery for its own customers and end-users. Second, and more importantly, the NCDN owns and manages the content servers as well as the underlying network. Content providers that purchase content delivery service from the NCDN publish their content to origin servers that they maintain external to the NCDN itself.

Each PoP is associated with a distinct set of end-users who request content such as web, video, downloads etc. An end-user's request is first routed to the content servers at the PoP to which the end-user is connected. If a content server at that PoP has the requested content in their cache, it serves that to the end-user. Otherwise, if the requested content is cached at other PoPs, the content is downloaded from a nearby PoP and served to the end-user. If the content is not cached in any PoP, it is downloaded directly from the content provider's origin servers.

2.1 Why NCDNs Change the Game

Managing content distribution as well as the underlying network makes the costs and objectives of interest to an NCDN different from that of a traditional CDN or a traditional ISP. Figure 3 (top) shows the traditional concerns of content distribution and traffic engineering as addressed by a traditional CDN and a traditional ISP respectively,

while Figure 3 (bottom) shows the combined concerns that an NCDN must address. We explain these in detail below.

2.1.1 Content Distribution

A traditional CDN has two key decision components—*content placement* and *request redirection*—that seek to optimize the response time perceived by end-users and balance the load across its content servers. Content placement decides which objects should be cached at which nodes. An object may be stored at multiple nodes in the network or not stored in the network at all and be served from the origin server instead. Request redirection determines which server storing a replica of the object is best positioned to serve it.

Content placement schemes can either be *planned* or *unplanned*. A planned scheme calculates placement using a *content matrix* that specifies the demand for each content at each location. The content matrix is learned by monitoring a recent history of system-wide requests and possibly including hints, if any, from content providers about anticipated demand for some objects. A planned scheme uses a recent content matrix to decide on a placement periodically (e.g., daily) but does not alter its placement in between. In contrast, an unplanned scheme can continually alter its placement potentially even after every single request. A simple and widely used example of an unplanned placement scheme is LRU, where each server evicts the least-recently-used object from its cache to make room for new ones.

2.1.2 Traffic Engineering

A key component of ISP network operations is traffic engineering, which seeks to route the traffic demands through the backbone network so as to balance the load and mitigate hotspots. Traffic engineering is commonly viewed as a routing problem that takes as input a *traffic matrix*, i.e., the aggregate flow demand between every pair of PoPs observed over a recent history, and computes routes so as to minimize a network-wide cost objective. The cost seeks to capture the severity of load imbalance in the network and common objective functions include the maximum link utilization (MLU) or a convex function (so as to penalize higher utilization more) of the link utilization aggregated across all links in the network [11]. ISPs commonly achieve the computed routing either by using shortest-path routing (e.g., the widely deployed OSPF protocol [11]) or by explicitly establishing virtual circuits (e.g., using MPLS [10]). ISPs perform traffic engineering at most a few times each day, e.g., morning and evening each day [12].

Routing can also be classified as *planned* or *unplanned* similar in spirit to content placement. Traffic engineering schemes as explained above are implicitly planned as they optimize routing for recently observed demand. To keep the terminology simple, we also classify online traffic engineering schemes [19, 10] (that are rarely deployed today) as planned. In contrast, unplanned routing schemes are simpler and rely upon statically configured routes [3, 5], e.g., InverseCap is a static shortest-path routing scheme that sets link weights to the inverse of their capacities; this is a common default weight setting for OSPF in commercial routers [12].

2.1.3 NCDN Management

As NCDNs own and manage the infrastructure for content distribution as well as the underlying network, they are in a powerful position to control all three of placement, routing, and redirection (Figure 3). In particular, an NCDN can place content in a manner that "shapes" the traffic demands so as to jointly optimize both user-perceived latency as well as network cost.

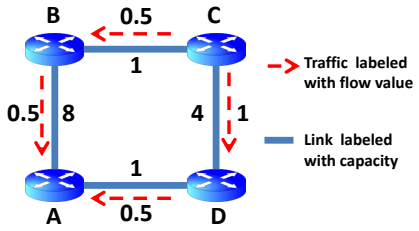


Figure 4: A simple NCDN example

To appreciate how placement can shape traffic, consider the simple example in Figure 4. Node C has an object in its cache that is requested by end-users at nodes A and D. Suppose that one unit of traffic needs to be routed from C to A and 0.5 units from C to D to satisfy the demand for that object. The routing that achieves the minimum MLU of 0.5 to serve the demanded object is shown in the figure. Note that the routing that achieves the MLU of 0.5 is not possible with a simple, unplanned protocol like InverseCap as that would route all the traffic demand from C to A via B, resulting in an MLU of 1. Thus, a (planned) traffic engineering scheme is necessary to achieve an MLU of 0.5.

On the other hand, NCDNs can shape the traffic demand matrix by using a judicious placement and redirection strategy. Suppose that there is some space left in the content server's cache at node B to accommodate an additional copy of the demanded object. By creating an additional copy of the object at B, the traffic demand of A can be satisfied from B and the demand of D from C achieving the an MLU of 0.125. In this case, judicious content placement decreased the MLU by a factor of 4. Even more interestingly, this best MLU can be achieved using a simple routing scheme like InverseCap while also improving user-perceived latency (assuming that the latency of link BA is lower than that of the two-hop paths from C to A).

The above toy example suggests benefits to jointly optimizing placement, routing, and redirection, but raises several natural questions. How much additional benefit does such joint optimization offer compared to treating CDN and ISP concerns independently as practiced today? Is the added complexity of joint optimization strategies worth the benefit? Which of the three—placement, routing, and redirection—is the most critical to reducing network cost and user-perceived latency? How sensitive are these findings to characteristics of the content workload (e.g., video vs. download traffic)?

3. NCDN MANAGEMENT STRATEGIES

To answer the above questions, we develop an optimization model for NCDNs to jointly optimize placement, routing, and redirection so as to optimize network cost or user-perceived latency. We formulate the optimization problem as a mixed-integer program (MIP), present hardness and inapproximability results, and discuss approximation heuristics to solve MIPs for realistic problem sizes.

3.1 NCDN Model

Table 1 lists all the model parameters. An NCDN consists of a set of nodes V where each node represents a PoP in the network. The nodes are connected by a set of directed edges

Input variables and descriptions	
V	Set of nodes where each node represents a PoP
E	Set of edges where each link represents a communication link
o	Virtual origin node that hosts all the content in K
X	Set of exit nodes in V
D_i	Disk capacity at node $i \in V$ (in bytes)
C_e	Capacity of link $e \in E$ (in bits/sec)
K	the set of all content accessed by end-users
S_k	Size of content $k \in K$.
T_{ik}	Demand (in bits/sec) at node $i \in V$ for content $k \in K$
Decision variables and descriptions	
α	MLU of the network
z_k	Binary variable indicating whether one or more copies of content k is placed in the network
x_{jk}	Binary variable indicating whether content k is placed at node $j \in V \cup \{o\}$
f_{ij}	Total traffic from node j to node i
f_{ije}	Traffic from node j to node i crossing link e.
t_{ijk}	Traffic demand at node $i \in V$ for content $k \in K$ served from node $j \in V \cup \{o\}$

Table 1: List of input and decision variables for the NCDN problem formulation.

E that represent the backbone links in the network. The set of content requested by end-users is represented by the set K and the sizes of content are denoted by $S_k, k \in K$. The primary resource constraints are the link capacities $C_e, e \in E$, and the storage at the nodes $D_i, i \in V$. We implicitly assume that the content servers at the PoPs have adequate compute resources to serve locally stored content.

A *content matrix* (CM) specifies the demand for each content at each node. An entry in this matrix, $T_{ik}, i \in V, k \in K$, denotes the demand (in bits/second) for content k at node i. CM is assumed to be measured by the NCDN a priori over a coarse-grained interval, e.g., the previous day. The infrastructure required for this measurement is comparable to what ISPs have in place to monitor traffic matrices today.

Origin servers, owned and maintained by the NCDN's content providers, initially store all content published by content providers. We model origin servers using a single virtual origin node o external to the NCDN that can be reached via a set of exit nodes $X \subset V$ in the NCDN (Figure 2). Since we are not concerned with traffic engineering links outside the NCDN, we model the edges (x, o), for all $x \in X$, as having infinite capacity. The virtual origin node o always maintains a copy of all the requested content. However, a request for a content is served from the virtual origin node only if no copy of the content is stored at any node $i \in V$. In this case, the request is assumed to be routed to the virtual origin via the exit node closest to the node where the request was made (in keeping with the commonly practiced *early-exit* or *hot potato* routing policy).

ISP networks carry transit traffic in addition to NCDN traffic, which can be represented as a transit traffic matrix (TTM). Each entry in the TTM contains the volume of transit traffic between two PoPs in the network.

3.2 Cost Functions

We evaluate NCDN-management strategies based on two cost functions. The first cost function is maximum link utilization (or MLU) which measures the effectiveness of traffic engineering in an NCDN. MLU is a widely used network cost function for traditional TE.

The second cost function models user-perceived latency and is defined as $\sum_{e \in E} X_e$, where X_e is the product of traffic on link e and its link latency $L(e)$. The latency of a link $L(e)$ is the sum of a fixed propagation delay and a variable utilization dependent delay. For a unit flow, link latency is defined as $L_e(u_e) = p_e(1 + f(u_e))$, where p_e is the propagation delay of edge e, u_e is its link utilization, and $f(u)$ is a piecewise-linear convex function. This cost function is similar to that used by Fortz and Thorup [11]. At small link utilizations (< 0.6), link latency is determined largely by propagation delay hence f is zero. At higher link utilizations (0.9 and above) an increase in queuing delay and delay caused by retransmissions significantly increase the effective link latency. The utilization-dependent delay is modeled as proportional to propagation delay as the impact of (TCP-like) retransmissions is more on paths with longer links. Since L_e is convex, a set of linear constraints can be written to constraint the value of X_e (as in [11]).

3.3 Optimal Strategy as MIP

We present here a joint optimization strategy for NCDN-management formulated as a MIP. This formulation takes as input a content matrix, i.e., the demand for each content at each network point-of-presence (PoP), and computes content placement, request redirection and routing that minimizes an NCDN cost function while respecting link capacity and storage constraints. The decision variables for this problem are listed in Table 1. The MIP to minimize an NCDN cost function C (either MLU or latency) is as follows:

$$\min C \tag{1}$$

subject to

$$\sum_{j \in V} t_{ijk} + t_{iok} = T_{ik}, \quad \forall k \in K, i \in V \tag{2}$$

$$\sum_{k \in K} t_{ijk} = f_{ij}, \ \forall j \in V - X, i \in V \tag{3}$$

$$\sum_{k \in K} t_{ijk} + \sum_{k \in K} \delta_{ij} t_{iok} = f_{ij}, \ \forall j \in X, i \in V \tag{4}$$

where δ_{ij} is 1 if j is the closest exit node to i and 0 otherwise. Note that δ_{ij} is not a variable but a constant that is determined by the topology of the network, and hence constraint (4) is linear.

$$\sum_{p \in P(l)} f_{ijp} - \sum_{q \in Q(l)} f_{ijq} = \begin{cases} f_{ij} & \text{if } l = i, \\ -f_{ij} & \text{if } l = j, \\ 0 & \text{otherwise,} \end{cases} \quad \forall i, j, l \in V \tag{5}$$

where $P(l)$ and $Q(l)$ respectively denote the set of outgoing and incoming links at node l.

$$\sum_{i \in V, j \in V} f_{ije} \leq \alpha \times C_e, \quad \forall e \in E \tag{6}$$

$$\sum_{k \in K} x_{ik} S_k \leq D_i, \quad \forall i \in V \tag{7}$$

$$x_{ok} = 1, \quad \forall k \in K \tag{8}$$

$$\sum_{i \in V} x_{ik} \geq z_k, \quad \forall k \in K \tag{9}$$

$$x_{ik} \leq z_k, \quad \forall k \in K, i \in V \tag{10}$$

$$t_{ijk} \leq x_{jk}T_{ik}, \quad \forall k \in K, i \in V, j \in V \cup \{o\} \quad (11)$$
$$t_{iok} \leq T_{ik}(1 - z_k), \quad \forall k \in K \quad (12)$$
$$x_{jk},\ z_k \in \{0,1\}, \quad \forall j \in V, k \in K$$
$$f_{ije},\ t_{ijk},\ t_{iok} \geq 0, \quad \forall i, j \in V, e \in E, k \in K$$

The constraints have the following rationale. Constraint (2) specifies that the total traffic demand at each node for each content must be satisfied. Constraints (3) and (4) specify that the total traffic from source j to sink i is the sum over all content k of the traffic from j to i for k. Constraint (5) specifies that the volume of a flow coming in must equal that going out at each node other than the source or the sink. Constraint (6) specifies that the total flow on a link is at most α times capacity. Constraint (7) specifies that the total size of all content stored at a node must be less than its disk capacity. Constraint (8) specifies that all content is placed at the virtual origin node o. Constraints (9) and (10) specify that at least one copy of content k is placed within the network if $z_k = 1$, otherwise $z_k = 0$ and no copies of k are placed at any node. Constraint (11) specifies that the flow from a source to a sink for some content should be zero if the content is not placed at the source (i.e., when $x_{jk} = 0$), and the flow should be at most the demand if the content is placed at the source (i.e., when $x_{jk} = 1$). Constraint (12) specifies that if some content is placed within the network, the traffic from the origin for that content must be zero.

Updating the content placement itself generates traffic and impacts the link utilization in the network. For ease of exposition, we have deferred a formal description of the corresponding constraints to Appendix C. Finally, a simple extension to this MIP presented in Appendix B jointly optimizes routing given a TTM as well a CM. We have presented a CM-only formulation here as our findings (in §5) show that a joint optimization of the CM and TTM is not useful for NCDNs.

3.4 Computational Hardness

Opt-NCDN is the decision version of the NCDN problem. The proofs for these theorems are presented in Appendix A.

THEOREM 1. *Opt-NCDN is NP-Complete even in the special case where all objects have unit size, and all demands, link capacities, and storage capacities have binary values.*

COROLLARY 1. *Opt-NCDN is inapproximable to within a constant factor unless P = NP.*

3.5 Approximation Techniques for MIP

As solving the MIP for very large problem scenarios is computationally infeasible, we use two approximation techniques to tackle such scenarios.

The first is a two-step local search technique. In the first step, we "relax" the MIP by allowing the integral variables x_{jk} and z_k to take fractional values between 0 and 1. This converts an MIP into an LP that is more easily solvable. Note also that the optimal solution of the relaxed LP is a lower bound on the optimal solution of the MIP. However, the LP solution may contain fractional placement of some of the content with the corresponding x_{jk} variables set to fractional values between 0 and 1. However, in our experiments only about 20% of the variables in the optimal LP solution were set to fractional values between 0 or 1, and the rest took integral values of 0 or 1. In the second step, we search for a valid solution for the MIP in the local vicinity of the LP solution by substituting the values for variables that were set to 0 or 1 in the LP solution, and re-solving the MIP for the remaining variables. Since the number of integer variables in the second MIP is much smaller, it can be solved more efficiently than the original MIP.

The second approximation technique reduces the number of unique content in the optimization problem using two strategies. First, we discard the tail of unpopular content prior to optimization. The discarded portion accounts for only 1% of all requests, but reduces the number of content by 50% or more in our traces. Second, we sample 25% of the content from the trace and, in our experiments, select trace entries corresponding only to the sampled content. These approximations reduce the number of content from tens of thousands to under 5000. An MIP of this size can be solved using local search in an hour by a standard LP solver [15] for the ISP topologies in our experiments.To check for any untoward bias introduced by the sampling, we also performed a small number of experiments with the complete trace and verified that our findings remain qualitatively unchanged.

4. AKAMAI CDN TRACES

To conduct a realistic simulation of end-users accessing content on an NCDN, we collected extensive traces of video and download traffic from Akamai as described below.

Video traces. Videos are the primary source of traffic on a CDN and are growing at a rapid rate [22, 7]. Our video trace consists of actual end-users accessing on-demand videos on the Akamai network over multiple days. To make the traces as representative as possible, we chose content providers with a whole range of business models, including major television networks, news outlets, and movie portals. The videos in our traces include a range of video types from short-duration video (less than 10 mins) such as news clips to longer duration (30 min to 120 min) entertainment videos representing TV shows and movies. In all, our traces represent a nontrivial fraction of the overall traffic on Akamai's media network and accounted for a total of 27 million playbacks of over 85000 videos, 738 TBytes of traffic, served to 6.59 million unique end-users around the US. Since we only had US-based network topologies with accurate link capacity information, we restricted ourselves to US-based traffic.

We collect two sets of video traces called *news trace* and *entertainment trace* respectively. The news trace was collected from a leading news outlet for an 11-day period in Sept 2011, and consists mostly of news video clips, but also includes a small fraction of news TV shows. The entertainment trace was collected for a 6 day period in January 2012, and includes a variety of videos including TV shows, clips of TV shows, movies and movie trailers from three major content providers.

The trace collection mechanism utilized a plugin embedded in the media player that is capable of reporting (anonymized) video playback information. Our traces include a single log entry for each playback and provides time of access, user id, the location of the user (unique id, city, state, country, latitude, and longitude), the url of the content, the content provider, the total length of the video (in time and bytes), the number of bytes actually downloaded, the playback duration, and the average bitrate over the playback session.

Downloads traces. The second largest traffic contributor in a CDN is downloads of large files over HTTP. These include software and security updates, e.g., Microsoft's Windows or Symantec's security updates, as well as music, books,

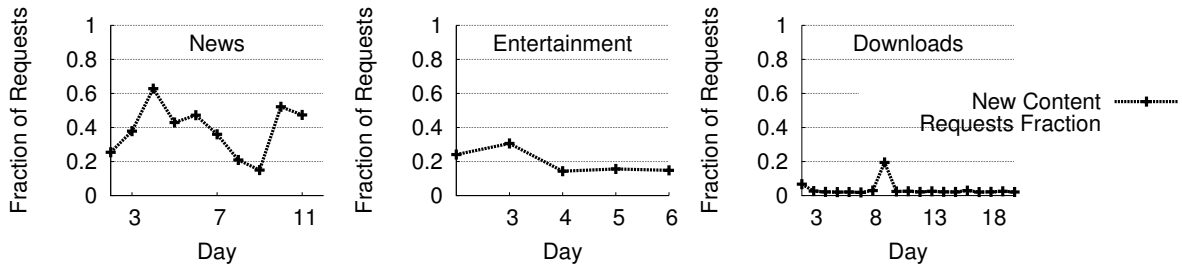


Figure 5: News and entertainment have a significant fraction of requests for new content on all days. Downloads has a small fraction of requests for new content on all days, except one.

movies, etc.. The large file downloads at Akamai typically use a client-side software called the download manager [23]. We collect extensive and anonymized access data reported from the download manager using Akamai's NetSession interface [16] for a large fraction of content providers for a period of a month (December 2010). Our traces represent a nontrivial fraction of the overall US-based traffic on Akamai's downloads network and accounted for a total of 1.2 million downloads, 717 TBytes of traffic, served to 0.62 million unique end-users around the US. Our traces provide a single log entry for each download and provide time of access, user id, location of the user (city, state, country, latitude, and longitude), the url identifier of the content, content provider, bytes downloaded, and file size.

Figure 5 shows the fraction of requests for new content published each day relative to the previous day for news, entertainment, and downloads traces. The news trace has up to 63% requests due to new content because the latest news clips generated each day are the most popular videos on the website. The entertainment trace also has up to 31% requests each day due to new content such as new episodes of TV shows, and the previews of upcoming TV shows. The downloads trace has only 2-3% requests due to new content on a typical day. However, on the 9th day of the trace major software updates were released, which were downloaded on the same day by a large number of users. Hence, nearly 20% requests on that day were for new content. The fraction of requests for new content impacts the performance of planned placement strategies as we show §5.

5. EXPERIMENTAL EVALUATION

We conduct trace-driven experiments to compare different NCDN-management strategies. Our high-level goal is to identify a simple strategy that performs well for a variety of workloads. In addition, we seek to assess the relative value of optimizing content placement versus routing; the value of being planned versus being unplanned and the value of future knowledge about demand.

5.1 Trace-driven Experimental Methodology

To realistically simulate end-users accessing content on an NCDN, we combine the CDN traces (in §4) with ISP topologies as follows. We map each content request entry in the Akamai trace to the geographically closest PoP in the ISP topology in the experiment (irrespective of the real ISP that originated the request). Each PoP has a content server as shown in Figure 2, and the request is served locally, redirected to the nearest (by hop-count) PoP with a copy, or to the origin as needed.

ISP topologies. We experimented with network topology maps from two US-based ISPs. First is the actual ISP topology obtained from a large tier-1 ISP in the US (referred to as US-ISP). Second is the Abilene ISP's topology [26].

MLU computation. We compute the traffic that flow through each link periodically. To serve a requested piece of content from a PoP s to t, we update the traffic induced along all edges on the path(s) from s to t as determined by the routing protocol using the bytes-downloaded information in the trace. To compute the MLU, we partition simulation time into 5-minute intervals and compute the average utilization of each link in each 5-minute interval. We discard the values of the first day of the trace in order to warm up the caches, as we are interested in steady-state behavior. We then compute our primary metric, which is the 99-percentile MLU, as the 99^{th} percentile of the link utilization over all links and all 5-minute time periods. We use 99-percentile instead of the maximum as the former is good proxy for the latter but with less experimental noise. Finally, for ease of visualization, we scale the 99-percentile MLU values in all graphs so that the maximum 99-percentile MLU across all schemes in each graph is equal to 1. We call this scaled MLU the *normalized MLU*. Note that only the relative ratios of the MLUs for the different schemes matter and scaling up the MLU uniformly across all schemes is equivalent to uniformly scaling down the network resources or uniformly scaling up the traffic in the CDN traces.

Latency cost computation. Our latency cost metric, which models user-perceived latencies, is a sum of the latency on ISP backbone links and the the latency from user to its nearest PoP. Traffic served from origin incurs an additional latency from origin to the exit locations in the network. We assume origin servers to be located close to exit locations so that latency from exit locations to origin servers is a small fraction of the overall end user latency. The latency cost of a link e for a interval of a second when traffic (in bits/sec) on link e is V_e and link utilization is u_e, is calculated as $V_e \times L_e(u_e)$, where L_e is the latency function defined in §3. The aggregate latency cost of a link is calculated by summing the latency costs for all 1 sec intervals during the experiment (excluding the first day). The user-to-nearest PoP latency cost is calculated by summing the traffic (in bits) requested by a user times the propagation delay to its nearest PoP for all users.

Storage. We assume that storage is provisioned uniformly across PoPs except in §5.6 where we analyze heterogenous storage distributions. We repeat each simulation with different levels of provisioned storage. Since the appropriate amount of storage depends on the size of the working set of the content being served, we use as a metric of storage the *storage ratio*, or the ratio of total storage at all PoPs in the network to the average storage footprint of all content accessed in a day for the trace. The total storage across all

nodes for a storage ratio of 1 is 228 GB, 250 GB, and 895 GB for news, entertainment and downloads respectively.

5.2 Schemes Evaluated

Each evaluated scheme has a content placement component and a routing component.

InvCap-LRU uses LRU as the cache replacement strategy and InverseCap (with ECMP) as the routing strategy. InverseCap is a static, shortest-path routing scheme where link weights are set to the inverse of the link capacity. This scheme requires no information of either the content demand or the traffic matrix. If content is available at multiple PoPs, we choose the closest PoP based on hop count distance. We break ties randomly among PoPs with equal hop count distance.

We added a straightforward optimization to LRU where if a user terminates the request before 10% of the video (file) is viewed (downloaded), the content is not cached (and the rest of the file is not fetched); otherwise the entire file is downloaded and cached. This optimization is used since we observe in our traces that a user watching a video very often stops watching it after watching the initial period. A similar phenomenon is observed for large file downloads, but less frequently than video.

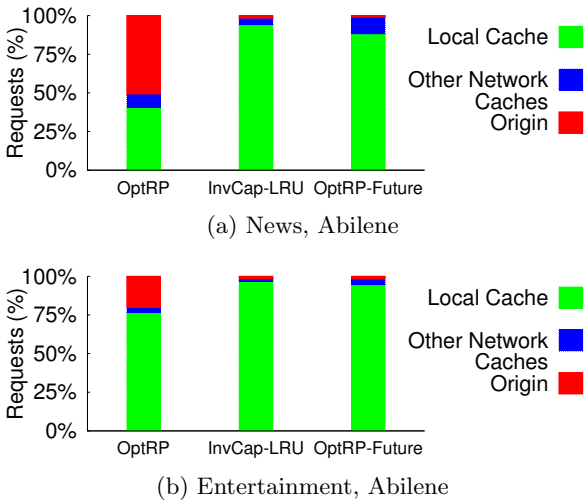
OptR-LRU uses an unplanned placement, LRU, but it uses an planned, optimized routing that is updated every three hours. The routing is computed by solving a multi-commodity flow problem identical to the traditional traffic engineering problem [11]. We assume that the NCDN measures the traffic matrix over the preceding three hours and computes routes that optimize the MLU for that matrix. The matrix incorporates the effect of the unplanned placement and the implicit assumption is that the content demand and unplanned placement result in a traffic matrix that does not change dramatically from one monitoring interval to the next—an assumption that also underlies traffic engineering as practiced by ISPs today.

OptRP computes a joint optimization of placement and routing once a day based on the previous day's content matrix using the MIP formulation of §3.3. **OptRP-Future** has oracular knowledge of the content matrix for the next day and uses it to calculate a joint optimization of placement, redirection and routing. OptRP and OptRP-Future are identical in all respects except that the former uses the content matrix of the past day while the latter has perfect future knowledge. These two schemes help us understand the value of future knowledge. In practice, it may be possible for an NCDN to obtain partial future knowledge placing it somewhere between the two extremes. For instance, an NCDN is likely to be informed beforehand of a major software release the next day (e.g., new version of the Windows) but may not be able to anticipate a viral video that suddenly gets "hot".

To determine the value of optimizing routing alone, we study the **InvCap-OptP-Future** scheme. This is a variant of OptRP-Future where InverseCap routing is used and content placement is optimized, rather than jointly optimizing both. This scheme is computed using the MIP formulation in §3.3 but with an additional constraint modification that ensures that InvCap routing is implemented.

We add a suffix **-L** to the names of a scheme if it is optimizing for latency cost instead of MLU, e.g. **OptRP-L**.

For all schemes that generate a new placement each day, we implement the new placement during the low-traffic period from 4 AM to 7 AM EST. This ensures that the traffic generated due to changing the content placement occurs when the links are underutilized. For these schemes, the routing is updated each day at 7 AM EST once the placement update is finished.



(a) News, Abilene

(b) Entertainment, Abilene

Figure 7: [Videos, Abilene] OptRP serves 50% and 21% of news and entertainment requests respectively from the origin. InvCap-LRU and OptRP-Future serve at most 2% from the origin.

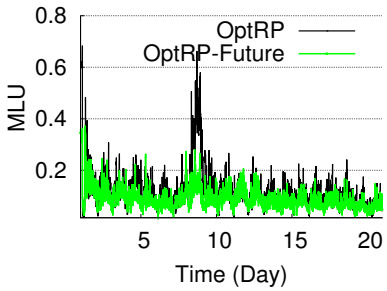


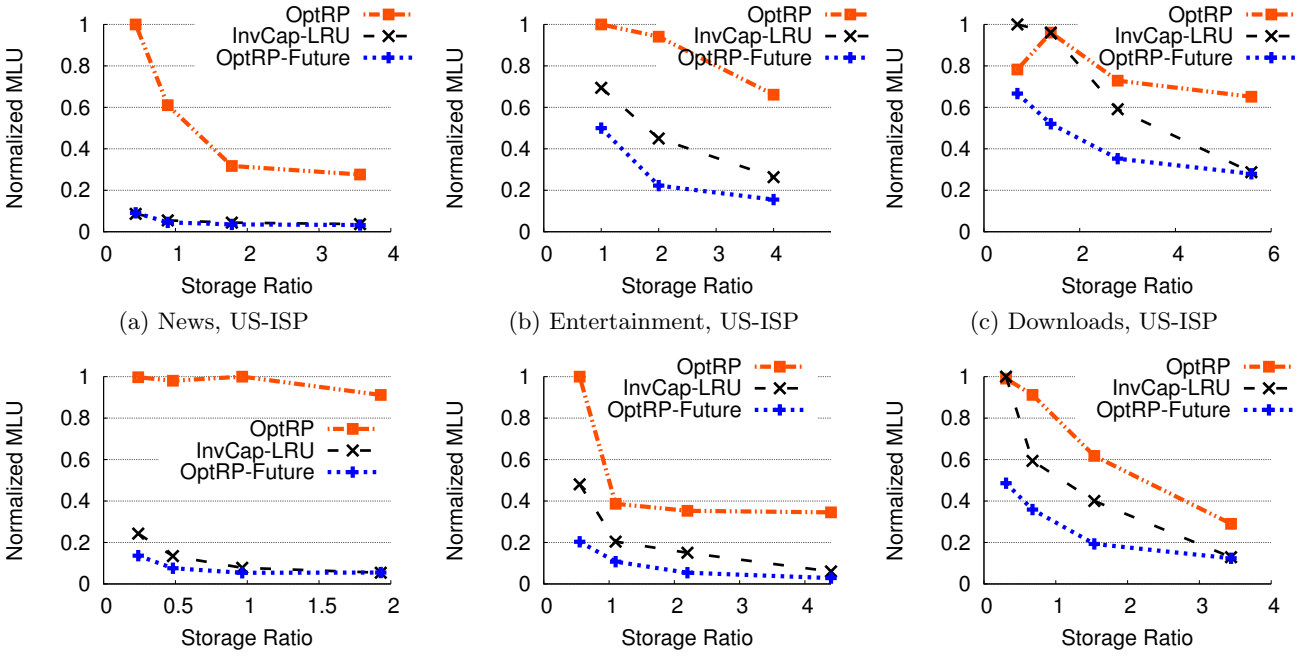
Figure 8: [Downloads, US-ISP] OptRP incurs a very high MLU on one "peak load" day.

5.3 Comparison of Network Cost

5.3.1 *Analysis of Video & Downloads Traffic*

Figure 6 shows the results for the news, entertainment and downloads traces on Abilene and US-ISP. Our first observation is that a realistic planned placement and routing scheme, OptRP, performs significantly worse than a completely unplanned scheme, InvCap-LRU. OptRP has 2.2× to 17× higher MLU than InvCap-LRU even at the maximum storage ratio in each graph. OptRP has a high MLU because it optimizes routing and placement based on the previous day's content demand while a significant fraction of requests are for new content not accessed the previous day (see Figure 5). Due to new content, the incoming traffic from origin servers is significant, so the utilization of links near the exit nodes connecting to the origin servers is extremely high.

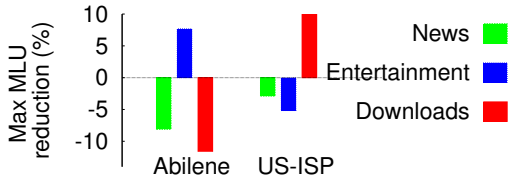
The fraction of requests served from the origin is much higher for OptRP compared to InvCap-LRU and OptRP-Future



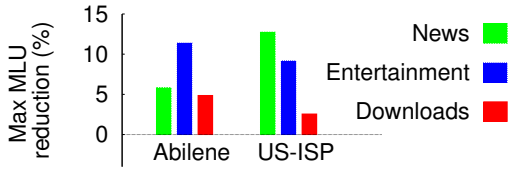
(a) News, US-ISP (b) Entertainment, US-ISP (c) Downloads, US-ISP

(d) News, Abilene (e) Entertainment, Abilene (f) Downloads, Abilene

Figure 6: Planned OptRP performs much worse than unplanned InvCap-LRU. OptRP-Future performs moderately better than InvCap-LRU primarily at small storage ratios.



(a) MLU reduction with OptR-LRU compared to InvCap-LRU



(b) MLU reduction with OptRP-Future compared to InvCap-OptP-Future

Figure 9: [All traces] Optimizing routing yields little improvement to MLU of either InvCap-LRU or InvCap-OptP-Future

on the news and the entertainment traces. Figure 7 shows that OptRP serves 50% and 21% of requests from the origin for news and entertainment respectively. In comparison, InvCap-LRU and OptRP-Future serve less than 2% of requests from the origin. Therefore, OptRP has a much higher MLU than both InvCap-LRU and OptRP-Future on the two traces.

The downloads trace differs from other traces in that, except for one day, the traffic is quite predictable based on the previous day's history. This is reflected in the performance of OptRP that performs nearly the same as OptRP-Future on all days except the ninth day of the trace (see Figure 8). The surge in MLU for OptRP on the ninth day is because nearly 20% of requests on this day is for new content consisting of highly popular software update releases (see Figure 5). The surge in MLU on this one day is mainly responsible for the poor performance of OptRP on the downloads trace.

Next, we observe that InvCap-LRU does underperform compared to OptRP-Future that has knowledge of future content demand. However, InvCap-LRU improves with respect to OptRP-Future as the storage ratio increases. The maximum difference between the two schemes is for the experiment with entertainment trace on US-ISP topology. In this case, at a storage ratio of 1, InvCap-LRU has twice the MLU of the OptRP-Future scheme; the difference reduces to 1.6× at a storage ratio of 4. This shows that when storage is scarce, planned placement with future knowledge can significantly help by using knowledge of the global demand to maximize the utility of the storage. However, if storage is plentiful, the relative advantage of OptRP-Future is smaller. An important implication of our results is that an NCDN should attempt to do planned placement only if the future demand can be accurately known or estimated. Otherwise, a simpler unplanned scheme such as LRU suffices.

How are the above conclusions impacted if InvCap-LRU were to optimize routing or OptRP-Future were to use InverseCap routing? To answer this question, we analyze the maximum reduction in MLU by using OptR-LRU over InvCap-LRU across all storage ratios in Figure 9. We similarly compare OptRP-Future and InvCap-OptP-Future. We find that OptR-LRU improves the MLU over InvCap-LRU by at most 10% across all traces suggesting that optimizing routing is of little value for an unplanned placement scheme. OptRP-Future reduces the network cost by at most 13% compared to InvCap-OptP-Future. As we consider OptRP-Future to be the "ideal" scheme with full future knowledge, these

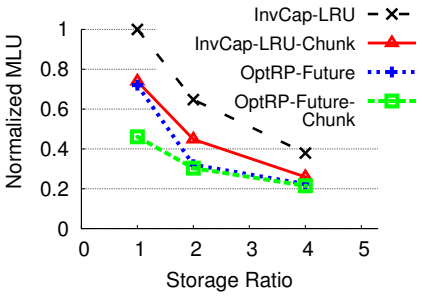


Figure 10: [Entertainment, US-ISP] Content chunking helps bridge the gap between InvCap-LRU and OptRP-Future.

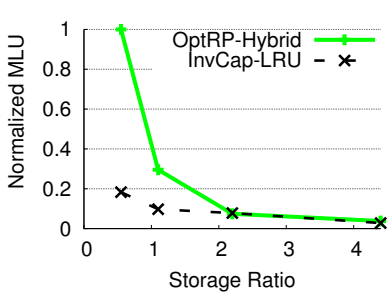


Figure 11: [Entertainment, Abilene] Hybrid placement schemes perform at best as well as InvCap-LRU.

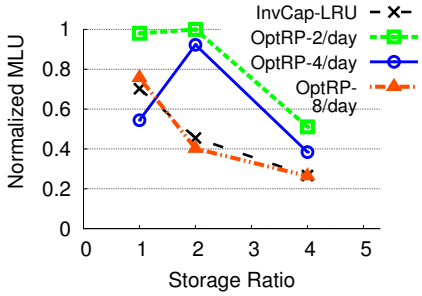


Figure 12: [Entertainment, US-ISP] OptRP does not outperform InvCap-LRU despite engineering 8 times a day.

results show that the best MLU can be achieved by optimizing content placement alone; optimizing routing adds little additional value.

Somewhat counterintuitively, the MLU sometimes increases with a higher storage ratio for the OptRP scheme. There are three reasons that explain this. First, the optimization formulation optimizes for the content matrix assuming that the demand is uniformly spread across the entire day, however the requests may actually arrive in a bursty manner. So it may be sub-optimal compared to a scheme that is explicitly optimized for a known sequence of requests. Second, the optimization formulation optimizes the MLU for the "smoothed" matrix, but the set of objects placed by the optimal strategy with more storage may not necessarily be a superset of the objects placed by the strategy with lesser storage at any given PoP. Third, and most importantly, the actual content matrix for the next day may differ significantly from that of the previous day. All of these reasons make the so-called "optimal" OptRP strategy suboptimal and in combination are responsible for the nonmonotonicity observed in the experiments.

5.3.2 *Content Chunking*

Content chunking is widely used today to improve content delivery and common protocols such as HTTP [24] and Apple HLS [1] support content chunking. This experiment analyzes the effect of content chunking on our findings. In these experiments, we split videos into chunks of 5 minute duration. The size of a video chunk depends on the video bitrate. For the downloads trace, we split content into chunks of size 50 MB.

Our results show that although chunking improves performance of both InvCap-LRU and OptRP-Future, it significantly improves the performance of InvCap-LRU relative to OptRP-Future (see Figure 10). Due to chunking, the maximum difference between the MLU of InvCap-LRU and OptRP-Future reduces from 2.5× to 1.4×. At the maximum storage ratio, InvCap-LRU is at most 18% worse compared to OptRP-Future. Our experiments on other traces and topologies (omitted for brevity) show that InvCap-LRU has at most 4% higher network cost than OptRP-Future at the maximum storage ratio. An exception is the news trace, where chunking makes a small difference as more than 95% content is of duration less than our chunk size. Hence, chunking strengthens our conclusion that InvCap-LRU achieves close to the best possible network cost for an NCDN. Even with chunking, OptRP has up to 7× higher MLU compared to InvCap-LRU (not shown in Figure 10). This is because chunking does not help OptRP's primary problem of not being able to adapt effectively to new content, so it continues to incur a high cost.

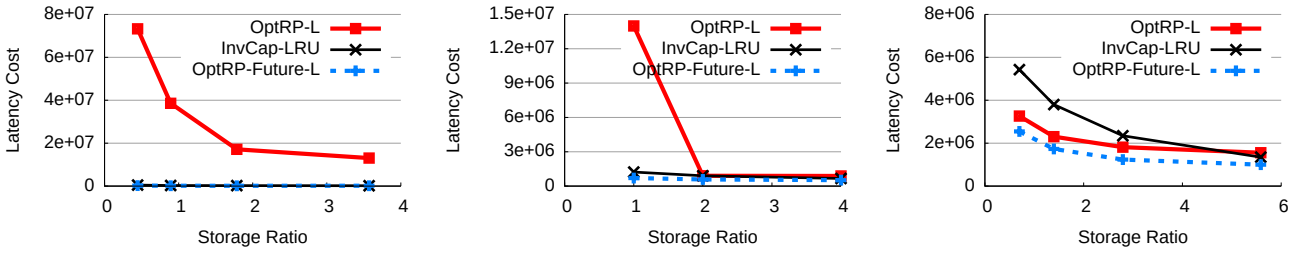
5.3.3 *Alternative Planned Schemes*

The experiments so far suggest that a planned scheme that engineers placement and routing once a day based on the previous day's demand performs poorly compared to an unplanned scheme, InvCap-LRU. Therefore, in this section, we evaluate the performance of two alternative planned schemes.

First, we evaluate a hybrid placement scheme, which splits the storage at each node into two parts - one for a planned placement based on the previous day's content demand (80% of storage) and the other for placing the content in a unplanned LRU manner (20% of storage). This hybrid strategy is similar to that used in [2]. We find that InvCap-LRU performs either as well or better than the hybrid scheme. We also experimented with assigning a greater fraction of storage to unplanned placement (omitted for brevity), but the above conclusions remain unchanged in those experiments. Of course, a carefully designed hybrid scheme by definition should perform at least as well as the unplanned and planned schemes, both of which are extreme cases of a hybrid strategy. However, we were unable to design simple hybrid strategies that consistently outperformed fully unplanned placement and routing.

Next, we analyze the performance of planned schemes that engineer placement and routing multiple times each day at equal intervals - twice/day, 4 times/day, and 8 times/day. In all cases, we engineer using the content demand in the past 24 hours. As Figure 12 shows, OptRP needs to engineer 8 times/day to match the performance of the InvCap-LRU scheme. In all other cases, InvCap-LRU performs better. In fact, the experiment shown here represents the best case for OptRP. Typically, OptRP performs worse even when engineering is done 8 times/day, e.g., on the news trace, we find OptRP incurs up to 4.5× higher MLU compared to InvCap-LRU even on engineering 8 times/day.

Executing a planned placement requires considerable effort—measuring content matrix, solving a computationally intensive optimization, and moving content to new locations. Further, a planned placement needs to be executed 8 times a day (or possibly more) even to match the cost achieved by an unplanned strategy. Our position is that NCDNs are better served by opting for a much simpler unplanned strategy and provisioning more storage, in which case, an unplanned strategy already obtains a network cost close to the best a planned strategy can possibly achieve.



(a) News, US-ISP (b) Entertainment, US-ISP (c) Downloads, US-ISP

Figure 13: A realistic planned scheme, OptRP-L causes excessively high latency costs in some cases. InvCap-LRU achieves latency costs close to ideal planned scheme, OptRP-Future-L, at higher storage ratios.

5.4 Comparison of Latency Cost

Latency cost metric models user-perceived latency in the network. In our evaluation, we compare InvCap-LRU scheme, which is a completely unplanned scheme, against OptRP-L and OptRP-Future-L that optimize latency cost based on previous day's content matrix and based on next day's content matrix respectively.

We experiment with ISP topologies in which links are scaled down uniformly. We needed to scale down the links as our traces did not generate enough traffic to fill even 5% of the capacity of the links during the experiment; ISP networks are unlikely to operate at such small link utilizations. The network topology is scaled such that the 99-percentile MLU for results is 75% link utilization for the InvCap-LRU scheme. This ensures that network has sufficient capacity to support content demand at all storage ratios and network links are not heavily under-utilized.

We present the results of our comparison on the US-ISP topology in Figure 13. Experiments on the Abilene topology show qualitatively similar conclusions (graph omitted for brevity). We find that on the news and entertainment traces, OptRP-L scheme results in an order of magnitude higher latency costs. OptRP-L scheme is similar to OptRP scheme except it optimizes latency instead of network cost. Like the OptRP scheme, OptRP-L is unable to predict the popularity of new content resulting in high volume of traffic from origin servers and high link utilization values. OptRP-L either exceeds link capacities or operates close to link capacity for some links which results in very high latencies.

The latency cost of InvCap-LRU relative to OptRP-Future-L improves with an increase in storage ratio. At the smallest storage ratio, InvCap-LRU has 70-110% higher latency cost than OptRP-Future-L. The difference reduces to 14-34% at the maximum storage ratio. Higher storage ratio translate to higher cache hit rates, which reduces propagation delay of transfers and lowers link utilizations. Both these factors contribute to a smaller latency cost for InvCap-LRU. This finding shows that NCDNs can achieve close to best latency costs with an unplanned scheme InvCap-LRU and provisioning moderate amounts of storage.

The performance of OptRP-L on the downloads trace is much closer to OptRP-Future-L than on the other two traces. Unlike other traces, content popularity is highly predictable on the downloads trace based on yesterday's demand, except for a day on which multiple new software releases were done. On all days except one, OptRP-L has nearly optimal latency cost and it incurs a higher latency cost on one day of the trace. As a result, OptRP-L's aggregate latency cost summed over all days is only moderately higher than that of OptRP-Future-L.

5.5 Effect of NCDN Traffic on Network Cost

This experiment, unlike previous experiments, considers a network consisting of both ISP and NCDN traffic. Our goal is to evaluate how network costs change as the fraction of NCDN traffic increases in the network. Second, we seek to examine the benefit of optimizing routing over an unplanned routing scheme, InverseCap. To this end, we compare the performance of InvCap-LRU and OptR-LRU schemes. The latter scheme optimizes routing for the combined traffic matrix due to NCDN traffic and ISP transit traffic. In order to estimate the best gains achievable with an optimized routing, we provide to the OptR-LRU scheme knowledge of future ISP traffic matrices. OptR-LRU cannot be provided the knowledge of future NCDN traffic matrices because NCDN traffic matrices can only be measured from experiment itself and we do not know them beforehand. We optimize routing once a day in this experiment. Varying the frequency of routing update did not improve OptR-LRU's performance.

We experiment with hourly transit traffic matrices spanning 7 days from the same Tier-1 ISP — US-ISP. These matrices were collected in February, 2005. Since ISP traffic volumes are much higher than NCDN traffic volumes, at first, we performed this experiment by scaling down the ISP traffic matrices, so that ISP and NCDN traffic have comparable volumes. Of the total NCDN traffic, less than 10% reaches the backbone links, rest is served locally by PoPs. For equal volumes of NCDN and ISP traffic we expected the MLU of a network with ISP traffic only to be much higher than MLU for the network with only NCDN traffic. Our experiment showed that MLU for ISP traffic and NCDN traffic are nearly the same.

We found that this was because the NCDN traffic showed highly variable link utilization even over the course of a few minutes: the maximum link utilization differed by up to 3× in the course of 15 minutes. The hourly ISP traffic matrix that we experimented with retained the same, smoothed utilization level for an hour. As a result, 99-percentile MLU's for NCDN traffic are the same as that for ISP even though its aggregate backbone traffic was much lesser.

To make the variability of NCDN traffic comparable to ISP traffic, we scaled up the volume of NCDN traffic. The scaling is done by introducing new content similar to a randomly chosen content in the original trace. Each new content is of the same size, and same video bit rate as the original content. All requests for the new content are made from the same locations, at approximately the same times (within an 1-hour window of the request of the original content), and

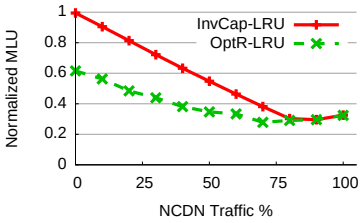


Figure 14: [News, US-ISP]Network costs at varying fractions of NCDN traffic in an ISP network.

are of the same durations as the requests for the original content. Our scaling preserves the popularity distribution of objects and the geographic and temporal distribution of requests. We scaled our trace to the maximum level so as to not exceed the memory available (8 GB) in our machine.

We present the results of our experiments on the news trace in Figure 14. We vary the fraction of NCDN to ISP traffic, and report MLUs normalized by the total volume of ISP and NCDN traffic. Our results are not independent of the scale of simulations: a larger or a smaller scaling of CDN trace may give quantitatively different conclusions. Hence, we only make qualitative conclusions from this experiment. First, we find that as the fraction of NCDN traffic increases, MLU decreases for both schemes. This is intuitive since a large fraction of NCDN traffic is served from caches located at PoPs. Second, as NCDN traffic increases optimizing routing (OptR-LRU) gives lesser benefits compared to InverseCap routing. In a network dominated by NCDN traffic, optimizing routing gives almost no benefits over InvCap-LRU. We find these results to be consistent with our earlier experiments with NCDN traffic only.

5.6 Other Results and Implications

We summarize our findings from other experiments with NCDN traffic here due to space constraints.

Link-utilization aware redirection: We evaluate a request redirection strategy for InvCap-LRU that periodically measures link utilizations in the network and prefers less loaded paths while redirecting requests. Our evaluation shows that such a redirection gives small benefits in terms of network cost ($7\% - 13\%$) and gives almost no benefits on latency costs. This implies that sophisticated network-aware redirection strategies may be of little value for an NCDN.

Request redirection to neighbors: If each PoP redirects requests only to its one-hop neighbor PoPs before redirecting to the origin, InvCap-LRU incurs only a moderate (6%-27%) increase in the MLU. However, if a PoP redirects to no other PoPs but redirects only to the origin, the MLU for InvCap-LRU increases significantly (25%-100%). Thus, request redirection to other PoPs helps reduce network cost, but most of this reduction can be had by redirecting only to neighboring PoPs.

Heterogenous storage: Heterogenous storage at PoPs (storage proportional to the number of requests at a PoP in a trace, and other simple heuristics) increases the MLU compared to homogenous storage for both InvCap-LRU and OptRP-Future, and makes InvCap-LRU more sub-optimal compared to OptRP-Future. This leads us to conclude that our results above with homogeneous storage are more relevant to practical settings.

OptR-LRU parameters: Whether OptR-LRU updates routing every 3 (default), 6, or 24 hours, makes little difference to its performance. Further, whether OptR-LRU optimizes routing using traffic matrix measured over the immediately preceding three hours (default) or using traffic matrices measured the previous day, its network cost remains nearly unchanged. These experiments reinforce our finding that optimizing routing gives minimal improvement over InvCap-LRU.

Number of exit nodes: When the number of network exit nodes is increased to five or decreased to one, our findings in §5.3.1 remain qualitatively unchanged.

Link failures: The worst-case network cost across all single link failures for InvCap-LRU as well as OptRP-Future is approximately twice compared to their network costs during a failure-free scenario. Comparing the failure-free scenario and link failure scenarios, the relative sub-optimality of InvCap-LRU with respect to OptRP-Future remains the same at small storage ratios but reduces at higher ratios.

5.7 Limitations

Although we have evaluated several NCDN management strategies, our experimental methodology suffers from some shortcomings. First, we assume that servers deployed at each PoP have enough resources to serve users requests for locally cached content. In cases when server resources are inadequate, e.g., due to flash crowds, a simple redirection strategy, e.g., redirection to the closest hop-count server used by the InvCap-LRU scheme, may result in poor user-perceived performance. In practice, NCDNs should adopt a redirection strategy that takes server load into account to handle variability of user demands. Second, we model user-perceived latency using a latency cost function that considers propagation delays and link utilization levels. Our latency cost function is a crude approximation of user-perceived latency. A better metric would be based on the TCP throughput experienced by a user. However, an accurate estimation of TCP throughputs of users at the scale of an ISP network with dynamic workloads is extremely challenging. We defer addressing these concerns to future work.

6. RELATED WORK

Traffic engineering and content distribution have both seen an enormous body of work over more than a decade. To our knowledge, our work is the first to consider the NCDN problem, wherein a single entity seeks to address both concerns, and empirically evaluate different placement, routing, and redirection strategies.

Joint optimization: Recent work has explored the joint optimization of traffic engineering and "content distribution", where the latter term refers to the *server selection* problem. P4P (Xie et al. [30]) shows that P2P applications can improve their performance and ISPs can reduce the MLU and interdomain costs, if P2P applications adapt their behavior based on hints supplied by ISPs. Jiang et al. [18] and DiPalantino et al. [9] both study the value of joint optimization of traffic engineering and content distribution versus independent optimization of each. CaTE (Frank at al. [13]), like P4P, shows that a joint optimization can help both ISPs and content providers improve their performance. These works equate content distribution to server selection (or request redirection in our parlance), while the NCDN problem additionally considers content placement itself as a degree of freedom. We find that the freedom to place content is powerful enough that even unplanned placement and routing strategies suffice to achieve close to best latency

and network costs for NCDNs, making joint optimization of content distribution and traffic engineering unnecessary.

Placement optimization: Cohen [8] propose an algorithm to optimizing placement of *services* in the network to help traffic engineering objectives. Jiang et al [17] study how to jointly optimize placement of virtual machines and routing for traffic engineering inside a data center. Applegate et al. [2] study the content placement problem for a VoD system that seeks to minimize the aggregate network bandwidth consumed. However, they assume a *fixed routing* in the network, while one of our contributions is to assess the relative importance of optimizing routing and optimizing placement in an NCDN.

Furthermore, they find that an optimized, planned placement with a small local cache (similar to our "hybrid" strategy in §5.3.3) outperforms LRU. In contrast, our experiments suggest otherwise. There are three explanations for this disparity. First, their workload seems to be predictable even at weekly time scales, whereas the Akamai CDN traces that we use show significant daily churn. Second, their scheme has some benefit of future knowledge and is hence somewhat comparable to our OptRP-Future. For a large NCDN, obtaining knowledge about future demand may not be practical for all types of content, e.g., breakout news videos. Finally, our analysis suggests that LRU performs sub-optimally only at small storage ratios, and the difference between LRU and OptRP-Future reduces considerably at higher storage ratios (not considered in [2]).

Traffic engineering: Several classes of traffic engineering schemes such as OSPF link-weight optimization [11], MPLS flow splitting [10], optimizing routing for multiple traffic matrices [29, 31], online engineering [19, 10], and oblivious routing [3, 5], have been studied. All of these schemes assume that the demand traffic is a given to which routing must adapt. However, we find that an NCDN is in a powerful position to change the demand traffic matrix, so much so that even a naive scheme like InverseCap, i.e., no engineering at all, suffices in conjunction with a judicious placement strategy and optimizing routing further adds little value. In this respect, our findings are comparable in spirit to Sharma et al. [25]. However, they focus on the impact of location diversity, and show that even a small, fixed number of randomly placed replicas of each content suffice to blur differences between different engineering schemes with respect to a capacity metric (incomparable to MLU), but find that engineering schemes still outperform InverseCap.

7. CONCLUSIONS

We posed and studied the NCDN-mangament problem where content distribution and traffic engineering decisions can be optimized jointly by a single entity. Our trace-driven experiments using extensive access logs from the world's largest CDN and real ISP topologies resulted in the following key conclusions. First, simple unplanned schemes for routing and placement of NCDN content, such as InverseCap and LRU, outperform sophisticated, joint-optimal placement and routing schemes based on recent historic demand. Second, NCDN traffic demand can be "shaped" by effective content placement to the extent that the value of engineering routes for NCDN traffic is small. Third, we studied the value of the future knowledge of demand for placement and routing decisions. While future knowledge helps, what is perhaps surprising is that a small amount of additional storage allows simple, unplanned schemes to perform as well as planned ones with future knowledge. Finally, with a mix of NCDN and transit traffic, the benefit of traditional traffic engineering is commensurate to the fraction of traffic that is transit traffic, i.e., ISPs dominated by NCDN traffic can simply make do with static routing schemes. Overall, our findings suggest that content placement is a powerful degree of freedom that NCDNs can leverage to simplify and enhance traditional traffic engineering.

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APPENDIX

A. COMPLEXITY OF NCDN PROBLEM

Opt-NCDN is the decision version of the NCDN problem described in §3. Opt-NCDN asks if the MLU of the network can be α while satisfying the constraints of the problem.

THEOREM 1 *Opt-NCDN is NP-Complete even in the special case where all objects have unit size, all demands have unit value, and link and storage capacities have binary values.*

Proof: We show a reduction from the well known SetCover problem. We first define the SetCover problem that we will reduce to Opt-NCDN.

SetCover: Let $S = \{1, 2, ..., n\}$ be a set of n elements. Let $X = \{S_1, ..., S_m\}$ where $S_i \subseteq S, 1 \leq i \leq m$. Let k be an integer. SetCover asks if there exists $Y = \{Y_1, ..., Y_k\}$, where $Y_k \in X$ and $Y_1 \cup ... \cup Y_k = S$. Set Y is called a set cover of size k.

The reduction from SetCover to Opt-NCDN is described using the network in Figure 15. Set $V_1 = \{1, ..., m\}$ refers to nodes in the top row. Each node $i \in V_1$ maps to the set $S_i \subset S$. Set $V_2 = \{1, ..., n\}$ refers to nodes in the bottom row excluding node s. Each node $i \in V_2$ maps to element $i \in S$. Node s is called a special node.

Directed links (i, j) exist from all nodes $i \in V_1$ to all nodes $j \in V_2$. The capacity of (i, j) is 1 unit if $i \in S_j$, otherwise capacity is zero. Node s has incoming links (i, s) from all nodes $i \in V_1$ such that the capacity of all incoming links is 1 unit.

All nodes in the top row V_1 have unit storage whereas nodes in the bottom row $V_2 \cup \{s\}$ have zero storage.

The set of objects is $\{o, 1, 2, ..., (m-k)\}$ and all objects have unit size. Object o is a special object that has unit demand at nodes in set $V_2 = \{1, ..., n\}$ and zero demand at all other nodes. Objects 1, 2, .. $(m-k)$ have unit demand at special node s and zero demand at all other nodes.

CLAIM: There is a set cover of size k if and only if the above network can achieve MLU ≤ 1.

If there is a set cover of size k, then the network can achieve MLU of 1. Store the special object o at the k set cover locations in the top row and satisfy demand for o at nodes $V_2 = \{1, ..., n\}$ in the bottom row from these locations with MLU = 1. The remaining $(m-k)$ nodes in the top can be used for objects $\{1, 2, ..., (m-k)\}$ to satisfy the demand at special node s with MLU of 1.

If there is no set cover of size k, then the network must have a MLU > 1. Objects must be placed in some $(m-k)$ nodes in the node $V_1 = \{1, ..., m\}$ in the top row to satisfy the demand for special node s. Thus, at most k nodes are available for placing special object o. Since there is no set cover of size k, some bottom node $i \in V_2$ must satisfy its demand for special object o using an edge whose capacity is zero resulting in MLU $= \infty$ on that edge.

It is easy to show that Opt-NCDN $\in$ NP. Hence, Opt-NCDN is NP-Complete.

THEOREM 2 *Opt-NCDN is inapproximable within a factor β for any $\beta > 1$ unless P = NP.*

The proof of THEOREM 1 shows that if there is a set cover of size k, MLU = 1 and MLU $= \infty$ otherwise. Thus, if we find a solution for which MLU is finite, it implies that MLU = 1, which immediately gives a solution to the corresponding SetCover instance.

Lets assume a β-approximation ($\beta > 1$) exists for Opt-NCDN. Then, we can solve SetCover in polynomial time by mapping SetCover instance to Opt-NCDN instance, and checking if MLU $\leq \beta$ (which implies MLU = 1). As SetCover $\in$ NP-Complete, therefore, no $\beta-$approximation for Opt-NCDN exists unless P = NP.

B. JOINT OPTIMIZATION OF TRANSIT TRAFFIC MATRIX AND CONTENT MATRIX

We present here a modification to the MIP in §3.3 to jointly optimize routing for an ISP transit traffic matrix (TTM) and a content matrix. Let D be a TTM and D_{ij} denote the traffic from PoP i to PoP j. We modify only the constraints (3) and (4) in the earlier MIP as follows:

$$\sum_{k \in K} t_{ijk} + D_{ij} \quad = \quad f_{ij}, \ \forall j \in V - X, i \in V \qquad (13)$$

$$\sum_{k \in K} t_{ijk} + \sum_{k \in K} \delta_{ij} t_{iok} + D_{ij} \quad = \quad f_{ij}, \ \forall j \in X, i \in V \qquad (14)$$

C. LIMITING CONTENT PLACEMENT UPDATE TRAFFIC

In this section, we describe our extension to the MIP presented in §3.3 which allows us to limit the MLU due to traffic from updating the content placement. To this end, we add constraints to the MIP to ensure that the MLU due to the placement update traffic is less than a constant β. In our experiment, we dynamically update the value of β to be two/third of the MLU within the past 24 hours of the experiment.

We follow the same notation as in §3.3. The binary variable x_{ik} denotes if the content $k \in K$ is stored at node $i \in V$, S_k denotes the size of the content. To describe the constraint, we define the following parameters : T denotes the duration over which traffic due to placement update will be spread out. X_{jk} denotes whether content $k \in K$ is stored at node $j \in V$ currently. The current routing in the network is r_{ije}, the fraction of traffic from node j to node i crossing link e. In addition we define a function $\gamma(i, j, k)$. $\gamma(i, j, k) = 1$ if $X_{jk} = 1$ and node j is the closest node in terms of hop count from node i which has stored a copy of content k, otherwise. Both r_{ije} and $\gamma(i, j, k)$ depend on current routing and placement in the network and hence are known constants. We assume that the transfer of content of size S_k happens at a constant bit rate of S_k/T. In terms of these variables we can define the total traffic u_e on any link $e \in E$ during the placement update period.

$$u_e = \sum_{i \in V} \sum_{j \in V} \sum_{k \in K} \gamma(i, j, k) r_{ije} x_{jk} S_k / T \quad \forall e \in E \qquad (15)$$

Finally, in order to limit the maximum utilization of any link $e \in E$, we add the following constraint,

$$u_e / C_e < \beta \quad \forall e \in E \qquad (16)$$

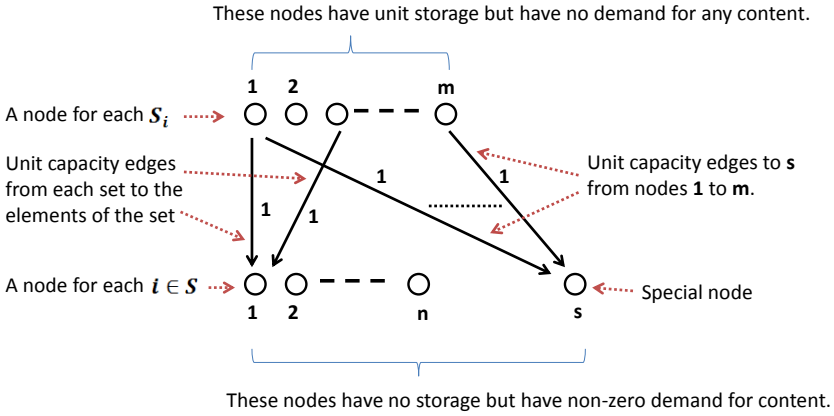

Figure 15: Reduction from SetCover to Opt-NCDN