Guaranteeing Deadlines for Inter-Datacenter Transfers

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Abstract

Inter-datacenter wide area networks (inter-DC WAN) carry a significant amount of data transfers that require to be completed within certain time periods, or deadlines. However, very little work has been done to guarantee such deadlines. The crux is that the current inter-DC WAN lacks an interface for users to specify their transfer deadlines and a mechanism for provider to ensure the completion while maintaining high WAN utilization.

This paper addresses the problem by introducing a Deadline-based Network Abstraction (DNA) for inter-DC WANs. DNA allows users to explicitly specify the amount of data to be delivered and the deadline by which it has to be completed. The malleability of DNA provides flexibility in resource allocation. Based on this, we develop a system called Amoeba that implements DNA. Our simulations and testbed experiments show that Amoeba, by harnessing DNA's malleability, accommodates 15% more user requests with deadlines, while achieving 60% higher WAN utilization than prior solutions.

1. Introduction

Global online services and cloud platform providers, such as Google, Microsoft, and Amazon, construct multiple datacenters (DCs) across the world to deliver their services [8, 9]. The wide area network (WAN) that connects these geographically distributed DCs is one of the most critical and expensive infrastructures that costs hundreds of millions of dollars annually [8]. The shared infrastructure provides transit services for tenants. In public clouds (*e.g.*, Amazon AWS), a tenant could be a customer that launches multiple virtual private clouds (VPC) in multiple DCs. In private clouds (*e.g.*, Google and Microsoft's internal DCs), a tenant could be a service team that launches multiple VMs globally.

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The inter-DC traffic can be broadly classified into three categories based on time-sensitivity: *interactive* traffic that is most sensitive to delay; *larger transfers* which require delivery within certain time periods (*e.g.*, hours); and *background* traffic without strict time requirements [4, 8]. One key characteristics of inter-DC traffic is that a significant amount of transfers have deadlines, either hard or soft. Hard deadline means a transfer is useless to applications once late, whereas soft deadline means the value of a transfer degrades after the deadline, affecting application performance (§3).

Thus, providing deadline guarantees for inter-DC transfers is essential for many applications. To the best of our knowledge, however, no existing mechanism is in place to guarantee the deadlines:

- In private clouds, state-of-the-art inter-DC traffic engineering (TE) techniques do not guarantee deadlines. For example, SWAN [8] and B4 [9] enforce a strict priority among traffic categories, but do not explicitly account for deadlines and thus can cause many transfers to miss their deadlines (§8). Tempus [13] maximizes the minimal fraction of delivery of all transfers until deadlines, but does not guarantee the completion of any of them before deadlines (§3).
- In public clouds, the current practice does not even differentiate among different traffic categories. Our measurements of a real inter-DC WAN show that only rate limiting is applied to provide isolation across tenants. In addition, even with the rate limiting, bandwidth varies dramatically across time and DC sites (§2).

This makes it difficult for critical business applications to run on top of the infrastructure. As a result, the inter-DC WAN is under increased pressure to provide service level agreements (SLAs) [1]. The crux is that the current inter-DC WAN lacks both an interface for tenants to specify their transfer deadlines and a mechanism for provider to meet the deadlines. We seek such an interface and a mechanism in this paper. We aim to fully utilize the scarce WAN bandwidth resource to guarantee deadlines for as many transfers as possible.

Existing solutions of intra-DC bandwidth guarantees [2, 6, 23] cannot be adopted to solve our problem. The reason is that although these pre-determined bandwidth reservation models (either flat [2, 6] or time-varying [23]) can guarantee

deadlines by providing minimum bandwidth guarantees, they cannot fully utilize the WAN bandwidth due to their inflexibility (§3).

In this paper, we introduce DNA, a Deadline-based Network Abstraction, tailored for inter-DC WANs. DNA allows tenants to explicitly express what they want from the network in terms of the data volume and the deadline by which it must be delivered. Note that DNA allows bandwidth allocation for a single request to change over time as long as the total transfer volume is kept. Such intrinsic malleability enables providers to schedule the scarce WAN bandwidth in a more flexible and efficient way based on network conditions. Providers can now arrange *when* and *how much* data to transfer to achieve better multiplexing and to ensure higher network utilization.

We develop a system, Amoeba, that implements DNA in a scalable manner. Amoeba employs a temporal-spatial allocation algorithm for on-line admission control, and our algorithm strikes a good balance between scalability and optimality: it achieves 30× speedup in terms of allocation time at the expense of sacrificing 3% in performance compared to a global optimal strategy. Amoeba further considers a series of practical design and implementation issues, *e.g.*, how to handle network dynamics and be robust to failures and traffic mispredictions. Finally, we discuss a simple pricing model to encourage tenants to reveal their authentic requirements under Amoeba.

In short, this work makes the following contributions:

- Using measurements of a production Inter-DC WAN and simulations, we reveal that the current Inter-DC WAN is insufficient to guarantee deadline-sensitive Inter-DC transfers.
- We introduce DNA, a deadline-based network abstraction tailored for inter-DC WANs, and develop Amoeba, a system that implements DNA. We deploy Amoeba on a small testbed emulating a 6-site inter-DC WAN, and evaluate our design using testbed experiments as well as large-scale simulations with realistic inter-DC WAN topologies.
- Our evaluation shows that Amoeba accommodates 15% more transfer requests with deadlines guaranteed than state-of-the-art solutions, while achieving 60% higher network utilization. Using a simple pricing model, this directly translates to 40% more revenue for the provider.

2. Measuring an inter-DC WAN

While prior work [8, 9, 15] describes how TE is done in private clouds, very little is known about how public clouds perform. To get a sense of the quality of service of public clouds, we perform measurements on Amazon AWS intra- and inter-DC networks. We choose 6 DCs to measure: Virginia (US east), Oregon (US west), Ireland (Europe), S.Paulo (South America), Tokyo (Asia) and Sydney (Oceania). In each DC, we choose 3 machine types whose network performance metrics are labeled *low*, *moderate*, and *high*.

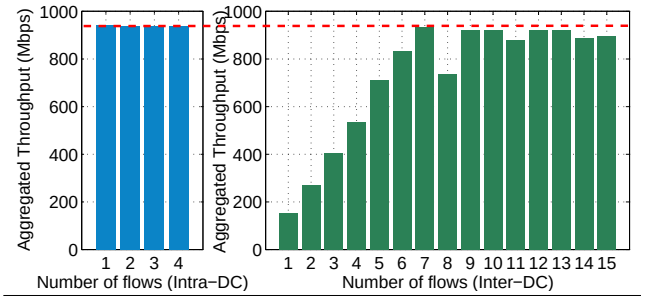


Figure 1. Aggregate throughput between VMs of high network performance type

Type \ Region	Oregon	Ireland	S.Paulo	Tokyo	Sydney
Low	61	58	47	27	29
Moderate	180	150	106	82	69
High	296	223	182	126	107

Table 1. The throughput of inter-DC flows measured from Virginia (Mbps).

Variate \ Region	Oregon	Ireland	S.Paulo	Tokyo	Sydney
Bandwidth ratio	5.05	2.59	2.13	4.01	4.12
Transfer time ratio	2.67	1.43	1.39	1.97	2.41

Table 2. The Inter-DC WAN performance variability on bandwidth and time (95th percentile vs 5th percentile ratio).

Our measurement results show the performance heavily depends on rate limiting, and varies significantly over time and across DCs.

Rate limiting: We measure the total TCP throughput when increasing the number of TCP flows between each pair of VMs from 1 to 15. To observe the difference between intra- and inter-DC traffic, we vary the VM locations. We first place all VMs in the same DC (Virgina). Then, one VM in each pair is moved to Ireland. Figure 1 shows the aggregate throughput between VMs of the *high* network performance type. Similar patterns are observed in other types. We make two observations (which have been confirmed with Amazon engineers):

- *Per-VM rate limiting:* The bandwidth is capped at the same limit for both Intra-DC and Inter-DC (while different VM types have different rate limits). As shown in the figure, the cap for *high* performance VM type is around 1000Mbps.
- *Additional per-flow rate limiting for Inter-DC transfers:* The results in Figure 1 suggest that inter-DC traffic is rate-limited on a per-flow basis. At the beginning, the total throughput increases almost linearly to the number of flows, but eventually reaches the per-VM rate limit. This

is not a consequence of TCP's per-flow fairness because the total throughput stabilizes only after a specific number of TCP flows. We have also verified that the observed per-flow rate limiting is not due to a small receive window. For example, the throughput remains the same when we double the TCP receive buffer.

WAN performance variability: Even though strict rate limiting is in place, inter-DC WAN performance significantly varies across DCs and over time. We measure the throughput from VMs in Virginia to VMs in the other five DCs respectively every 5 minutes over a total period of 35 hours. For each pair of VMs, we have 420 measurement points.

Table 1 shows the maximum throughput of all samples for each VM pair. We find that the throughput varies between different DCs by a factor of up to 2.8. Table 2 shows the ratio between the 95th percentile value over 5th percentile value over the 35 hours, which varies from 2 to 5. The largest variability occurs between Virginia and Oregon. One possible cause of such variability is congestion in inter-DC WAN. However, we do not observe such high variability for intra-DC VM pairs. To further quantify the consequence of inter-DC WAN bandwidth variability, we simply transfer 1GB data between each VM pair at different time and measure the variations in completion time. The measurement in Table 2 shows that the variation can be as large as 2.67×. This suggests that it is difficult to ensure timely data delivery for traffic with deadline.

3. Background and Motivation

Deadlines: The nature of many DC applications has imposed hard or soft deadlines to a large amount of inter-DC WAN traffic [4, 8, 9]. Deadline is important for inter-DC transfers. The main reason is that the total demand for inter-DC transfers typically far exceeds the available capacity. Many online services and applications like search, email, cloud storage etc., want geo-replication to improve performance (closer to users) and reliability (robustness against single-DC failure). Given this, cloud providers set different data replication SLAs (or deadlines) for different applications based on factors such as their delay tolerance and price (paid by customers).

Typical data transfer sizes between DCs range from tens of terabytes to petabytes; deadlines range from an hour to a couple of days [13]. For example, a web search application must update and propagate a new index once every 24 hours across DCs. A web document application must geo-replicate user data once every 2 hours to ensure that only the changes in the most recent 2 hours could be lost due to single DC outage. A key characteristic of such transfers is that they are elastic to bandwidth allocation as long as they complete before the deadlines. Missing deadlines will violate the application SLAs and greatly degrades application performance.

However, state-of-the-art solutions and the current practice, such as rate limiting, TE [8, 9, 13], and network virtualization approaches [2, 6, 23], are all insufficient when handling deadline-based Inter-DC transfers.

Public inter-DC rate limiting does not respect deadlines. Rate limiting provides isolation among flows, but it is far from deadline guarantee. Even with rate limiting, the inter-DC transfer time is highly variable, as shown in our AWS measurements. Meeting deadlines requires fine-grained service differentiation. However, the current practice does not differentiate among different traffic classes.

Private inter-DC TE techniques do not guarantee deadlines. SWAN and B4 take a TE approach to improve the inter-DC WAN network utilization. They consider traffic characteristics and priorities (e.g., interactive $>$ elastic $>$ background) to enhance application performance. However, such prioritization is too coarse-grained and does not guarantee any specific transfer deadlines. Because there exists no interface for tenants to specify their transfer deadlines, and the provider has no way to honor them. In our evaluation (§8.4) we find that a large portion of transfers will miss their deadlines in SWAN.

Tempus [13] is deadline-aware and promises each request a maximal fraction of transfer before deadline without guaranteeing the completion, especially when demand exceeds the network capacity. However, for many applications, partial data transfer is useless as the applications move forward up on the completion of last byte of the last flow. As a result, this paper focuses on how to fully utilize the WAN bandwidth to guarantee the completion of as many transfers as possible before deadlines.

Applying solutions for intra-DC to inter-DC are insufficient to ensure high WAN utilization. The bandwidth guarantee provided by virtual network abstractions [2, 6, 23], such as the hose model, supports transfer deadlines by guaranteeing minimum bandwidth. However, when applied to inter-DC WAN, they are insufficient to fully utilize the WAN bandwidth. The reason is that these pre-determined bandwidth reservation models (either static [2, 6] or time-varying [23]) are less flexible than the deadline based reservation. They provide fixed bandwidth guarantees over time while our design focuses on guaranteeing the total transfer volume given a deadline. Their models place a more stringent requirement at the admission time, while our model is more flexible because the bandwidth allocation can change over time as long as the total volume is delivered within the time limit. In our evaluation (§8.3), we find that pre-determined bandwidth reservations under-utilize the WAN resources, leaving many transfer requests unsatisfied.

4. Deadline-based Abstraction

The overarching goal of our work is to seek a user-provider interface and a mechanism to fully utilize the expensive WAN bandwidth to meet deadlines for as many transfers as possible. Realizing this needs an abstraction satisfying two objectives:

1. *Expressive specification:* The abstraction must allow tenants to easily express their deadline requirements in an explicit fashion to ensure application-level SLAs [10].
2. *Provider flexibility:* The abstraction must provide flexibility in provider's resource allocation. Leveraging its flexibility, the provider is then able to maximize the utilization of the expensive inter-DC WAN, and at the same time accommodate as many deadline transfers as possible.

To this end, we present DNA, an explicit deadline-based network abstraction, that allows the tenants to directly express their transfer deadlines.

Transfer: A transfer represents a tenant's data delivery demand from a source DC to a destination DC. Note that this captures a tenant-level aggregate demand between a pair of DCs. Scheduling individual flows within a tenant is handled by tenants, which is not the fcous of this paper. A transfer, T, is specified as a tuple $\{src, dst, Q, ts, td_1, td_2\}$, where src and dst are the source and destination DCs, Q is the data volume, ts is the starting time, and (td_1, td_2) captures the deadline, either hard or soft. Specifically, td_1 represents the completion time before which the transfer suffers no utility loss, and after td_1, the utility degrades gradually to 0 at time td_2. Note that, if $td_1 = td_2$, it indicates a hard deadline. A similar model has been adopted in Tempus [13] as well.

Request: A tenant may have multiple co-related transfer demands across many DCs. For example, when running MapReduce as a single geo-distributed operation across DCs [11], multiple shuffle transfers from several mappers to a reducer are barrier synchronized, and the completion of a single transfer does not improve the job completion time. To this end, DNA allows tenants to specify such a demand by submitting a request $\mathbf{R} = \{T_1, \cdots, T_n\}$, where each T_i is a transfer. The provider accommodates all transfers of a request in an atomic fashion.

5. AMOEBA

In this section, we introduce Amoeba, a system that implements DNA. We set up the following objectives for Amoeba.

- **High WAN utilization & acceptance rate:** The system must fully utilize inter-DC WAN bandwidth to maximize the acceptance rate of tenant requests with deadlines, which is also the chief design goal of this paper.
- **Ensure coexistence:** The system must work with all types of traffic. Interactive traffic must be delivered without any delay, while background traffic is served in a best-effort manner.
- **Handle dynamics:** The system must be able to handle network dynamics and be robust to failures and mispredictions in interactive traffic. Temporal variations in interactive traffic demand and network failures are the major sources of dynamic events that the system must deal with.

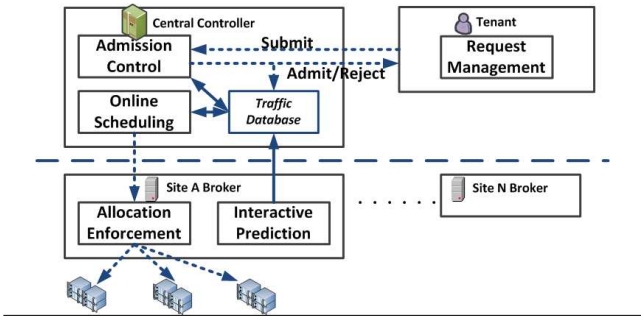


Figure 2. System model

- **Scalability & deployability:** The admission control decision must be made in near real-time upon request. The enforcement of delivery schedule must also be done in a scalable fashion to support many transfers and to scale up to tens of DCs. For practical deployment, the system must not require modification to existing network devices.

5.1 System Overview

In general, Amoeba implements a two-level bandwidth sharing policy. First, priority classes are enforced (*i.e.*, interactive $>$ deadline transfers $>$ background) and bandwidth is allocated in strict precedence across these classes. Second, within the deadline transfer class, bandwidth is scheduled to meet the deadlines of the transfer requests.

Figure 2 illustrates the system architecture of Amoeba, which contains a logically centralized *controller* and *site brokers*. The central controller is the core of Amoeba and orchestrates all network activities[1]. To be fault-tolerant, the controller is replicated across multiple DCs, and one of them is elected as master using distributed consensus protocols such as Paxos [14]. The controller maintains global information about the network bandwidth and traffic demand, and performs the spatial-temporal resource allocation (§5.2). A site broker, located in each DC, is a local representative. It predicts and reports interactive traffic for a local DC to the central controller periodically, and coordinates the bandwidth enforcement to realize the decision made by the controller. Note that the bandwidth is fixed within a timeslot, but varies across different timeslots. We set the timeslot to 3-5 minutes in our implementation to achieve a reasonable balance between performance and overhead, similar to SWAN [8].

Amoeba works as follows. When a new request arrives, the controller quickly determines if the request can be admitted in an online fashion (§5.2.1). The design of our spatial-temporal resource allocation also considers handling practical system factors, such as mispredictions (§5.2.2) and failures (§5.2.3). For each accepted request, before the beginning of each timeslot, the controller will inform the site brokers of the

[1] The control latency introduced by the centralized control is acceptable for large transfers, and therefore centralized resource allocation is widely adopted for large transfers in inter-DC WAN recently [8, 13, 15, 16]. Amoeba follows this trend.

actual bandwidth allocated to each request. The site brokers, in turn, enforce this via host/hypervisor-level rate limiting. In practice, any distributed rate limiting solutions [18] can be applied to translate aggregate tenant-level allocations into flow-level allocations for practical enforcement. In our implementation, the end hosts perform per-flow rate limiting and the site brokers ensure that the sum of individual flow rate does not exceed the aggregate tenant-level allocation.[2]

5.2 Spatial-Temporal Allocation

5.2.1 Admission Control

Similar to bandwidth guarantee services provided in intra-DC networks [2, 6, 23], the admission control of Amoeba is performed in a first-come first-served (FCFS) manner, and no preemption is allowed. To make effective online admission decisions, the key to our admission control algorithm is to balance scalability and optimality. On one hand, the algorithm can be fast if we simply assume all the previous request schedules are fixed and perform allocation on the new request with the residual bandwidth. However, this is sub-optimal. As we will show in §8.6, Amoeba can bring 7%-12% performance improvement over such a solution. On the other hand, the algorithm can be optimal if for any incoming new request, all existing requests, together with the new one, are rescheduled. However, this is time-consuming. As we will show in §8.5, such an algorithm takes tens of seconds per allocation, and the time cost increases dramatically as flow arrival rate increases. Furthermore, we note that the *all-or-nothing* nature of guaranteeing transfer completion in Amoeba makes it hard to optimize as it cannot be captured with a linear constraint. Thus, the optimization framework developed for fractional allocation in Tempus [13] cannot be directly adopted for Amoeba.

Our algorithm seeks a tradeoff between scalability and optimality. We briefly summarize the high-level idea of our algorithm here and defer the details to §6.

1. When a request arrives, we quickly find out a schedule with completion time t' as early as possible, assuming all previous decisions are fixed. We refer to this step as adaptive scheduling (AS, §6.1). AS essentially tries to use residual network capacity to quickly accept a request by solving a min-cost flow problem (§6.1). For a request, if it can be satisfied at this step (i.e., $t' \leq td_1$), go to step 3; otherwise, go to step 2.
2. We try to reduce the completion time t' by rescheduling bandwidth schedules of previously accepted requests without violating their deadlines. Opportunistic rescheduling (OR, §6.2) is designed to select a small subset of previous schedules that are most relevant to the current request and performs a cost-effective joint rescheduling. This increases the chance of reducing t' while being computationally more efficient than considering all previous requests. After performing OR, if we can at least accommodate it as a soft deadline request (i.e., $t' \leq td_2$), go to step 3; otherwise, go to step 4.
3. Accept the request with a guaranteed transfer time of $t^* = max\{td_1, t'\}$. If the original request is a soft-deadline request, this step transforms it to a hard-deadline request with t^* as the guaranteed deadline. Given t^*, the central controller calculates an initial bandwidth schedule that meets this deadline (§6.3). This initial schedule is subject to changes when handling future requests, mispredictions, and failures.
4. Reject the request. Note that a rejected request can be submitted again later.

Our evaluations in §8 show that our algorithm strikes a good balance between scalability and optimality. Amoeba achieves 30× speedup at the cost of sacrificing only 3% in performance compared to a global optimal strategy.

5.2.2 Handling Mispredictions

According to our experiences with production DCs and prior work [8], interactive traffic takes only a small portion of the overall Inter-DC traffic, e.g., $5\% - 15\%$. While the interactive traffic demand is bursty and highly diurnal, the average volume over a 5 minute window is relatively stable and can be largely predicted [8]. However, misprediction is inevitable. Without proper handling, it may degrade the quality of service. In particular, extra interactive traffic can preempt the bandwidth allocated to deadline transfers as interactive traffic has higher priority, which may cause accepted requests to miss their deadlines.

We address this problem by setting aside different headrooms for different timeslots proportional to how far away the timeslot is. This is motivated by our observation that the degree of misprediction may be large for a timeslot far into the future, but gradually becomes more accurate as it comes closer. For example, for the next timeslot, the headroom can be just 5% of the predicted interactive traffic, whereas for a timeslot an hour later, the headroom can be set to 15% of the predicted interactive traffic. Through this approach, we can safely accept requests for future timeslots. As time advances, the overprovisioned headroom of a timeslot can be released for accepting new requests or speeding up existing requests. To prevent resources from being wasted, we periodically run an algorithm similar to OR at the beginning of each timeslot and move allocation towards the current timeslot opportunistically.

Furthermore, interactive traffic may surge inside a timeslot. In Amoeba, the site broker is in charge of this. The basic idea is that interactive traffic can borrow bandwidth from deadline transfers whenever needed, and return in the future. More specifically, the site broker maintains a record of the interac-

[2] An alternative way is to rate limit the aggregate tenant-level allocation on switches. However, the number of transfers that can be rate limited is bounded by the number of policers on the switch [23];

tive "debt" of each destination for each bandwidth allocation cycle (*i.e.*, 10 seconds). It keeps monitoring the interactive traffic fluctuation: if the headroom cannot absorb the interactive fluctuation to a destination, it dynamically decreases bandwidth from user request with the same destination and farthest deadline; the debts are paid back when the interactive traffic becomes lower than the headroom. Note that such debts can be transferred between timeslots so that even large interactive surges can be handled.

In addition, Tenant's demand specification can be inaccurate. Amoeba simply handles this as follows. For an over-estimated request, the over-estimated part can be reclaimed once reported, and the tenant will be charged partially for this part. For an under-estimated request, the additional demand will be treated as a new request for allocation. If the new request cannot be satisfied, the tenant will be informed and it is up to the tenant whether the transfer should continue. If not, the tenant only pays for the transferred amount.

5.2.3 Handling Failures

In Amoeba, link/switch failures can be detected and communicated to the controller by the site brokers according to the framework introduced in [8]. However, when failures happen, Amoeba may not be able to satisfy all the requests that have been accepted. In this case, Amoeba has to remove some accepted requests. However, obtaining an optimal solution (either minimizes throughput loss or minimizes the number of removed requests) requires solving an integer linear program (ILP) which is NP-hard. Instead, we perform online rescheduling similar to our admission control. First, we remove all the requests that pass through the failed link, and set the residual bandwidth as the available bandwidth after failure. Then, we treat these removed requests as new requests and perform admission control one by one according to their arrival times. Moreover, failures of the central controller and site broker are handled in a similar way as in [8].

5.3 Pricing Model

We discuss a simple pricing model to encourage tenants to reveal their authentic transfer requirements to the provider, *i.e.*, class, volume, and deadlines.

Encouraging true class declaration can be done by simply setting a "higher price for better service" policy. Interactive traffic is assigned the highest priority, thus deserves the highest unit price (price per GB) p_{int}. Background traffic receives a best-effort service, and should be charged at the lowest unit price p_{bck}. Deadline transfer lies in-between, and its unit price $p_{ddl}(\cdot)$ varies depending on both volume and deadline. To distinguish different classes, we simply set $p_{int} \geq p_{ddl}(\cdot) \geq \alpha * p_{int}$ and $\beta * p_{ddl}(\cdot) \geq p_{bck}$[3], where $\alpha, \beta \in (0, 1)$ can be flexibly adjusted according to the supply-demand relationship.

[3] We use "$\geq$" as $p_{ddl}(\cdot)$ varies and we only restrict the upper/lower bound.

Encouraging true volume declaration is also simple. For under-claimed requests, the extra volume beyond requested is handled as background traffic in a best-effort manner; For over-claimed requests, the unused bandwidth can be exploited by background traffic, but the tenant should pay for the entire volume claimed.

Encouraging true deadline declaration is necessary: consider two requests transferring the same amount of data from site A to site B with deadlines of 2 timeslots and 20 timeslots respectively; although they transfer the same volume, the pressure they exert to the network is different. Thus, the charging of the deadline traffic should depend on both volume Q and deadline guaranteed t^*. For this, we can use the expected bandwidth $\overline{B} = Q/t^*$ as the criteria for charging, i.e., $p_{ddl}(\cdot)$ should be a non-decreasing function of $\overline{B}$. Note that users may reduce their costs by splitting their requests into smaller chunks and use the same deadline for all chunks. However, it is risky to do so because some chunks may be rejected. Moreover, a lower bound on the smallest chunk size can be set in order to regulate user requests.

Moreover, such a pricing model also helps to substantiate the benefit brought by our deadline guarantee service. As we will show in the evaluation, Amoeba results in 60% higher network throughput than fixed bandwidth abstractions (§8.3), and achieves much higher goodput (throughput of transfers that meet their deadlines) compared with prior deadline-oblivious Inter-DC TE solutions (§8.4). Under the above pricing model with $\alpha = \beta = 0.5$, the performance improvement can directly translate to over 40% higher provider revenue compared to both fixed bandwidth abstractions and deadline-oblivious Inter-DC TE solutions.

Utility function: Different tenants may desire different utility functions describing their utility decrease from td_1 to td_2. Amoeba can be easily extended to account for arbitrary utility functions. More specifically, the benefit of a tenant equals the utility minus the payment, and both the utility and the payment are functions of the guaranteed transfer time t^*. Thus, instead of setting $t^* = max\{td_1, t'\}$ (step 3 in §5.2.1), Amoeba can calculate the best t^* which maximizes the tenant's benefit. Moreover, it is also possible to accept an incoming request by delaying the completion of some accepted ones, as long as it increases the overall benefit. We consider these extensions as our future work.

6. Algorithm Details

We elaborate the algorithm in §5.

6.1 Adaptive Scheduling (AS)

AS tries to embed a new request $\mathbf{R}$ into the WAN substrate along two dimensions, time and space, without changing the bandwidth schedules of existing requests. To do so, we keep track of the residual bandwidth on each link, and denote the residual bandwidth of link l at time t as $R^l(t)$. To determine the feasibility and routing paths, we solve a min-cost flow problem on a temporally expanded flow graph.

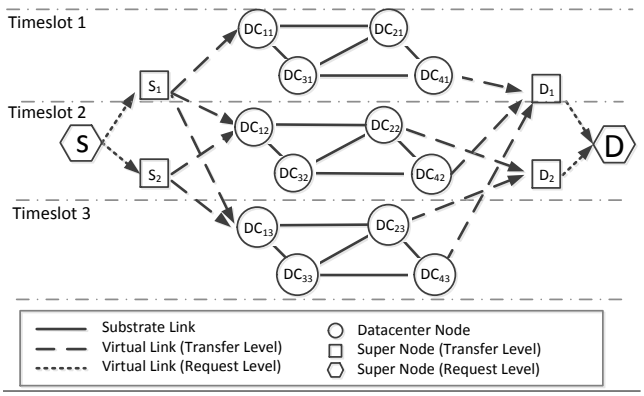


Figure 3. Creating temporally expanded flow graph for adaptive scheduling over multiple timeslots.

Creating the expanded flow graph: First, we construct a flow graph G by creating a virtual node for each DC at every timeslot, as shown in Figure 3. Each virtual node $DC_{n,t}$ represents a DC n at timeslot t. In each timeslot, these virtual nodes are connected to each other just as they were in the original inter-DC topology. Each link l between two virtual nodes of the same timeslot t is assigned a capacity of $c(l) = R^l(t)$.

Second, we add a pair of super nodes S_i and D_i for each transfer T_i in $\mathbf{R}$, and connect S_i to all source DCs $DC_{j,t}$ with timeslot t inside T_i's possible transmission period $[ts, td_2]$. We then connect the destination DCs to D_i in a similar way.

Finally, we add a source node S and a sink node D in the graph, and connect all S_is and D_is to S and D respectively. The link capacity $c(l)$ of each link is set to Q_i. Such time expansion can be regarded as a variation of the technique introduced in [5].

Figure 3 shows an example to expand a request $\mathbf{R}$ over 3 timeslots, where $\mathbf{R}$ includes two transfers $T_1 = \{DC_1, DC_4, Q_1, ts = 1, td_1 = 2, td_2 = 3\}$ and $T_2 = \{DC_1, DC_2, Q_2, ts = 2, td_1 = 2, td_2 = 3\}$. T_1 is expanded over timeslot 1 to 3, and T_2 is expended over timeslot 2 to 3.

Finding the shortest possible completion time: Given G, we approximate the minimal completion time by assigning different weights to edges in the flow graph, and then solving the corresponding min-cost flow problem (problem formulation in Algorithm 1). More specifically, for each edge l from S_i to the source $DC_{j,t}$, we assign weight $w(l) = 2^{t-ts}$. Through this way, the solution to Algorithm 1 tends to pack more flows in the earlier timeslots in order to minimize the cost. Note that we use only k-shortest paths between each source-destination DC pairs as input of Algorithm 1. This reduces the number of rules enforced in each switch and simplifies data plane updates[4]. In our simulation in G-scale topology, we find that $k = 10$ already results in negligible loss on both request acceptance rate and throughput.

[4] Moreover, AS is essentially a multicommodity flow problem, and it is equivalent to the min-cost flow presentation (the LP formulation is the same) with path constraint.

Input: $\mathbf{R} = \{T_1, T_2, ...T_n\}$: A tenant request with n transfers;
$\mathbf{P_i} = \{p_1, p_2, ...p_k\}$: k-shortest paths between the DC pair of transfer $i \in [1, n]$;
$I_{p_m,l}$: 1 if $l \in p_m$; and 0 otherwise;
$c(l)$: residual link capacity for link l in the expended graph;

Output: Return the latest timeslot t' in the solution of the following problem;

$$minimize \sum_{i,t,p_m} \sum_{l \in E} w(l) \cdot f_{itp_m} \cdot I_{p_m,l}$$

s.t.

$$\forall l, t, \quad \sum_i \sum_{p_m \in \mathbf{P_i}} f_{itp_m} \cdot I_{p_m,l} \le c(l)$$

$$\forall i, t, p_m, \quad f_{itp_m} \ge 0$$

$$\forall i \in \mathbf{R}, \sum_t \sum_{p_m \in \mathbf{P_i}} f_{itp_m} = Q_i$$

% f_{itp_m}: the allocation to the flow over path $p_m \in \mathbf{P_i}$ in timeslot t for transfer T_i;

Algorithm 1: Min cost flow formulation on the expended flow graph

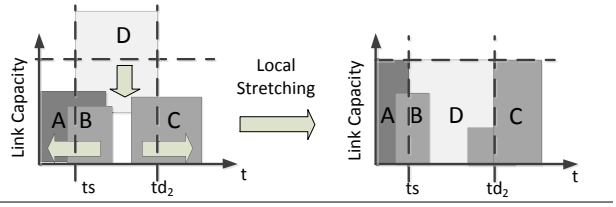


Figure 4. Local stretching implements OR

After AS, if the completion time $t' \le td_1$, then the provider will accept the request with deadline td_1 directly. Otherwise, we proceed to OR, where we try to further reduce t' by rescheduling existing accepted requests.

6.2 Opportunistic Rescheduling (OR)

OR reschedules existing requests to achieve better t' for the new one. We design a two-step heuristics for OR: local stretching and joint rescheduling.

Local stretching is a simple greedy algorithm. As illustrated in Figure 4, to accommodate request $\mathbf{R}$, we "shift" the bandwidth schedules of previous requests out of $\mathbf{R}$'s time window $[ts, td_2]$. This is performed on every path that $\mathbf{R}$ passes through. By local stretching, we set aside more residual bandwidth to accommodate $\mathbf{R}$. Thus, when performing AS again, it is more likely to reduce t'. If t' is still larger than td_1 after local stretching, we proceed with joint rescheduling.

Joint rescheduling is a partial optimization, in which we select some existing requests to do coordinated rescheduling together with the new one, i.e., running AS on all these requests collectively. Note that the time cost of AS is related to the number of requests. Therefore, instead of considering all existing requests, the idea is to find a subset of most relevant requests to reschedule so that the chance of further reducing the completion time t' of the new request maximizes.

Request selection: For each transfer X_i in $\mathbf{R}$, we define a scoring metric, $S(X_i, Y_j)$, between X_i and an existing ac-

cepted transfer Y_j to estimate Y_j's rescheduling effectiveness, i.e., how much Y_j's rescheduling will help in reducing t' of X_i. $S(X_i, Y_j)$ is related to the following two factors:

1. The possibility that Y_j's traffic can be shifted out of X_i's transmission window $[ts, td_2]$. We estimate this as $\frac{td^j - ts^j}{t^+ - t^-}$, where $[ts^j, td^j]$ is the transmission range of Y_j, and $[t^-, t^+]$ is the overlapping time period of X_i and Y_j's transmission time.
2. The amount of Y_j's traffic that goes through X_i's bottleneck link. This is quantified by the amount of X_i and Y_j's traffic that goes through the same link weighted by the link's utilization:

$$\sum_{t=t^-}^{t^+} \sum_{l \in p_m}^{\forall p_m \in \mathbf{P}(Y_j)} (U_l(t) \cdot I_{l,X_i} \cdot I_{l,Y_j} \cdot f_{jtp_m});$$

where $I_{l,X_i}/I_{l,Y_j}$ indicates whether link l is used in X_i/Y_j, and $\mathbf{P}(Y_j)$ is the set of k-shortest paths from src_j to dst_j in Y_j, and $U_l(t)$ is the link utilization of l.

For each transfer $X_i \in \mathbf{R}$, we select a set of n existing requests that have the highest scores, denoted as $H_n(X_i)$. We then define the set of n highly relevant requests with $\mathbf{R}$, $H_n(\mathbf{R})$, as $\cup_{X_i \in \mathbf{R}} H_n(X_i)$.

Partial optimization: We create a new request $\mathbf{R}' = H_n(\mathbf{R}) \cup \mathbf{R}$. We run AS over $\mathbf{R}'$ on the WAN substrate where the residual link capacities are obtained by removing the requests in $H_n(\mathbf{R})$. Then, AS tries to accommodate all transfers in $\mathbf{R}'$. If it fails, we finally reject $\mathbf{R}$.

6.3 Bandwidth Schedule

For each accepted request with guaranteed deadline t^*, the controller calculates a bandwidth schedule that meets t^* and updates the residual bandwidth $R^l(t)$ accordingly. Note that a deadline t^* may correspond to many feasible spatial-temporal schedules, and different schedules may have different impacts on the admission control of future requests.

To increase the chance of accepting future requests using AS only (time-efficient), a heuristic is that for each new request, AS should minimize the link utilization across all involved timeslots. That is, we always try to allocate a request with shorter paths. This is realized by assigning each link with an uniform link weight of 1, and then solve the corresponding min-cost problem in Algorithm 1 with an extra constraint $t \leq t^*$. In this case, the bandwidth schedule may not always favor earlier time slots. Therefore, in our implementation, at the beginning of each timeslot if Amoeba detects available bandwidth in the current slot, it runs an OR alike heuristic to pull more traffic from the future timeslots back to the current one, in order to fully utilize the bandwidth.

7. Implementation

Our prototype consists of the controller, site brokers and enforcement modules. We implement our algorithm in §6 for the controller and site brokers. For routing enforcement we use the SDN technology, and for bandwidth enforcement we leverage the Linux Traffic Control (TC).

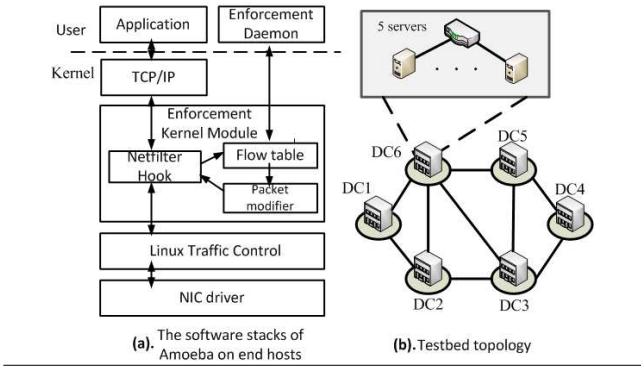


Figure 5. Implementation & Testbed

Amoeba's bandwidth enforcement consists of a kernel module and an enforcement daemon, as shown in Figure 5. The enforcement daemon communicates with the kernel module via iotcl. The enforcement daemon interacts with the site brokers to obtain VM-level rate limits. It is responsible for managing the flow table, such as inserting, updating or deleting flow marking rules. The kernel module is located between TCP/IP stack and the Linux TC module. The kernel module intercepts all outgoing packets and modifies the nfmark field of socket buffer after looking up the flow table. Then these packets are directed to TC for rate limiting. In virtualized environments, we envision that the kernel module runs in the hypervisor and Dom0 to control all traffic going through physical NICs.

To perform distributed per-flow rate limiting on end hosts, we leverage the Hierarchical Token Bucket (HTB) in TC. We use the two-level HTB: the leaf nodes enforce per-flow rates and the root node classifies outgoing packets to their corresponding leaf nodes based on nfmark field which has been modified by Amoeba kernel module.

To make sure that the overhead of Amoeba's enforcement module is negligible, we measure the extra CPU usage it introduces. We generate more than 900Mbps of traffic with more than 100 flows on a Dell PowerEdge R320 server with 8GB of memory and a quad-core Intel E5-1410 2.8GHz CPU. The extra CPU overhead introduced is around 3% compared with the case that Amoeba's enforcement module is not used (no rate limiting). The throughput remains the same in both cases.

8. Evaluation

In this section, we answer five specific questions through extensive evaluations:

- **Does Amoeba provide deadline guarantees for inter-DC transfers in practice?** In §8.2, we show that Amoeba guarantees deadlines for all accepted requests, and all flows complete within the scheduled time given by the

controller. We also show that Amoeba ensures this while achieving no worse (much better in some cases) network utilization than the state-of-the-art solutions.

- **How does Amoeba compare with existing solutions that provide a fixed minimum bandwidth guarantee?** In §8.3, we show that Amoeba achieves up to 60% higher utilization while satisfying up to 15% more requests with deadlines.
- **How does Amoeba compare with existing SDN-based inter-DC TE solutions?** In §8.4, we show that Amoeba accommodates 60% more requests with deadlines while achieving similar levels of utilization.
- **How effective is Amoeba and how scalable is it?** In §8.5, we show that our heuristics make reasonable trade-offs. They achieve 30× speedup at the cost of sacrificing only 3% of network utilization compared to a strategy which tries to find an optimal schedule.
- **How do Amoeba's components contribute to performance and computational cost?** In §8.6, we show the performance breakdown of each component, present some results on misprediction and failure handling, and analyze the effect of supporting soft deadlines.

8.1 Evaluation Methodology

We evaluate Amoeba with both testbed experiments and simulations. On the testbed, we show the overall performance of Amoeba and also demonstrate that the obtained schedules from our algorithm can be effectively enforced. Through simulations, we unravel the details of Amoeba across different settings, topologies, and workloads.

Testbed setup: We build a small testbed with 30 servers to emulate an inter-DC WAN with 6 DCs as in Figure 5. Each DC has 5 physical servers and a Pronto 3295 48-port Gigabit Ethernet switch. The switch has installed PicOS 2.0.4 system which supports both Layer2/Layer3 and OpenFlow. Each inter-DC link is emulated using one physical 1G link. The central controller locates in DC 1 and we add a delay to emulate the WAN environment. The OS of each server is Debian 6.0 64-bit version with Linux 2.6.32 kernel. Each server has a qual-core Intel E5-1410 2.8GHz CPU, 8G memory, 500GB hard disk with 1G Ethernet NIC. The CPU, memory or hard disk is not a bottleneck in our testbed evaluation. We use iperf to generate TCP flows.

Simulation Setup: We simulate two production inter-DC WANs: (i) G-Scale, Google's inter-DC WAN with 12 DCs and 19 inter-DC links [9], and (ii) IDN, with 40 DCs, each connected to 2-16 other DCs [8]. We assume that each link has a uniform capacity of 160 Gbps. Interactive traffic on each link is randomly generated between 5% and 15% of the link capacity for each timeslot, which is also assumed to be the predicted interactive workload. Based on such predicted workload we leave extra headroom and keep updating the headroom as we discussed in §5.2.2. Each run simulates 150 5-minute timeslots (about 12 hours). We report the average of 5 runs.

Metrics: We measure three performance metrics: network utilization (i.e., the average link utilization of interactive traffic and all accepted requests), request acceptance/rejection rate, and network throughput.

Workload: The inter-DC deadline traffic demand is generated with the following parameters:

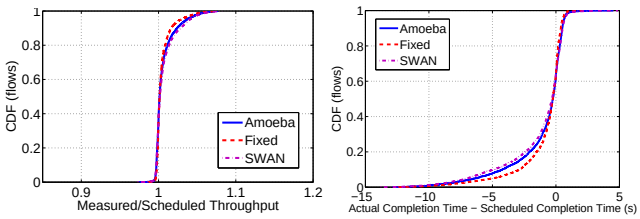
- *Request arrival time* is modeled as a Poisson process with arrival rate λ per timeslot.
- *Deadlines:* The maximum transfer time without utility loss, i.e., $td_1 - ts$, is modeled under exponential distribution with a mean of one hour, and the deadline td_1 can be calculated accordingly. We consider soft deadlines in §8.6.
- *Transfer volume* is the total data volume needs to be transmitted for each transfer. As transfer volume and transmission time are usually related, we define the average transfer throughput of a transfer as the transfer volume over the transfer time $td_1 - ts$, and model this parameter under exponential distribution with a mean of 20 Gbps. The transfer volume can then be calculated accordingly.
- *Number of transfers per request:* each request contains 1-6 transfers.

8.2 Testbed Experiments

We perform experiments on our testbed for a duration of 50 3-minute timeslots (2.5 hours). At any given time, the actual traffic per DC-pair is composed of 20 to 200 TCP flows. Our experiment results demonstrate: 1) Amoeba guarantees deadlines by generating effective bandwidth schedules and accurately enforcing the schedules at each timeslot; and 2) Amoeba delivers higher utilization/throughput compared to others, including solutions that provide fixed minimum bandwidth (*Fixed*) and SDN-based TE (SWAN).

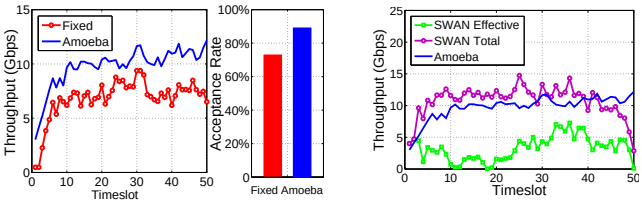
To demonstrate that Amoeba performs effective bandwidth schedules and accurate real-time enforcement, we show the difference between the scheduled bandwidth allocation and the throughput actually measured in the experiment in Figure 6 (a). We observe that for more than 95% of requests, the difference is less than 5%. In addition, Figure 6 shows that for a majority of flows, the completion times on the testbed matches their schedules (note one flow lasts at least for one timeslot). Furthermore, we note that the throughput measured is slightly higher (and the completion time is slightly smaller) than scheduled. One possible reason is that the completion time measured by iperf is the time to copy data from user space to kernel space at sender side, which is smaller than that from user space of sender side to user space of receiver side (i.e., the actual completion time), especially for short flows.

We further compare Amoeba with two baseline algorithms (*Fixed* and SWAN) in terms of throughput/utilization



(a)Throughput deviation (b)Completion time deviation

Figure 6. Deviation between schedules and testbed results



(a) Amoeba *vs*. *Fixed* (b) Amoeba *vs*. SWAN

Figure 7. Experiment results

in Figure 7. Figure 7 (a) shows that Amoeba achieves around 40-50% higher throughput than *Fixed*. This is mainly because Amoeba has the flexible DNA model. The higher utilization translates to higher acceptance rate. As shown in the figure, Amoeba has an acceptance rate of 89%, whereas the acceptance rate for *Fixed* is 72%. Figure 7 (b) shows the results for SWAN versus Amoeba. SWAN achieves a slightly better throughput/utilization than Amoeba. However, SWAN is deadline-agnostic and many flows miss their deadlines despite of the higher total throughput. In terms of the effective throughput (i.e., the throughput of flows that meet their deadlines), SWAN is less than half of Amoeba.

8.3 Amoeba vs. Fixed Minimum BW Guarantee

We compare Amoeba with *Fixed* using large-scale simulations. We generate requests with randomly selected sources and destinations in both IDN and G-scale topologies. The request arrival rate for IDN is higher because IDN is larger than G-Scale[5]. The minimum bandwidth guarantee in *Fixed* is set to satisfy the deadlines, *i.e.*, $B_{fix} = \frac{Q}{td_1 - ts}$.

Figure 8 (a) and Figure 9 (a) show the rejection rates for IDN and G-scale respectively. It is obvious that Amoeba show much better performance than *Fixed*. In both cases, Amoeba accepts around 15% more tenant requests than *Fixed* consistently. This is because Amoeba resource allocation algorithm fully takes advantage of the malleability provided by the flexible DNA model. In contrast, in *Fixed* the bandwidth reservation is pre-determined and cannot be changed during runtime, and such inflexibility leads to higher rejection rate.

[5] We set the arrival rate to be at most 8/50 in G-scale/IDN because the network is already saturated under such rate and higher arrival rate will not cause obvious changes in network utilization and throughput.

Figure 8 (b)/(c) and Figure 9(b)/(c) show the network utilization and throughput. Due to the same reason as above, Amoeba outperforms *Fixed* in both topologies. In many cases, Amoeba achieves 40%-60% higher network utilization than *Fixed*. In terms of throughput, Amoeba also outperforms *Fixed* by 50%-60% in most cases.

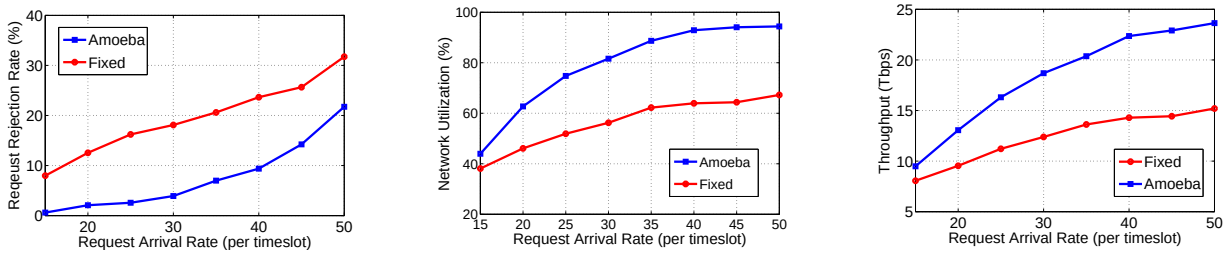
8.4 Amoeba vs. Current Inter-DC TE

We compare Amoeba with deadline-oblivious TE solutions, such as SWAN [8] and Netstitcher [15], in G-scale topology. We adopt SWAN's allocation algorithm per timeslot with an objective of maximizing the throughput in the current slot. Netstitcher models the data delivery for each request as a minimum transfer time (MTT) problem [15]. We approximate its allocation algorithm for each incoming request. We define request success rate as the percentage of requests that meet deadlines. As Amoeba offers deadline guarantees, the request success rate of Amoeba equals to its request acceptance rate.

Note that we omit the comparison between Amoeba and Tempus [13]. The reason is that Tempus focuses on fairness and maximizes the minimal fraction among all transfers delivered until deadlines, but does not guarantee the completion of any transfer before deadline. When demands exceed network capacity, Tempus always tries to fairly share the limited bandwidth among all requests, leading to a very low or even 0 request success rate.

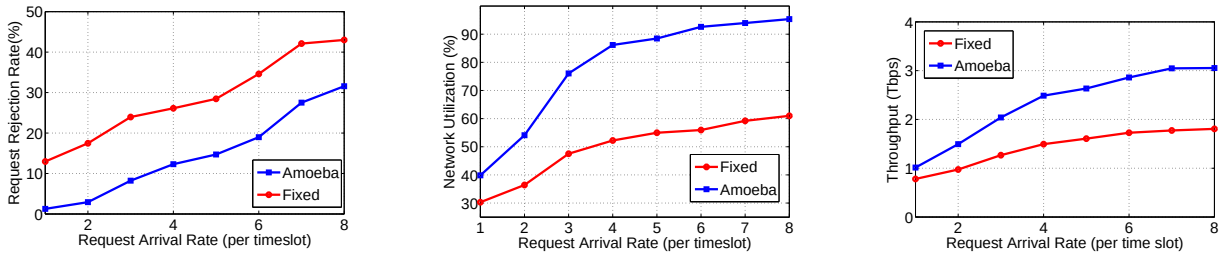
Figure 10 (a) shows the request success rates for SWAN, Netstitcher, and Amoeba respectively. As the arrival rate increases, the request success rate decreases for all three solutions. However, SWAN and Netstitcher experience a more dramatic drop than Amoeba. This is because SWAN greedily allocates requests per timeslot without considering the deadlines, while Netstitcher only tries to minimize the transfer time regardless of the deadlines. As a result, as the arrival rate increases, more requests will miss their deadlines. We also find that the request success rate of Netstitcher is higher than that of SWAN. This is because SWAN splits bandwidth among multiple transfers and it is possible that very few of them can meet their deadlines when the number of requests is large. On the other hand, Netstitcher serves requests in a first-come first-served fashion, and thus the first few requests can always meet their deadlines.

Figure 10 (b) and Figure 10 (c) show the network utilization and throughput. In the figures, *total* network utilization refers to the network utilization of all (including partially allocated) requests, and *effective* network utilization only refers to the requests that meet their deadlines. *Total* and *effective* throughput are defined in a similar way. From the figures, we observe that the deadline-agnostic solutions achieve high total network utilization and throughput, but very low effective network utilization and throughput. This result is expected because they do not respect deadlines. In contrast, Amoeba maintains much better effective network utilization, as it has a much higher request success rate by guaranteeing deadlines.



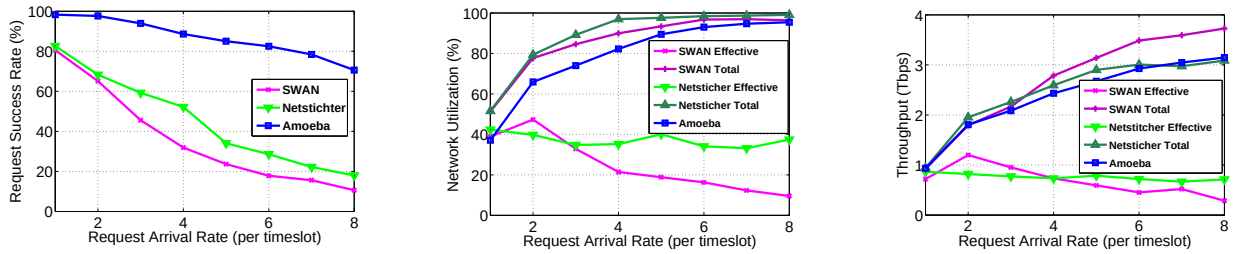
(a) Request rejection rate (b) Network utilization (c) Throughput

Figure 8. Amoeba vs. Fixed minimum bandwidth guarantee in IDN topology



(a) Request rejection rate (b) Network utilization (c) Throughput

Figure 9. Amoeba vs. Fixed minimum bandwidth guarantee in G-Scale topology



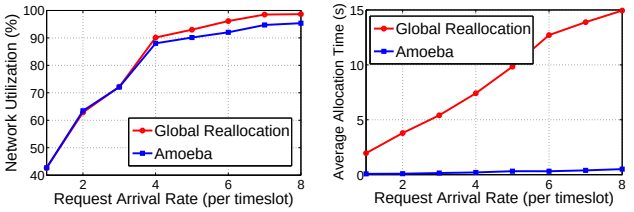
(a) Request success rate (b) Network utilization (c) Throughput

Figure 10. Amoeba vs. deadline-oblivious TE in G-Scale topology

8.5 Effectiveness and Scalability

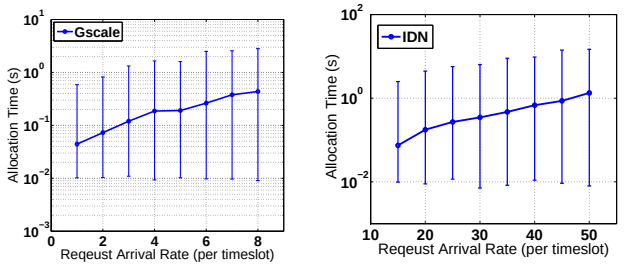
Effectiveness: To demonstrate the effectiveness of Amoeba, we compare it with a strawman global optimization algorithm in G-Scale. Whenever a request comes, the global optimization algorithm reallocates all previous requests using a similar formulation as AS. Figure 11 (a) shows the network utilization of Amoeba and the global optimization algorithm (we observed similar results in terms of request acceptance rate and throughput as well). We find that Amoeba performs almost the same as the global optimization algorithm under low arrival rate, and is slightly worse than it (by around 3%) as the arrival rate increases. The reason behind this is as follows. First, when the arrival rate is low, both algorithms are able to accept most of the requests, thus achieving almost the same performance. Second, as the arrival rate increases, there are more requests to handle. Since Amoeba only reallocates a subset of relevant requests when handling the new ones (§6.2), it becomes less effective than the optimal solution that performs a global reallocation. As a consequence, some requests accepted by the global reallocation may be rejected by Amoeba.

In Figure 11 (b) we can see that Amoeba achieves 30× speedup in terms of average allocation time compared to the global optimization algorithm. Note that the allocation time of the global optimization algorithm in Figure 11 (b), i.e., tens of seconds, might be acceptable for some transfer requests, however Amoeba can achieve comparable performance in a much shorter time. And it is always desirable to have shorter time in admission control for timely decision on user requests. Furthermore, as the global optimization algorithm requires reallocation of all previous allocated requests, the time cost can increase dramatically as the arrival rate increases, which eventually results in unacceptable allocation time under higher arrival rate. In this regard, the time cost of Amoeba increases much slowly as shown in Figure 11 (b).



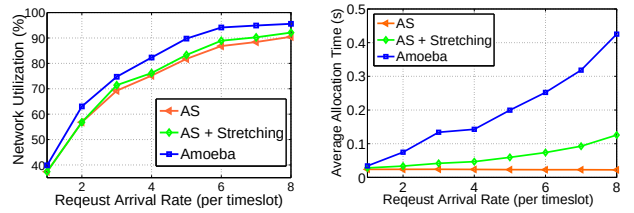
(a) Network utilization (b) Average allocation time

Figure 11. Amoeba vs. strawman global optimization



(a) G-Scale (b) IDN

Figure 12. The min/mean/max Amoeba allocation time



(a) Network utilization (b) Average allocation time

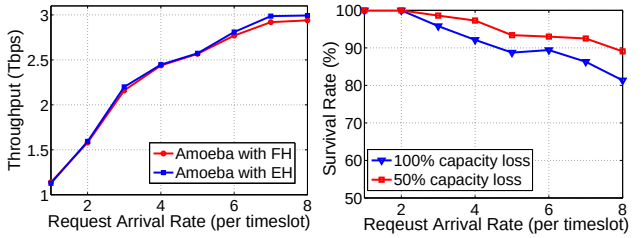
Figure 14. The incremental benefit of local stretching and joint rescheduling

Scalability: We quantify Amoeba's scalability by measuring the allocation time per request in both G-Scale and IDN. The simulation is performed on a server with 384G memory and 2 quad-core 2.8GHz Xeon CPUs.

As shown in Figure 12, the average allocation time is less than 0.5 second in G-Scale and less than 1.5 seconds in IDN, and the maximal allocation time is only about 6 seconds. The results indicate that the allocation time has positive correlation with the network size; IDN is larger and thus has a longer allocation time in general. Another observation is that the allocation time increases as the arrival rate increases. This is because most requests can be easily and quickly allocated using only AS under low arrival rate. However as the arrival rate increases, the average allocation time increases since OR is more frequently invoked.

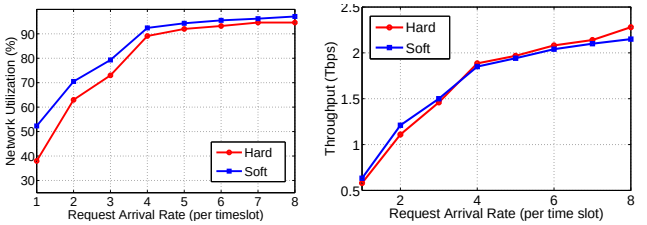
8.6 Component-wise Benchmark

Performance breakdown: We use simulations to show the benefits of AS and OR individually. Figure 13 shows



(a) Benefit of EH (b) Amoeba under link failure

Figure 15. Mispredictions and failures



(a) Network utilization (b) Throughput

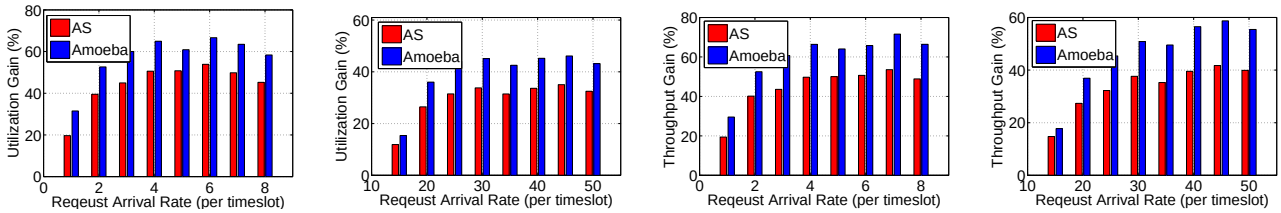
Figure 16. Soft-deadline vs. hard deadline

the gain of AS and Amoeba (AS + OR), and we use *Fixed* as the baseline. From the figure, we can see that AS contributes around 20%-40% performance gain over *Fixed* under most arrival rates, and OR can bring additional 7%-12% performance gain.

We further check the benefits of two operations in OR, i.e., local stretching and joint rescheduling. Figure 14 shows the results. Local stretching brings around 2%-4% utilization gain and 2%-3% improvement in acceptance rate (not shown in the figure), at the cost of increasing allocation time from 0.02 to 0.1 second on average. Joint rescheduling brings 4%-8% utilization gain at the cost of increasing allocation time from 0.1 to 0.4 second on average.

Mispredictions and failures: To show the benefit brought by Amoeba's evolving headroom (EH) when dealing with mispredictions, we simulate a variant of Amoeba with a fixed headroom (FH). Figure 15 (a) shows that, with EH, Amoeba can set aside more bandwidth for deadline transfers, and thus results in 2% higher throughput. Note that this is not a small number considering that the total interactive traffic only accounts for 5%-15% of the link capacity.

To test Amoeba under link failure, we use G-Scale and randomly fail an inter-DC link. Since an inter-DC link can contain multiple physical fibers [8], we consider two cases: 100% link capacity loss and 50% link capacity loss. We run the failure handling procedure described in §5.2.2 and calculate the survival rate, which is the portion of successfully reallocated requests over all affected requests. Figure 15 (b) shows the result. We observe that almost all the affected requests can be successfully reallocated under low arrival rate. Moreover, Amoeba still achieves over 80% and 90% survival rate respectively under high arrival rate.



(a) Utilization gain (G-Scale) (b) Utilization gain (IDN) (c) Throughput gain (G-Scale) (d) Throughput gain (IDN)

Figure 13. The benefit of the two components of Amoeba

Effect of soft deadlines: So far we assume that all requests have hard deadlines. We now extend hard deadlines to soft deadlines, and we use G-Scale in our simulation. In Figure 16, the red curve shows the performance when all requests are assigned with hard deadlines, and the blue curve shows the performance with soft deadlines (20% extension based on the hard deadlines). We observe that under low request arrival rate, soft deadlines bring better network utilization and throughput. This is because a rejected request with a hard deadline still has a chance to be accepted with a looser soft deadline.

However, under high arrival rate, soft deadlines do not always perform better than hard deadlines in terms of throughput. One possible reason is that many previously rejected requests are accepted. These requests are "harder" to accommodate and less "cost-efficient" (i.e., can only be accepted by taking some longer paths), thus are likely to hinder some more cost-efficient requests (requests which are easily accepted using shorter paths) later on. Therefore, the link capacity are less effectively used because more requests use longer paths. Network utilization is not affected by this as the link capacity are eventually exhausted in both cases.

9. Related Work

There are many related works on datacenter traffic optimization or deadline-aware flow scheduling. However none of them can directly solve our problems in Amoeba.

TE for Inter-DC WAN networks has attracted great interest recently. B4 [9] presents Google's inter-DC WAN solution based on the popular software-defined networking technology; its centralized TE drives links to near full utilization. Similarly, SWAN [8] also boosts the utilization of inter-DC WAN by scheduling the service traffic in a centralized manner; it further achieves congestion-free and disruption-free updates. However, they both are deadline-agnostic.

More recently, Tempus [13] has been proposed to maximize the fraction of transfer delivered before deadline. It achieves fairness among all the requests, but does not guarantee the completion of any of them. Relative to Tempus, Amoeba maximizes the number of transfers completed before their deadlines, which is more suitable for applications with hard deadlines. Moreover, the abstraction of Tempus deals with each transfer individually, whereas Amoeba takes the correlation among multiple transfers into consideration.

NetStitcher [15] focuses on using a store-and-forward approach to schedule large scale data transfers between DCs, but without considering any transfer deadlines. In contrast, Amoeba moves one step further by adding a deadline-aware transfer interface into the system so that providers can develop algorithms to better utilize expensive WAN bandwidth to guarantee transfer deadlines.

In the context of Intra-DC networks, there are several bandwidth guaranteed abstractions [2, 6, 12, 17, 20, 23]. For example, SecondNet [6] enforces bandwidth reservation between every pair of VMs. Oktopus [2] proposes two virtual cluster (VC) models, one non-oversubscribed and one oversubscribed of bandwidth. Gatekeeper [20] and EyeQ [12] can enforce hose model for congestion-free networks. TIVC [23] tries to catch the time-varying nature of the networking requirement by defining time-interleaved virtual clusters. ElasticSwitch [17] achieves bandwidth guarantee and work conservation simultaneously. Our DNA abstraction allows requests to be expressed in terms of the volume of data to be delivered and the deadlines by which they must be delivered. This is more appropriate for deadline-driven inter-DC bulk transfers.

There are new protocols designed to meet the flow deadlines (or finish flows faster) in intra-DC networks, e.g., [7, 21, 22, 24]. They are handling flow deadlines at the millisecond level, and most rely on the short round-trip-time in intra-DC environment for effective congestion or rate control. The problem of scheduling large transfers in inter-DC WAN is fundamentally different, as it operates at a much longer time scale (with a deadline of minutes or hours) and schedules requests which are aggregations of many flows [13].

In the context of Grid networks, some works such as [3, 19] have studied the problem of deadline-aware data transfer. However, the discrepancy between the Grid networks and the inter-DC WANs makes it hard to directly apply their solutions to our problems in Amoeba. First, they do not consider practical issues in inter-DC WANs such as traffic priorities, mispredictions, traffic dynamics and failures. Second, the modelings and abstractions in [3, 19] cannot capture the demands of inter-DC applications, e.g., soft deadlines, and barrier-synchronized deadline transfers in a request. Moreover, neither of these works achieves a good balance between

scalability and optimality. For example, Chen's scheduling algorithm [3] and the SR module in [19] are ineffective as they assume the previous allocations to be fixed. On the other hand, the RR module proposed in [19] is too time-consuming for real-time allocations because it blindly applies a global optimization.

10. Conclusion

A large portion of Inter-DC transfers have deadlines, however, currently no mechanism is in place to ensure such deadlines. This paper introduces a deadline-based network abstraction, DNA, as an interface that allows tenants to explicitly express an inter-DC transfer request in terms of the data volume and the deadline by which it must be delivered. Our system, Amoeba, performs on-line admission control and enforcement to implement DNA in a scalable manner. Our evaluation shows that Amoeba effectively accommodates more transfer requests with deadline guarantees, while achieving around 60% higher network throughput than state-of-the-art bandwidth guarantee solutions.

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