Sharing the Cost of Backbone Networks
Cui Bono?

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ABSTRACT
We study the problem of how to share the cost of a backbone network among its customers. A variety of empirical cost-sharing policies are used in practice by backbone network operators but very little ever reaches the research literature about their properties. Motivated by this, we present a systematic study of such policies focusing on the discrepancies between their cost allocations. We aim at quantifying how the selection of a particular policy biases an operator's understanding of cost generation.

We identify F-discrepancies due to the specific *function* used to map traffic into cost (*e.g.*, volume vs. peak rate vs. 95-percentile) and M-discrepancies, which have to do with where traffic is *metered* (per device vs. ingress metering). We also identify L-discrepancies relating to the *liability* of individual customers for triggered upgrades and consequent costs (full vs. proportional), and finally, TCO-discrepancies emanating from the fact that the *cost of carrying a bit* is not uniform across the network (old vs. new equipment, high vs. low energy or real estate costs, *etc.*).

Using extensive traffic, routing, and cost data from a tier-1 network we show that F-discrepancies are large when looking at individual links but cancel out when considering network-wide cost-sharing. Metering at ingress points is convenient but leads to large M-discrepancies, while TCO-discrepancies are huge. Finally, L-discrepancies are intriguing and esoteric but understanding them is central to determining the cost a customer inflicts on the network.

Categories and Subject Descriptors
C.2.3 [**Computer-Communication Networks**]: Network Operations; J.4 [**Social and Behavioral Sciences**]: Economics

Keywords
cost sharing, backbone network, network economics, fairness

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1. INTRODUCTION
After several years of growth during which Internet Service Providers (ISPs) have enjoyed healthy profit margins, we are entering a new era in which margins are progressively declining. This is due to intense competition that pushes prices down, while at the same time traffic increases faster than the ability of technology to reduce capital (CAPEX) and operational (OPEX) expenses. The viability of an ISP in such a competitive ecosystem will largely depend on its ability to understand and manage its costs.

Understanding and optimizing the total cost of ownership (TCO) of a network, *i.e.* both CAPEX and OPEX, is an important aspect of network operations and therefore it has received substantial attention from procurement, network development, and network planning departments of large telcos [23]. However, the impact of individual customers on the cost of the network, which in the case of backbone networks are other (smaller) networks and big enterprises, is much less understood. There are multiple reasons for this, including the difficulties of monitoring usage statistics for each customer at each device, variable per device TCO, and non-linearities of cost-capacity functions. There is also the issue of which customer's additional traffic demand forces the operator to upgrade his network in order to maintain the Service Level Agreement (SLA) for all customers, that is, which customer is liable for a *triggered upgrade* and to what extent.

Overcoming such challenges and quantifying in detail how individual customers affect the TCO of a network is crucial and can be used for provisioning and operations purposes, including routing and peering. It can also be used for creating better tariff schemes, *e.g.*, to give discounts to customers inflicting low costs or justify premiums in the opposite case. Tariffs are also influenced by additional factors including regulation, competition, and demand, and thus their relationship to cost is not necessarily directly proportional. In this paper we analyze a wide range of cost-sharing policies used in practice by backbone operators and contrast their outcome using extensive input data from a tier-1 backbone network, including 590 ingress interfaces to large customers, 691 main backbone links, and 71 core routers spread over 3 continents. Our main objective is to see *how the selection of a certain cost-sharing policy impacts the picture that an operator has about which customers generate high costs.*

Our main contributions are:

- The development of a methodology for studying multiple facets of cost-sharing in multi-resource environments such as a backbone network. [1]

- We analyze multiple cost-sharing policies of varying complexity and accuracy under various settings. Our analysis reveals large discrepancies among different policies when splitting the cost of an individual network element among the customers that use it: in 20% of cases the ratio of costs associated by two different policies is under 0.5 or over 2. This in turn implies that operators must be careful in selecting among different policies since their cost-allocation outcomes may vary widely for individual devices or small networks.

- The above is a negative result but luckily it becomes less severe when one considers cost-sharing among all the devices that constitute a large network. In this case, individual discrepancies at the device level cancel out as one sums them up across a network. This in turn points to an opportunity for selecting cost-sharing policies from the least complicated side of the spectrum without risking much sacrifice in terms of accuracy.

- Metering only at ingress links (which is the de-facto norm in monitoring the customer's usage) may greatly under- or over-estimate the actual costs, depending on the locality of the traffic and temporal characteristics of the customer.

- We study additional aspects of cost-sharing related to the issues of liability for triggered upgrades, and discrepancies due to non-uniform TCO costs of different network elements.

The structure of the paper is as follows. In Section 2 we give an overview on what determines the cost of a backbone network and present why the sharing of these costs is a challenging task. We present our methodology in Section 3, where we introduce four different aspects that affect the quantified costs of the customers. We describe our datasets in Section 4. We investigate the costs of customers and the severity of the different types of discrepancies in Section 5. Afterwards, we review the related work in Section 6 while we draw the conclusions of our work in Section 7.

2. BACKGROUND

What contributes to the cost of a backbone? The cost of a network consists of CAPEX and OPEX for all devices and Points-of-Presence (PoPs). The CAPEX is the one-time cost paid whenever equipment is bought and installed [23]. It depends on the amount of traffic the device must carry at a specific level of Quality-of-Service (QoS). A key observation is that *the capacity needed to guarantee a certain QoS depends on the peak traffic that needs to be carried*. This is because for a given capacity, QoS is minimized when the traffic peaks.

The OPEX corresponds to operational costs such as real estate, energy, and personnel. It also depends on the amount of traffic and the QoS; however, that dependence is more elastic. The cost sharing policies we discuss are generic enough to capture both CAPEX and OPEX with appropriate parameterization.

Why is it difficult to split cost among customers? From the above discussion, one may conclude that splitting the cost among customers is straightforward: for each device of the network each customer should pay in proportion to his contribution to the peak traffic carried by the device and then sum up over all devices. Things, however, are not that simple:

- **Accounting complications.** It is difficult to know for each network device the contribution of each customer to its peak. This is because backbone operators need to measure and keep state at many points in the network, which requires costly monitoring equipments. In addition, computing traffic rates introduces the problem of identifying the appropriate time-scale for the computation owing to the limited resources of the monitoring tools.

- **Liability complications.** If we were to build from scratch a new network for a fixed set of customers of known demand, then the cost attributed to each customer should be proportional to the sum of its contributions to the peaks of individual devices. Splitting costs based on the contribution to the peak is indeed exact, but only for this "offline problem". However, in reality, networks are not deployed as a single event but grow organically with the addition of new customers and the ramping up of their traffic. Under this more realistic case, peak-based cost-sharing is not guaranteed to be fair. Consider for example the case in which a network is already operating at the maximum utilization allowed by QoS constraints and a small new customer triggers an expensive upgrade that leads to a new network with plentiful unallocated capacity (upgrades typically involve large jumps, *e.g.*, 1Gbps to 2.5Gbps, to 10Gbps, *etc.*). Peak-based cost sharing would attribute to the new customer only a small fraction of the overall cost. Is that fair? The answer depends on what happens with the unallocated capacity. If the network can easily sell it to new or existing customers then indeed it is fair. If, however, selling this leftover capacity is not guaranteed, then the new customer may have a larger liability for the upgrade costs.

For the above reasons, we will present a methodology in which we first compare among policies of varying complexity, and then switch to comparing among policies that assign different liability levels.

3. METHODOLOGY

In this section, we present a thorough classification of the discrepancies between methods when a backbone operator quantifies the costs that its customers inflict on the network. By *discrepancy* we mean the difference in a customer's costs according to two cost sharing policies. Each type of discrepancy reveals a separate facet of the challenge of customer cost quantification. These facets relate to the following questions:

- How does the backbone operator compute the cost of the customers?

[1] Our methodology is sufficiently general to be applied in settings beyond backbone networks, such as 3G networks, datacenters, *etc.*, but we do not examine such cases here.

- What kind of traffic metering does the backbone operator apply in the network?
- Which customers are liable for the incurred costs?
- How diverse are the costs of the components of the network?

Before presenting the taxonomy of discrepancies, we first introduce the metric we use to quantify the discrepancies of a pair of cost sharing procedures. Let N denote the set of customers who utilize resources in the network. Let A and B denote the sets of costs allocated to each customer using two different cost sharing policies. It holds that $|A| = |B| = |N|$. Accordingly, $a_i \in A$ denotes the cost of customer $i \in N$ quantified based on the first cost sharing policy while $b_i \in B$ represents customer i's cost based on the second policy. We define the discrepancy of the costs of customer i as

$$d(a_i, b_i) = \max\left\{\frac{a_i}{b_i}, \frac{b_i}{a_i}\right\} \tag{1}$$

We use this measure of discrepancy because it describes the relation of the costs with a simple, comprehensible value. We use several statistics of the customers' individual discrepancies to quantify the discrepancy of two cost sharing policies including the 95th percentile and the median.

We now describe how we determine the aggregate cost that the sharing policies distribute. A network consists of various network devices, such as routers and links. Let L denote the set of devices of the network. Let $x_i^l(t)$ denote the traffic volume of customer $i \in N$ on network device $l \in L$ during the time interval $t \in [1, T]$. Furthermore, let c^l denote the cost of network device $l \in L$.

The cost of a specific device depends on the maximum amount of traffic that it has to carry during a certain time interval. Thus, we obtain c^l by examining the available capacity rates of the device (*e.g.*, 1 *Gbps*, 10 *Gbps*, *etc.*) and then using the cost of the smallest device whose capacity satisfies the requested Service Level Agreement (SLA) for the given traffic demand. We assume that the backbone operator fulfills its SLA by upgrading its devices when utilization hits the 50% threshold. To this end, we assume that the costs follow a step function $C : \mathbb{R} \to \mathbb{R}$. Thus, the cost of device l is

$$c^l = C\left(\max_{t \in T} \sum_{i \in N} x_i^l(t)\right) \tag{2}$$

3.1 F-discrepancies

The first source of discrepancies between cost allocation methods is the *function* that the backbone operator uses to compute the contribution of the customers to the aggregate cost. We next present four policies that strike different balances between precision and resource needs, which we discuss in more details at the end of this section. We consider these methods because backbone operators apply some of these policies (*e.g.*, the 95Percentile-Customer and the Aggregate-Peak-Device) in practice to determine the costs a customer inflicts and consequently the price the customers pays. For example, one can easily map some of the tariffs (*e.g.*, based on the purchased raw capacity or on the 95th percentile of the traffic) used in practice to the introduced policies (*e.g.*, Volume-Customer and 95Percentile-Customer).

- **Volume-Customer.** We measure the amount of data that a single customer sends on a specific network device (e.g., on a single link) for the whole analyzed time period. Afterwards, we share the cost of the device proportionally to the traffic volumes of the customers using it. Hence, the cost of customer i for device l is:

$$c_i^l = c^l \cdot \frac{\sum_{t \in T} x_i^l(t)}{\sum_{j \in N} \sum_{t \in T} x_j^l(t)} \tag{3}$$

- **95Percentile-Customer.** We distribute the cost of the device proportional to the 95th percentile [12] of the customers' traffic that traverses the particular device:

$$c_i^l = c^l \cdot \frac{P_{95}\left(\ldots, x_i^l(t), \ldots\right)}{\sum_{j \in N} P_{95}\left(\ldots, x_j^l(t), \ldots\right)} \tag{4}$$

where $P_{95}()$ denotes the 95th percentile of the arguments.

- **Peak-Customer.** Under this policy, we share the expenditure of the network device proportional to the customers' maximum usage volumes for the given time interval:

$$c_i^l = c^l \cdot \frac{\max_{t \in T} x_i^l(t)}{\sum_{j \in N} \max_{t \in T} x_j^l(t)} \tag{5}$$

- **Aggregate-Peak-Device.** Backbone operators plan the capacity of the network based on the maximum utilization, *e.g.*, the 50% of the capacity of a device is larger than the expected maximum of the traffic that traverses it. Accordingly, we distribute the cost of the devices based on the contribution of individual customers to the peak utilization. Assuming that the peak utilization of device l happens at time step $t_m = \arg\max_t \sum_{j \in N} x_j^l(t)$, we allocate the following cost to customer i as:

$$c_i^l = c^l \cdot \frac{x_i^l(t_m)}{\sum_{j \in N} x_j^l(t_m)} \tag{6}$$

We evaluate F-discrepancies by comparing a policy with Aggregate-Peak-Device, which shares the costs in a fair way when it is guaranteed that new unallocated capacity from an upgrade will soon find a customer to amortize it. The F-discrepancies of the policies arise from the misalignment of traffic peaks: the peak of a customer's traffic may not coincide with the peak of the aggregate traffic the device carries.

Illustrative example: Let us assume that two customers utilize device l_1 with the time-series depicted in Fig. 1. Based on the time-series we compute the costs of the customers. The percentages of the cost that customer 1 covers are 69.9%, 56.2%, 60%, and 53.3% of the total cost of the device for the Volume-Customer, Peak-Customer, 95Percentile-Customer, and Aggregate-Peak-Device policies, respectively. For example, in case of the 95Percentile-Customer policy, customer 1 has a traffic of 0.9 Gbps while the cumulative traffic is 1.5 Gbps resulting in 60% cost share. The main cause behind the discrepancies of the costs are the misalignment of the customers' peak, and that the different policies consider diverse parts of the time-series to compute a value that describes the traffic of the customer.

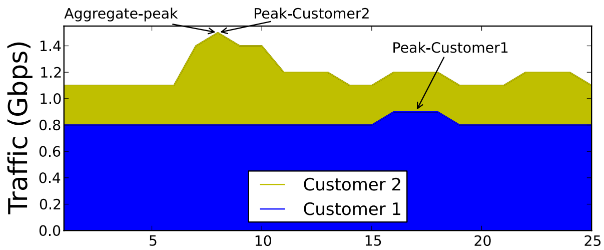


Figure 1: Illustrative example for F-discrepancies. The misalignment of the customers' peak causes cost differences across policies.

The introduced policies quantify the cost of the customers using different functions on a per device basis. The F-discrepancies of the customers emerge at two different levels:

- **Device-level discrepancies.** We compute separately for each network device the discrepancy among different policies based on the customers' costs. In this case, the set of costs is

$$\left\{c_i^l \mid \forall i \in N\right\}, l \in L \tag{7}$$

and has cardinality $|N||L|$. For example, the F-discrepancy of customer i in case of policies a and b is $d(a_i^l, b_i^l)$.

- **Network-level discrepancies.** We first summarize the costs of a customer over all the devices of the network, *i.e.*, we compute the total cost of each customer. Afterwards, we compute the discrepancies of the policies. In this case, the set of the costs over which we compute the discrepancies is

$$\left\{\sum_{l \in L} c_i^l \mid \forall i \in N\right\} \tag{8}$$

and has cardinality $|N|$. For example, for policies a and b the F-discrepancy of customer i is $d(\sum_{l \in L} a_i^l, \sum_{l \in L} b_i^l)$.

3.2 M-discrepancies

The traffic *metering* method is the second source of discrepancies. The resource requirements of the traffic monitoring tools depend on the resolution of metering. The main cause behind the M-discrepancies is the trade-off that backbone operators face: increasing the precision of the metering improves the validity of the quantified cost, however, this comes with an elevated cost for traffic monitoring. We study the two corner cases of traffic metering:

- **Customer-Ingress.** Each customer has several ingress devices through which it injects its traffic to the network. The backbone operator keeps track of the customers' usage solely on the ingress devices. This is the least expensive metering method. The operator uses the ingress traffic time-series to share the network-wide expenditures among the customers.

- **Customer-per-Device.** If the backbone operator deploys more advanced network monitoring tools, it can capture the time-series of the customers not only on the ingress devices but on all the devices located in the network. This is the most expensive metering method and is typically done using NetFlow technology, which comes at a high procurement and administration cost. Metering the actual traffic on each network device allows the backbone operator to compute the costs of the customers based on the device specific time-series. Therefore, the backbone operator faces a trade-off: more accurate expenditure sharing vs. more cost efficient operation.

We define the M-discrepancies as follows. First, we compute the cost of customer i on each device l using a given cost allocation function (*e.g.*, based on the Volume-Customer policy of Section 3.1), and we compute the network-level cost of customer i as $\sum_{l \in L} c_i^l$. Second, we compute using the given cost allocation function the customer's share (c_i^*) of the network's total cost ($c = \sum_{l \in L} c^l$) using the ingress traffic time-series of the customers. The total ingress traffic of customer i is $x_i^*(t) = \sum_{l \in I_i} x_i^l(t)$ where I_i denotes the set of ingress devices that customer i has. Accordingly, the M-discrepancy of customer i is

$$d_i\left(\sum_{l \in L} c_i^l, c_i^*\right) \tag{9}$$

where d_i is our metric of discrepancy (Eq. 1).

Illustrative example: Let us now assume that the ingress traffic of the customers is as we show in Fig. 2. The backbone network consists of two devices: L_1 on which the traffic of the customers is as depicted in Fig. 1 and L_2 which is solely utilized by customer 1 with a constant traffic of 1 *Gbps*. For illustration purposes, we separate the two flows of customer 1, one on L_1 and the other on L_2, with a dashed line in the Fig. 2. Because the traffic on device L_2 is modest it can be transmitted on a 2.5 *Gbps* device while the capacity of L_1 should be 10 *Gbps*. The diverse device capacities imply diverse costs as well. In the case of ingress metering, *i.e.*, sharing the cost of the network just based on the aggregate traffic shown in Fig. 2, the cost of customer 1 is 83.9%, 73.1%, 76%, and 72% of the cost of the whole network for the Volume-Customer, Peak-Customer, 95Percentile-Customer, and Aggregate-Peak-Device policies, respectively. However, if we measure the traffic of the customers on all the devices then customer 1's shares of costs are 75.9%, 65%, 68%, and 62.7%. If we compare these cost fractions we encounter large discrepancies caused by the level of the metering.

3.3 L-discrepancies

The third type of discrepancies is caused by the different types of customer *liability* as discussed in Section 2. We will examine the following policies:

- **Aggregate-Peak-Device.** This is the already introduced policy that is the measure of fairness when the customer liability is proportional to the aggregate peak of devices.

- **Trigger.** With this policy, the backbone operator allocates the cost of the device exclusively to the customer

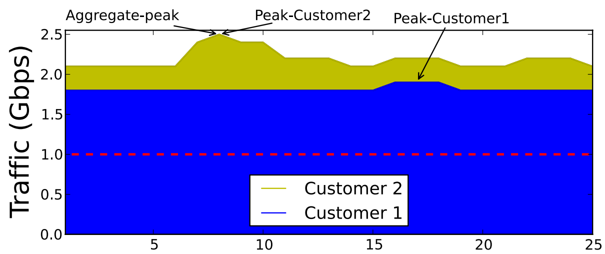


Figure 2: Illustrative example for M-discrepancies: metering traffic only at the ingress link causes customer 1 to have a larger share of the cost than if we meter at all devices.

that triggered the capacity upgrade. This policy is applied when the backbone operator is not confident that it can sell the newly obtained but unallocated capacity.[2]

To this end, the backbone operator utilizes the historical traffic patterns of the customers and their arriving order. For example, the cost of the first customer is equal to the cost of the device that is capable to transmit his traffic demand. We assume that the customers are numbered based on their arriving order while t_i denotes the time when the customer started to use the network. Accordingly, the cost of customer i in case of the Trigger policy is

$$c_i^l = C(\max_{t \le t_i} \sum_{j \in \{N|j \le i\}} x_j^l(t)) - C(\max_{t \le t_i} \sum_{j \in \{N|j<i\}} x_j^l(t_i)) \tag{10}$$

The main drawbacks of Trigger are: a) it assigns cost only to the customer whose traffic trigger upgrades and 0 to everyone else, therefore order of arrival can have a huge impact on the costs attributed to a customer; and b) it is difficult to compute Trigger since it requires extensive historical data on the order of customer arrival and traffic build up.

- **Shapley.** The Shapley cost sharing policy lies between the two above presented extremes; the Aggregate-Peak-Device and Trigger policies. It assigns to customers partial liability for upgrades, thereby avoiding the all-or-nothing assignments of Triggers. Therefore it is less strict than Trigger but more strict than Aggregate-Peak-Device since it assigns "averaged" liabilities rather than proportional liabilities based on a single time interval when a device peaks.

  The main advantage of the Shapley over the Aggregate-Peak-Device policy is that its allocations are more stable than that of the Aggregate-Peak-Device policy in view of customer churn. For example, let us imagine that the aggregate peak traffic of a device is P and appears at t_1. We also assume that the device at time t_2 has load $P - \epsilon$. Now let us suppose that customer X is responsible for 90% of P at t_1 and 1% of $P - \epsilon$ at t_2. Then if a small 2ϵ customer leaves from P at t_1 then the peak will move to t_2 and X will go from paying 90% to paying only 1% after a tiny 2ϵ perturbation of the aggregate traffic. On the contrary, the Shapley policy is aware of such situations as it takes into account all the local maxima of the aggregate traffic in quantifying the costs of the customers.

  Under the Shapley policy, the cost of each customer is proportional to its average marginal contribution to the device's total cost. Particularly, let us consider all the possible $S \subset N$ subsets (coalitions) of the customers who utilize resources of the network device l. The cost of coalition S depends on the aggregate traffic volume of the participants, *i.e.*, it is equal to the cost of a network device that has sufficient capacity:

$$v^l(S) = C\left(\max_{t \in T} \sum_{j \in S} x_j^l(t)\right) \tag{11}$$

  Based on the v cost function of the coalitions, we compute the Shapley value of customer i as

$$\phi_i(v^l) = \frac{1}{N!} \sum_{\Pi \in S_N} \left(v^l(S(\Pi, i)) - v^l(S(\Pi, i) \setminus i)\right) \tag{12}$$

  where Π is a permutation of arrival order of the set N and $S(\Pi, i)$ denotes the set of players who arrived no later than i. The $(\phi_1(v), \ldots, \phi_N(v))$ Shapley values describe the fair distribution of costs in the case of the $S = N$ grand coalition. Fair in a way that it satisfies four intuitive fairness criteria [1, 13, 22]. We quantify the cost of customer i based on its Shapley value for the device l as

$$c_i^l = c^l \cdot \frac{\phi_i(v^l)}{\sum_{j \in N} \phi_j(v^l)} \tag{13}$$

  While computing the aggregate traffic volumes of the coalitions, we assume that the routing inside the network is static, *i.e.*, removing some traffic from the network device does not affect the traffic volumes of other customers (*e.g.*, the backbone operator does not apply load balancing mechanisms).

[2]Recall that upgrades generally involve large jumps that can leave substantial unallocated capacity.

Illustrative example: We present the traffic patterns of two customers and the thresholds where the capacity of the device needs to be upgraded in Fig. 3. Customer 1 is liable for 53.3% and 87.5% of the cost of the device in case of the Aggregate-Peak-Device and Shapley policies. The peak of the aggregate traffic happens in a time step where the customers' traffic volumes are balanced. Although there are local maxima where the traffic of customer 2 is small, it is not considered by the Aggregate-Peak-Device policy. From a Shapley policy viewpoint, the traffic peak of customer 1 is too large to be transmitted with a lower-capacity device, *i.e.*, its traffic is mainly responsible for the total cost of the device. If we assume that customer 1 arrived first it causes 100% of the costs according to the Trigger policy because its peak needs a larger-capacity device whose leftover capacity can be used by customer 2 afterwards.

Customers can have both *device-* or *network-level* L-discrepancies, depending on whether we consider the costs

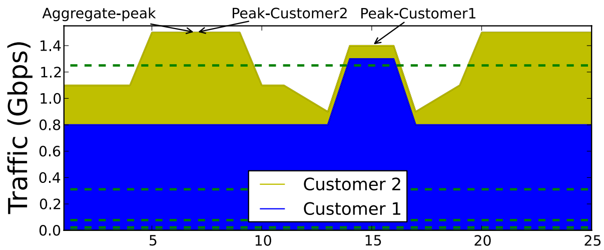


Figure 3: Illustrative example for L-discrepancies

of the customers on particular devices (*e.g.*, c_i^l) or on the aggregate (*e.g.*, $\sum_{l \in L} c_i^l$).

3.4 TCO-discrepancies

The final class of discrepancies is related to the *Total Cost of Ownership (TCO)* of different devices of the network. Due to the heterogeneous nature of the network—caused by the geographic and technological differences of its parts—the same traffic patterns imply diverse expenditures for the backbone operator on different devices. Therefore, additional discrepancies occur when we consider the TCO of the network in more detail. The following levels of TCO impact the costs and the discrepancies of the customers:

- **Pieces of costs.** Even if the capacity of two particular equipment are equal, their costs can vary significantly due to technology differences (newer vs. older generation), location (cost of shipping), differences in purchase price, *etc.*.
- **Point-of-Presence (PoP) costs.** The backbone network operator deals with diverse costs at each geographic location where it has a presence. The causes behind the varying costs include but are not limited to the following factors: energy (*e.g.*, the energy price in Germany can be twice as much as in the UK), facility costs (*e.g.*, the rental cost of office space in Hong Kong can be four times higher than in Germany [9]), taxation, and personnel costs.

Contrary to the former types of discrepancies, in the case of the TCO only network-level discrepancies exist. At the network level, where we summarize the costs of the customers across all the devices, additional discrepancies appear due to the diverse costs of the equipments.

Formally, we define the network-level TCO-discrepancy of customer i as

$$d\left(\sum_{l \in L} c_i^l, \sum_{l \in L} c^l \cdot \frac{\sum_{l \in L} e_i^l}{\sum_{l \in L} \sum_{i \in N} e_i^l}\right) \tag{14}$$

where the first term considers the diverse costs of the devices contrary to the second. e_i^l denotes the cost of customer i in case of device l assuming uniform cost across all the devices ($e^l = e^*, \forall l \in L$).

Illustrative example: If we consider the traffic pattern of the customers in Fig. 1 but we assume that the cost of the investigated device is five times more than before, *e.g.* it is located in a developing country, the costs of the customers also increase by a factor of 5. Accordingly, the TCO-discrepancy is 5 in the case of all the customers.

3.5 Discussion

The cost sharing methods introduced strike various tradeoffs in terms of computational complexity, amount of required information, and accuracy. The Volume-Customer, Peak-Customer, Aggregate-Peak-Device, and 95Percentile-Customer policies require the least *computational resources* due to their sum, maximum, and percentile computations. The Trigger method determines when the device upgrade thresholds are surpassed. Finally, the Shapley policy has the largest complexity as it computes the costs based on the sub-coalitions of the customers. For computational reasons, we consider the 15 largest customers per network device in our evaluations to quantify the Shapley costs. On average, these customers cover 96% of the traffic of the devices.

In terms of the amount of *information*, all the policies except the Shapley and Trigger are similarly modest. They utilize single values for the historical usage (sum and maximum, respectively) and the current traffic volumes. However, the Shapley policy uses the whole time-series of traffic volumes to compute the costs. The information need of the Trigger policy is even larger as it needs both the historical traffic volumes of the customers and their arriving orders.

From a *fairness* point of view, the Aggregate-Peak-device policy is the absolute measure of fairness when the customer liability is proportional to the aggregate peak of devices (Section 3.3). Otherwise, the liability of the triggered network upgrade should be considered. The Shapley policy lies in between the two extreme policies because: a) unlike Trigger, it does not allocate the cost only to the late-comers but to the previous customers as well by considering all possible orders of arrivals; and b) unlike Aggregate-Peak-Device, it does not consider only the time instance of the peak utilization.

We postpone the analysis of the cost sharing policies' *accuracy* to Section 5 where we present a thorough investigation of the policies based on dataset-driven evaluations. Our comparative study has the following structure. We first compare the Aggregate-Peak-Device policy with other more practical, albeit less accurate policies. Then, we compare the Aggregate-Peak-Device policy with the Shapley policy and comment on how much error is introduced ignoring the local peaks.

4. DATASETS

We use several datasets from a tier-1 backbone network, which interconnects with other ISPs that it serves. In our dataset, the network consists of 26 Points of Presence (PoPs) and each customer connects to the network at one or more PoPs through one or more interfaces. Overall there are 590 ingress links, and each ingress link is used by exactly one customer. Internally, the backbone has 71 routers and 691 links, which are typically used by more than one customer. We collected detailed NetFlow-based statistics for each of the internal and ingress links including the traffic volumes to and from each customer on every link in the network. Such information allows us to assess which customer uses which component in the shared infrastructure and how it affects the load on each component.

The per-link and per-customer traffic statistics cover the period from 18 March 2012 to 10 April 2012, with a 2-hour granularity (*i.e.*, reporting volumes sent and received within 2 hours). We have two additional datasets containing time-series with a 5-min and 30-min granularity for one day and one week, respectively. The traffic aggregated over all ingress links peaks at around 1.35 $Tbps$ in both inbound and outbound directions. Thus, without loss of generality, we utilize the time-series of the customers' incoming traffic.

The cost of a network link depends on the one hand on the capacity of the interface, *i.e.*, how much traffic it is capable of forwarding. On the other hand, the geographic location and the applied technology have an impact as well. Hardware costs, energy prices, deployment costs, and taxation, among others, contribute to the cost of a network device. Thereby, it is challenging to accurately quantify the cost of every single device.

To estimate the cost of the network links, we use the wholesale point-to-point transport price database of TeleGeography [29]. We stress that these are the prices of wholesale physical layer circuits, however, do not differ substantially from the actual cost of ownership. In our empirical analysis, we apply the prices of network links with different bandwidth, ranging from E-1 (2 $Mbps$) throughout STM-4 (622 $Mbps$) and 2.5G waves to 40G waves (40000 $Mbps$). The costs of these links define a step function for the network expenditures. Exact values can be provided to interested parties if confidentiality requirements are met. As future work, we intend to extend our analysis using more detailed expenditure datasets that contains information on the OPEX costs related to for example power supply, hosting centers, *etc.*.

5. DATA-DRIVEN EVALUATION

In this section we use the datasets introduced in Section 4 to evaluate the various discrepancies discussed in Section 3. In case of the F-, M-, and L-discrepancies, we use a uniform cost function for the network devices to focus on the specific properties of cost-sharing.

5.1 F-discrepancies

We start by looking at the effect of the function applied to the traffic of a customer.

5.1.1 Device-level F-discrepancies

To showcase the intricacies of F-discrepancies we start with an example based on a backbone link between two major PoPs in Europe. The monthly cost of this link is \$2163. In Fig. 4 we plot the amount of this cost attributed to each one of the 10 largest customers according to the four different policies detailed in Section 3.1. The F-discrepancy, *i.e.*, the ratio of the cost computed by the Aggregate-Peak-Device policy and the cost computed by the simpler policy X∈ [Volume-Customer, 95Percentile-Customer, Peak-Customer] is as high as 2.36 for customer 4 in this example. This particular customer impacts the aggregate peak of the device disproportionally more than the other customers when we focus on the traffic volumes of the customers. For several other customers the F-discrepancies are much milder, *i.e.*, the different cost-sharing policies are more or less in agreement.

We now look at F-discrepancies across all customers and all links in our dataset. In Fig. 5, we plot the the F-discrepancies for the three simpler policies and we summarize the main statistics in Table 1. The results show generally high F-discrepancies. For example, 60% of the customers are assigned 25% higher or lower cost than the

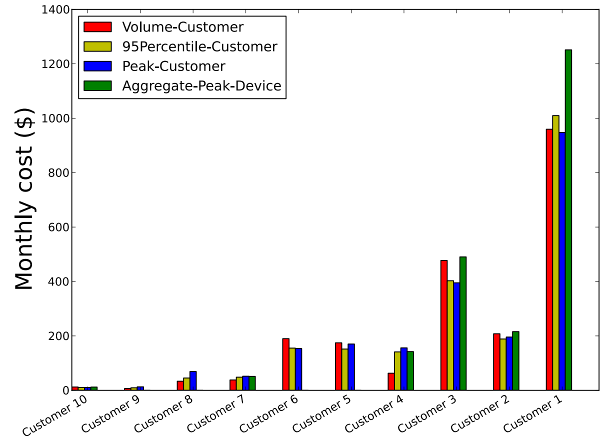


Figure 4: Device-level cost of customers for varying cost-sharing policies. Link between two European PoPs.

Method	>25%	95th percentile	median
Volume-Customer	0.592	63.07	1.372
Peak-Customer	0.520	89.55	1.263
95Percentile-Customer	0.508	80.79	1.259

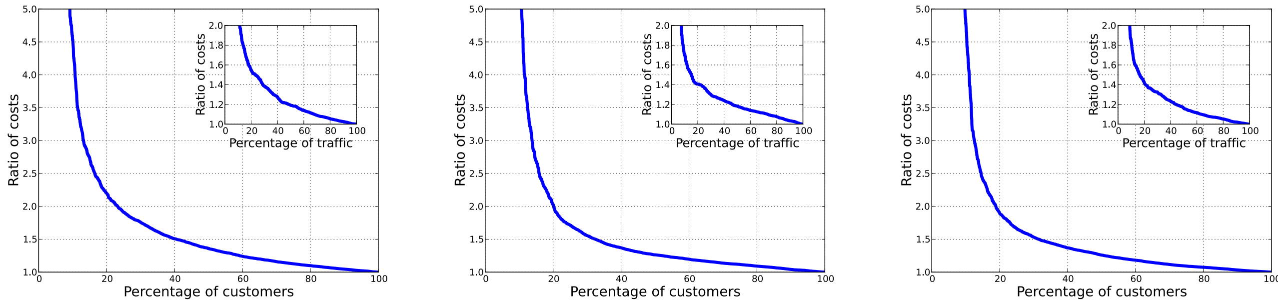
Table 1: Device-level F-discrepancies compared to the Aggregate-Peak-Device policy.

real one they inflict according to Aggregate-Peak-Device. F-discrepancies are particularly high for Volume-Customer and smaller for Peak-Customer and 95Percentile-Customer. The last two policies are sensitive to peaks, albeit those of particular customers instead of peaks of the aggregate traffic on the device. Volume-Customer is even less accurate since it is not looking at any peaks, but only at aggregate volume over a longer time scale.

One may expect that there is a strong correlation between the traffic volumes and the discrepancies of the policies. For example, the other policies may always overestimate the cost of customers, compared to the Aggregate-Peak-Device, if the customers inject a large amount of traffic. However, our results refute this as we illustrate in Fig. 6, where we present the F-discrepancies as a function of the traffic volumes.

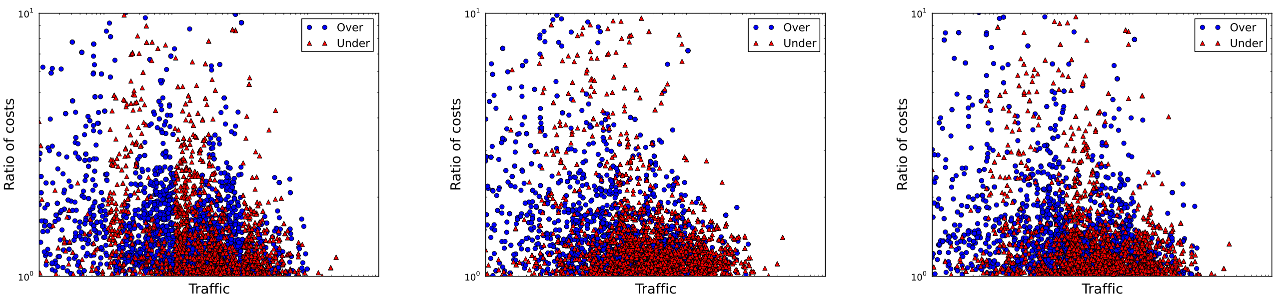
To illustrate the differences between the policies, Fig. 7 depicts a portion of the time-series of a link where a large F-discrepancy (3.07) exists between the Volume-Customer and the Aggregate-Peak-Device policies. The figure shows the traffic pattern of the customer with the large F-discrepancy and the aggregate traffic pattern of the other customers. The traffic of the customer is marginal compared to the traffic of the others, yielding a very low Volume-Customer cost. However during the peak, the customer with the large discrepancy contributes a significant portion to the aggregate traffic, thereby inducing a 3.07 times higher Aggregate-Peak-Device than Volume-Customer cost.

Summary and implications: In the case of device-level discrepancies, numerous and substantial F-discrepancies exist. This implies that backbone operators should apply the Aggregate-Peak-Device policy for computing the costs in case of a single device instead of the simpler policies.



(a) Volume-Customer (b) Peak-Customer (c) 95Percentile-Customer

Figure 5: Distribution of the device-level F-discrepancies between the simpler cost-sharing policies and the Aggregate-Peak-Device policy. Distributions are based on the percentage of the customers and the traffic (insets). All the policies have high F-discrepancies, especially the F-discrepancies of the Volume-Customer policy are large.



(a) Volume-Customer (b) Peak-Customer (c) 95Percentile-Customer

Figure 6: There does not exist a strong correlation between the traffic volumes and the discrepancies of the policies. Moreover, there is no significant difference between the over- and under-estimation of the costs. The axes are logarithmically scaled.

5.1.2 Network-level F-discrepancies

We now examine F-discrepancies in the context of the entire network. We do this by summing the costs of a customer over all the network's devices. We present the relative aggregate costs of the 10 largest customers in Fig. 8; we consider the largest cost as the baseline. We present the F-discrepancies of the policies in Table 2. The results reveal that F-discrepancies at the network-level are much smaller than at the device-level. For example, the network-level median F-discrepancies are ∼40% less than the device-level ones. This is because in large networks positive and negative cost differences at each device cancel each other out, thus the cost predictions of the simpler policies become more aligned.

Summary and implications: F-discrepancies although important for individual links or small networks tend to become less significant for larger networks. Thus, backbone operators can use simpler policies than the Aggregate-Peak-Device without running a high risk of miscalculating the costs of the customers if they are just interested in the aggregate costs of the customers.

Method	>25%	95th percentile	median
Volume-Customer	0.5	3.141	1.251
Peak-Customer	0.35	12.71	1.151
95Percentile-Customer	0.37	5.046	1.181

Table 2: Network-level F-discrepancies compared to the Aggregate-Peak-Device policy.

5.2 M-discrepancies

Next we compute the discrepancy between the customer's network-level cost derived by (1) metering its traffic at its ingress links (Customer-Ingress or CI) and (2) metering its traffic on each device that the customer uses (Customer-per-Device or CD). All of the policies result in high M-discrepancies (ratios as high as 34) as summarized in Table 3.

Up to this point, we analyzed the impact of different discrepancies separately. Next, we quantify the joint effect of F-discrepancies and M-discrepancies, *i.e.*, how large can the difference be between the most and the least accurate combination of function and metering schemes. We do this by comparing the network-level costs of customers under the Volume-Customer+CI, Volume-Customer+CD, and

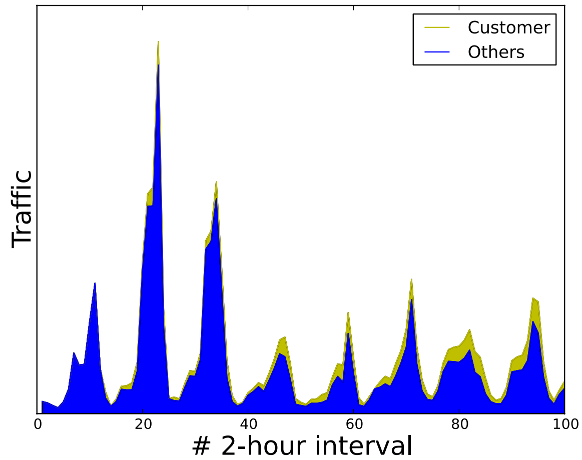


Figure 7: Time-series of the traffic of a customer with a large (3.07) F-discrepancy on a single link. Volume-Customer vs. Aggregate-Peak-Device policy.

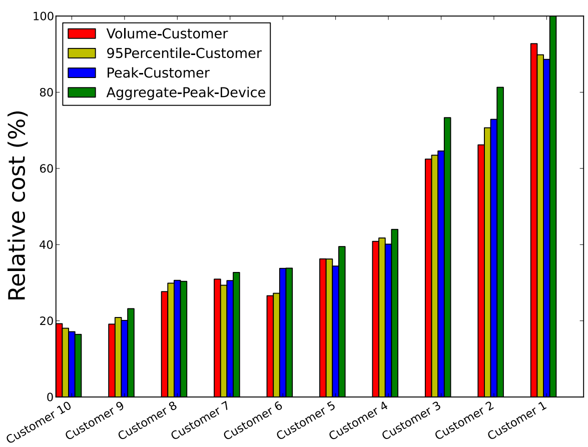


Figure 8: Aggregate relative costs of the 10 largest customers; comparison normalized by the largest cost.

Aggregate-Peak-Device+CI policies with the nominally accurate one, namely, the Aggregate-Peak-Device+CD policy. The results are summarized in Table 4. The Volume-Customer policy has the smallest M-discrepancy, that is, the median ratio of the Customer-Ingress and the Customer-per-Device costs is 1.5. On the contrary, the Aggregate-Peak-Device policy yields the largest M-discrepancies. The reason behind this is twofold. First, when metering traffic at the ingress links, traffic that results in peaks at individual links does not result in peaks of the aggregate ingress traffic. Second, under Customer-Ingress, the Aggregate-Peak-Device policy takes into account only the time interval with the largest aggregate traffic while the peaks of the internal devices may happen in other time intervals neglected by the Aggregate-Peak-Device+CI policy. We observe that under the Aggregate-Peak-Device+CI combination, the costs diverge by at least 25% for 76% of the customers. In addition we note that under the Volume-Customer+CI policy and metering, the discrepancy can be as high as 32.

Method	>25%	95th pct	median
Volume-Customer	0.695	34.53	1.543
Peak-Customer	0.752	32.34	1.738
95Percentile-Customer	0.750	19.10	1.630
Aggregate-Peak-Device	0.763	28.52	1.801

Table 3: Network-level M-discrepancies of the cost-sharing policies. Comparison of the Customer-Ingress and the Customer-per-Device costs of the customers.

Method	>25%	95th pct	median
Volume-Customer+CI	0.760	32.69	1.816
Aggregate-Peak-Device+CI	0.763	28.52	1.801
Volume-Customer+CD	0.500	3.141	1.251
Aggregate-Peak-Device+CD	0.0	1.0	1.0

Table 4: Discrepancies with the Aggregate-Peak-Device policy using Customer-per-Device (real traffic) metering (CI – Customer-Ingress, CD – Customer-per-Device).

Summary and implications: The level at which the backbone operator meters the traffic of the customers has a large impact on the quantified costs. Based on the medians, the most and the least accurate policies diverge by 80%. Therefore, the backbone operators should apply sophisticated metering strategies (*e.g.*, network-wide deployment of NetFlow-capable traffic monitoring devices) in order to accurately quantify the costs of the customers. Moreover, the simple methods are no longer aligned with the real cost of the customers (*i.e.*, with the Aggregate-Peak-Customer policy) if the traffic is metered on the ingress links. From an accuracy point of view, this implies that backbone operators should reconsider the pricing of IP transit services, which they currently price based on simpler policies such as the 95Percentile one.

5.3 L-discrepancies

Next, we focus on the L-discrepancies. Out of the three policies described in Section 3.3, one, the Trigger policy, requires historic information on customer arrival events as well as customer traffic information on long time scales that relate to network upgrade events. Since we do not have full historic information on all the links, we approximate the Trigger policy as follows. We assume for each customer he was the last one arriving to the network. Then we compute the marginal cost contribution of the customer as the actual cost of the device minus the cost of the device without the traffic of the customer. Formally, we quantify the marginal contribution of customer i as:

$$m_i^l = C\left(\max_{t \in T} \sum_{j \in N} x_j^l(t)\right) - C\left(\max_{t \in T} \sum_{j \in N \setminus \{i\}} x_j^l(t)\right) \quad (15)$$

Finally, we allocate the cost of the device to the customers in proportion to their marginal contributions:

$$c_i^l = c^l \cdot \frac{m_i^l}{\sum_{j \in N} m_j^l} \quad (16)$$

In the following, we refer to this method as Trigger*.

Method	>25%	95th percentile	median
Shapley	0.674	472.4	1.497
Trigger*	0.861	1188	2.475

Table 5: Device-level L-discrepancies compared to the Aggregate-Peak-Device policy.

5.3.1 Device-level L-discrepancies

We present the L-discrepancies in Table 5 by computing the ratio between X∈ [Trigger*,Shapley] and the Aggregate-Peak-Device policy. L-discrepancies are quite high (ratios up to 1180) pointing to the fact that liability can bias significantly the cost-sharing picture that a telco has. For example, if we compute costs based on the Trigger* and based on the Aggregate-Peak-Device policy, the gap between the two is very large: in more than 85% of the cases the L-discrepancy is larger than 25%. The Trigger* policy allocates the cost in a full-liability fashion, while the Aggregate-Peak-Device policy applies a proportional liability scheme. Our empirical results confirm that the Shapley policy, which estimates the customers' average contribution to the capacity upgrade considering every possible arriving order, lies in between these two extremes. Again, the difference between the costs of the Shapley and the Aggregate-Peak-Device policy is substantial: the median ratio of the costs is 1.5; however, in some cases the ratio can be larger than 400.

We further examine the L-discrepancy between the Aggregate-Peak-Device and the Shapley policies. In Fig. 9 we plot the L-discrepancies for all customers and all links as a function of the traffic volumes, which the customers had on the particular device in the analyzed time period. The magnitude of the L-discrepancy is inversely proportional to the traffic volumes. Thus, smaller customers tend to have larger L-discrepancies. Small customers usually do not significantly influence the peak utilization of the devices, *i.e.*, they have some marginal share of the costs. However, they may trigger a capacity upgrade of the link and therefore have a larger share of the costs because of the link's step-based cost function. The figure also reveals that whether the Shapley policy over- or under-estimates the Aggregate-Peak-Device policy' costs is not significantly influenced by the customers' traffic volume or by the magnitude of their L-discrepancies.

We present in Fig. 10 a part of the time-series of a customer with a large L-discrepancy (3.25) along with the aggregate time-series of the other customers who utilize the same link. The dashed horizontal lines denote the traffic volumes where the capacity of the link needs to be upgraded. The traffic of the customer is small enough to be transmitted over a link with lower capacity. However, the traffic of the other customers pushes the link to have larger capacity and thus larger cost. The Shapley policy considers this fact when it computes the average marginal contribution of the customer. As a result, the cost of the customer is less than if we compute it based solely on time of the largest utilization of the device. On the contrary, the Aggregate-Peak-Customer focuses only on the time-interval when the link has its aggregate peak. The particular customer has significant share of the aggregate peak and thus of the cost of the link according to the Aggregate-Peak-Customer. This however masks who is responsible for the link's larger capacity. However, this single time-interval masks the fact that the specific customer is not responsible for the link's needing a larger capacity.

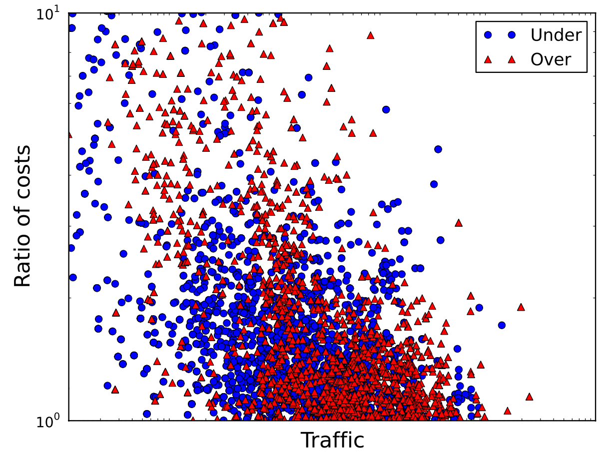


Figure 9: Device-level L-discrepancies as a function of the traffic volumes. The Shapley policy both over- or underestimates the Aggregate-Peak-Device policy.

Method	>25%	95th percentile	median
Shapley	0.54	179.3	1.316
Trigger*	0.771	231.2	1.767

Table 6: Network-level L-discrepancies compared to the Aggregate-Peak-Device policy.

5.3.2 Network-level L-discrepancies

We show the network-level L-discrepancies in Table 6. At the network level, the number and the magnitude of the L-discrepancies is smaller than at the device level. Nevertheless, for more than 50% of the customers the costs are off by at least 25%. The median L-discrepancies of the policies are notable too, *e.g.*, 1.3 under the Shapley policy.

Summary and implications: The liability of network upgrades plays an important role in the quantification of the costs of customers in backbone networks. The median value of L-discrepancies is at least 1.3 while the L-discrepancies impact more than half of the customers with at least 25%. The implication of the results is that if the backbone network is not built in one-shot but is rather organically grown and upgraded then the Aggregate-Peak-Customer policy may induce cross-subsidization problems: customers may be accounted for costs of upgrades for which they are not liable (or not in that degree). From a customer point of view, this cross-subsidization may not be tolerated in a long-run given the competitive environment of the backbone networks. That is the customers may select other backbone network operator where they are not liable for the costs of others. From the operator point of view, the large L-discrepancies dictate that he needs to take them under serious consideration. If it is anticipated that the market for backbone services will be healthy, the operator should choose the Aggregate-Peak-Device policy. If however, he expects difficulties in selling its capacity, our results indicate that Shapley should be the policy of choice.

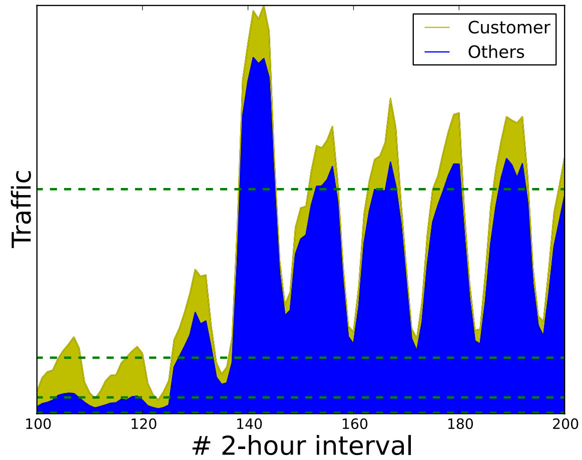


Figure 10: Time-series of a customer with large (3.25) L-discrepancy (Shapley vs. Aggregate-Peak-Device policy). The dashed lines represent the traffic volumes where the capacity of the link needs to be upgraded.

Method	>25%	95th percentile	median
Volume-Customer	0.830	961.1	4.305
Peak-Customer	0.802	933.1	4.187
95Percentile-Customer	0.817	922.4	4.079
Aggregate-Peak-Device	0.840	862.1	4.019
Shapley	0.830	761.1	3.460

Table 7: Network-level TCO-discrepancies, *i.e.*, the costs of the customers based on uniform vs. diverse link costs

5.4 TCO-discrepancies

In this section we take into account that our dataset contains a geographically distributed set of links with diverse costs as we introduced in Section 4. We compute the TCO-discrepancies by computing the ratio between the customers' costs given links with uniform and diverse costs. In Fig. 11 we illustrate the TCO-discrepancies under the Aggregate-Peak-Device policy. Each customer is affected by the TCO-discrepancies. The difference between the two costs can be as high as 5% of the cost of the entire network.

We report the quantified TCO-discrepancies of five policies in Table 7. The results show generally extreme TCO-discrepancies; some customers have TCO-discrepancies as high as 900. In addition, 80% of the customers are assigned 25% higher or lower cost when the diverse costs of the links is considered. The Shapley value is affected the least based on the medians of the TCO-discrepancies.

Summary and implications: TCO-discrepancies have a very large impact on the costs of the customers. The median ratio of the customers' costs is as high as a factor of four. Similar to the L-discrepancies, cross-subsidization problems arise if the impact of TCO differences is neglected. Backbone operators are aware of the fact that different parts of their network have different TCOs. The implication of our results is that this diversity should also be reflected in the quantification of the customers' costs— and eventually in the tariffs too, based on which customers are charged.

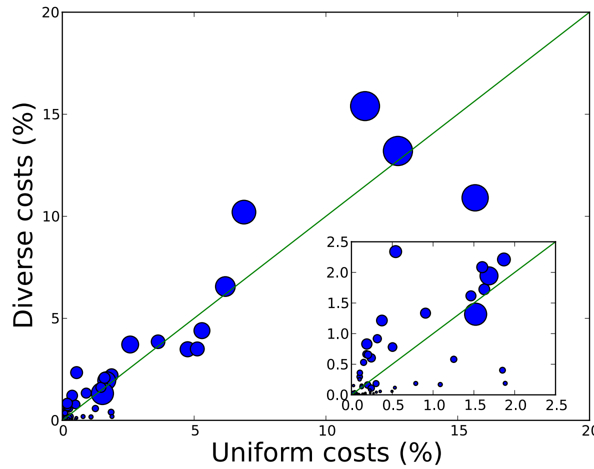


Figure 11: The customers' total costs for the uniform and diverse link costs using the Aggregate-Peak-Device cost-sharing policy; the size of the circles is proportional to the aggregate traffic volume of the customers.

Method	>25%	Median
Peak-Customer (5-min)	0.3	1.157
Peak-Customer (30-min)	0.3	1.157
Peak-Customer (2-hour)	0.35	1.151
Volume-Customer (5-min)	0.49	1.261
Volume-Customer (30-min)	0.51	1.261
Volume-Customer (2-hour)	0.50	1.251
95Percentile-Customer (5-min)	0.27	1.186
95Percentile-Customer (30-min)	0.4	1.186
95Percentile-Customer (2-hour)	0.37	1.181
Shapley (5-min)	0.56	1.359
Shapley (30-min)	0.54	1.359
Shapley (2-hour)	0.54	1.316

Table 8: The impact of time intervals on the network-level discrepancies. The policies are compared to the Aggregate-Peak-Device policy for the same time interval.

5.5 Sensitivity analysis

We investigate the robustness of the cost-sharing policies from two additional angles. First, we quantify the costs of the customers for time-series with 5-minute, 30-minute, and 2-hour intervals. We compare the network-level costs of the methods to the Aggregate-Peak-Device policy in Table 8, where the two policies are compared based on the same time interval. The results reveal that all the policies are affected equally, *i.e.*, the duration of the time-interval does not introduce additional discrepancies among the schemes. For example, the median ratios of the costs based on the Volume-Customer and the Aggregate-Peak-Device policies are 1.261, 1.261, and 1.251 in the case of the datasets with 5-minute, 30-minute, and 2-hour intervals, respectively.

Second, backbone operators apply different utilization thresholds at which they upgrade the capacity of their devices. We compute the costs of the customers in the case

Upgrade policy	>25%	95th percentile	Median
40%	0.642	512.5	1.453
50%	0.673	472.4	1.497
60%	0.689	451.3	1.542

Table 9: Network-level discrepancy for varying network upgrade thresholds (Aggregate-Peak-Device vs. Shapley policy).

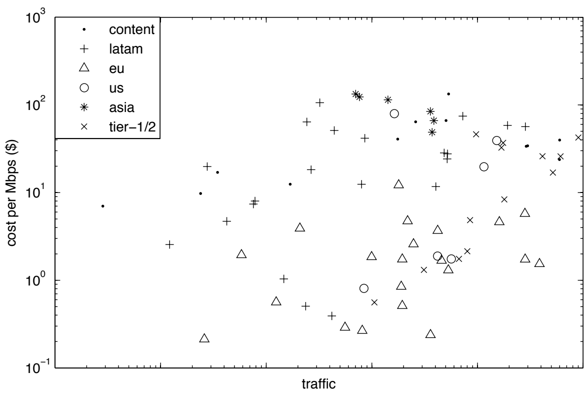


Figure 12: Cost per $Mbps$ for different types of customers.

of 40%, 50%, and 60% threshold values and quantify the ratio between the customers' costs based on the Aggregate-Peak-Device and the Shapley policies (Table 9). Similar to the time intervals, the impact of the network upgrade policy is modest. The median ratio of the costs increases only by 0.1 if the upgrade threshold is increased from 40% to 60%.

Summary and implications: Neither the time-intervals, over which we aggregate the traffic of the customers, nor the upgrade policy, which is determined by the utilization level when the capacity of a device is upgraded, have a significant impact on the discrepancies between the different cost-sharing policies.

5.6 Costs in different type of customers

We next dive deeper into the costs and focus on the different types of the customers present in our datasets. In Fig. 12 we depict the cost per $Mbps$ and the peak data rate for all customers classified into six different types: content ISPs, tier 1/2 ISPs, and EU, Latin American, US and Asian access providers. We consider the network-level costs quantified based on the Aggregate-Peak-Device policy. The figure reveals the following three main properties of the costs. First, the cost per $Mbps$ of individual customers covers a wide range of several orders of magnitude. Second, even within a single type of customer, one can expect large variability of cost per $Mbps$ though there is a tendency for lower costs for the EU/US ISPs, compared to the LatAM and Asian ones. This is a consequence of the fact that the EU/US ISPs send most of their traffic to EU/US and thus utilize lower-cost infrastructure. Finally, content providers fall consistently in the range of 'expensive' customers (over 10$ per $Mbps$) in terms of the cost per $Mbps$ served. This indicates that a large fraction of their traffic crosses expensive intercontinental links. We were able to justify this assumption based raw data in our datasets.

6. RELATED WORK

We refer to the textbook of Courcoubetis and Weber [8] for a thorough treatment of pricing in communication networks. A workshop version preceded this work [14] where we focused on the different cost-sharing policies that can be applied in backbone networks. Our current work extends that preliminary work with the following: a) we propose a methodology for cost-sharing in backbone networks and introduce the different types of discrepancies; b) we evaluate the liability facet of the cost-sharing domain; and c) we utilize a much richer dataset that describes the traffic patterns of a backbone network with three-times more links.

Several studies investigated how to reduce the transit costs including ISP peering [2, 11, 10], CDNs [24], P2P localization [6], and traffic smoothing [20]. Dimitropoulos et al. [12] presented a comprehensive analysis of the 95th percentile pricing. A proposal by Laoutaris et al. [16, 15] showed how traffic can be transferred in the network without increasing the 95th percentile of the customers. A recent proposal by Stanojevic et al. [27] proposes to the customers of transit providers to form a coalition to reduce their transit costs. Valancius et al. [30] show that a small number of pricing tiers are enough to extract close-to-optimal efficiency in the transit provider. In our work we augment the price efficiency analysis of [30] with a methodology that quantifies how individual customers affect the cost of running the network that demonstrate the complex nature of the customers' costs in the real-world networks.

Motiwala [21] et al. developed a cost model that operators can use to evaluate the costs of their routing and peering decisions. Their study is complementary to ours, as we can use their model to assess the CAPEX and OPEX cost of the network instead of using our step function (Section 3). A difference is that we primarily focus on how the cost can be more fairly and accurately distributed among the customers of an operator.

The net neutrality debate is in many ways related to the question of who is responsible for the costs in the network [7], and our work contributes towards better understanding of such costs.

Due to the desirable fairness properties [1, 13, 22] of the Shapley value [25], recent studies proposed pricing and cost sharing mechanisms using Shapley values. Briscoe [3, 4] motivates the usage of mechanisms that share the costs of the users fairly as a way to reduce widely known cross-subsidization[3] of the common infrastructure that often happens in the communication networks [5]. Cooperative approaches for cost sharing are investigated in case of inter-domain routing [19, 26] and IP multicast [1, 13]. Ma et al. [17, 18] presented a fair revenue sharing method for ISPs that quantifies the importance of each ISP in the Internet ecosystem. The work of Stanojevic et al. [28] is the closest to ours. The authors empirically investigated the temporal usage effects using the Shapley and the 95Percentile-Customer method. This work is different in several ways: a) we focus on the costs of the large customers of a backbone network with geographically diverse links; b) we study additional cost

[3]The phenomenon in which a small set of customers is subsidized by a large fraction of other customers of the service.

sharing policies and aspects such as liability and TCO; and c) we study a more detailed cost and traffic dataset.

7. CONCLUSIONS

With the increasing traffic volumes, intense market competition, and technological barriers, most commercial backbone operators are faced with the challenge of maintaining healthy profit margins. Providing services to their customers, which are often ISPs themselves, carries significant maintenance and upgrade costs. Attributing these costs to individual customers is critical for ensuring smooth operations of the backbone network as well as offering fair tariffs to customers. However, the process of quantifying the cost contribution of customers in a distributed backbone network is far from simple involving the complex interaction of many factors ranging from temporal/spatial characteristics of the customers and non-linear cost-capacity relationships to measurement infrastructure issues and high variability of the component costs.

In this paper, we make a step towards understanding the relationship between several cost-sharing policies and how they affect the individual customers. While our analysis reveals several important properties of the backbone network cost-sharing, there are many questions that remain open. For example, how can one utilize the global view of cost allocation per customer to create simple yet profitable tariffs? Based on our findings, such tariffs should include device-level expenditures and measurements to assure its accuracy. Another open research question is how tariffs inspired by the presented cost sharing policies would alter the behavior of the customers, *i.e.*, their traffic patterns to minimize their expenditures. Additionally, it would be interesting to study if our observed properties of the cost-sharing could be mapped to other types of networks that are spatially less diverse but serve a more populous customer base, such as the residential broadband or 3G access networks.

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8. REFERENCES

[1] Aaron Archer, Joan Feigenbaum, Arvind Krishnamurthy, Rahul Sami, and Scott Shenker. Approximation and collusion in multicast cost sharing. *Games and Economic Behavior*, 47(1):36 – 71, 2004.

[2] Brice Augustin, Balachander Krishnamurthy, and Walter Willinger. Ixps: mapped? In *Proceedings of the 9th ACM SIGCOMM conference on Internet measurement conference*, IMC '09, pages 336–349, New York, NY, USA, 2009. ACM.

[3] Bob Briscoe. Flow rate fairness: dismantling a religion. *SIGCOMM Comput. Commun. Rev.*, 37(2):63–74, 2007.

[4] Bob Briscoe. A Fairer, Faster Internet. *IEEE Spectrum*, 45(12):42–47, 2008.

[5] Kenjiro Cho, Kensuke Fukuda, Hiroshi Esaki, and Akira Kato. The impact and implications of the growth in residential user-to-user traffic. SIGCOMM '06, pages 207–218, New York, NY, USA, 2006. ACM.

[6] David R. Choffnes and Fabián E. Bustamante. Taming the torrent: a practical approach to reducing cross-isp traffic in peer-to-peer systems. In *Proceedings of the ACM SIGCOMM 2008 conference on Data communication*, SIGCOMM '08, pages 363–374, New York, NY, USA, 2008. ACM.

[7] kc claffy. "network neutrality": the meme, its cost, its future. *SIGCOMM Comput. Commun. Rev.*, 41(5):44–45.

[8] C. Courcoubetis and R. Weber. *Pricing and Communications Networks*. John Wiley & Sons, Ltd, 2003.

[9] Cushman & Wakefield. Office Space Across the World, 2012.

[10] A. Dhamdhere, C. Dovrolis, and P. Francois. A Value-based Framework for Internet Peering Agreements. In *Teletraffic Congress (ITC), 2010 22nd International*, 2010.

[11] Amogh Dhamdhere and Constantine Dovrolis. The internet is flat: modeling the transition from a transit hierarchy to a peering mesh. In *Proceedings of the 6th International COnference*, Co-NEXT '10, pages 21:1–21:12, New York, NY, USA, 2010. ACM.

[12] Xenofontas Dimitropoulos, Paul Hurley, Andreas Kind, and Marc Stoecklin. On the 95-percentile billing method. In Sue Moon, Renata Teixeira, and Steve Uhlig, editors, *Passive and Active Network Measurement*, volume 5448 of *Lecture Notes in Computer Science*, pages 207–216. Springer Berlin, Heidelberg, 2009.

[13] Joan Feigenbaum, Christos H. Papadimitriou, and Scott Shenker. Sharing the cost of multicast transmissions. *Journal of Computer and System Sciences*, 63(1):21 – 41, 2001.

[14] L. Gyarmati, M. Sirivianos, and N. Laoutaris. Simplicity vs Precision: Sharing the Cost of Backbone Networks. In *NetEcon 2012 - Seventh Workshop on the Economics of Networks, Systems, and Computation*, 2012.

[15] Nikolaos Laoutaris, Michael Sirivianos, Xiaoyuan Yang, and Pablo Rodriguez. Inter-datacenter bulk transfers with netstitcher. In *Proceedings of the ACM SIGCOMM 2011 conference*, SIGCOMM '11, pages 74–85, New York, NY, USA, 2011. ACM.

[16] Nikolaos Laoutaris, Georgios Smaragdakis, Pablo Rodriguez, and Ravi Sundaram. Delay tolerant bulk data transfers on the internet. In *Proceedings of the eleventh international joint conference on Measurement and modeling of computer systems*, SIGMETRICS '09, pages 229–238, New York, NY, USA, 2009. ACM.

[17] Richard T. B. Ma, Dah ming Chiu, John C. S. Lui, Vishal Misra, and Dan Rubenstein. Internet economics: the use of shapley value for isp settlement. In *Proceedings of the 2007 ACM CoNEXT conference*, CoNEXT '07, pages 6:1–6:12, New York, NY, USA, 2007. ACM.

[18] Richard T. B. Ma, Dah-ming Chiu, John C. S. Lui, Vishal Misra, and Dan Rubenstein. On cooperative settlement between content, transit and eyeball

internet service providers. In *Proceedings of the 2008 ACM CoNEXT Conference*, CoNEXT '08, pages 7:1–7:12, New York, NY, USA, 2008. ACM.

[19] Ratul Mahajan, David Wetherall, and Thomas Anderson. Negotiation-based routing between neighboring isps. In *Proceedings of the 2nd conference on Symposium on Networked Systems Design & Implementation - Volume 2*, NSDI'05, pages 29–42, Berkeley, CA, USA, 2005. USENIX Association.

[20] M. Marcon, M. Dischinger, K.P. Gummadi, and A. Vahdat. The Local and Global effects of Traffic Shaping in the Internet. In *Third International Conference on Communication Systems and Networks (COMSNETS)*, 2011.

[21] Murtaza Motiwala, Amogh Dhamdhere, Nick Feamster, and Anukool Lakhina. Towards a cost model for network traffic. *SIGCOMM Comput. Commun. Rev.*, 42(1):54–60.

[22] HervĂŠ Moulin and Scott Shenker. Strategyproof sharing of submodular costs:budget balance versus efficiency. *Economic Theory*, 18:511–533, 2001. 10.1007/PL00004200.

[23] W. B. Norton. *The Internet Peering Playbook: Connecting to the Core of the Internet*. DrPeering Press, 2012.

[24] L. Qiu, V.N. Padmanabhan, and G.M. Voelker. On the Placement of Web Server Replicas. In *IEEE INFOCOM*, pages 1587–1596, 2001.

[25] L. S. Shapley. A value for n-person games. *Annals of Mathematical Studies*, 1953.

[26] Gireesh Shrimali, Aditya Akella, and Almir Mutapcic. Cooperative interdomain traffic engineering using nash bargaining and decomposition. *IEEE/ACM Trans. Netw.*, 18(2):341–352, April 2010.

[27] Rade Stanojevic, Ignacio Castro, and Sergey Gorinsky. Cipt: using tuangou to reduce ip transit costs. In *Proceedings of the Seventh COnference on emerging Networking EXperiments and Technologies*, CoNEXT '11, pages 17:1–17:12, New York, NY, USA, 2011. ACM.

[28] Rade Stanojevic, Nikolaos Laoutaris, and Pablo Rodriguez. On economic heavy hitters: shapley value analysis of 95th-percentile pricing. In *Proceedings of the 10th ACM SIGCOMM conference on Internet measurement*, IMC '10, pages 75–80, New York, NY, USA, 2010. ACM.

[29] TeleGeography. Wholesale IP transit price database, `http://www.telegeography.com/`.

[30] Vytautas Valancius, Cristian Lumezanu, Nick Feamster, Ramesh Johari, and Vijay V. Vazirani. How many tiers?: pricing in the internet transit market. In *Proceedings of the ACM SIGCOMM 2011 conference*, SIGCOMM '11, pages 194–205, New York, NY, USA, 2011. ACM.