A Datacenter Network Tale from a Server's Perspective

Robert Birke, Lydia Y. Chen, and Cyriel Minkenberg
IBM Research Zurich Lab
Rüschlikon, Switzerland
{bir, yic, sil}@zurich.ibm.com

***Abstract*—The scalability of many datacenter applications is largely dependent on the networking infrastructure. Several studies addressed the network traffic characteristics from the perspective of network equipment, i.e., collecting and analyzing traffic data from routers, switches, or other network aggregation points. However, little is known about how traffic is directly generated by the servers. In this paper, we conduct an empirical study to characterize datacenter traffic from a server-centric perspective. We analyze data from more than 30,000 servers, located across more than 50 production datacenters, over a two-year time span. Our evaluation encompasses traffic statistics as well as network resources, based on short-term snapshots and long-term evolution of the collected metrics. In particular, we characterize the temporal and spatial characteristics of incoming and outgoing traffic volumes across servers, in packets as well as bytes per second. Our analysis provides a baseline for datacenter network modeling and workload model calibration.**

I. Introduction

Datacenters are emerging as the standard IT solution for enterprise and cloud service providers due to ease of management and economies of scale [1]. Owing to the advancement of virtualization technology, modern datacenters host multiple tenants, who demand a wide variety of services, e.g., Internet facing, data crunching, backing up. There is a growing interest pertinent to datacenter network design and traffic engineering. Obtaining traffic measurement from production datacenter is widely considered as the first step to gain the deep understanding of such networks.

Related studies on characterizing network are often conducted from a network perspective and focus on a few specific datacenters. On one hand, such characterization studies, e.g. [2], [3], capture network traffic *within* the network, i.e., by instrumenting the network equipment (switches, bridges, routers) and using protocols and tools, such as NetFlow [4], WireShark [5], Aurora [6], etc. Their aims are to provide insights into the characteristics of traffic flows, such as flow size, flow duration, and end-to-end communication patterns. On the other hand, their data collection is based on few specific datacenters, catering particular types of services and applications, in a fine granularity and short period. The generalization and applicability of their findings and derived implications on datacenter traffic engineering can be thus shadowed, depending on the representativeness of datacenters and observation periods considered.

Given a vast amount of related studies about datacenter network, very little is known about the generic characteristics of network resources and the network traffic sent and received by the datacenter servers. Metrics of interest are, for instance: the number of network interface cards (NICs) installed and/or active per server and their utilization; traffic volumes and rates in the inbound and outbound directions; peak, average, minimum data rates; and evolution of rates at different time scales. Moreover, servers associated with different services exhibit disparate network patterns [7]. Additionally, virtual servers dominating today's datacenters use resources disparately from physical servers [8]. These issues are crucial when trying to improve datacenter network performance. To gain a deeper understanding, we conducted a large scale measurement study from the server perspective, i.e., collecting and analyzing network traffic pattern at the servers, across a wide range of datacenters. Overall, our objective here is to characterize how packet traffic is generated at server ends, instead of enhancing typical flow-centric analysis.

In this study, we analyze network traffic data collected from about 30,000 servers, distributed across more than 50 mature enterprises and cloud datacenters, collected over a 2-year time span. Our analysis focuses on network resources and traffic per server and adopts two resolutions: a day snapshot based on 15-minute average samples and a two year evolution based on monthly average samples. We particularly analyze transmitting and receiving patterns of servers in terms of the number of packets and bytes. Our aim here is to present and verify simple and crucial facts, which are important for generating synthetic traffic and dimensioning server network resources.

Our contribution is highlighted by the scale of this study and the applicability of our presented analysis, which is not only based on a large number of servers but also on a wide range of datacenters, hosting diverged applications. In contrast to existing studies, we focus on short-term and long-term network traffic as well as network resources. We highlight the difference of traffic patterns between physical and virtual servers. Our analysis provides a baseline for datacenter workload generation and model calibration, which is instrumental in: (i) efficient capacity dimensioning and planning of datacenter network infrastructure; (ii) network traffic engineering; (iii) providing a basis for credible workload patterns that can be used to evaluate research proposals in this field.

The outline of this work are as follows. In Section II, we provide an overview of the dataset presented. The snapshot and evolution of network usages at datacenters are summarized in Section III and IV respectively. The comparison between traffic of physical and virtual servers is summarize in Section V. Section VI presents related work. A summary of our findings in Section VII concludes this paper.

978-1-4799-0590-4/13/$31.00 ©2013 IEEE

II. Measurement and Data Analysis

Our study is based on large-scale server network performance measurements collected between start of June 2010 to end of April 2012, covering more than 30,000 servers sampled from 56 datacenters. The geographic distribution covers all continents and a wide range of countries, including developed and developing countries. These servers are used by different industries, including banking, pharmaceutics, IT, consulting, and retail. Most datacenters have multiple tenants, i.e., their infrastructure is shared by different enterprises. The number of enterprises in multi-tenant datacenters covered by this study ranges from 2 to 46, with an average of 11. Some of them are so-called cloud datacenters, which offer cloud-like services and usually have a higher number of servers.

We focus on the network resources at servers, i.e., NICs, and their generation pattern of network traffic. For all servers, the `netstat` command was used to collect the following statistics: number of NICs, maximum transfer unit (MTU), and input/output packet rates in thousands of packets per second (Kpps) per NIC, input/output rates in megabits per second (Mbps) per NIC. Statistics are sampled once every minute and averaged over 15-minutes to reduce the storage footprint.

We adopt two resolutions to analyze the data: a day snapshot and the monthly evolution. The former focuses on the daily average, maximum and minimum values computed from the 15-minute averages within a day, whereas the latter focuses on monthly averages (covering full two years), which are aggregated from daily averages, rolling from the 15-minute averages. The storage space required for daily data is 5 GB/day and for coarse-grained yearly data is 1.5 GB/year.

A limitation of our analysis is that, because of the aggregation of data into 15-minute averages, we inevitably lose fine-grained resolution, in particular the traffic peaks. For example, the maximum Kpps identified in this study is based on 15-minute averages and is much lower than the instantaneous maximum Kpps observed during those 15-minutes. In contrast to other studies, we do not provide flow/link level analysis, inter/intra communication pattern of servers, nor network topology, because of the different nature of collecting our statistics. However, the coarseness of the information gathered is contrasted by the huge dataset the study is based on: more than 30000 servers over a two year timespan.

III. Network Usage in a Day

To analyze the short term traffic patterns and network resources of datacenter servers, we take statistics of all servers from a week day (March 29th, 2012) and a weekend day (April 1st, 2012). We outline the characteristics of server network usages by their number of NICs, maximum transfer unit (MTU), traffic volumes in terms of Mbps and Kpps, average packet sizes, and traffic peak-dip times. We first present the overview of traffic pattern by the mean values across all servers and then discuss detailed distributions of each characteristic.

A. Overview of Servers' Traffic Generation Pattern

We first present a coarse grained overview showing the average network traffic generated by a server. In Table I, we summarize the mean value of the following per-server statistics across servers: number of NICs, number of inactive NICs, daily average traffic volume in Mbps and Kpps, and daily average packet size and MTU. The mean values indicate the general trend across servers. Because the values of NICs numbers and MTU sizes do not vary in a short time span, we reported values from one time instance of those two days. As the traffic volumes and packet sizes vary over the time, we present the daily average of both statistics computed from the 96 15-minute averages in a day.

TABLE I. Overview of network resources and traffic characteristics across servers at different data centers.

	Network resources		
	No. of NICs	**Inactive NICs**	**MTU**
mean	2.38	0.38	1806.81
median	2	0	1500

	Traffic on a week day		
	Avg Kpps	Avg Mbps	Avg. pkt size
mean	1.16	5.74	301.75

	Traffic on a weekend day		
	Avg Kpps	Avg Mbps	Avg. pkt size
mean	1.13	5.64	278.40

We split NICs into two categories, i.e., active and inactive, based on the number of transmitted packets. An inactive NIC does not transmit any packet but may still receive packets due to broadcast packets such as ARP requests. The average traffic volumes of a server are computed from the inbound and outbound traffic aggregated over all NICs belonging to the server. Moreover, we estimate the average packet sizes as the ratio between the average traffic in bytes and in packets of the entire day.

For the network resources, one can observe from Table I that: (i) a server typically uses 2 NICs, shown both by subtracting the average number of inactive NICs (0.38) from the average number of NICs (2.38) and by the median value; (ii) the average MTU is 1806.81 bytes due to the dominance of the traditional Ethernet MTU value equal to 1500 bytes as shown by the median MTU value. For the network load on each server, we see that: (i) the average server network traffic is roughly 1.16 Kpps and 5.7 Mbps; (ii) the average packet size is 300 bytes, and (iii) the weekend day network traffic is only slightly lower than the week day traffic. Aforementioned observations can be used to infer the efficiency of network resources used in systems of any given number of servers. Moreover, these observations are very important criteria to calibrate traffic generators used in studies of data center network design.

B. Number of NICs and their Activity

In Figure 1, we present the probability density function (PDF) of the number of NICs per server detected by the operating system (OS). Roughly 85% of servers have one to three NICs, and the remaining 15% of servers have more than four NICs. A very small number of servers has a large number of NICs and the distribution tail is almost invisible and truncated here. Such a long distribution tail can be attributed to the usage of virtual network interfaces. For example, one specific server had up to 74 NICs because of using VLANs and creating a high number of virtual interfaces.

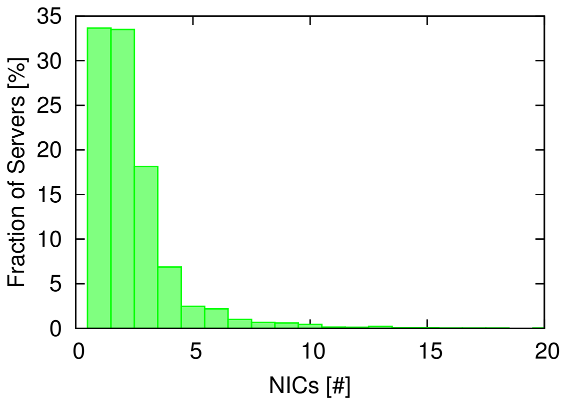


Fig. 1. PDF of total NICs per server.

Furthermore, we split the NICs by their transmitted packets over a day, using two threshold values, i.e., 0 and 10 packets per second (pps). We consider a NIC inactive if its transmission never exceeded the threshold value over the whole weekday. We do not consider received packets since the NIC could still receive broadcast packets from the network. The PDFs of the number of inactive NICs based on these two thresholds are shown in Figure 2. When considering 0 pps threshold, roughly 79% of servers have no inactive NICs, i.e., all their NICs are active. About 14% of servers have one inactive NIC. With decreasing probability there are more inactive NICs up to a very few cases which had 10 inactive NICs. Changing the threshold value from 0 pps to a small amount of transmitted packets (10 pps) to exclude spurious packets sent by the OS, the lump barycenter of the PDF shifts towards the right but the same shape is maintained. Another fact worth mentioning is that the fraction of servers having all their NICs active drops from roughly 79% to 42%, as indicated by the two leftmost bars in Figure 2.

In general, we show that there is a high redundancy in NICs. This brings two main advantages: first, extra NICs are used to increase the reliability (hot standby), especially as the cost of NICs is rather low compared to other system components. Second, additional NICs are used as a control interface to connect external devices, such as a laptop, to do extraordinary maintenance on the server. Last, bundling allows to aggregate NICs into faster logical links which can be a convenient solution if smaller upgrades are needed then going to the next network technology generation.

C. Maximum Transfer Units (MTU)

We present the PDF of the maximum transfer unit for each NIC in Figure 3. Surprisingly, only a small fraction of NICs (roughly 2%) support jumbo frames. The MTU exhibits a bimodal pattern, with most of the NIC MTU sizes clustering around 1500 and 9000 bytes, corresponding to 96% and 2% of servers, respectively. The dominance of Ethernet technology is clear: the first peak corresponds to the MTU size of traditional Ethernet while the second peak corresponds to the MTU value of Ethernet jumbo frames. When taking a closer look at the PDF, there is roughly one percent of NICs that set their MTU values slightly lower than 1500, say between 1400 and 1500. This can be explained by the use of additional

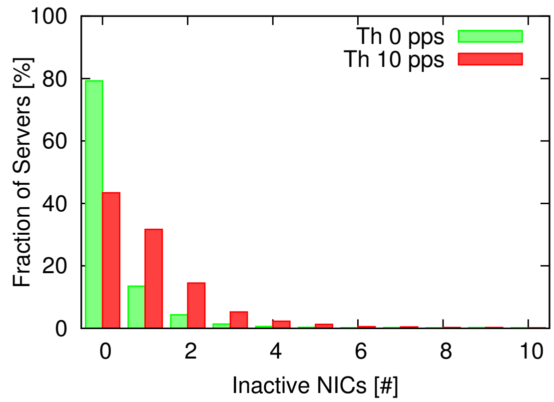


Fig. 2. PDF of inactive NICs per server, using two threshold values (0 pps and 10 pps) to define inactive NICs.

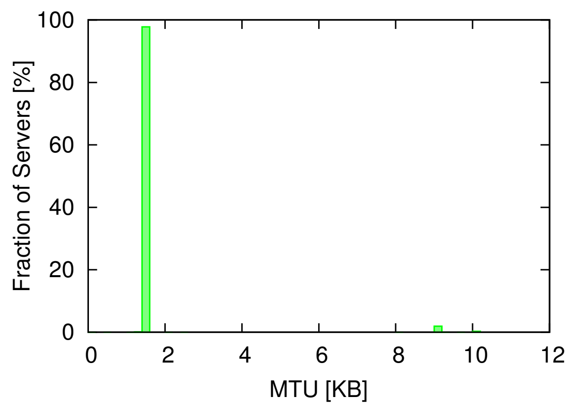


Fig. 3. PDF of maximum transfer unit (MTU) sizes.

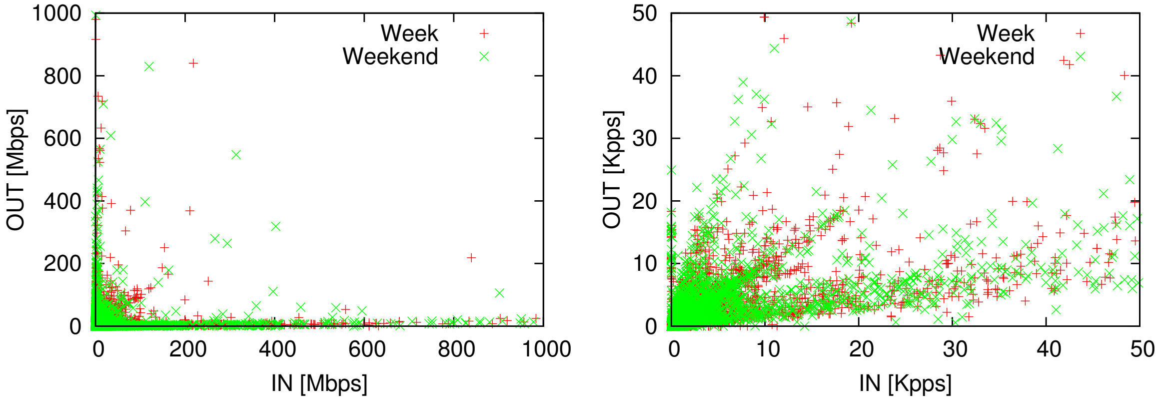
protocols on top of Ethernet for VPNs and tunneling, which add their own overhead and the MTU value has to be decreased correspondingly to avoid packet fragmentation or packet drops.

From the PDF of MTU sizes, we conclude that nearly all servers use Ethernet. Small MTU sizes have the advantages of lower error probabilities, smaller delays and smaller loss rates, although their efficiency is hampered due to bigger header overheads. On the other hand, only roughly 2% of servers employ jumbo frames.

D. Aggregate Inbound and Outbound Traffic

In this subsection, we present the inbound and outbound traffic per server aggregated over all its NICs. The day average of a server is computed from its 15-minute averages over a day, and the day maximum and minimum are identified from the maximal and minimal values among its 15-minute averages.

1) Day Average: In Figure 4, we present scatter plots, showing the distribution of day average inbound (x-axis) versus outbound (y-axis) traffic both in terms of Mbps (Figure 4(a)) and Kpps (Figure 4(b)) for both a week and weekend day. To better present the data, we truncate the outliers having more than 50 Kpps or having more than 1000 Mbps, respectively. One can immediately observe that: (i) there are certain trends of output/input ratios r. When $r > 1$ (i.e., points above the diagonal), it implies that those servers have more outbound



(a) day average in Mbps (b) day average in Kpps

Fig. 4. Scatter plots of average in- vs outbound traffic per server.

than inbound packets (bytes); whereas servers with ratio $r < 1$ have more input than output packets (bytes); (ii) the two days are rather similar and the comments hold for both.

Figure 4(a) shows two main trends: the servers are either squeezed along the x-axis or along the y-axis, implying that the servers mostly either receive data or send data, respectively. Very few exhibit symmetric ($r \approx 1$) data exchanges. One possible explanation is the server-client programming paradigm, where servers are generally expected to receive small requests from clients and send back bigger data chunks in response to those requests, e.g., an incoming URL request and the outgoing web page. Such an example reflects the servers along the y-axis. The servers along the x-axis represent instead backup or database servers used to store large amounts of data. Furthermore, we observe that the inbound traffic is more spread out, showing higher variability. When designing data center network, especially for routing and link technology, inbound capacity should be well dimensioned due to a higher potential of becoming a bottleneck.

On the other hand, in Figure 4(b) we can clearly observe multiple input/output ratios closer to 1, indicating more symmetric packet exchanges. Indeed, this matches with our expectation that most flows will have roughly the same amount of packets in both directions due to acknowledgments (ACKs) sent by the client back to the server. This is especially true for TCP-based flows. The divergence from the diagonal can easily be explained by the presence of cumulative ACKs, other traffic types like UDP, lost and retransmitted packets, and multicast/broadcast packets which disrupt this symmetry.

Changing viewpoint, Figure 5 presents the cumulative distribution functions (CDFs) for both the inbound and outbound traffic, and for both week and weekend day. We fitted the data from both week and weekend days using the log-normal [9] and Weibull [10] distributions. The resulting parameters are summarized in Table II.

As there are only slight variations between the week and weekend day, to enhance the readability of the plots, in the following sections we focus only on the week day data, skipping the presentation of the weekend day data.

2) Day Max and Day Min: We summarize the CDFs of the maximum and minimum traffic both in terms of Mbps and Kpps in Figure 6. In both sub figures, it is not surprising to find that almost all servers have minimum Mbps and Kpps close to zero for both input and output traffic. In particular, all servers receive or transmit almost zero bytes in at least one of the 15-minute intervals, even though 2% of the servers never stop receiving or transmitting. This implies that those servers receive and transmit very small number of packets, possibly due to some heartbeat mechanisms.

TABLE II. OVERVIEW OF THE DISTRIBUTION FITTING PARAMETERS FOR THE AVERAGE TRAFFIC.

Packets	**Dir.**	**Distribution**	**Parameters**
Kpps	IN	Log-normal	$\mu = -3.25$ $\sigma = 2.25$
	OUT	Log-normal	$\mu = -3.59$ $\sigma = 2.51$

Bytes	**Dir.**	**Distribution**	**Parameters**
Mbps	IN	Log-normal	$\mu = -3.13$ $\sigma = 2.91$
	OUT	Weibull	$a = 0.32$ $b = 0.34$

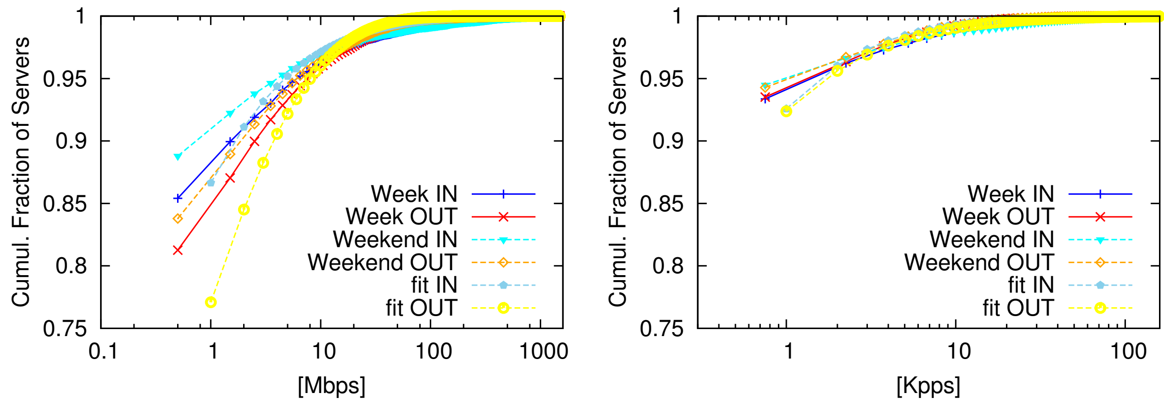
TABLE III. OVERVIEW OF THE DISTRIBUTION FITTING PARAMETERS FOR THE MAXIMUM TRAFFIC.

Packets	**Dir.**	**Distribution**	**Parameters**
Kpps	IN	Log-normal	$\mu = -1.44$ $\sigma = 2.41$
	OUT	Weibull	$a = 0.90$ $b = 0.42$

Bytes	**Dir.**	**Distribution**	**Parameters**
Mbps	IN	Log-normal	$\mu = -1.23$ $\sigma = 3.24$
	OUT	Weibull	$a = 4.72$ $b = 0.34$

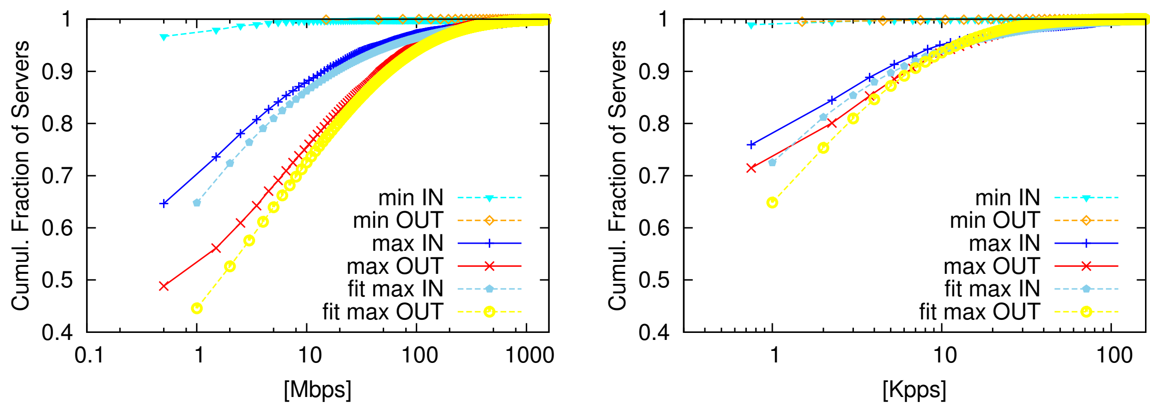
The difference between maximum output and maximum input traffic is more visible. Considering traffic in Mbps, the maximum output traffic is more evenly distributed than the maximum input traffic, while considering the traffic in Kpps this difference is attenuated. This reflects our initial observations on the scatter plots where the input traffic is more spread out than the output traffic in Mbps, while in Kpps the traffic is more symmetric. Hence, this observation not only applies to the average but also to the maximum values.

Again we fit the above maximum distributions using both log-normal and Weibull distributions. The coefficients are reported in Table III. One can further use those fittings and the fittings from the previous section for the purpose of traffic generation and validating network management policies.



(a) In Mbps (b) In Kpps

Fig. 5. CDF of average in- and outbound traffic.



(a) In Mbps (b) In Kpps

Fig. 6. CDF of max/min in- and outbound traffic.

E. Average Packet Sizes

In Figure 7, we present the CDF of average inbound and outbound packet sizes. The average inbound packet size is slightly smaller than the average outbound packet size, shown by a inbound packet curve closer to the top-left corner. Roughly 90% of servers have average inbound and outbound packet size below 500 bytes. Moreover, both inbound and outbound packet size distributions show a cut-off knee at 1500 bytes. This knee can be easily explained by the fact that (as observed previously) most NICs use a standard 1500 bytes MTU. The two distributions can be used to synthetically generate the average inbound and outbound packet sizes.

F. Peak and Dip Time

In this section, we examine the timing when the maximum output/input rates in Mbps/Kpps occur. We refer to an interval as *peak time* when the maximum packets/bytes occurred in it and as *offpeak time* when the minimum packets/bytes occurred in it; i.e., we consider absolute maximums and minimums in the traffic time series of a server. We summarize the PDF of *peak times* happening in each 15-minute interval of a day in Figure 8, whereas we summarize the PDF of *offpeak times* happening in each 15-minute interval of a day in Figure 9. Notice that, the maximum and minimum value can happen in multiple intervals. This is especially true for the minimum

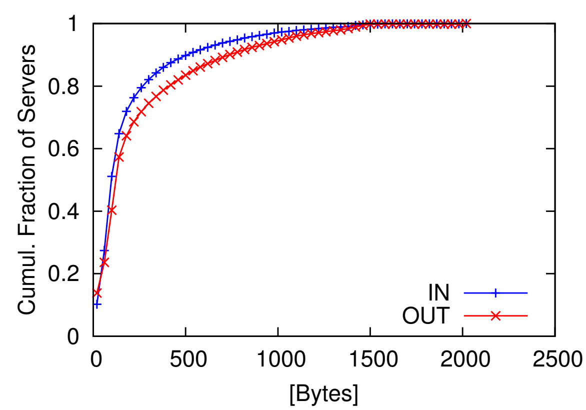
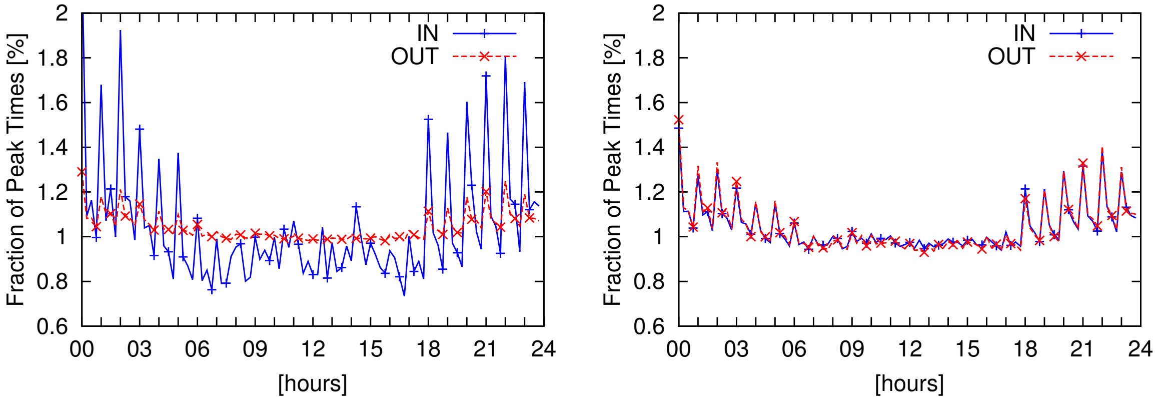


Fig. 7. CDF of in- and outbound average packet size.

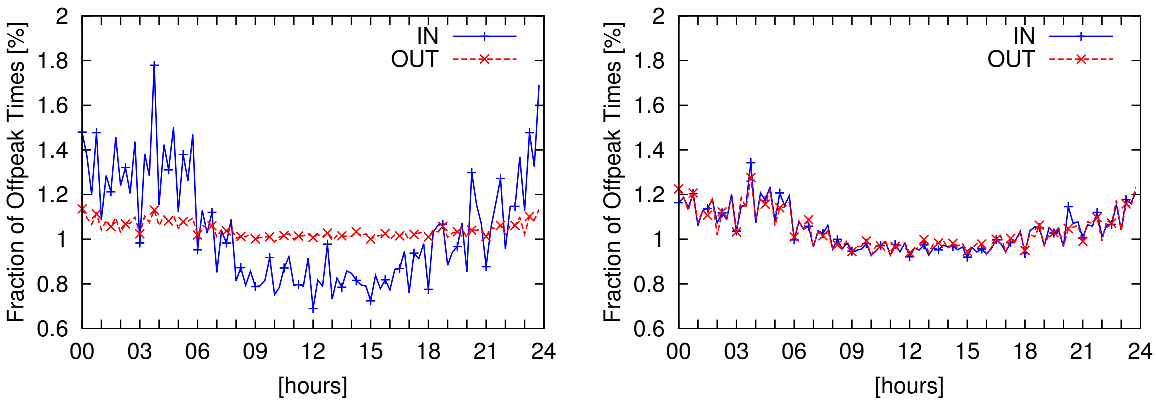
value, which in most cases is zero. As such, we compute the PDF based on the number of occurrences of *peak times* and *offpeak times*.

We first observe that more servers have their *peak times* at midnight than at noon, indicating a higher network activity at night than during the day. This can be explained by the common practice to do heavy backup operations during the night. The *offpeak times* on the other hand occur slightly more



(a) In Mbps (b) In Kpps

Fig. 8. PDF of in- and outbound *peak time*.



(a) In Mbps (b) In Kpps

Fig. 9. PDF of in- and outbound *offpeak time*.

evenly during the whole day and surprisingly not at times opposite to the *peak times*; i.e., more during the day than during the night. This is due to the fact that the minimum value (zero), is more likely to happen multiple times, smoothing out the day/night trends. Another interesting observation is that within an hour we have a periodic pattern. Considering *peak times* we always have higher PDF values at the start of an hour, while the probability decreases for the next three intervals, i.e., quarter past, half past, and three quarters past. In this case the *offpeak times* show exactly the opposite trend with higher probabilities at the three quarters past times. This can be related to the execution of periodic on-the-hour scheduled jobs.

Regarding the difference between input and output traffic in Mpbs, input *peak times* show a higher temporal variability than output*peak times*, see Figure 8(a). In particular, during the night, there are clearly more inbound *peak times* than outbound *peak times*, whereas during the day it is the other way around. This is possibly due to a prominence of the backup servers mainly operating at night. This difference between input and output disappears when measuring the traffic in Kpps. This is expected because, as already observed previously, the traffic in Kpps is much more symmetric.

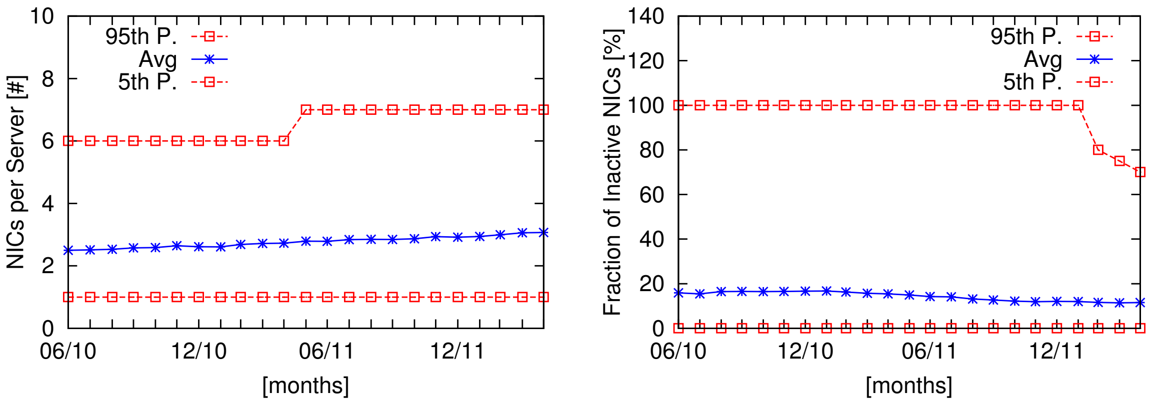
IV. Evolution of Network Usage

In this section, we present the 2-year evolution of the aforementioned statistics related to NICs and inbound/outbound traffic. In contrast to the day analysis, we show how the mean value of statistics across all servers vary over the two year span.

A. Evolution of NICs and MTU

We present the mean number of NICs per server and 5th and 95th percentile, computed from the average values of all servers in Figure 10. The percentiles give an idea on how spread out the values are. We use the percentiles instead of min and max because they are less sensitive to outliers. From Figure 10 (a), the average number of NICs per server increases slightly, while the percentage of inactive NICs per server actually decreases slightly, as shown in Figure 10 (b). The reason behind this is that the average number of inactive NICs per server remains constant. Combining both observations, one can conclude that the demand of NICs per server increases steadily over the two years.

From the percentiles we observe that the distribution of NICs per server is opening up. This observation can be explained by the increasing population of NICs due both to the growing population of servers under observation and the use



(a) Number of NICs (b) Percentage of inactive NICs

Fig. 10. Evolution of NICs per server: average, 5th percentile, and 95th percentile.

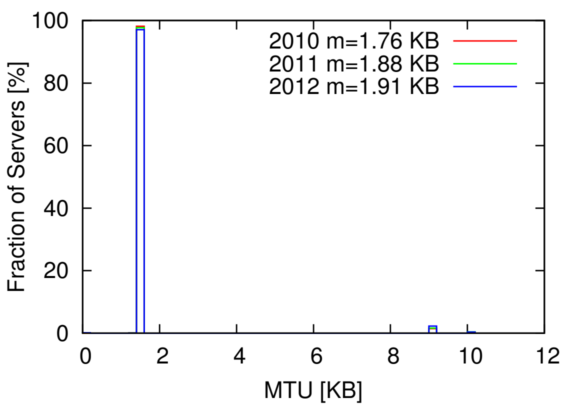


Fig. 11. PDF of MTU for June 2010, July 2011 and April 2012, where *m* denotes the average value.

of virtualization technologies which increases the number of virtual NICs. On the other hand, distribution of inactive NICs per server is closing indicating that the ratio of active/inactive NICs across servers converges over time.

As for the evolution of MTU distribution, we compare the mean MTU values across servers in June 2010, July 2011 and April 2012. The resulting PDFs are shown in Figure 11. The mean MTU value across servers increases slightly from 1.76 KBytes (2010) to 1.91 KBytes (2012), but the bimodal distribution with two peaks at 1500 bytes and 9000 bytes persist over all years; i.e., over the years we observe a shift form the 1500-bytes peak to 9000-bytes meaning that the jumbo frame adoption gets wider.

B. Inbound vs Outbound Traffic

We summarize the time series of 15-minute and monthly average traffic across all servers in Figure 12(a)-(b) and 12(c)-(d), respectively. We separate inbound and outbound traffic. Both time series are computed by first taking the 15-minute and monthly average of each server and then averaging over all the servers for each point in time. Overall, the total traffic seems extraordinary low but we have to keep in mind that the averaging operation hides the peak usages. It is worth noting that network traffic either in the world wide web [11], [12] or datacenter network [7] is quite bursty. The input traffic is higher than the output traffic both in Mbps and Kpps and in daily and monthly scale. This is opposite of the result presented in Benson et. al. [2]. However, they present the inbound and outbound traffic measured at the router level, which resides at the border of the datacenter network and hence it might not capture traffic like the inter-datacenter backup traffic.

Within a day shown in Figure 12 (a) and (b), the network is most active during the night and least active during the afternoon. Surprisingly, this contradicts the usual diurnal traffic pattern observed in the Internet [13]. In addition, throughout the whole day there are several smaller spikes on the hour. Those small spikes can be explained by the common practice of scheduling jobs on the hour. Moreover, the difference between inbound and outbound traffic changes over the time, i.e., bigger difference at night and smaller difference in the afternoon. We thus conclude that server traffic is most symmetric during the day than at night. Note that the time series shown here also support and explain the peak time patterns shown in Figure 9.

When focusing on the two year span in Figure 12(c) and 12(d), one can clearly see that the traffic per server both in Mbps and Kpps increases. The growth rates are roughly 0.75 Mbps/year and 0.2 Kpps/year, respectively. The difference between inbound and outbound traffic is almost constant in Kpps, and slightly decreases in Mbps. This indicates that the traffic is becoming slightly more symmetric in Mbps. Overall, servers at datacenters have increasing and asymmetric traffic in the long run, but exhibit no visible periodical patterns.

V. Virtual Machines Network Demand

Motivated by the growing prevalence of virtual machines in today's datacenters, in this section we intend to answer the question of how differently physical and virtual servers use the network.

We summarize the distribution of no. of NICs, MTU, and average packet sizes per physical and virtual server in Figure 13(a), 13(b), and 13(c) respectively. In terms of NICs, physical servers tend to have a higher number of NICs than virtual machines, as indicated in Figure 13(a) by a right shift of the barycenter in the PDF of the number of NICs belonging

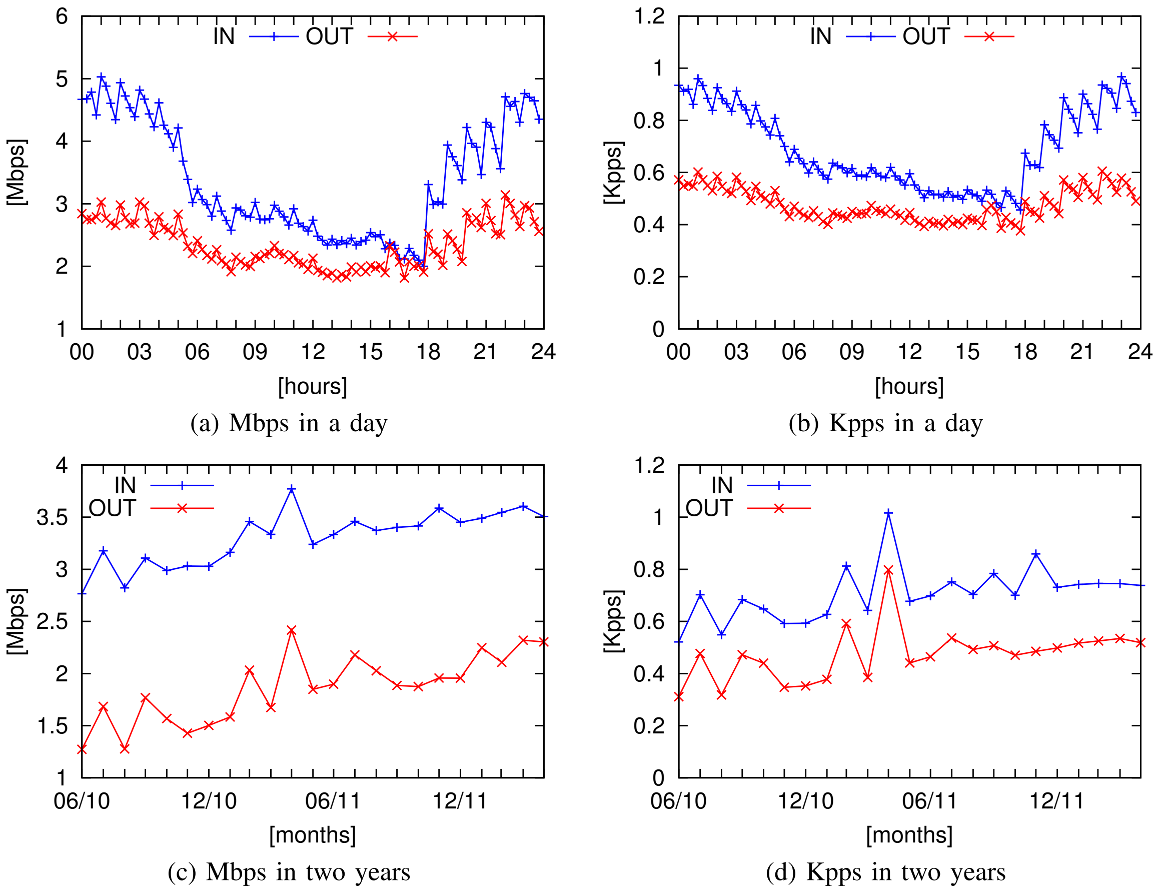


Fig. 12. Time series of inbound and outbound traffic during a day and two year observation periods.

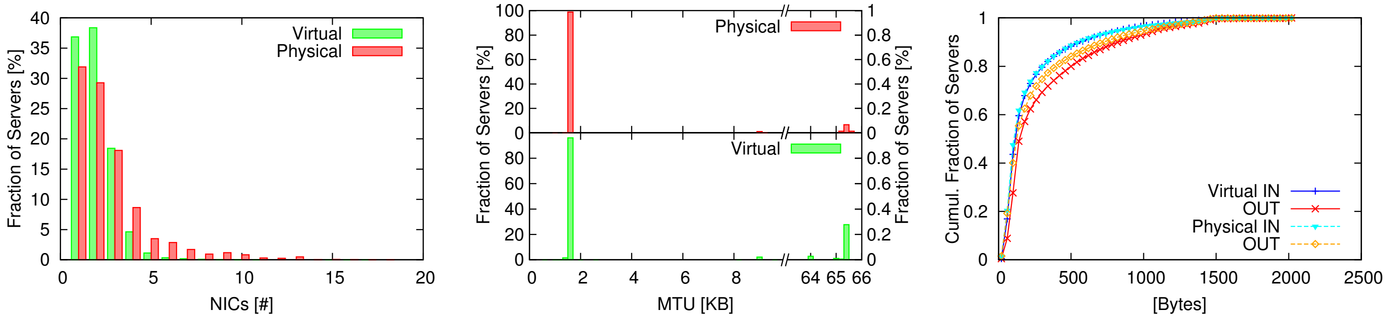
to physical servers. For the MTU sizes distribution, depicted in Figure 13(b), the virtual one is more spread out than the physical one. Indeed, most physical servers have 1500 bytes as MTU size value (see the spike of nearly 100% of physical servers), whereas virtual machines have two small additional peaks: one for MTU values slightly smaller than 1500 bytes and one around 65 KBytes (shown by the rightmost bars in split region of Figure 13(b)). The former case is due to the (encapsulation) overhead for additional protocols as used for example to create overlay networks to isolate traffic from different tenants. The later case is because virtual machines have better flexibilities to set higher MTU values allowing to reduce the per-packet processing overhead. Correspondingly, virtual machines have higher average packet sizes of outbound traffic than physical servers, as observed in Figure 13(c), though there is almost no difference between their average packet size of inbound traffic. We suspect that bigger packet sizes can facilitate the communication of virtual machines hosted on the same physical server since switching and routing software code incurs typically in per-packet processing costs which is only slightly dependent on the size of the packets.

Furthermore, we separate the inbound and outbound traffic volume of virtual machines and physical servers and present the corresponding time series in Figure 14. For both virtual machines and physical servers, the average inbound traffic is still higher than the outbound traffic in Mbps as well as in Kpps. However, the traffic from virtual machines fluctuates more than the traffic from physical servers. We explain this observation by the fact that multiple virtual machines are hosted on a physical server and therefore there is an aggregation/averaging effect at the physical server level. Another very interesting comparison between virtual machines and physical servers is that physical servers have higher input traffic (in Mbps and Kpps), whereas virtual machines generate more output Mbps. This is probably due to the different uses assigned to the machines. Virtual machines are normally used to run a broad variety of different applications ranging from web services to email servers, which are more or less network intensive. However, the backup applications, which typically are the most inbound network intensive ones in the datacenter, normally run on physical servers.

VI. Related Work

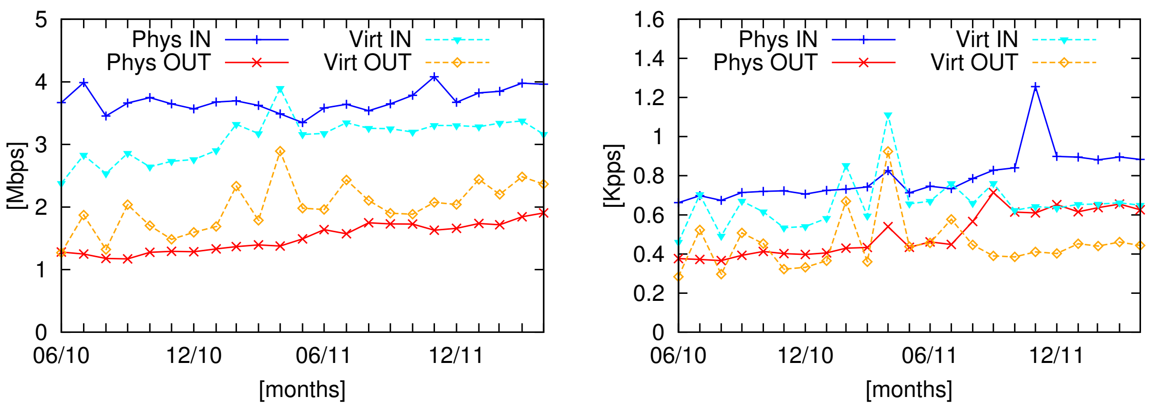
In recent years, datacenter networking has evolved mainly into two directions, i.e., network architectures [14]–[17] and network performance [2], [3]. In the latter category, several studies focus on characterization of datacenter networks, using traces collected from different types of datacenters, e.g., enterprise datacenters and cloud-like datacenters. Both [18] and [19] report the measurement studies on enterprise networks, with regard to their flow statistics. Greenberg et al. [20] further use the collected flow characteristics to guide the enterprise datacenter network design.

On the other hand, the following studies [2], [3], [7]



(a) Number of NICs (b) MTU size (c) Average packet size

Fig. 13. The comparison between virtual machines and physical servers in terms of network resources and packet sizes.



(a) In Mbps (b) In Kpps

Fig. 14. Inbound and outbound traffic of virtual machines vs physical servers.

consider cloud-like datacenters and the majority of their analysis span only over several days, not years. The former two focus on datacenters hosting MapReduce applications or web service applications, whereas the third one considers cloud and enterprise datacenters. They analyze network traffic from the perspective of the network gear, meaning that statistics are collected at the routers and switches. Kandula et al. [7] use socket level logs, instead of switches, whereas Benson et al. [2] use link-level utilization; one of their conclusions is that the traffic generated by servers under-utilizes network resources.

The aforementioned related studies indeed provide tremendous insight as to how network traffic flows in either enterprise or cloud-like datacenters, especially on the shorter time scale. Most long-term network measurement studies are carried out in worldwide web domain, such as [11], [21]. However, little is known about the deployment of network resources and their configuration, except for [22]. Our analysis augments the prior work from a server's perspective, by focusing on the generation of network traffic from the servers. Network-centric measurement studies can leverage our studies to benchmark their findings.

VII. Summary & Conclusion

Data center network traffic has been well characterized from the network perspective by several recent studies. However, little is known about the in- and outbound network traffic patterns from the server perspective. This paper is the first attempt to characterize server inbound and outbound traffic patterns with respect to different metrics, i.e., Mbps and Kpps, using two time resolutions. Our empirical findings about network usage in datacenters can be summarized as follows:

- On average, a server generates network traffic of 1.15 Kpps and 5.7 Mbps, combining the inbound and outbound traffic. The average packet size is roughly 300 bytes.
- Inbound and outbound traffic across servers can be well captured by either the Weibull or log-normal distribution. Typically, within a day and over years, a server receives more traffic than it transmits, both in terms of bytes and number of packets.
- A server handles peak traffic at night, especially around 3 AM, and especially inbound traffic. The peak inbound traffic has higher concentration during a certain period at night, whereas the peak outbound traffic is more evenly distributed over night and day.
- Physical servers and virtual machines show a disparate traffic pattern. Physical servers generate more traffic than virtual machines, except output traffic in Mbps. Virtual machines have larger packet sizes in their outbound traffic than physical servers.
- Although many servers have more than two NICs, only two NICs are used actively, on average. In the long run, the demand of NICs per server is increasing.
- Roughly 92% of servers set their Maximum Transfer

Unit (MTU) at 1500 bytes, indicating the dominance of Ethernet technology. In the past two years there has been a slightly increasing trend of using 9000 bytes Jumbo frames. Also, inbound traffic pattern among servers is more widely varied than outbound traffic.

- A generic server tends to transmit bigger packets and receive smaller packets. The average packet size does not vary significantly over the duration of the study.

Overall, the inbound traffic has a higher potential to become a bottleneck than the outbound traffic. We believe that due to the disparate nature, the traffic from virtual machines and physical servers should lead to different network management strategies. Our analysis complements prior network-centric analysis and provides a basis for efficiently dimensioning datacenter network capacity and traffic engineering.

REFERENCES

[1] A. G. Greenberg, J. R. Hamilton, D. A. Maltz, and P. Patel, "The cost of a cloud: research problems in data center networks," *SIGCOMM Computer Communication Review*, vol. 39, no. 1, pp. 68–73, 2009.

[2] T. Benson, A. Akella, and D. A. Maltz, "Network traffic characteristics of data centers in the wild," in *Internet Measurement Conference*, 2010, pp. 267–280.

[3] T. Benson, A. Anand, A. Akella, and M. Zhang, "Understanding data center traffic characteristics," *SIGCOMM Computer Communication Review*, vol. 40, no. 1, pp. 92–99, 2010.

[4] Netflow, "http://www.ietf.org/rfc/rfc3954.txt."

[5] WireShark, "http://www.wireshark.org/."

[6] Aurora, "http://www.zurich.ibm.com/aurora/."

[7] S. Kandula, S. Sengupta, A. G. Greenberg, P. Patel, and R. Chaiken, "The nature of data center traffic: Measurements & analysis," in *Internet Measurement Conference*, 2009, pp. 202–208.

[8] R. Birke, L. Y. Chen, and E. Smirni, "Data centers in the cloud: A large scale performance study," in *IEEE Cloud*, 2012.

[9] J. Aitchison and J. Brown, *The Lognormal Distribution*. Cambridge University Press, 1957.

[10] A. Papoulis, *Probability, Random Variables, and Stochastic Processes, 4th Edition*. McGraw Hill, 2002.

[11] M. Arlitt and T. Jin, "Workload characterization of the 1998 world cup web site," *IEEE Network*, vol. 14, no. 3, pp. 30–37, 2000.

[12] V. Paxson and S. Floyd, "Wide area traffic: the failure of poisson modeling," *IEEE/ACM Transactions on Networking*, vol. 3, no. 3, pp. 226–244, 1995.

[13] K. Thompson, G. Miller, and R. Wilder, "Wide-area internet traffic patterns and characteristics," *IEEE Network*, vol. 11, no. 6, pp. 10–23, 1997.

[14] M. Al-Fares, A. Loukissas, and A. Vahdat, "A scalable, commodity data center network architecture," in *SIGCOMM*, 2008, pp. 63–74.

[15] B. Heller, S. Seetharaman, P. Mahadevan, Y. Yiakoumis, P. Sharma, S. Banerjee, and N. McKeown, "Elastictree: Saving energy in data center networks," in *NSDI*, 2010, pp. 249–264.

[16] C. Guo, H. Wu, K. Tan, L. Shi, Y. Zhang, and S. Lu, "Dcell: a scalable and fault-tolerant network structure for data centers," in *SIGCOMM*, 2008, pp. 75–86.

[17] D. Maltz, G. Xie, J. Zhan, H. Zhang, G. Hjálmtýsson, and A. Greenberg, "Routing design in operational networks: a look from the inside," *SIGCOMM Computer Communication Review*, vol. 34, no. 4, pp. 27–40, 2004.

[18] R. Pang, M. Allman, M. Bennett, J. Lee, V. Paxson, and B. Tierney, "A first look at modern enterprise traffic," in *Internet Measurement Conference*, 2005, pp. 2–2.

[19] S. Guha, J. Chandrashekar, N. Taft, and K. Papagiannaki, "How healthy are today's enterprise networks?" in *Internet Measurement Conference*, 2008, pp. 145–150.

[20] A. Greenberg, J. Hamilton, N. Jain, S. Kandula, C. Kim, P. Lahiri, D. Maltz, P. Patel, and S. Sengupta, "Vl2: a scalable and flexible data center network," in *SIGCOMM*, 2009, pp. 51–62.

[21] S. Ihm and V. S. Pai, "Towards understanding modern web traffic," in *Internet Measurement Conference*, 2011, pp. 295–308.

[22] H. Kim, T. Benson, A. Akella, and N. Feamster, "The evolution of network configuration: A tale of two campuses," in *Internet Measurement Conference*, 2011, pp. 499–514.