Persistent Last-mile Congestion: Not so Uncommon

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ABSTRACT

Last-mile is the centerpiece of broadband connectivity, as poor last-mile performance generally translates to poor quality of experience. In this work we investigate last-mile latency in 646 ASes using traceroute data from RIPE Atlas and focus on recurrent performance degradation. We find that in normal times only 10% ASes experience persistent last-mile congestion but we record 55% more congested ASes during the COVID-19 outbreak. Persistent last-mile congestion is not uncommon, usually seen in large eyeball networks and may span over years. With the help of CDN access log data, we dissects results for major ISPs in Japan, the most severely affected country in our study, and ascertain bottlenecks in the shared legacy infrastructure.

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1 INTRODUCTION

Internet resources are shared among a varied number of users with diverse demands. The exhaustion of network resources is the main source of packet loss and increased latency which usually translates into degraded web services and poor quality of experience [26]. Understanding Internet congestion causes and detecting it in time and space is, hence, crucial for maintaining quality services.

To that end, the research community has spent multiple efforts. Past studies have exposed the relationship between persistent inter-domain congestion and under provisioned links [7, 16], and between transient in-network congestion and routing mishap [11]. For broadband users home network and last-mile are the main bottlenecks [25], last-mile is also a common place for transient self-induced congestion [12, 24] and a key factor to quality of experience [26]. Nonetheless, a recent analysis of access networks in US and UK reveals that last mile latency is usually stable and features no recurrent congestion [3]. On the contrary, our study shows that for some Autonomous Systems (ASes) last-mile congestion may be a pervasive and perpetual problem. Hence, this paper complements the literature by documenting persistent last mile congestion, that is, congestion close to users' premises that spans over an extended period of time.

Using RIPE Atlas, we conduct an exploratory survey of last-mile latency in 646 Autonomous Systems (ASes). We find that 90% ASes exhibit no significant last-mile congestion but the few congested ASes are usually large eyeball networks and congestion may last over years. We also show that the number of impacted ASes increased by 55% during the COVID-19 outbreak. Finally we present a case study focused on major Japanese ISPs and show that CDN access logs support our findings. Our comparison between different access technology in Japan narrows down the problem to the extensive use of the shared legacy infrastructure over PPPoE and shows that wired broadband throughput for some ISPs is consistently lower than LTE during peak hours.

This work provides valuable insights to the operational community with the following research contributions:

- We propose (§2) and validate (§4) a methodology to measure persistent last mile congestion. We make our tools publicly available so that our experiments can be reproduced and extended [21].
- We report last-mile conditions in 2018 and 2019 for 646 ASes registered in 98 countries, and we estimate the impact of COVID-19 on last-mile latencies (§3). All this is publicly available [1], the interested reader may refer to that for more details.
- Our case study illustrates how a nation-wide infrastructure which had successfully opened the telecommunication market to competition [9], is now failing to cope with the increasing demand (§4). Given the extent of this proprietary infrastructure and the difficulties to upgrade it, we reiterate the importance of scaling and upgradability in these deployments.
- Finally, we give recommendations to handle persistent last-mile congestion in delay measurements with RIPE Atlas, and discuss the adverse consequences of BBR in this context (§5).

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2 FROM TRACEROUTE TO LAST-MILE CONGESTION

With over ten thousands probes deployed world-wide, the RIPE Atlas measurement platform is ideal for surveying last-mile condition in numerous ASes. Also, as our interest lies in the closest segment to the probes, we can recycle the numerous public measurement data offered by Atlas. Hence, we retrieve data from the 22 IPv4 built-in traceroute measurements [22] to obtain a steady number of RTT samples. These measurements are executed by all probes towards all root DNS servers and RIPE Atlas controllers every 30 minutes, and two randomly selected addresses every 15 minutes.

For our experiments, we filter out some undesired traceroutes. First, we ignore traceroutes from Atlas anchors as this type of probe is usually located in datacenters, thus without a typical last-mile connectivity. Second, for each probe, we group its traceroutes into 30-minute time-bins and discard traceroutes in bins that have less than 3 traceroutes. This ensure that we have a sufficient number of traceroute to infer RTTs and avoid wrong inference when a probe is disconnected. Although past research has shown that v1 and v2 probes can be less reliable [13], in our experiments we observe only slight differences in our aggregated results when using these probes. As a trade-off between precision and coverage, we avoid using these probes when it is not needed (§4) but we include them when surveying last-mile latency at large scale (§3).

In this paper, we focus on eight measurement periods. Six periods are used for longitudinal analysis, these stand for the 1st to the 15th of March, June, and September, 2018 and 2019. We assess the impact of COVID-19 using traceroutes collected from the 1st to the 15th of April 2020. Finally, we collect traceroute data during the time period covered by the CDN log data employed in §4. To avoid confusion, all dates are in UTC.

2.1 Estimating last-mile RTT

The last-mile is generally regarded as the segment connecting the probe's premises to the ISP IP infrastructure. In practice, we identify the ISP edge infrastructure as the first public IP address seen in the traceroute (i.e. not a RFC1918 private address). We notice that some of these IP addresses are not announced on BGP, thus when we need to identify the ASN corresponding to the last-mile, we use the probes' public address for longest prefix match with BGP data.

To estimate the last-mile RTT, we simply subtract the last private IP RTT to the identified first public IP RTT. Past work has shown that this is a practical estimate when paths are symmetric [7, 11] which is expected for private LANs hosting Atlas probes.

Using the traceroute dataset mentioned above, every 30 minutes we obtain 24 traceroutes and compute 9 RTT samples per traceroute (pairwise subtraction of the 3 RTTs for each of the last private IP and the first public IP), that is 216 samples per probe. To filter out noise as in [11], we compute the median RTT per probe in 30-minute time-bins.

Congestion is monitored by estimating the deviation (i.e. queuing delay) from a base latency (i.e. propagation delay). To measure these delay changes we subtract the minimum median RTT value from all median RTT values for each probe. Consequently, we obtain a rough estimate of last-mile queuing delay for each probe where the lowest point is set to zero and other values correspond to delay increase in milliseconds.

Finally, we derive the overall last-mile conditions from a population of probes. In this paper we select population of probes based on their ASN (§3), or their ASN and geographical location (§4). To combine delays from a population, we compute the median value across all last-mile queuing delay estimates from that population. This gives us an aggregated queuing delay where large fluctuations reveal times when the majority of the probes experience high latency.

2.2 Examples

To give a concrete example, we present results from two of large eyeball networks hosting numerous Atlas probes. One is located in U.S.A. (hereafter referred as ISP_US) and the other one in Germany (ISP_DE).

Figure 1 depicts aggregated queuing delay for each measurement period and AS. For ISP_DE (upper plot) we observe very stable delays for all measurement periods. Even in April 2020, during COVID-19 lockdown, we observe no particular change. These results and our large-scale survey (§3) support past observations [3] by showing that last-mile RTTs are usually stable.

For some networks, however, we found interesting patterns that reveal persistent delay increases. For example, ISP_US (Fig. 1 lower plot) features a small but consistent diurnal pattern during 2018 and 2019. In April 2020 this pattern is even more pronounced with peak hours widening over daytime. As discussed in § 3, we attribute this to the impact of COVID-19 lockdowns. The aggregated queuing delay increase is apparently small, only over 1ms during peak hours, but looking at the delays of each probe we observe that the proportion of probes that experience daily queuing delay over 5ms has tripled

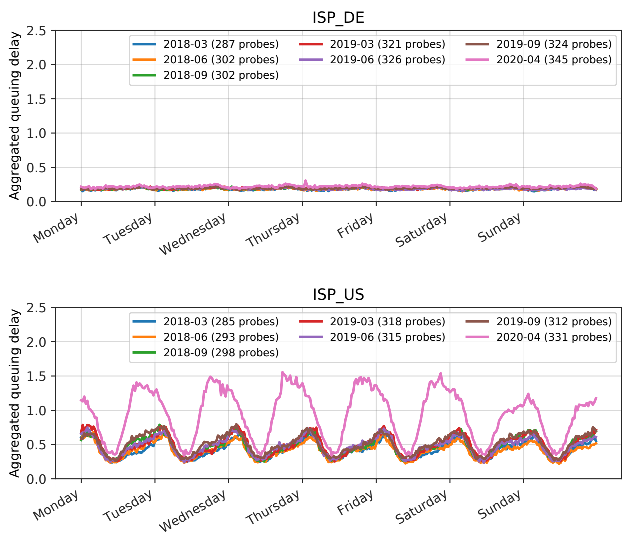

Figure 1: One week of aggregated last-mile queuing delay for large German (top) and American (bottom) ISP in 2018-2020.

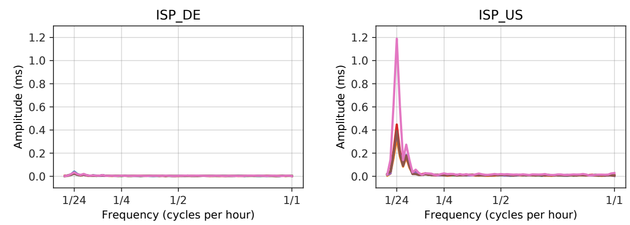

Figure 2: Periodograms computed with Welch method and aggregated queuing delays of Fig.1. The y-axis is normalized to read directly average peak-to-peak amplitude. See legend in Fig.1.

when compared to results in 2018 and 2019, representing a quarter of the probes in 2020.

For now we would like to stress two key observations: (1) Similar to persistent inter-domain congestion [7], persistent last-mile congestion is characterized by a clear daily pattern, but (2) these two types of congestion differ by their amplitude. In the case of last-mile congestion we aggregate delays from numerous links, hence, unless most links are congested we measure only small aggregated variations. In § 4 we show that significant throughput drops occur when aggregated delays are over 1ms. Furthermore, our metrics are designed to be robust to outliers thus only long lasting congestion across multiple probes can cause the aggregated delay increase. Indeed, by computing probes' median RTT in 30-minute time-bins, we filter out bins that are congested for less than 15 minutes. Combining probe signals with the median also implies that the majority of the probes should experience delay increase to be visible at the AS level.

2.3 Detecting persistent congestion

As illustrated above, and more broadly in our survey (§3), persistent congestion is visible on a daily basis. We leverage this observation to systematically identify persistent last-mile congestion in our large collection of traceroutes.

We employ basic signal processing techniques to decompose aggregated delay signals in frequency components and extract the daily patterns. Namely, we convert the aggregated delay signals to the frequency domain using the Welch method. This method splits the delay signals in overlapping segments and compute the periodogram (i.e. power measurements vs. frequency bins) of each segment using Fourier transform. Then all periodograms are averaged to obtain a final periodogram that is less affected by noise in the original signals.

The Welch method enables us to identify the prominent frequency component of signals by finding the frequency bin with the highest power in the periodogram. Then we check if the frequency bin corresponds to daily fluctuations, and we derive from the corresponding power in the periodogram the average peak-to-peak amplitude of these fluctuations. These two markers (frequency and amplitude) allow us to classify aggregated delay signals into four categories:

Severe: prominent daily pattern and amplitude over 3ms.
Mild: prominent daily pattern and amplitude over 1ms.
Low: prominent daily pattern and amplitude over 0.5ms.
None: no prominent daily pattern or daily pattern amplitude below 0.5ms.

The 0.5ms threshold value is set to focus mainly on the most congested networks. The 1ms and 3ms threshold values are set such that the size of classes Severe, Mild, Low, are well balanced in our experiments (see Fig.4).

Going back to our example with ISP_DE and ISP_US, Figure 2 depicts the periodograms derived from the signals shown in Figure 1. Here the periodograms are displayed such that the y-axis represent the peak-to-peak amplitude. For ISP_DE (left plot) the spectrum is mostly flat, meaning that the signal is mainly composed of noise. However, the daily frequency bin (x=1/24) is clearly dominant for ISP_US (right plot). The average daily amplitude is usually estimated around 0.4ms except on April 2020 where it goes up to 1.19ms. Thus we classify ISP_US as mildly congested on April 2020 and as not congested during the other measurement periods.

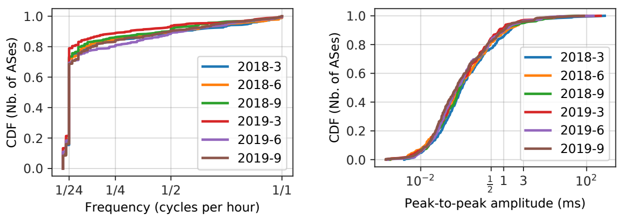

Figure 3: Distribution of prominent frequencies in all monitored signals (left plot), and distribution of peak-to-peak amplitude for prominent daily components (right plot).

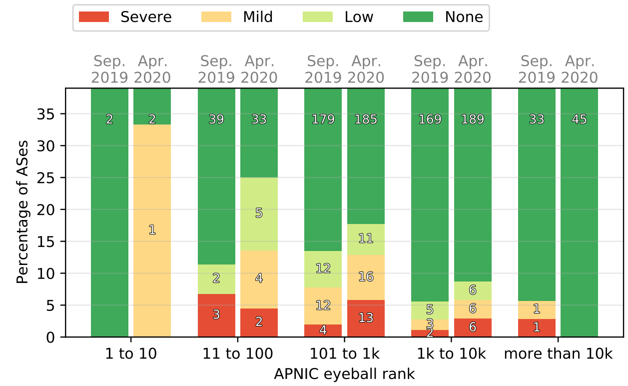

Figure 4: Classification breakdown for results in September 2019 and April 2020. Cropped at 40% for better visibility.

3 PERSISTENT LAST-MILE CONGESTION IN ATLAS

Now we extend our last-mile congestion analysis to all ASes hosting at least three Atlas probes. Here we include v1 and v2 probes for a better coverage and obtain classification results for a total of 646 ASes in 2018-2019.

3.1 A small number of congested ASes

On average about 90% of the monitored ASes are classified as *None*, meaning that they exhibit no significant diurnal pattern. The number of reported ASes (i.e. not classified as None) is quite stable over time with an average of 47 ASes per measurement period. We observe little churn over the two years, 36 ASes are reported for at least half of the measurement periods.

In the previous section, we assume that persistent congestion is commonly seen on a daily basis. We check this hypothesis by identifying the main frequency component in each AS using the Welch method. Figure 3 (left plot) reveals that the majority of the ASes exhibits a daily fluctuation (x=1/24), and other ASes are uniformly distributed across the whole spectrum. Figure 3, right plot, displays the amplitude corresponding to identified daily fluctuations. Around 83% of the ASes have a daily amplitude lower than 0.5ms thus barely noticeable, then about 7% are between 0.5ms and 1ms, another 6% are between 1ms and 3ms, and the rest (4%) are over 3ms. Using these values for our classification let us focus mainly on the distribution tail, that is the top congested networks.

3.2 Congestion in eyeball networks

To get a sense of the number of Internet users impacted by the identified congestion, we classified our results with the help of the APNIC eyeball population estimates [2]. Figure 4 breakdowns the September 2019 results into APNIC rankings. This suggests that last-mile congestion tends to appear in large eyeball networks (i.e. top 1000 ASes in APNIC ranking). Breakdown for preceding measurement periods are similar hence not displayed.

COVID-19. In April 2020 we observe an increase of last-mile congested ASes that we attribute to the impact of lockdowns due to the COVID-19 pandemic. The number of reported ASes increased by 55% (45 to 70 ASes) from September 2019 to April 2020. As expected large eyeball networks are the most impacted ones (Fig. 4). The largest reported network being ISP_US with an average daily amplitude of 1.19ms as shown in Figure 1.

Notice that this work is, however, only looking at last-mile congestion, the increase of traffic during lockdowns may create congestion at other locations. For example Italy has reportedly been experiencing significant end-to-end delay increases [5, 15] but is not particularly outstanding in our results on April 2020.

Geographical distribution. Using the country code provided with the APNIC ranks, we also look into the geographical distribution of congested ASNs before COVID-19. Out of the 98 monitored countries, 53 have at least one reported ASN, and only 23 have at least one ASN reported as severely congested. Japan contains the highest number of *Severe* reports (18% over the two years), followed by U.S.A. (8%). Out of the top 10 monitored Japanese ASes (in terms of APNIC rankings), 5 are reported at least once in 2018 and 2019, including 3 that are constantly reported. In contrast to the low number of congested ASes found across the Atlas platform, Japan has a relatively high number of congested ASes. Policy makers [17] and network operators [18] have previously pointed out the overwhelming use of Japan's legacy infrastructure and mention it as source of congestion. As this serves as a good example to illustrate persistent last-mile congestion and surrounding circumstances, in the next section we present a brief summary of Japan's legacy infrastructure and provide detailed analysis for Japan's top three eyeball networks.

4 LAST-MILE CONGESTION IN TOKYO

Japan is one of the top ranking fiber-to-the-home (FTTH) countries, with 70% household penetration [14] as of 2018, and holds a competitive telecommunication market. This situation was fostered by Japanese government forcing the former state monopoly to grant unbundled access to other ISPs and maintain a nation-wide fiber network, hereafter referred as the legacy network [20]. The legacy network accounts for about 70% of FTTH access in Japan, with customers usually reaching their ISP via PPPoE. PPPoE was an enabler for the competitive ISP market when introduced in 2000, but has been gradually ossified because carrier-specific PPPoE equipment is too expensive to upgrade for low-profit broadband services, also requiring cumbersome negotiations among the carrier, ISPs, and government. Although comprehensive measurement is lacking, legacy's PPPoE equipment has been considered as source of congestion [18, 23].

Accordingly, we investigate the relation between observed persistent last-mile congestion and legacy's PPPoE usage. Our investigation starts with the following hypothesis: networks relying on the legacy network via PPPoE are more prone to congestion. We check this hypothesis by looking at delays from networks relying mostly on the legacy network, ISP_A and ISP_B, and one network with its own fiber network, ISP_C. These are the three major ISPs in Japan.

Because the number of Atlas probes is limited with a potential bias towards tech-savvy users, last-mile latency results are cross referenced with CDN log data collected in Tokyo in order to assess the presence of congestion, and validate our approach with much larger (about 150k unique IPs) and unbiased samples. For a fair comparison between traceroute and CDN data, we select only Atlas probes in the Greater Tokyo Area (i.e. Tokyo, Yokohama, Chiba, Saitama) which gives a total of 21 probes in the three selected ISPs. The last-mile latency for these ASes is computed exactly as presented in §2 but selecting only probes located in Tokyo. The CDN and traceroute datasets span from September 19^{th} until the 26^{th}, 2019.

4.1 Last-mile delays

Figure 5 shows the aggregated last-mile delays computed for probes in Tokyo. The three networks are performing

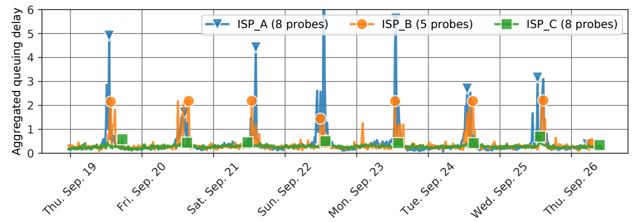

Figure 5: Aggregated last-mile queuing delays for major eyeball networks in Tokyo. Markers are placed on daily maximum delay values.

with similar queuing delays outside of peak hours. During peak hours, however, ISP_A and ISP_B exhibit consistent delay increases whereas ISP_C keeps stable. For ISP_C we do observe maximum delays during peak hours (depicted by markers in Fig.5) but by an order of magnitude lower than the two other networks.

4.2 Throughput measurements

To validate our results and estimate the impact of observed congestion on traffic, we estimate average throughputs from a large commercial CDN access logs collected in Tokyo. Since the studied ASes provide both broadband and mobile services, we filter out all entries corresponding to mobile prefixes as advertised on their website (Appendix A). Then we select only requests for objects greater than 3MB and marked as cache-hit. This allows us to account for TCP dynamics [10] and artifacts caused by CDN functioning. As with the delay measurement, we measure throughput per IP and compute ASN aggregates by computing the median value in 15-minute time-bins.

The top plot of Figure 6 shows the median throughput for ISP_A and ISP_B broadband, both marked by significant daily drops. The throughput for these networks decreases to less than half during peak hours approximately coinciding with delay increases observed in Figure 5.

We can also check the PPPoE hypothesis by comparing these results to mobile users throughput. Figure 6 middle plot depicts the median throughput for ISP_A and ISP_B mobile users (ISP_A mobile users are from a different AS). We see no similarity between broadband and mobile throughputs, cellular networks show consistent performance by maintaining median throughput above 20Mbps. ISP_C throughput also exhibits no significant daily drop for both broadband and mobile users (bottom plot). The stable performances of ISP_C and cellular networks also confirm that the observed throughput drops are not due to congestion at the CDN.

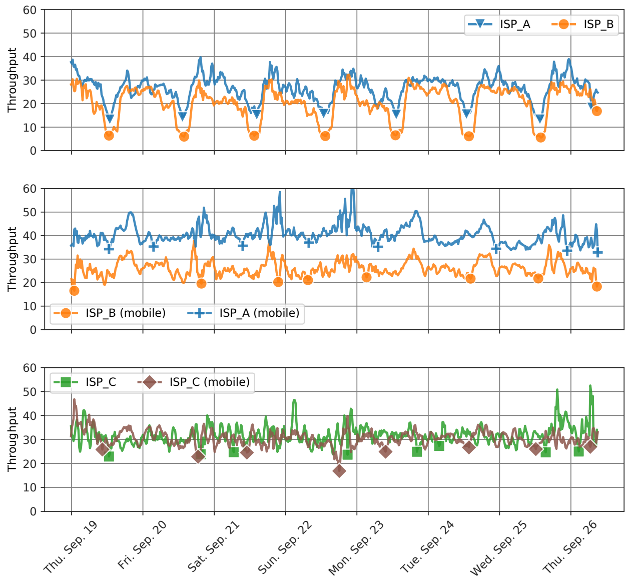

Figure 6: Median throughput (Mbps) for major Japanese ISPs, displayed in 30-minute bins. Top plot: ISP_A and ISP_B broadband users. Middle plot: ISP_A and ISP_B mobile users. Bottom plot: ISP_C broadband and mobile users. Markers are placed on daily minimum throughput.

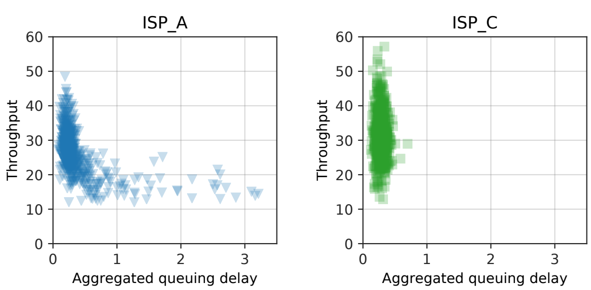

Figure 7: Aggregated last-mile queuing delay and throughput for ISP_A and ISP_C. Cropped at 3.5ms and 60Mbps for better visibility.

4.3 Delay and throughput correlation

To better understand the relationship between delay and throughput fluctuations we cross-reference both datasets. For congested ASes, we find that there is clear non-linear correlations between delay and throughput, hence we report correlation using Spearman's rank correlation coefficient. Figure 7 shows the relationship between delay and throughput. For ISP_A (left plot) delay increases concur with throughput decreases ($\rho = -0.6$). For instance, we always observe low throughput when aggregated delay is above 1ms. For ISP_C (right plot) there is absolutely no correlation between the two metrics ($\rho = 0.0$), meaning that throughput and delay fluctuations are driven by different factors.

Although these results cannot imply causation, they agree with our hypothesis hence support previous observations [18]. We also argue that these are strong evidences of persistent last-mile congestion and thus validate the monitoring technique of §2.

5 DISCUSSIONS

Results presented in this paper have several implications for the networking community.

We believe the original version of BBR [6] that disregards packet loss may be detrimental in the context of persistent last-mile congestion, as it may put more burden to already overwhelmed devices. Thus, the improvements brought by BBR v2 (i.e. account for loss and ECN) are essential in this context [19].

Special care is also required when working with measurement platforms, such as RIPE Atlas. For instance, geolocation studies and services based on latency [4, 8, 27] should avoid making inferences during peak hours and with probes affected by persistent last-mile congestion. More generally, we recommend inspecting last-mile latency for any Internet delay study as last-mile congestion may induce wrong inferences.

Although omitted here for brevity, we have made a few more observations in Japan using Atlas anchor's delay (Appendix B) and IPv6 traffic (Appendix C) and noticed that the use of IPoE (instead of PPPoE) for IPv6 in most Japanese ISPs help circumvent congested legacy devices. This could suggest that the newer IPv6 infrastructure scales better but this could also be due to the different traffic volume carried by each protocol. Comparing protocol performances is however beyond the scope of this paper and left for future work.

6 CONCLUSIONS

In this paper we have presented an analysis of persistent last-mile congestion and found that this type of congestion appears in 10% of monitored ASes, including large eyeball networks. In addition, we recorded 55% more congested ASes during the COVID-19 outbreak. Our detailed analysis of Japan's major ISPs confirmed that detected last-mile congestions have a drastic impact on users throughput.

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Appendices

A MOBILE PREFIXES OF JAPANESE ISPS

Major Japanese Mobile Network Operators (MNOs) publicly share the IP prefixes used for mobile connectivity. This is an effort to help web services to provide adapted content to cellular users. The following links are example of such list of prefixes:

- https://www.nttdocomo.co.jp/service/developer/smart_phone/spmode/index.html
- https://www.support.softbankmobile.co.jp/partner/home_tech1/index.cfm
- https://www.support.softbankmobile.co.jp/partner_st/home_tech1/ios/index.cfm
- http://www.au.kddi.com/developer/android/kaihatsu/network/
- http://www.au.com/ezfactory/tec/spec/ezsava_ip.html

B ANCHOR VS. PROBES DELAY

Another way to check the hypothesis of Section 4 is to compare results from Atlas probes with results from anchors for networks relying on the legacy network. As we expect anchors to be located in datacenters, anchors are closer to the backbone network and are not using the legacy network. In other words the main differences

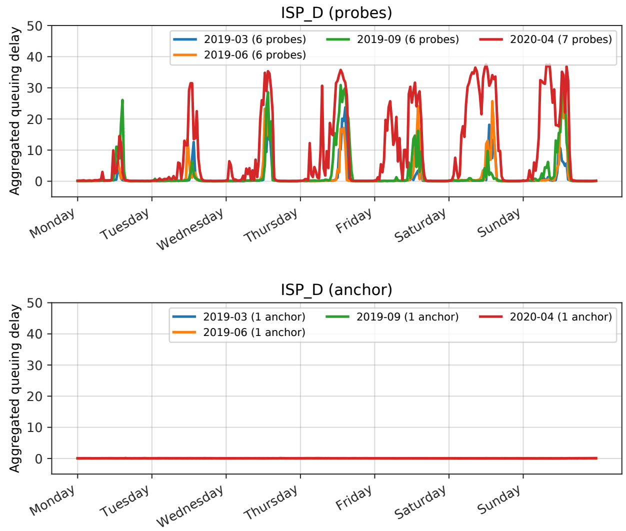

Figure 8: Comparison between last-mile queuing delay of Atlas probes and anchor in ISP_D.

between probes and anchors hosted in the same AS is the access link. And if the AS relies on the legacy network, then we expect to see congestion for probes but not for anchors.

We found only one AS (hereafter referred as ISP_D) that relies on the legacy network for its broadband service and that hosts both Atlas probes and anchor. Figure 8 shows the aggregated last-mile queuing delay for ISP_D's probes (top plot) and its anchor (bottom plot). Both are close to 0ms during off-peak hours but the probes' delay increases significantly during peak hours while the anchor's delay stays at the same level. This is another example illustrating congestion at the legacy network.

C IPV6 THROUGHPUT ANALYSIS

For the legacy network, an alternative to PPPoE is IPv6 IPoE [18, 20], although not all IPv6 is over IPoE. Thus, we expect IPv6 is less affected by PPPoE congestions. Figure 9 shows the IPv4 and IPv6 throughput for the three major ISPs of Section 4. Overall we found that IPv6 throughput is better than IPv4 and this is especially true during peak hours for ISP_A and ISP_B. IPv6 is not showing performance degradation during peak hours which suggests that the IPv6 infrastructure scales better but it could also be due to the lower volume of traffic observed for this protocol (not shown here).

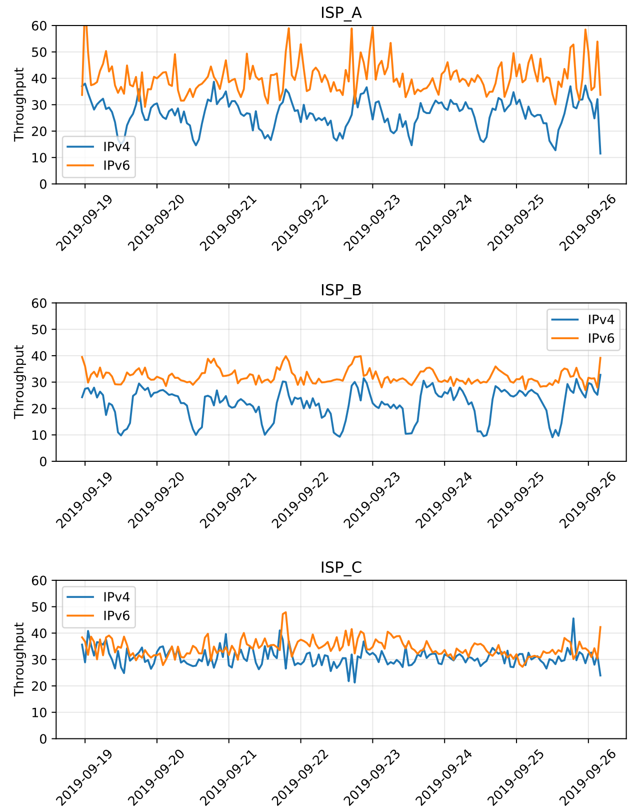

Figure 9: IPv4 and IPv6 throughput for the three major ISPs of Section 4.