Chapter 1

POWERPING: MEASURING THE IMPACT OF POWER OUTAGES ON INTERNET HOSTS IN THE US

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Abstract Power outage is a well-known threat to Internet communication systems. While Internet Service Providers (ISPs) address this threat via power-backup systems (*e.g.,* diesel generators and UPS) in PoPs and datacenters, office buildings or private homes may not have similar capabilities. In this paper we describe an empirical study that assesses how power outages in the US impact end host access to the Internet. To conduct this study we built a system named *PowerPing* that monitors a power outage reporting website (`poweroutage.us`) and measures end host responsiveness in the affected areas. We use PowerPing to collect power outage and end host responsiveness data over one year from June 2020 through July 2021. We find that power outages that affect more than 10% of customers in a county occur at a rate of about 50 events/day; each outage typically affects about 3k customers, and service is typically restored in just under 2 hours. We also report on the end host responsiveness characteristics for typical power-outage events. Surprisingly, we find only a weak correlation between power-outage impact and service restoration periods vs. end host responsiveness. This suggests that improving backup power for network devices in homes and office buildings may enable end hosts to maintain access to Internet services during typical power outages.

Keywords: Networks, Internet Physical Layer, Outages

1. Introduction

Robust availability of Internet service[1] to end hosts is essential for many day-to-day activities. This was highlighted when many people moved from offices and classrooms to their homes due to the COVID-19

pandemic. Disruptions to service are not just irksome or inconvenient, but can have real consequences in terms of lost work time and missed opportunity. The importance of connectivity is directly reflected in Service Level Agreements (SLAs) between providers and their customers, which typically include specific guarantees of service availability [1]. However, a variety of factors determine the *realized* availability of service to end hosts.

Access to the Internet can be impaired by both endogenous and exogenous events that affect single users or groups of users in a geographic area. Endogenous events include misconfigurations and equipment failures. There are well-understood best practices that minimize the impact and duration of such events. Exogenous events include natural disasters, infrastructure failures, accidents and attacks. By definition, these are outside of the direct control of Internet Service Providers (ISPs) and often require other entities to make repairs before service can be restored. Understanding the causes and effects of exogenous events is essential to improving end-to-end network reliability.

Prior studies of communication systems availability in the face of exogenous events have focused on retrospective studies of natural disasters (*e.g.,* hurricanes [22] and earthquakes [18]) and the impact of severe weather (*e.g.,* [46, 41]). These studies include detailed measurements of the number of end hosts that lost service during events and on the amount of time required to restore service, and provide a road map for study of other types of events.

In this paper, we consider the problem of how *power outages* impact the availability of Internet service to end hosts. We seek to answer questions such as *(i)* how do power outages impact Internet service to end hosts on a day-to-day basis? *(ii)* what is the scope and duration of typical power outages vs. service availability? and *(iii)* how can understanding typical power outage events inform new techniques or practices that improve network reliability? Our work contrasts with prior studies on exogenous events that impact communications systems in that *power outages are common events that take place on a daily basis* in the US [19]. There is also a simple solution to power outages – backup power supplies – assuming the outage duration is relatively modest.

To conduct our study, we developed a measurement system called *PowerPing*, which has two major components. The first component monitors `poweroutage.us`, a website that publishes real time power outage reports by county in the US. We use this data to identify counties to target with active probe-based measurement of end host responsiveness. The second component of PowerPing is a ZMap-based probing system that operates in two modes. First, it conducts background probing of

IP addresses that have been geolocated to counties across the US to establish baselines for responsiveness (*i.e.,* hosts that respond to probes). Second, when an outage is identified PowerPing sends probe packets to the IP addresses in the target area until power is restored.

There were several challenges in developing, configuring and deploying PowerPing. First, we needed timely data on power outages so that active probing of the affected area can begin as soon after the outage as possible. We used `poweroutage.us` for this data with a 12 minute collection interval. Second, we needed a database of IP addresses mapped to US counties as probe targets. We generated this database using Esri's ArcGIS [4] to assign IP addresses to counties based on Lat/Lon coordinates provided by MaxMind [5]. Our use of the term "end hosts" throughout this paper refers to the IP addresses that are geolocated by MaxMind, which in many cases may actually be home routers instead of computers. Third, we had to configure PowerPing to ensure that ZMap would effectively send and receive probes without biasing results. We deployed PowerPing in three different CloudLab [9] locations to evaluate vantage point location bias, probe scaling and consistency. Through a series of tests, we found that deploying PowerPing in a single location with a maximum probe limit of 60K packets per second (PPS), was sufficient for consistent results. Finally, we established a baseline for responsive IP addresses in each county while minimizing the overall probe load on the network.

We deployed PowerPing to collect data over a 14-month period from June 2020 through July 2021. During that time there were 330K total reported power outages with over 14K of these affecting more than 10% of customers in a county. The power outages varied in impact from fewer than 100 customers to 3.7M customers in Harris, TX on 16 February 2021, and varied in duration from less than 24 minutes to an outage in Linn, IA that lasted for 10 days starting on 10 August 2020. We found that outages across the US follow a strong diurnal cycle with the largest number of events taking place at about midday. This can be explained in part by reports from power companies that outages are typically caused by humans through scheduled maintenance, vehicle accidents, and high demand failures [21, 25]. Even power outages that are relatively significant in impact are not uncommon. Outages that affect more than 10% of customers in a county occur at a rate of about 50 events/day with service restoration typically in just under 2 hours.

Active probing of IP addresses after reports of power outages reveals a wide range of impact on service availability. The vast majority of power outages impact fewer than 1K end hosts in a target area and the service restoration period is similar to power restoration period (about

2 hours). Although in aggregate across all power outages at a given time, we find a strong correlation ($R^2 = 0.99$) between the number of customers impacted by a power outage and the number of unresponsive end hosts, we find that, at the county level, this relationship does not hold as strongly ($R^2 = 0.66$). We provide possible explanations for this result in Section 1.5.3.

Ethical considerations for this research include web scraping and active measurement. We conducted low-rate scraping on publicly available data for research purposes toward the goal of improving the public good (we do not profit from it). No laws were broken to obtain the data [54, 50], and we did not violate any stated ethical principles of major computing organizations such as the Electronic Frontier Foundation (EFF) or Association for Computing Machinery (ACM) [37, 48]. In terms of active measurement, we followed previous active measurement methodologies (*e.g.,* [34, 46, 24]) and specifically focused on developing a probing methodology that would limit impact to end hosts and ISPs.

In summary, this paper makes the following contributions. First, we describe PowerPing, a system for measuring the impact of power outages on Internet service availability.[2] Second, we present results of a 14-month, first-of-its-kind study on the impact and duration of host responsiveness during power outages. Third, our results highlight the fact that power and Internet service are related but separate critical infrastructure systems, and that it may well be possible to improve the overall resilience of end-to-end Internet service to common causes of power outages through improved deployment of battery backup for network devices.

2. Related Work

Many techniques have been developed to measure Internet events and outages. These include active probe-based methods [43, 46, 41], measuring BGP advertisements [23], measuring changes in NTP traffic [51], passive techniques such as Chocolatine that leverage Internet background radiation [33], combinations of passive and active measurement such as Disco [47], and analyzing service provider logs [44]. An important difference between these studies and ours is that they are often focused on identifying network outages without any signal of their cause. This requires an entirely different design approach for measurement than ours.

Of particular relevance to our work are two studies on the impact of weather events on residential Internet service, [46, 41]. These studies developed and employed ThunderPing to measure end host responsiveness in areas affected by severe weather events. Our methodology was

inspired by ThunderPing, but our objective, to understand end host responsiveness in areas affected by power outages, is different. This distinction is significant because severe weather is one of several causes of power outages, which also include routine maintenance, human operator error, accidents and overload. In contrast to the rare weather events studied using ThunderPing, as we demonstrate in the following sections, power outages are *common events*, with hundreds of outages occurring every day. Finally, while weather forecasting is an established science to predict the occurrence of weather, power outages are announced publicly only *after* they begin. Because of these differences, we developed a completely new code base to conduct our study of how power outages affect end host Internet service, improving our understanding of the relationship between these two critical infrastructure sectors.

Tools and techniques for conducting active measurement of Internet hosts have evolved significantly over the years, and our research is enabled by these advances. Because of hardware and network limitations in sending and processing active network probes, many early active probing studies focused on a small set of representative IP addresses for the area of interest [34, 27]. In contrast to these studies, our research actively probes as many IP addresses as possible in select geographic areas during specific events. Many tools exist for conducting active Internet surveys, including `nmap` [6] and `scamper` [36]. After our own testing of different tools, we ultimately chose `ZMap` because of its ability to rapidly and accurately scan large numbers of IP addresses in targeted IP subnets [24]. Our study benefits from the open release of these tools to the research community.

3. Datasets

In this section, we describe the three datasets that are critical to our research: current power outages, geographic information on US counties, and geographic distribution of IP subnets.

3.1 Power Outages

There are two primary sources of information on power outages in the US: (1) the US government and (2) private power generation and distribution utilities. At the federal government level, the US Energy Information Administration (EIA) [14] publishes data on the efficient operation of the US energy grid, including information on electricity supply, demand, generation, and even major disturbances and unusual occurrences [11, 10]. The EIA data suffers from two major drawbacks that make it inappropriate for our research: (1) the outage data only

includes very large or very long duration outages and (2) there is a delay of hours to days before the data is published.

Private power utility companies are the primary source of outage data. In the US, there are over 1K power utility companies that serve more than 140M customers (households). Many of these power utilities maintain online systems to track the occurrence and current status of power outages for their customers [39, 31]. These online systems present a map of the utility's service area along with pins showing the geographic location, number of customers that are without power, the reason for the outage, and expected time of resolution. These maps display current outage information, but they do not share historical outage information. Collecting and parsing information from diverse power utilities is a non-trivial task.

The maintainers of `poweroutage.us` aggregate information from the major utilities and present a consolidated national view [7]. This website monitors over 680 power utility companies that serve more than 135M customers (households) across the US to provide a count of the number and percent of customers that are without power in most US counties. The information is updated every 10 minutes, pending updates on the utilities' public-facing websites. On its overview page, `poweroutage.us` lists over 20 companies and government organizations that use the website's outage data, and the website is frequently quoted by the US news media when reporting on major power outages [3, 17, 55, 52, 38].

For this study, we leverage the consolidated information from `poweroutage.us`. This approach has several limitations (see Section 1.4.4). In particular, the information we gather about outages is most likely delayed and can be incomplete. On the other hand, power utilities aim to provide accurate and timely information on current outages to reduce individual inquiries about outage status and to satisfy customers' demands for status updates. Further, since `poweroutage.us` does not track approximately 500 smaller power utilities that serve 5.5M customers, our results do not reflect all outages in the US. However, we posit that our large sample is representative of conditions experienced by most of the population in the US.

3.2 County Geographic Data

Our study measured the effect of power outages on end host responsiveness in counties in the conterminous 48 US states. The US Census Bureau identifies the geographic boundaries of 3,108 counties in the conterminous US [2]. We process this data with Esri ArcGIS [4]. The Census Bureau data also includes county area, population, and popula-

Table 1: Top ISPs by subnet count represented in MaxMind data for US counties.

ISP Name	ASN	Subnet Count	Network Type
CHARTER	20115	277,471	cable/fiber
TWC-MIDWEST	10796	142,494	cable
TWC-TEXAS	11427	118,322	cable
BHN	33363	115,763	cable
TWC-PACWEST	20001	92,052	cable
COMCAST	7922	81,287	cable
TWC-CAROLINAS	11426	79,053	cable
TWC-NORTHEAST	11351	67,616	cable
TWC-NYC	12271	53,692	cable
ATT-INTERNET4	7018	45,640	cable/fiber
UUNET	701	27,327	DSL/fiber
CENTURYLINK-US-LEGACY-QWEST	209	23,289	DSL/fiber
ASN-CXA-ALL-CCI-RDC	22773	16,247	cable
WINDSTREAM	7029	9,600	DSL/cable/fiber
FRONTIER-FRTR	5650	8,615	DSL/fiber

tion density, which we use in our study. PowerPing uses counties as the unit of geographic area to study primarily because that is the smallest geographic resolution from `poweroutage.us`.

3.3 End Host IP Subnets

Our objective is to probe as many IPv4 addresses as possible in each target county during power outages to measure their impact and duration. To this end, the MaxMind database provides (approximate) geographic locations (Lat/Lon) of variable-sized IP subnets worldwide [5]. We use ArcGIS to spatially join the location data for each IPv4 subnet from the MaxMind database with the US Census Bureau county shapefiles to identify the subnets within each county.

We consider 1,377,238 variable-length subnets from MaxMind in US counties within power utility service areas that are tracked by `poweroutage.us`. These subnets are owned by 9,441 different ISPs by Autonomous System Number (ASN), with 44 ISPs each having more than 1,000 subnets. The top ASNs used in this study are shown in Table 1, which is dominated by the largest fixed service residential ISPs. We frequently refer to responsiveness of "Internet hosts" or "end hosts" in this paper. Given the representation of service providers noted above, we argue that the IP addresses that we use for probe targets are most likely home routers and if they are responsive during a power outage, it indicates that service to that location is available.

Limitations from this dataset include inaccuracies in the MaxMind geolocation information, incompleteness in the identified subnets, ISPs using subnet address space in multiple geographic locations, as well as understanding baseline end host responsiveness in each subnet. Additionally, DHCP churn must be considered. ISPs in North America do not change IP addresses assigned to end hosts as frequently as in other parts of the world and most IP addresses are consistently assigned to the same end host for at least several weeks [40]. To account for IP subnet geographic relocation, we updated the IP subnets from MaxMind three times during the course of our study.

4. PowerPing

We developed and deployed *PowerPing* to conduct our study. The system has two major functions: (1) identifying the number of customers without power in 2,987 counties in the US, and (2) conducting active measurement of end hosts in counties both experiencing and not experiencing power outages. PowerPing is implemented in Python 3.6 and packaged for deployment from a GitHub repository on an Ubuntu 18.04 server in cloud-based infrastructures.

During our research, we deployed PowerPing on CloudLab nodes. CloudLab is a distributed computing infrastructure available for researchers to conduct experiments from data centers in Utah, Wisconsin, and South Carolina [9]. In the subsections below, we provide a description of the system along with design considerations.

4.1 Power Outage Identification

After a power outage occurs, several steps are taken by the power utility and by `poweroutage.us` to post information online about that event. The power utility must first identify the occurrence of an outage and post the location and number of customers affected to their websites. Next, `poweroutage.us` must scrape each power utility's website to identify all outages and update their own website. The duration between the occurrence of the event and posting on `poweroutage.us` is uncertain, but utilities and `poweroutage.us` have incentives to post the information as quickly as possible.

PowerPing harvests the total number of customers tracked and the number of customers without power in each of 2,987 counties from the `poweroutage.us` website. Since power outages are unpredictable (other than scheduled maintenance), we collect data on all counties every 12 minutes to identify changes. We refer to each 12 minute interval as an *epoch*. We calculate the percentage of customers without power in each

county and divide counties into three categories: *(i)* those experiencing an outage that affects >10% of customers, *(ii)* counties in which an outage was resolved within 4 hours, and *(iii)* counties with fewer than 10% of customers without power.

We consider the start of an outage as the first epoch in which a county experiences more than 10% of customers out of power. After that, when fewer than 2% of customers are without power, we label that outage as resolved. A county with a resolved outage is maintained as a "county of interest" for four hours after resolution, after which the county is removed from the list of counties of interest. We maintain this list since there could be cases where Internet services are unavailable even though power has been restored. Every epoch, the county power outage status is passed to the active measurement component of PowerPing.

There are three issues that we considered with the outage identification component of PowerPing. First, there are inherent delays between the start of a power outage and PowerPing's identification of a power outage in a county. Most of this delay is external to PowerPing: utilities identifying an outage, utilities posting outage information to their public-facing websites, and `poweroutage.us` posting the outage information. Besides initial outage identification, which may require customers manually informing their utility of an outage, these external processes are automated. We acknowledge these delays, but cannot reduce them further. We posit that the impact is a modest reduction in outage duration measurements. Internal to PowerPing, we selected a 12 minute interval between harvesting outage information. We experimented with this interval and found that it provided a good balance between the *(i)* load on `poweroutage.us`, *(ii)* timeliness of outage update reporting and *(iii)* host responsiveness probing (described below).

Second, once during our research, the `poweroutage.us` website changed its format, which prevented us from harvesting outage information. We adapted our code to correctly process outages. We expect that future changes to the `poweroutage.us` website will require additional code updates to our system.

Third, we only consider counties with >10% of customers without power. We adopt this convention for three reasons: *(i)* it improves efficiency of our system by limiting the number of active probes sent during an epoch, *(ii)* it reduces the impact of probe traffic on the network, and *(iii)* it helps to differentiate the impact of an outage on responsiveness vs. IP response churn for events that affect a small number of customers. However, there is the risk that we would never measure outages in any of the largest counties. During our study we identified power outages affecting >10% of the population in 5 of the 10 largest counties and in

13 of the 20 largest. We collected end host responsiveness measurements during the power outages in all 13 of these counties.

4.2 Active Measurement

The active measurement component of PowerPing has two subcomponents: pre-processing and IP probing.

4.2.1 Pre-processing. Because of the frequency of probing and the potentially large number of IP addresses in target areas, efficiency is a requirement for our system design. To that end, PowerPing includes a set of pre-processing tasks. These include classifying each IP subnet by the county it is within, identifying the counties with IP subnets that are tracked by `poweroutage.us`, and defining system parameters for data collection, storage, and processing.

Each IP subnet from MaxMind has an associated latitude and longitude. We used ArcGIS to first associate each IP subnet with a state and county from the US Census Bureau shapefile of all counties in the US. Of the 3,108 counties in the conterminous US, we identified 3,093 counties with subnets from MaxMind within their geographic perimeters.

During each active probe period, we collect up to 10s of megabytes of compressed and archived data on ongoing outages and ICMP responses. We developed a standard directory structure, file naming convention, and file organization for storing and processing the results of each probe period.

4.2.2 Probing for End Host Responsiveness. The IP probing component of PowerPing is informed by prior studies that measure end host responsiveness (*eg.,* [34, 46, 24]). During each epoch, after counties are classified by their power outage status (experiencing/recently resolved/not experiencing), PowerPing *(i)* identifies all IP subnets from counties with outages; *(ii)* identifies all IP subnets from counties with outages that have been resolved within 4 hours; *(iii)* identifies all IP subnets from a select set of counties not experiencing power outages; *(iv)* sends probes to all IP addresses in the selected subnets and processes replies; and *(v)* stores measurement and logging data.

We save all targeted IP subnets classified as above in a single "allow list" file for input to ZMap. In accordance with previous research, we use ICMP echo requests as our probes [34]. Although ZMap is capable of sending probes at up to 1Gbps [24], we conducted tests at multiple probe rates with our network administrators and determined that the highest effective rate our system could support without overwhelming other network traffic was 60K PPS. When ZMap receives a response to

a probe, it records the responding IP address. Each iteration completes within a variable amount of time, typically 5 to 10 minutes, depending primarily on the number of probes we send during the epoch.

Using active probing to identify unresponsive end hosts requires careful consideration. First, IP address responsiveness is a complex, moving target as end hosts are naturally cycled on and off the Internet, as the devices that they are attached to are moved about, and as their exact locations are unknown [16]. Thus, it is difficult to assess how many IP addresses are actually in a county, how many are typically responsive, how many are responsive prior to an outage, how many are impacted by the outage, and how many return after the outage is resolved. To account for these dynamic changes, we identified all end hosts that responded to all of our probes over one hour each week during a non-outage period. We considered each of these IP addresses as a candidate end host for any outages that occurred that week. Then, during an outage period, if we received a response from that IP address, we considered that end host *responsive*; if we did not receive a response from that IP address, we considered that end host *unresponsive*. Next, because we send probe packets to IP addresses without express consent from the address users, there is a risk that our traffic could be considered as unwanted or malicious. In over a year of conducting active probing, we received a total of 20 requests to cease probing specific IP addresses. We accommodated all requests using ZMap blocklists. Finally, we made system design decisions about probing rates, number of probes to send to each end host, and the number of vantage points required. We verified our design decisions through experimentation, as discussed in Section 1.4.3.

4.3 Deployment

Two important considerations in deploying PowerPing were the selection of measurement vantage points and the number of probes that would be sent to each target IP address. Prior studies that have considered these issues include (*e.g.,* [43, 41, 34, 24]). Wan et al. found that scanning from two vantage points with a single probe increased the network coverage from 95.5% to 98.3%, and that sending two probes vs. one increased network coverage from 95.5% to 96.9% [56].

We configured PowerPing to send one probe to each target IP address in an epoch from one vantage point. While this could result in false negative responses, we made this decision for the following reasons: *(i)* since power outages are common events, we wanted to limit the impact on the network; *(ii)* because severe power outages can affect a wide geographic area, the number of hosts that we observe in each

Table 2: Cumulative percent of measurements during power outages with indicated network coverage from vantage points at CloudLab Wisconsin and CloudLab Utah from 16 to 25 October 2020.

Network Coverage	**Cumulative Percent (Wisconsin)**	**Cumulative Percent (Utah)**
99%	90.52%	81.24%
98%	95.66%	93.66%
97%	97.37%	95.64%
96%	97.94%	96.58%
95%	98.24%	97.56%
90%	98.69%	99.74%

collection epoch can exceed 10M; processing probes from so many end hosts can push PowerPing up against the 12 minute interval for each collection epoch (sending multiple probes would push PowerPing past the 12 minute collection period); *(iii)* there is very little information gain from sending multiple probes (95.5% network coverage to 96.9%); *(iv)* Wan et al. observed that vantage points in the same country as end hosts have marginally better coverage than vantage points outside the country of the end hosts they are probing, and we only studied end hosts in the US [56].

To verify our design choices, we set up one server on each of the CloudLab nodes at the University of Wisconsin, University of Utah, and Clemson University. Each server ran PowerPing to identify power outages and to conduct active probing of IP addresses in the affected counties. Each server was configured with the same list of IP subnets for each county. We ran the servers simultaneously for one week.

During this testing, we noticed differences in the number of probe replies received by the servers. We experimented with different configuration parameters and determined that reducing the ZMap probe rate resulted in consistent response rates between the Wisconsin and Utah nodes (the Clemson node had a consistently lower response rate). The downside of reducing the ZMap probe rate is that it takes longer to complete a round of sending and processing probes, which limits the number of IP addresses that we actively probe during each 12 minute epoch.

We quantified the difference in active probe network coverage between the servers hosted on CloudLab in Wisconsin and Utah from 16 to 25 October 2020. During those 10 days, each server took 10,414 active probe measurements during power outages in 179 counties and 37 states. Consistent with our methodology, each server sent a single ICMP probe to each targeted IP address. For each county during each measurement period, we determined the number of IP addresses

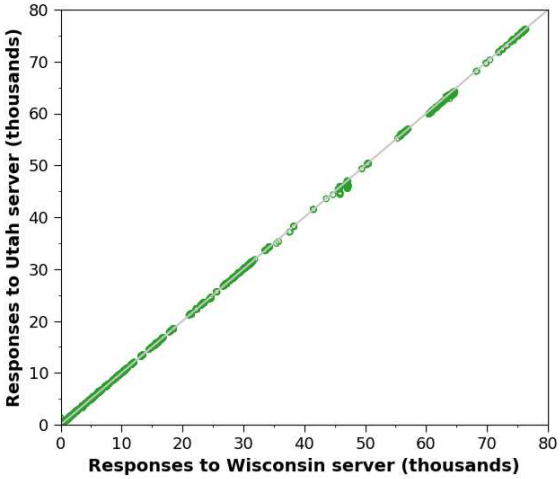


Figure 1: Total number of responses from end hosts in each targeted county to servers hosted in CloudLab Wisconsin and CloudLab Utah during power outages from 16 to 25 October 2020.

that respond to each server (R_{wisc} and R_{utah}), the total number of discrete end hosts that responded to *either* server ($R_{total} = R_{wisc} \cup R_{utah}$), and the percent of end hosts observed at each server as network coverage, $C_{server} = (R_{server}/R_{total}) * 100$. We measured network coverage as shown in Table 2. In particular, we measured network coverage of >97% as $C_{wisc} = 97.37\%$ and $C_{utah} = 95.64\%$.

We plot R_{wisc} vs R_{utah} for each county for each measurement period in Figure 1 to show the consistency across measurements for both servers. These results show that we can expect fewer than 4.36% of end hosts to be improperly identified as unreachable in more than 97% of measurement periods from a single vantage point. We posit that this is an acceptable level of uncertainty that will not significantly bias our results since power outages are a common daily occurrence and we conducted our study over a period of 14 months. Further, given the minor differences in response rates, we concluded that employing multiple vantage points or sending multiple probes to each end host was an unnecessary use of Internet resources. The remainder of our measurements were conducted from a single CloudLab node at the University of Wisconsin.

4.4 System Design Considerations

While end hosts require power for operation, there are a number of reasons why hosts may be reported as responsive during power outages

in our results. First, there is a delay between the time that a power outage occurs and when it is reported. Since most power outages are typically short-lived, they may already be resolved before they are recognized by PowerPing. Second, the reported number of customers affected may not accurately reflect the actual number and location of customers affected by a power outage. For some outages, we observed that power companies do not frequently update the number of customers who are out of power. We routinely observed instances where the number of reported customers out of power does not change, but we find a variable response rate to our probes. In these cases, the number of end hosts that respond to probes may provide a more accurate indication of the number of customers out of power. Third, most counties have multiple power utility providers. Although PowerPing determines the number and percent of all customers without power at a given time in a county, it does not distinguish between customers served by different utility providers. Fourth, we cannot match individual IP addresses with customers that receive service from a specific power company. Although we limit our active measurement to IP subnets geographically located within a county experiencing a power outage, we cannot be certain that the IP addresses that we are probing belong to customers that are affected by the power outage. Finally, some customers may have backup power supplies, such as UPS, for their Internet routers. ISPs may maintain either redundant power providers, UPS, or backup generators for their network equipment. When ISPs provide backup power for their equipment and end users attach an UPS to their home modem and router, end hosts may maintain Internet connectivity during power outages. While the factors listed above lead to uncertainty in measurement of specific events, we argue that our findings are statistically meaningful since power outages are common events, and we collect and analyze their characteristics over 14 months. During that time, we observed more than 330K outages through `poweroutage.us` in 48 states and 2,495 counties. Also, by focusing on the 14K outages that affect more than 10% of customers, we effectively eliminated nearly all events in which the issues noted above were most likely to have an impact on our results.

5. Results

In this section, we present results from our study, which include *(i)* characteristics of end host responsiveness outside of power outages, *(ii)* characteristics of power outages and *(iii)* characteristics of end host responsiveness during power outages.

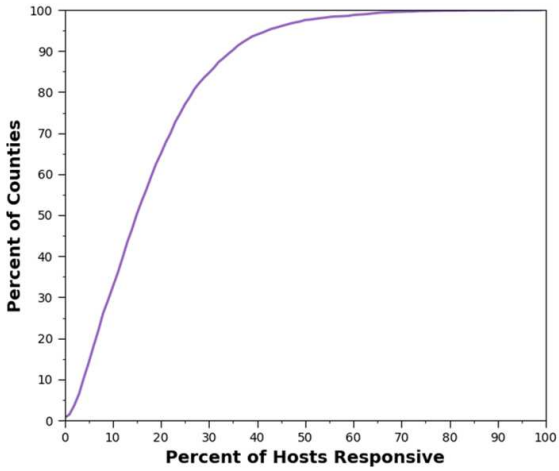


Figure 2: Cumulative distribution of percent of responsive end hosts from all targeted IP addresses in each county during non-outage periods.

5.1 Characteristics of End Host Responsiveness During Non-Outage Periods

Establishing a baseline of responsiveness for each county during non-outage periods was essential to our study. It indicates not only how many, but which specific IP addresses we expected to respond to our probes for each county. We use this baseline in our impact and recovery analyses reported in Section 1.5.3.

We explored the possibility of using existing datasets to identify live end hosts in the subnets we studied. One measurement dataset provides an "IP address space hitlist" by selecting a single IP address for each /24 subnet as representative of all end hosts in the subnet [13]. An alternate existing database provides responsiveness information on hosts running specific services (HTTP, HTTPS, SSH, etc), but (*i*) only collects measurements once a day and (*ii*) does not test responsiveness using ICMP [8]. Although these datasets are useful for understanding Internet characteristics at the network subnet or service level, because our study aims to understand individual end host responsiveness, we decided to collect our own baseline data.

We conducted periodic measurements to quantify the responsiveness of end hosts in each county during non-outage periods. We set up a separate server in the same CloudLab datacenter as our PowerPing server and used ZMap with the same configuration as our PowerPing server

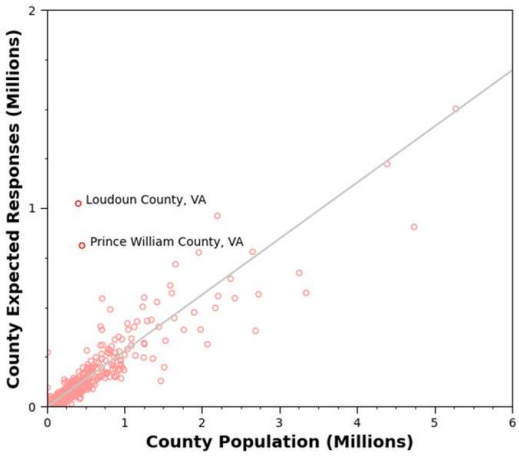


Figure 3: County population (as per US Census Bureau) vs. number of expected responses from end hosts for each county during non-outage periods.

to periodically probe all IP addresses in each county every 10 minutes for a 24 hour period. To complete each round of probing in 10 minutes at a rate of 60K PPS, we selected all subnets from 100-150 counties in each 24 hour period. We conducted this measurement campaign for all counties from 21 August to 9 October 2020.

The results of probing during non-outage periods showed that in most counties the ping reply rate was relatively low. In an average county, we observed 18.6% of IP addresses from MaxMind respond to our probes. Figure 2 shows the distribution of responses we expected to receive from all IP addresses in MaxMind. Despite the low response rate, we found that >100K end hosts responded to our probes in 183 counties (6% of

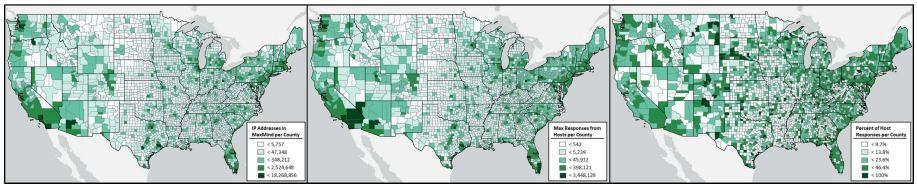


Figure 4: Distribution of IP addresses in MaxMind by county (left); Number of end host responses received from target pings (center); Percent of hosts from MaxMind that responded to target pings (right).

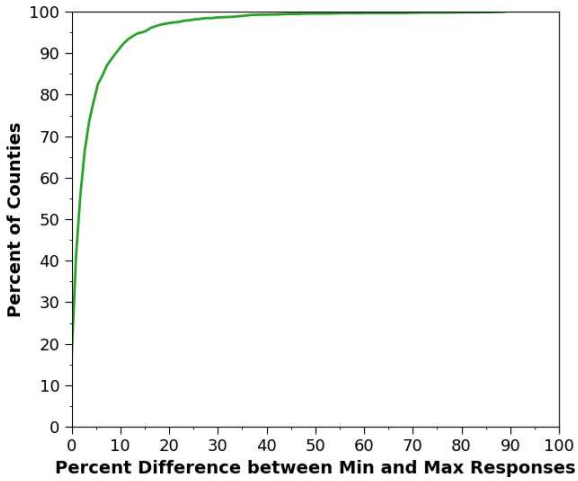


Figure 5: Cumulative distribution of the percent difference in the maximum and minimum number of responses received in counties without power outages over 24 hours.

counties), >10K end hosts responded in 911 counties (29% of counties), and >1K end hosts responded in 2,171 counties (70% of counties). As seen in Figure 3, we received the most ping replies from counties with the highest populations, with the greatest number from: Los Angeles, CA (3.4M replies); Cook, IL (1.5M replies); and Maricopa, AZ (1.2M replies). The counties with the highest fraction of replies to the ping requests were not associated with the largest metropolitan areas. Figure 4 shows the geographic distribution of responses by county.

The number of ping responses that we received from each county was consistent for the duration of the 24 hour measurement period. We configured ZMap to send one probe to each targeted IP address. In this configuration the authors of ZMap measured a 2% single packet loss rate [24]. In 2,766 of 2,987 targeted counties, we measured a difference of 10% or less in the greatest number of replies we received compared to the fewest number of replies. The difference was less than 2% in 1,391 counties, as seen in Figure 5. We did not observe diurnal variation in the number of responses that we received.

We reassessed our baseline of IP address responsiveness by selecting a uniform random sample of subnets for each county and conducted an additional measurement campaign over a one-month period from 13 March to 13 April 2021. To conduct these measurements, we selected three to five subnets from the MaxMind dataset for each county and used

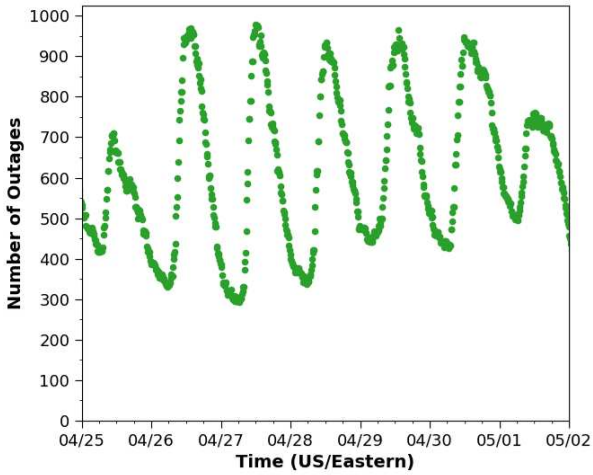


Figure 6: Number of power outages detected during each measurement epoch for the week of 25 April 2021.

ZMap to send ICMP probes to all IP addresses in the selected subnets once every 12 minutes.

The week of 14 March 2021 was typical of the results seen during this testing. In this week, 2,709 counties did not have any power outages affecting more than 10% of customers and we conducted 840 active polling iterations. Although only 5.8% of end hosts that responded to at least one probe responded to *every* probe over the entire week, 76.2% of end hosts responded to 99% of probes and 91.3% of end hosts responded to at least 90% of probes. Only 7.3% of end hosts responded to fewer than 80% of probes over the entire week. *This indicates a high level of consistent responsiveness from IP addresses during non-outage periods in our study.*

5.2 Characteristics of Power Outages

Power outages are a relatively common occurrence and most follow a distinct cycle. An outage begins with an event that interrupts normal service. Power companies identify many different events, the most common of which are severe weather and motor vehicle accidents. Others include equipment failures, wildlife interference, high demand, damage from construction work, and maintenance [21, 25]. The outage is detected by the power company, sometimes through automated means and other times through reports from customers. The utility then deploys the necessary assets to restore power. The outage may be resolved

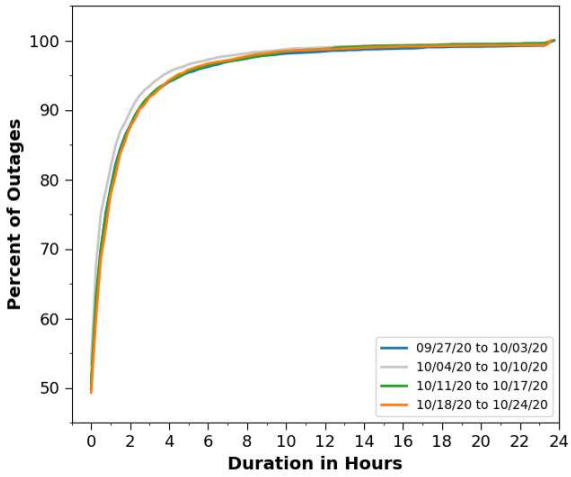


Figure 7: Cumulative distribution of duration of power outages for each week from 27 Sep 2020 to 18 Oct 2020.

simultaneously for all affected customers or incrementally resolved for groups of customers.

As described in Section 1.3.1, most power companies maintain online trackers of known power outages. The online trackers are updated after an outage is detected. Further updates on specific outages necessarily follow changing conditions on the ground. Complete resolution of the outage may not be updated on the tracker concurrently with the resolution on the ground.

As shown in Figure 6, over a typical week there is a strong diurnal pattern in number of power outages in the US. On a daily basis, the most outages occur during the early afternoon. We observed a steady rise in the number of reported power outages from the early morning until the early afternoon. Then, from the early afternoon to the late evening, we observed a steady decrease in the number of reported outages. The fewest outages occur late at night. This is consistent with previous observations that the majority of power outages are caused by maintenance or operational disturbances, which are more likely to occur during business hours [35]. We measured fewer power outages on the weekends and on major holidays. We found that there are typically 50 power outage events per day that affect more than 10% of customers in a given county.

Most outages are short-lived: 80% are resolved in under 1 hour and 90% are resolved in under 2 hours. A small number of long duration outages pushes the average duration to just under 2 hours. Figure 7

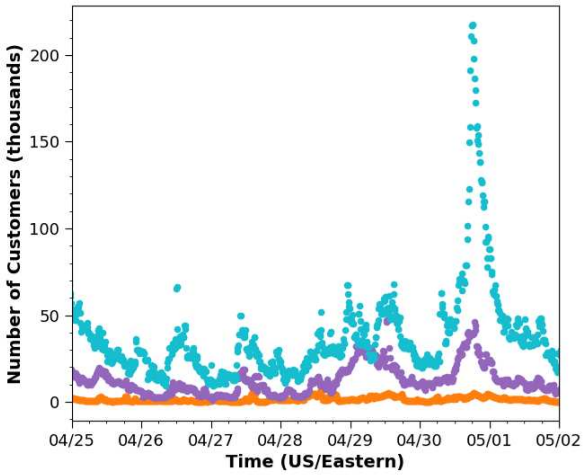


Figure 8: Customers without power in (a) large (teal), (b) medium (purple), and (c) small (orange) counties.

shows the distribution of power outage duration (*i.e.,* from the time of first report on `poweroutage.us` until the event is removed from the site) over a period of several typical weeks.

While the number of power outages follows a consistent diurnal pattern, we found that the number of customers affected by power outages does not. In fact, most weeks showed strikingly different patterns of number of customers affected. Figure 8 shows the number of US customers that were without power for the week of 25 April 2021. We observe that the most customers without power were in counties with the highest populations. We also observe a spike in the number of customers without power on the night of 30 April when strong winds and rain caused power outages along the East Coast [20]. We found numerous instances of spikes in the number of customers out of power that did not follow diurnal patterns. Further, we found that many counties have a small number of customers (typically fewer than 10) out of power during most probing epochs.

In summary, we find that power outages follow a strong diurnal pattern, with most occurring on weekday afternoons. Nearly all outages are resolved within 1 hour. However, the daily number of affected customers is more variable than the daily number of outages.

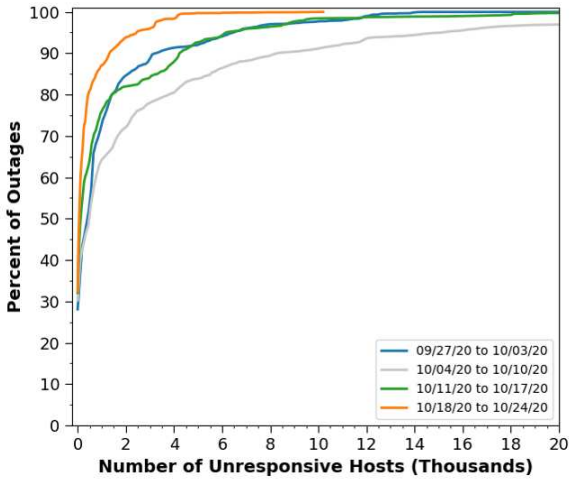


Figure 9: Cumulative distribution of unresponsive end hosts in counties with power outages by week.

5.3 Characteristics of End Host Responsiveness in Power Outage Areas

To assess the impact of power outages on end host responsiveness, we focus on two key metrics: *impact i.e.,* the percent of end host IP addresses (versus background response rate for a county) that are unresponsive to pings during a power outage, and *duration i.e.,* the length of time end host IP addresses in a county are unresponsive during and after a power outage.

In terms of impact, we found that most power outages affect fewer than 1K end hosts. Figure 9 shows the distribution of the number of unresponsive end hosts in counties experiencing a power outage for four typical weeks during our period of study. The figure shows that in most weeks, 80% of outages affect fewer than 1,000 end hosts. The outlier is the week of 4 October 2020. We attribute this particular increase in the number of end hosts affected to Hurricane Delta, which struck the Gulf Coast on 9 October 2020 and led to an increase in customers without power, as well as unresponsive end hosts [45].

We observed a positive correlation between the aggregate number of customers without power and the aggregate number of unresponsive end hosts during power outages across all counties for each measurement period. For the six-month period from February to July 2021, we found $R^2 = 0.99$ between the total number of customers without power and the total number of unresponsive end hosts for each measurement epoch,

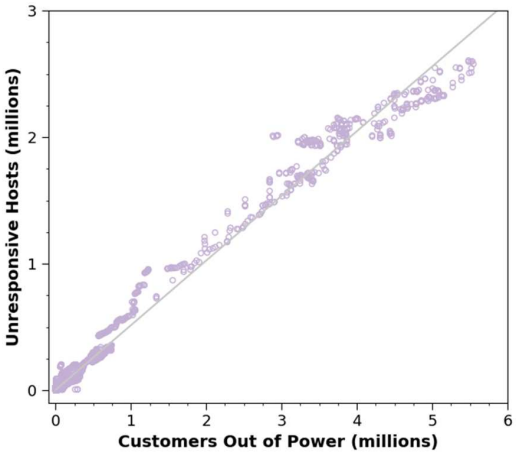


Figure 10: Scatter plot for total customers without power vs. total unresponsive end hosts from February to July 2021 ($R^2 = 0.99$).

as seen in Figure 10. However, the correlation results are skewed by the Texas power outages that occurred over four days in February 2021 and affected up to 4.5 million customers [42]. On shorter timescales (*i.e.,* over month-long periods) we calculated R^2 values between 0.19 (April 2021) and 0.99 (February 2021), with $R^2 = 0.76$ over the same six-month period excluding the week of the Texas power outages. Figure 11 shows an example of this temporal variation across all major power outages for the week of 25 April 2021. The number of customers without power corresponds closely with number of unresponsive end hosts, with the exception of 1 May 2021.

In contrast to the national aggregate, at the county level we often observed power outages that affect most customers *without* affecting responsiveness of end hosts. Across all power outages from February to July 2021, we calculated $R^2 = 0.66$ for the number of customers without power in each county vs. the number of unresponsive hosts in that county. For example, over the week of 25 April 2021, we tracked 118 power outages in which we observed an increase in end host unresponsiveness during the power outage and 98 events in which we did not observe an increase in end host unresponsiveness.

At the county level, we further measured distinct patterns when comparing the percent of customers without power with the percent of unresponsive end hosts. We divided these patterns into the following outage classification categories: *category 1:* percent of hosts unresponsive roughly follows percent of customers without power throughout

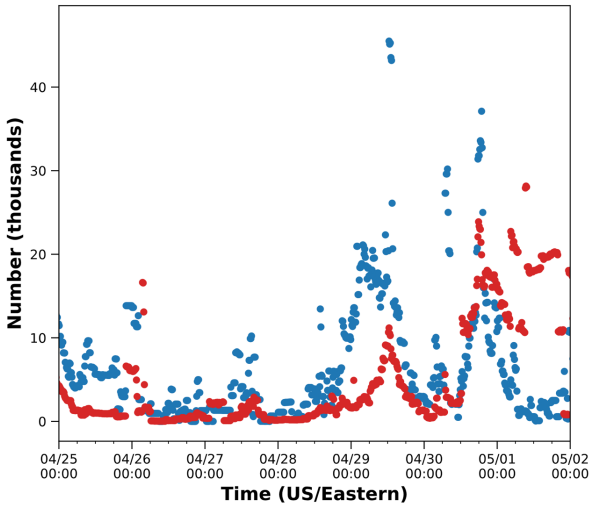
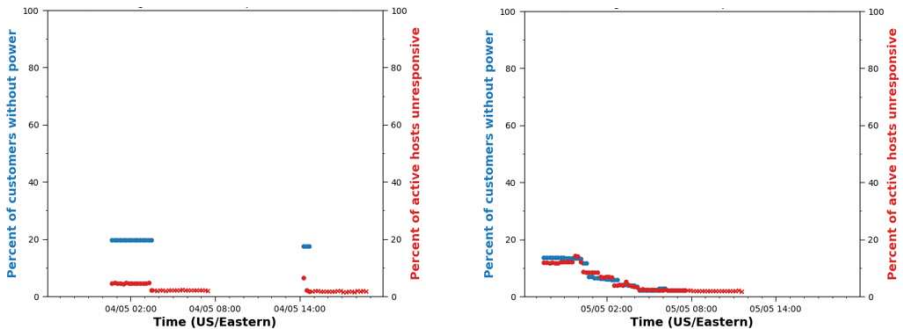


Figure 11: Total customers without power (blue) vs. total unresponsive end hosts (red) in counties with major power outages for the week of 25 April 2021.

the outage; *category 2:* percent of hosts unresponsive remains largely unchanged throughout the outage; *category 3:* percent of hosts unresponsive smoothly changes during each collection period throughout the power outage, while the percent of customers without power either remains constant or undergoes frequent large changes; *category 4:* percent of hosts unresponsive largely diverges from the percent of customers without power. We discuss these patterns and the frequency of occurrence below.

Figure 12 shows two outages from different counties on different dates that demonstrate category 1. As the percent of customers without power in a county increases, the percent of unresponsive end hosts increases, and *vice versa*. While we show this behavior in two examples, we observed it in geographically distinct areas, with counties of various sizes (both by area and by population), for outages of varying duration and intensity, as well as with counties with different numbers of subnets and expected numbers of end hosts that reply to our active probes.

In contrast, Figure 13 shows different behaviors of end hosts that do not align with intuitive expected behavior during outages. Figure 13a and Figure 13b demonstrate category 2 outages. Figure 13a shows an outage in Forest, WI in which the percent of customers without power decreases smoothly from about 15% to 5% over about one hour. However, the percent of unresponsive end hosts does not vary during or after



(a) Dawson, MT on 5 April 2021 (b) Barbour, AL on 5 May 2021

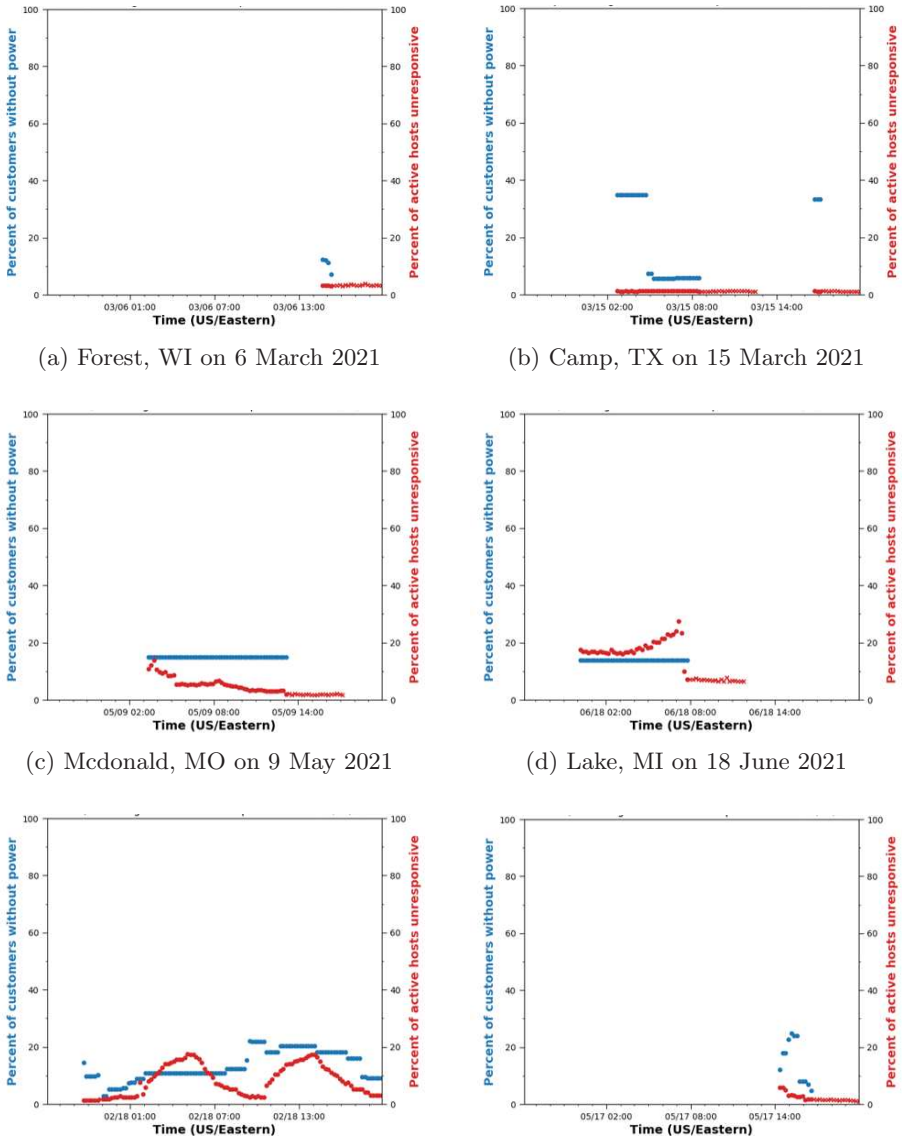
Figure 12: Comparison of percent of customers without power with percent of end hosts unresponsive when unresponsive hosts closely follow customers without power.

the outage. We observe a similar pattern in Figure 13b, in which we note two different outages that affect almost 40% of the power utility customers in Camp, TX. However, we again measured no effect on the responsiveness of end hosts during either outage.

We also observed instances in which the reported percent of customers without power stayed almost constant throughout the outage, but the percent of unresponsive hosts varied (category 3). Figure 13c shows an outage in Mcdonald, MO lasting about 10 hours in which there are a reported constant 18% of customers without power. Toward the beginning of the outage, there are approximately 12% of hosts unresponsive. The percent of hosts unresponsive then decreases to about 5% approximately 2 hours into the outage, remains near-constant for 3 hours, then decreases slowly over the remaining 5 hours of the outage. After the outage is resolved, there is a consistent percent of unresponsive hosts.

Figure 13d depicts a similar situation in Lake, MI, but the power outage seems to affect an increasing number of end hosts from 20% gradually up to nearly 30% at the end of the outage. When the outage is reported as resolved by the power utility, we observe an immediate drop in the percent of unresponsive end hosts. In both these situations, we surmise that our active probing may be a better predictor of customers out of power than what is reported by the power utility. However, as shown in Table 3, this pattern of outages is the least common that we observe.

Finally, we observe outages in which the percent of customers without power varies and the percent of unresponsive end hosts varies differently, but we cannot definitively state which metric most accurately describes



(a) Forest, WI on 6 March 2021

(b) Camp, TX on 15 March 2021

(c) Mcdonald, MO on 9 May 2021

(d) Lake, MI on 18 June 2021

(e) Carroll, MS on 18 February 2021

(f) Seminole, OK on 17 May 2021

Figure 13: Comparison of percent of customers without power with percent of end hosts unresponsive in situations when unresponsive hosts diverge from customers without power.

Table 3: Quantity of outages in each category throughout March 2021.

Category	Number of Outages	Percent of Outages
1	402	38.8%
2	423	40.8%
3	34	3.3%
4	177	17.1%

the situation on the ground (category 4). In Figure 13e, we observe a slowly-changing percent of customers without power, ranging from hours of a consistent percent of customers without power, then increasing or decreasing in distinct steps from 5% to 20% of customers without power. In contrast, the percent of unresponsive end hosts rises and falls in two distinct "hills", with peaks at 5am and 2pm.

Figure 13f shows another category 4 outage that lasts approximately three hours in which the percent of customers without power slowly rises to almost 30%, then drops distinctly to fewer than 10% of customers without power toward the end of the outage. The percent of unresponsive hosts tells a different story, with a peak of nearly 10% of hosts unresponsive at the beginning of the outage, dropping steadily throughout the entire power outage, with nearly all end hosts responding at the outage resolution.

To quantify the frequency of occurrence of these different behaviors, we considered all outages by county in the month of March 2021. We quantified the occurrence of each type of outage as seen in Table 3. The results show that the majority of events fall into the first two category types. Although we cannot confirm it, category 1 outages may result when backup power at both the ISP and customer locations helps to preserve connectivity during power outages.

We also calculated the duration of end host unresponsiveness during and after a power outage. We determined that more than 80% of end hosts that will regain responsiveness to active probing do so within one hour of the power outage resolution and 90% recover within 2 hours. For many long power outages where power is restored to customers incrementally over hours or days, we measured a similar rise in the number of responsive end hosts as power is restored.

In summary, we find that most power outages affect responsiveness of fewer than 1K end hosts. In aggregate, the number of unresponsive end hosts is closely correlated with the number of customers without power. But, at the county level this relationship is not as strong. Unresponsive end hosts typically regain responsiveness within 2 hours of outage resolution.

6. Maintaining Communications During Power Outages

Our results show that power outages are frequent events and often last less than 2 hours. A natural question is whether it is possible for end users to maintain Internet connectivity during power outages?

To maintain Internet connectivity, three categories of devices and equipment must have an alternate power source: *(i)* end host devices (computers, TV's, etc.), *(ii)* home network equipment (modems, routers), and *(iii)* local ISP network equipment. Disruption at any of those levels will constitute a disruption of service.

Some home devices, such as laptops and smartphones, have batteries to provide hours of service during power outages. Other home devices, such as printers, game consoles, smart speakers, TV's, etc., do not. Users have the option to install their own battery backup for many of these devices [26].

In the US, there is no government regulation requiring home network equipment to have built-in battery backup [28, 29]. However, situations may arise where voice (telephone) service may continue during power outages, while the customer loses Internet service. This may be a result of the design of the battery backup for the home modem. Some models provide battery backup for voice services, but not Internet services [57, 58]. This research specifically focused on how power outages affect Internet service. Users take various precautions to ensure uninterrupted Internet connectivity by installing batteries internal to appropriate devices when that option is available or plugging the modem/router into an UPS [15, 49, 12]. Less common are users who install residence-level batteries and/or power generation, such as with solar panels [53, 30].

Through private communication with network operators via `nanog.org`, we found that it is standard practice for service providers to deploy various levels of backup power for their equipment. These include battery backup, which provides uninterrupted service for short-term outages, or backup power generators at their aggregation centers and PoPs. Additionally, ISPs may provide short-term (several hours) battery backup for local nodes in residential neighborhoods.

Interruption of the power supply to devices or equipment at any of these levels will necessarily interrupt Internet service. These disruptions to Internet service can affect peoples' lives in a variety of ways, including those that are merely inconvenient (*e.g.,* loss of access to online gaming or streaming video), to necessary (*e.g.,* inability to bank, shop, or conduct business communications), to critical (*e.g.,* disrupting access to

emergency communications services, disrupting access to news, or impairing medical devices that require Internet access) [32]. Given the ubiquity of laptops and other end user devices with batteries, our findings suggest that the availability of backup power for network devices is not geographically uniform across the US and that end host connectivity during power outages could be improved with backup power for network devices at both ISPs and within households.

7. Future Work

This study extended our understanding of the relationship between power outages and the availability of Internet service to end hosts in the US. Our findings point toward multiple opportunities for future research. First, PowerPing could be deployed in other geographic areas to assess regional variation in end host responsiveness. One challenge in an expanded geographic scope is that power outage information is not universally reported publicly, accurately, or in a timely fashion.

Second, our data indicates that power utilities may not always update their outage management systems with the outage status in a timely manner. However, given the correlations that we found between power outages and Internet service outages, active measurement of end host service availability may be able to serve as a proxy for a more accurate picture of the prevalence and extent of power outage events. Pursuing such an approach would require ground truth power outage data from a source like `poweroutage.us` to build and assess this kind monitoring technique, and a carefully-considered probing strategy to minimize impact on the network.

Third, conducting similar studies for cellular service interruptions during power outages and to include end hosts using IPv6 addresses are important next steps. In each case, these objectives present challenges since PowerPing could not be directly adapted. Such studies would likely require different techniques to measure outages.

Finally, in contrast to the complete loss of power which this study focused on, there may also be periods when the power utility reduces the flow of electricity for customers. This may be caused when electricity demand exceeds generation capacity, which causes a *brownout* [59]. In this study, we only considered power outages, and did not measure periods of power brownouts. We took this approach as an initial step to understanding the relationship between power outages and Internet service. With the right dataset on real-time power brownouts, in future work we could consider the impact of brown outs on Internet service.

8. Summary

In this paper we report on our empirical study of how power outages impact Internet service availability to end hosts. We developed a system, *PowerPing*, to monitor active power outages in the US and probe end hosts in IPv4 subnets geolocated within counties where power outages are occurring. We used PowerPing to monitor power outages and end host responsiveness over a period of 14 months. During this time we monitored over 330K power outages, including 14K power outages (approximately 50 events per day) that affected more than 10% of customers in a county. We found that most power outages last less than 2 hours. Although we found many examples in which there is a strong correlation between the power outage impact and duration and end host responsiveness, at the county level we found this relationship to be weak. Our findings highlight the diverse impacts on connectivity at the county level. Our results suggest that providing improved backup power for network devices, especially the modem/router in a residence, may be sufficient for end hosts to maintain uninterrupted Internet service during typical power outages.

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Notes

1. In this paper we focus on wireline Internet service that is typically delivered to end hosts via cable, DSL or fiber, and exclude consideration of access via cellular service.
2. All code and data described in this paper is available to the community upon request.

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