# LOGGING, VISUALIZATION, AND ANALYSIS OF NETWORK AND POWER DATA OF IOT DEVICES

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ABSTRACT

Logging, Visualization, and Analysis of Network and Power Data of IoT Devices

Neal Nguyen

It is estimated that there are 23.14 billion IoT(Internet of Things) devices currently in use worldwide. This number is projected to grow to over 75 billion by 2025. Despite their ubiquity little is known about the security and privacy implications of IoT devices. Several large scale attacks against IoT devices have already been recorded.

To help address this knowledge gap, we have collected a year's worth of network traffic and power data from 16 common IoT devices. From this data, we show that we can identify different smart speakers, like the Echo Dot, from analyzing one minute of power data on a shared power line.

# ACKNOWLEDGMENTS

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TABLE OF CONTENTS

# LIST OF TABLES

LIST OF FIGURES

LIST OF CODE LISTINGS

# Chapter 1

# INTRODUCTION

There are 23.14 billion IoT devices in use worldwide that nubmer is expected to grow to 75.44 billion by 2025 [1]. With so many manufacturers creating IoT devices, each with differing update policies, some devices inadvertently have better support. For example, some devices may drop out of a manufacturer's update cycle and become unsupported, introducing privacy and security concerns.

To address these concerns, this thesis contributes an IoT testbed that logs network and power data from 16 IoT devices over one year, accumulating 184.94 GB of data and 172,445,929 rows into a database. To help researchers sort and view this data, this thesis adds a Python program that graphs network traffic and power data over time from the database. The graphs created by this tool were used to analyze IoT devices network and power usage in the testbed while idle, during startup, and while in use. From these graphs, it is possible to identify the smart speaker in use when viewing just one minute of the shared power usage.

This paper focuses on addressing security and privacy flaws, that if fixed, do not affect the core features of an IoT device. For example, a smart speaker must store audio snippets to parse for the wake word. If the smart speaker occasionally hears a false positive wake word and sends the audio to its server, that is reasonable. However, Google Homes had an issue with their wake button, which caused the Home to listen 24/7 [2]. This is not expected behavior and highlights privacy concerns. In another case, one of the largest IoT cybersecurity attacks, Mirai, was able to use weak login credentials to take control of 2.5 million IoT devices to perform a denial of service attack [3]. This is on many events that introduces security concerns. This paper uses these flaws as a focus when analyzing network and power usage.

## 1.1 Previous Work

This section presents and analyzes related works on the topic of analyzing and characterizing IoT devices. It presents the previous works individually. Because these papers are similar to each other, commentary on how their work is different from ours and how it is useful to us as a group in section 1.2.

### 1.1.1 An Analysis of Home IoT Network Traffic and Behaviour

The scope and work of *An Analysis of Home IoT Network Traffic and Behaviour* [4] are most like the work and goals of this paper. In *An Analysis of Home IoT Network Traffic and Behaviour* [4], the authors analyze IoT traffic in the home. The authors created an IoT testbed by setting up multiple IoT devices, connecting them to a router, sniffing their network packets while idle, and storing these packets on a Linux box's disk. The IoT testbed consists of a smart air quality monitor, Amazon Echo, a few Apple devices, a smart hub, and a smart vacuum cleaner.

After 22 days of network logging, the authors analyzed each IoT device individually and as a whole. For example, they noticed that they can identify most devices from the first three MAC address bits. The Hue bridge broadcasts credentials over HTTP, which is unencrypted. The authors state that these seemingly small security flaws create a privacy risk. A user's presence in a room or house can be determined from these unencrypted HTTP packets. The authors also show the percentage of network packets by protocol and various other device network patterns. This general analysis fingerprints each device.

### 1.1.2 ProfilIoT

The paper, *ProfilIoT: A Machine Learning Approach for IoT Device Identification Based on Network Traffic Analysis* [5] uses machine learning algorithms to classify IoT devices. The researchers of this paper collect traffic from 13 different IoT and non-IoT devices. The IOT devices include a baby monitor, motion sensor, printer, refrigerator, security camera, socket, thermostat, smartwatch, and television. The

non-IoT devices include two PCs and two smartphones for comparison. These devices connect to a Wi-Fi access point that recorded their network traffic with Wire Shark[6].

The researchers use machine learning on single-sessions to classify a device as an IoT device or non-IoT device. Then, they can classify the IoT devices by brand and model(e.g. Samsung Refrigerator, LG TV, WeMo Motion Sensor) with multi-sessions. A single-session is a 4-tuple formatted as source IP, destination IP, source port Number, destination port Number. When intercepting network traffic, they extracted the information they needed from each TCP packet to form the four-tuple data type. A multi-session is a list of single-sessions. Another machine learning model determines the minimum number of single-sessions needed to classify each device, determining the size of a multi-session. With single-sessions, they could determine if the device is an IoT device or not with 100 percent accuracy. Then out of their nine IoT devices, they can classify brand and model of the IoT device with 99.281 percent accuracy when run 7376 times.

### 1.1.3 Logging and Analysis of Internet of Things (IoT) Device Network Traffic and Power Consumption

*Logging and Analysis of Internet of Things (IoT) Device Network Traffic and Power Consumption*[7], written by Ryan Frawley, was formed in conjunction with this paper. Frawley's paper and this paper were both directed by advisor Andrew Danowitz at Cal Poly.

Frawley's paper documents the steps necessary to construct a reliable IoT testbed capable of capturing network traffic and power data for connected devices, and analyzing these devices further. He performed GeoIP[8] lookups on each device, showing the percentage of packets originating from each country and company. He also analyzed the packets of any unencrypted data in the devices.

## 1.2 Scope

The first paper from subsection 1.1.1 most closely matches this paper. The authors have the same overall idea to collect network data and then use it to analyze metadata

surrounding the networks. Our work expands on this concept by contributing a portable database consisting of 10 months of data rather than 22 days of data. This paper adds more devices in our study and focuses more on device power/network usage over time rather than specific network packet information.

Then, like the second paper from subsection 1.1.2, this paper also focuses on classification of devices from data. However, instead of using machine learning techniques on network data, this paper focuses on manual analysis, looking for spikes in power usage, the height of the spike, the length of the power spike, and other graphical heuristics.

In comparison to the first paper in 1.1.1 and second paper in 1.1.2, this paper adds power usage over time to the data set. The two papers mentioned only focus on network traffic. This paper also puts a significant emphasis on creating an extensive database rather than a smaller set of data to create graphs on network and power usage over time.

This paper is a continuation of the third paper in subsection 1.1.3. Due to overlap between these two works, certain aspects of the IoT testbed setup and usage is only covered in cursory detail here. The reader is advised to access Frawley's work for full information. We both assembled the IOT test bed and interacted with the devices on a daily basis to simulate regular usage. We both also performed a preliminary analysis of the device network and power usage together.

The unique contribution of this work is its analysis of IoT device power usage and the introduction of a custom data visualization tool that attaches to the database. This paper focuses on a select few devices, analyzing their startup, idle, and in use network and power usage over time. I compare the smart speakers' network and power usage and show that it is possible to identify a smart speaker through analysis of the powerline over time.

## 1.3 Thesis Organization

Chapter 2 discusses my steps in setting up the IOT test bed, the analysis tool, and the logging system for interaction with devices. Chapter 2 also highlights the steps to

set up a developer environment to run the analysis tool and how to use it. Chapter 3 presents power and network traffic for smart speakers and streaming devices while idle, in use, and during startup in the form of line graphs and discuss the implications of these graphs. Chapter 3 also shows the graphs used to fingerprint the smart speakers while handling different commands and under noise. Finally, Chapter 4 finishes with concluding thoughts and future work.

# Chapter 2

# METHOD

To log and analyze network and power usage for our IoT devices, we set up an IoT testbed to log this data to our database. This chapter documents the setup process for each IoT device, the logging process, and the software created to analyze the logged data.

## 2.1 IoT Testbed Overview

When referring to our IoT testbed, we refer to the IoT devices and any connected hardware to log the power data.

The flow diagram in figure 2.1 outlines the IoT test bed constructed for this project. IoT devices pull power from the outlets through the smart switches, which log the power usage, and the WAP queries the smart switches for that data and pushes it to an AWS (Amazon Web Services)[9] MySQL[10] database as an entry in the 'power' table.

The wireless net provided through the WAP intercepts network packets of devices connected to it (IoT devices in testbed), parses them into power and network entries, and pushes them to the database. Finally, for analysis, a python script called realTimeGrapher.py pulls from the database and graphs this data in real time or from set intervals in the past.

Section 2.2 discusses what devices we used, the setup of each device, and the physical layout of the IoT test bed. Section 2.3 covers the software part of the IoT test bed. It covers the usage flow of this test bed and what was done to obtain results for analysis.

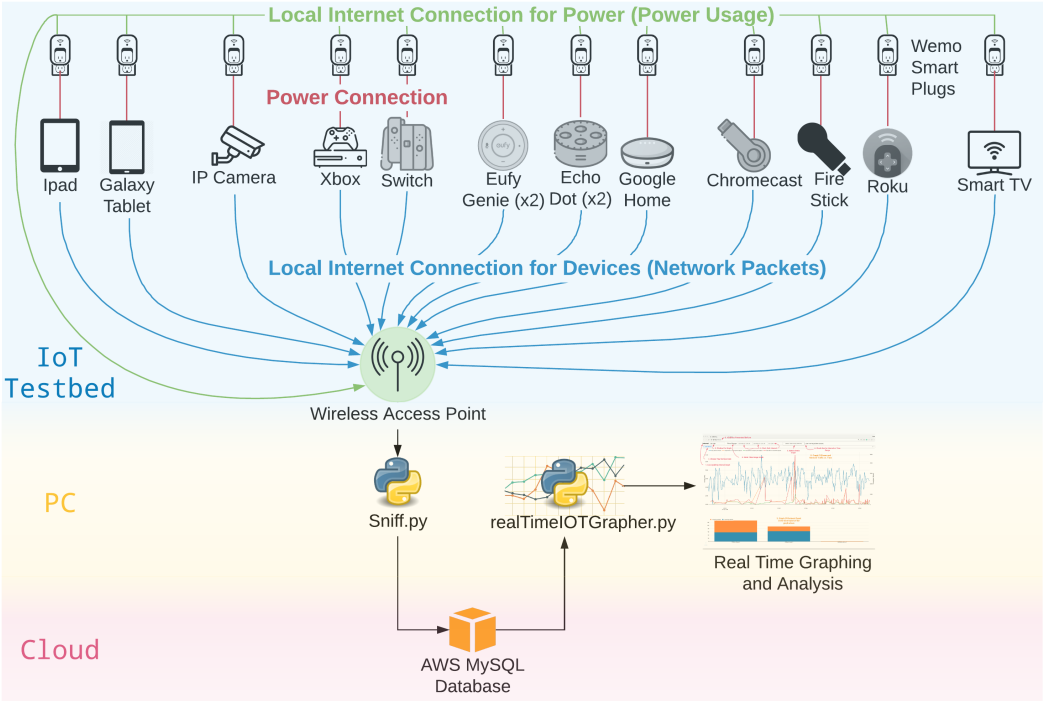



**Figure 2.1: IoT testbed.**

**Figure 2.2: Smart Speakers Connected to WeMo Insight Switches**

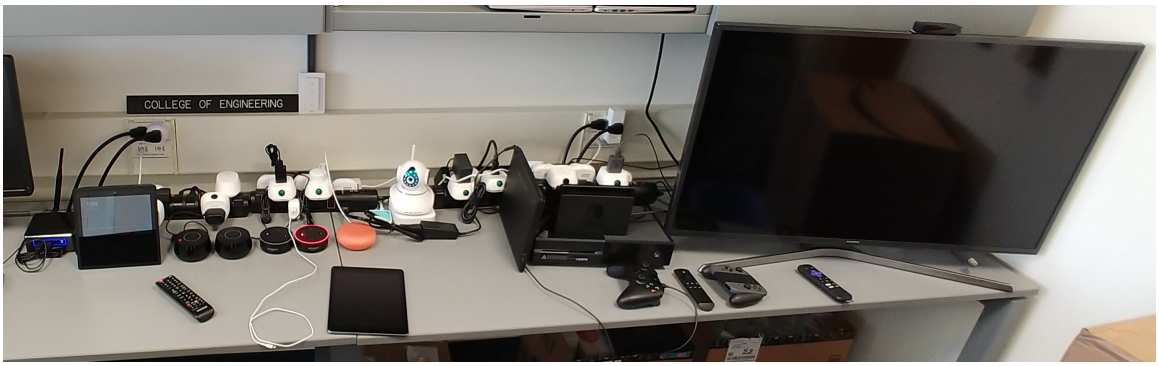



**Figure 2.3: IoT Devices Under Examination**

## 2.2 Physical Layout and Setup

This section covers the physical setup and layout of the hardware used when setting up the IoT test bed, the IoT devices we tested, and how each device is set up. Figures 2.2 and 2.3 show the IoT testbed set up. Setup was performed with Ryan Frawley and explained in his paper 1.1.3, this paper provides an updated description.

### 2.2.1 Wireless Access Point

The wireless access point is an Intel NUC [11]. We loaded Ubuntu[12] on it because it is the most common Linux OS [13] and most flexible for developing scripts and programs to log network packets, query power information, and push those values to a database.

One challenging thing about the NUC is that its internal wireless chip is very slow. The throughput when using the wireless chip was measured to be 12 Mb/s down on Speedtest.net by Ookla [14] when connected to with a Chromebook [15] (25 Mb/s is the minimum possible for broadband). This rate limitation caused many of the Belkin WeMo smart switches [16] to drop their connection intermittently, causing gaps in recorded power data. To solve this, we added a USB wireless antenna to the NUC. This antenna improved our internet speed to 30 Mb/s down when tested on Speedtest.net by Ookla with the same Chromebook, solving the issue where devices would lose network connectivity.

### 2.2.2 Smart Power Plugs

Smart power plugs are Wi-Fi capable, pass through outlets that another device plugs into. The outlets collect and transmit power usage over the network. They are critical to the power consumption logging in this research.

We used the Belkin WeMo Insight. We chose this smart plug because there are many open source Python libraries for pulling power information from them, and they are relatively affordable.

When setting these smart plugs up, we named each smart plug based on the device connected to it so that when we pull power information with our scripts, we can easily reference data to a smart plug. This informal naming led to issues when the wrong device is connected to the wrong smart plug, as discussed in section 2.3.7

### 2.2.3 Devices

This section goes over the smart speakers, streaming devices, video game consoles, tablets, security cameras, or other devices as listed in figure 2.1. These devices were included based on their popularity, as the goal of the paper is to build a data set from common household IoT items.

**Table 2.1: IoT Devices Being Monitored**

| Category | Manufacturer | Device | Quantity |
|---|---|---|---|
| Game Console | Nintendo | Switch | 1 |
| Game Console | Microsoft | Xbox One | 1 |
| Laptop | HP | Chromebook | 1 |
| Media Player | Samsung | Smart TV | 1 |
| Media Player | Google | Chromecast | 1 |
| Media Player | Amazon | Fire TV Stick | 1 |
| Media Player | Roku | Express | 1 |
| Security Camera | Eray | Hi3518 Wi-Fi Camera | 1 |
| Smart Speaker | Amazon | Echo Dot | 2 |
| Smart Speaker | Eufy/Anker | Genie | 2 |
| Smart Speaker | Amazon | Echo Show | 1 |
| Smart Speaker | Google | Home Mini | 1 |
| Tablet | Amazon | Fire 7 Tablet | 2 |
| Tablet | Samsung | Galaxy Tablet | 1 |
| Tablet | Apple | iPad | 1 |

#### Smart Speakers

Smart speakers are IoT devices that combine speakers with built-in voice assistants, such as Amazon Alexa, Google Assistant, or Apple's Siri. These devices are mainly controlled by voice commands, preceded by a wake word such as "hey Google".

Currently, around 39 million people (16 percent of the US population) use smart speakers[17]. It is one of the top-selling IoT devices and it can act a central voice control for other IoT devices. In 2022 it is projected that 70 million US households will have at least one smart speaker (55 percent of US households) and around 175

million smart speakers total[18]. For these reasons, we included this group of devices in our research.

Within the smart speaker category, we included the Amazon Echo Dot, Google Home, and Eufy Genie. The Amazon Echo Dot and the Google Home are the two leading smart speaker products. We added the Eufy Genie because it is an Amazon Alexa device that we can compare with the Echo Dot. We also included the Amazon Show, which is a voice assistant with a screen.

#### Streaming Devices

Streaming devices are IoT products that connect to a television or are built into a television (smart TVs) and streams videos or music from online services. In 2017 it was recorded that 70 million US households (58.7 percent of homes) had a television connected to streaming devices [19].

The specific streaming devices we look at include the Roku Express, Amazon Fire TV, and the Google Chromecast. These devices represent three popular streaming platforms (Roku, Google Chromecast, Amazon Fire TV) that have a combined user base of over 110 million users who watch content at least once a month [20].

To view content from these streaming devices, we use a Samsung smart TV. This TV also as streaming capabilities which we log but do not analyze in this paper.

#### Video Game Consoles

Video game consoles are systems specifically built to play video games. We use two out of the three most popular gaming devices including the Nintendo Switch which sold 17.8 million units [21] and the Xbox One, which sold 30 million units [22] as of January 2018.

#### Tablets

Tablets are devices that have phone operating systems running on them such as the Apple iPad, Samsung Galaxy tablet, and the Amazon Fire tablet. These devices were

used for interacting with the other IoT devices, which require a smartphone or tablet for set up or control. Some of the IoT devices are limited to either Android, which runs on the Galaxy, or IOS, which runs on the iPad. Although there is no analysis on these devices in the paper, the network packets are logged. There is no way to track the power usage of these devices because they run on battery.

#### Security Camera

Security cameras are cameras meant to run constantly as surveillance, streaming the video footage so a user can view it from any connected device at any time. Two out of the five largest recorded cybersecurity attacks targeted security cameras [23]. The specific camera we use is the Eray camera. It is a generic Alibaba device with a weak username:password of admin:1234. A weak username and password make it very susceptible to cyber-attacks. There have also been reports that smart cameras have been found to send unencrypted data [24]. We selected this device because it has weak login credentials and is susceptible to Mirai. We wanted to see if it would get hacked by Mirai or some other attack, but we found no indication of such.

#### Other Devices

We also connected several other devices that are harder to categorize, analyze, or both.

We have a smart hub connected to a smart lock, an indoor room temperature sensor, and smart LED light bulbs. These devices are difficult to analyze because they communicate with the smart hub through Zigbee or Bluetooth at which point the smart hub aggregates the data and communicates with the network. To look at the network traffic caused by smart lights individually, we prevented all devices besides the smart LED bulbs from communicating with the smart hub. This isolation minimized other packet noise to the smart hub so that we can monitor the smart hub traffic as a replacement for the smart LED bulbs. However, even then, the smart hub might have extra overhead for other tasks, making isolated analysis difficult.

We also have a Chromebook which we used to control the Chromecast. However,

because this is more a laptop than an IoT device, we decided to leave this out of our research

### 2.2.4 Wiring and Configuration

We also tried to set static IPs for each device, but we decided that the average user would not set up a static IP for their device and left dynamic IPs.

The next step was to setup each device and corresponding smart plug through their corresponding setup application, filling in the device's, user name, email, network configuration, etc. We used the device's name as its user name, e.g. the Echo Dot was given the username "Echo Dot".

When plugging in all the devices for the first time for power, we worked to plug each device into the corresponding WeMo smart plug and connected to our WAP during device set up so that we could instantly log power and network traffic information. It was essential to log power as soon as possible to capture a first-boot power profile for each device. Some devices had already been used, so they do not contain startup information(Xbox and the Echo Dot 1).

Set up and configuration took up a significant portion of the research time. We worked to set up each device with a separate email account. To do this, we made around 20 AOL accounts. We wanted email addresses that were not under control of the manufacturer of any of the devices. For example, we did not want to use any Gmail accounts because we did not want the Google Home or Google Chromecast to perform domain-specific optimizations. When setting up AOL accounts, we also faced a limitation of the number of email accounts tied to a single phone number. We had to use different phone numbers to circumvent this.

We set up each device in waves, taking around a week to set everything up. Incremental device setup with no plan resulted in a messy work environment, which made it difficult to match a device to it is corresponding smart plug. After a month of data logging in a disorganized scheme where it was difficult to keep track of each device, we unplugged everything, renamed the WeMos, organized the wiring, and organized the location of each smart device resulting in the set up in figures 2.2 and 2.3. With limited power strips, the organization helped maximize power ports. We

also made sure to face the button for each power plug towards our view so that we could quickly notice whether the power plugs were on or off. Organization streamlined the logging process overall; debugging network and connection issues was much simpler with an ordered set up. We could quickly identify redundant devices (there are two Echo Dots and Eufy Genies), run procedures on groups of devices, and determine the corresponding smart plug for each device.

## 2.3 Software

This section covers the software components used to control the IoT test bed. It discusses the scripts for logging power and network traffic, the database information, and the python script for visually viewing the database.

### 2.3.1 Wireless AP Code

To turn the NUC into a wireless access point, we used a create_ap script [25]. This app takes in the Wi-Fi name, Wi-Fi password, and the wireless interface. This script turned the NUC into a wireless access point (WAP). We later found that, with newer versions of Ubuntu, there is a built-in feature for creating a hotspot through a wireless interface on the device [26]. We later used this feature to simplify the number of programs running and instead have the OS handle the hotspot. Partially through our research, as we set up more IoT devices and demand for bandwidth through the WAP increased, we had to switch to an external antenna and rerun the script to set the USB antenna as the WAP wireless interface. During this time, there is a void in network and power entries in the database.

### 2.3.2 sniff.py

Sniff.py runs a thread for power logging and a thread for network logging. As each logger runs, it writes the network packets and power information to a MySQL database hosted on AWS through the python MySQL client [27] library. If the database connection is lost, the script automatically reconnects.

#### Network Logging

It begins by opening a socket on the wireless interfaces connected. All IP packets are sniffed through this socket connection as shown in listing 2.1.

```
1 self.socket = socket.socket(socket.AF_PACKET, socket.
    SOCK_RAW, socket.htons(ETH_P_ALL))
2 self.socket.setsockopt(socket.SOL_SOCKET, socket.SO_RCVBUF,
    2**30)
3 self.socket.bind((self.interface_name, ETH_P_ALL))
4 while True:
5     packet, address = self.socket.recvfrom(MTU)
```

**Listing 2.1: Open and Read from a Socket**

Once we have sniffed a packet, we can obtain the metadata from the hex dump. We preserve this hex dump because in case we would want to extract more information from it later. From each hex dump, we extract and store the source IP, source host, destination IP, destination host, time, size, type, protocol, source port, destination port, source host, destination host, and hex dump. We explain what each field in section 2.3.3.

#### Power Logging

The second addition to our IoT device analysis is the power information. To obtain this information, we rely heavily on the Belkin WeMo Insights. Each WeMo connects to an outlet and each IoT device plugs into the WeMos.

We used the PyWemo python script [28] to read power usage from the WeMos once per second. This is the highest frequency we could poll for power. The WeMo is capable of reading both power and energy in mW and kW hours.

Once the script queries the WeMo for its power information, we relate the WeMo to the device connected to it by extracting the name of the WeMo. This information is used when pushing power data to our database.

One issue with PyWemo and the Belkin WeMos was that they would sometimes disconnect, and the script would miss power data. To solve this issue, the script rescans for WeMos until it finds all 16 WeMos in our testbed. The rescan code for this is shown below in listing 2.2

```
1     def scan_until_all_found():
2         print("Discovering WeMos")
3         switches = pywemo.discover_devices()
4         print("Discovered {} switches".format(len(switches))
              )
5         print(switches)
6         try_num = 1
7
8         while len(switches) < 16:
9             print("Did not discover enough switches, trying
                  again{}...".format(try_num))
10            switches = pywemo.discover_devices()
11            try_num += 1
12            print("Discovered {} switches".format(len(
                  switches)))
13
14        return switches
```

**Listing 2.2: Rescan if all WeMos not found.**

### 2.3.3 Database

To store all the result of the sniffed packets and power data, we push the data to a MySQL database hosted on an Amazon AWS server. As of writing, the database holds 172,445,929 entries that take up 184.94 GB of space. The database contains

two tables, one for the network traffic and one for the power usage data. To interface with our database, we used a combination of the RealTimeIoTGrapher from section 2.3.7, Navicat [29], and MySQL's command line tool [30].

#### Network Table

The largest part of our database is the IP network table. This table contains all the network packets that have gone through the NUC WAP. It is currently 179.1 GB and contains 116,830,077 entries. It is so large because it consists of all network traffic generated over a 12-month period. In those 12 months, we did many high bandwidth tasks such as playing music or video. These entries contain the raw hex dump of the whole packet, which contains all the metadata plus data load, further contributing to the massive size of this table. The data table's rows represent a single packet with the columns shown in the table below 2.2. The columns this research uses from this table are the time, source, destination, and size fields to get network throughput over time.

**Table 2.2: Columns in Network Traffic Table**

| Column Number | Column Name | Data Type |
|---|---|---|
| 1 | time | datetime |
| 2 | source | varchar |
| 3 | src_host | varchar |
| 4 | destination | varchar |
| 5 | dst_host | varchar |
| 6 | protocol | varchar |
| 7 | type (in/out) | varchar |
| 8 | src_port | varchar |
| 9 | dst_port | varchar |
| 10 | size | int |
| 11 | hexdump | longtext |

Common SQL commands we used for our analysis include those shown in listings 2.5 and 2.6. The most useful commands generally required examining total throughput or device throughput using ROLLUP, shown in figure 2.4.

```
SELECT time, source, destination,
       CASE WHEN type IS NULL THEN 'total' ELSE type END type,
       SUM(size) AS total_throughput
FROM ip_log.ip
WHERE
  time BETWEEN '2018-05-17 16:30:00' AND '2018-05-17 16:40:00'
    AND
  (source = '192.168.12.48' OR destination = '192.168.12.48')
GROUP BY time, type WITH ROLLUP
LIMIT 20
```

| time | source | destination | type | total_throughput |
|---|---|---|---|---|
| 2018-05-17 16:30:27 | 192.168.12.48 | 184.31.3.33 | outgoing | 540 |
| 2018-05-17 16:30:27 | 192.168.12.48 | 184.31.3.33 | total | 540 |
| 2018-05-17 16:30:29 | 184.31.3.33 | 192.168.12.48 | incoming | 52 |
| 2018-05-17 16:30:29 | 184.31.3.33 | 192.168.12.48 | total | 52 |
| 2018-05-17 16:30:33 | 192.168.12.147 | 192.168.12.48 | incoming | 392 |
| 2018-05-17 16:30:33 | 192.168.12.147 | 192.168.12.48 | total | 392 |
| 2018-05-17 16:30:39 | 184.31.3.33 | 192.168.12.48 | incoming | 1500 |
| 2018-05-17 16:30:39 | 184.31.3.33 | 192.168.12.48 | total | 1500 |
| 2018-05-17 16:30:55 | 192.168.12.48 | 192.168.12.147 | incoming | 171 |
| 2018-05-17 16:30:55 | 192.168.12.48 | 192.168.12.147 | total | 171 |
| 2018-05-17 16:30:57 | 172.217.4.142 | 192.168.12.48 | incoming | 52 |
| 2018-05-17 16:30:57 | 172.217.4.142 | 192.168.12.48 | total | 52 |
| 2018-05-17 16:31:02 | 192.168.12.48 | 35.186.224.44 | outgoing | 94 |
| 2018-05-17 16:31:02 | 192.168.12.48 | 35.186.224.44 | total | 94 |
| 2018-05-17 16:31:12 | 172.217.4.142 | 192.168.12.48 | incoming | 855 |
| 2018-05-17 16:31:12 | 192.168.12.48 | 172.217.4.142 | outgoing | 569 |
| 2018-05-17 16:31:12 | 192.168.12.48 | 172.217.4.142 | total | 1424 |
| 2018-05-17 16:31:18 | 192.168.12.48 | 184.31.3.33 | outgoing | 52 |
| 2018-05-17 16:31:18 | 192.168.12.48 | 184.31.3.33 | total | 52 |
| 2018-05-17 16:31:35 | 35.186.224.44 | 192.168.12.48 | incoming | 91 |

**Figure 2.4: Navicat IP query with rollup.**

The hex dump column drastically increases the size of each entry in the network table. However, as a raw network packet, it is very flexible and can be manipulated for many more use cases than the targeted columns we have. This flexibility is useful for future research, that may require data we did not explicitly pull out for this project

In the database, each device can be tracked down by looking for the IP address of that device in the source or destination columns. However, note that during set up, we did not set up static IPs for these devices. Because of this, a single device can be under multiple IPs within the table. We ignored this issue until a query for a particular IP stopped working. At which point we would invoke a command on the device whose IP changed to flood the database with packets from that device, query the database in the time frame of the command, and obtain the new IP. We logged all devices and their current IP in a Google Sheets [31] file covered in subsection2.3.4.

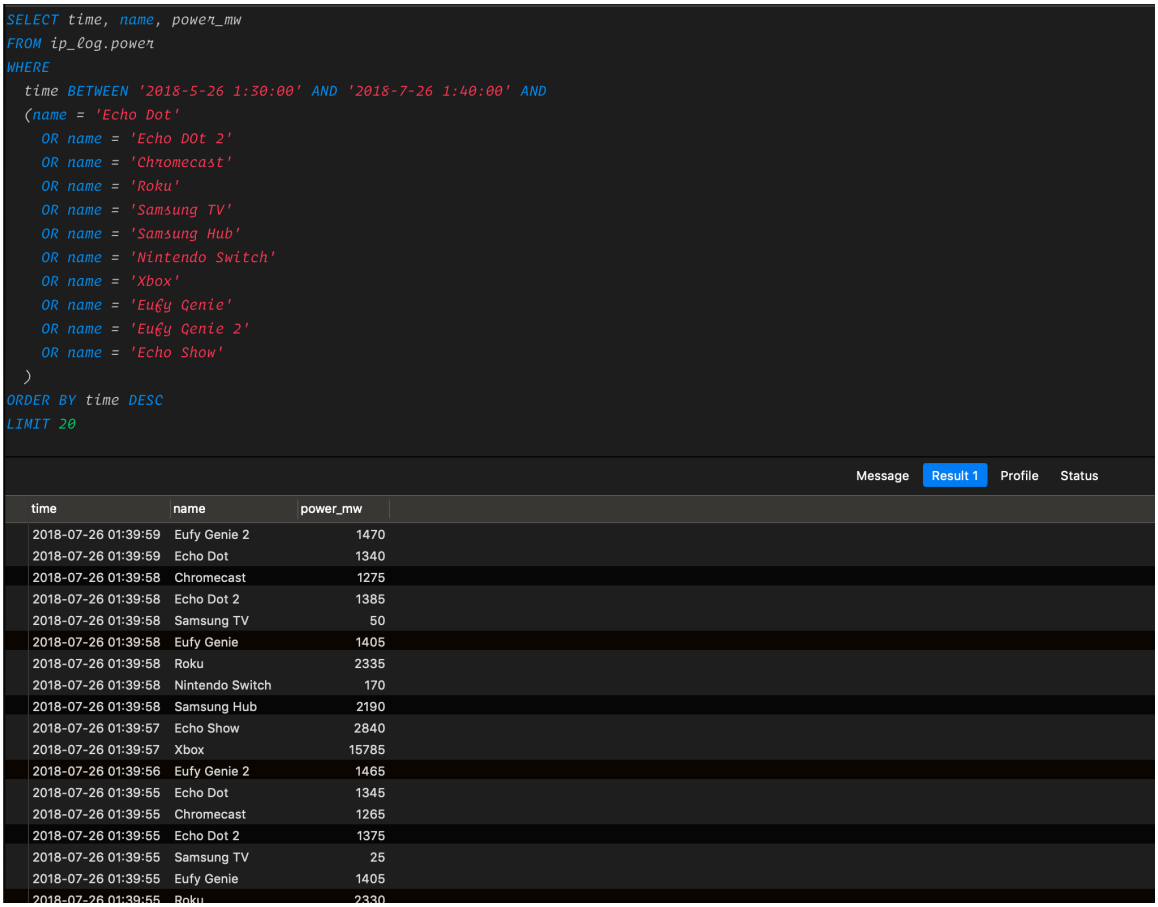
#### Power Table

The power table holds the most important data for this portion of the research, and we refer to it for the majority of the paper's findings. The size of this table is much smaller than the network table. It contains 5.84 GB of data and 61,240,189 entries in the database. The significant difference in size between the IP table and power table is because each device only produces one entry power entry every second. The columns of the power table are shown below in figure2.3. This pa

**Table 2.3: Columns in Power Table**

| Column Number | Column Name | Data Type |
|---|---|---|
| 1 | name | varchar |
| 2 | power_mw | int |
| 3 | time | datetime |
| 4 | today_kwh | varchar |
| 5 | on_for | varchar |
| 6 | today_on_time | varchar |

When working with this database, we generally query for a range of power packets in a given time range. We do this for either all devices, a subset of devices, or a single device. Some of the commands and results are shown below in figures 2.5 and 2.6.

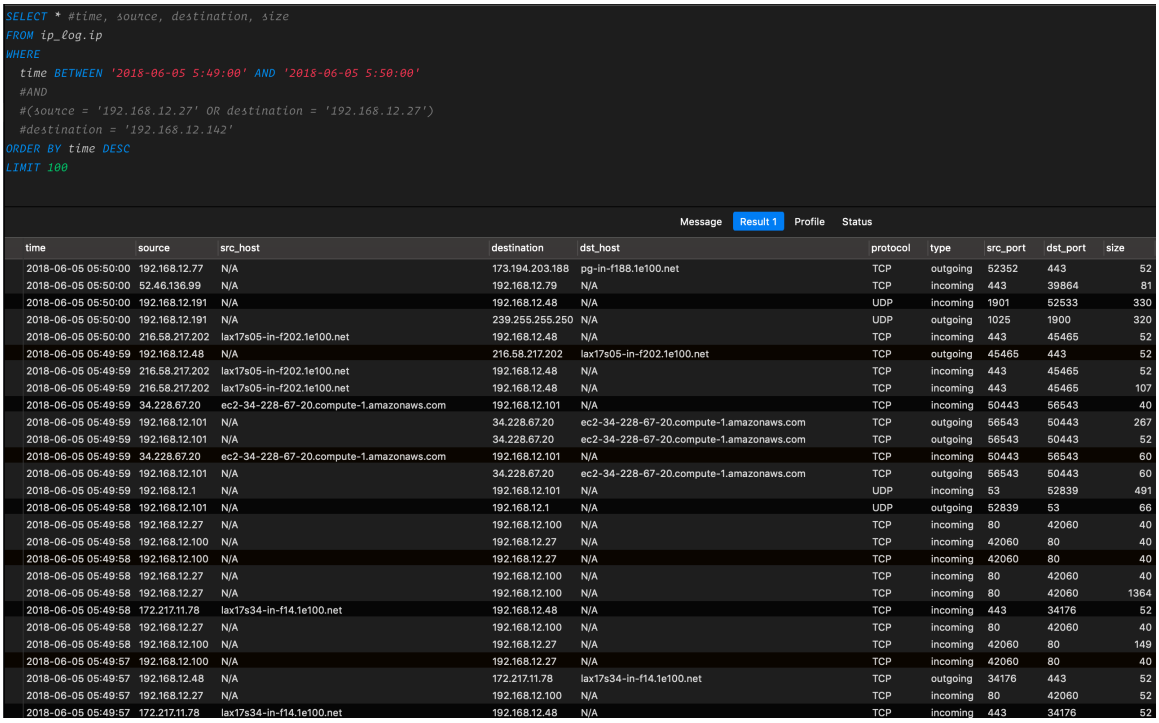


```
SELECT time, name, power_mw
FROM ip_log.power
WHERE
  time BETWEEN '2018-5-26 1:30:00' AND '2018-7-26 1:40:00' AND
  (name = 'Echo Dot'
    OR name = 'Echo DOt 2'
    OR name = 'Chromecast'
    OR name = 'Roku'
    OR name = 'Samsung TV'
    OR name = 'Samsung Hub'
    OR name = 'Nintendo Switch'
    OR name = 'Xbox'
    OR name = 'Eufy Genie'
    OR name = 'Eufy Genie 2'
    OR name = 'Echo Show'
  )
ORDER BY time DESC
LIMIT 20
```

Message | Result 1 | Profile | Status

| time | name | power_mw |
|---|---|---|
| 2018-07-26 01:39:59 | Eufy Genie 2 | 1470 |
| 2018-07-26 01:39:59 | Echo Dot | 1340 |
| 2018-07-26 01:39:58 | Chromecast | 1275 |
| 2018-07-26 01:39:58 | Echo Dot 2 | 1385 |
| 2018-07-26 01:39:58 | Samsung TV | 50 |
| 2018-07-26 01:39:58 | Eufy Genie | 1405 |
| 2018-07-26 01:39:58 | Roku | 2335 |
| 2018-07-26 01:39:58 | Nintendo Switch | 170 |
| 2018-07-26 01:39:58 | Samsung Hub | 2190 |
| 2018-07-26 01:39:57 | Echo Show | 2840 |
| 2018-07-26 01:39:57 | Xbox | 15785 |
| 2018-07-26 01:39:56 | Eufy Genie 2 | 1465 |
| 2018-07-26 01:39:55 | Echo Dot | 1345 |
| 2018-07-26 01:39:55 | Chromecast | 1265 |
| 2018-07-26 01:39:55 | Echo Dot 2 | 1375 |
| 2018-07-26 01:39:55 | Samsung TV | 25 |
| 2018-07-26 01:39:55 | Eufy Genie | 1405 |
| 2018-07-26 01:39:55 | Roku | 2330 |

**Figure 2.5: Power query from database with Navicat.**



```
SELECT * #time, source, destination, size
FROM ip_log.ip
WHERE
  time BETWEEN '2018-06-05 5:49:00' AND '2018-06-05 5:50:00'
  #AND
  #(source = '192.168.12.27' OR destination = '192.168.12.27')
  #destination = '192.168.12.142'
ORDER BY time DESC
LIMIT 100
```

Message | Result 1 | Profile | Status

| time | source | src_host | destination | dst_host | protocol | type | src_port | dst_port | size |
|---|---|---|---|---|---|---|---|---|---|
| 2018-06-05 05:50:00 | 192.168.12.77 | N/A | 173.194.203.188 | pg-in-f188.1e100.net | TCP | outgoing | 52352 | 443 | 52 |
| 2018-06-05 05:50:00 | 52.46.136.99 | N/A | 192.168.12.79 | N/A | TCP | incoming | 443 | 39864 | 81 |
| 2018-06-05 05:50:00 | 192.168.12.191 | N/A | 192.168.12.48 | N/A | UDP | incoming | 1901 | 52533 | 330 |
| 2018-06-05 05:50:00 | 192.168.12.191 | N/A | 239.255.255.250 | N/A | UDP | outgoing | 1025 | 1900 | 320 |
| 2018-06-05 05:50:00 | 216.58.217.202 | lax17s05-in-f202.1e100.net | 192.168.12.48 | N/A | TCP | incoming | 443 | 45465 | 52 |
| 2018-06-05 05:49:59 | 192.168.12.48 | N/A | 216.58.217.202 | lax17s05-in-f202.1e100.net | TCP | outgoing | 45465 | 443 | 52 |
| 2018-06-05 05:49:59 | 216.58.217.202 | lax17s05-in-f202.1e100.net | 192.168.12.48 | N/A | TCP | incoming | 443 | 45465 | 52 |
| 2018-06-05 05:49:59 | 216.58.217.202 | lax17s05-in-f202.1e100.net | 192.168.12.48 | N/A | TCP | incoming | 443 | 45465 | 107 |
| 2018-06-05 05:49:59 | 34.228.67.20 | ec2-34-228-67-20.compute-1.amazonaws.com | 192.168.12.101 | N/A | TCP | incoming | 50443 | 56543 | 40 |
| 2018-06-05 05:49:59 | 192.168.12.101 | N/A | 34.228.67.20 | ec2-34-228-67-20.compute-1.amazonaws.com | TCP | outgoing | 56543 | 50443 | 267 |
| 2018-06-05 05:49:59 | 192.168.12.101 | N/A | 34.228.67.20 | ec2-34-228-67-20.compute-1.amazonaws.com | TCP | outgoing | 56543 | 50443 | 52 |
| 2018-06-05 05:49:59 | 34.228.67.20 | ec2-34-228-67-20.compute-1.amazonaws.com | 192.168.12.101 | N/A | TCP | incoming | 50443 | 56543 | 60 |
| 2018-06-05 05:49:59 | 192.168.12.101 | N/A | 34.228.67.20 | ec2-34-228-67-20.compute-1.amazonaws.com | TCP | outgoing | 56543 | 50443 | 60 |
| 2018-06-05 05:49:59 | 192.168.12.1 | N/A | 192.168.12.101 | N/A | UDP | incoming | 53 | 52839 | 491 |
| 2018-06-05 05:49:58 | 192.168.12.101 | N/A | 192.168.12.1 | N/A | UDP | outgoing | 52839 | 53 | 66 |
| 2018-06-05 05:49:58 | 192.168.12.27 | N/A | 192.168.12.100 | N/A | TCP | incoming | 80 | 42060 | 40 |
| 2018-06-05 05:49:58 | 192.168.12.100 | N/A | 192.168.12.27 | N/A | TCP | incoming | 42060 | 80 | 40 |
| 2018-06-05 05:49:58 | 192.168.12.100 | N/A | 192.168.12.27 | N/A | TCP | incoming | 42060 | 80 | 40 |
| 2018-06-05 05:49:58 | 192.168.12.27 | N/A | 192.168.12.100 | N/A | TCP | incoming | 80 | 42060 | 40 |
| 2018-06-05 05:49:58 | 192.168.12.27 | N/A | 192.168.12.100 | N/A | TCP | incoming | 80 | 42060 | 1364 |
| 2018-06-05 05:49:58 | 172.217.11.78 | lax17s34-in-f14.1e100.net | 192.168.12.48 | N/A | TCP | incoming | 443 | 34176 | 52 |
| 2018-06-05 05:49:58 | 192.168.12.27 | N/A | 192.168.12.100 | N/A | TCP | incoming | 80 | 42060 | 40 |
| 2018-06-05 05:49:58 | 192.168.12.100 | N/A | 192.168.12.27 | N/A | TCP | incoming | 42060 | 80 | 149 |
| 2018-06-05 05:49:57 | 192.168.12.100 | N/A | 192.168.12.27 | N/A | TCP | incoming | 42060 | 80 | 40 |
| 2018-06-05 05:49:57 | 192.168.12.48 | N/A | 172.217.11.78 | lax17s34-in-f14.1e100.net | TCP | outgoing | 34176 | 443 | 52 |
| 2018-06-05 05:49:57 | 192.168.12.27 | N/A | 192.168.12.100 | N/A | TCP | incoming | 80 | 42060 | 52 |
| 2018-06-05 05:49:57 | 172.217.11.78 | lax17s34-in-f14.1e100.net | 192.168.12.48 | N/A | TCP | incoming | 443 | 34176 | 52 |

**Figure 2.6: Network query from database with Navicat.**

Within the power table, the name field is extracted from the name of the WeMo, which we manually name through the app. This can cause issues if the wrong device is connected to a WeMo. For example, the Echo Dot could have accidentally been connected to the WeMo named Google Home. There is no way to check for this besides manual examination, which we did after a few weeks, resetting all devices and causing a temporary void in power data. When we reset all devices, we also renamed some of the WeMos. For example, we changed "echoDot" to "Echo Dot". This way, all devices would follow the naming convention of separating words with spaces and capitalizing each word. Another possible naming convention could have been to name the WeMo by the IPs of the devices they connect to, but they are not static.

The sampling frequency for the power table is also low and missing some points. The script to query power data is not consistent and is unable to get power data at every second. To handle missing points, I interpolate them as shown in subsection 2.3.7. The interpolation process may introduce imprecise data as it fills a missing data point by extrapolating a linear path from the closest points before and after it.

### 2.3.4 Device Inventory

To keep track of all devices and important details about them, we log a device's service, distributor, related email, IP address, dependencies, previous usage, and password into a Google Sheets file. An example of entries into the Device Inventory are shown below in table 2.4. The service field denotes the service a device provides, for example, the Google Home is a smart speaker. The device field denotes the specific manufacturer and device name. The Email and password fields denotes the email and password used when setting up the device. Some devices such as the Nintendo Switch were setup without an account. The IP address field denotes the IP address of the device within our local network. The dependencies field denotes anything the device is connected to or uses. For example, the Roku express is connected to a WeMo for power logging and comes with a controller for use. The used flag denotes whether the device was previously used or not, at which point, we could not log first time startup data for that device.

**Table 2.4: Device inventory excerpt. Password column not shown.**

| Service | Device | Email | IP Address | Dependencies | Used |
|---|---|---|---|---|---|
| Speaker | Amazon Echo Dot 1 | amazonEchoDotSS0@aol.com | 192.168.12.79 | WeMo | yes |
| Speaker | Google Home | googleHomeMiniSS0@aol.com | 192.168.12.48 | WeMo | no |
| Streaming | Google Chromecast | googleChromecastSD0@aol.com | 192.168.12.78 | WeMo | no |
| Streaming | Roku Express | rokuExpressSD0@aol.com | 192.168.12.68 | WeMo, controller | no |
| Game Console | Nintendo Switch | n/a | 192.168.12.160 | WeMo, controller | no |

### 2.3.5 IP History

A Google Sheets file is used to keep track of the IP address of each device's IP address as it changes as shown in table 2.5. The 'Date Noticed' column is the date that the IP address was noted to have changed. The 'Device' is the name of the device that changed IP address. The the 'Old IP' and 'New IP' are the IP addresses for the device before and at that current time respectively. Table 2.5 was added near the end of the research for this paper for future students to use when cleanign up the database.

**Table 2.5: History of IP addresses for each device**

| Date Noticed | Device | Old IP | New IP |
|---|---|---|---|
| April 10, 2:15 PM | Samsung TV | 192.168.12.148 | 192.168.12.149 |
| April 11, 2:27 PM | Chromecast | 192.168.12.77 | 192.168.12.78 |
| April 12, 5:16 PM | Fire Stick | 192.168.12.113 | 192.168.12.114 |
| April 20, 10:31 PM | Galaxy Tablet | 192.168.12.222 | 192.168.12.223 |
| April 20, 5:37 PM | Camera | None | 192.168.12.57 |
| April 24, 5:36 PM | Home Montioring Kit | None | 192.168.12.191 |
| May 8, 5:59 PM | Home Montioring Kit | 192.168.12.191 | 192.168.12.100 |
| May 8, 6:21 PM | Camera | 192.168.12.57 | 192.168.12.84/83 |
| May 18, 12:04 | Samsung TV | 192.168.12.149 | 192.168.12.191 |

### 2.3.6 Usage Flow

One of the goals of this work is to create a data set that represents the baseline of normal network traffic and power usage. To do this, we used each IoT device at least twice a week for the year length of this research. To build a proper dataset that other people could use for research, we set up a list of things that we should do for each device interfacing with it. We logged the activities into Google Sheets so that these events could be correlated to entries in the database, giving context when looking back on this data. For example, if someone were to look at the database and notice that the power and network traffic was high for 3 minutes, they could look at our logs and see that the device was streaming music for those 3 minutes and assume that it was normal usage.

When logging events into Google Sheets, we include the start, end time, name of the device(s), action performed, and any individual notes. When naming the devices, we used the same naming as we did for the WeMos to maintain consistency from the log to the database. An example of entries into the table is shown in Table 2.6.

**Table 2.6: Event Log Excerpt**

| Date | Start Time | End Time | Device | Event |
|---|---|---|---|---|
| 5/25/2018 | 12:44:42 | 12:47:04 | Home Mini | Ask for news |
| 5/25/2018 | 12:55:07 | 12:56:37 | Echo Dot | Ask for news |
| 5/25/2018 | 12:55:57 | 12:56:17 | Echo Show | Ask for weather |
| 5/25/2018 | 12:56:44 | 13:03:07 | Home Mini | Play music |

The following subsections explains the script created to automate the event logging portion of the research. Then it explains the specific procedure we ran each group of IoT devices through whenever we interfaced with them.

#### Google Sheets Script

Logging information into the spreadsheet is a tedious task, especially when trying to analyze each device while running tasks on them. The code for the script is shown below in Listing 2.3.

```
function onEdit() {
  var s = SpreadsheetApp.getActiveSpreadsheet().
     getSheetByName("Event Log");
  var r = s.getActiveCell();
  var c = r.getColumn();

  if( c == 4 || c == 5) { // checks the column
    var dateCell = r.offset(0, -3);

    if( dateCell.getValue() === '' ) {// is empty?
      var startTimeCell = r.offset(0, -2);

      // fill in the start time and date
      var date = new Date();
      dateCell.setValue(date);
      startTimeCell.setValue(date.toLocaleTimeString());
    }
  }

  if( c == 6 ) { // checks that the description is being
     entered
    // if so fill in the end time
    var endTimeCell = r.offset(0, -3);

    if ( endTimeCell.getValue() === '' ) {
      endTimeCell.setValue(new Date().toLocaleTimeString());
    }
  }
}
```

**Listing 2.3: Open and Read from a Socket**

#### Smart Speakers

Whenever interfacing with these devices, we always queried for the weather and the news. The specific phrases we used "<wake word> what's the weather" and "<wake word> what's the news", we set a reminder for a random task in a random timeframe, and we muted the devices for a few minutes to see if they were still listening if we said the wake word.

#### Video Game Consoles

When interfacing with these devices, we played a game on the device for at least 15 minutes. Every week, we also browsed for games on the game store and downloaded free demos.

Afterward, we would turn off the Xbox and put the Nintendo Switch into sleep mode. The Nintendo Switch could not be put to sleep when docked, only when disconnected from the dock, so it was set to sleep rather than power off.

#### Streaming Devices

Within the Media Players section, we include the Roku Express, Chromecast, Amazon Firestick, and Samsung Smart TV. When interfacing with these devices, we watched YouTube for at least either one video or 3 minutes.

For the Chromecast, we cycled through different devices to cast videos from, including the iPad and the Chromebook. We wanted to get varied data in case the Chromecast prioritized streaming from different devices.

#### Tablets

In this experimental setup, we used the tablets less for investigative purposes, but more to set up and interface with other devices.

However, we still tracked the data and had a small set list of things to do on these devices. We used each tablet to browse the web, watch YouTube, and use various apps.

#### Security Camera

The only security camera we worked with was the Eray Security Camera.

Whenever interfacing with this device, we used the device under the app NVAS2 in the iPad for at least 2 minutes. Usage included streaming video from the camera to iPad and viewing it. We also controlled the camera through the app with pan and

tilt commands. When done experimenting with the security camera, we disconnected the tablet from the camera by using the "end stream" button in the NVAS2 app.

### 2.3.7 realtimeIoTGrapher.py

This section covers a visual tool I created to look for trends. We initially graphed the data into Google Sheets and graphed it. The tables and formulas are shown in figure 2.7. This process was tedious and time-consuming. We had to copy the data over after making a SQL query, extract unique time values, and then get the total network and power usage at each time interval.

To address these problems, I created a python script that automatically forms graphs, including the one shown in figure 2.10 when given the time range and the devices. This automation sped up the analysis process and provided extra features covered in section 2.3.7.

This Python script leverages the Plotly library, which, given data, graphs it onto a local web page for viewing. Plotly comes with many useful tools for further analysis and can be extended to run on a public web page for public viewing.

I plan to distribute this out with our database so that researchers can view the power and network information of any device at a glance.

fx =UNIQUE(A:A)

| | A | B | C | D | |
|---|---|---|---|---|---|
| 1 | time | size | time | SUMIF(A:A, C2, B:B) | |
| 2 | 2018-04-17 11:25:40 | 331 | 2018-04-17 11:25:40 | 331 | |
| 3 | 2018-04-17 11:25:41 | 272 | 2018-04-17 11:25:41 | 2144 | |
| 4 | 2018-04-17 11:25:41 | 390 | 2018-04-17 11:25:42 | 1183 | |
| 5 | 2018-04-17 11:25:41 | 399 | 2018-04-17 11:25:43 | 2043 | |
| 6 | 2018-04-17 11:25:41 | 396 | 2018-04-17 11:25:44 | 865 | |
| 7 | 2018-04-17 11:25:41 | 334 | 2018-04-17 11:25:45 | 431 | |
| 8 | 2018-04-17 11:25:41 | 353 | 2018-04-17 11:25:46 | 7916 | |
| 9 | 2018-04-17 11:25:42 | 40 | 2018-04-17 11:25:47 | 8153 | |
| 10 | 2018-04-17 11:25:42 | 52 | 2018-04-17 11:25:48 | 3580 | |

**Figure 2.7: Manual Analysis of IoT devices in Google Sheets: Raw data shown in columns A and B are then formatted into columns C and D for Graphing**

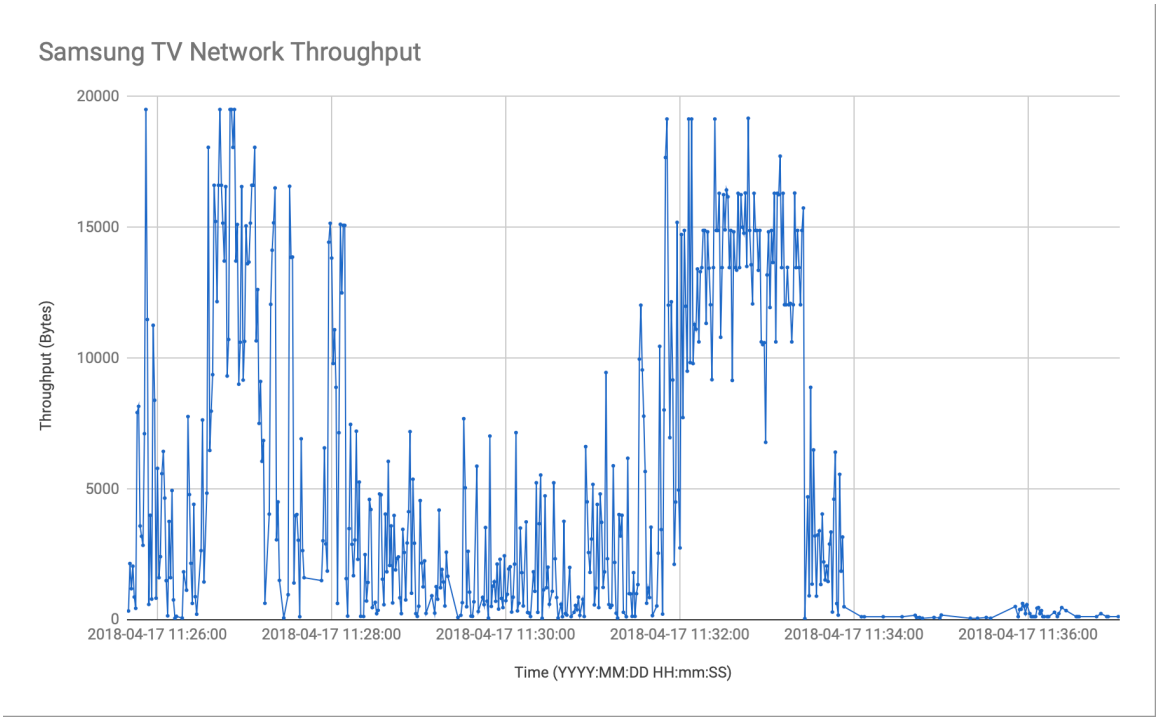



**Figure 2.8: Resulting graph of dataset shown in Figure 2.7**

**Features**

This section discusses the features that RealTimeIoTGrapher (grapher) provides.

At its core, this program automates the creation of the graph shown in figure 2.8. The user can specify a time range that the graph should cover and what devices to graph. By default, the graph shows power, input traffic, output traffic, and total network traffic over the time range specified.

The grapher also annotates the data by including a line denoting the average for each of the traces over the time range currently displayed. It also annotates the maximum and minimum values in the time range for each trace. The grapher can also display information in real time for a user settable interval amount of time, updating every second.

The Plotly libraries also provide useful tools when displaying these IoT graphs. It is possible to zoom in and out the displayed graph, select specific traces for viewing, save the graph, and hover over data points to display the specific value. Finally, once a graph is saved Plotly allows further editing of the graph so that it is formatted the way the user wants.

```
1     def throughput_query_in_range(db_connection, device,
          start_time, end_time):
2     sql_query = """
3         SELECT
4             time,
5             CASE WHEN type IS NULL THEN 'total' ELSE type
                  END type,
6             SUM(size) AS total_throughput
7         FROM ip_log.ip
8         WHERE
9             time BETWEEN '%s' AND '%s' AND
10            (source = '%s' OR destination = '%s')
11        GROUP BY time, type WITH ROLLUP;
12    """ % (start_time, end_time, ip[device], ip[device])
13
14    dataframe = pd.read_sql_query(sql_query, db_connection)
15
16    return dataframe
```

**Listing 2.4: Efficient SQL query to obtain total Network throughput at each second.**

To reduce local computation, the grapher offloads work to the server through a SQL query. When querying for network data, it performs a SQL ROLLUP to sum the incoming and outgoing network throughput to obtain the total throughput. ROLLUP is required because it provides nested queries and causes the query to sum up the data by time for each type of packet. This query is formatted as shown in listing 2.4.

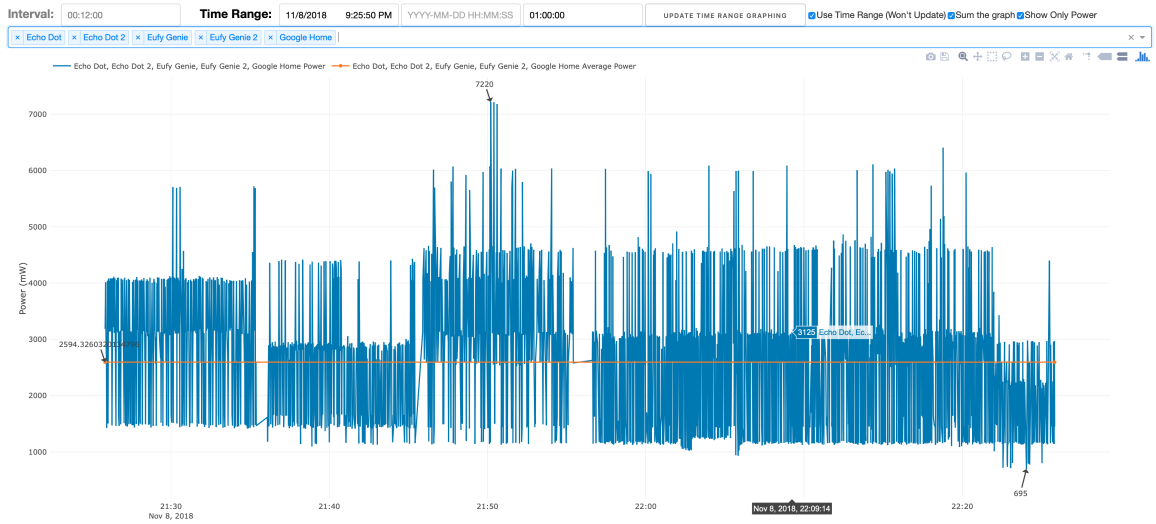



**Figure 2.9: Summed power traces without interpolation.**

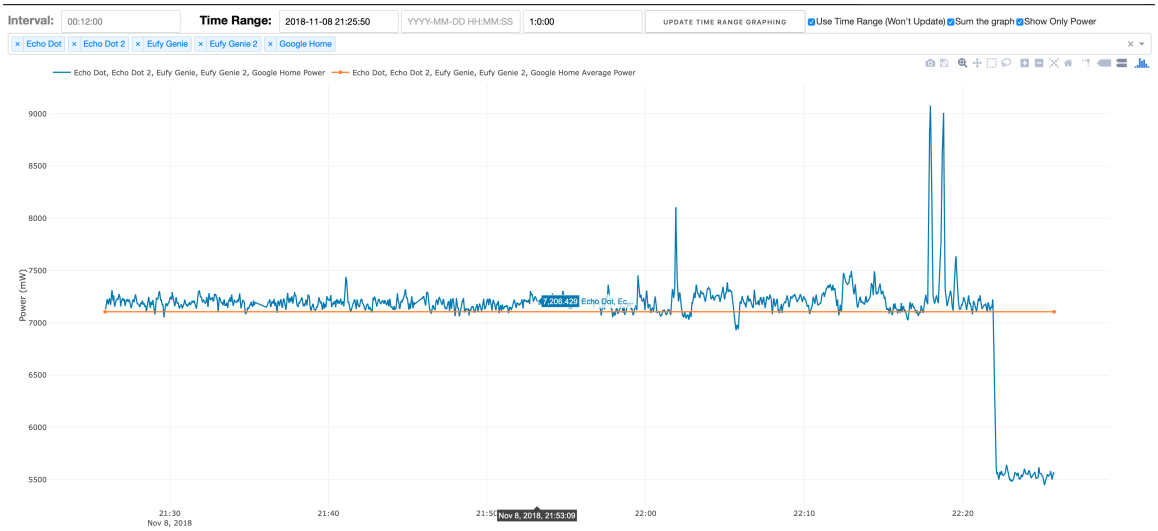



**Figure 2.10: Summed power traces with interpolation.**

The grapher can also sum up all power traces into one single trace. Originally, when summing the graphs, it would add the two Pandas [32] data frames that represent each trace, and graph the result, shown in figure 2.9. Pandas is a Python library that represents a multidimensional array as a table, providing useful methods for manipulating the dataset. However, the WeMo does not always sample every second. This is an issue if, at time, one device X has a power point, but another device does not. The summation counts the empty data point as 0, resulting in an erroneous sum.

This was solved by interpolating data for every second for each device before summing data frames, with a built-in Pandas feature. Interpolation is shown in 2.10 as a graph.

#### Visual Takeaway

This tool created most of the images shown in section 3. A few other researchers such as Frawley's have used this tool for data visualization. The grapher provides real-time or historical graphs on any in the database device for individual analysis or comparison with little effort or time. Additional features from Plotly also provides an easy way to format graphs for presentations or papers.

The summation feature can simplify the graph and provide a more holistic view of power usage, making it easier to spot patterns. In this paper, the summation feature is used to simulate the concept of a household's "powerline" where all energy usage would be summed up into one power meter.

#### Limitations

As this tool was created entirely for research purposes, there are some edge cases that it fails to handle.

When the database has too many connections, the software refuses to connect, and the grapher will not work. When graphing in real time, the grapher makes a new connection for each query. If a query fails, connections can quickly build up.

The graphing tool also slows as the time frame requested increases. We have noticed a slow down for queries with time frames longer than seven hours. In the static graphing mode, the tool slows down before graphing the information. However, in real time graphing mode, the tool makes many slow queries, eventually causing too many connections to the database and undefined behavior.

The graphing tool uses a lookup table that maps the IP address of the device to the corresponding name given to the WeMos. Because we manually create the lookup table, when any of these fields change, the graphing is not able to find the device. In some cases, this causes the graphing tool to crash. To solve this, the user must

manually change the IP addresses defined in the lookup table in lines 23-39 shown in listing 2.5 below.

To figure out the new IP address for the table, the user must perform a SQL query in the time frame that a device is doing something, and manually examine the network traffic to see which IP has the highest network throughput. With this method, we had to ensure only one device was in use so that an IP address for another device would not be confused for the current device.

```
1    #region IP Addresses of all devices we are tracking
2    ip = {
3        'Chromecast':       '192.168.12.77',
4        'Echo Dot 2':       '10.42.0.132',
5        'Echo Dot':         '10.42.0.150',
6        'Eufy Genie':       '10.42.0.223',
7        'Eufy Genie 2':     '10.42.0.172',
8        'Fire Stick':       '192.168.12.113',
9        'Google Home':      '10.42.0.236',
10       'IP Camera':        '192.168.12.58',
11       'Nintendo Switch':  '192.168.12.160',
12       'Roku':             '192.168.12.68',
13       'Samsung Hub':      '192.168.12.100',
14       'Samsung TV':       '192.168.12.191',
15       'Smart Light':      '192.168.12.27',
16       'Xbox':             '192.168.12.251',
17       'Echo Show':        '192.168.12.122',
18       'Appliance':        '192.168.12.122',
19       'Appliance1':        '192.168.12.122',
20   }
```

**Listing 2.5: IP lookup table in real time IoT grapher.**

# Chapter 3

# RESULTS AND DISCUSSION

This chapter covers different network and power usage patterns for the IoT devices in the testbed. First, section 3.1 informally compares the smart switches between devices to show that they are accurate for this research's purposes. Section 3.2 covers the percentage of each protocol in the database for an overall view of home IoT devices. Section 3.3 covers smart speakers' and streaming devices' network and power use while idle, in use, and during first boot. Sections 3.2 and 3.3 serve as precursory analysis to fingerprint devices and give example usages of the database and visualizer tool.

After general analysis, section 3.4 shows how the presence of a user in their house and a smart device can be determined form power traces. This starts the focus of the research to use a shared power line (simulation for a home power line) to determine what smart speaker is in use visually. Sections 3.5 and 3.6 cover summed power graphs of the smart speakers with and without noise from high power household devices. Finally, section 3.7 ends with a comparison between smart speakers for further general analysis.

Within each section, after presenting the results, the paper discusses the implications of the data. The results and discussion presented are visual and informal, but strongly support the claims they make.

When obtaining data, most of the packets are encrypted, so the data presented focuses on metadata such as size, protocol, source IP, and destination IP. For power analysis, we focus on the power used at each second.

## 3.1 Swapping the Power Switch

To check if the smart switch voltage readings are accurate, we swapped various devices with various power switches. Some examples are shown 3.1, 3.2, and 3.3. After swapping the switches, each device would take some time to start up, the colored box in figures 3.1, 3.2, and 3.3 highlight this time.

In every case, the traces swapped as we swapped the device connected to each smart switch. This informal sanity check confirmed accurate enough power switches for visual analysis.

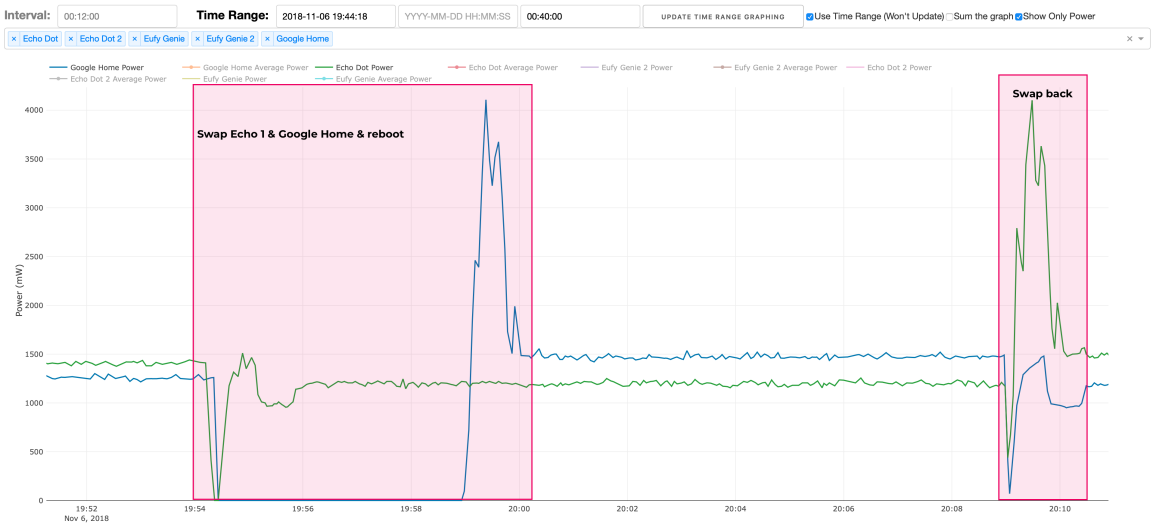



**Figure 3.1: Connected the Echo Dot 1 to WeMo for 'Eufy Genie 1' and vice versa. The traces swap before and after switching.**

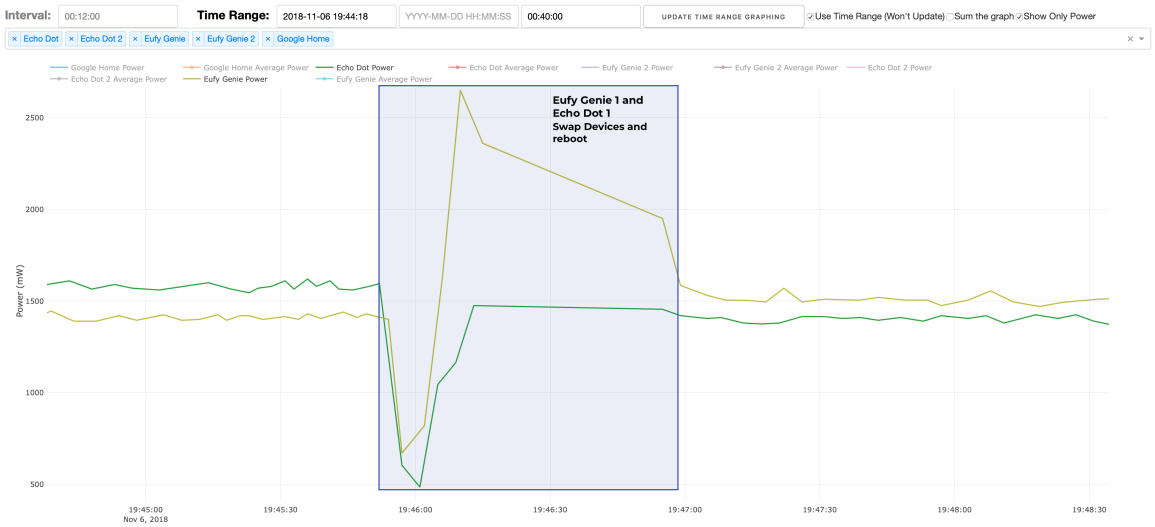



**Figure 3.2: Connected the Eufy Genie 1 to WeMo for 'Echo Dot 1' and vice versa. The traces swap before and after switching.**


**Figure 3.3: Connected the Google Home to WeMo for 'Eufy Genie 1' and vice versa. The traces swap before and after switching.**

## 3.2 Whole Database

When examining the whole database, most of the traffic is TCP packets. The second most significant protocol is UDP. This figure is an example of some information the database provides.

It shows the percentage of certain protocols that would pass through a typical home, adding to the fingerprint of IoT devices. Refer to Frawley's paper for more information on trends in the whole database1.1.3.

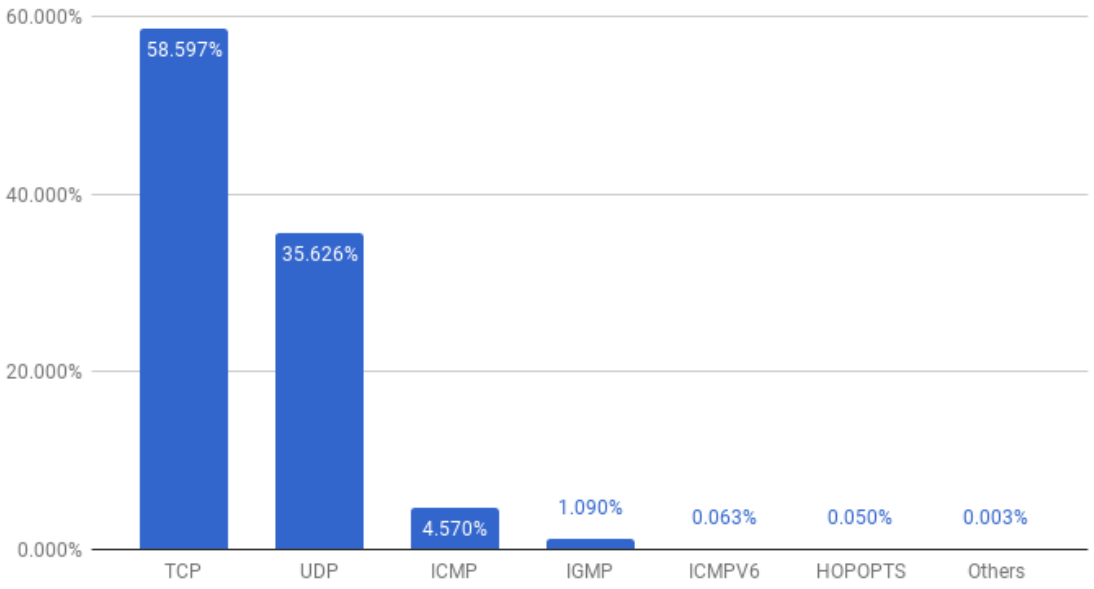



**Figure 3.4: Internet and Transport Layer Protocols in Database**

## 3.3 General Analysis

The figures shown in this section give examples of how the database and grapher tool is used. The figures also demonstrate a strong correlation between what the device is doing and its network/power usage, serving as data to fingerprint each smart speaker.

Frawley's paper contains a more in-depth analysis of this section. His paper includes GeoIP [8] information from Cal Poly's ITS servers [33] that highlight the locations and companies the network packets are sent to and received from. Frawley's paper also includes data of unencrypted packets being sent and received along with the text within them.

### 3.3.1 Google Home Mini General Analysis

The Google Home Mini's idle traffic broadcasts SSDP (Simple Service Discovery Protocol) packets once every minute. The SSDP packets are a discovery request packet

for every IoT device on the network that supports UPnP (Universal Plug and Play). At which point, devices such as the Echo Dot, Samsung TV, and the Chromebook respond with information about themselves in a .xml file. This XML file contains details regarding the device operating system and more. Google also sends encrypted TCP packets to Google every 10 minutes. Figure 3.5 shows the Google Home Mini's idle traffic. The large spikes are the encrypted TCP packets, and the smaller spikes are the SSDP/UPnP packets.

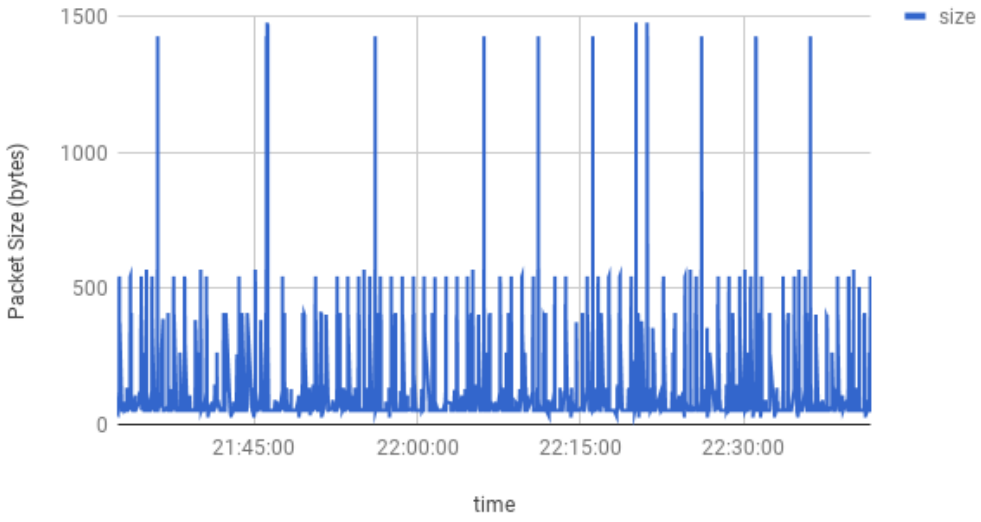



**Figure 3.5: Idle Traffic of Google Home Over 1 Hour Period**

Figure 3.6 shows a graph of the Google Home Mini's network and power usage under various commands. The Google Home Mini is first asked for the news and then told to stop. After waiting for 40 minutes, we ask it for the weather forecast.

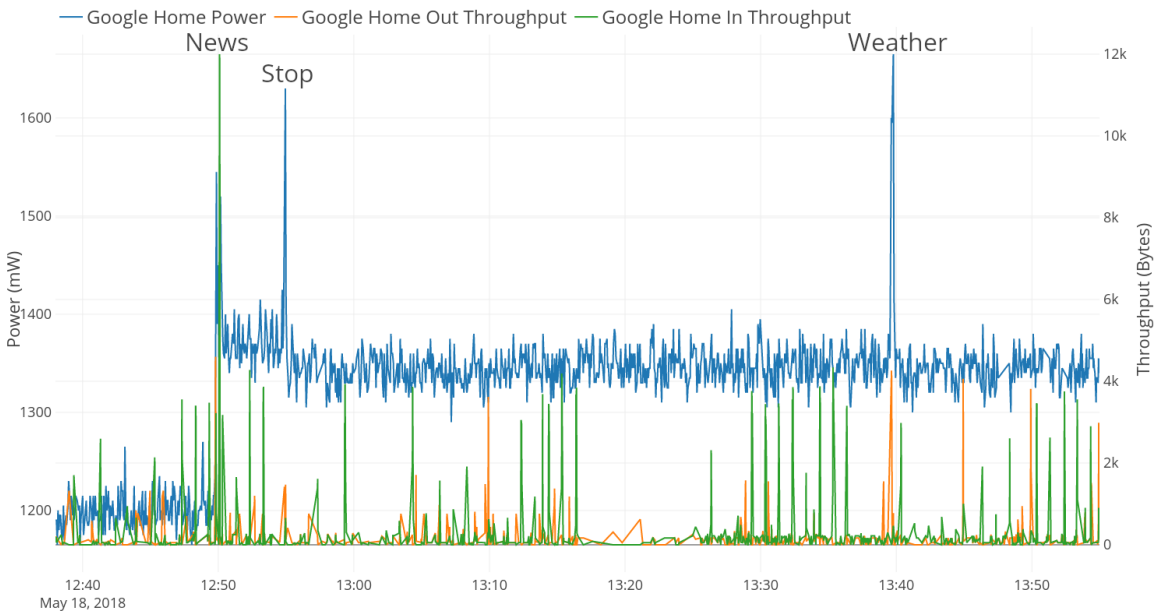



**Figure 3.6: Home Mini Response to News and Weather**

### Google Chrome Cast

Figure 3.7 shows the Chrome Cast startup graph. On startup, the Chrome Cast shows an intro tutorial video and downloads a firmware update. After rebooting twice, it is ready to go.

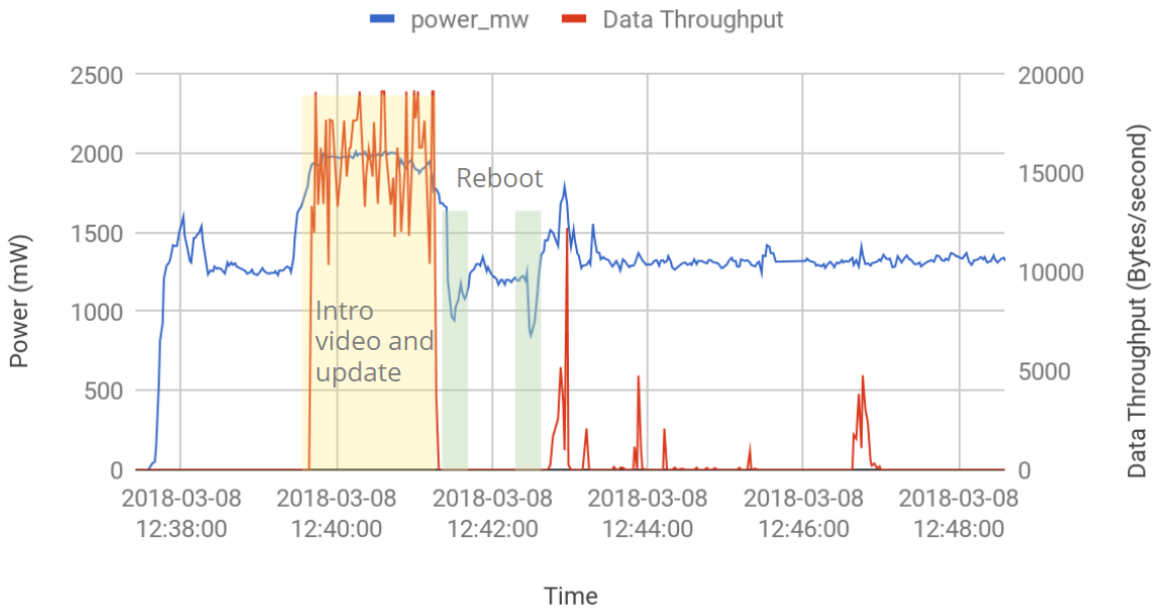



**Figure 3.7: Chromecast First Time Boot Network Traffic and Power Consumption**

Figure 3.8 shows the Chrome Cast streaming graph. In this time frame, the chrome cast streams video in the marked box.

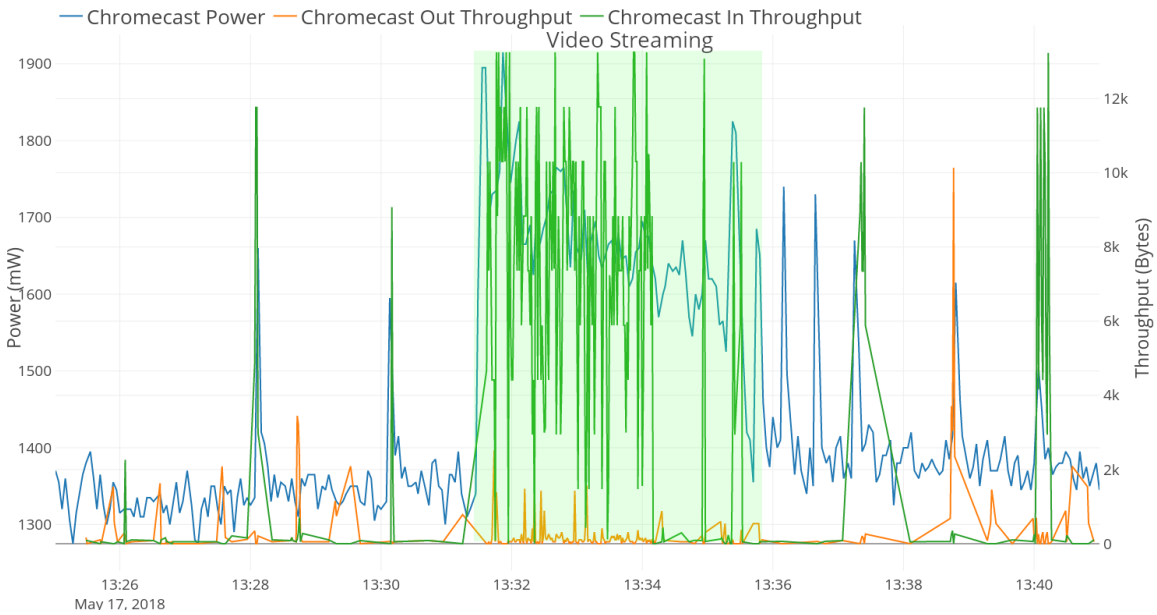



**Figure 3.8: Chromecast Video Streaming**

Additionally, the Chrome Cast idle graph is shown in figure 3.9. In this time frame, there are consistent spikes to the chrome cast every 2 minutes. During these spikes, the chrome cast is showing a new background that it downloads from Google Servers.

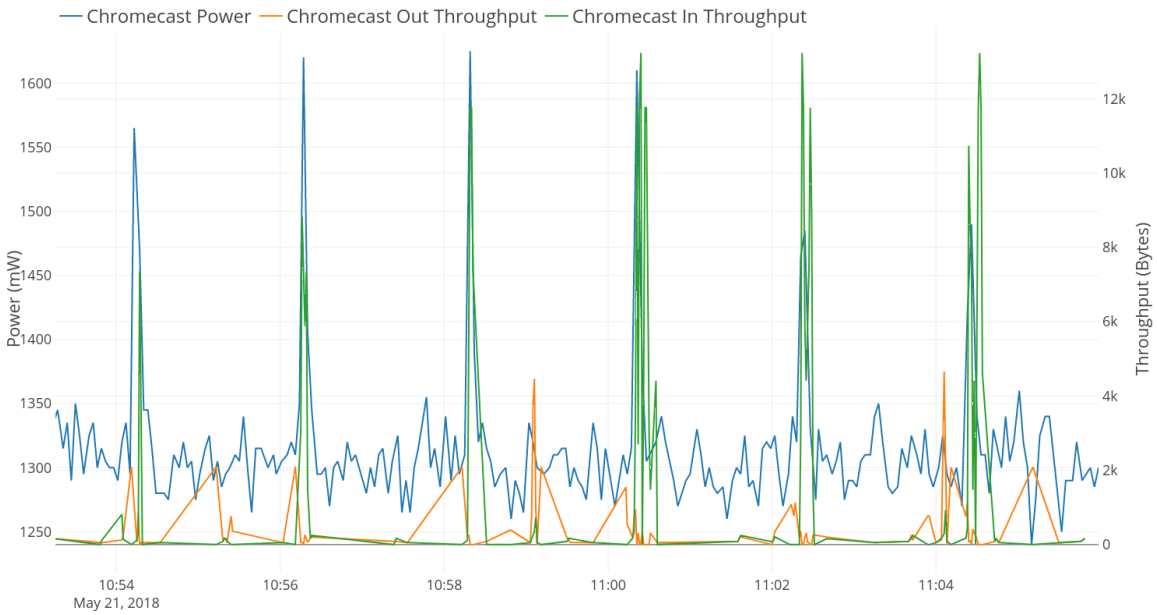



**Figure 3.9: Chromecast Idle Traffic**

### Amazon Fire Stick

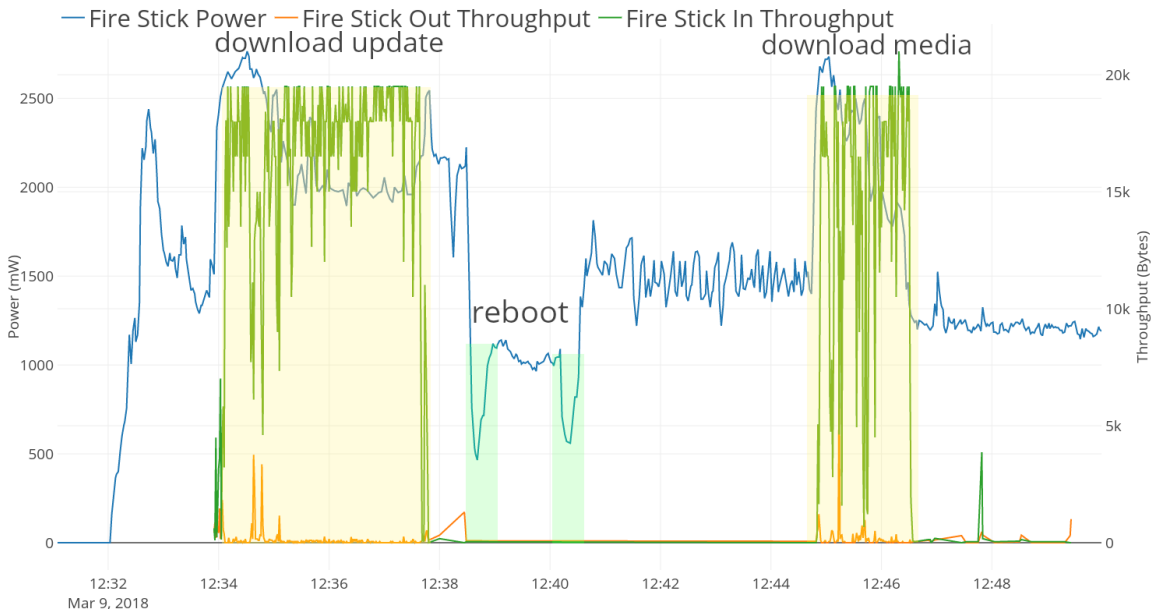



**Figure 3.10: Fire TV Stick First Time Boot Network Traffic and Power Consumption**

Figure 3.10 shows the Amazon Fire Stick startup graph. On first boot, the fire stick downloads an update, reboots twice, then downloads certificates from Symantec and Verisign.

When streaming, the Fire Stick increases throughput and power usage with a spike at the beginning and end of streaming in power usage as shown in figure 3.11.

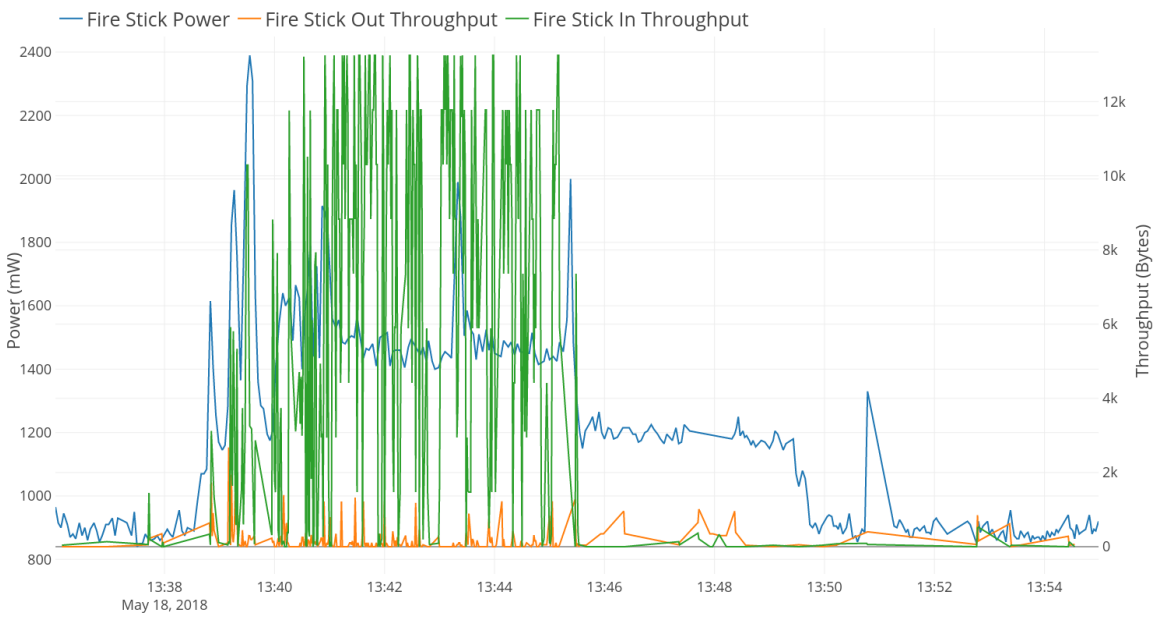



**Figure 3.11: Fire TV Stick Video Streaming**

### Roku Express

When streaming, the Roku's power usage and network throughput rise and stay at a constant level until the video streaming is complete. At which point it drops back down when done.

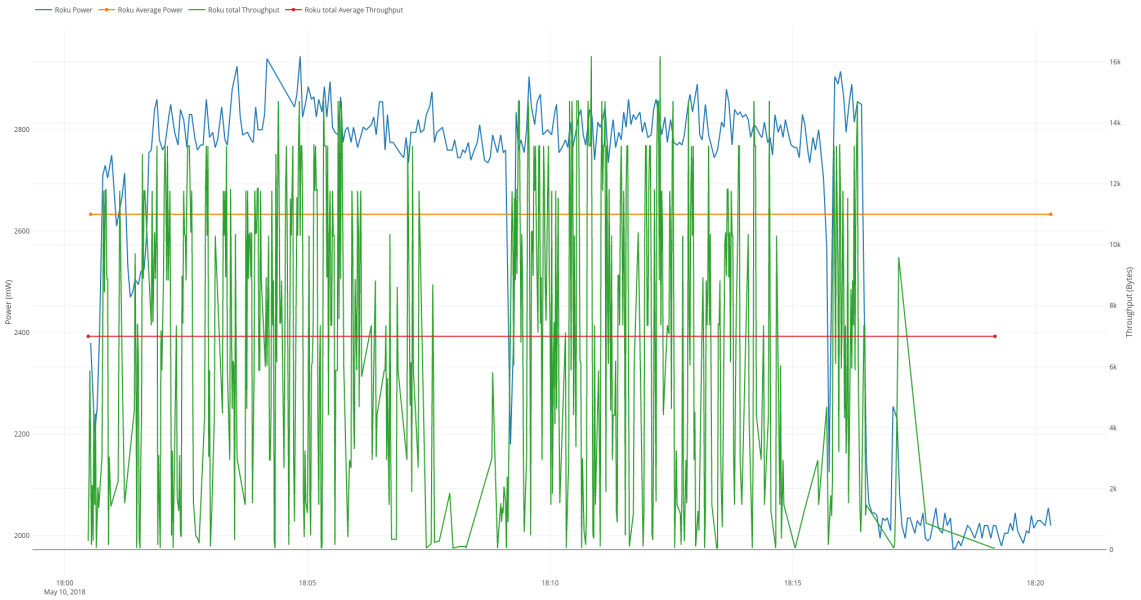



**Figure 3.12: Roku Express Video Streaming**

### 3.3.2 General Analysis Discussion

From all the figures in this section, there is a visual correlation between network/power usage and what each device is doing. During periodic updates, the smart speakers and streaming devices would have periodic network/power usage spikes as shown in figure 3.9. While streaming, the power/network usage would increase for the period of the stream as shown in 3.8, 3.11, and 3.12. This strong correlation shows the value of the database and visualizer tool for visual pattern recognition. It also shows the viability of using network throughput/power usage over time to understand what a device is doing.

## 3.4 Power Analysis on Smart Speakers

After determining a strong correlation between network/power usage and device operation, this section begins to focus on power usage over time. There is already significant analysis on network usage as shown in the previous works section 1.1. This paper focuses on the smart speakers' power usage to focus the scope of research.

This section first examines the power usage of the smart speakers separately before examining total power usage in section 3.5. Subsection 3.4.2 examines the idle power of smart speakers separately, and how correlates to a specific smart speaker. Then subsection 3.4.3 shows that through visual examination of a power trace of an individual smart speaker, we can tell what smart speaker is in use.

### 3.4.1 Echo Dot Brightness Sensor

One interesting finding from the Echo Dot is that it has a light monitor. When turning on the lights, the LEDs on the Echo Dot brighten to adapt. The brightness change causes the Echo Dot to use more idle power as shown in figure 3.13.

Figure 3.13 shows that the power usage of an Echo Dot can show if the lights are on in a house. This can help someone determine if someone is in their house or not or event what room they are in, introducing some privacy concerns.


**Figure 3.13: Echo Dot Response to Lights**

### 3.4.2 Baseline Speaker Power

Once discovering how much a smart speaker's power usage can show, this section examines the power usage of each smart speaker while idle. Figure 3.14 shows this from 1:00 AM to 2:30 AM when none of the devices are in use.

The Echo Dot 1 has the highest idle traffic as shown in the pink trace, the Echo Dot 2 has second highest idle traffic as shown in the green trace, the Eufy 1 and Eufy 2 have the same idle power usage as shown in the yellow and purple trace, then the Google Home has the lowest idle power usage as shown in the blue trace. With visual analysis, the smart speaker can be matched to idle power usage. But the power usages can overlap between the Echo Dot 2 and Eufys. This would make it difficult to differentiate them and shows this method to determine a device is difficult. Also, when summing the power usages together, these idle traces would disappear, with no way to differentiate what idle devices are contributing to the total power usage.

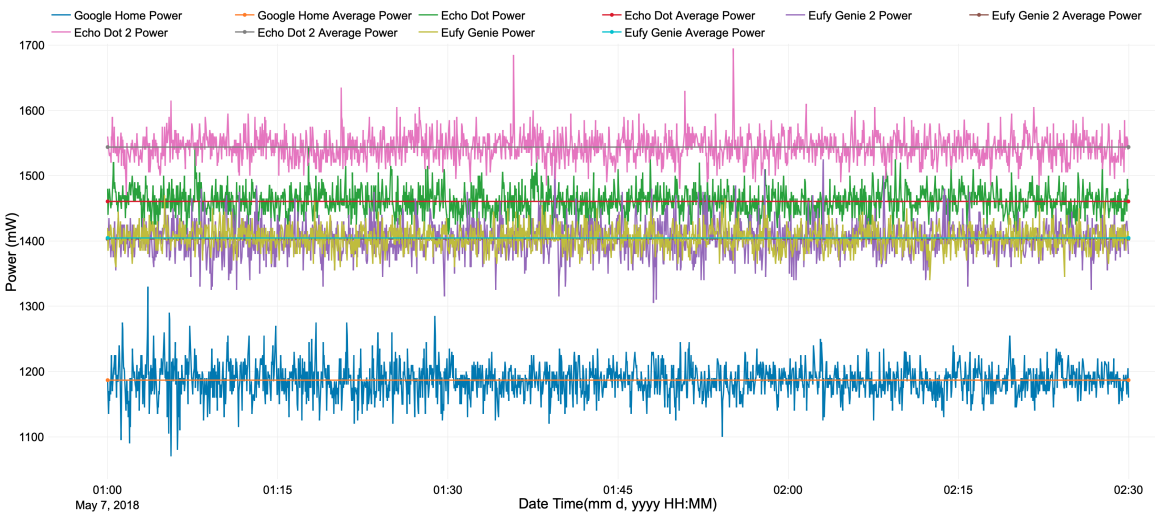



**Figure 3.14: Baseline smart speaker power usage.**

### 3.4.3 Smart Speaker Power Spikes When Asked for Weather

This section continues to see if a smart speaker can be determined from an individual power trace, focusing on traces while the device is in use. Figure 3.15 shows this, where each device is asked for the weather four times.

In figure 3.15 there is a visual spike for each device while it is giving the weather forecast. Each device is highlighted while in use, showing four spikes. The Google Home was queried for the weather five times, thus containing an extra spike. From this, we can determine a Eufy trace if it has small 400 mW peak to peak spikes, the Google Home if there is a medium 600 mW peak to peak spikes, and the Echo Dot if there is a large 2,100 mW peak to peak spikes. This implies that a device can be determined from a power trace if the device is asked for the weather. The next section analyzes more use cases, and the traces are summed together to simulate a shared home powerline more closely.

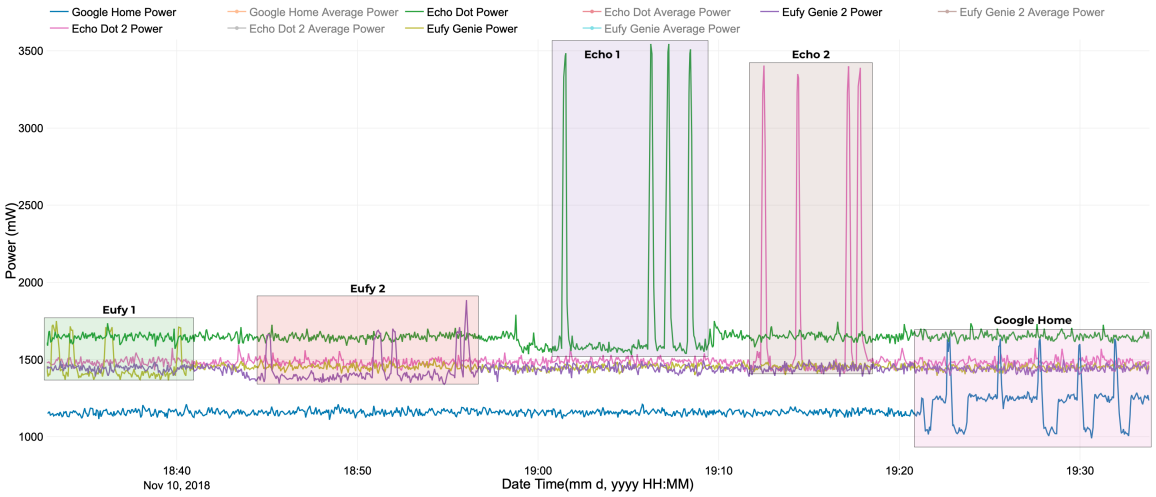



**Figure 3.15: Smart speakers' power usage when asked 'whatś the weather' four times.**

This section highlights initial power findings, and how visual examination of a power graph over time gives a lot of information. Once discovering the insight, a power trace can provide, the research focused on the overarching goal to see if given a graph of a house's total power usage, is it possible to determine the device in use.

## 3.5 Summed Power Graph

This section visually analyzes the power usages of all 5 of the smart speakers summed together under different commands.

The first graph in figure 3.16 shows a time frame where each device was unmuted

and muted for a period. This shows if muting and unmuting the devices affected the power or network usage. There are changes on the first run-through, but when repeating the process nothing happens. Further run-throughs show that power usage stayed the same. In the last half of the graph, we queried each smart speaker for the weather while all other smart speakers were muted at the 18:30 mark. We query each device 3-4 times for the weather. The Eufy had the smallest spike for the "whatś the weather" command at 400 mW, then the Google Home at 600 mW, and finally the Echo Dot at 2000 mW.

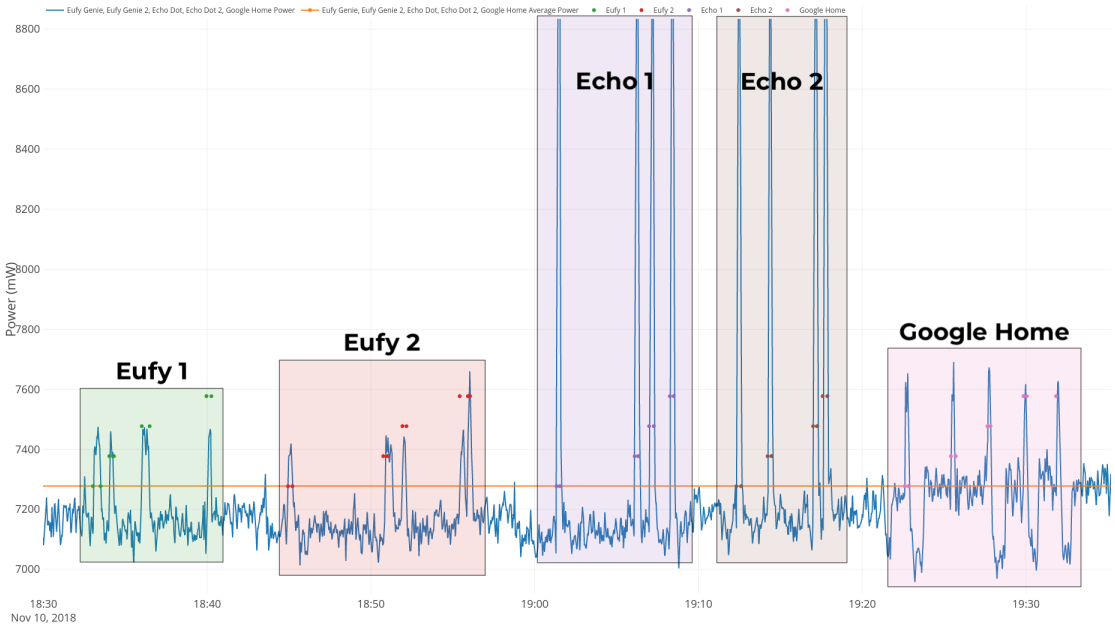



**Figure 3.16: 5 Smart Speakers Power Summed Up. Toggled the mute button and queried each device for the weather.**

The next graph, 3.17, shows the smart speakers power usage when asked for the news. Each speaker was asked for the news. This graph and the rest of the summed graphs in this section use the same notation for signifying commands. Two dots of the same color on the same y-axis level signify the start and end of the command for a specific device.

In figure 3.17, all devices have a spike at the beginning and end of the command and maintain a steady energy usage in between that is slightly higher than the idle energy used. The peak to peak spike of the Eufy Genie is the smallest at 350 mW, then the Google Home at 500 mW, and finally the Echo Dot at 1900 mW.

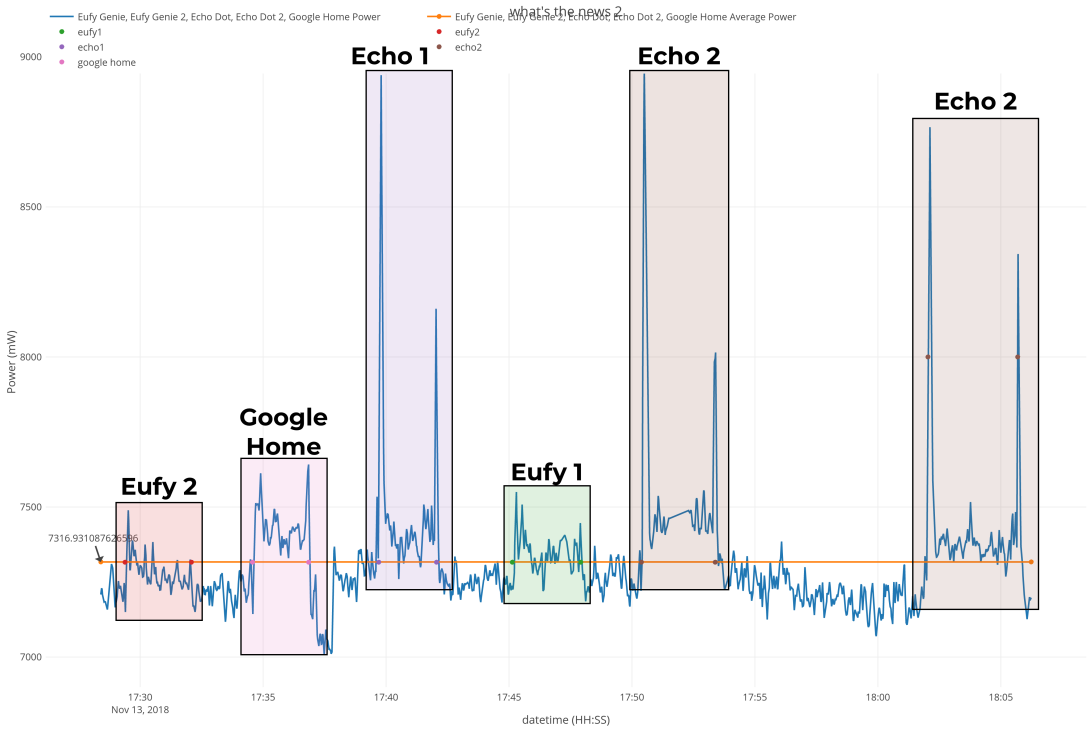



**Figure 3.17: 5 Smart Speakers Power Summed Up. Queried each device for the news.**

The next graph, 3.18, shows the smart speakers when asked for the best basketball player. The annotation scheme is the same as before. Each smart speaker is queried for the best basketball player in consecutive order four times. Like before, the Eufy has a power spike of 420 mW peak to peak, the Google Home has a power Spike of 720 mW, and the Echo Dot has a power spike of 2180 mW.

When looking at graph 3.18, there is a power spike that is unaccounted for in correspondence to the event log at 18:12. We made a query, invoking all other power spikes but we did not do anything for the power spike at 18:12 that is higher than the other Eufy power spikes shown in figure 3.18.

To figure what the power spike at 18:12 is, we separated the graphs into individual power traces as shown in figure 3.19. From this graph, the power spike at 18:12 is attributed to the Echo Dot 2 because it is the only trace with a spike occurring. We then looked at the individual network usage for each of these devices in this time frame as shown in figure 3.20. At 18:12, there is no significant network usage.

From figures 3.19 and 3.20, we speculate that because there is no network usage

during this time, the Echo Dot was doing anything data recording, listening, or was activated. We believe that the computer was covering the Echo Dot, but is briefly moved, exposing the Echo Dot to more light, thus causing the LEDs to brighten. The power usage before the spike and during the spike exactly match that of figure 3.13, starting at around 1500 mW, rising to about 2300 mW.

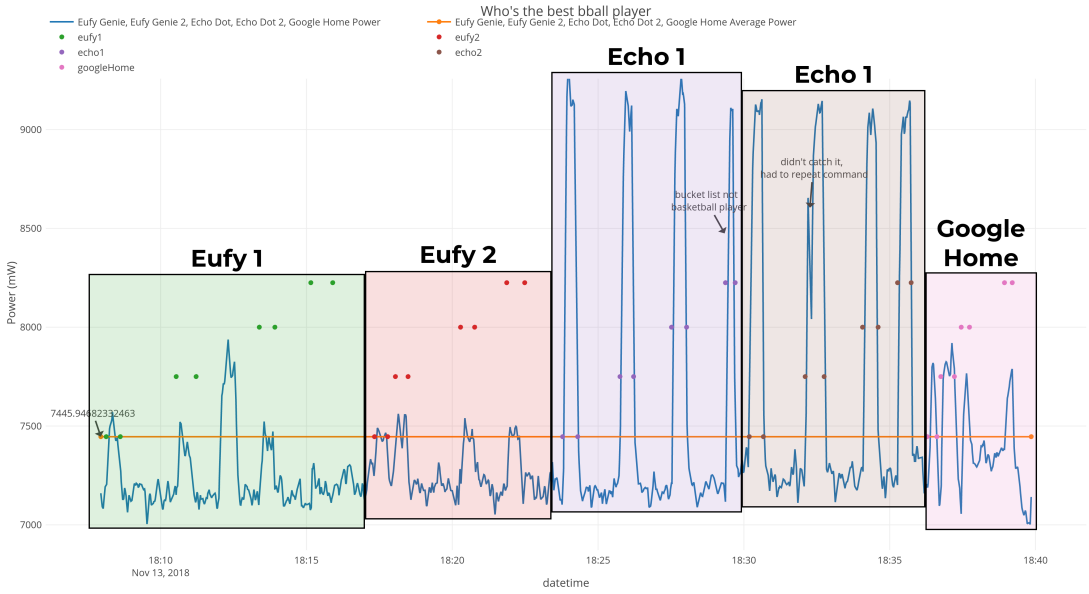



**Figure 3.18: 5 Smart Speakers Power Summed Up. Queried each device for the best basketball player.**

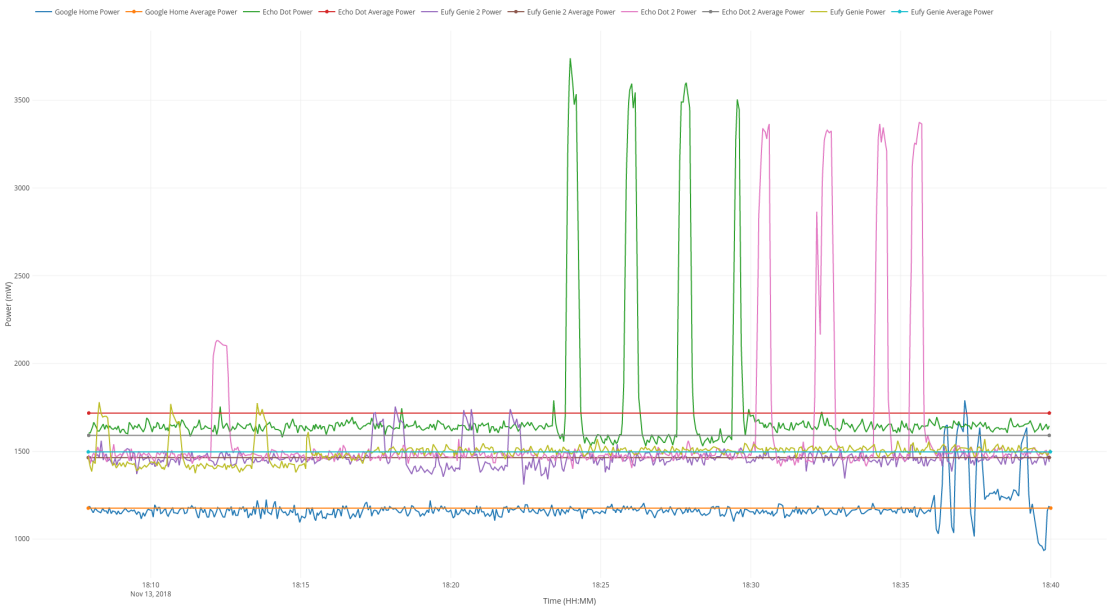



**Figure 3.19: 5 Smart Speakers Power Usage over time. Queried each device for the best basketball player.**


**Figure 3.20: 5 Smart Speakers Network throughput over time. Queried each device for the best basketball player.**

Figure 3.21 shows the power spike information for each query type ("what's the weather" "what's the news", "who's the best basketball player"). For each of these commands, there is always a characteristic power spike that occurs at the beginning

of the command. This bar graph also includes the total average spike height for each all three of these commands. The black line at the top of each bar shows the standard deviation. Averaging peak to peak voltage spikes for each device shows the Eufy Genie with a 390 mW spike with 36.1 mW standard deviation, the Google Home with a 606.7 mW spike with 110 mW standard deviation, and the Echo Dot with a 2026.7 mW spike with 149.89 mW standard deviation.

Figure 3.21, shows that it is possible to determine a smart speaker from a shared power trace if a power spike occurs within the thresholds shown. From this, we conclude it is possible to determine a device model from visual examination of its power usage. This is the first step to testing our hypotheses that it is possible to see what devices are in use from analysis of someone's power line.

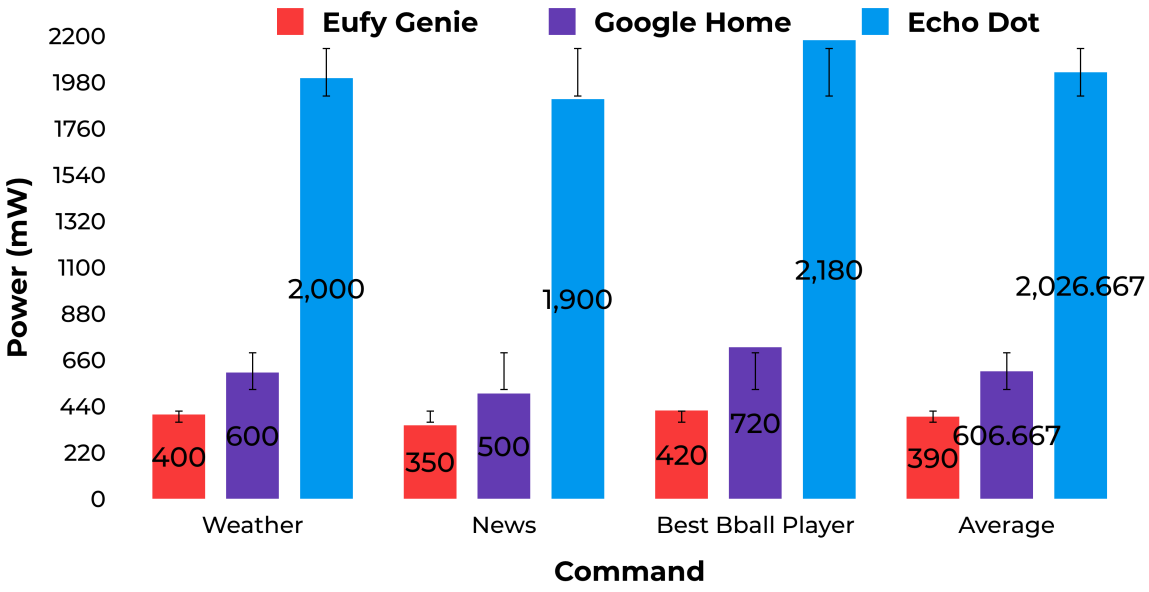



**Figure 3.21: Spike summary of for each query.**

But in a real house, there are more than just five smart speakers on a power line. The next step is to add noise from high power devices to see if it is still possible to visually determine the device in use from power spikes 3.6.

### 3.6 Summed Power Graph with Noise

In this section, we introduce noise into the system so that we can determine if the power spike from each smart speaker is still discernible within a summed power graph when we add high power devices.

In each subsection, there are three traces. The first trace (blue trace) is the summed power usage of our five smart speakers (2 Echo Dots, 2 Eufy Genies, 1 Google Home) when asked for the best basketball player four times. This is the same trace as shown in 3.18. The second trace (purple trace) is the power usage of a high power device. This trace is the added noise. It maps to various devices as we switch them out. The third trace (red trace) is the sum of both trace 1 and 2. It is the power usage of the smart speakers in the blue trace with the noise from the device in the purple trace.

The x-axis is the time elapsed in seconds. There is no time because the smart speaker trace and 'noise' trace are in different time frames. The y-axis is the power used by each device at that time.

Below, in figure 3.22, is an example of the traces used separately. Taking the blue trace (smart speaker power usage) and the purple trace (noise-introducing device) the summed up graph results in the red trace (total power usage). This is shown separately at first, but are summed together for the rest of the paper so that the scale of the noise can be understood.

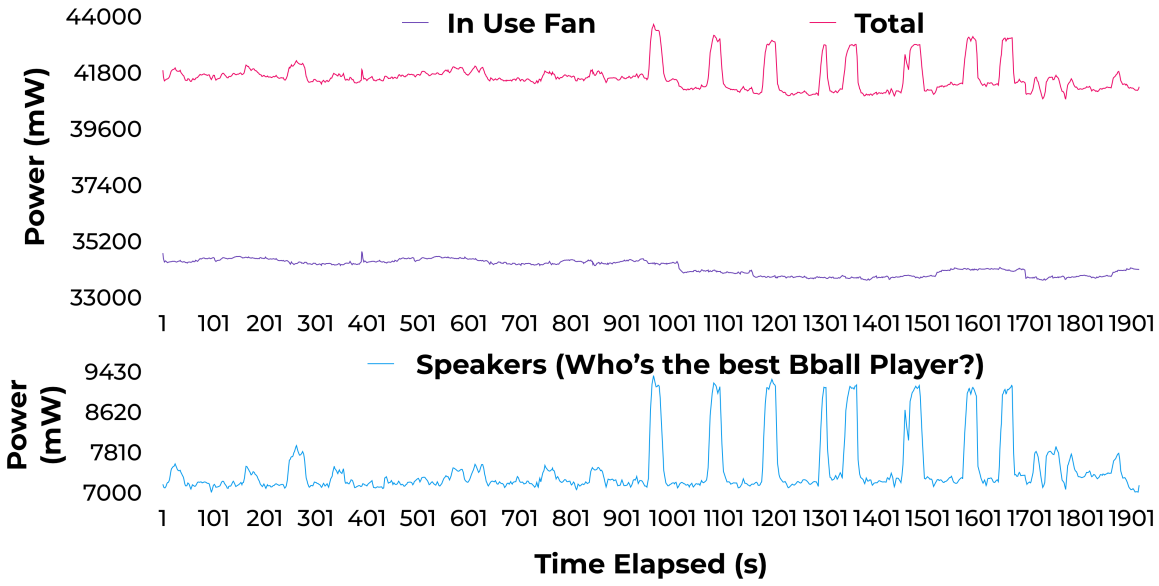



**Figure 3.22: Idle Fan with figure 3.18 trace shown separately.**

Below, we display the smart speaker trace with a PC (Intel NUC), fan, refrigerator, or microwave. Figures 3.22, 3.23, 3.24, 3.25, 3.26, and 3.27 begin with noise from devices while idle or during steady power usage to set a baseline. Then figures 3.29, 3.30, and 3.31 show noise from devices while in use, introducing noise that make visual detection of smart speakers most difficult.

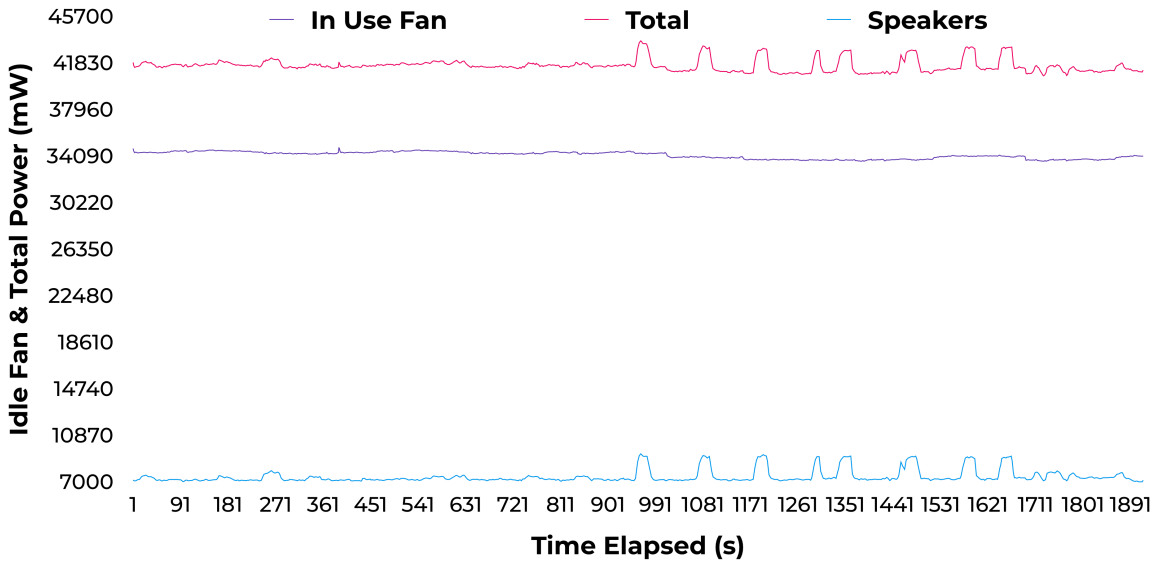



**Figure 3.23: Idle Fan with figure 3.18 trace.**

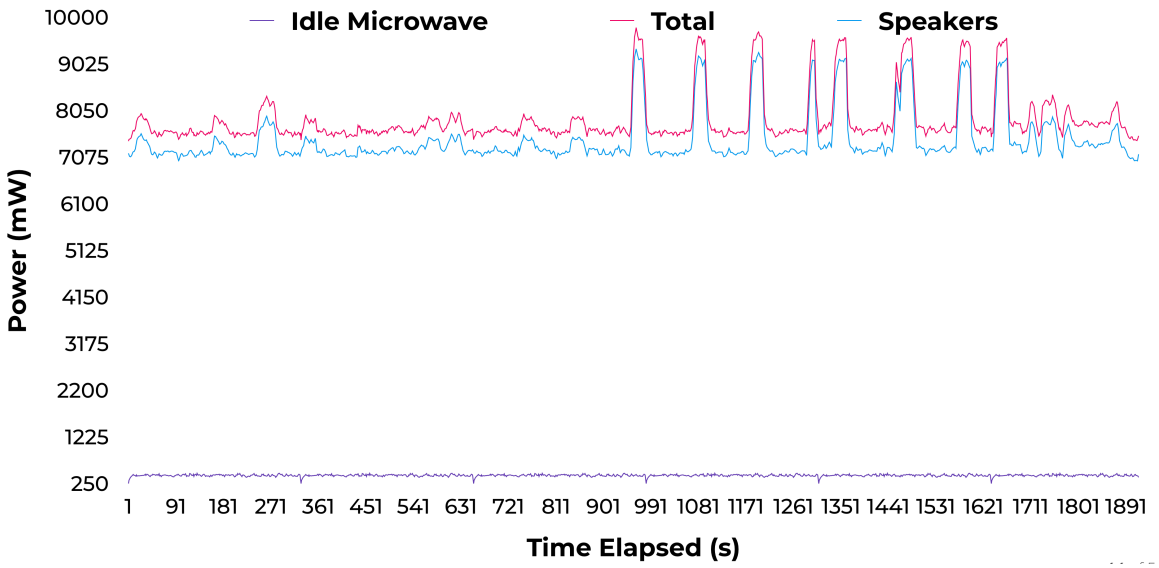



Figure 3.24: Idle microwave with figure 3.18 trace.

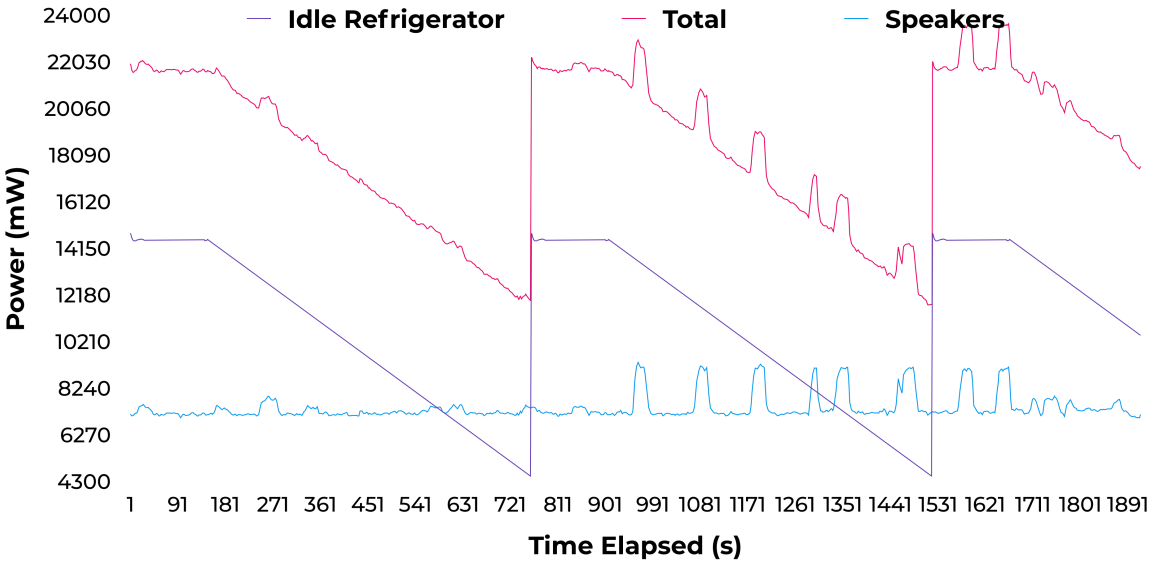



Figure 3.25: Idle refrigerator with figure 3.18 trace.

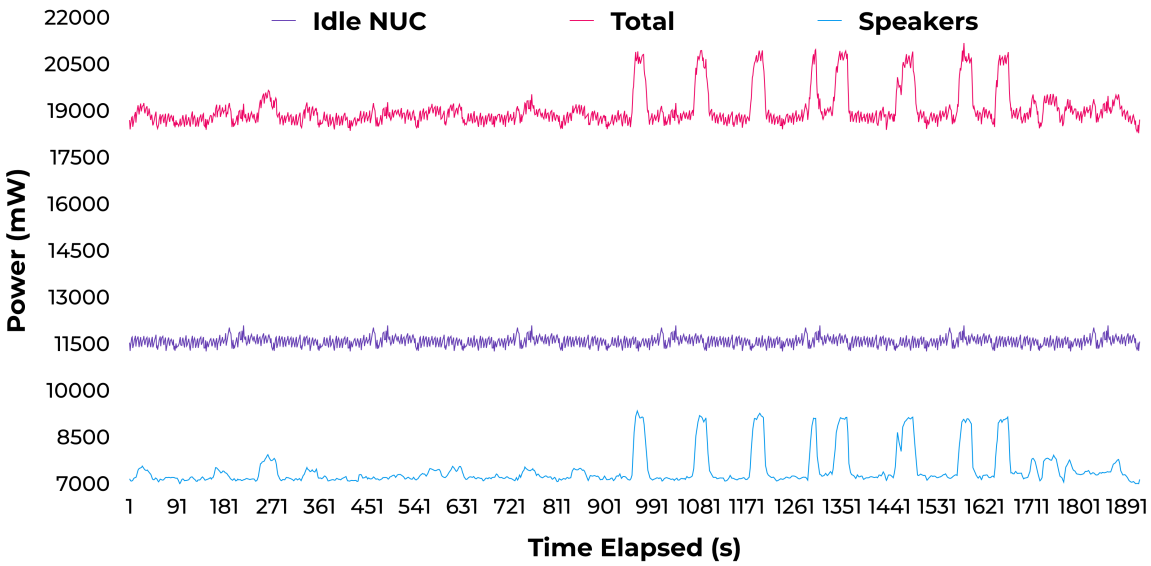



**Figure 3.26: Idle PC (Intel NUC) with figure 3.18 trace.**

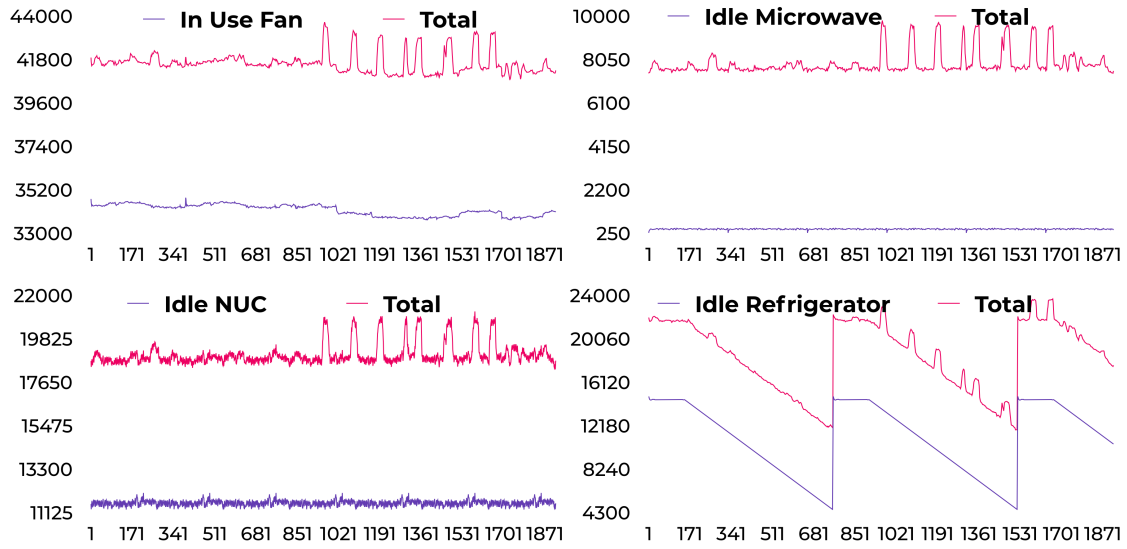



**Figure 3.27: 3.23, 3.24, 3.25, and 3.26 figures zoomed in**

In figures 3.23, 3.24, 3.25, and 3.26, the power spikes from the smart speakers can still be seen. The Echo Dot power spikes are still visible in the red trace for each graph. The power spikes for the Google Home and Eufy Genie are less visible but can still be seen. Especially when zoomed in as shown in figure 3.27 where the smart speaker trace is removed.

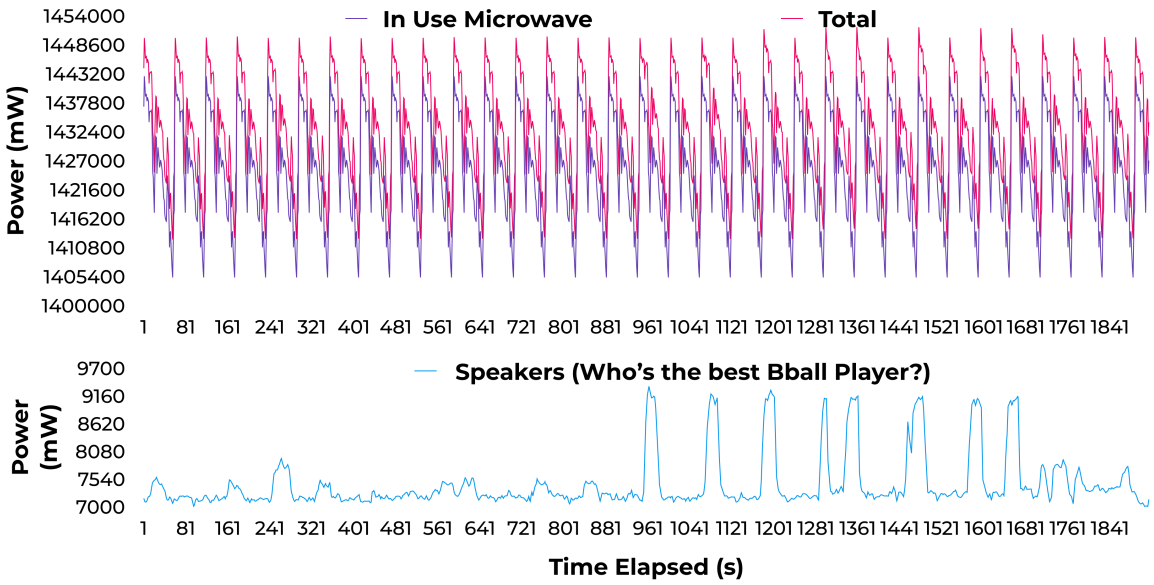



Figure 3.28: In use Microwave with figure 3.18 trace separately.

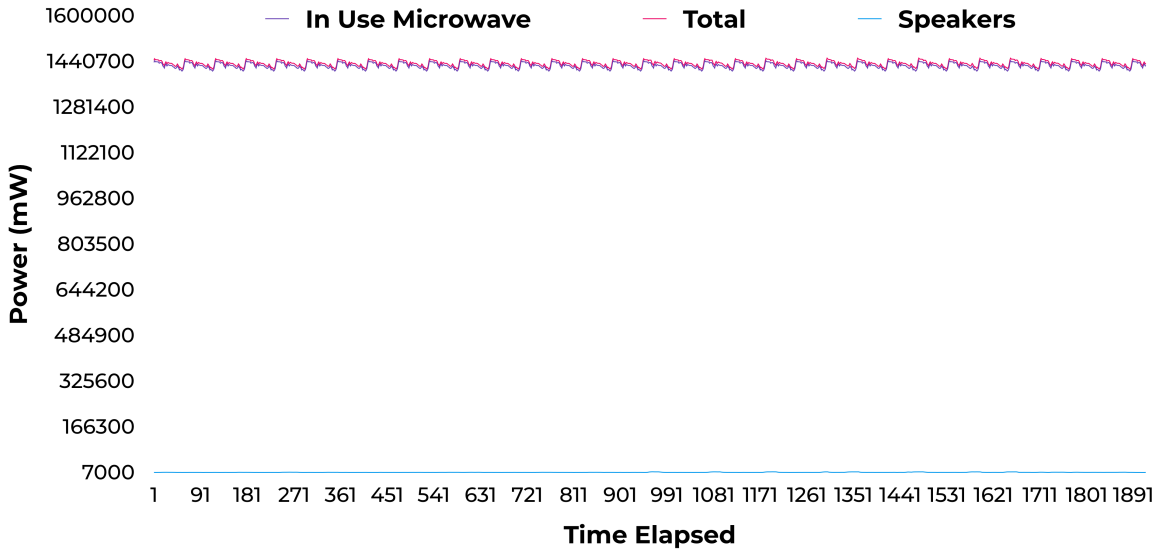



Figure 3.29: In use Microwave with figure 3.18 trace.

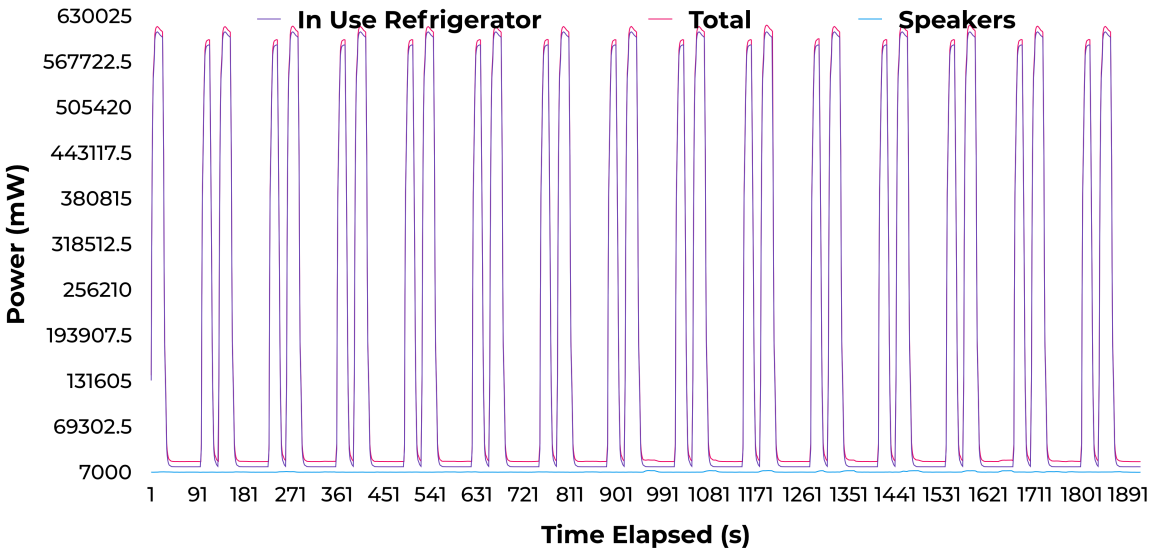



**Figure 3.30: Fridge in the middle of cooling with figure 3.18 trace.**

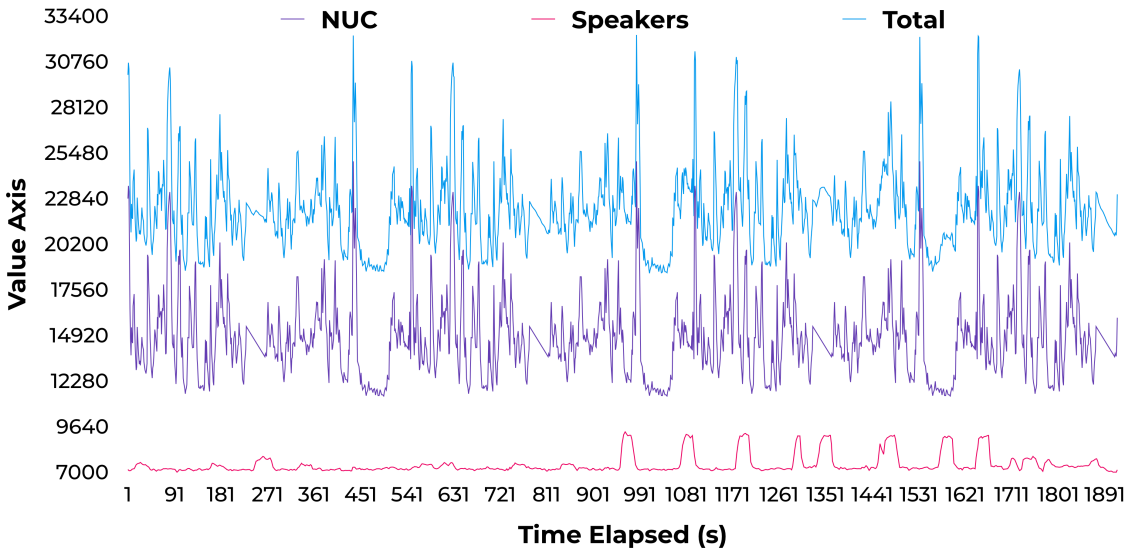



**Figure 3.31: PC in use with figure 3.18 trace.**

The figures above show that it is possible to determine the smart speaker in use from visual examination of power spikes even in the presence of noise. If the noise within the house is stable, the power spikes are shifted up as shown in figure 3.23. If the noise within the house is low power then, the spikes visually overpower the noise, as shown in figure 3.26.

But if the noise within the house is considerable in magnitude such as the microwave or fridge while in use 3.29 3.30, this noise will squash the power spikes from the smart speakers. The spikes can no longer be seen, even when zoomed in, as shown in figure 3.28. The smart speaker spikes also disappear if the noise of a device is on the same or a larger magnitude than the power spikes, as shown in figure 3.31. The power spikes can still be seen in the sum graph for this figure, but it would be impossible to visually differentiate between a power spike from a speaker and the noise without knowing the original smart speaker graph.

These two cases vary depending on the household. If many battery power devices such as laptops (replacing the NUC) or phones are used, then it would still be possible to determine the power spikes visually. Alternatively, in another case, if high power devices such as the microwave or fridge are not in use often, then the smart speaker spikes can be visually correlated. But if a household has many devices plugged into an outlet for power, then the smart speaker power spikes will disappear from the additive noise of all the devices. Regardless, there are privacy implications in a household's power line. With easy, direct (even remote nowadays), access to a household's power line [34], someone could determine the device in use within a household or what room they are in.

## 3.7 Smart Speaker Comparison

The figures in section 3.5 show that the Echo Dot uses a lot more energy than the other smart speakers. Because of this, we wanted to compare the energy and network usages of the three smart speakers individually so that we can determine trade-offs that they make.

In the figures 3.32 and 3.33, we display the power and network traces for the Echo Dot 1, Eufy Genie 1, and Google Home. We used the same time frame as the graph in figure 3.19 for the two graphs below. We removed the second Echo Dot 2 and Eufy Genie 2 so that there is one of each device.

In the time frame of figures reffig:smartSpeakerSeperate and 3.33, the average power, from greatest to least starts with the Echo Dot (1650 mW), then the Eufy

Genie (1325 mW), and the Google Home (1175 mW). For average throughput, from greatest to least, we have the Eufy Genie (1743 bytes), Google Home (800 bytes), and Echo Dot (325 bytes). These results are shown in figure 3.34

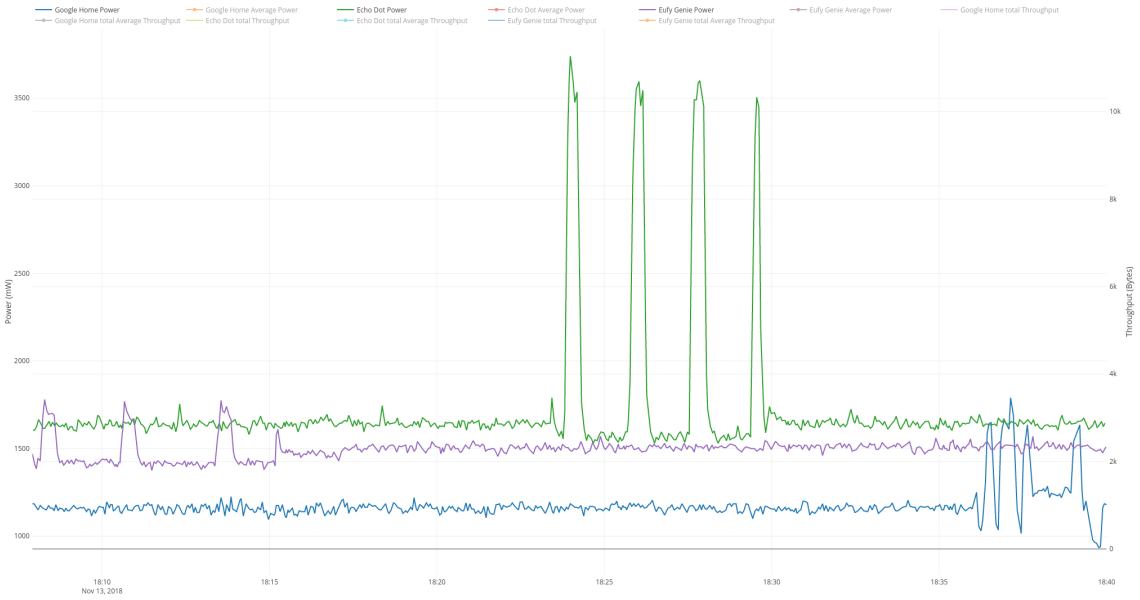



**Figure 3.32: Power usage of Echo Dot 1, Eufy Genie 1, and Google Home over time when asked "who is the best basketball player". Same graph as figure 3.19 with Echo Dot 2 and Eufy Genie removed.**

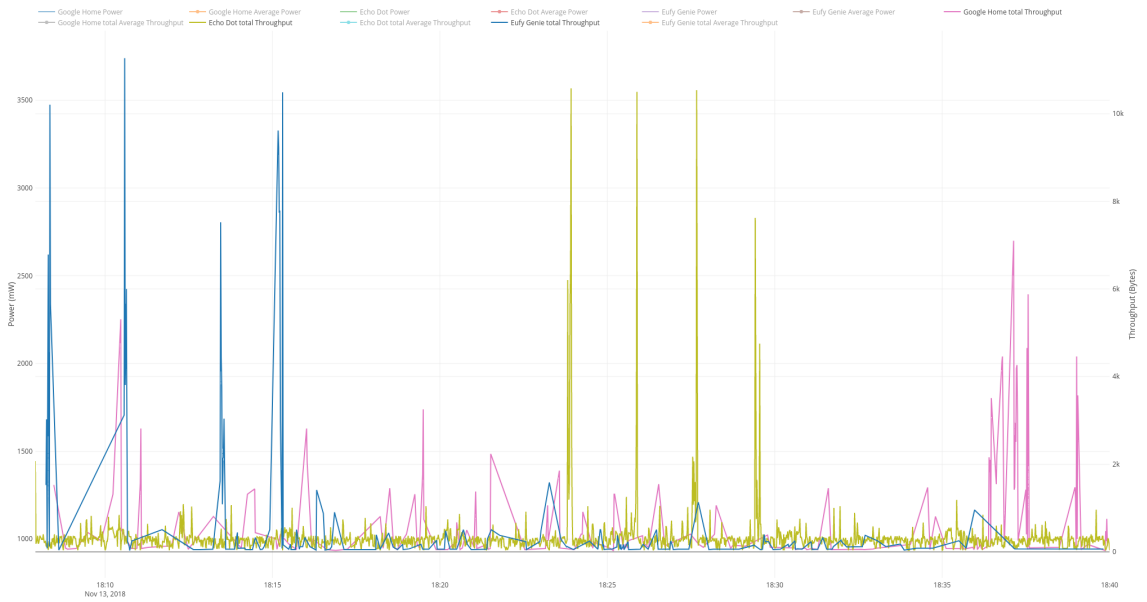


**Figure 3.33: Power usage of Echo Dot 1, Eufy Genie 1, and Google Home over time when asked "who is the best basketball player". Same time frame as figure 3.32**

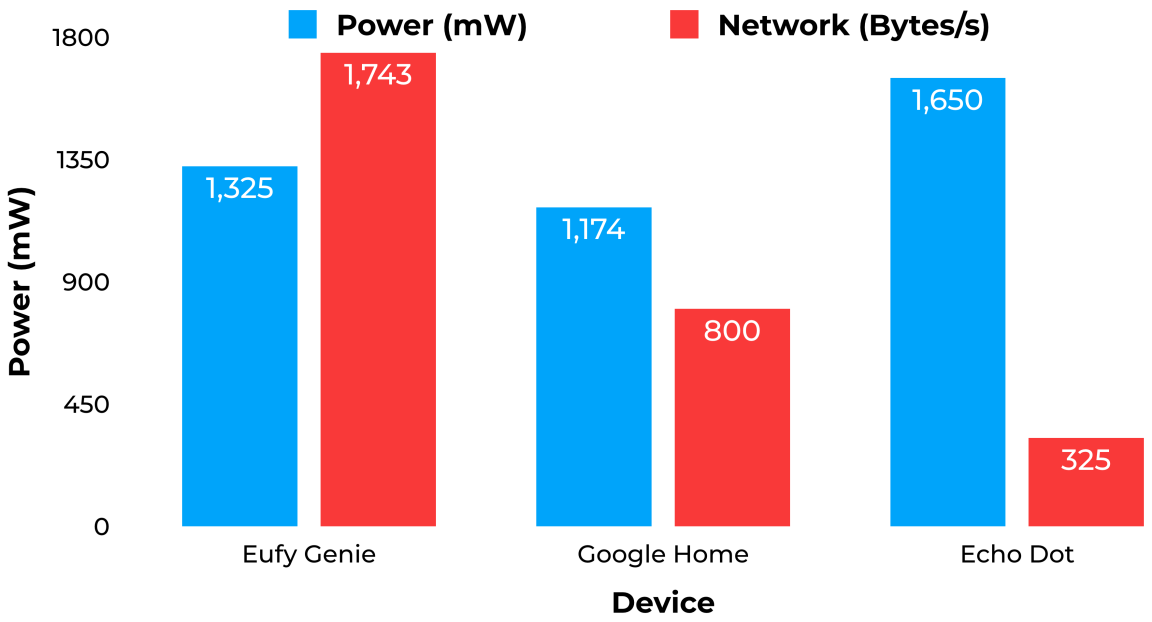



**Figure 3.34: Average power and network usage at each second for the Echo Dot, Eufy Genie, and Google Home in the time frame of figures 3.32 and 3.33**

From figure 3.34, we can see that the Echo uses the most power, then the Eufy, then the Google Home. However, the Eufy uses the most network throughput, then

the Google Home, then the Echo Dot. At its core, we believe each device is making some tradeoff between power and network usage. Possibly, the Echo dot is trying to do as much on board operations as possible, increasing the power usage. Possibly, the Eufy Genie is constantly querying for information, thus reducing power usage, but increasing network usage. Further analysis to prove this would be interesting.

# Chapter 4

# CONCLUSION

To conclude, this paper shows that it is easy to tell which smart speaker is in use based on just the initial spike. Devices are each making their unique trade-off between power and network throughout when idle and in use. This tradeoff leads to unique signatures that allow us to classify devices. For the smart speakers, it is as obvious as the first power spike during usage.

Some patterns can be difficult to make out with so much noise coming from within a house for power data. However, if enough devices are idle, it is still possible. The results show an indirect security flaw in our powerline and how that defense should be fortified. This paper shows it is possible to determine what smart speaker is in use and whether the lights are on in the house from the power data. With more research, it is likely that other private information can be inferred from the power line data.

This proves that more research should be done to analyze and classify IoT devices. We created an expansive database of network and power data for 16 IoT devices that spread over ten months, accumulating 184.94 GB of data and 172,445,929 entries in the database. Along with that, we created an analysis tool to examine the database visually.

## 4.1 Future Work

With an ever-growing database, its maintenance is necessary. We want to clean up the database by indexing all columns for quick lookup, as of now, only some columns are indexed. There are also some inconsistencies in the database because an IP address of devices and naming of WeMos change over time. Changing the IP addresses and WeMo names that refer to the same device is necessary.

The next plan is to improve the realtimeIoTgrapher and add features. Hosting it on a public domain would make this tool more easily accessible, rather than running

it locally and going to a local domain. Including more automated annotation on the graphs would also make anomoly detection easier.

We want to also utilize both power and network data in tandem for analysis to see if that yields better classification results.

With many botnet attacks in the recent past, we also attempted to hack into these devices with Mirai and analyze power usage and network throughput of these devices. Getting Mirai working in the restricted time turned out to be unfeasible, but would be interesting to continue for future work.

Finally, applying machine learning to the power data would be novel work. We quickly tried a feed forward neural net with 0 percent accuracy and an LSTM and achieved 30 percent accuracy given five devices (slightly better than random). We had also planned to alter a human activity recognition machine learning (HAR) model to fit the database for classification of device model given power data over a set period. Due to time restraints, I did not explore this further.

Regardless, there are many opened opportunities for future work because of the database. Researchers can quickly utilize the realtimeIoTGrapher to analyze the database or manually query data. There have already been students who have used the database for various research projects.

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# APPENDICES

## Appendix A

## HOW TO INSTALL AND RUN REALTIMEIOTGRAPH.PY

This chapter discusses how to install, run, and use the database visualization tool.

### A.1 How To Install and Run

To install and run this analysis tool, follow the instructions at the GitHub site: github.com/nealhnguyen/realtimeiotgrapher.

First, pull the code for this tool from git hub and install the dependencies in the requirements file through pip. At this point, the dependencies are set to run this code on python 2.7.

Next, a 'loginCredentials' file must be created containing the host, user, password, and database information. At which point, running 'python realTimeIoTGraph.py' starts the backend and display its current operation onto the terminal.

The link to the local IP address contains the graphing tool. Clicking on that opens it onto the default browser for the computer.

### A.2 Usage Directions

Once the software is running, the grapher can be viewed on a web browser as shown in figure A.1. This section describes each numbered element in the image.


**Figure A.1: RealTimeIoTGrapher usage image**

0. The local IP address presented in the terminal where the grapher is hosted.

1. The interval field and the text box next to it is dark when the software is in live update mode.

2. The text box here relates to the live update feature of the graph. This is a time field, denoting the window of time the graph displays at a time while it updates. The format is HH:MM:SS where HH is the hour, MM is minutes, and SS is seconds.

3. The time range field and the four elements consecutively after it are dark instead of grey when it is in static graph mode. In this state, the graphing tool specifies the network traffic and power information in the time window specified.

4. In these three text boxes, the time window for static graphing is specified. The first box is the start time, the second box is the end time, and the last box is the interval. To specify the time range, fill in any 2 of the three text boxes, and the graphing tool infers the other number. If all three text boxes are filled, then the

graphing tool uses the start and end time text box. To further explain, if the start time and interval are specified, then the window is start time → start time + interval. If the end time and interval are specified, then the time window is the end time - interval → end time.

5. This button causes the graph to update. After updating the time range in step 4, clicking this button updates the graph with the new time range.

6. The "Use Time Range" checkbox toggles the software between live graph mode and static mode. The "Sum Graph" checkbox sums up all power graphs into one. The "Show Only Power" checkbox allows the grapher to avoid a SQL query for the network throughput, speeding up the process in case of pure power analysis.

7. This selection field specifies all the devices the software creates graphs. One, or many devices can be specified at a time. If too many devices are specified at a time, the software may run slow.

8. The traces shown can be selected or deflected to toggle its visibility.

9. This line graph displays the number of bytes sent through the network by a device going in, out, and in total. It also shows the power usage over time. Also, it shows the average value for a graph in the interval of the graph

10. This bar graph displays the spread of network traffic by protocol for each device. It displays the outgoing packets as orange and incoming packets as blue. It displays an individual bar graph for each device and protocol. Similarly, the traces can be clicked on to hide its visibility.