Quantitative Analysis of IoT Data Generation in Smart Homes

TINTIN WONGTHANAPORN, University of Twente, The Netherlands

The integration of Internet of Things (IoT) devices into smart home environments has grown rapidly in recent years, enhancing convenience, comfort, and energy management. This significant growth is paralleled by an increase in the number of smart home users globally. Despite significant research efforts, including simulation studies, we have observed a tendency to overlook the accurate estimation of data volume parameters in these simulations. Often, the values used lack empirical support from real-world evidence. In response, our study presents an estimation of the data volume by IoT devices in smart homes. We analyze various factors influencing data generation and develop different scenarios to estimate data volumes that align with diverse simulation needs.

Additional Key Words and Phrases: IoT, Data Generation Patterns, Smart Homes, Quantitative Analysis, User Behavior Inference, Smart Home Efficiency

1 INTRODUCTION

Integrating Internet of Things (IoT) devices into smart home environments has expanded rapidly in the past decades, offering convenience, comfort, and energy management. The survey by Transforma Insights sees the number of IoT devices increase from 13.8 billion to 15.9 billion between 2022 and 2023 and forecasts the number of IoT devices to be 32.1 billion by the year 2030 [11]. This exponential growth reflects the increasing integration of IoT technology into daily life. Concurrently, the number of smart home users worldwide is expected to grow significantly as shown in the last few years from 191.38 million to 360.68 million between 2019 and 2023, with projections suggesting it will reach 785.16 million by 2028 [9]. As IoT technologies continue to expand into our homes, it led to the growing need for research to study the data generation pattern in smart homes for various objectives including better resource management and enhancing overall system performance.

While there is substantial research in the field of IoT devices, including studies on device performance, anomaly detection, and energy efficiency [1, 2, 10, 14], some of these studies rely on simulations to test their findings [2, 13, 14]. However, there is a gap in understanding the data volume used in these simulations. Thus, there is a need for a more accurate estimate of the data volume by different types of IoT devices and settings. For this research, we focused on application-specific data which refers to the data generated from a single event that requires a connection to a data centre or server for the core functionality of devices.

To fill in this gap, we aim to estimate data volume generated by various types of IoT devices. We rely on available IoT datasets in the literature for this estimation. Our research seeks to answer the following research question: "What factors influence the data generation and what is the estimated data volume of application purpose data on different scenarios?". The different scenarios are combinations of the human presence, types of devices, time of the day and home.

To address this research question, we break it down into the following sub-research questions:

(1) How is the data generation pattern affected by the user presence?
(2) What are the average data sizes for different types of IoT devices per event?
(3) What is the relationship between the value of data generated by IoT devices and the frequency of events?

These sub-research questions aim to elucidate the factors influencing data generation. The insights gained from this sub-research are necessary to make different scenarios in which we will be estimating the data volume.

The main content of this research is structured into several distinct analyses, followed by an estimation of the data volume. First, we analyze the impact of user presence on data generation patterns. Second, we conduct a detailed examination of the data flow sizes for various devices. Third, we explore the correlation between the volume of data generated and the frequency of events. Finally, we estimate the data volume generated specifically for application purposes in each scenario.

2 RELATED WORKS

In this section, we review previous works that characterize IoT devices.

Hazhar and Shafiq [4] captured and analyzed the network traffic logs of IoT devices at a large scale from more than 200 homes. They reported traffic characteristics related to the functionality of the devices, such as traffic volume, and diurnal patterns and also revealed some security and privacy concerns.

Ren, J. et al. [5] has studied a set of controlled experiments involving 81 devices across the US and UK, along with additional uncontrolled experiments approved by an Institutional Review Board (IRB). They support that even though the devices used encryption, they do not hide the communication pattern allowing an observer to potentially deduce what actions or commands were being exchanged between the IoT devices and the service provider.

The research by Xu et al. [12] further supports this correlation of the communication found in IoT devices. Their research analyzed real network traffic data collected from 22 edge networks over 4 months. The finding was IoT devices have a traffic cycle leading to predictability, often due to heartbeat signals between IoT devices and cloud servers.

A paper by C. Sharma and N. K. Gondhi [7], provides reasoning for the selection of a common IoT communication protocol by understanding the characteristics of existing communication protocols. This classification was crucial for filtering out non-application data packets in our analysis.

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While these studies offer valuable insights into IoT device characteristics, none of them combined the volume of data generated with the factors influencing data generation. Our study aims to integrate the factors influencing data generation with the volume of data generated by estimating data volume across different scenarios, each scenario varying in the factors influencing data generation.

3 DATASETS

In this section, we will discuss the process of selecting datasets for our research. Additionally, we will address the data processing for each dataset if there are any.

The first dataset employed in this research is the one used in [6] for context-based detection of stealthy IoT infiltration attacks. We refer to this dataset as the Argus dataset throughout the paper. The Argus dataset is an IoT dataset collected from five different smart home settings. Each home setting includes various IoT device events, a different number of inhabitants, and a different number of days during which data was collected, as shown in Table 1. The dataset contains the status changes of all IoT devices along with their timestamps, as visualized in Table 2. This dataset suits our research since it includes multiple types of entities, not only related to IoT devices but also human presence state. Additionally, the events provide values, including numeric values from sensors such as 'co2.value', 'humidity', 'ipCamera.sound', and 'ipCamera.motion'. These unique features allow us to compare data generation patterns in the context of user presence and data values, rather than just the frequency of data.

The second dataset used in our research is used in [8] for analysing network packet data to determine the possibility of predicting the types of devices on their network behaviours. We refer to this dataset as the The Test-bed dataset throughout the paper. The Test-bed dataset comprises packet captures (PCAP files) from 28 unique consumer IoT devices over a span of 20 days. These devices encompass a range of functionalities including cameras, lights, plugs, motion sensors, appliances, and health monitors. The reason for choosing these data sizes was to complement the lack of data sizes for each event of the Argus dataset, allowing us to estimate the data volume.

To ensure data integrity and consistency in the Argus dataset, we have removed all data values where the timestamp does not match the date indicated in the comma-separated values (CSV) file name. Additionally, all files are combined, and duplicate values are removed. Lastly, we parse all the timestamps to the Central European Time Zone (CET), aligning with the timezone in Germany where the data was collected. This adjustment ensures that the relation to the time of day accounts for daylight saving time. As for the Test-bed dataset, no data preparation was required.

Home	1	2	3	4	5
Number of events	29	26	13	26	37
Number of days	140	34	53	88	19
Number of inhabitant	1	1	4	4	4

Table 1. Argus dataset overview

time_stamp	entity	new_status
1625224200.0	co2.value	505
1625224429.362805	co2.value	613
1625227302.366654	humidity	49.80
...	...	...

Table 2. Argus dataset example from Home 1 from file name '2021-07-02.csv'.

4 USER PRESENCE AND DATA GENERATION PATTERN ANALYSIS

In this chapter, we will discuss the methodology and result of the effect of user presence on the data generation pattern.

4.1 Methodology

For this analysis, we utilize the Argus dataset to examine the effect of user presence on device activity. The dataset includes the event 'person.home', which indicates whether user is at home or not. We use this event to categorize events into two states: 'home' and 'not home'.

Then we calculate the frequency of events for both 'home' and 'not home' states throughout the day. The results are plotted by the hour of the day allowing us to understand how user presence affects the event frequency and identifying the peak hour in each event. This analysis aims to determine the overall impact of user presence on data generation and the specific times of day when these differences are most pronounced.

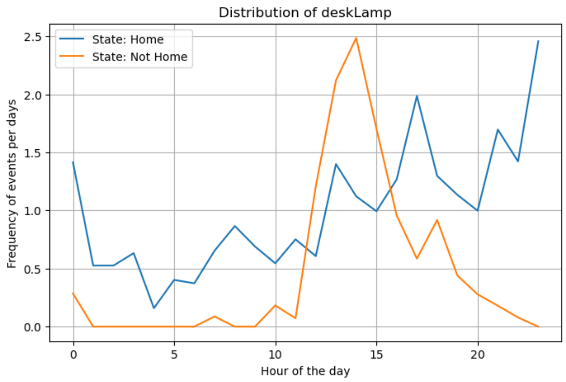
4.2 Result

Our analysis reveals that it is common for all events to have a higher frequency when users are at home. This is particularly evident for events that users can manipulate or trigger, such as the door or desk lamp.

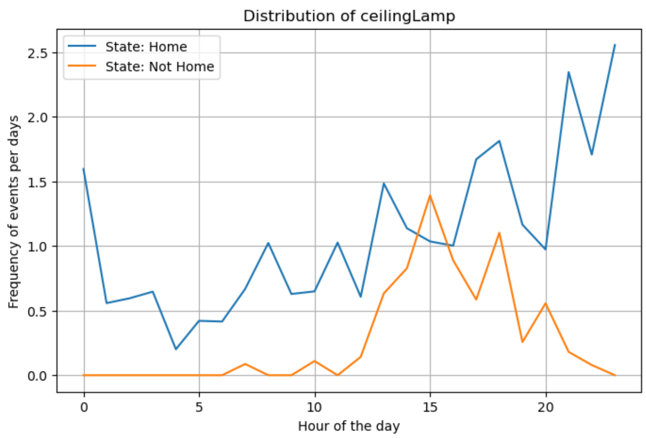
In Figure 1a, we observe that the frequency of events remains significantly higher when comparing the state 'home' and 'not home'. As predicted, the desk lamp is more frequently used when there are users at home. This is further supported by a higher frequency of events during the evening when events 'on' are often triggered. However, there are some exceptions between hours 14 and 16. We assume that around that time of the day, devices refresh their state to receive software updates or request new IP addresses via Dynamic Host Configuration Protocol (DHCP). This assumption is supported by the test-bed dataset, which frequently shows DHCP packets occurring at daily intervals.

Moreover, monitoring events such as ipCamera.lightLevel, ipCamera.motion, and others show significantly higher frequencies when comparing the states 'home' and 'not home'. This is not surprising, as these monitoring values can be influenced by user activities like moving inside the house, closing blinds, and other interactions. This observation prompts us to investigate whether the frequency is directly related to the values themselves rather than merely increasing due to user presence.

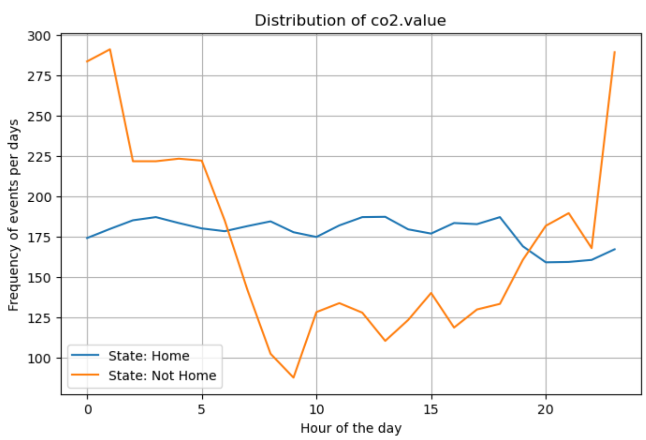
Overall, we observe user presence is a prominent factor affecting the number of events generated by IoT devices. This leads us to demonstrate the data volume of IoT devices based on the user presence factor in various scenarios. For analysis of more events, check Appendix A.



(a) Event 'deskLamp'



(b) Event 'ceilingLamp'



(c) Event 'co2.value'

Fig. 1. Temporal Frequency Patterns of Different Events with Distinction Between 'Home' and 'Not Home'.

5 DEVICE FLOW SIZE ANALYSIS

In this section, we will calculate the outgoing device flow sizes (data sizes per event). The section is broken down into methodology and results.

5.1 Methodology

For the device flow size analysis, we split the analysis into 2 sub-analysis: TCP flow analysis and UDP flow analysis.

- **TCP flow analysis**: we will only consider application layer protocols which are used for sending application data such as Transport Layer Security (TLS), Extensible Messaging and Presence Protocol (XMP) and Hypertext Transfer Protocol (HTTP). The protocols are detected using their TCP destination port. This analysis utilized the 'TShark' tool, which processes network traffic at the flow level rather than analyzing individual packets. By aggregating data into flows, we measured the volume of information exchanged by each device, considering each flow as an event.
- **UDP flow analysis**: we considered each packet as one event trigger due to the connection-less nature of UDP. The analysis filtered out all packets that used ports not intended for transmitting application data. Examples of such ports include port 53 (Domain Name System, DNS), port 1900 (Simple Service Discovery Protocol, SSDP), and port 5353 (Multicast Domain Name System, mDNS). This filtering ensured that only application data transmission events were included in the analysis.

The results were visualized in Table 3 displaying average and standard deviations of flow sizes. The result allows observation of characteristic data transmission behaviours of each IoT device, highlighting their standard deviation, which helps us understand the distribution of data flow size among different device types.

5.2 Result

Upon examining the results, it becomes evident that each device exhibits varying data sizes and standard deviations. A notable pattern observed is that devices with fewer functionalities tend to have lower standard deviations. This is expected because these devices transmit a narrower range of data types, resulting in less variability in their data sizes. An example of such a device are Netatmo weather station.

Conversely, devices such as the Netatmo Welcome and TP-Link Day Night Cloud camera demonstrate significantly higher standard deviations. This variance can be attributed to the diverse types of data they handle. For instance, the TP-Link Day Night Cloud camera processes motion, sound, and video data, each contributing to the device's overall data variability.

When examining smart cameras such as the Nest Dropcam, Dropcam, Samsung SmartCam, and TP-Link Day Night Cloud cameras, a noticeable pattern emerges: devices that use the UDP protocol tend to have lower flow sizes in the TCP protocol. This is likely because TCP is used to send video data from the smart cameras which are the majority of data volume. For example, transferring 1080p video can use approximately 1.8 GB to 3.6 GB per hour [3].

It is important to note that the network conditions are different in each home, which could affect the number of re-transmissions

Device	TCP Flow Size		UDP Flow Size	
	Average	Standard Dev.	Average	Standard Dev.
Smart Things	215.8 kB	358.11 kB	-	-
Amazon Echo	1.76 kB	27.75 kB	196.00 B	5.04 B
Netatmo Welcome	32.23 kB	55.67 kB	-	-
TP-Link Day Night Cloud camera	86.99 kB	1.82 MB	540.29 B	619.05 B
Samsung SmartCam	650.19 kB	17.48 kB	645.94 B	542.66 B
Dropcam	10.40 MB	13.15 MB	-	-
Withings Smart Baby Monitor	4.19 kB	52.84 kB	-	-
Belkin Wemo switch	5.26 kB	4.42 kB	350.1 B	0.45 B
TP-Link Smart plug	8.02 kB	2.94 kB	749.96 B	4.20 B
iHome	9.24 kB	39.15 kB	-	-
Belkin wemo motion sensor	771.91 B	1.80 kB	350.39 B	3.49 B
NEST Protect smoke alarm	7.29 kB	10.52 kB	-	-
Netatmo weather station	963.15 B	79.71 B	-	-
Withings Smart scale	22.89 kB	2.43 kB	-	-
Withings Aura smart sleep sensor	8.65 kB	111.74 kB	103.64 B	24.13 B
Light Bulbs LiFX Smart Bulb	144.51 kB	126.85 kB	-	-
PIX-STAR Photo-frame	1.71 kB	733.99 B	167.97 B	70.70 B
Nest Dropcam	3.26 MB	10.12 MB	-	-

Table 3. Flow Size Calculation for Each Device

for TCP packets or unsuccessful transmission of UDP packets. This effect is still part of understanding how devices generate data by each event and is used for estimating the data volume of different IoT types of devices. Particularly, the TCP flow sizes will be used for estimating the data volume. TCP flows are preferred over a UDP protocol for our analysis because the TCP protocol is known for its reliability. This aligns with the Argus dataset where only the critical events are reported requiring reliability in data delivery.

Critical events are those that must be delivered to the server, such as the 'ipCamera.motion' event, which is essential for detecting intruders. In contrast, the UDP protocol is used for less critical events, such as transferring live feed from a smart camera or real-time voice communication from Amazon Echo. Additionally, even with filtering only application ports, it is challenging to identify each UDP protocol's specific events since a single UDP connection can transfer data for multiple events. Due to these limitations, it is more practical to use average TCP flow sizes rather than UDP flow sizes for our analysis.

6 CORRELATING DATA VALUES AND DATA FREQUENCY ANALYSIS

In this section, we will present findings on the values of data and frequency of the data generated focusing on monitoring devices.

6.1 Methodology

For this analysis, we employ two analytical approaches to understand the relationship between data values and their generation frequency.

(1) Correlation Between Data Values and Frequency
(2) Correlation Between Differences in Data Values and Frequency

For both analyses, we utilize the Argus dataset, focusing specifically on events that produce numeric values, such as 'ipCamera.sound', 'ipCamera.motion', 'temperature', and 'humidity'. The analysis involves grouping events into 30-minute intervals. For 30-minute intervals, we calculate the average values and average (absolute) values difference between consecutive events. Finally, we compute the correlation coefficient.

6.2 Result

Entity	Home				
	1	2	3	4	5
ipCamera.sound	0.585	0.520	-	-	0.800
ipCamera.LightLevel	0.302	0.313	-	-	0.664
ipCamera.motion	-0.213	-0.063	-	-	-0.288
hue.lightLevel	-	0.167	0.410	0.294	0.408
hue.temperature	-	-0.101	0.055	0.017	-0.009
thermostat.heating-Temperature	-0.141	-	-	-	-
radiatorThermostat.-measuredTemperature	-	-	-0.026	-	-

Table 4. Correlation Coefficient of Frequency and Data Values

In this section, we analyze the correlation between the values generated by IoT devices and the frequency of data generation events. By examining the correlation coefficients for various types of data, we can assess the strength and nature of these relationships, as detailed in Table 4 and Table 5

Overall, we observed that most events have a weak positive correlation coefficient between both data values and differences from the data frequency. These moderate positive correlations suggest

Entity	Home				
	1	2	3	4	5
ipCamera.sound	0.632	0.493	-	-	0.831
ipCamera.LightLevel	0.114	0.313	-	-	0.374
ipCamera.motion	-0.196	-0.034	-	-	-0.323
hue.lightLevel	-	0.283	0.229	0.423	0.340
hue.temperature	-	0.290	0.194	0.139	0.087
thermostat.heating-Temperature	0.143	-	-	-	-
radiatorThermostat.-measuredTemperature	-	-	-0.031	-	-

Table 5. Correlation Coefficient of Frequency and Data Values Differences

that changes in these values have some impact on the frequency of data generation events. However, the correlations are not strong, indicating that other factors might play a more significant role, such as user presence or the update cycle of each event.

Unexpectedly, entity 'ipCamera.motion' shows a weak negative correlation. This is surprising because one would expect the camera to trigger events when it detects motion. This further suggests that data values are less likely to be correlated with event frequency in general cases.

These findings highlight that while certain data-generated patterns correlate with the values of the events, many correlations are weak or absent altogether. Consequently, due to the limited types of events which provide numeric data, we have chosen to not include data values as a factor in scenarios for estimating data volume.

7 ESTIMATING DATA VOLUME

In this section, we will be answering the second part of our research question namely 'What are the estimated data sizes of application purpose data on different scenarios?'.

7.1 Methodology

Our goal is to estimate data volume per hour in different scenarios. These scenarios are defined by the combination of time of the day, user presence, types of devices and home setting. This is linked to our previous analysis where we observed how these factors affect the pattern of data generation.

There are four types of devices being estimated, listed in Table 6. The table contains associated events and the device types, ensuring that the people who develop or test the simulation understand the factor on which the estimation is based. The associated events are mapped directly from the Argus dataset and the names of the devices are mapped directly from the Test-bed dataset.

To the estimation of the data sizes per event, we utilized the TCP flow sizes which are calculated in Section 5. The devices from which the TCP flow sizes are taken are selected based on their functionality and the sensors they are equipped with. This selection provides the best possible estimation given the two datasets.

Following the previous analysis 4, where we observed a clear pattern for user presence and time of day as a factor affecting data generation pattern, we base our scenarios on the combination of time of day and user presence status separately in addition to the combination of devices. The results for the combinations of time are segmented by hour of the day, as shown in Table 8, and the user's presence status is categorized as 'home' or 'not home', as shown in Table 7. Separating user presence and time of day allows for more versatile scenarios that can be universally applied in simulations."

For the experiment using the hour of the day, we filter the data by the hour of the day to be used as a factor for each scenario. For the users' presences, we apply the algorithm to sort the events into 'home' and 'not home' statuses and filter each status into different factors of scenarios.

Here is the methodology for obtaining the estimated range of data volume after we have filtered out values based on their scenario:

(1) **Calculating Data Frequency**: This is done by taking the number of events with distinct hours, dates and homes.
(2) **Estimating the range of Frequency**: The lower bound for our estimation is the 40% percentile and the upper bound are 60% percentile of the calculated data frequency in the previous step. This range is chosen to strike a balance between excluding outliers and capturing a representative sample of the data. The 40th percentile removes the lower extreme values that might skew the analysis due to infrequent events, while the 60th percentile cuts off the higher extremes, which might represent unusually high activity. This approach ensures that our estimation reflects the central tendency of typical scenarios without being distorted by atypical data points while allowing for a margin of error and provides a more robust estimate by accounting for variability in the data.
(3) **Obtaining Estimated Data Volume**: The last step is to multiply the estimated range of frequency by the average TCP flow sizes of the associated device of that specific scenario. The reason for choosing TCP flow sizes over UDP flow sizes is due to the reliability of TCP protocol in ensuring data delivery, which is crucial given our research focus.

Each experiment will be done separately by each home. The results shown in Table 7 and Table 8 are for Home 2. For results for other homes see Appendix B.

7.2 Result

The results presented in Table 7 and in Table 8 can be utilized to simulate IoT device data volumes per hour across different scenarios. In Table 8, it is evident that data volumes are consistently higher during the day compared to night across all devices. However, this difference is less pronounced for weather stations, which regularly report status regardless of time. In Table 7, we observe that user presence significantly increases data volume across all devices, as noted in Section 4. This effect is particularly notable for smart light bulbs, which directly respond to user interactions.

It is important to note that the estimated values represent data volumes for application-specific purposes, meaning only crucial events reported in the Argus dataset were included. When applying our data volume estimation, researchers should ensure they incorporate these additional factors unique to their study. For example, if the simulation involves a camera with a resolution of 1080p, the estimation of data volume for 1080p video transmission should be added to our estimated values of the associated scenario.

Device Type	Associated Events	Name of Device for Flow Size
Smart Light Bulb	hue.motionSensor.motion, hue.temperature, and hue.lightLevel	Light Bulbs LiFX Smart Bulb
Smart Camera	ipCamera.LightLevel, ipCamera.motion, ipCamera.motionActive and ipCamera.sound	Samsung SmartCam
Smart Plug	lamp.consumption, lamp.current, lamp.dailyConsumption, lamp.totalConsumption and lamp.voltage	TP-Link Smart plug
Weather Station	co2.status, co2.value, temperature and humidity	Netatmo weather station

Table 6. Correlation Coefficient of Frequency and Data Values Differences

Device	User Presence	
	Home	Not Home
Smart Light Bulb	9.36 MB - 12.11 MB	1.42 MB - 1.87 MB
Smart Camera	1.12 MB - 1.24 MB	716.17 kB - 850.59 kB
Weather Station	40.63 kB - 44.91 kB	24.95 kB - 29.30 kB
Smart Plug (No user presence data)	-	-

Table 7. Estimated Daily Data Volume by User Presence in Home 2

Overall, these estimated data sizes can be leveraged for further simulations aiming to replicate real-world IoT device usage scenarios more accurately. The scenarios we have divided, including the time of day and user presence, are supported by evidence from real-world data, reducing the gap in understanding the data volume parameter used and improving the realism of the simulations.

8 DISCUSSION

In this chapter, we will discuss the limitations of the study and suggestions for further work are discussed.

8.1 User Presence Discrepancy Limitation

We observed that the dataset included a significantly higher number of days where the individual was present at home than the general population's typical home presence. For example in Figure 2 for Home 1, the peak number of day users not at home is only 34 days compared to 100 days. The same discrepancy can also be found in Home 4. This discrepancy suggests that the users may be older individuals or that this is a controlled experiment where participants were encouraged to stay at home and interact with the IoT devices. As a result, there is an over-representation of user presence in our analysis. Consequently, the correlation between events and user presence might not accurately reflect the actual patterns of a broader user base due to a disproportionate of data when the users are not at home.

8.2 Mapping Between 2 Datasets

As we have estimated the data volume for each scenario in Section 7 by mapping the events to types of devices and selecting the types of devices from the test-bed dataset, it is important to acknowledge potential issues with this approach. For instance, the frequency of different events in the test-bed datasets can differ significantly; for example, It could be possible that Samsung Smart-Cams have different conditions in triggering 'ipCamera.motionActive' events.

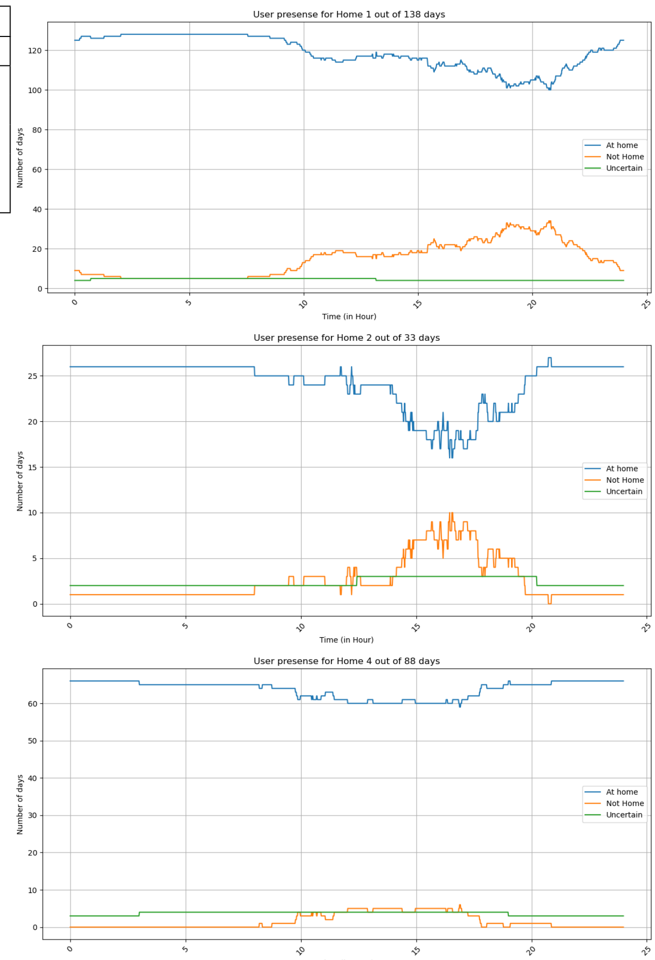


Fig. 2. User Presence Status

Despite this limitation, the estimated values still provide a good approximation because they are based on evidence from real-world data. The detailed condition provided for estimating data volume, including the devices and events from the Argus Dataset, allows adjustment to better fit specific simulations by incorporating additional factors

Time	Device			
	Smart Light Bulb	Smart Camera	Smart Plug (No Data)	Weather Station
12 am	1011.58 kB - 1.27 MB	777.74 kB - 812.86 kB	-	33.67 kB - 36.68 kB
1 am	1011.58 kB - 1.27 MB	756.74 kB - 772.58 kB	-	43.08 kB - 46.28 kB
2 am	2.26 MB - 3.10 MB	963.66 kB - 993.95 kB	-	44.77 kB - 47.03 kB
3 am	6.52 MB - 9.54 MB	1.07 MB - 1.29 MB	-	50.79 kB - 53.80 kB
4 am	15.98 MB - 17.87 MB	1.13 MB - 1.34 MB	-	53.24 kB - 60.20 kB
5 am	16.65 MB - 19.62 MB	1.36 MB - 1.49 MB	-	53.05 kB - 57.94 kB
6 am	18.91 MB - 21.87 MB	1.41 MB - 1.49 MB	-	47.59 kB - 50.98 kB
7 am	16.94 MB - 21.03 MB	1.52 MB - 1.54 MB	-	44.21 kB - 47.41 kB
8 am	15.38 MB - 20.60 MB	1.48 MB - 1.55 MB	-	45.15 kB - 47.03 kB
9 am	16.94 MB - 21.00 MB	1.46 MB - 1.59 MB	-	38.94 kB - 45.71 kB
10 am	17.08 MB - 20.18 MB	1.49 MB - 1.60 MB	-	42.14 kB - 49.66 kB
11 am	17.08 MB - 19.19 MB	1.35 MB - 1.50 MB	-	44.96 kB - 52.30 kB
12 am	10.02 MB - 14.59 MB	1.21 MB - 1.41 MB	-	38.38 kB - 44.58 kB
1 pm	6.63 MB - 10.58 MB	1.31 MB - 1.48 MB	-	38.56 kB - 42.89 kB
2 pm	10.02 MB - 14.68 MB	1.29 MB - 1.49 MB	-	41.57 kB - 47.03 kB
3 pm	11.57 MB - 17.78 MB	1.08 MB - 1.39 MB	-	44.58 kB - 49.47 kB
4 pm	9.03 MB - 15.81 MB	1.16 MB - 1.33 MB	-	43.45 kB - 47.78 kB
5 pm	4.94 MB - 12.00 MB	1.32 MB - 1.48 MB	-	42.51 kB - 50.04 kB
6 pm	1.83 MB - 2.96 MB	1.04 MB - 1.20 MB	-	39.50 kB - 41.39 kB
7 pm	1.13 MB - 1.41 MB	802.87 kB - 883.44 kB	-	35.55 kB - 37.81 kB
8 pm	867.07 kB - 1011.58 kB	766.04 kB - 812.17 kB	-	34.61 kB - 36.68 kB
9 pm	1011.58 kB - 1.13 MB	785.66 kB - 813.20 kB	-	34.61 kB - 37.62 kB
10 pm	1011.58 kB - 1.13 MB	760.18 kB - 782.91 kB	-	33.67 kB - 35.74 kB
11 pm	1.13 MB - 1.27 MB	747.79 kB - 792.89 kB	-	32.54 kB - 35.93 kB
Total	8.53 MB - 11.29 MB	1.12 MB - 1.24 MB	-	41.71 kB - 45.92 kB

Table 8. Estimated Hourly Data Volume by Time of the Day in Home 2

8.3 Future work

This study utilizes existing datasets, which could be biased and may contain hidden conditions influencing the results. Additionally, we use two different datasets containing various types of devices to estimate data size. Consequently, we could not differentiate between the sizes of each event, and similar types of events might have completely different data sizes.

In future work, the data should be collected specifically for the study to conduct a more comprehensive analysis. The additional useful analysis includes examining the effect of the number of inhabitants on the data generated, assessing the variability in data generation among devices within the same category, and exploring the reasons behind this variability. By gaining these insights, IoT developers can better understand the integration of IoT devices to support larger homes or public areas.

9 CONCLUSION

To conclude our research, we have analysed several critical factors influencing data generation in IoT devices: user presence, temporal patterns, and data value correlation. Our analysis revealed that peak data generation occurs during user presence, highlighting the importance of implementing load-balancing strategies to enhance IoT network performance and reliability.

Furthermore, our findings indicate a strong positive correlation between user presence and data generation frequency, demonstrating the dynamic nature of data creation in smart environments. In terms of data values correlation, our study observed varying degrees of correlation among different events, suggesting the need for tailored correction approaches for each event type.

In summary, this research provides valuable insights into IoT data generation patterns, essential for developing strategies to optimize efficiency, sustainability, and security in smart homes. We utilized these insights to create scenarios where we estimated data volumes, which can be used in simulation for more realism using real-world data. Factors for each scenario included time of day, device types, user presence status, and home settings. These combinations of factors offer flexibility for a wide range of simulations for our values to be used for data volume parameters or, at the very least, adapt our methodology to estimate data volume in any scenario.

10 USE OF AI

During the preparation of this work, the author(s) used ChatGPT and Grammarly to enhance understanding of resources during the literature review, ensuring correct grammar and consistency in writing and helping uncover missing ideas that could be analysed to expand the depth of the research. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the work.

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Appendices

A USER PRESENCE AND DATA ANALYSIS ADDITIONAL FIGURE

Here is the analysis of all the other events.

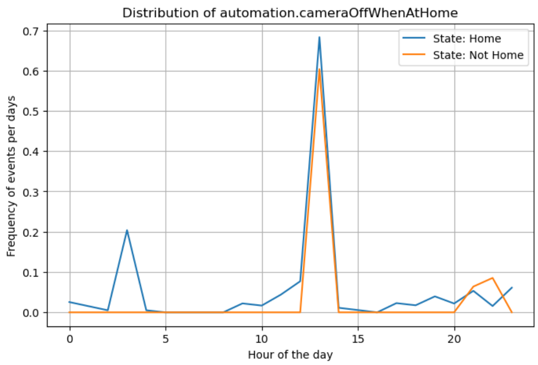

Fig. 3. Event 'automation.cameraOffWHenAtHome'

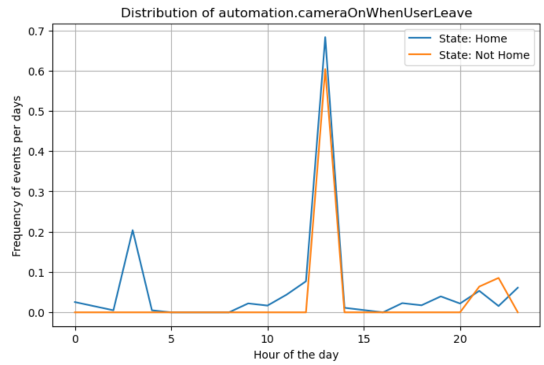

Fig. 4. Event 'automation.cameraOnWhenUserLeave'

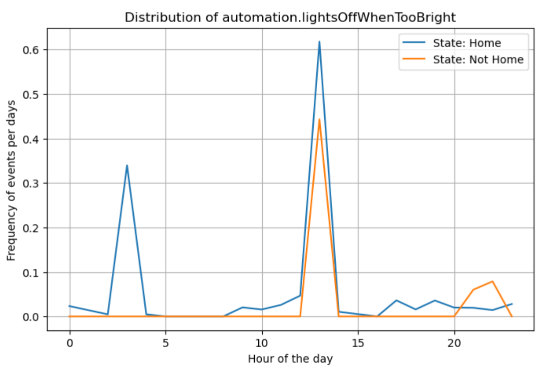

Fig. 5. Event 'automation.lightsOffWhenTooBright'

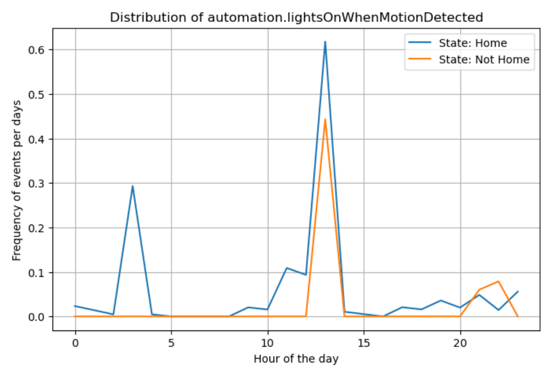

Fig. 6. Event 'automation.lightsOnWhenMotionDetected'

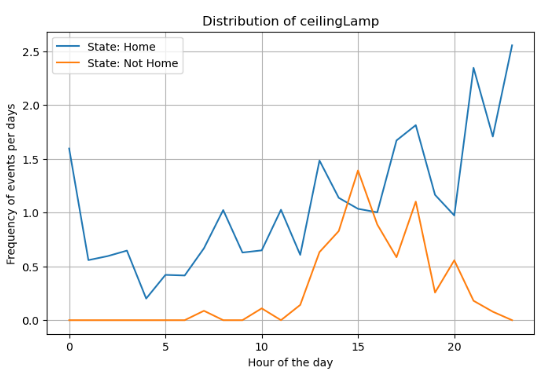

Fig. 7. Event 'ceilingLamp'

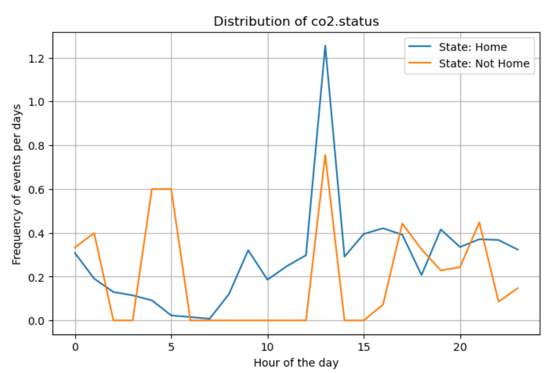

Fig. 8. Event 'co2.status'

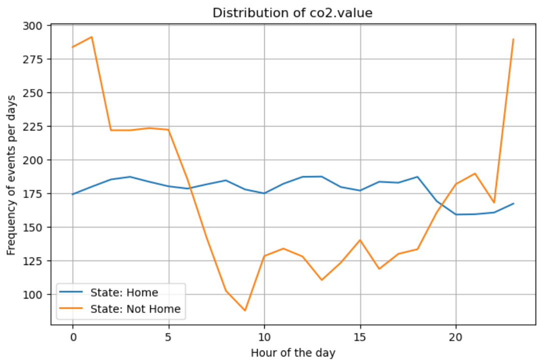

Fig. 9. Event 'co2.value'

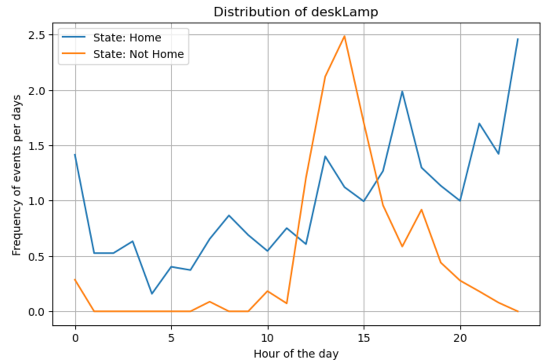

Fig. 10. Event 'deskLamp'

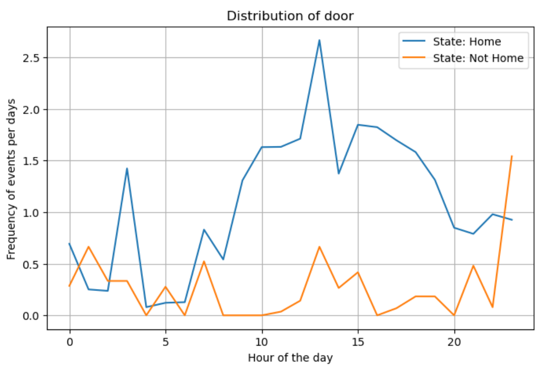

Fig. 11. Event 'door'

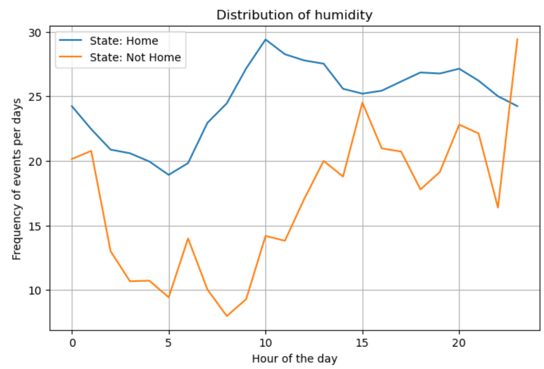

Fig. 12. Event 'humidity'

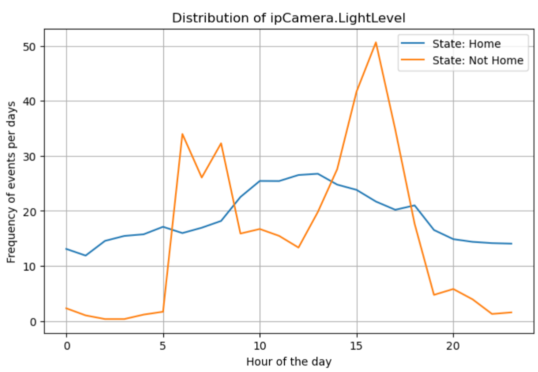

Fig. 13. Event 'ipCamera.LightLevel'

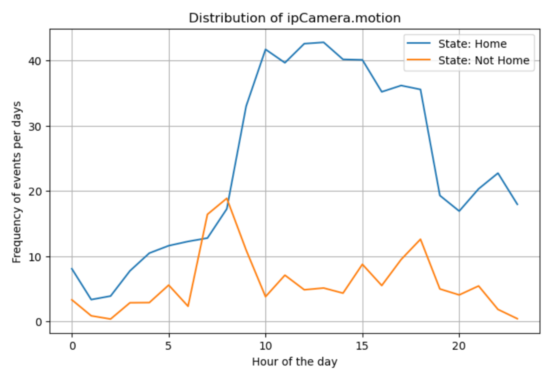

Fig. 14. Event 'ipCamera.motion'

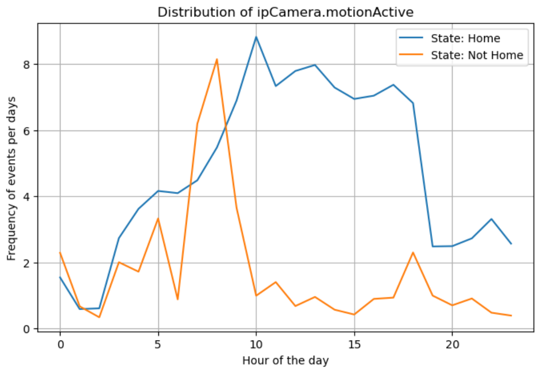

Fig. 15. Event 'ipCamera.motionActive'

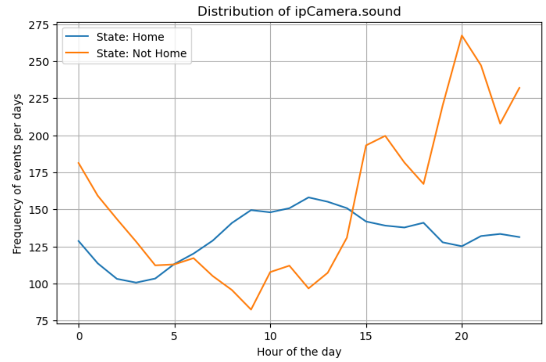

Fig. 16. Event 'ipCamera.sound'

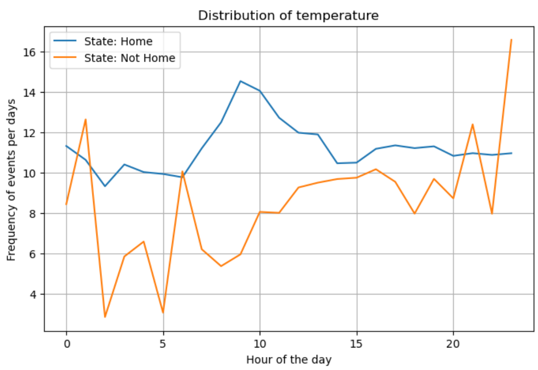

Fig. 17. Event 'temperature'

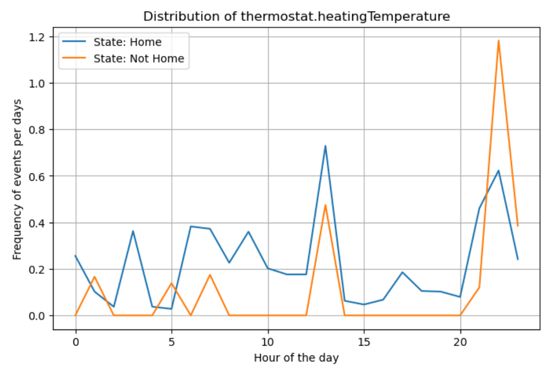

Fig. 18. Event 'thermostat.heatingTemperature'

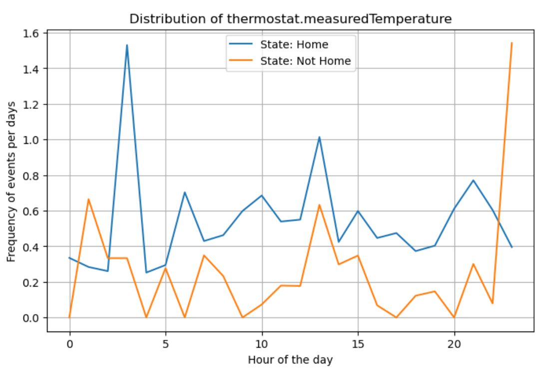

Fig. 19. Event 'thermostat.measuredTemperature'

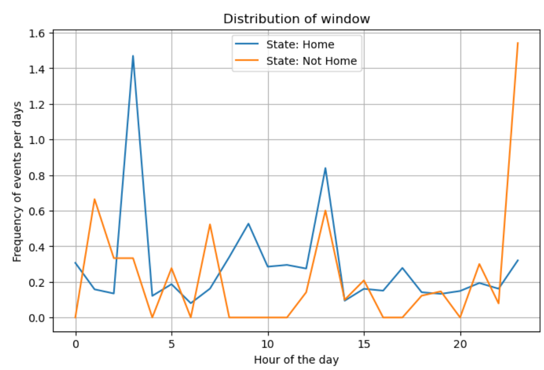

Fig. 20. Event 'window'

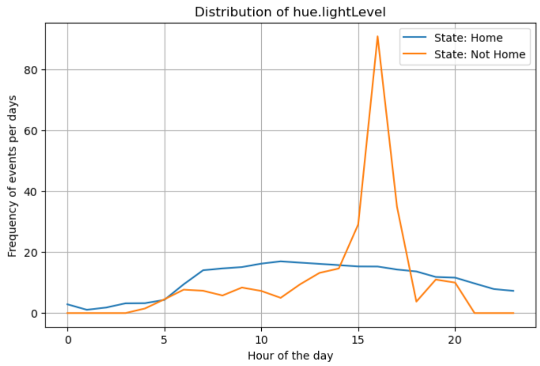

Fig. 21. Event 'hue.lightLevel'

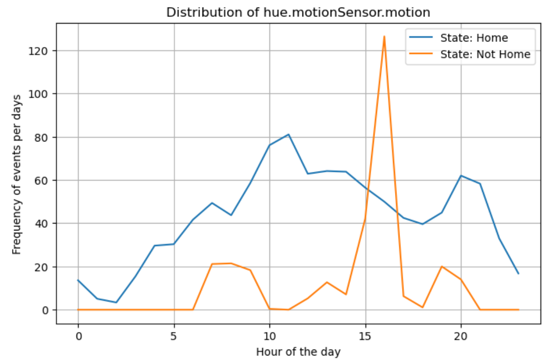

Fig. 22. Event 'hue.motionSensor.motion'

B ESTIMATE DATA VOLUME

Here is the result for estimate data volume

B.1 User Presence Base Scenario

Device	User Presence	
	Home	Not Home
Smart Light Bulb	-	-
Smart Camera	527.90 kB - 592.03 kB	368.80 kB - 453.61 kB
Weather Station	247.05 kB - 298.22 kB	116.26 kB - 209.56 kB
Smart Plug (No user presence data)	-	-

Table 9. Estimated Daily Data Volume by User Presence in Home 1

Device	User Presence	
	Home	Not Home
Smart Light Bulb	9.36 MB - 12.11 MB	1.42 MB - 1.87 MB
Smart Camera	1.12 MB - 1.24 MB	716.17 kB - 850.59 kB
Weather Station	40.63 kB - 44.91 kB	24.95 kB - 29.30 kB
Smart Plug (No user presence data)	-	-

Table 10. Estimated Daily Data Volume by User Presence in Home 2

Device	User Presence	
	Home	Not Home
Smart Light Bulb	3.87 MB - 6.24 MB	3.01 MB - 3.73 MB
Smart Camera	11.54 kB - 12.20 kB	13.77 kB - 13.77 kB
Weather Station	30.35 kB - 37.38 kB	25.27 kB - 30.10 kB
Smart Plug (No user presence data)	-	-

Table 11. Estimated Daily Data Volume by User Presence in Home 4

B.2 User Presence Base Scenario

Time	Device			
	Smart Light Bulb (No Data)	Smart Camera	Smart Plug (No Data)	Weather Station
12 am	-	480.28 kB - 543.28 kB	-	244.36 kB - 293.65 kB
1 am	-	376.99 kB - 437.59 kB	-	246.43 kB - 304.18 kB
2 am	-	335.68 kB - 375.27 kB	-	246.43 kB - 299.67 kB
3 am	-	329.48 kB - 359.78 kB	-	260.92 kB - 301.55 kB
4 am	-	329.48 kB - 351.52 kB	-	263.17 kB - 296.66 kB
5 am	-	387.32 kB - 402.81 kB	-	262.42 kB - 300.04 kB
6 am	-	435.18 kB - 451.70 kB	-	262.80 kB - 296.28 kB
7 am	-	476.84 kB - 488.89 kB	-	258.66 kB - 298.73 kB
8 am	-	518.49 kB - 538.81 kB	-	266.75 kB - 302.87 kB
9 am	-	566.35 kB - 628.32 kB	-	226.68 kB - 300.99 kB
10 am	-	622.12 kB - 685.47 kB	-	242.67 kB - 299.29 kB
11 am	-	650.70 kB - 706.47 kB	-	251.13 kB - 295.53 kB
12 am	-	635.21 kB - 723.00 kB	-	256.97 kB - 295.91 kB
1 pm	-	466.51 kB - 657.59 kB	-	117.57 kB - 285.94 kB
2 pm	-	638.31 kB - 708.20 kB	-	258.10 kB - 296.85 kB
3 pm	-	657.59 kB - 748.82 kB	-	259.04 kB - 302.11 kB
4 pm	-	634.52 kB - 723.00 kB	-	258.66 kB - 298.16 kB
5 pm	-	614.55 kB - 718.52 kB	-	266.37 kB - 306.25 kB
6 pm	-	602.50 kB - 717.84 kB	-	272.77 kB - 305.12 kB
7 pm	-	574.96 kB - 619.71 kB	-	249.25 kB - 304.75 kB
8 pm	-	570.83 kB - 607.32 kB	-	240.79 kB - 292.52 kB
9 pm	-	565.32 kB - 626.60 kB	-	228.94 kB - 294.59 kB
10 pm	-	562.91 kB - 638.65 kB	-	231.19 kB - 294.40 kB
11 pm	-	544.66 kB - 591.83 kB	-	247.75 kB - 302.87 kB
Total	-	524.03 kB - 585.46 kB	-	246.66 kB - 298.70 kB

Table 12. Estimated Hourly Data Volume by Time of the Day in Home 1

Time	Device			
	Smart Light Bulb	Smart Camera	Smart Plug (No Data)	Weather Station
12 am	1011.58 kB - 1.27 MB	777.74 kB - 812.86 kB	-	33.67 kB - 36.68 kB
1 am	1011.58 kB - 1.27 MB	756.74 kB - 772.58 kB	-	43.08 kB - 46.28 kB
2 am	2.26 MB - 3.10 MB	963.66 kB - 993.95 kB	-	44.77 kB - 47.03 kB
3 am	6.52 MB - 9.54 MB	1.07 MB - 1.29 MB	-	50.79 kB - 53.80 kB
4 am	15.98 MB - 17.87 MB	1.13 MB - 1.34 MB	-	53.24 kB - 60.20 kB
5 am	16.65 MB - 19.62 MB	1.36 MB - 1.49 MB	-	53.05 kB - 57.94 kB
6 am	18.91 MB - 21.87 MB	1.41 MB - 1.49 MB	-	47.59 kB - 50.98 kB
7 am	16.94 MB - 21.03 MB	1.52 MB - 1.54 MB	-	44.21 kB - 47.41 kB
8 am	15.38 MB - 20.60 MB	1.48 MB - 1.55 MB	-	45.15 kB - 47.03 kB
9 am	16.94 MB - 21.00 MB	1.46 MB - 1.59 MB	-	38.94 kB - 45.71 kB
10 am	17.08 MB - 20.18 MB	1.49 MB - 1.60 MB	-	42.14 kB - 49.66 kB
11 am	17.08 MB - 19.19 MB	1.35 MB - 1.50 MB	-	44.96 kB - 52.30 kB
12 am	10.02 MB - 14.59 MB	1.21 MB - 1.41 MB	-	38.38 kB - 44.58 kB
1 pm	6.63 MB - 10.58 MB	1.31 MB - 1.48 MB	-	38.56 kB - 42.89 kB
2 pm	10.02 MB - 14.68 MB	1.29 MB - 1.49 MB	-	41.57 kB - 47.03 kB
3 pm	11.57 MB - 17.78 MB	1.08 MB - 1.39 MB	-	44.58 kB - 49.47 kB
4 pm	9.03 MB - 15.81 MB	1.16 MB - 1.33 MB	-	43.45 kB - 47.78 kB
5 pm	4.94 MB - 12.00 MB	1.32 MB - 1.48 MB	-	42.51 kB - 50.04 kB
6 pm	1.83 MB - 2.96 MB	1.04 MB - 1.20 MB	-	39.50 kB - 41.39 kB
7 pm	1.13 MB - 1.41 MB	802.87 kB - 883.44 kB	-	35.55 kB - 37.81 kB
8 pm	867.07 kB - 1011.58 kB	766.04 kB - 812.17 kB	-	34.61 kB - 36.68 kB
9 pm	1011.58 kB - 1.13 MB	785.66 kB - 813.20 kB	-	34.61 kB - 37.62 kB
10 pm	1011.58 kB - 1.13 MB	760.18 kB - 782.91 kB	-	33.67 kB - 35.74 kB
11 pm	1.13 MB - 1.27 MB	747.79 kB - 792.89 kB	-	32.54 kB - 35.93 kB
Total	8.53 MB - 11.29 MB	1.12 MB - 1.24 MB	-	41.71 kB - 45.92 kB

Table 13. Estimated Hourly Data Volume by Time of the Day in Home 2

Time	Device			
	Smart Light Bulb	Smart Camera (No Data)	Smart Plug (No Data)	Weather Station (No Data)
12 am	1011.58 kB - 1.02 MB	-	-	-
1 am	1011.58 kB - 1.13 MB	-	-	-
2 am	982.68 kB - 1.02 MB	-	-	-
3 am	867.07 kB - 1011.58 kB	-	-	-
4 am	1011.58 kB - 1.13 MB	-	-	-
5 am	722.56 kB - 895.98 kB	-	-	-
6 am	867.07 kB - 1.02 MB	-	-	-
7 am	1.24 MB - 1.44 MB	-	-	-
8 am	1.81 MB - 2.15 MB	-	-	-
9 am	2.09 MB - 2.40 MB	-	-	-
10 am	2.40 MB - 2.57 MB	-	-	-
11 am	433.54 kB - 2.20 MB	-	-	-
12 am	2.40 MB - 2.54 MB	-	-	-
1 pm	2.54 MB - 2.79 MB	-	-	-
2 pm	2.65 MB - 2.68 MB	-	-	-
3 pm	2.62 MB - 2.68 MB	-	-	-
4 pm	2.51 MB - 2.68 MB	-	-	-
5 pm	2.40 MB - 2.54 MB	-	-	-
6 pm	2.40 MB - 2.54 MB	-	-	-
7 pm	2.48 MB - 2.68 MB	-	-	-
8 pm	2.26 MB - 2.29 MB	-	-	-
9 pm	1.38 MB - 1.83 MB	-	-	-
10 pm	1011.58 kB - 1.13 MB	-	-	-
11 pm	867.07 kB - 1.10 MB	-	-	-
Total	1.66 MB - 1.89 MB	-	-	-

Table 14. Estimated Hourly Data Volume by Time of the Day in Home 3

Time	Device			
	Smart Light Bulb	Smart Camera	Smart Plug (No Data)	Weather Station
12 am	1.27 MB - 2.40 MB	0.00 B - 0.00 B	-	27.28 kB - 31.98 kB
1 am	1011.58 kB - 1.13 MB	13.77 kB - 13.77 kB	-	23.51 kB - 28.22 kB
2 am	867.07 kB - 1011.58 kB	6.89 kB - 6.89 kB	-	19.75 kB - 25.40 kB
3 am	1.13 MB - 1.27 MB	6.89 kB - 6.89 kB	-	19.75 kB - 25.40 kB
4 am	867.07 kB - 1011.58 kB	13.77 kB - 13.77 kB	-	18.81 kB - 24.46 kB
5 am	867.07 kB - 1011.58 kB	13.77 kB - 13.77 kB	-	16.93 kB - 22.57 kB
6 am	2.12 MB - 2.68 MB	0.00 B - 0.00 B	-	21.63 kB - 29.16 kB
7 am	2.68 MB - 5.50 MB	13.77 kB - 13.77 kB	-	28.22 kB - 37.62 kB
8 am	2.54 MB - 3.10 MB	13.77 kB - 13.77 kB	-	29.16 kB - 33.86 kB
9 am	3.10 MB - 6.49 MB	13.77 kB - 13.77 kB	-	29.16 kB - 36.68 kB
10 am	5.22 MB - 9.60 MB	19.28 kB - 22.03 kB	-	38.56 kB - 51.73 kB
11 am	4.52 MB - 9.46 MB	13.77 kB - 13.77 kB	-	37.62 kB - 43.27 kB
12 am	5.22 MB - 8.19 MB	12.39 kB - 15.15 kB	-	36.68 kB - 43.27 kB
1 pm	6.63 MB - 10.30 MB	6.89 kB - 6.89 kB	-	35.93 kB - 45.15 kB
2 pm	4.63 MB - 9.68 MB	9.64 kB - 11.02 kB	-	30.66 kB - 38.94 kB
3 pm	4.06 MB - 7.93 MB	6.89 kB - 6.89 kB	-	31.98 kB - 38.38 kB
4 pm	4.71 MB - 7.48 MB	13.77 kB - 13.77 kB	-	32.92 kB - 37.62 kB
5 pm	4.54 MB - 7.20 MB	0.00 B - 0.00 B	-	31.60 kB - 38.94 kB
6 pm	4.66 MB - 7.93 MB	8.26 kB - 12.39 kB	-	35.74 kB - 41.39 kB
7 pm	6.21 MB - 9.46 MB	6.89 kB - 8.26 kB	-	38.56 kB - 48.53 kB
8 pm	9.43 MB - 14.00 MB	6.89 kB - 8.26 kB	-	45.52 kB - 51.36 kB
9 pm	8.75 MB - 12.79 MB	13.77 kB - 13.77 kB	-	43.27 kB - 47.97 kB
10 pm	4.26 MB - 7.42 MB	13.77 kB - 13.77 kB	-	33.86 kB - 42.51 kB
11 pm	3.16 MB - 4.46 MB	13.77 kB - 13.77 kB	-	31.04 kB - 35.37 kB
Total	3.85 MB - 6.31 MB	10.10 kB - 10.67 kB	-	30.76 kB - 37.49 kB

Table 15. Estimated Hourly Data Volume by Time of the Day in Home 4

Time	Device			
	Smart Light Bulb	Smart Camera	Smart Plug	Weather Station
12 am	1011.58 kB - 1.33 MB	428.29 kB - 643.81 kB	2.07 MB - 2.17 MB	27.09 kB - 29.35 kB
1 am	867.07 kB - 1011.58 kB	192.11 kB - 231.36 kB	1.92 MB - 1.98 MB	24.46 kB - 26.34 kB
2 am	838.17 kB - 1011.58 kB	194.52 kB - 218.62 kB	1.88 MB - 1.95 MB	16.74 kB - 23.14 kB
3 am	1.27 MB - 1.44 MB	186.60 kB - 205.88 kB	1.93 MB - 1.99 MB	23.89 kB - 26.34 kB
4 am	838.17 kB - 1011.58 kB	174.55 kB - 191.77 kB	1.94 MB - 2.00 MB	21.63 kB - 24.46 kB
5 am	867.07 kB - 1011.58 kB	189.36 kB - 228.95 kB	2.05 MB - 2.12 MB	24.46 kB - 25.58 kB
6 am	1.13 MB - 1.16 MB	286.45 kB - 347.73 kB	2.33 MB - 2.46 MB	23.14 kB - 26.52 kB
7 am	1.04 MB - 1.27 MB	465.82 kB - 562.56 kB	2.53 MB - 2.78 MB	34.05 kB - 39.88 kB
8 am	982.68 kB - 1.27 MB	425.54 kB - 452.05 kB	2.31 MB - 2.50 MB	42.14 kB - 48.16 kB
9 am	1.50 MB - 2.43 MB	482.00 kB - 578.06 kB	2.40 MB - 2.50 MB	40.63 kB - 48.91 kB
10 am	3.64 MB - 4.71 MB	530.89 kB - 639.68 kB	2.41 MB - 2.52 MB	47.03 kB - 50.79 kB
11 am	4.94 MB - 7.39 MB	592.17 kB - 695.80 kB	2.41 MB - 2.44 MB	40.44 kB - 44.58 kB
12 am	5.02 MB - 9.34 MB	693.74 kB - 728.51 kB	2.40 MB - 2.43 MB	37.44 kB - 43.08 kB
1 pm	6.07 MB - 6.80 MB	741.59 kB - 802.53 kB	2.36 MB - 2.45 MB	37.44 kB - 43.45 kB
2 pm	6.77 MB - 9.06 MB	662.75 kB - 725.07 kB	2.32 MB - 2.41 MB	37.62 kB - 42.70 kB
3 pm	4.23 MB - 8.50 MB	630.73 kB - 729.20 kB	2.34 MB - 2.39 MB	37.06 kB - 40.63 kB
4 pm	3.73 MB - 8.07 MB	547.07 kB - 654.49 kB	2.35 MB - 2.41 MB	34.61 kB - 36.68 kB
5 pm	3.19 MB - 4.43 MB	551.55 kB - 647.60 kB	2.40 MB - 2.44 MB	41.01 kB - 50.98 kB
6 pm	2.79 MB - 4.66 MB	628.67 kB - 721.62 kB	2.46 MB - 2.56 MB	47.78 kB - 59.26 kB
7 pm	2.17 MB - 4.26 MB	719.90 kB - 752.95 kB	2.65 MB - 3.17 MB	51.54 kB - 54.55 kB
8 pm	2.34 MB - 3.27 MB	683.75 kB - 744.00 kB	3.47 MB - 3.67 MB	47.59 kB - 57.38 kB
9 pm	1.83 MB - 2.99 MB	721.62 kB - 759.84 kB	3.35 MB - 3.52 MB	42.33 kB - 45.34 kB
10 pm	1.33 MB - 2.15 MB	821.81 kB - 949.88 kB	3.01 MB - 3.39 MB	34.43 kB - 38.75 kB
11 pm	982.68 kB - 1.30 MB	616.62 kB - 793.23 kB	2.40 MB - 2.92 MB	31.79 kB - 33.11 kB
Total	2.47 MB - 3.74 MB	507.00 kB - 583.55 kB	2.40 MB - 2.55 MB	35.26 kB - 40.00 kB

Table 16. Estimated Hourly Data Volume by Time of the Day in Home 5