Theory/Practice Transfer Paper

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1 Introduction

In todays modern world, electricity is being used everyday, everywhere by everyone. Long distance transportation via train, short distance transportation through an elevator, lighting, cooking, and even entertainment relies on it. Technology and thus electricity is omnipresent. The typical daily routine incorporates at least a dozen different pieces of technology where each and every one uses it.

For this reason, it is not surprising that knowing which appliances a person uses can uncover a surprising amount of information about their lifes. Starting with the daily routine including cooking habits, entertainment usage, sleep-, work-, and eating-schedules. The list goes on with habits like ones diet, shower temperature preferences, or even religious alignment.

With the advent of the internet topics like big data and personal profiling became more prevailing. Social networks are far ahead in collecting personal data, preferences and habits. They are using it to show filtered information feeds and to do targeted advertising. External entities which gained access to this data even used it to perform large scale manipulations of elections [1].

Knowing which appliances an individual uses thus poses a significant privacy risk. Since most appliances use electricity, having access to the household power consumption data may allow foreign parties to run an analysis on it to determine which appliances are in use. This could then be monitored to derive personal information like routines, habits and preferences. Having access to this data may allow grid providers to optimize their deliver. On the flip side, it may allow an evil spirited attacker to for example manipulate the target.

However, this requires a method to clearly discern individual appliances by looking at the electricity data. Finding out which appliances can be identified is going to be the goal of this research paper. The primary research question will be: “Which appliances provide a characteristic and isolatable power profile?”. To answer it, existing research will be evaluated and based on the information gathered, an analysis of the authors private household will be performed using inexpensive off-the-shelf electronics equipment. The latter is known as non-intrusive appliance load monitoring (NIALM) in most existing research [2].

2 Existing research

In a common household there are three phases, where each one serves different appliances which are usually located in different areas. This is done to distribute the load. In the context of monitoring appliances it provides a means of isolation and reduces the amount of over-shadowing where one appliance mixes and masks the profile of another. While it is easiest to monitor power consumption on the three phases, results can be improved further by monitoring each circuit individually. Much like the three phases it further reduces over-shadowing and might even allow room-based classification, depending on the available knowledge about the household. [3]

Measuring equipment can be installed in two possible ways. The most precise method is in-circuit measurement where the meter is placed in between the incoming supply and the household. This requires knowledge in electronics and is usually complicated to install compared to the second method. An alternative is to use clamp-on meters which can be wrapped around existing cables. This technology can for example be incorporated into a glove making it easy to use for non-experts. However, it usually lacks the precision of the former method with maximum accuracy hovering around 0.2A which resolves to about ±50W in Europe. [4]

Electricity is defined not only through instantaneous usage in watts. There is a multitude of other metrics which can be collected to improve the accuracy of appliance classification algorithms by up to 30%. These include the exact shape of transient states when an appliance is turned on or off (although this requires a very high sampling frequency). However, even in the steady state of an appliance different metrics are available. A fast-fourier transform on the current wave returns the harmonics, plotting the voltage and current trajectory of the wave gives a trajectory which is usually unique to appliances, distortions of the waveform introduced during operation are also indicative of specific devices, and finally the ratio of active and reactive power use can help discerning devices which are otherwise similar. Additionally, different appliances have different states. For example a light is binary with only an on and off state, while a coffee machine might have three possible states (off, warming up, brewing coffee). Some appliances like for example computers have a nearly infinite amount of states which usually transition smoothly. [2] [5]

In order to identify consumers, various different methods have been researched. One paper created an isolated lab environment which resembles a small apartement. They installed a current meter on the incoming supply line which measures both active and reactive instantaneous power usage. Using a simple clustering algorithm, they managed to discern a wide range of devices (stove burners, electric kettle, oven, toaster, range hood fan, coffee maker, microwave, hair dryer with two modes, blender, mixer, stereo, refrigerator) with 98.3% accuracy. Additionally, scenario recognition has been successful as well, detecting specific daily routines with a 97% accuracy. However, using just instantaneous current as the underlying data, they were not able to clearly differentiate lights, entertainment systems and personal computers. [2]

A different research paper used a similar methodology and also managed to identify an electric kettle and refrigerator with high confidence. Additionally, they were able to discern the television from other devices on the grid. However, like the first paper, they also recognized that using just current data some devices can not be discerned without further knowledge of the household or more input data. They suggested that analysing the harmonics in addition to current amplitude could resolve this issue for most appliances. [6]

Another team of researchers attempted classification based on current using machine learning algorithms. They succeeded in not only identifying the devices used (coffee machine and refrigerator) but also in which state they were. This allows to for example detect the type of coffee that is being brewed or when a refrigerator has been opened. [7]

These results can be improved further by using temporal contextual information gained by collecting and storing samples over longer periods of time. This can increase the accuracy by up to 10% and is especially useful for identifying devices which exhibit short power spikes and specific temporal patterns, which is often the case with entertainment electronics and refrigerators among others. [8]

Additionally, factoring in the current draw harmonics can yield even better results. The first row of figure 1 shows the current harmonics, the second the overall current draw, and the third the change in load. It becomes evident that especially the latter gives valuable insight in the type of device when just looking at the current. However, the harmonics in the first row are also of interest. While in this example only the amplitude changes, figure 2 shows various harmonics of other appliances. Especially the microwave oven and blender have very distorted waveforms which are unique. [9] [3]

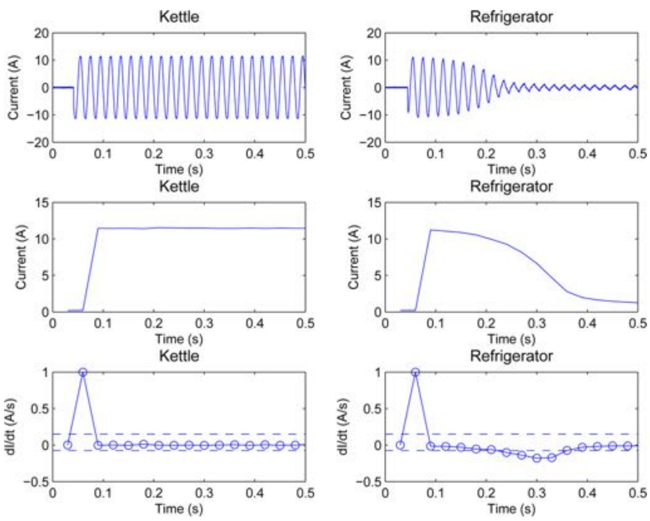

Figure 1: Kettle & Refrigerator harmonics [9]

Building on this knowledge, a two stage approach can be used. First, devices are categorised based on their current draw, state transitions and temporal contextual information. In their research paper, Meehan et al. grouped appliances into three categories: “linear nonreactive”, “linear reactive”, and “nonlinear reactive”. They then identified individual appliances within each category using the characteristics during the state transition. Using a Naive Bayes classifier an accuracy of ~87% was achieved. [9]

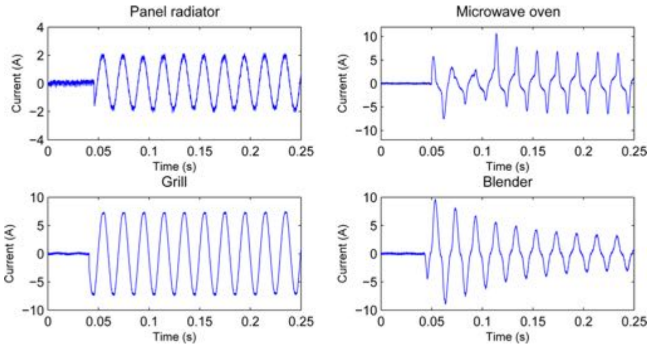

Figure 2: Various power harmonics [9]

Other research papers combined the Bayes classifier with a k-nearest neighbor algorithm and achieved roughly 77% confidence [10]. However, all classifiers mentioned so far require manual labelling and training which is mostly unviable for analysing individual households as each may contain different appliances from different vendors with different power signatures. For this reason, unsupervised clustering of appliances is an active field of research and some promising solutions have been developed so far [11].

Now that the appliances have been classified, the data can be put to use. By combining it with other external data source about a household even more insights can be gained [12].

A study which observed five sites with a total of 72 dwellings over a time period of two years. They captured current samples every five minutes. Using the data, they discovered trends in appliance use and noticed an increase in standby appliances per household as well as an increase in both very low power and high power devices. Few households bought new devices that fall into the medium range. Using such data, general domestic trends can be generated which provide valuable insights for electricity providers, governments and other parties. [13]

Another potential use of the collected data is in healthcare. As habits and daily routines can be derived from appliance use, deviations from the usual habits can be detected easily. Especially in elderly care this can be employed to identify households where the inhabitants are no longer able to care for themselves. Existing research indicates that it is possible to recognize patterns in appliance use like for example using a computer while having lunch with high accuracy. [14]

While households and office spaces are generally different in both layout, size, and appliance use it is expected that most research is transferrable [15].

Especially in a corporate and industrial context it may be interesting for electricity providers to use such information for personalised billing. However, sharing power usage data always remains a tradeoff between privacy and gain as this data is highly sensitive. For this reason an effort has been made to modify the samples returned from a meter so that they do not reveal any sensitive information while still being valuable for e.g. providers. [16]

3 Houshold data collection

3.1 Methodology

In order to evaluate which appliances might be recognizable, a data source is required. For this research paper, the household of the author will be used. It is a house with two floors, three bathrooms, two bedrooms and one living room. There are two inhabitants (including the author) where one is out for work from roughly 8am to 2pm, while the other stays at home working remotely. Notable appliances include an electric water heater in all bathrooms, a large TV set and an attached AV Receiver, and that most light fixtures are using halogen bulbs instead of LED ones.

The household has a central, accessible power meter which has been installed by the local electricity provider. It has been manufactured by EMH metering and is the model ITZ. Due to the technical knowledge required, the installation of a in-circuit meter is not viable. It would also incur significant up-front costs. For this reason, harmonics and waveform distortions will not be measured. The voltage-current trajectory and reactive power are also unavailable for the same reason[1]. The meter provided by the electricity provider does capture voltage and current across all three phases.

To access the data recorded by the meter an interface is required. The model present does have two serial interfaces according to the manufacturer. One uses the RS232 standard and communicates through a copper wire. The connector for this port is located below the cover of the unit which has been locked by the provider. For this reason, the second interface will be used. It is an optical port on the front of the unit. The timings are standardised by standard EN 62053-31, the protocol is defined in EN 62056-21:2002 and the optical wavelengths are specified by IEC 65056-21.

Communicating through the optical interface requires a unit which magnetically attaches to the port and contains a phototransistor for incoming communication and an infrared emitter for outgoing communication. For this experiment, a Osram SFH309FA-3/4 T1 phototransistor and an IRL81A infrared emitter by the same company will be used which both operate at or around a 880nm wavelength. They will be attached to a 3D printed housing using hot-glue and this housing will then be secured on the front panel through common household magnets. The wiring diagram can be seen in figure 3 and has been adopted from a blog at 404.at. While the diagram shows a Raspberry Pi as the microcontroller driving the interface, other MCUs can be used as well. During the development of the interface, an Arduino Mega and an Espressif ESP32 have been used. It is noteworthy however, that the polarity of

[1]Private households are usually not billed for reactive power and thus it is not measured by most meters

the interface was reversed and in order for the hardware serial chips to decode the data, a logic inverter using two BC547 transistors had to be inserted.

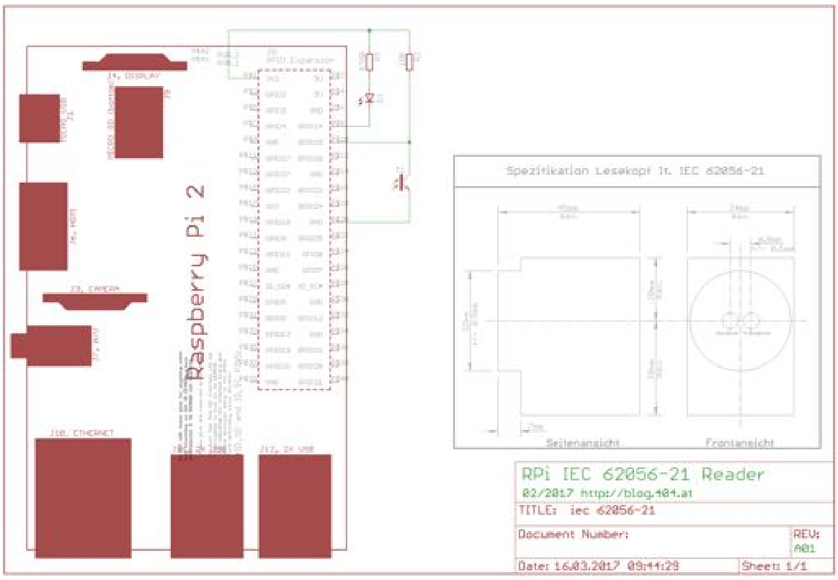

Figure 3: Optical interface wiring diagram

Once the interface was operational, serial communication had to be established. Some meters do passively broadcast their data at a fixed baudrate without a handshake. This model does require an explicit request. According to EN 62056-21:2002 the communication begins with a handshake at a baudrate of 300 with 7 data bits, even parity and one stop bit. The handshake must contain a meter-identification code which matches a hardcoded value. In this case, that value was encoded in a barcode on the front of the unit. Upon receipt of the handshake, the unit sends out an acknowledgement containing the new communication baudrate. According to the standard, this will be the minimum of the baudrate stated in the handshake and that is supported by the meter. However, changing the maximum supported baudrate in the handshake did not yield an increase in communication speed for unknown reasons. Thus, this interface is constrained to 300 bits per second which translates to a sample every 95 seconds. Since most transient state signatures are shorter than this, they will not be considered.

The final interface was built using an inexpensive, WiFi capable ESP32 MCU by Espressif (in this case the development board). It communicates with the meter at the fastest possible rate and stores the latest sample in memory. An HTTP endpoint is then provided which serves this data in a standardised format which adheres to the Prometheus data model[2] to increase interoperability with existing tools. An example of the data returned can be found in the appendix section A.

Since the MCU has no meaningful persistent storage, the samples have to be accessed from and stored elsewhere. In order to achieve this, the NAS server of the household will be running a simple bash script which will retrieve the current sample using the `curl` command-line tool and append the output

[2] https://prometheus.io/docs/concepts/data_model/

to a text file with a timestamp and separator. This script will be executed every 95 seconds through a cronjob.

After two weeks of capturing, the text file will be retrieved and parsed into a simple data structure using Swift. Since the interface does not verify the checksum of the data received for simplicity reasons, the only safe-guard is the parity bit. This results in some damaged samples which will be filtered out during this stage. Any samples which are missing fields, contain invalid characters in the numeric fields, or have values that are unreasonable (current on a single phase above 80A) will be discarded. The remaining data is then reformatted into a comma separated list containing timestamped current and voltage values for each phase. To evaluate the data, it will be plotted using the `plotly` python library which allows the easy creation of interactive graphs. Excerpts from the full graph are then exported using the built-in snapshot feature.

The source code for all processing steps as well as the collected data samples are available in the accompanying GitHub repository[3].

To identify individual appliances, the graph will be searched for distinct power signatures without any contextual knowledge about the circumstances. No record of past events in the household is kept and a distance of two weeks between capture and evaluation is kept to remain as unbiased as possible. The power signatures will then be analysed based on their shape and characteristics to determine a list of potential appliances that could have caused it. Matching appliances will then be turned on during a time where there is minimal interference from other devices (e.g. when nobody else is home or late during the night) and the power signatures will be recorded. They will then be used to verify the assumptions made about the original power signatures.

3.2 Analysis

This section contains four different distinct power signatures which have been captured. Note that some of the verification signatures do contain a few invalid samples which passed the syntax and plausability analysis. As the interface was in operation for a prolonged time period, more and more invalid samples accumulated. It is unclear how exactly this happened but a memory leak in the MCU or a deteriorating physical connection / increasing misalignment of the interface are strong suspects.

The figures referenced in the following sections show the time on the x-axis and power consumption in Amps on the y-axis. In some diagrams there is all three phases while others only contain individual ones if the others are not relevant.

[3] Link is excluded in this version of the document

3.2.1 Appliance 1: Water heater

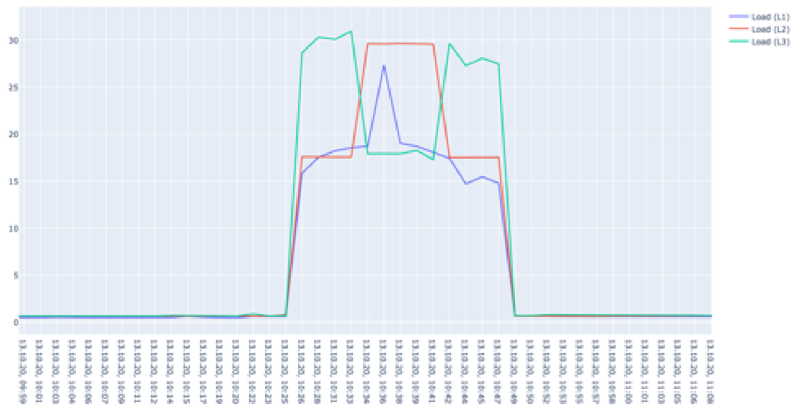

Figure 4: Captured power signature 1

The power signature in figure 4 starts off with a peak on all three phases to about 17A with phase three surpassing it and reaching 30A. After approximately seven minutes the green phase switches place with the red phase. This change happenes again after another seven minutes. The current then falls sharply after a total duration of 25 minutes.

As the load is spread across all three phases it is unlikely to be a plugged in appliance as common sockets only provide access to a single phase. While there are high-power sockets like the one specified by DIN VDE 0623 they are usually not available in households as most appliances require less than $16A * 240V = 3600W$ of power. This reduces the number of possible appliances as they likely have to be installed permanently to gain access to all three phases. The best contender is an electric water heater and given the duration of the power signature it is likely being used for a long shower (handwashing, dishwashing, or other types of hot water usage are unlikely to take half an hour of constant water flow).

To verify this, the author took a shower for 25 minutes during a time period where no other inhabitants were present. The resulting data can be seen in figure 5 which mostly matches the original signatures. The overall draw is equal and the switching between phases is similar although the green phase has been used for a shorter time period for unknown reasons.

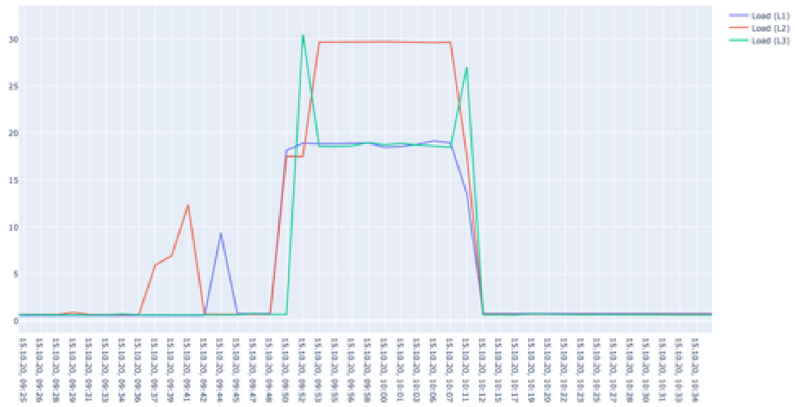

Figure 5: Water heater signature

3.2.2 Appliance 2: Refrigerator

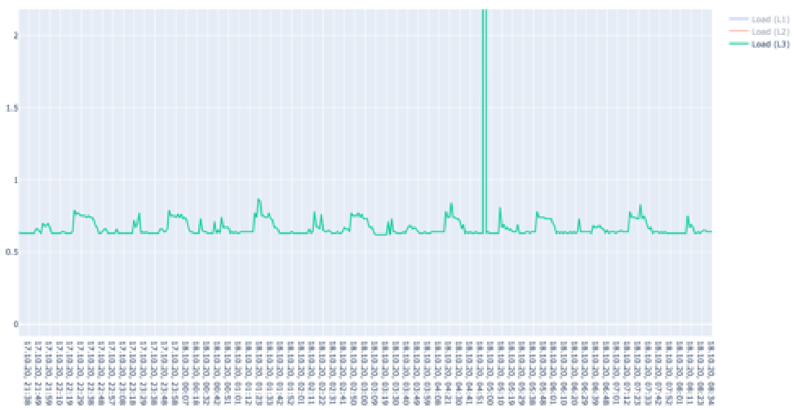

Figure 6: Captured power signature 2

This power signature has been discovered during the night where close to no other interference was observable. It is shown in figure 6 and repeats seven times in the shown time window. It starts with a small bump of less than 0.1A, continues with a pause and then has a larger sub-signature. This sub-signature starts with a peak, which is presumably varying in intensity due to the slow sampling rate, then exhibits a roughly constant use and finishes with a smooth decline back to the baseline.

The initial surge followed by a roughly constant load of the sub-signature suggests that the appliance is a primarily inductive load like for example an electric motor. As it is operating in a regular pattern even during the night and expected to contain a motor, it is unlikely to be appliances like a garage door or electric window blinds. A likely contender is some sort of cooling appliance. It would contain a compressor which uses a motor, have a constant influx of heat which causes it to frequently and more importantly regularly turn on for a short time period. The fact that there are two sub-signatures might indicate that it is either two cooling appliances or one combined unit with two individual compressors.

Since cooling appliances can not be turned off for prolonged time periods without spoiling their contents, a different method for validation is required. Since the pattern is fairly regular and expected to be based on the heat influx, opening the refrigerator should yield a decreased interval. The resulting power graph can be seen in figure 7. The appliance has been left running uninterrupted for a few hours and has been opened at 11:55. As expected, the compressor turned on shortly after audibly and the power graph shows the pattern repeating earlier.

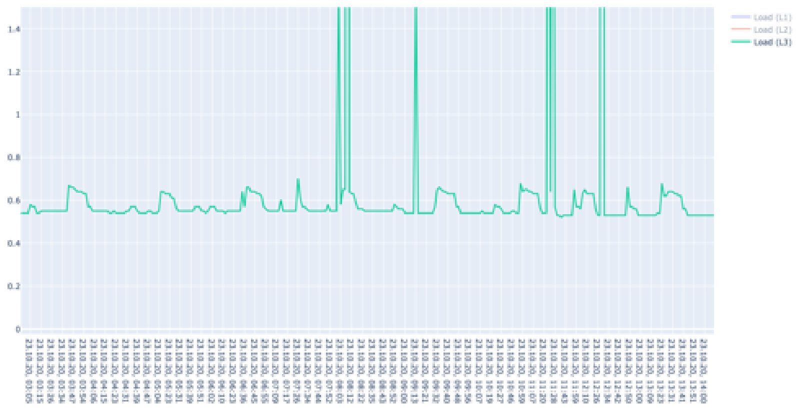

Figure 7: Refrigerator signature

3.2.3 Appliance 3: Entertainment systems

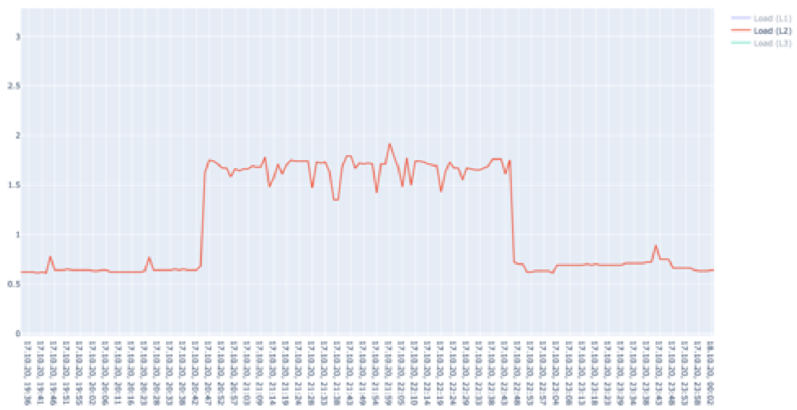

Figure 8: Captured power signature 3

Another very frequently repeated signature is visible in figure 8. It begins with a very sharp rise and ends with a sharp fall. The remainder of the profile is fluctuating by about 0.3A around a roughly constant level which is around 1.1A higher than baseline. The whole pattern takes approximately two hours.

Due to the long duration it is very likely that this is a manually switched appliance. In its on state it uses approximately 1A of power and smoothly fluctuates around this level. This suggests that it is an appliance which has smoothly transitioning, potentially infinite states. This hints at some kind of entertainment electronics or a computer. These kinds of devices display and process different contents which may or may not use more power. However, it is next to impossible to discern a computer, TV, and sound system with the data present.

Regardless, an attempt at verifying the hypothesis will be made. The television set will be turned on for a prolonged time period (in this case for four hours) while there is no other activity on the electricity network. The results can be seen in figure 9. Both the edges and the amplitude match the original signature. The reproduced signature also exhibits the fluctuations. However, without further analysis it is not clear whether this signature would be differentiatable from a personal computer or loudspeakers.

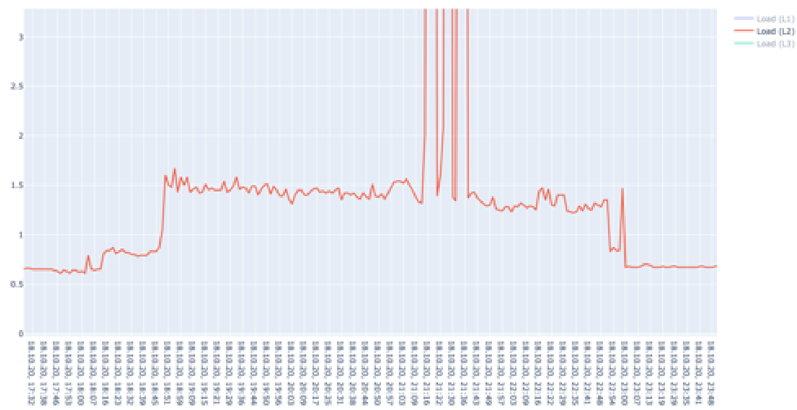

Figure 9: Entertainment system signature

3.2.4 Appliance 4: Mobile devices chargers

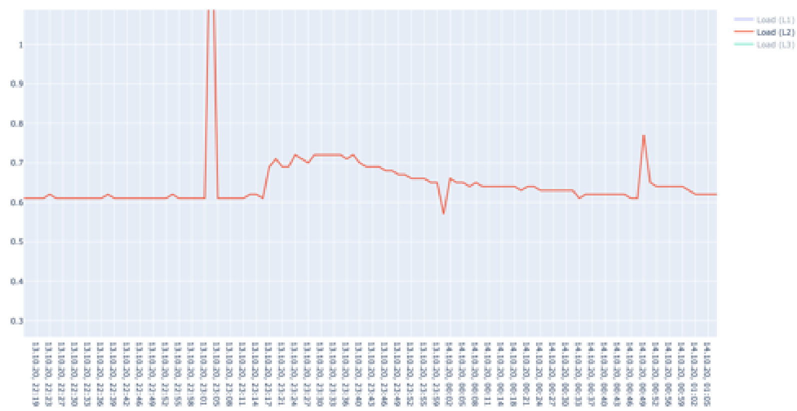

Figure 10: Captured power signature 4

Next up is the signature in figure 10. At around 23:00 the current rises by roughly 0.1A which equates to 24W. It stays at the elevated level for approximately half an hour and then slowly declines back down over the next hour. This pattern is very typical for battery chargers [17]. Especially lithium polymer batteries which are common in mobile devices like phones, tablets, and laptops are known to start with a high initial charging current until it reaches 80% capacity. From there it continues slowly trickle-charging with decreasing currents until the target voltage is reached [18].

As mentioned previously, devices that come into question are phones, tablets, and laptops. Phones usually charge with a lower wattage of 8-12W unless they are employing a quick-charge technology like for example Qualcomm QuickCharge or USB-C PD. Laptops are usually using upwards of 80W of power unless it is a low-powered ultrabook. This leaves tablets as the remaining suspect. According to technical documentation from Apple, their high-end tablets charge with 2A at 9V which puts them at 18W. However, this is the output wattage and does not incorporate losses during transformation. Therefore it is reasonable to assume that the power signature belongs to a tablet being charged. Given the time of day, it is reasonable to assume that the inhabitants are sleeping and plugged the devices in for a charge overnight.

For verification, the 12.9" iPad Pro in the household will be discharged completely and then attached to the charger that was provided in the box. This will be performed during a time period when no other inhabitants are at home (in this case during the morning). The results can be seen in figure 11. While the amplitude is ever so slightly higher and the duration of the high-current phase is longer, the overall shape matches the original. The amplitude might be different because the device has been charged using a different charger which is capable of slightly higher output. Since the device has been discharged fully prior to verification it is plausible that the duration is longer. It is unlikely that the device has been discharged fully at the end of the day.

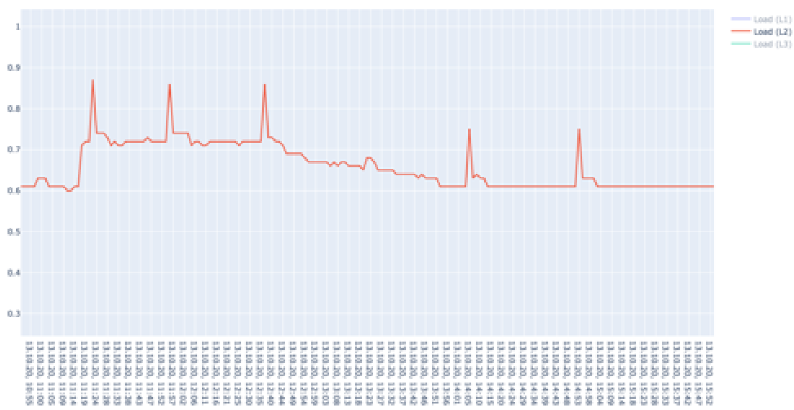

Figure 11: Mobile device charger signature

4 Conclusion

In this research paper, a number of methods for recognizing various appliances have been analyzed. It has been shown that some appliances like for example refrigerators or water heaters are clearly discernable using only the current as input. However, it also became clear that other appliances like entertainment and computers are harder to discern and require more specialised equipment. A low-cost method of interacting with common household electricity meters has been presented and used to capture data about the authors household. With this data it was possible to identify some appliances using no prior inside knowledge.

A number of different use cases ranging from trend analysis, individualized billing, grid optimizations and cost saving measures all the way to healthcare applications and habit tracking which could potentially safe lives of elderly inhabitants. However, it also became clear that this kind of data poses a major security hazard if it were to become public or evil spirited people gained access to it. With todays technology it is possible to capture, read, and parse electricity data and, to a certain degree, this is done by electricity providers today for individualized billing. Currently, this data is not shared in real-time and it remains to be seen if this would be a good route to take. To decrease the impact on privacy, research is being undertaken to develop algorithms which obfuscate the data just enough so that they are not giving insights into personal lifes while still being rich enough to be useful.

While this analysis has been focused around private households, some research suggests that the results are transferable to office spaces as well. While this topic has not been covered in-depth, it remains a possibility. This allows companies to make use of all the advantages but also pay for the disadvantages that come with recording and sharing this type of data. Especially in shared households and office spaces where the electricity meters are not located within the apartement, special caution should to be taken in order to preserve the privacy of all inhabitants and employees.

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Appendix

A Example data returned by interface

```
# HELP power_current_usage_kW Power consumption of the household
# TYPE power_current_usage_kW gauge
power_current_usage_kW 0.18


# HELP power_phase_voltage_volts Power grid voltage per phase
# TYPE power_phase_voltage_volts gauge
power_phase_voltage_volts{phase="L1"} 231.8
power_phase_voltage_volts{phase="L2"} 231.9
power_phase_voltage_volts{phase="L3"} 230.0


# HELP power_phase_load_amps Household load per phase
# TYPE power_phase_load_amps gauge
power_phase_load_amps{phase="L1"} 0.43
power_phase_load_amps{phase="L2"} 0.70
power_phase_load_amps{phase="L3"} 0.63


# HELP power_usage_total_kWh Accumulated power usage
# TYPE power_usage_total_kWh counter
power_usage_total_kWh{tarif="overall"} 678.7
power_usage_total_kWh{tarif="1"} 244.7
power_usage_total_kWh{tarif="2"} 213.8
power_usage_total_kWh{tarif="3"} 74.0
power_usage_total_kWh{tarif="4"} 145.9
```

B Source code

B.1 HTTP recorder

```sh
#!/bin/sh
while sleep 95; do
    echo `date +"%s %d-%m-%y %H:%M:%S"`
    echo `date +"%s %d-%m-%y %H:%M:%S"` >> out.txt
    curl 10.0.0.37/metrics \
        --retry 10 \
        --retry-delay 10 \
        --retry-connrefused >> out.txt
    echo "------" >> out.txt
done
```

B.2 Python graphing tool

```python
import pandas as pd
import plotly.express as px
import plotly.graph_objects as go

df = pd.read_csv('data/processed/combined.csv', sep=';')

layout = go.Layout(autosize=True, width=1280, height=720)
fig = go.Figure(layout=layout)

fig.add_trace(go.Scatter(x=df['time'], y=df['load L1'], name="Load (L1)"))
fig.add_trace(go.Scatter(x=df['time'], y=df['load L2'], name="Load (L2)"))
fig.add_trace(go.Scatter(x=df['time'], y=df['load L3'], name="Load (L3)"))

fig.show()
```

Glossary

NIALM non-intrusive appliance load monitoring. 1