Applying Peak-Shaving to Household Devices using an Event-Driven Algorithm

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ABSTRACT

Having peaks in the power usage of households requires the electricity infrastructure to have capacity that can be superfluous at most times. Requiring this extra capacity causes higher electricity generation costs, amongst others. This paper proposes an approach using an event-driven algorithm that is designed to shave peaks of the total power usage of a household. The approach is able to operate with smart plugs that can be attached to almost any device, no matter how old, hereby making the approach highly flexible. The performance of the approach is demonstrated using experiments comprising both real and simulated devices. The results of the experiments indicate that the approach has high potential for lowering peaks in the power usage of households.

Keywords

peak-shaving, demand side management, device constraints, intelligent control, slack

1. INTRODUCTION

The introduction of renewable energy sources (RES) such as wind turbines and photovoltaic (PV) panels, combined with the increasing market share of electric vehicles (EVs) and heat pumps, pose major threats to our current energy infrastructure. In an electricity system, supply and demand need to be balanced to have a working system. When there is too little energy provided, devices cannot work; when there is too much electricity produced, it has no place to go. With non-renewable energy sources we are able to control the supply side of the system. When a lot of electricity is demanded at one moment, we could e.g. raise the heat in our fossil-fuel power station by injecting more fuel. With the introduction of RES this changes, since for example PV panels and wind production are uncontrollable energy sources.

To regain control over the balance in the system we use Demand Side Management (DSM). With DSM, the responsibility of keeping the system in balance shifts from the supply side to the demand side. To fulfil this responsibility, decisions need to be made on whether to increase or decrease power usage at any given moment.

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Another use case of DSM is peak-shaving. Peaks occur when a single or multiple devices draw a significantly higher amount of power at one moment, compared to their combined nominal power usage. These devices could be located across a neighbourhood or in a single house. The electricity grid needs production and transport capacity to deal with such peaks, whereas this capacity might barely be used in nominal use. Requiring this capacity means, amongst others, higher transmission and generation costs. Therefore, it is beneficial to have as few, and as little in size, peaks as possible. Peak-shaving tries to minimise peaks by making the overall power usage as constant as possible. This can, for example, be achieved by letting an EV spread its power consumption by charging at a lower power, or letting devices be planned to draw at a higher power sequentially instead of in parallel, hereby preventing simultaneous high usage.

Even though bigger gains can be obtained by applying peak-shaving to e.g. EVs, see for example [4], it is interesting to investigate what applying peak-shaving to typical white good devices can yield because these white good devices are already in most households. For example, [11] states that refrigerators have an estimated penetration rate of 106% in Europe. Another benefit of trying to control refrigerators is that they can easily be controlled with a smart plug, that needs to do nothing different than being able to measure the power usage and enable and disable the power supply to the refrigerator. These smart plugs can also be used with older refrigerators, that do not have any DSM capabilities of their own, and are therefore easy to use also in households that are not willing to invest in a smart refrigerator.

In this paper, an algorithm is proposed that can apply peak-shaving to household devices by controlling devices with a smart plug, using the total power usage of the household as its main input. Then, the algorithm is demonstrated using real-life experiments. The results of these experiments are analysed and discussed, and afterwards an overview is given on how the proposed algorithm compares to related work.

2. APPROACH

An approach is proposed that can apply peak-shaving using smart plugs that can enable and disable the power supply to a device, and measure the power usage of said device. The approach is built upon the capability of the smart plugs to report the device's power usage when a significant change occurs. If such capabilities are lacking in a smart plug, it is trivial to implement an algorithm that can turn a constantly recurring input of power usage data into an output where the power usage is only reported on a significant change.

The approach uses a metric called *slack*, which expresses the flexibility that a device has left (further explained in section 2.2), to calculate what devices should be turned off. This metric is chosen since it should keep flexibility high while conforming to required objectives. For example, in a hypothetical case of two refrigerators the approach using slack should not get into a situation where only flexibility of one of the refrigerators is used, making it reliant on the second refrigerator only. If in this situation this second refrigerator would lose its flexibility (for example due to a minimum on/off time requirement), no flexibility to remedy peaks would be left at all.

In this section first the different device classes are explored, then the term slack is explained, and then the proposed algorithm is given. The term system is used to refer to the set of devices controlled by the algorithm.

2.1 Device classes

All devices connected to the algorithm are divided into three classes: *Uncontrollables*, *Time shiftables* and *Switchables*. This division of devices is required to know what can be achieved in terms of control for every device.

2.1.1 Uncontrollables

The class of *Uncontrollables* consists of all devices that can not be controlled in any manner (for example because of user availability requirements). These devices solely contribute to the total power usage, and are not used anywhere else in the algorithm.

Examples: microwave, coffee machine

2.1.2 Time shiftables

Devices in the *Time shiftables* class are devices of which the power usage profile can not be changed or interrupted, but are shiftable in time, i.e. the starting time can be controlled. At the moment the algorithm does not control devices in the *Time shiftables* class, but only reads their power usages.

Examples: dishwasher, washing machine

2.1.3 Switchables

Devices in the *Switchables* class have the most control capability of all considered devices. The power supply to these devices can be interrupted at any moment (respecting minimum run-time requirements). Devices in this class often also have a objective to fulfil. For example: a refrigerator has to keep its internal temperature between e.g. 2 and 7 degrees C.

Examples: refrigerator, air conditioning unit

2.2 Slack

Barker et al. define slack in [1] as ”a measure of how long each background load is able to remain off without affecting its objective”. This slack is expressed in minutes, and gives an abstract number that can be implemented per type of device. For example: when a refrigerator's internal temperature increases with 0.5°C per minute, its current temperature is 2°C, and its maximum temperature is set at 7°C, it has $(7-2)/0.5 = 10$ minutes of slack remaining.

2.3 Algorithm

The proposed algorithm is purely event-driven. When a device's slack or power usage changes, an event is triggered that causes a corresponding method to be called. For the overall system a power usage threshold T is configured. This T needs to be set such that on a power usage lower than T no peak-shaving needs to be applied.

When a device's slack changes (for example because of an internal temperature change, in the case of a refrigerator), it is calculated whether the current slack still complies with the device's objective, if not, the supply of power to the device is enabled. In the refrigerator example this ensures the internal temperature stays within defined limits.

When a device's power usage changes, the total power usage P_{sum} of the entire system is measured. If $P_{sum} > T$, the difference $\delta = P_{sum} - T$ is calculated. Then the devices are sorted in descending order of available slack, giving the sorted list $(d_1, ..., d_n)$, with n being the number of devices in the system. Given that P_{d_i} is the power usage of device d_i, devices $(d_1, ..., d_k)$, with $1 \leq k \leq n$, are chosen such that $\sum_{i=1}^{k} P_{d_i} \geq \delta$ and $\sum_{i=1}^{k-1} P_{d_i} < \delta$ if $k > 1$. In words: $(d_1, ..., d_k)$ is the set of devices with the most slack available out of all the devices that are required to be switched off to bring the total power usage below threshold T.

3. EXPERIMENTS

To test the proposed algorithm, real-life experiments were conducted.

3.1 Setup

To test the algorithm several real devices and some virtual ones were used. The real devices consisted of two refrigerators, a microwave, a coffee machine and a dishwasher. Smart plugs of type PlugWise Circle [9] were installed in-between the devices' plugs and the wall outlet. These Circles measure the power usage of the devices and are able to switch the power supply on and off. In one of the refrigerators a temperature sensor was installed. More on this temperature sensor in section 3.1.1.

The Circles were wirelessly connected to a Raspberry Pi [10] running openHAB2 [8]. The openHAB platform supports Jython [6] scripts to automate the control of the devices and implement the virtual devices. These virtual devices are implementations of a model of a refrigerator, mostly based on one of the real refrigerators of the experiment. Section 3.1.2 goes into more details on these virtual refrigerators.

Both the virtual refrigerators and the controlled real-life refrigerator were given a minimum on/off time of two minutes. This means that when the state of the supply of power is changed (for example from off to on), no change is allowed to occur in the next two minutes. This is to prevent damage or lifetime degradation to a (hypothetical) refrigerator caused by rapid switching of the compressor (see e.g. [2]). Although a shorter time than two minutes could probably be sufficient to prevent possible damage, the time is intentionally set long to explicitly show the effects of such a minimum on/off time on the performance of the algorithm.

3.1.1 Temperature sensor

In one of the refrigerators of the experiment, a temperature sensor was installed. This temperature sensor was connected wirelessly to the openHAB controller. The readings from the sensor allowed the actual slack of the refrigerator to be calculated. The sensor was placed in the door of the refrigerator, packed between goods. This means the temperature measured did not increase and decrease as fast as the air temperature inside the refrigerator. For reference, appendix A.2 shows the characteristics of the same refrigerator, but with the temperature sensor placed freely on a shelf in the middle of the refrigerator. The temperature sensor was moved from the middle of the refrigerator

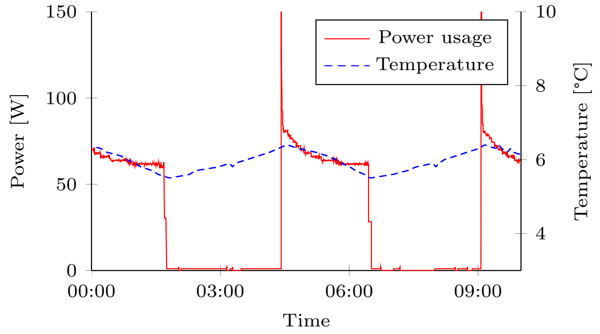

Figure 1. Sample characteristics of a refrigerator, with temperature sensor placed in the door

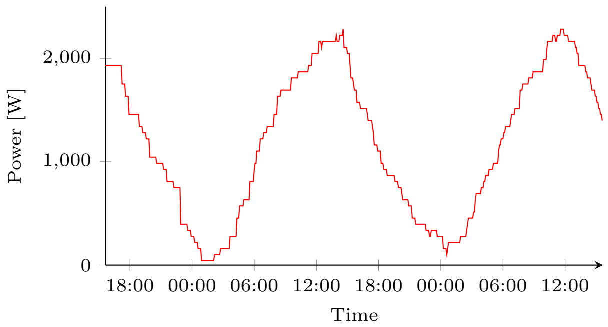

Figure 2. Two days of the power usages of forty virtual refrigerators after start-up, summed

to its final place in the door of the refrigerator to ensure connectivity between the transmitting sensor and the receiver. For the virtual refrigerators the speed of change of temperature were derived from the measurements taken from the sensor placed in the door of the refrigerator, but the turn on and turn off temperatures are set further apart, to increase variance between virtual refrigerators. Also note that the actual temperature of the virtual refrigerators does not matter for the experiments, as long as each refrigerator has a varying temperature, and thereby slack.

3.1.2 Virtual refrigerators

In the experiments system there is only one real device of which the actual slack can be obtained, namely the refrigerator which has a temperature sensor installed. Since the effects of the proposed algorithm can hardly be shown with this single *Switchable* device, simulated refrigerators are added.

The virtual refrigerators are modelled with the following characteristics, derived from the characteristics of a real-life refrigerator shown in figure 1:

- The temperature at which the refrigerator would start cooling (if it has power) is set at 7.0°C;
- The temperature at which cooling is stopped is set at 2.0°C;
- The cooling power usage is set at 60W;
- The idling power usage is set at 1.05W;
- The internal temperature increases with 0.005°C each minute when not cooling;
- The internal temperature decreases with 0.01°C each minute when cooling;
- Every minute there is a 1/100 chance of having the refrigerator's door opened. A door opening increases the refrigerator's internal temperature with 0.2°C.

When the openHAB system was turned on, each virtual refrigerator would start in the following state:

- Power supply switched on;
- Internal temperature of either 2.0, 3.0, 4.0, 5.0 or 6.0°C.

The possible internal temperatures were distributed as equally as possible. The behaviour of the virtual refrigerators after start-up is shown in figure 2.

Although not completely representative compared to real refrigerators, these virtual refrigerators did have characteristics that were most important to this research, namely being controllable with an on/off switch, having a significant power usage at moments (when cooling), and having an easy to read slack characteristic. A linear model for the temperature changes was chosen because of its simplicity.

3.2 Results

The results of the proposed peak-shaving algorithm will be analysed using the function v_{peak} given by Gerards and Hurink in [5]. This function v_{peak} uses the objective function M_2, which takes a set of power usage measurements $\overrightarrow{p}$ as input, and is given as

$$M_2(\overrightarrow{p}) := \sqrt{\frac{1}{N}\sum_{n=1}^{N} p_n^2}.$$

The objective function aims to penalise peaks, and does so by squaring the power usage measurements.

v_{peak} is formulated as

$$v_{peak} := M_2(\overrightarrow{p}) - M_2(\overrightarrow{p^*})$$

where $\overrightarrow{p}$ is the vector of power usages measured during baseline measurements, and $\overrightarrow{p^*}$ is the vector of power usages measured when the proposed peak-shaving algorithm is applied. The better of a job a peak-shaving algorithm does, the higher the result of v_{peak} is expected to be.

3.2.1 Baseline measurements

First, we take a look at the power usages of the real devices when no control is applied. Figure 3 shows a one hour sample of the power usages of the devices. It is clear to see that there is one specific device (the coffee machine) causing peaks that are approximately seven times the nominal power usage. The lines of the other devices are barely visible.

3.2.2 Five virtual refrigerators

First the algorithm was applied to a system with five virtual refrigerators. However, the algorithm was not given control. This phase of the experiments was purely used to investigate the possible actions of the algorithm and whether it was implemented correctly.

What was found is that the power usage of several devices in the *Uncontrollable* class largely outweighed the flexibility in the *Switchable* class (including the virtual devices). During this phase the threshold T was set at 1.5kW. As can be seen from figure 3 the power usage of only the coffee machine alone was more than 1.5kW at times. Meaning that when this device had such a peak, the algorithm turns off all refrigerators, and when the device did not have such a peak, all refrigerators could be turned on. While this result did show the algorithm was correctly implemented, it also showed this shortcoming in the setup.

3.2.3 Forty virtual refrigerators

To give the system more flexibility, the number of virtual refrigerators was increased to forty. The threshold T was

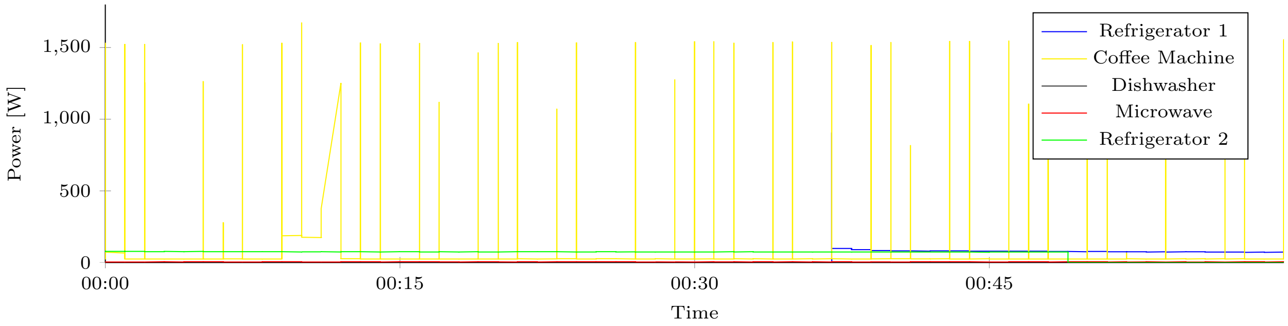

Figure 3. Sample one hour power usage per device

changed from 1.5kW to 2.0kW, to deal with this increase in virtual refrigerators. It was again seen that the algorithm was well implemented, and acted as it was expected to do. However, even though the shortcoming found when using five virtual refrigerators was mostly mended, another shortcoming of the algorithm was found. To demonstrate this shortcoming, figure 4 shows the typical power usages of the forty virtual refrigerators over the period of one hour.

What can be seen is that there are recurring states of having a lot of virtual refrigerators on and having almost none on at all. What was found is that this is an effect of a few factors: the implemented minimum on/off time of two minutes, the fact that the virtual refrigerators themselves are counted in the total power usage (which is as it is supposed to be), the threshold T was set too low, and the virtual refrigerators having too little starting variance. Starting at a situation at time t where no restrictions on power supplies are in place, the accumulated power usage of the virtual refrigerators is almost 2kW on its own, as can be seen from figure 4. When then a peak happens in one of the real devices, the system would often exceed the threshold T of 2kW. Peaks often occurring were peaks from the coffee machine of about 1.5kW. When one of these peaks occurs the algorithm would switch off the power supply of most devices in the *Switchable* class. Since the minimum on/off time then prevents these devices from turning on again in the next two minutes, all slack remaining is in the few *Switchable* devices that are still on. Now, after these two minutes all devices' power supplies are switched on again. Again, the power supply status of all of these devices is not allowed to change for two minutes. At the end of the two minutes, the system is in a similar state to the one on time t, causing the cycle to repeat.

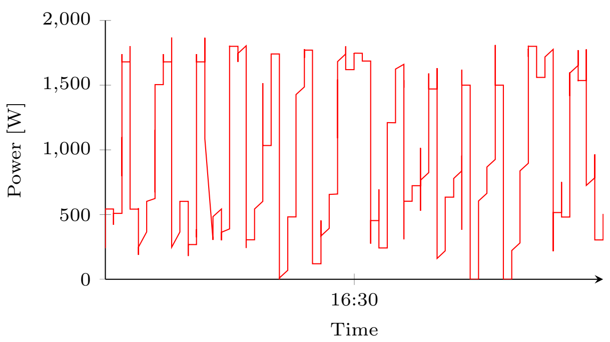

Figure 4. Typical one hour power usages of forty virtual refrigerators with algorithm running, summed

However, this does not mean the algorithm did not perform its job. Taking two five-day samples, one with the algorithm running, and one with the algorithm not running gives the following results:

State	M_2
Algorithm turned off	1555.09
Algorithm turned on	1264.04

This gives a value of v_{peak} of 291.05. Although this value does not mean much on itself, it could be used to compare the performance of the proposed approach with performances of different approaches using the same setup.

3.3 Experiments evaluation

In this section the results of the experiments are evaluated, and afterwards possible improvements to the setup are listed.

3.3.1 Evaluation of results

The value of v_{peak} indicates good performance of the algorithm. Even though cyclic behaviour was found, as shown in figure 4, v_{peak} indicates that the overall number of, and size of, peaks has decreased when the algorithm was running, compared to when it was not. It has to be noted that the results are based on five days of measurements. Even though no preference was taken in choosing these days, it could be that external factors contributed to the demonstrated performance of the algorithm. For example, if in the period where the algorithm was turned off the dishwasher ran, and in the period where the algorithm was turned on it did not, this would possibly influence the value of v_{peak} significantly.

3.3.2 Possible improvements to the setup

Improvements could be made to the setup to improve the relevance of the results of the experiments. Due to time constraints, these improvements were not implemented during the course of this research. Even though there most likely are more, three possible improvements stand out, namely that there could be more variation in the virtual refrigerators, that there could be a better spread of devices turning on after a minimum off time, and the experiments should be done over the course of more days.

The variation in virtual refrigerators, and especially their starting values, could be increased so that there is more variance in the amount of slack per refrigerator. Now, the virtual refrigerators show very similar behaviour, as can be clearly seen from figure 2. This can be explained by the fact that there are only five states a virtual refrigerator can have at start-up, namely

- Power supply switched on;

- Internal temperature of either 2.0, 3.0, 4.0, 5.0 or 6.0°C.

Following from this is that the only variation between virtual refrigerators with the same starting internal temperature is developed over time by the random chance of door openings and different number of times the refrigerator's power supply is switched of by the algorithm. By adding variance to the starting state, e.g. by having some refrigerators' power supply switched off, this synchronisation can be remedied.

Spreading out the turn on moments of the virtual refrigerators might remedy situations as described in section 3.2.3, where a cyclic behaviour of the power supply statuses of the virtual refrigerators is observed. Future research would have to show whether spreading out the power supply switch on moments would actually remedy this problem. Gerards and Hurink in [3] propose a method designed to enable DSM algorithms to incorporate minimum run-time constrained devices that might be of use when improving the algorithm proposed in this paper.

As noted in section 3.3.1 the time span of the experiments might have been to short to conclusively show the performance of the approach. Future research would have to re-run the experiment with a larger time span to prove the performance of the proposed algorithm more conclusively.

4. COMPARISON TO RELATED WORK

4.1 SmartCap

Barker et al. in [1] propose an approach called SmartCap that is very similar to the one proposed in this paper. They also propose an online scheduler that chooses which devices to turn off based on the devices' slack, and they also only deal with on/off switching. There is however one major difference between their approach and the one proposed in this paper; where their approach calculates what devices to give power once every minute, the one in this paper reevaluates the division of power on each power usage change.

A possible drawback of their approach lies in a situation where the power usage division is calculated at time t, and then a peak occurs a second later. Their approach would only respond to this peak almost a full minute later, whereas the approach proposed in this paper would theoretically respond to the peak immediately.

This event-based nature of the approach proposed in this paper does have a possible drawback compared to the one presented by Barker et al. however. In a situation where multiple power usage changes occur within a very short time span, the controlling system might not be able to calculate its actions before a new change occurs. This could potentially cause a situation where the difference in time between a change occurring and its consequences being applied would continue to grow, since the system cannot find a time to process the entire "backlog" of changes. A possible solution to this problem would be to discard triggers while processing a previous one, but further research needs to be done to find the implications of this change. Note that no manifestation of this possible drawback was noticed during the experiments described in this paper.

4.2 Robust EV peak-shaving

Gerards and Hurink in [4] propose an online planning algorithm initially designed to control the charging of EVs in a neighbourhood. The algorithm is designed such that it has a low communication overhead and uses few inputs. Even though this algorithm can adjust its predictions at the start of an interval, it still has the same characteristic as SmartCap, where a sudden peak is not dealt with until the start of a new interval. The algorithm from [4] is more suited to reducing large, long-lasting peak loads, in contrast to the approach presented in this paper that is designed for sudden peaks, and probably is more suited to deal with short peaks. Research would have to show how well the peak-shaving algorithm from [4] performs in a situation with sudden and short peaks.

5. CONCLUSIONS AND DISCUSSION

In this paper an approach was presented to apply peak-shaving to household devices, using only simple smart plugs to control and measure the devices. Using an experiment that included several real devices, as well as simulated ones, it was shown that the proposed approach seems to perform well. It has to be noted that these results were based on measurements taken from experiments that spanned five days. External factors could have played a significant role in the perceived performance of the approach. Still, it is expected that the approach has significant potential based on the value of v_{peak}. Also, even though the approach is only applied to controlling refrigerators in this paper, it would need no adaptations to also control freezers, which have a much larger potential for use as a buffer device according to [7]. Also other devices such as air conditioning units could be incorporated in a system using the proposed approach without further adaptations to the approach itself.

6. FUTURE WORK

Future work could be performed to improve the approach and the knowledge about its characteristics. In this section several topics for future work are listed.

6.1 Incorporation of control of devices in the Time shiftables class

In its current form, the approach uses power usage measurements from devices in the *Time shiftables* class, but does not control them, even though high flexibility can be offered by some of these devices (see for example [7]). It therefore is interesting to research how these devices can be incorporated in the proposed approach. A possible approach would be to implement the *Time shiftables* devices' slack function as reaching 0 when

6.2 EV (dis)charging

The charging and possible discharging of an EV can offer large amounts of flexibility to a system (see for example [7]). Again, incorporating EV (dis)charging into the approach is therefore highly interesting. It could be a possibility that the (dis)charging of EVs can be incorporated by regarding the charger as a device in the *Switchables* class and introducing a device-specific slack function. For example, this function can be defined such that slack is 0 when the charger needs all available time until planned departure time to complete charging. Barker et al. use a similar method in [1] to incorporate EV charging into their scheduler. Future research would have to show whether it indeed is a possibility to incorporate EV charging into this paper's approach, and what the resulting performance would be.

6.3 Setting the threshold T

In the experiments in this paper, it was attempted to set T such that the total power usage was mostly below T, but would exceed T at times to show the performance of the approach. This, however, has no value in a real world setting. Therefore, it needs to be investigated what a good method for finding the best value for T is.

6.4 Dealing with possible controller overloading

In section 4.1 a possible problem is presented where the controller would be overloaded with changes in power usage and/or slack. It needs to be researched whether this problem could actually present itself. It is highly possible that with the processing speed of current-day computers, such a problem cannot occur. However, when the number of devices connected to the controller is increased, also the load on the controller is increased. For example, no controller would be able to handle an infinitely high frequency of power usage/slack changes with the approach presented in this paper. This means that for any controller there is a maximum frequency of changes it can handle before the problem mentioned in section 4.1 would occur. It could be interesting to research if the possibility of reaching this maximum would limit the possible applications of the proposed approach.

7. ACKNOWLEDGMENTS

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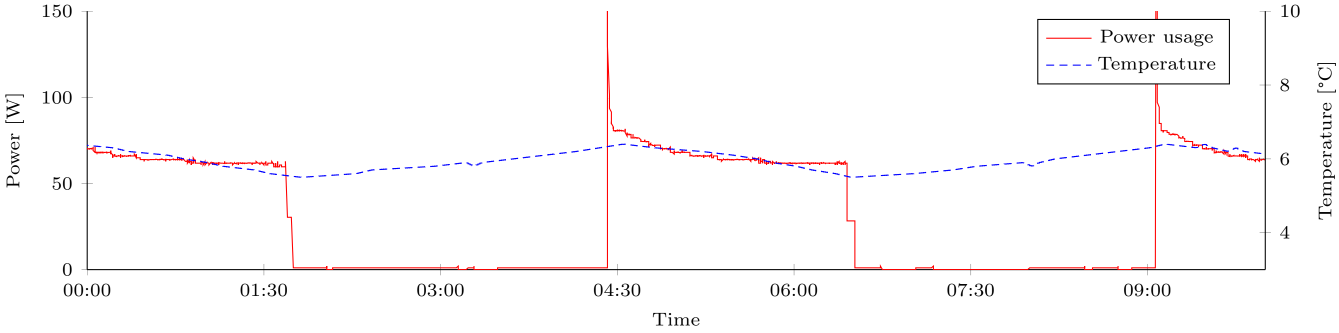
APPENDIX

A. REFRIGERATOR CHARACTERISTICS SAMPLES

A.1 Sample characteristics of a refrigerator, with temperature sensor placed in door



A.2 Sample characteristics of a refrigerator, with temperature sensor placed in the middle of the refrigerator