Tool for optimal dispatch of portfolio of DERs

Ecogrid 2.0, D4.4.2-v2

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1 Introduction

In the project deliverable (Ziras 2019), a model describing the aggregate flexibility of a portfolio of residential thermostatically controlled loads was presented. This model relied on evaluating a large number of flexibility identification tests to understand the behaviour of the portfolio under varying ambient temperature conditions and different hours throughout the day.

The goal of this report is to describe the optimal dispatch of the loads, in conjunction with the flexibility model. In other words, it produces a series of control actions so that a block obtained by the flexibility model can be achieved with the best possible accuracy. The second section describes the loads control during the response period, and the third section during the rebound period.

Due to the limited available information and the considerable uncertainties arising from small aggregations of residential customers with behind the meter measurements, flexibility was modelled by following a top-down approach. In other words, individual models are not constructed for each load, but flexibility is considered in an average, per household manner. Even though each individual load may not offer the same amount of flexibility and may deviate from the expected value, an aggregation of tens of loads will offer the expected flexibility with much higher accuracy. This approach, of expressing flexibility in an average (per household) sense, was followed and tested for the thermal loads participating in EcoGrid 2.0.

2 Control of loads during the response period

An important limitation, which must be taken into account when controlling the available portfolios, is the relatively slow communication and IT infrastructure. The effect of the slow ICT infrastructure on the loads' control is presented in subsection 2.1. Subsection 2.2 elaborates on the stochastic control approach for achieving a specified load reduction.

2.1 Effect of delays

During the tests it was identified that significant delays of the infrastructure may have an undesired effect on the control of loads. As can be seen in Figure 1, load is not substantially reduced at the first 5 min time step of the service (9.05 am), as a result of those delays. It takes 10-15 minutes for all loads to be activated and contribute to the load reduction. Similarly, when the service period ends (9.30 am), load increases by a small amount in the first 5 minutes and then results in a large peak at 9.40 am. Note that the available metering data responds to accumulated energy consumption. Therefore, a reading corresponds to the total energy consumption within a 5 min interval.

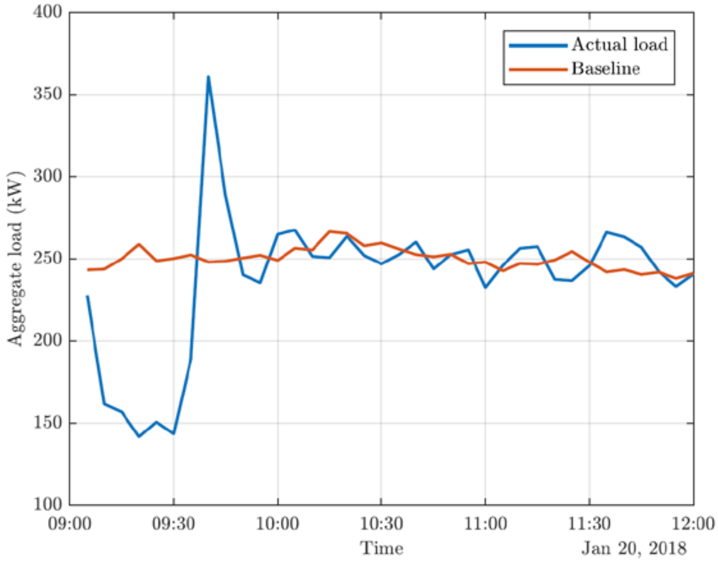

Figure 1: Effect of communication delay on the load response

These delays distort the block shape, which is dictated by the balancing service requirements, even with 15 min metering granularity. This is more stressed during the rebound phase, due to the change of the power deviation sign. In Figure 2 the average, normalized response of the loads from a large number of tests is shown. Regarding both DSO and TSO services, a smaller load reduction value by 33% (compared to the full load reduction) was observed on the first 15 minutes of service delivery, resulting in a "staircase" load reduction. By activating loads 5 minutes before the actual service delivery, this reduction can become smaller than 4%, essentially delivering an almost constant load reduction.

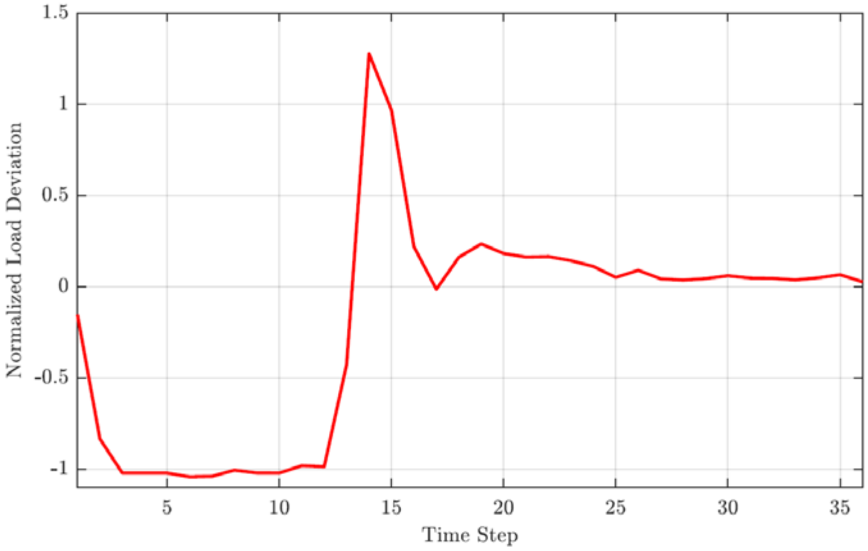

Figure 2: Averaged normalized response and rebound for 60 min tests, in the uncontrolled rebound case [the duration of each time step is equal to 15 min].

As for the rebound, if 15 minutes metering granularity is considered, then the perceived rebound is significantly smaller. An average actual peak of 130% (with reference to the load reduction) on a 5 min metering granularity was identified for 60 tests. This is perceived as a peak of only 60%, when a 15 min granularity is used. This may have a large impact on DSO services delivery. If an aggregator delivers a service with a contracted maximum rebound of 60%, a behaviour like the one shown in Figure 2 will be considered acceptable from a verification point of view, due to the delays and the 15 min metering. A 5 min verification overcomes this problem, as large peaks in consumption are not "masked" by averaging.

For TSO services the impact is similar. A block with a rebound of 60% (with reference to the response) will be considered acceptable from a service verification point of view with 15 minutes granularity. However, in the first 5 minutes of the rebound, the loads will be still offering up regulation, while the TSO would expect the loads to offer down regulation. In the next 10 minutes, loads will offer down regulation, but three times more than the TSO would expect. These large deviations from the ideal rebound behaviour may be acceptable according to the service requirements, but it is possible that they will have a negative impact on system-balancing, resulting in increased activation of frequency reserves.

Remark:

Delays depend on the type of equipment (Siemens vs Greenwave), the use of the Flexibility Interoperability Platform (FIP), and the number of activated loads. The use of the FIP initially caused problems with large delays and failure rates, which were later on to a large extent resolved. Various modifications on the ICT side (with and without using the FIP) and the smaller size of the portfolios used during testing significantly reduced delays throughout the project. In general, such delays can be overcome by more careful design and use of the ICT infrastructure, or some modifications on the control of the loads. It is also worth-noting that physical delays in the control of electric panels are negligible, whereas in heat pumps these can be larger, especially in their deactivation.

2.2 Control of response

Flexibility is described in normalized terms, i.e. in kW/house. In (Ziras 2019), flexibility per house was modelled via the following equation:

$$y = a_0 + a_1 T + a_2\, ToD_{real} + a_3\, ToD_{im}$$

Parameters a_0, a_1, a_2, a_3 were chosen by fitting the test results as a function of ambient temperature and time of day. The above equation describes load reduction potential as a function of ambient temperature T and hour of day h. Time of day is transformed to the real and the imaginary planes as follows:

$$ToD_{real}^{k} = cos(h2\pi/24),$$

$$ToD_{im}^{k} = sin(h2\pi/24).$$

If a portfolio of N loads is available for a service, then the maximum load reduction which can be achieved is equal to $P_{\mathrm{res}}^{\mathrm{max}} = y \cdot N$. If a specific load reduction $P_{\mathrm{res}}^{\mathrm{target}}$ smaller than $P_{\mathrm{res}}^{\mathrm{max}}$ needs to be achieved, then a fraction r of the loads will be activated, given by

$$r = \frac{P_{\mathrm{res}}^{\mathrm{target}}}{y \cdot N}.$$

Since loads have similar characteristics and we are interested in their aggregate response, flexibility is treated in an averaged manner. To this end, loads are selected randomly to be activated. It must be noted that the flexibility per household of a particular subset of the portfolio is assumed to be equal to the flexibility of the whole portfolio. For this reason, the same flexibility model (corresponding to the whole portfolio) is used for a subset of loads, assuming they present a similar behaviour. Stochastic control, i.e. random selection of houses to activate, is done because flexibility was modelled with a top-down approach and without modelling individual houses.

Two important control aspects must be mentioned. The first is the slow activation, as described in the previous subsection. By starting service delivery a few minutes earlier, the limitations of the slow ICT infrastructure can be overcome, since by doing so, most of the load reduction will be achieved in the first 5 minutes of the actual service delivery period.

The second aspect is related to control failures. During testing it was observed that not all houses can be used for providing flexibility. This can be attributed to a variety of reasons related to communication failures and software problems. An empirical success rate is required to upscale fraction r. The empirical success rate in HS2 was found to be approximately 85%. This means that if a service delivery would require 50% of the loads to be activated, then the aggregator would try to activate approximately 60% of the loads, to be able to activate the desired share of loads in the end.

3 Control of loads during the rebound

3.1 HS2

The simplest strategy to follow after a load reduction has ended is to release all loads, i.e. to reset their thermostat setpoints to their “normal” values. By normal setpoints we refer to the thermostat setpoints defined by the users, which are followed if no external control from the aggregator is applied.

A simultaneous reset of the thermostat setpoints after the load reduction results in the averaged uncontrolled rebound behaviour shown in Figure 2. The issue of the small load reduction in the first time step of the load reduction was addressed in the previous section, and can be corrected by an earlier activation of the loads. We refer to this behaviour as the uncontrolled rebound, because no effort to alter or shape the rebound is applied.

Due to the delays, a small load increase (in relative terms) occurs at the first 5 minutes of the rebound period, but still the load deviation is negative with the baseline as a reference. A peak (and an actual rebound with reference to the baseline), is observed 10 minutes after the end of the response period.

Rebound can be shaped to produce a smoother behavior, which is closer to the shape of a block, or which is lower than a specified maximum rebound level. The first is more interesting for the balancing market, where the bids submitted to the market have the form of asymmetric blocks. The second is more relevant for DSO services, where a load reduction must be followed by a rebound which does not exceed a predetermined level.

To shape the rebound, mostly cases of 60 minutes of load reduction were tested. It is assumed that loads which remained switched off after the response period continue to contribute with the same amount of load reduction. A share of loads that is released exhibits a rebound behavior as depicted in Figure 2. It is then possible to superimpose the load values of the released and unreleased loads. By sequentially releasing shares of households, their rebound can be calculated and superimposed on the behavior of the unreleased loads.

Let P_t^n describe the profile depicted in in Figure 2 with t = 1,…,36. If a represents the share of released load, then the expected behavior of the loads can be calculated as:

$$P_t^{reb} = \begin{cases} P_t^n, & t = 1, \dots, 12. \\ P_{12}^n \left(1 - \sum_{i=13}^{t} a_i\right) + \sum_{i=0}^{t-13} a_{t-i} P_{13+i}^n & t = 13, \dots, 36. \end{cases}$$

Note that in the above equation the rebound is controlled at the end of a 60 min load reduction test. Due to the delayed response, it is reasonable to start releasing loads before the end of the test. In this way, a rebound in the shape of a block can be better tracked. If loads are released gradually by starting at time step t_r, the expected behavior can be calculated as

$$P_t^{reb} = \begin{cases} P_t^n, & t = 1, \dots, t_r. \\ P_{12}^n \left(1 - \sum_{i=t_r+1}^{t} a_i\right) + \sum_{i=0}^{t-t_r-1} a_{t-i} P_{t_r+1+i}^n & t = t_r + 1, \dots, 36. \end{cases}$$

The evaluation of many demand response activations showed that for resistive heaters a large rebound is followed by a moderate increase of consumption. This increase largely diminishes after a period equal to the load reduction. Looking at Figure 2, for an hourly load reduction any noticeable rebound occurs for one hour. For this reason, a period equal to at least twice the load reduction was left for the households to return to their steady state. Heat pumps exhibit a similar behavior in terms of power, albeit with a longer rebound period (power after the initial peak takes longer to return to the steady-state value).

To limit any adverse effects on user comfort, most load reductions lasted for maximum one hour. Consequently, the considered rebound period of two hours was sufficient. A few tests with two-hour load reductions were carried out and showed that this results in an average temperature drop of 0.5ºC. However, only a limited number of such tests were conducted and normally load reductions were considerably shorter. For more details see deliverables (Heinrich, HS3 Evaluation: Extending the flexibility model by increased duration 2019), (Heinrich, HS3 Evaluation: Rebound effect 2019)

Due to the nature of the rebound and the relatively long time it takes to conclude, it is hard to control the loads such that near-perfect tracking of a block can be achieved. Even if the rebound peak is contained and is kept below a certain value, some "residue" load deviation will exist afterwards. To this end, for each rebound block of a certain duration, the rebound power which can be best tracked was found. To evaluate the tracking performance, the Euclidean norm was used. This results in a simple optimization problem, where the shares of load to be released are determined.

First, a rebound of 60 minutes was examined. The goal is to control the loads so that an approximately constant rebound power for 60 minutes after the load reduction is achieved. The block resulting from the optimization can be seen in Figure 3. The sequence of released shares is: [0.45, 0.1, 0.2, 0.1, 0.05, 0.05, 0.05], starting 5 minutes before the end of the load reduction. The rebound can be contained to a very small value of 0.2 relative to the reduction. Due to the aforementioned small, but long-lasting load increase, a relatively small tracking error results occurs between hours 2 and 3.

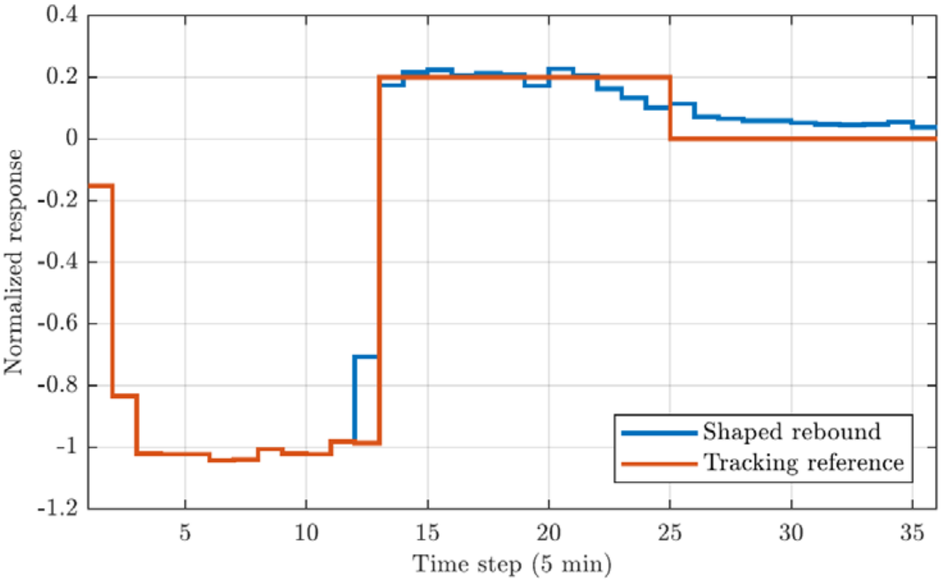

Figure 3: Shaped rebound behaviour for a 60 minutes rebound block

Next, a rebound of 45 minutes was examined. The block resulting from the optimization can be seen in Figure 4. The sequence of released shares for this case is: [0.5, 0.05, 0.2, 0.1, 0.05, 0.05, 0.05], starting 5 minutes before the end of the load reduction. The rebound is again contained to a very small value of 0.2 relative to the reduction. Due to the smaller rebound of 45 minutes, the tracking error after the rebound is larger compared to the 60 minutes rebound case.

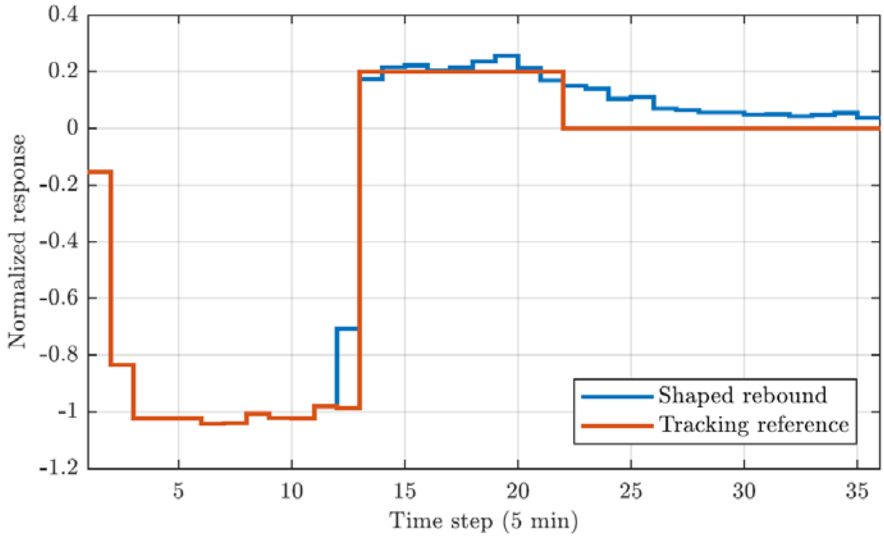

Figure 4: Shaped rebound behaviour for a 45 minutes rebound block

Finally, a rebound of 30 minutes was examined. The block resulting from the optimization can be seen in Figure 5. The sequence of released shares for this case is: [0.5, 0.1, 0.2, 0.1, 0.1], starting 5 minutes before the end of the load reduction. The rebound is now equal to 0.3 relative to the reduction, but even larger tracking errors after the rebound are expected.

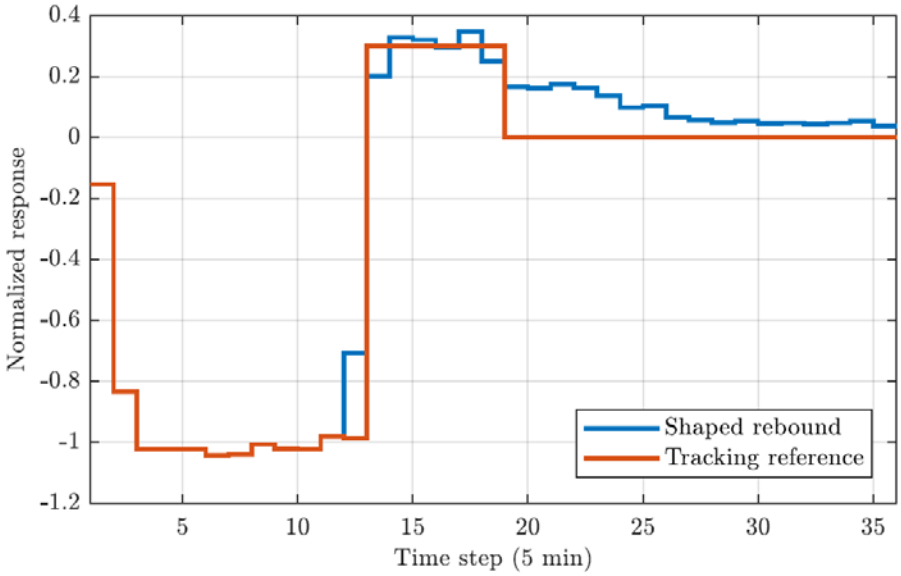

Figure 5: Shaped rebound behaviour for a minutes rebound block

The rebound model was validated by conducting a series of experiments. In Figure 6 the results from five different tests are presented. NH denotes the number of houses participating in the test, and T^{amb} is the ambient temperature during the test. The different release sequences are presented in Table 1. In the first column the release shares are shown, whereas in the second column the time these releases were executed is shown. The time reference is the end of the load reduction, i.e. 0 means that the corresponding release share was conducted right at the end of the load reduction.

Test	Release shares	Time [min]
(a)	[50, 10, 10, 10, 10, 10]	[0, 10, 20, 30, 40, 50]
(b)	[50, 25, 25]	[0, 15, 30]
(c)	[50, 25, 25]	[0, 15, 30]
(d)	[50, 25, 25]	[0, 15, 30]
(e)	[20, 20, 20, 20, 20]	[0, 10, 20, 30, 40]

Table 1 – Control release sequences for the 5 conducted experiments

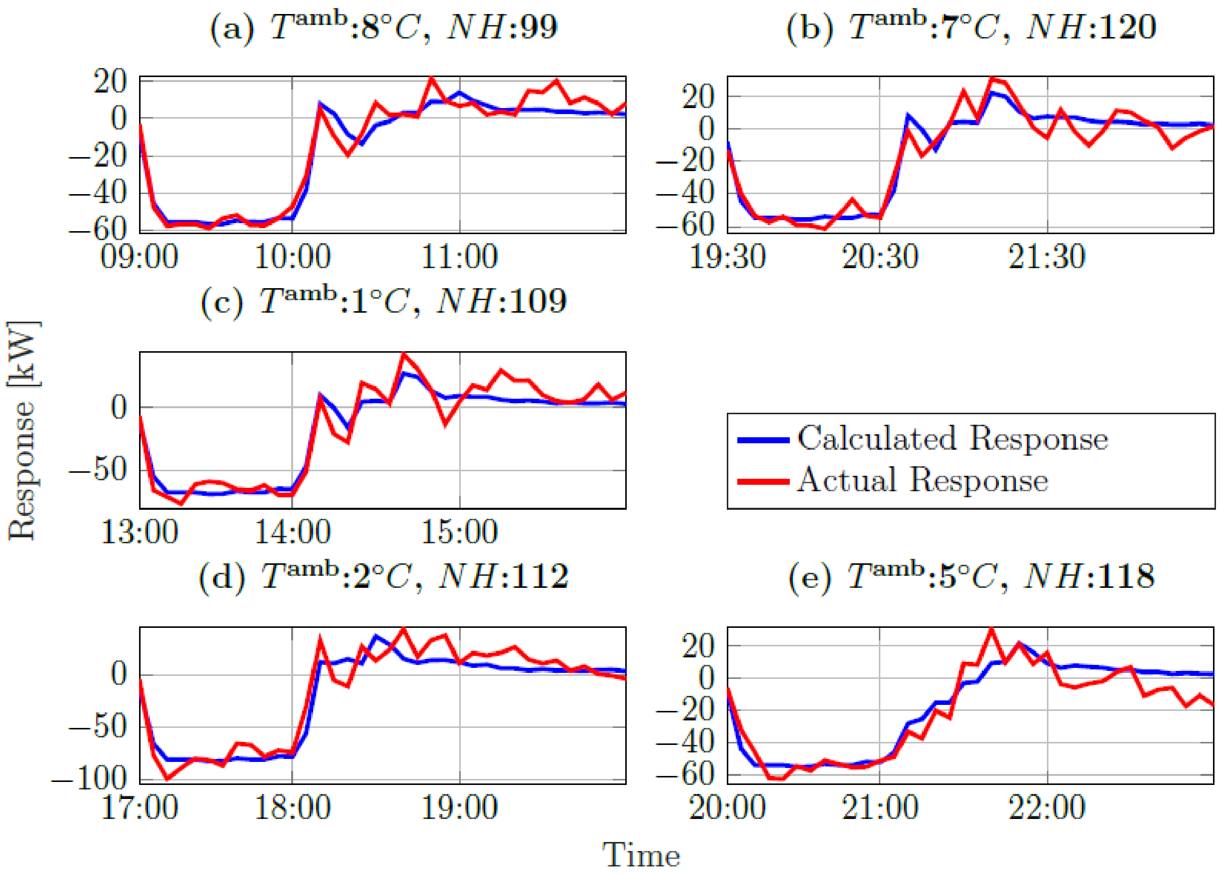

Figure 6: Test results from rebound validation

The rebound model was found to be able to model the behavior of the loads with very good accuracy, as can be seen from the conducted experiments. It is thus possible to use this model and obtain a strategy on how loads should be released, in order to shape the rebound according to the specified requirements.

3.2 HS3

In HS3 each aggregator was controlling both Siemens (resistive heaters) and Greenwave (heat pumps) systems. The same flexibility and control approach, which was developed for the Siemens households and the aggregator Insero, was applied on the mixed portfolio controlled by Insero in HS3.

Figure 7 shows the success rates for Insero in HS3, for both Siemens and Greenwave systems. These results correspond to 52 TSO tests conducted throughout the season and are chronologically ordered. It can be observed that Greenwave households had a considerably better performance, with an approximate success rate of 85 %. Siemens households performed significantly worse, with success rates of 65-80 % until the 30th test, and rates below 70 % afterwards. The overall success rate was approximately 80-85 % for the first 30 tests, dropping to 75 % later.

Two notable large failures of Greenwave households occurred (5th and 49th test). It is also interesting to note that the performance of Siemens households deteriorated substantially after the 30th test, but this is not fully reflected on the overall performance, because Greenwave households constituted the major part of the portfolio.

This relatively large uncertainty stemming from the large failure rates, as well as the large variability of the failure rate, has an effect on service delivery, as an additional uncertainty is added to the control of the portfolios.

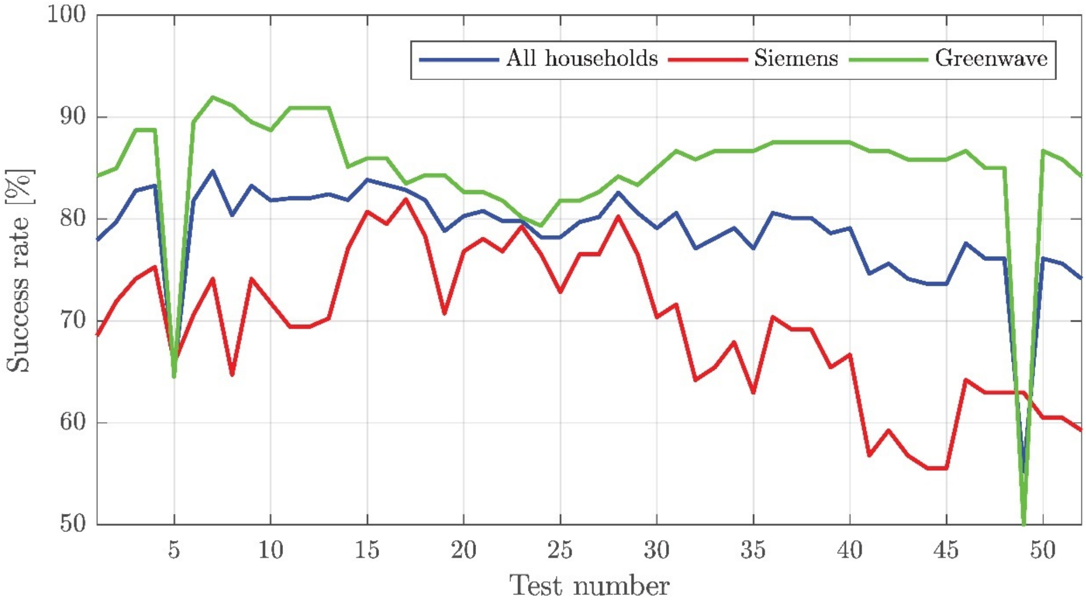

Figure 7: Failure rates in HS3

Various tests were conducted in HS3, both for TSO and DSO services. In Figure 8, the response evaluation results for 52 TSO tests are shown. An overestimation of flexibility of approximately 25 % was observed, which can be attributed to the larger than expected failure rates and the continuous activation of loads. As explained in (Heinrich, HS3 Evaluation: Rebound effect 2019), even though rebounds seem to last for a period roughly equal to one to two times the load reduction period, a small and hard to distinguish increase of consumption is caused, which may last a few more hours. In Figure 9 the rebound evaluation results for the same tests are shown.

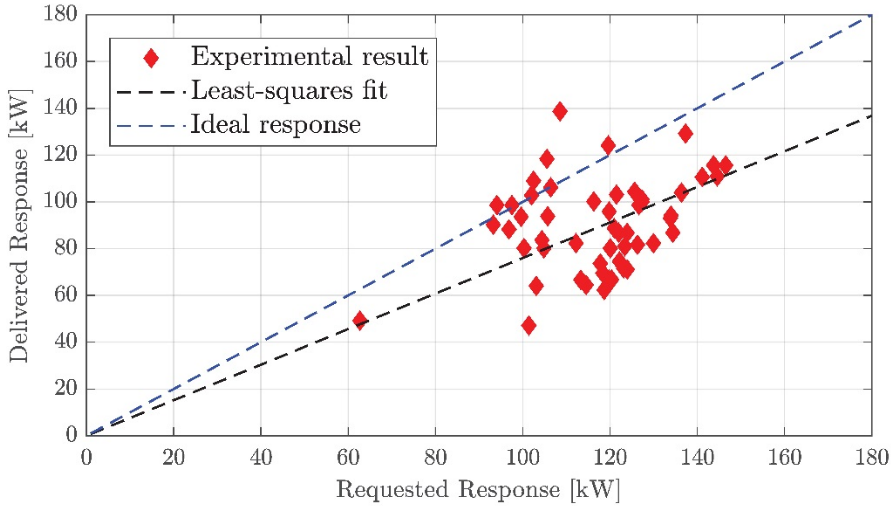

Figure 8: Delivered vs requested response for TSO services during HS3

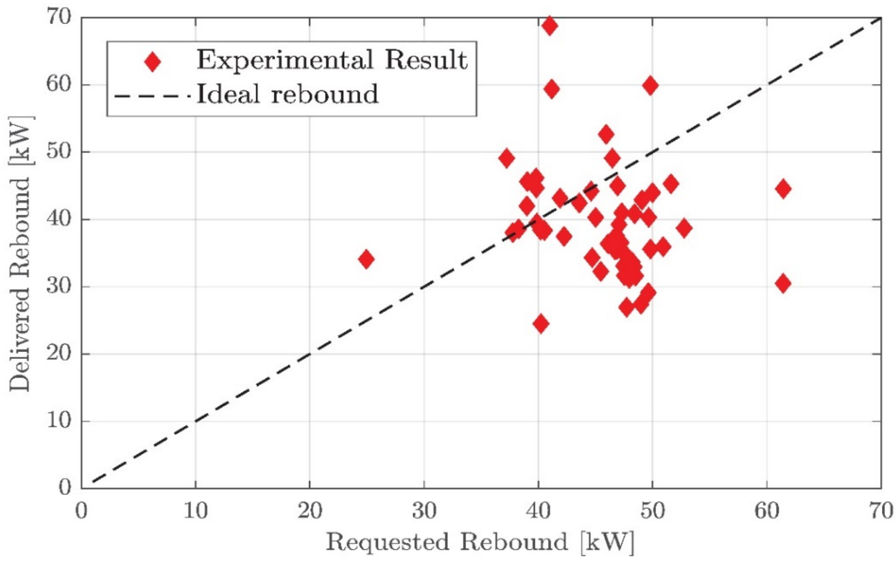

Figure 9: Delivered vs requested rebound for TSO services during HS3

After correcting the flexibility model by 25%, for most of the cases the errors between the requested and delivered response are in the ±30 kW region. This result shows that if the model is corrected to account for the very frequent activations, deliveries can be made with relatively good accuracy. One must note that service delivery is evaluated by constructing baselines, which also have an uncertainty. According to (Ziras 2019), baseline errors with a standard deviation of 7 kW are expected for aggregations of 150 houses, which was the typical portfolio size during the experiments. Also, in (Ziras 2019) portfolios of only resistive heaters are used, whereas in the evaluated experiments of this report a mixed portfolio is considered. The larger – in general – consumption of households with heat pumps most likely leads to larger baseline errors in absolute terms. This happens because houses with large thermal needs usually install heat pumps, and despite their much more efficient operation (compared to electric panels), the overall consumption is usually higher. Regarding the rebound shaping, a good accuracy is observed, especially when one considers the inevitable baseline errors. Most of the delivered vs requested rebound errors are in the range of ±10 kW. More details can be found in (Heinrich, HS3 Evaluation: Balancing service 2019).

4 Conclusion

This report describes the proposed control method to dispatch loads in order to achieve a specified load reduction and a subsequent rebound. A stochastic control approach was followed, where the required shares of loads to be activated are chosen randomly. This ensures that customers are treated fairly and the introduced stochasticity ensures that the expected load behaviours are obtained, because of the averaging effects when using a relatively large number of loads.

A rebound model is proposed, which is based on the average response obtained by a series of tests, where the uncontrolled rebound behaviour of the loads was observed. Based on this, a rebound model was constructed, which can describe the expected loads behaviour when different shares of loads are released at arbitrary points in time.

A series of tests were conducted in HS2 to validate the flexibility model and the rebound shaping, based on information and experience gained from the Siemens households controlled by Insero. The developed methods were able to model and predict flexibility with very good accuracy, considering that the accuracy of the baseline also adds some uncertainty/deviation. They were also able to substantially contain the large peaks in the rebound phase and shape the rebound consumption in the form of asymmetric blocks. An interesting finding is that the rebound, in terms of energy, is smaller than the response. This happens because a few houses are already cooling down during the activations due to a reduction in the temperature setpoint, therefore they don't increase their consumption afterwards. Also, some may heat up during an activation (for example due to cooking or solar irradiance), and do not need to recover heat.

In HS3 the whole Ecogrid 2.0 market setup was functional and aggregators were offering DSO and TSO services continuously, instead of conducting more "controlled" and announced experiments. Additionally, aggregators were controlling mixed portfolios of both heating load types. These additional challenges brought more realistic conditions in the operation of the portfolios by the aggregators. The approach developed for the Siemens households was applied to the Greenwave loads, and a model for mixed portfolios was derived. The evaluation of the results showed that both load reductions and rebounds can be offered with high accuracy. A notable finding is that the very frequent activation of flexibility decreases the load reduction potential and a correction of 25 % must be done to account for this.

Finally, it should be noted that only few load increase tests were conducted. This happened because a large share of the participants owned summer houses, for which a very large overall increase of energy consumption during the experiments was observed. More specifically, the rebound consumptions were very small after the load increases, leading to a substantial energy waste. This happens because usually these houses have very low set-points (of 5^{o} C). For the remainder of the houses, results indicate that load increases also lead to a large waste of energy, but to a much smaller extent compared to the summer houses.

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