European Union
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SUPPORTING THE ENERGY TRANSITION WITH THE INTERNET OF THINGS

OPTIMISING LOCALLY PRODUCED ENERGY ON THE ISLES OF SCILLY

APPENDICES

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Supporting the energy transition with the Internet of Things. Optimising locally produced energy on the Isles of Scilly.

Smart Energy Islands project - final report. Appendices.

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Autor's Note

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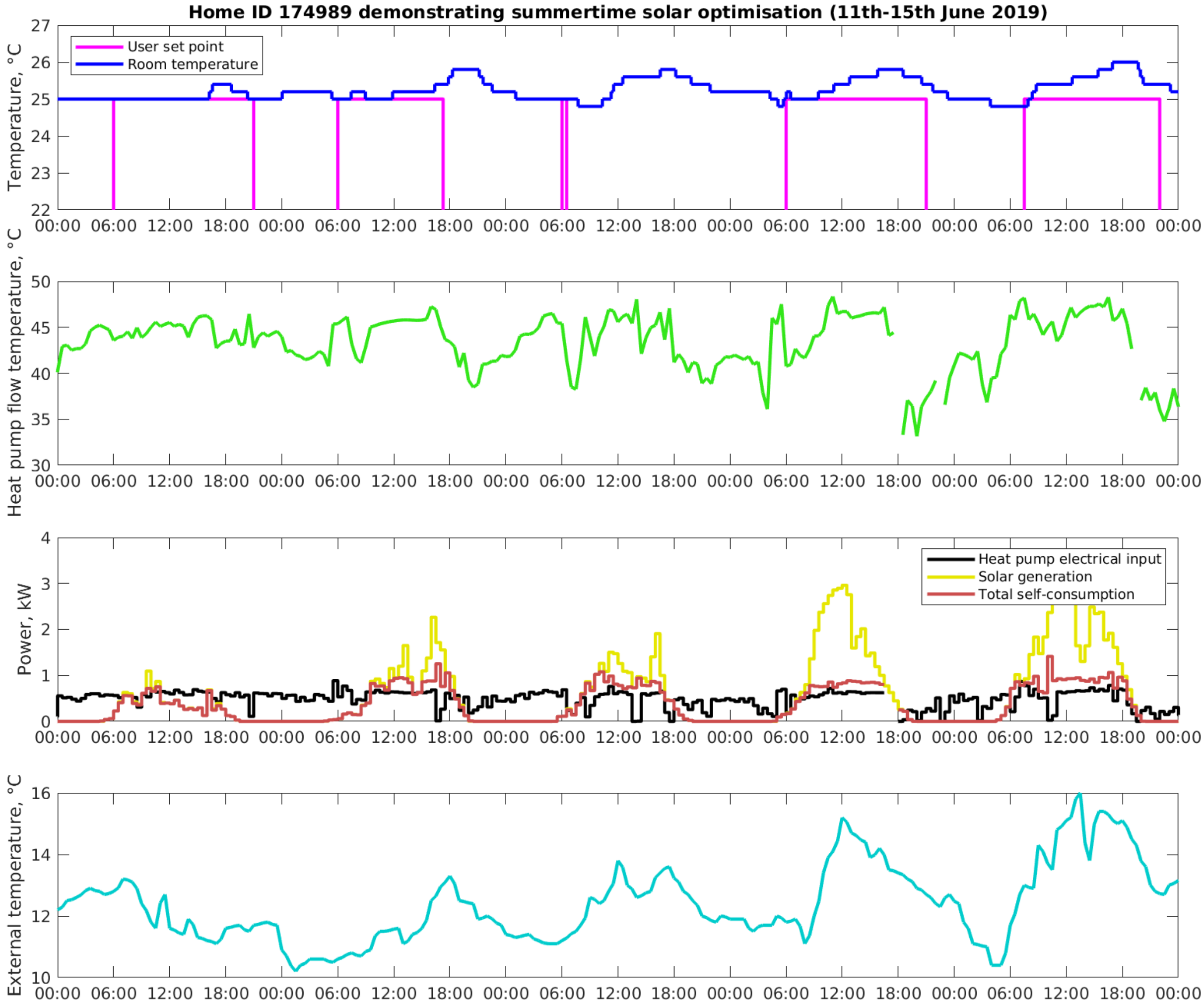
1.1 APPENDIX 1 A – SOLAR-OPTIMISED HEAT PUMPS

CASE STUDY: SUMMERTIME SOLAR OPTIMISATION

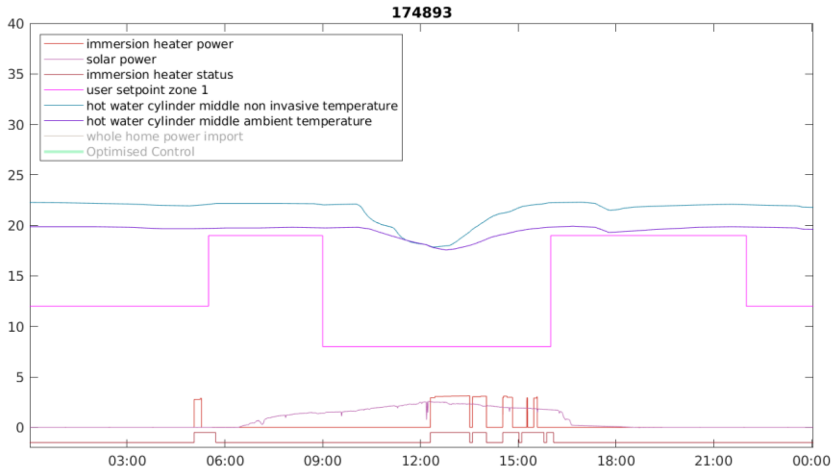


Case study shows time-series graphs of the heat pump at over five days in June 2019 with varying amounts of solar generation. The top figure displays room temperature and the users requested set-point. Solar optimisation is apparent from the increase in room temperature during the day, but never more than 1°C above the 25°C setpoint. The second figure shows the temperature of the water flowing from the heat pump to the radiators. The third graph shows the electrical power input to the heat pump, the solar PV generation, and the total amount of self-consumption. On the first three cloudy days the system is able to self-consume most of the available generation, but on the last two days the generated power (~3kW) is much greater than the maximum input power to the heat pump (~1kW) which is working flat out to try and consume the solar generation. Finally, the fourth figure at the bottom show the external temperatures during this period — it is quite a cold period for June.

1.2 APPENDIX 1 B – SOLAR-OPTIMISED IMMERSION HEATERS

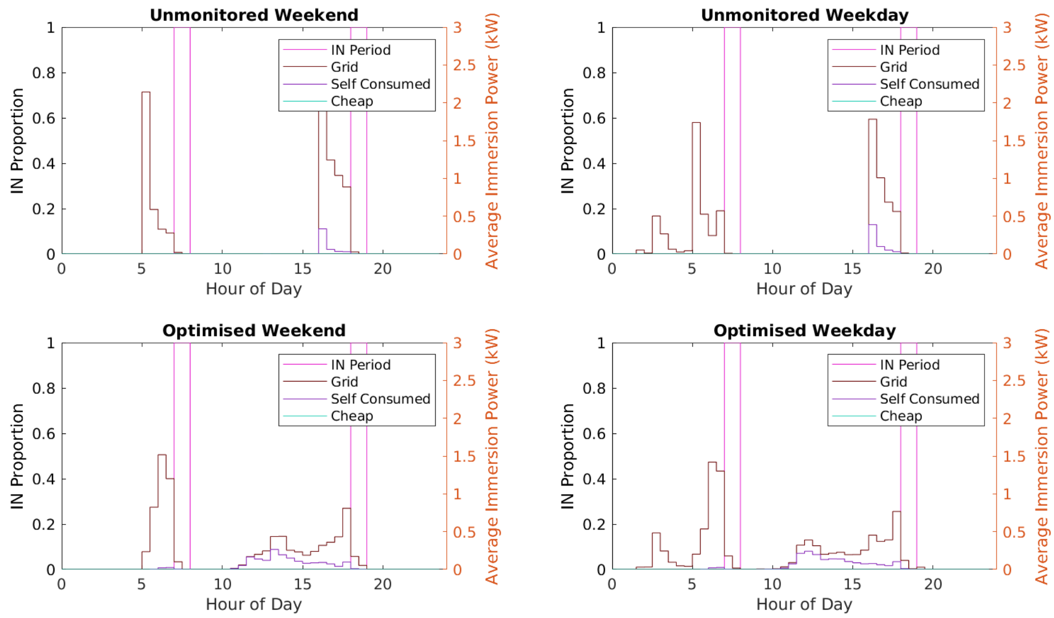
These case studies show the operation of solar-optimised immersion heaters and how much self-consumption was achieved.

CASE STUDY: SELF-CONSUMPTION OF PV GENERATION



In the graph above there is a large hot water consumption event (perhaps a shower) at around 10:00. It is a sunny day and thus the system is able to carry out a prolonged period of solar self-consumption during the day to get the tank up to temperature ahead of the IN period in the evening. The system has ensured that the times of maximum solar are used, to minimise grid electricity use: no further electricity is needed that day.

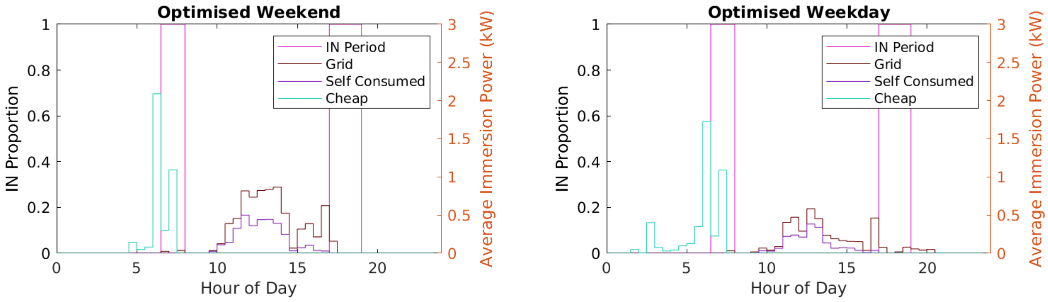
CASE STUDY: SELF-CONSUMPTION WITH AND WITHOUT OPTIMISED CONTROL



The graph above shows average daily profiles of immersion power usage, comparing the non-smart “unmonitored” control with the “optimised” control which carries out self-consumption optimisation and shifts load.

The benefits of just-in-time heating are apparent: under optimised control, the majority of the power is put into the tank immediately before the IN period (reacting to current tank level) as opposed to two hours ahead of the IN period, avoiding cooling losses. Looking at self-consumption, we see a reduction ahead of IN period peaks in the optimised case. This power requirement has been shifted to the middle of the day, where we see a self-consumption curve alongside further grid use (due to sizing of immersion vs. solar panel).

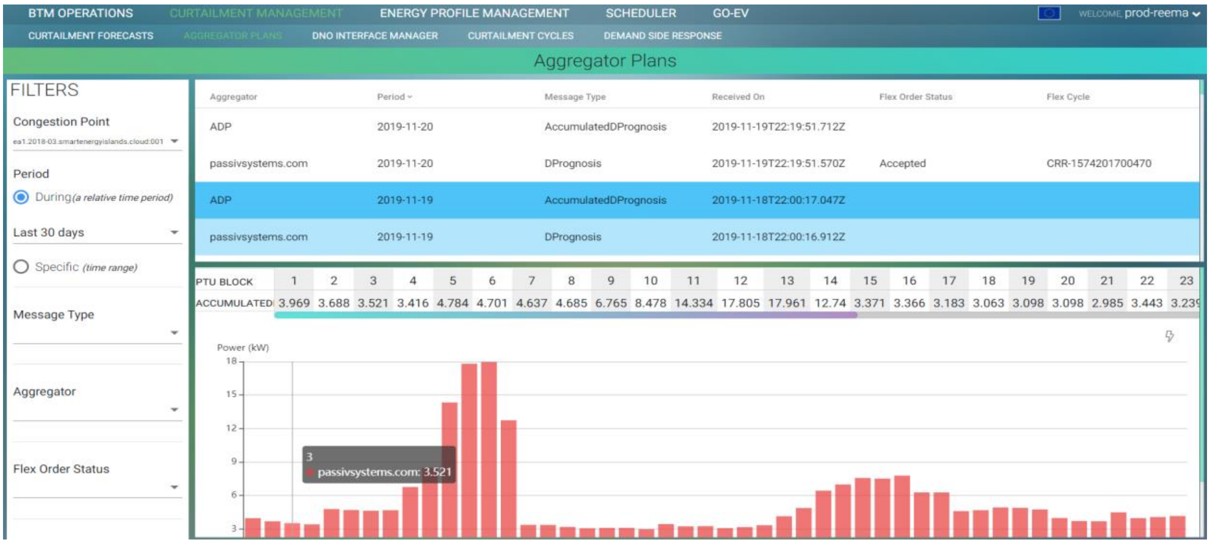
CASE STUDY: HEATING THE TANK WITH CHEAP RATE ELECTRICITY AND PV GENERATION



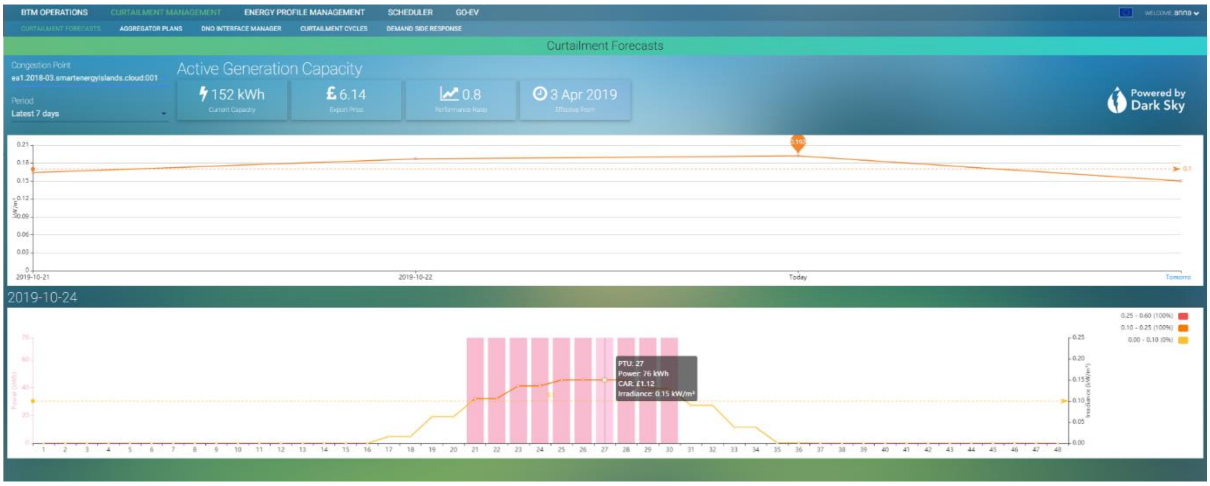
The graph above shows consumption profiles for a home with both solar panels and cheap rate (Economy 7) electricity periods. Most of the electricity heating the tank comes either from cheap rate periods or from solar generation.

2 APPENDIX 2 – HITACHI'S FLEX TRADER

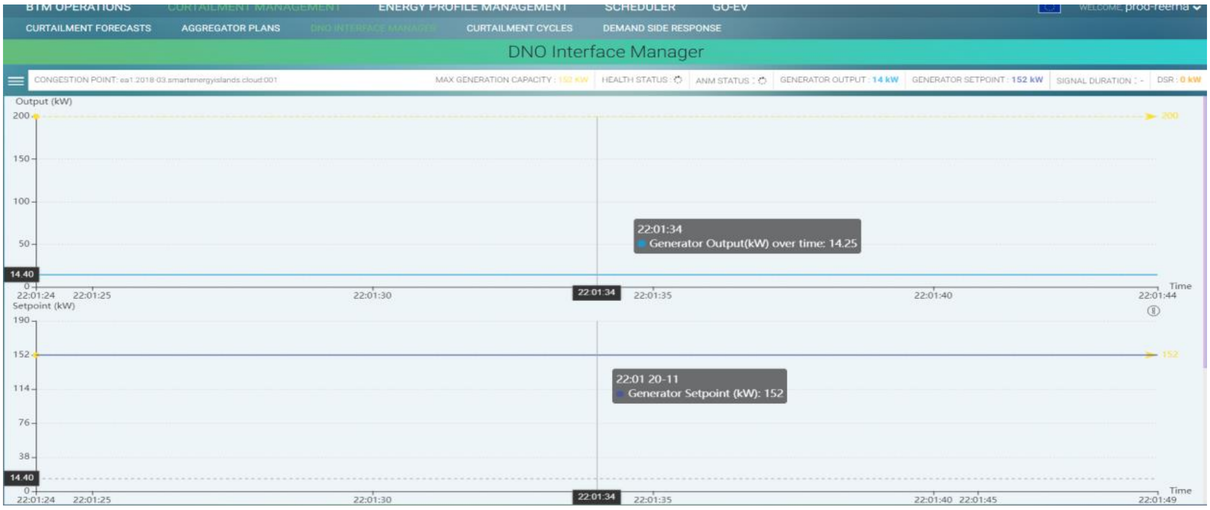
Example screenshots of the Flex Trader - Curtailment Management module:



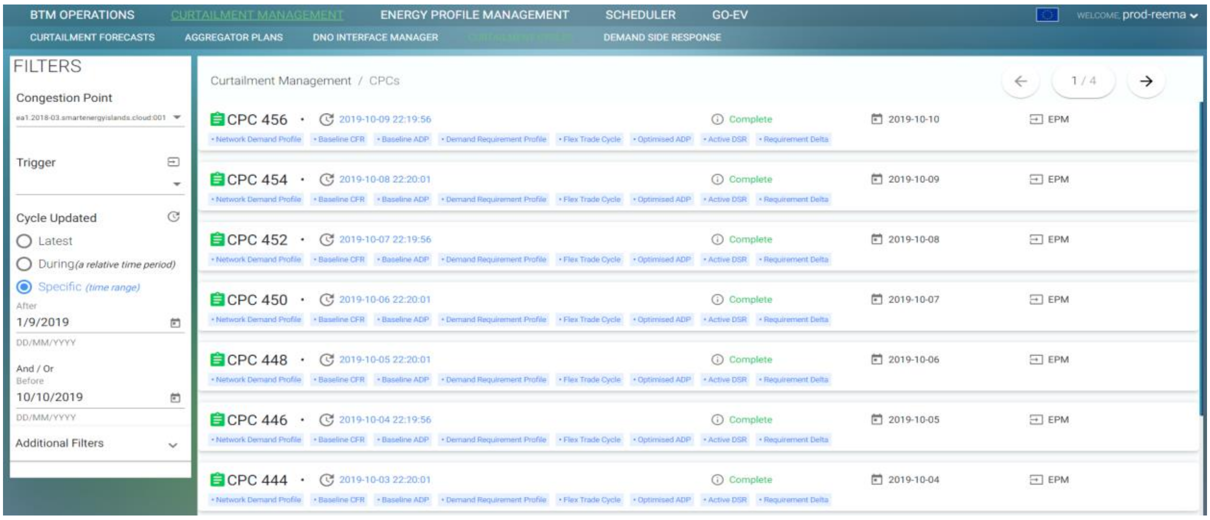
The Aggregator Plans dashboard shows the daily D-Prognosis plans received from the Aggregator for the defined Congestion Point. It indicates the Aggregator's plan for next day for all the households. The Power is defined per PTU (Program Time Unit), where1 PTU = 30 mins for this project. The Flex Trader then Accumulates the D-Prognosis (ADP) plan from all Aggregators to calculate the total power for the following day. This is used as a baseline for Flex Trading.



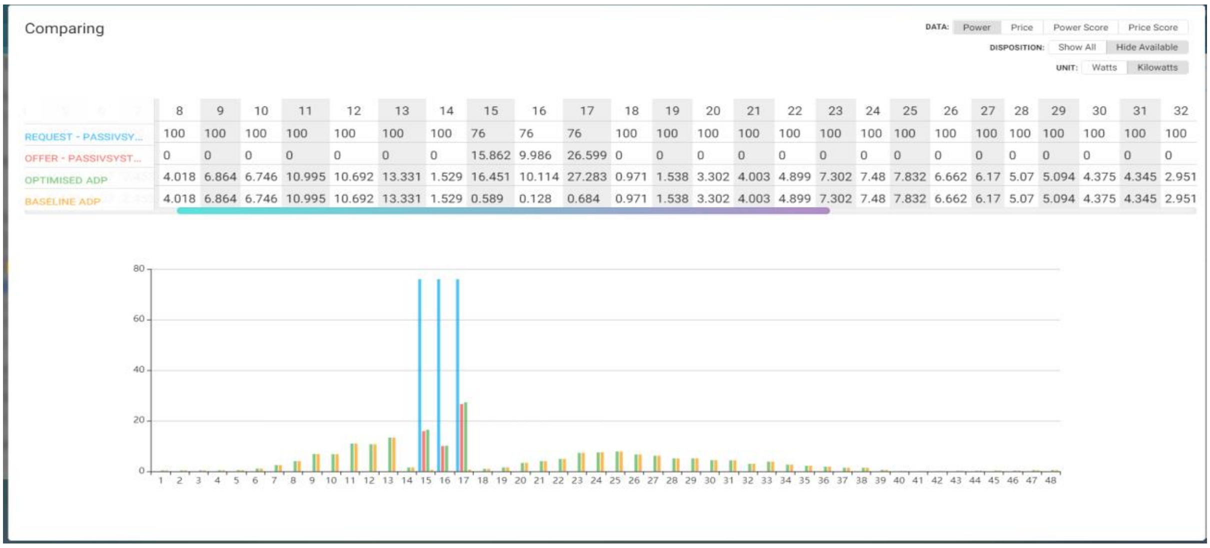
The Constraint Forecasts dashboard shows the solar forecast from Dark Sky and the likely resulting constraint for the following day in order to request flex from the aggregators. For example, the above graph shows that high solar irradiance is expected for PTUs 21 to 30 and therefore, increases the chances of curtailment during that time. This helps the Flex Trader with the Day-Ahead predictive Flex Request Planning.



The DNO Interface Manager shows the ANM status, Generator Output and the Generator Setpoint Signal coming from WPD. In a scenario where the DNO sends a Curtailment Signal, Flex Trader instantly triggers the Intra-Day Cycle to procure flexibility from the Aggregators. This scenario demonstrates use case for procuring flexibility for same day for short duration for e.g. increase or decrease demand in the next 2 hours. Flex Trading between Flex Trader and Aggregators is configured to happen in less than 5 minutes.



The Flex Trader dashboard shows the details of each flex Trading cycle that happened either Day Ahead or Intra-Day.



	8	9	10	11	12	13	14	15	16	17	18	19	20
REQUEST - PASSIVSY...	100	100	100	100	100	100	100	76	76	76	100	100	100
OFFER - PASSIVSYST...	0	0	0	0	0	0	0	15.862	9.986	26.599	0	0	0
OPTIMISED ADP	4.018	6.864	6.746	10.995	10.692	13.331	1.529	16.451	10.114	27.283	0.971	1.538	3.302
BASELINE ADP	4.018	6.864	6.746	10.995	10.692	13.331	1.529	0.589	0.128	0.684	0.971	1.538	3.302

	21	22	23	24	25	26	27	28	29	30	31	32
REQUEST - PASSIVSY...	100	100	100	100	100	100	100	100	100	100	100	100
OFFER - PASSIVSYST...	0	0	0	0	0	0	0	0	0	0	0	0
OPTIMISED ADP	4.003	4.899	7.302	7.48	7.832	6.662	6.17	5.07	5.094	4.375	4.345	2.951
BASELINE ADP	4.003	4.899	7.302	7.48	7.832	6.662	6.17	5.07	5.094	4.375	4.345	2.951

Example Flex Trading Cycle – In the above example the Flex Request was made for PTU 15, 16 and 17 in which PassivSystems offered a 15, 9 and 26 kW increase in demand on top of the baseline ADP- Prognosis. The Optimised ADP shows the adjusted Aggregator plan after the Flex was ordered by the Flex Trader.

3 APPENDIX 3 – EVALUATING AGGREGATOR PERFORMANCE - MOIXA CASE-STUDY

Assessing aggregators of flexibility is a difficult undertaking. Aggregators must be judged as to whether they supplied the change in demand that they offered. Using the aggregator Moixa as a case study, and data concerning their domestic batteries, it was found that using predictions at a household level as a baseline was not an effective means of assessing aggregator actions.

Flexibility calculations using the USEF method were found to be more sensitive to the aggregator's predictive capability than their control of assets. This leads to questions on the attribution of risk and who should be responsible for the risk of predicting household demand.

3.1 USEF IMPLEMENTATION

The USEF framework was adapted in partnership with PassivSystems and Moixa in order to best fit the scope of the project. One definition that is left for interpretation within the framework is the requirement to provide predictions, D-prognoses, at the "connection level".

This was interpreted slightly differently by the two aggregators. PassivSystems opted to supply D-prognosis at the asset level, while Moixa provided the D-prognosis at the whole home level.

3.2 MOIXA'S DATA

Due to a configuration error during the live trials, the actual metered data for the Moixa domestic batteries was deemed to not be representative of their normal operation. To enable a more representative analysis, a simulated data set was used. Real world parameters for the live flex cycles were fed into the simulation to give the battery behaviour with the correct configuration. The data has a simulation error of approx. 2% across the entirety of the simulation period. The mean simulation error of the tool used to simulate individual battery power values has been shown to be a 19.3% in other projects with larger samples. This was deemed a sufficient level of accuracy to be able to draw the conclusions below.

3.3 CASE STUDY

This case study looks at the cases where Moixa's interpretation of the USEF approach, making predictions at a whole home level, may be difficult to deliver for the aggregators. Situations where the aggregator has essentially done what was asked of them (assets under their control have changed their demand) – but the aggregator still falls short of what is required.

To exhibit this, a single flexibility cycle is discussed in detail. The cycle was a day-ahead request for demand reduction to be carried out from 05:00 – 06:30 on 28/11/19.

This cycle was chosen as it shows clearly the issue being explored, though this issue can be seen to a degree in all cycles run with the aggregator. It was also a cycle for which there was no concurrent Passiv cycle, so there are no coordination issues between Passiv and Moixa in the homes where assets are collocated. Also, this cycle took place before sunrise so there was no effect from changes in solar generation. This means that the aggregator was ideally placed to both make a reasonable offer and adhere to it without being influenced by external factors.

3.3.1 CYCLE FLEX DELIVERY

The cycle in question called for reduction in demand, as seen in the flex offer column (*Table 1*). In accordance with USEF, the delivery (the power of flex supplied) is the difference between the D-Prognosis and the Actual metered data.

The desired reduction in demand was only achieved in one of the three 30-minute portions of the flex period. By this measure the aggregator would be deemed to have performed poorly over the flex period with an average delivery of -73%. This would, in a commercial setting such as the WPD's Curtailment Management Zone (CMZ), lead to reduced earnings for the aggregator.

Time	D-Prognosis (Watts)	Actual (Watts)	Flex Offer (Watts)	Delivery (Watts)	Percentage delivery
05:00	5718	5198	-2300	-520	23%
05:30	5725	6695	-2110	970	-46%
06:00	3677	6839	-1604	3161	-197%

Table 1 Flex period for 28/11/19 aggregated to 30 min PTU level

However, this is not the full story. From this viewpoint it is not possible to see the behaviour of the individual devices controlled by the aggregator.

3.3.2 HOUSEHOLD PERFORMANCE

The assets controlled by the aggregator in this cycle were 5 domestic batteries situated in 5 different homes with a nominal 460W max output each.

Each home was assessed against 3 measures. Assessments were carried out for 30-minute periods to give a view of variation of key parameters over the flex period.

BATTERY PERFORMANCE – AGGREGATOR CONTROL OF ASSETS

In the case of demand reduction, this is how well the batteries can discharge (to reduce the total demand of the household from the grid). This battery discharge wattage is compared to a reference case, i.e. what the battery would be doing in the absence of flex, to determine if the discharge is indeed a deviation from normal behaviour. The deviation value is then compared to the flex offer to see how well the assets are supplying the flexibility offered by the aggregator.

ACCURACY OF AGGREGATOR PROGNOSIS

This is an assessment of the aggregator's predictive ability. The cycle took place without external factors that could affect prediction. The period was before sunrise so there was no variation in solar generation. There was also no concurrent flex carried out by PassivSystems with assets in the same homes. Lastly, with the lack of external factors, the battery would normally be inactive in this period. For this reason, the initial prognosis prediction is effectively a prediction of the properties' consumption without considering these other factors. The forecasted baseline property consumption is not affected by the flex cycle and allows for this assessment.

DEMAND REDUCTION ACHIEVED (USEF METHOD)

Demand reduction is calculated as the difference between the D-Prognosis and the Actual metered data. This was done for each 30-minute period.

3.3.3 PERFORMANCE

Table 2 below shows the colour coding used to categorise performance on each of the measures described above.

Measure	Colour	Key
Battery Performance		>80% of offered flex power
		60% - 80% of offered flex power
		<60% of offered flex power
Accuracy of aggregator prognosis		<10% error
		10% - 20% error
		>20% error (Hatched = prognosis overestimate, plain = prognosis underestimate)
Demand reduction achieved (USEF Method – meter readings vs. prognosis)		>80% of offered flex power
		0% - 80% of offered flex power
		<0% of offered flex power

Table 2 Performance measure key

Table three applies these categories to evaluate the performance of the flex cycle discussed in this case study.

	Time	Battery Performance	Property Demand within 10% of prognosis	Demand reduction achieved (USEF Method)
Property 1	05:00			
	05:30			
	06:00			
Property 2	05:00			
	05:30			
	06:00			
Property 3	05:00			
	05:30			
	06:00			

Property 4	05:00			
	05:30			
	06:00			
Property 5	05:00			
	05:30			
	06:00			

Table 3 Household performance during flex

Battery performance was generally good, with most of the batteries discharging at full capacity for large portions of the flex cycles. Predication of household demand proved challenging, with most of the errors being large (>20%). Both over and underestimates were present.

It is clear that in this case the performance of the battery was not a good predictor of whether flex was delivered on household level.

In cases where there is a significant overestimate in household demand, turn-down flex is delivered (on household level) regardless of battery performance. The reverse is not true. When the batteries are performing well but a significant underestimate in household demand was made, flex is not delivered, i.e. even when the batteries are exporting, this is outweighed by the unexpected increase in demand.

One example is property 2 in the period starting 5:30 am. The battery has exported less than the flex offered, however flex is still delivered on household level. This is due to the large overestimate that was made in the prediction of household consumption. With the real demand being lower than what was predicted, we see an artificial reduction in demand.

Figure 1 Property 2 flex cycle power overview

For property 3 at 5:00 am, the battery is performing well. However, with a large underestimate in the household demand, flex is not delivered on household level.

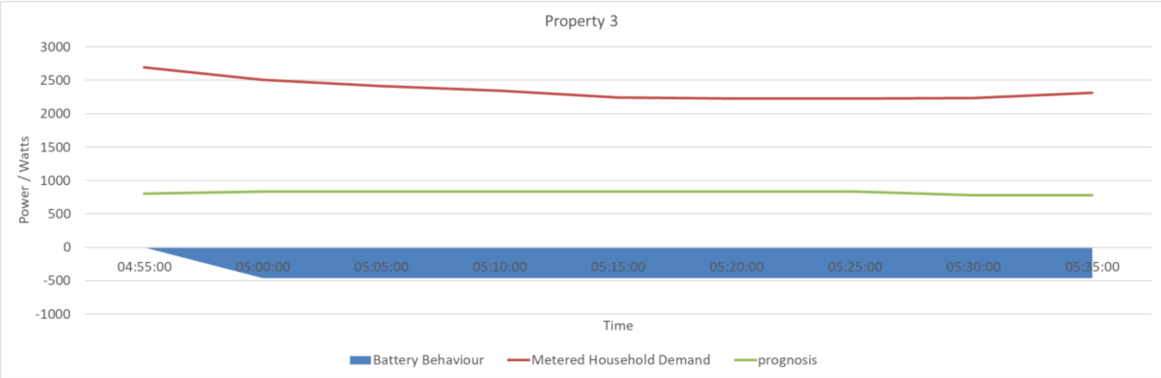


Figure 2 Property 3 flex cycle power overview

Given the small capacity of batteries relative to the whole home demand, the ability to deliver flex against a D-Prognosis on whole home level was more of a function of the aggregator's predictive ability than their control of flexible assets. Flex was only being delivered in cases where household prediction was good or had an error that lead to a favourable calculation.

3.3.4 RISK AND SCALE

With a small portfolio size, there is significant risk of not delivering when baselined against a whole home prognosis. This is a risk that can be mitigated somewhat with scale.

The 5 domestic batteries deployed in the SEI project (and therefore the 5 households used as a baseline) were not of the number required to filter high frequency and spikey usage patterns in single homes. When scale is reached these patterns are filtered, revealing lower frequency and therefore more predictable trends.

When it comes to who should assume this risk, it is Moixa's view that this should be the aggregator. With only the aggregator having the full picture as to the behaviour of their assets during flex, as well as what the behaviour would have been in the absence of flexibility. This risk would also need to be priced into flex offers that were made.

3.4 CONCLUSIONS

USEF leaves "connection level" open to interpretation – aggregators can provide flexibility on asset level or whole home level. Evaluating aggregators and the flexibility they provide at a whole home level may not be an ideal solution in situations where the aggregator controls assets accounting only for a small portion of the demand, or where the demand is highly variable.

We looked at a single cycle from the SEI trials in which the battery aggregator Moixa was deemed to have performed poorly when assessed based on whole home demand changes vs. D-Prognosis. Under closer inspection, it was seen that the assets under control performed well, however predicting household demand proved more challenging.

This brings into question how aggregator performance should be assessed, and the baseline that should be used in a commercial flexibility setting. The current commercial arrangements that Moixa is involved in with WPD and UKPN are based on a fixed baseline – while this may not be ideal from the DSO point of view, it is easier for an aggregator to manage and a good way to incentivise market participation.