SCCER – FURIES
Shaping the FUtuRe SwIss Electrical InfraStructure

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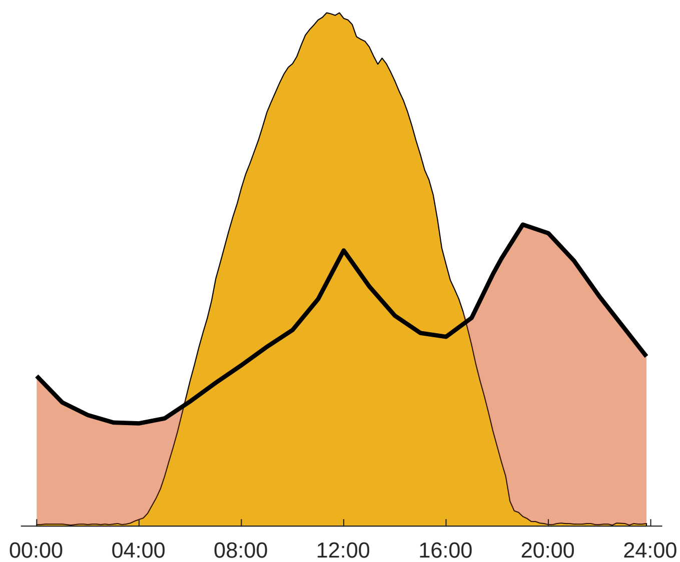
Determination of the flexibilisation potential of the electricity demand



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1 Description of deliverable and goals

1.1 Executive summary

The mismatch between household electricity consumption and solar energy production is a key issue for the fast deployment of this technology in a low-voltage grid. Namely, as high photovoltaic generation occurs during the day while the load remains low, the power flow can be reversed from the low-voltage grid to the medium voltage grid. This is a key parameter in the limitation of the photovoltaic hosting capacity.

In order to increase the penetration of solar energy in a low-voltage network, demand-side management is a promising solution. The principle is to encourage customers to shift their load toward high photovoltaic generation periods in exchange for a financial reward. Namely, time-of-use tariffs can be used as an incentive.

This report presents a field experiment, in which the flexibility potential of household electricity consumption is assessed. Additionally, the impact of this behavioural flexibility is evaluated on the extension of a low-voltage grid photovoltaic hosting capacity. The electricity consumption of about 600 households was analyzed over a period of more than 3 years. The load curves are coming from smart meter data at a 15 min resolution allowing to study the intraday consumption patterns.

The theoretical potential for flexible consumption is evaluated through a dedicated methodology based on non-intrusive load monitoring. It is estimated to be as high as 24% of the total energy consumption. The practical flexibility is evaluated by studying the households reaction to two different financial incentives. A first treatment group was facing a reduction of the electricity price of 15 cts/kWh between 11 am and 3 pm compared to the normal price, while the price was increased by 4 cts/kWh during the remaining of the day. A second treatment group was facing alternative pricing in a form of time-of-use pricing. Every night households received a short-text message (SMS) informing them of the time of the low rate period for the next day, that could potentially range from 10 am to 7 pm. Both treatment groups reaction are compared to a reference control group which receive no information about the experiment. The results showed a moderated reaction of the households. The increase in consumption during low rate period is marginal and doesn't necessarily involve a reduction in consumption during the rest of the day. Additionally, there are significant differences in reaction between the households. Although the financial incentive is significant, the potential gain is rather small and there was no possibility for loss as the households were guaranteed to pay at most the monthly bill calculated with their reference electricity price.

The gain in photovoltaic hosting capacity and penetration rate thanks to the theoretical demand flexibility was assessed to reach 20% while keeping the same total cost of energy with respect to the reference case without flexibility. In this case, it means that the flexibility does not bring any additional revenue. However, as the levelized cost of electricity decreases with respect to the feed-in tariff, the potential revenue generated by the flexibility increases. As an alternative solution, curtailing the exceeding photovoltaic generation always comes with a cost and thus cannot compete with the flexibility to increase the solar energy penetration rate.

1.2 Research question

Flexibility is the key component that every power systems will require in a near future. The willingness to set low carbon objectives in order to keep the global temperature rise below 2 degrees Celsius push for the development of renewable energy production such as wind and solar. Their share of the global electricity generation is expected to reach 36% and 22% respectively by 2050, according to the 2°C scenario (figure 1). Such high share of Variable Renewable Energy (VRE) will enforce the need for flexibility in order to match generation and demand. In other words, according to the latest IRENA report, flexibility in power systems can be defined as :

> "Flexibility is the capability of a power system to cope with the variability and uncertainty that VRE generation introduces into the system in different time scales, from the very short to the long term, avoiding curtailment of VRE and reliably supplying all the demanded energy to customers". IRENA : Power system flexibility for the energy transition [1]

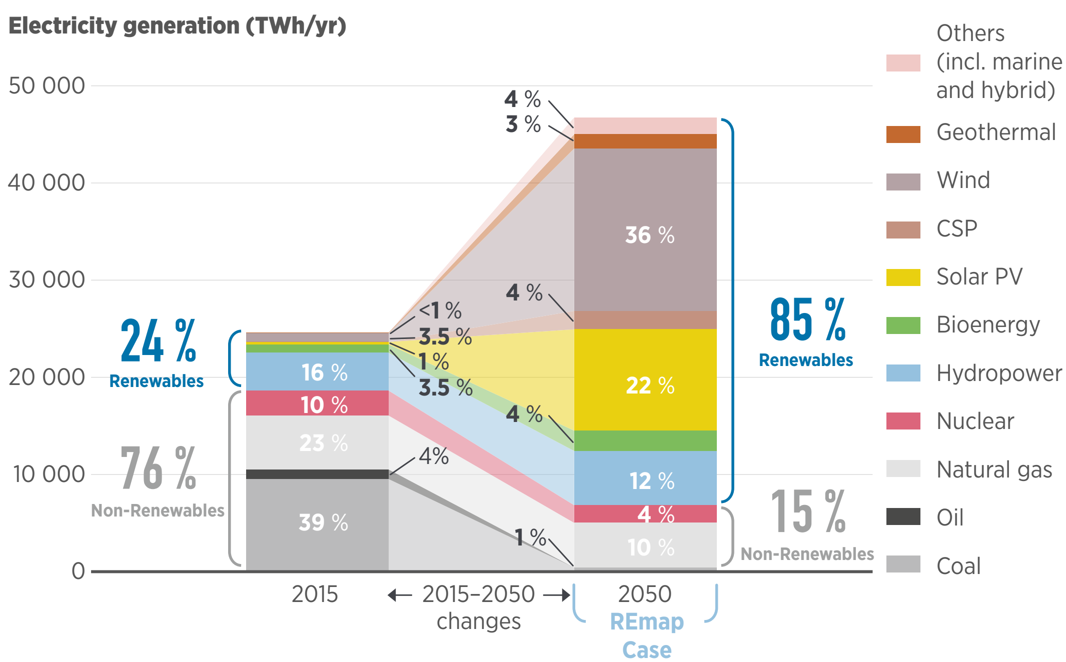


Figure 1: A 2-degree Celsius scenario for electricity generation, REmap Case, 2015–2050 [1]

Switzerland is following the global trend. The annual photovoltaic (PV) generation has been multiplied by a factor 15 between 2010 and 2017 as represented in figure 2. Moreover, to meet the objective for 2050, the annual PV generation should be increased from 1.7 TWh to 11 TWh. This would represent 18% percent of the current electricity consumption (61.5 TWh).

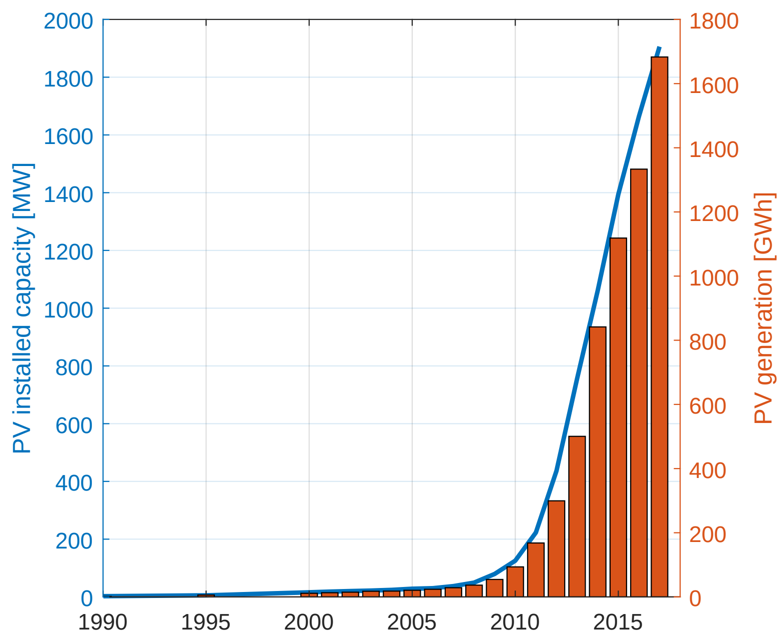


Figure 2: PV capacity and annual generation in Switzerland (data from [2])

In this context, the aim of this deliverable is to quantify the flexibility potential given by behavioural changes, both from a theoretical and practical point of view. The secondary objective is to study the impact of this additional flexibility at the scale of a distribution grid.

1.3 Novelty of the proposed solutions compared to the state-of-art

The approach of the flexi project is at the intersection of two fields. The first consists of technical studies, many of whom described in the review from Kondziella and Bruckner [3]. In this field, technical solutions are proposed to integrate large shares of renewable distributed generation using storage or grid reinforcement. For instance, assuming that washing machines, dryers would be controllable and programmed to be used during periods of high renewable generation, Pina [4] found in some scenarios that 40% of these activities would be shiftable.

In the second field, researchers study the effect of the information on residential electricity consumption, which presents also some sociological approaches. Among the recent contribution, we can cite the work of Buchanan and al. [5], Faruqui et al. [6], Vine et al. [7], and some meta-analysis by Delmas et al. [8] and Ehrhardt et al. [9]. High-frequency data are more and more used in recent work such as in [10, 11, 12, 13, 14, 15, 16] in which the main objective is to promote energy savings, whereas our goal is to induce an intraday shift of the electricity consumption without necessarily encouraging any reduction.

1.4 Description

This deliverable presents the methodology and results of the evaluation of the electricity demand flexibility potential and its impact on the photovoltaic hosting capacity of a distribution grid.

This research methodology is presented in section 4. The flexi experiment is introduced in more details in section 4.1 which also presents the performance metrics. Section 4.2 presents the algorithm used to evaluate the theoretical flexibility potential. Then the approach used to quantify the flexibility contribution to the integration of distributed generation is presented in section 4.3. Finally, section 4.4 introduces the main scores used to evaluate the PV integration.

The results can be found in section 5, where 5.1 focus on theoretical flexibility and 5.2 on the practical flexibility. The section 5.3 proposes an analysis of the impact of the flexibility on the PV hosting capacity. The last section 5.4 presents a brief comparison between the demand behavioural flexibility and the one from domestic hot water heating.

2 Achievement of Deliverable

2.1 Date

This deliverable was handed in December 2018.

2.2 Demonstration of the Deliverable

This deliverable capitalizes on the results of the flexi project demonstrating the electricity demand flexibility potential of residential households.

2.3 Added value of SCCER-FURIES: REeL

The outcomes of the flexi project are the results of a long-term collaboration between the EPFL-PVlab involved in the SCCER-FURIES and the UniNE involved in the SCCER-CREST.

3 Impact

This report is a preliminary study in the context of the work package 4 *Planning and operation of Distributed generation and MW-class distributed storage systems*. It will serve as a basis for the upcoming deliverables, namely *(WP4) Deployment recommendation for large penetration of PV and distributed storage* and *(WP5) Best investment strategies when prosumer capacities are increased in the grid* both due in December 2019.

4 Research methodology

4.1 Introduction to the flexi project

The flexi experiment consists in proposing an alternative energy tariff to a representative panel of households in order to evaluate their ability to change their energy consumption behaviour. In this field experiment, the load curves of over 600 households, customers from the Société des Forces Electriques de La Goule in the Jura region, were analyzed. All of these customers are equipped with smart meters, allowing to study their intraday consumption patterns.

The household panel was divided into two treatment groups. The first treatment group (T1) received, as an incentive to shift their energy consumption toward high PV generation time period, a reduction on the energy tariff of 15 cts/kWh (bonus) between 11 am and 3 pm while outside of this window, the energy tariff was increased by 4 cts/kWh (penalty). This time window corresponds to the period of potentially high PV injection. The aim is here to motivate the households to consume more energy during these time wndows in order to absorb the surplus of PV production. This tariff scheme is applied every day during the whole experiment. The bonus-penalty tariff was designed such that an average household that does not shift its energy makes no loss or gain.

The second treatment group (T2) received a similar incentive in terms of tariff, but the reduced tariff time was correlated with the weather forecasts. Three different time windows for a reduction of the energy tariff were defined:

- Between 10 am and 1 pm
- Between 1 pm and 4 pm
- Between 4 pm and 7 pm (only during summer months).

Each day a SMS were sent to the households mentioning when would the energy tariff be reduced (each window could be activated independently). The forecast of the low rate time window was based on local weather forecasts and precisely on insolation time and cloud coverage.

To motivate the households and prevent any financial risk to participate in this experiment, two bills were sent to the households. The first one contained the energy bill with the new tariff schemes, the second one contained the energy bill with their standard energy rate. The households had to pay the least expensive one. The evolution of the consumption behaviour of the two treatment groups was also compared with a reference group (called control group).

In order to recruit the participant to this experiment, a letter and a survey were sent to the customers of La Goule benefiting of a flat tariff scheme. This condition was set so that only customers without any electrical heating system were eligible in order to keep the focus on the behavioural contribution to the flexibility rather than using any technical artifact (such that central heating scheduling). The objectives of the survey were to gain socio-demographic information about the households, informations on the household composition and equipment and to get the cell-phone number to sent the SMS for the households participating to the second treatment. After the first recruitment wave the quota of participants wasn't high enough, thus a second recruitment was set up. To increase the number of participants, a third recruitment wave enrolled many participants by simply informing them of their participation in this experiment. This was possible thanks to the fact that the experiment is financially risk-less.

Table 1: **# of participants per groups and waves**

Wave	**Launch date**	**Groups**			**Total**
		C	**T1**	**T2**	
1	01.07.2016	14 (9)	15 (10)	15 (10)	44 (29)
2	01.10.2016	16 (14)	16 (12)	16 (4)	48 (30)
3	01.01.2017	253 (192)	252 (197)	-	505 (389)
Total		283 (215)	283 (217)	31 (14)	597 (446)

4.1.1 Assessing the performance of the households

In order to assess the performance of the households with respect to their treatment, two specific metrics are used. The first considers a flexibility score and assess the relative amount of energy consumed in the desired time window. However, if a household makes the choice to consume more during a specific time period, it is not clear whether the energy has been moved in this specific time period or if additional energy has been consumed due to the fact that the electricity rate is reduced in this time period. Alternatively, as the electricity rate is higher than the standard rate outside of the reduced tariff period, the energy consumption outside of this specific period could also be reduced. Hence the second metric is the daily energy consumption.

Definition of a flexibility score The flexibility score is defined for each household and each day according to equation 1. This score can be seen as the ratio between the energy consumed during the low rate period and the total energy consumed during the day. To take into account the fact that the low rate period can be different from day to day (for the second treatment group), the score is normalized by the relative duration of this low rate period.

$$S = \frac{\frac{E_{\text{flexi}}}{E_{\text{day}}}}{\frac{d_{\text{flexi}}}{24h}} \tag{1}$$

Where:

- E_{flexi} is the amount of energy consumed during a reduced tariff period, also called a flexi period in the following.

- E_{day} is the amount consumed during the considered day.
- d_{flexi} is the duration of a flexi period (always 4 hours for treatment 1 group but can vary between 3 and 9 hour for T2. In the case where no flexi period is scheduled for a day, the flexi score is obviously not defined.

These two metrics can be calculated for each treatment group for every day of the experiment. To assess the households' change in behaviour, the relative variations of these metrics between the period of experiment and a corresponding period before the experiment are evaluated.

Evaluation periods As depicted in table 1, the experiments started at three different dates for each recruitment waves. In order to cope with this issue, three different evaluation periods — each is one year long — have been defined and are summarized in table 2. The period before the experiment is exactly one year before the experiment period so that any seasonality effect can be accounted for.

Table 2: **Evaluation periods of the flexi experiment**

Wave	**Period before the experiment**		**Period after the experiment start**	
	Start	**End**	**Start**	**End**
1	01.07.2015	30.06.2016	01.07.2016	30.06.2016
2	01.10.2015	30.09.2016	01.10.2016	30.09.2016
3	01.01.2016	31.12.2016	01.01.2017	31.12.2017

4.2 Theoretical flexibility

In addition to the field experiment, the theoretical flexibility potential is evaluated. The underlying hypothesis is that it is possible to infer what composes the load curves, in term of appliances, without having to measure each of them individually. A suitable approach to perform this kind of exercise is called Non-Intrusive Appliance Load Monitoring (NIALM) [17]. According to the review of Esa et al. [18], one can classify the various techniques according to their supervised or unsupervised nature. A supervised method learns from a labelled dataset how to predict which appliance is on or off from the whole house power measurement. An unsupervised method doesn't require this step but obviously comes with greater uncertainties. Another way to categorize NIALM techniques is based on the measurement sampling frequency. High sampling frequency, typically in the range of 1 kHz or 0.5 MHz, enables to explore more electrical features and power signatures, namely active and reactive power measurements, or individual appliance signature as suggested by Liang et al. [19]. However such a high-frequency measurement requires more sensing capabilities than the smart meters and are currently not economically feasible [20]. In the context of the flexi experiment, the load profiles come from smart meters which sample the energy consumption every 15 min. Hence we developed a dedicated unsupervised methodology to disaggregate the households' load profiles with the help of informations collected from the household survey. The principle of this methodology and the derivation to extract the theoretical flexibility potential is described in this section.

4.2.1 An unsupervised disaggregation method

The primary goal of this method is to extract the share of the energy consumption that could be shifted in time to match with high PV generation time range. Contrary to many NIALM algorithms, this methodology doesn't aim to extract precisely when each appliance is on or off, but rather to have an estimation of the power consumption signal of categories of appliances. Indeed as depicted in figure 3, the algorithm disaggregated the main power signal into 8 sub-signals corresponding to eight pre-defined categories.

The methodology to disaggregate the whole-house energy consumption is based on a statistical approach. The basic principle is displayed in figure 3. From the survey, the employment state and age-group for each person living in the households are extracted. Additionally, a list of appliances owned by the household is collected. From this information, the algorithm acts as a hybrid between a load profile simulator and a standard NIALM algorithm. For each person of the household, an activity chain is generated as a Markov process (as illustrated in figure 4. From this activity chain, it is possible to infer the power demand required by each activity using the relation between the activity and the probable list of appliances that can be used during this activity (see table 3). The coefficients of the initial probability matrix and the transition matrix for Markov activity chain are derived from a Time-of-Use Survey conducted in the Netherlands [21]. These coefficients are adjusted in order to exclude activities that are consuming too much energy with respect with the available power budget derived from the measured load curve. Similarly, the list of appliances is restricted to keep for each activity only the appliances that have a nominal power smaller — in a given tolerance — than the power budget. At the end, the simulated power signal of each appliance is aggregated to the 8 categories according to table 4.

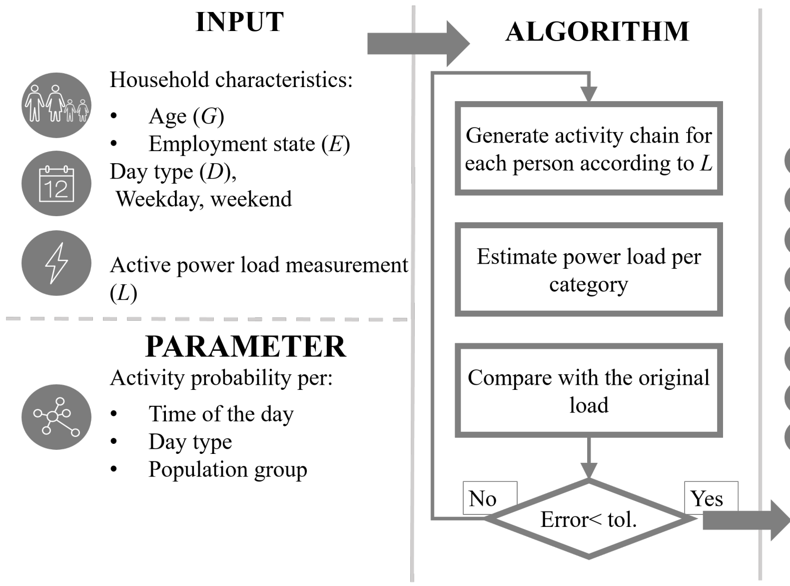


Figure 3: Basic principle of the developed disaggregation methodology

Table 3: **List of possible activities and related appliances.**

Activities	**Appliances**
Cleaning	vacuum, TV, stereo, lights
Using a computer	TV, stereo, PC, laptop, printer, lights
Cooking	stove, oven, microwave, kettle, TV, stereo, lights
Washing dishes	dishwasher, TV, stereo, light
Eating	coffee maker, microwave, kettle, TV, stereo, lights
Do the homework	TV, stereo, PC, printer, laptop, lights
Playing a game	TV, stereo, gaming console, lights
Laundry	washing machine, tumble dryer, TV, stereo, lights
Music	stereo, PC, tablet, laptop, lights
Outdoor	$\varnothing$
Sleeping	$\varnothing$
Watching TV	TV, DVD player, PC, tablet, laptop, lights
Showering	hairdryer, TV, stereo, lights
Working	$\varnothing$

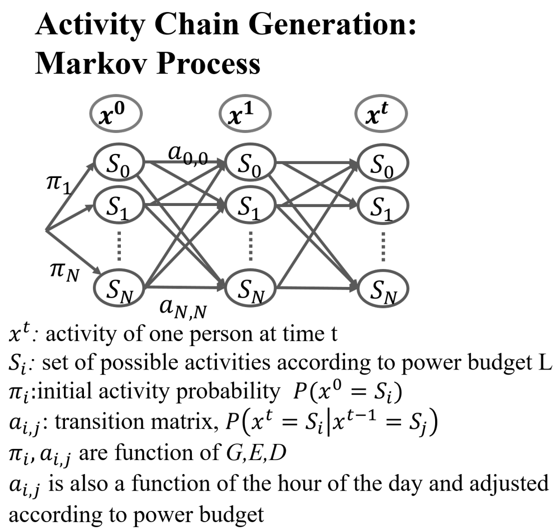


Figure 4: Illustration of a Markov chain

Table 4: **Appliances and corresponding nominal power grouped per category**

Category	**Appliance**	P_{Nominal} **(W)**
Cooking	coffee maker	800
	microwave	1250
	kettle	1800
	oven	2400
	stove	500
Entertainment	TV	124
	TV box	20
	DVD player	80
	PC	110
	laptop	55
	tablet	7
	stereo	100
	gaming console	180
Fridge	fridge (with a freezer)	94
	fridge (without a freezer)	66
	freezer alone	62
Heating	hairdryer	600
	boiler	2000
	heat-pump	1000
Housekeeping	washing machine	406
	tumble dryer	2500
	dishwasher	1131
	vacuum	2000
ICT[1]	printer	23
Light	lighting	137
Standby	modem (and similar)	8

As an illustration, the figure 5 presents an example of a household's load curve disaggregated with this methodology for a single day. One may note that sometimes the sum of the categories is smaller than the original load profile. This is due to the fact that at some times the algorithm cannot find any possible activity/appliance to fill the energy budget. On the opposite, it can happen that the total generated power signal is greater than the measured power profile, this is due to a small tolerance introduced in the energy budget allowing the algorithm to assign an appliance with high nominal power to prevent the phenomena just previously mentioned.

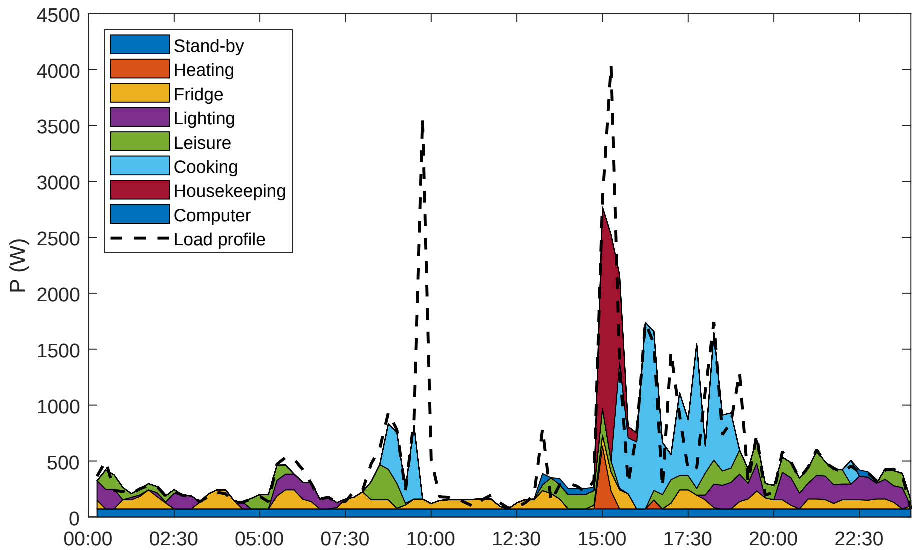


Figure 5: Example of disaggregated load curve for a single day

4.2.2 Load profile disaggregation as a tool to estimate flexibility potential

The methodology described before is hence used on all load profiles from the households that have answered the survey (84 in total). In order to determine the theoretical potential for flexibility, each category is judged according to its potential for load shifting. This potential is summarized in table 5.

Table 5: Potential for load shifting per category

Categories	**Potential**
Standby	not shiftable
Heating	hardly shiftable
Fridge	not shiftable
Light	not shiftable
Entertainment	hardly shiftable
Cooking	not shiftable
Housekeeping	easy shiftable
ICT	hardly shiftable

Figure 6 gives a representative idea of what share of energy is consumed in each category. The Heating category accounts for only 0.2% of the total energy consumption of the 84 households. This is because, as explained before, the households selected for the flexi experiment are not equipped with any electrical heating system thus this category only contains a marginal fraction of energy consumed by heating devices such as hair-dryer.

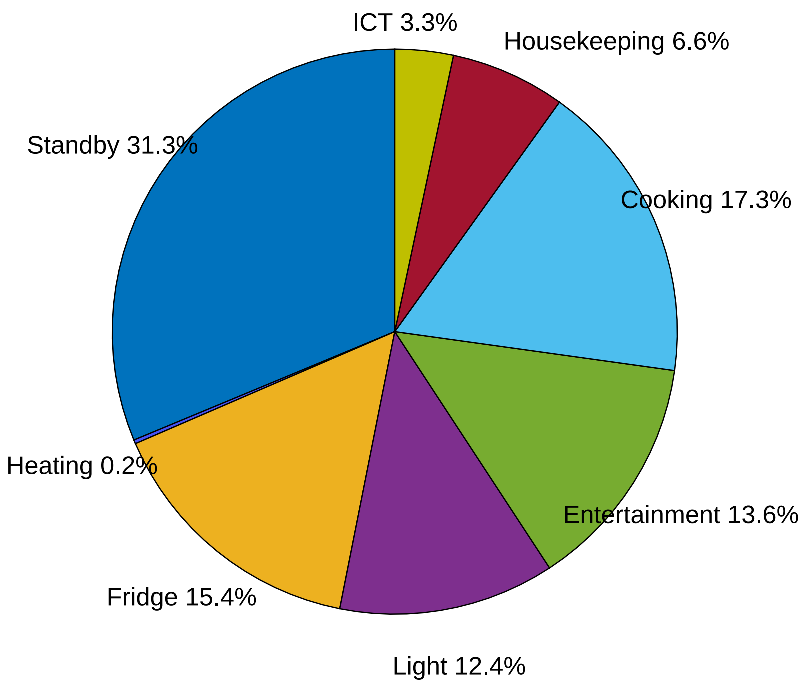


Figure 6: Share of energy consumed per category

From this analysis, it is possible to define a theoretical flexibility score similar to the one from equation 1 but using here the information gained with the disaggregation. The theoretical flexi score is hence calculated according to equation 2

$$S_{th} = \frac{\frac{E^0_{\text{flexi}} + E^{\text{easy shiftable}}_{\text{outflexi}} + E^{\text{hardly shiftable}}_{\text{outflexi}}}{E_{\text{day}}}}{\frac{d_{\text{flexi}}}{24h}} \tag{2}$$

Where:

- E^0_{flexi} is the energy already consumed during the flexi period (low rate period).
- $E^{\text{easy shiftable}}_{\text{outFlexi}}$ is the energy easily shiftable consumed outside the flexi period.
- $E^{\text{hardly shiftable}}_{\text{outFlexi}}$ is the energy hardly shiftable consumed outside of the flexi period.
- E_{day} and d_{flexi} are the total energy consumption of the day and the duration of the flexi period in hour respectively.

One has to note that this theoretical flexi score is based on the hypothesis that the energy is purely shifted, i.e. that the total daily energy consumption remains constant. This hypothesis will be discussed in the results section.

4.3 flexibility contribution to the integration of distributed generation

This section presents an approach to evaluate how much the theoretical demand flexibility bring as additional photovoltaic (PV) hosting capacity to a distribution grid. This approach is based on the following assumptions :

- The flexible demand can be freely shifted along the day.
- The PV hosting capacity is limited only by the power flow at the transformer.
- Line resistances, ampacity, and voltages constraints are neglected.

With these assumptions, a fraction of the energy demand can be shifted towards periods with high PV injection, thus increasing the PV hosting capacity of the distribution grid. To evaluate this potential for a real distribution grid, the load profiles from the flexi project have been allocated in the TR3716 low voltage grid of the Romande Energie in Rolle. This allocation is done using a two-stage optimization that takes care of minimizing the difference between the annual consumption of the allocated demand profile and the annual consumption measured by the meter. Moreover, the building category of the originated load profile has to match with the one of the meters. The aggregation of all the load profiles gives the total load profile of the distribution grid L computed for one year.

The total PV generation profile G for the distribution grid is computed as the aggregation of the PV profiles simulated for every roofs. This profile corresponds to a PV penetration well above the real hosting capacity of the grid. The power profile at the transformer P is defined as the difference between the total load and PV generation multiplied by a normalization factor n.

$$P(t) = L(t) - n \cdot G(t) \tag{3}$$

Without any flexibility the maximum normalization ratio n_0 that complies with power flow limit $P_{lim} < 0$ at the transformer is given by :

$$n_0 = \min_t \frac{L(t) - P_{lim}}{G(t)} \tag{4}$$

To find out what would be the PV hosting capacity using all the available demand flexibility, the share of easily shiftable energy is evaluated for each allocated load profile at each time step using the disaggregation. Then for each day d, the highest daily normalization ratio n that complies with the constraint at the transformer can be determined using the following the relation :

$$n_d = \min_{t \in d} \frac{L_{\text{flex}}(t, n_d) - P_{lim}}{G(t)} \tag{5}$$

Where $L_{\text{flex}}(t, n)$ is the aggregated load profile in which the flexible demand has been shifted in order to minimize the injection peak $(n_d G - L)$. This flexible load depends on the normalization ratio n because the period of time during which the power at the transformer is below the limit P_{lim} depends on n_d and only the flexible energy outside this period can be shifted in it.

Finally, the maximum normalization ratio is given by the minimum over all the day of the daily n_d.

$$n = \min_d n_d \tag{6}$$

4.4 General score for the integration of PV

Here are a few basic definitions about the integration of PV at the household and grid level.

- **Self-consumption (SC):** is the ratio between the PV generated energy that is directly consumed locally and the total PV generated energy.

$$\text{SC} = C/(B + C)$$

- **Self-sufficiency (SS):** is the proportion of the demand covered by the local PV generation.

$$\text{SS} = C/(A + C)$$

- **PV penetration (PVP):** is the ratio between the PV generation and electricity consumption.

$$\text{PVP} = (B + C)/(A + C)$$

All these scores are usually computed on a full-year basis in order to get rid of the seasonal effects.

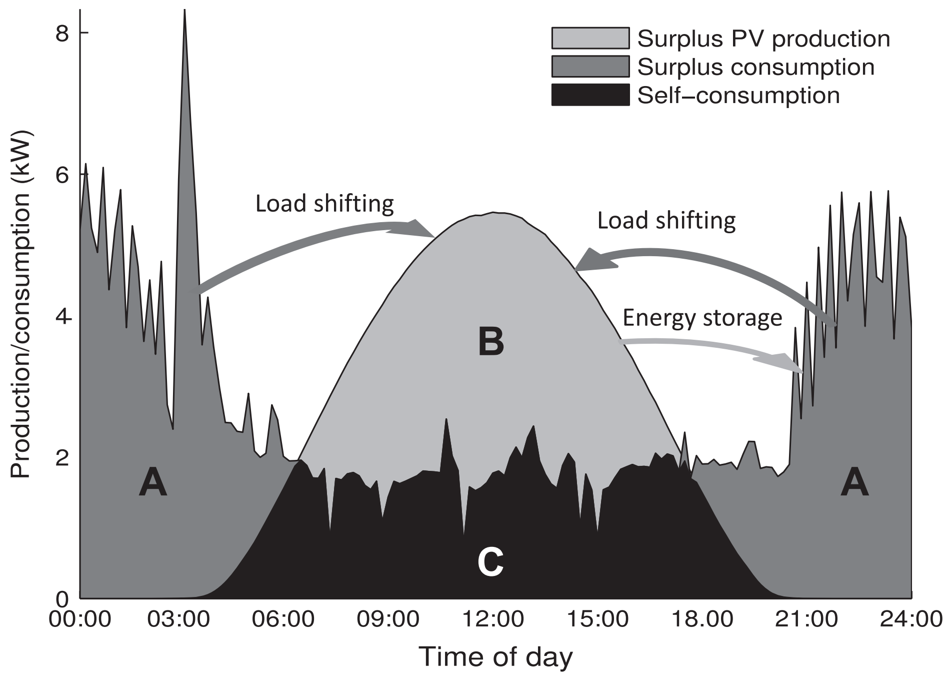


Figure 7: *Schema of load* $(A + C)$ *and a PV generation* $(B + C)$ [22]

5 Results

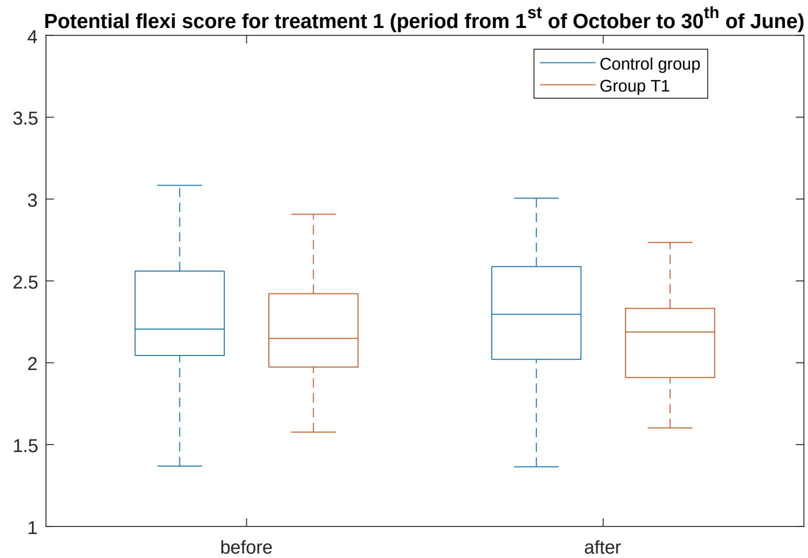
5.1 Theoretical flexibility

Figures 5 and 6 have already introduced an overview of the output of the disaggregation. The flexibilisation potential, for the 84 households is assessed in terms of share of energy, split by their shiftability potential. The resulting energy share per potential for demand-side management is presented in table 6 and split between weekend and weekday.

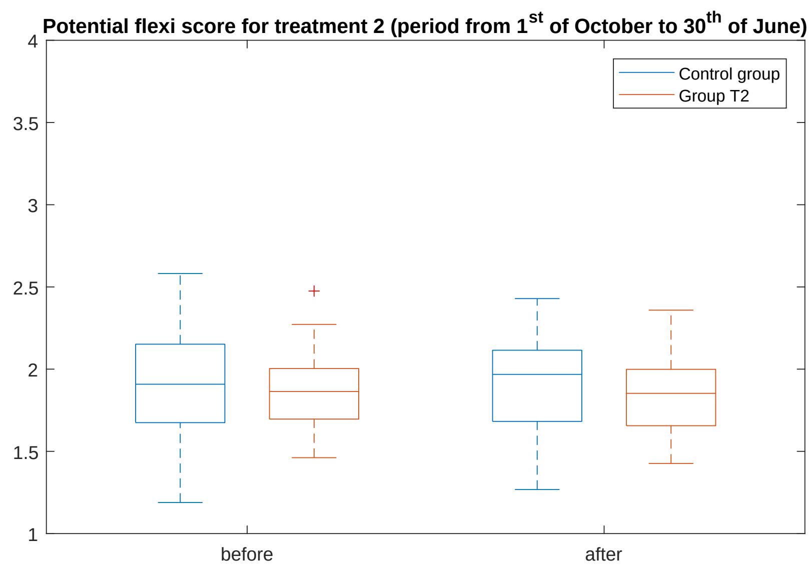
Table 6: Share of energy according to their shiftability potential

Share of energy...	**Weekday**	**Weekend**
Easily shiftable	6.45%	6.87%
Hardly shiftable	16.75%	18.05%
Not shiftable	76.80%	75.08%

The flexibility score is evaluated for each household, for each day and each treatment for both a period before the experiment and the period during the experiment. As the experiment launch dates are different for the first and second wave, a common period, between October 1st and the 30th of June, was defined in order to evaluate the flexi score for both waves. The potential flexibility scores are represented in figure 8. The potential is slightly higher for the treatment 1 group than for treatment 2 group. For both the control and treatment groups, the potential decreases between the period before the experiment and after the start of the experiment. Similarly, both treatment groups have a potential flexi score smaller than the one of the control group.



(a) treatment 1



(b) treatment 2

Figure 8: Theoretical flexi score

Now that an upper bound for the theoretical flexibility score has been evaluated, it's possible to assess the practical flexibility and compare it to the theoretical one.

5.2 Practical flexibility

5.2.1 Treatment 1 (fixed low rate period)

The practical flexibility is evaluated with the help of the flexi score defined above. The households in the first treatment were encouraged to shift their consumption to a period between 11 am and 3 pm every day. In order to illustrate the impact of the experiment on the way the households are using their energy along the day, we define the normalized hourly power profile for a day as follows.

$$P^*(t) = \frac{P(t)}{E(P)} \tag{7}$$

Where: $P(t)$ is the mean power during time $t-1$ and $\forall t = 1, \ldots, 24$ and $E(P)$ is the mean power during the day defined as :

$$E(P) = \frac{1}{24} \sum_t P(t) \tag{8}$$

As each wave started the experiment at a different date, it is not possible to compare them together. Hence figures 9, 10 and 11 show the median normalized power profile for each wave. When comparing the profiles before and during the experiment with respect to the control group, it is not clear whether the households have moved their consumption in the low rate window. Only the second wave shows a little trend in this direction. Similarly, the consumption during the evening and the night seems to follow a similar trend for both the control group and treatment group.

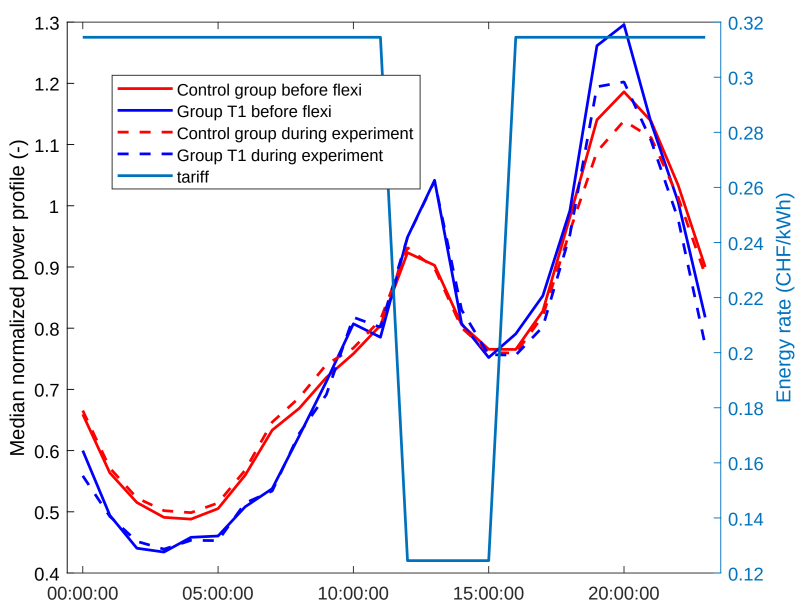


Figure 9: Normalized power profile group T1 wave 1

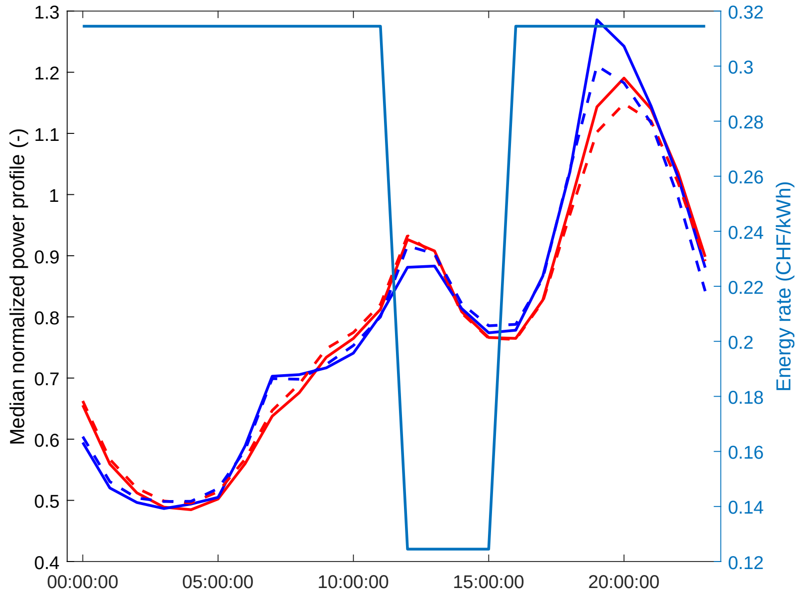


Figure 10: Normalized power profile group T1 wave 2

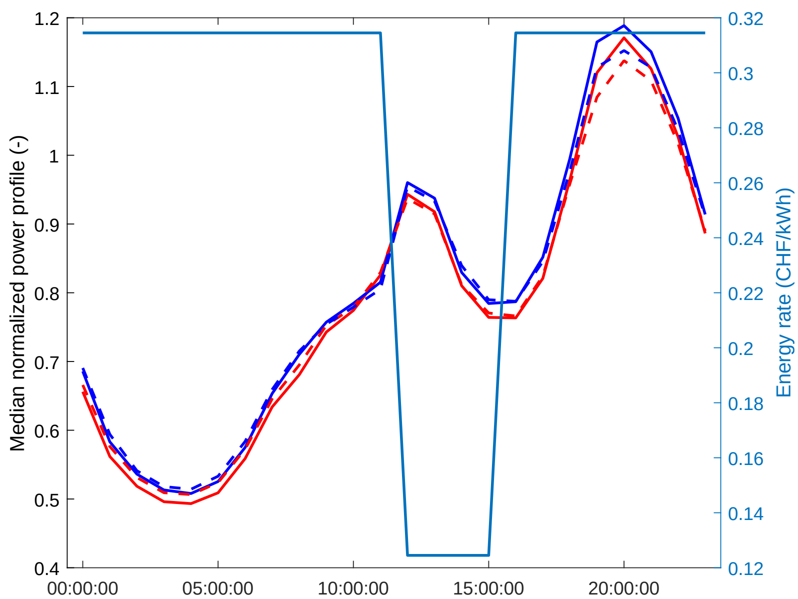


Figure 11: Normalized power profile group T1 wave 3

These results do not show a clear reaction of the households to the provided incentive. However, this has to be confirmed by the analysis of the two metrics defined in section 4.1.1, namely the flexi score and the average daily energy consumption. The figure 12 shows a map of the performance of each individual household of the first treatment group (first wave). The blue squares represent the metrics evaluated during the year before the experiment starts while the linked red cross display the same metrics evaluated during the experiment. It is clear that some households have clearly increased their flexi score while some other didn't.

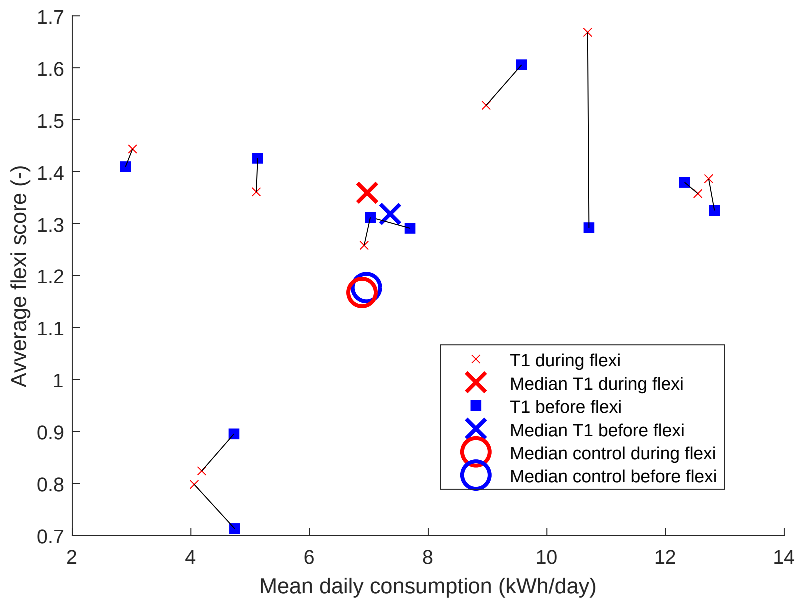


Figure 12: Performance of treatment group 1 wave 1

This progression in both the flexi score and the average daily consumption is reported in figures 13, 14 and 15 for the wave 1, 2 and 3 respectively. The vertical axis represents the variations of the flexi score with respect with the period before the experiment. The horizontal axis represents the variations of the average daily consumption. A household who reacted perfectly to the financial incentive would have at least increased its flexi score and eventually reduced its daily energy consumption, thus it would be placed in the top left quadrant of the figure. On the opposite, a household that has both reduced its flexi score and increased its energy consumption is placed in the bottom right quadrant. In each of the four quadrants of each figure is stated the fraction of households contained in the quadrant. The relatively low reaction of the household is pictured by the fact that between 50 and 53% of the households have increased their flexi score while this fraction lays in the range 44 to 46% for the control group.

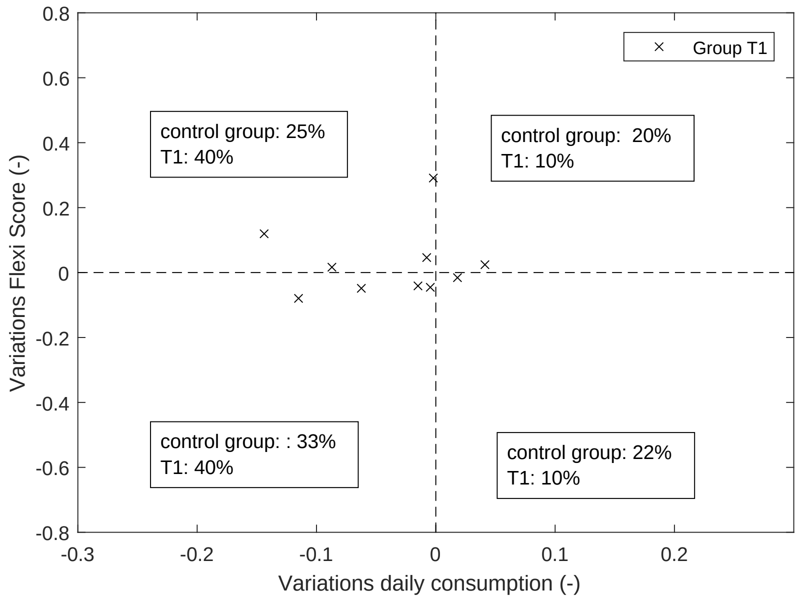


Figure 13: Performance variations of treatment group 1 wave 1

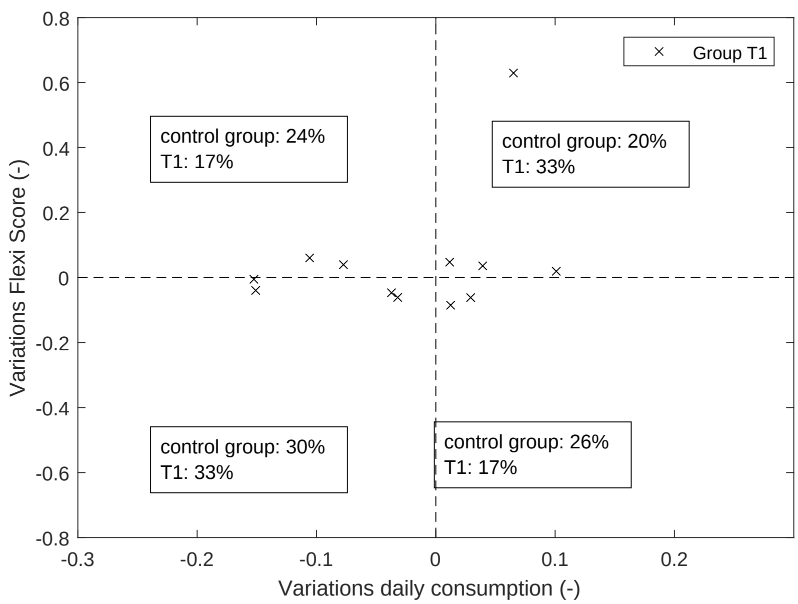


Figure 14: Performance variations of treatment group 1 wave 2

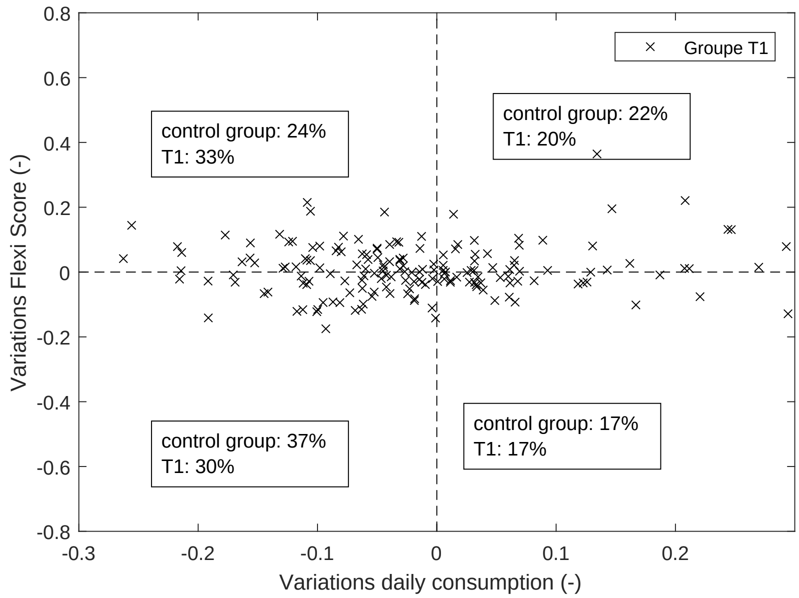
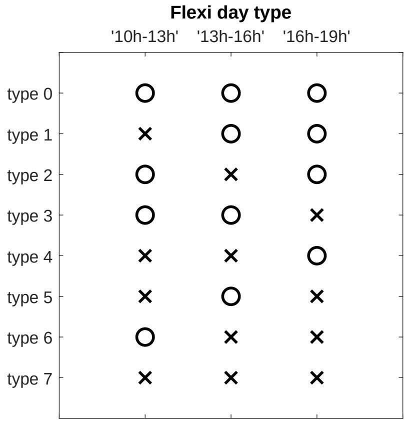


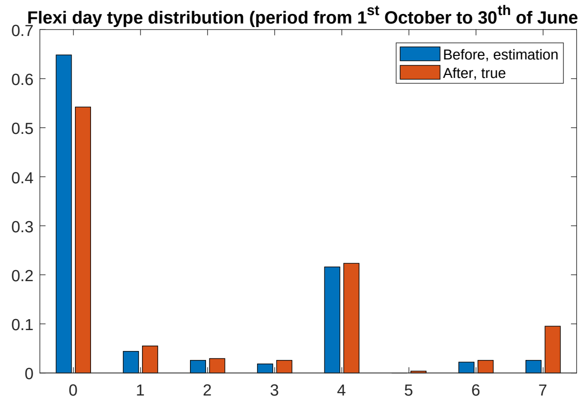
Figure 15: Performance variations of treatment group 1 wave 3

5.2.2 Treatment 2 (variable low rate periods)

The second treatment consisted in sending each day a SMS mentioning when the low rate period for the next day would occur. As three different flexi periods are possible, 8 different types of day can be distinguished as depicted in figure 16a. The distribution of the day type for the period between October 1st 2016 and the 30th of June 2017 (period after) is presented in figure 16b. As the forecast of the flexi period only started on July 1st 2016, the flexi period for the time range before had to be estimated for this analysis based on historical weather data. This is why the distribution for the flexi day type is labelled with the mention "estimation" for the period before the experiment.



(a) Definition of the day types, X/O represents low/high rate period



(b) Distribution of the day types type

Figure 16: Flexi day types and their distribution

Similarly to the first treatment, the effect of the incentives can be illustrated by the change in the normalized power profile. Because each day is significantly different and for readability, only the type of day 4 is pictured in figure 17. As the number of households is very low to allow each wave to be treated separately, both waves have been grouped on a common period between October 1^{st} 2016 and the 30^{th} of June 2017 as for the figure 16. Apparently, these households have increased the fraction of energy consumed during the low rate period compared to the control group. However, the analysis of the power profile for all other types of days does not show the same trend. Sometimes, the fraction of energy is reduced during the low rate period and increased during high rate period. As the reactions of the households are very dissimilar, the following part will focus on the variations of the flexi score and daily energy consumption.

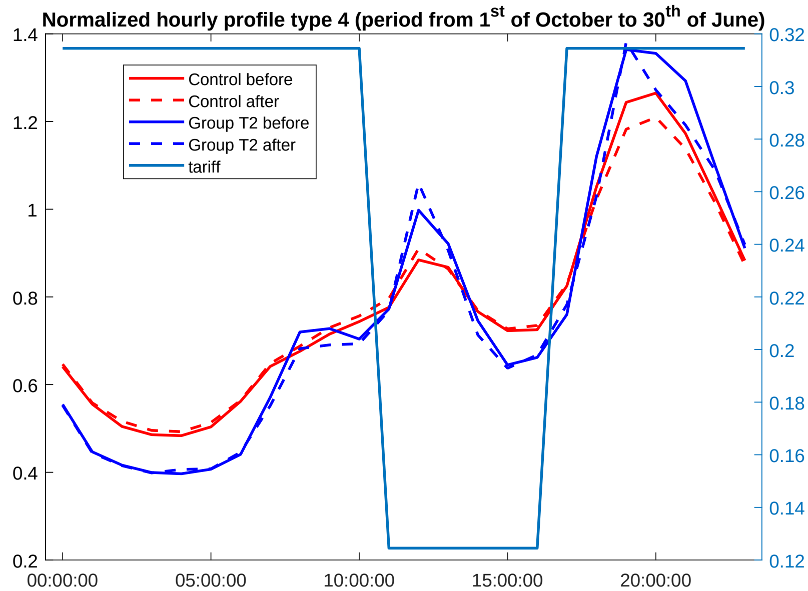


Figure 17: Normalized power profile group T2 wave 1 & 2

The performance of the group T2 wave 1 with respect to both flexi score and daily energy consumption is displayed in figure 18. The considered period corresponds to the full year from 1st of July 2016 to 30th of June 2017 (as reported in table 2). It is clear here again that some households reacted very positively by increasing their mean flexi score and reducing their energy consumption while other households behaved exactly oppositely. The variations of these performance scores are the main point of interest and are reported in figures 19 and 20.

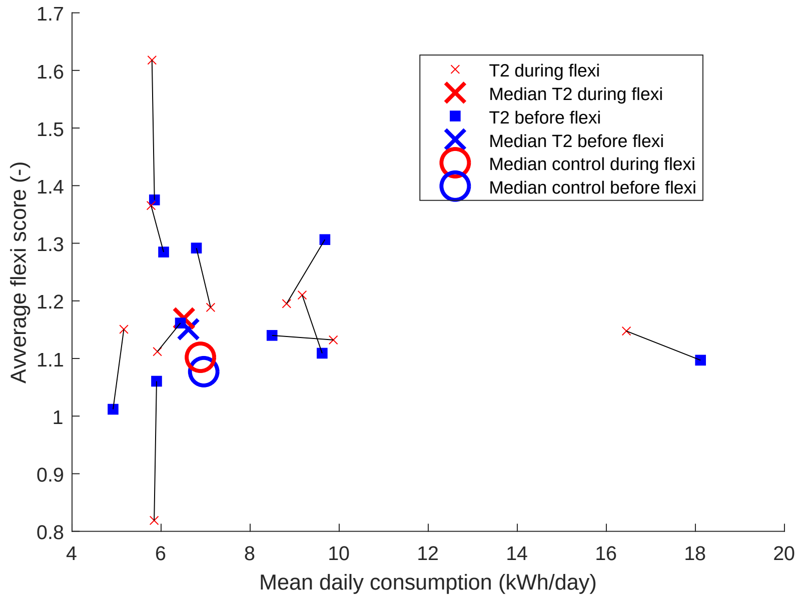


Figure 18: Performance of group T2 wave 1

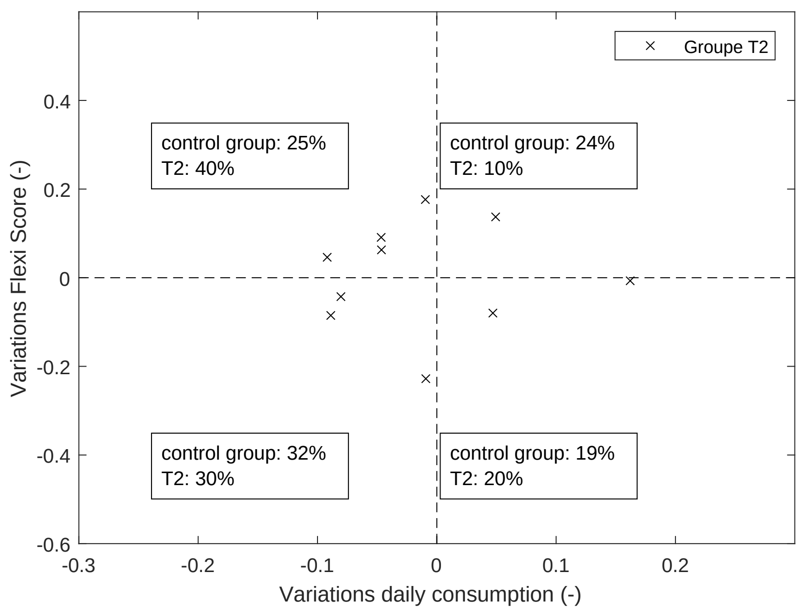


Figure 19: Performance variations of treatment group 2 wave 1

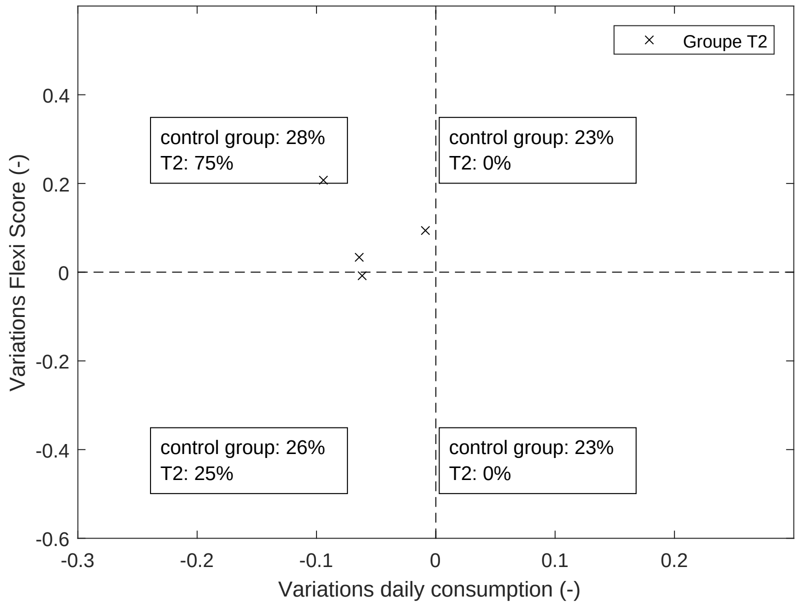
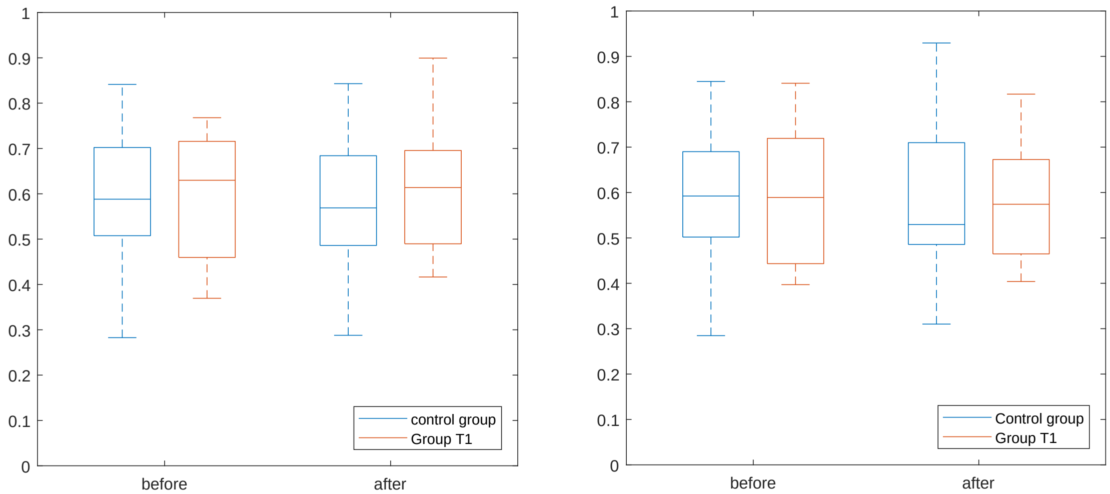


Figure 20: Performance variations of treatment group 2 wave 2

Similarly to the first treatment group, these results do not show a clear reaction of the households to the financial incentives, although the fraction of households that have both increase their flexi score and reduced their mean energy consumption is always higher in the treatment group compared to the control group.

5.2.3 Achieved flexibility

In order to put these results in perspective with the theoretical potential for flexibility (defined as the theoretical flexi score S_{th}), the level of achievement of the flexi score is calculated for each day and for each score as the ratio S/S_{th}. This level of achievement is displayed for each treatment and both wave 1 and 2 in figure 21 and 22.

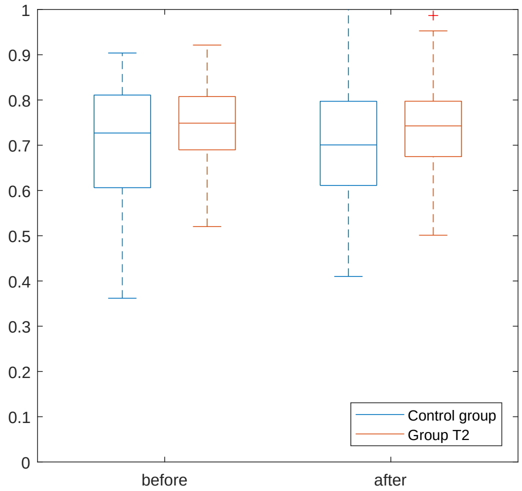


(a) wave 1 period

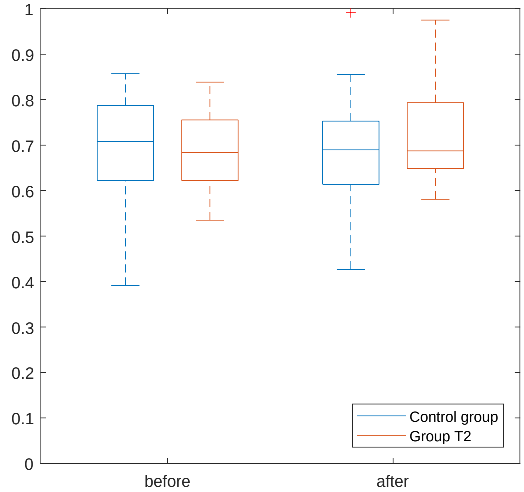
(b) wave 2

Figure 21: Level of achieved flexibility for treatment 1

The median level of the flexibility achievement is reported in table 7. In general, all households have decreased the ratio S/S_{th} including the control group who didn't receive any incentive to change its consumption habit. However, the decrease is less pronounced for the treatment groups (1 and 2 and both waves). The exception is the second wave of the group T2 who even increased its flexibility achievement. In general, the variations between of performance are smaller in magnitude for the variations for the treatment groups than the variations of the control group with can be considered as noise.



(a) wave 1



(b) wave 2

Figure 22: Level of achieved flexibility for treatment 2

Table 7: Median level of flexibility achievement for all groups and waves (%)

		Treatment 1			Treatment 2		
		before	**after**	**delta**	**before**	**after**	**delta**
wave 1	**Control group**	58.8	56.9	-1.9	59.2	52.9	-6.3
	Treatment group	63	61.4	-1.6	58.9	57.4	-1.5
wave 2	**Control group**	72.7	70.1	-2.6	70.8	69	-1.8
	Treatment group	74.9	74.2	-0.7	68.4	68.7	0.3

5.3 Impact of the flexibility on the PV hosting capacity

This section discuss the increase of PV hosting capacity enabled by the theoretical flexibility for the TR3716low voltage grid. The theoretical flexibility of the demand is based on the approach described in section 4.3. The annual electricity demand of the grid resulting from the load profiles allocation reached 721 MWh. The total PV potential considering all rooftops with an area above $10\,\mathrm{m}^2$ and for which the annual irradiance is higher than $1000\,\mathrm{kWh/m}^2$, is about 1484 MWh. This gives a maximum PV penetration of 2.1. However, such high PV capacity would violate the power flow constraint at the transformer limited in this case to $P_{lim} = -400\,\mathrm{kW}$. Here negative to express the limit on the power flow from the LV to MV grid. Equation 4 gives for this grid a PV normalization ratio $n_0 = 0.353$, which corresponds to a PV penetration of 0.73.

The day with highest reverse power flow at the transformer is illustrated in figure 23. The load minus the generation $L - n_0 \cdot G$ just reaches the transformer limit after noon.

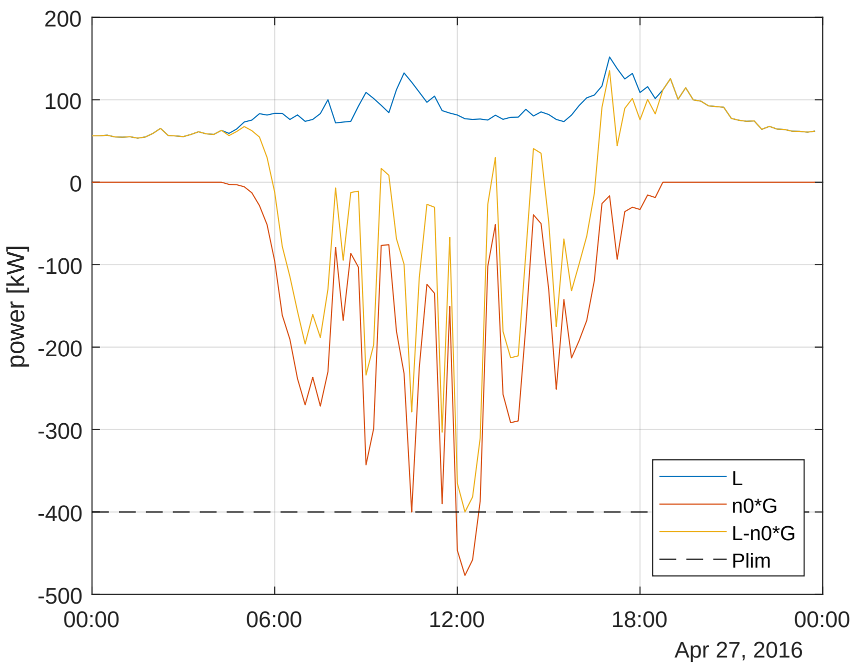


Figure 23: Load L and generation G during the day with the highest injection

The theoretical demand flexibility allows decreasing the peaks of the reverse power flow, in this way increasing the PV hosting capacity of the grid. The new normalization ratio thus obtained is $n = 0.424$ corresponding to a PV penetration of 0.87. Figure 24 shows the power flows for the day with the resulting highest injection. The energy shift around noon of the demand is just enough to keep power flow at the transformer above the limit $L_{\text{flex}} - n \cdot G > P_{lim}$.

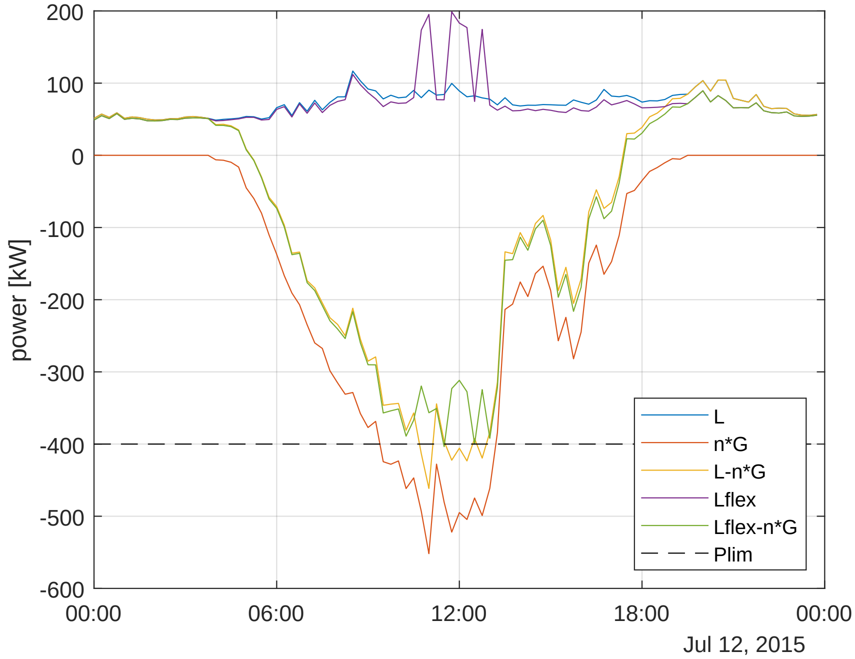


Figure 24: Load L and generation G during the day with the highest injection

We define here an electricity cost C [CHF/kWh] for the distribution grid defined as the energy import E^{IMP} multiplied by the import tariff c^{IMP} minus the export E^{EXP} multiplied by the export tariff c^{EXP} and plus the cost for the PV generation which is given by the produced energy E^{PV} times the levelized cost of electricity for the PV LCOE, the whole divided by the total energy consumed E^{L}.

$$C = \left(E^{\mathrm{IMP}} \cdot c^{\mathrm{IMP}} - E^{\mathrm{EXP}} \cdot c^{\mathrm{EXP}} + E^{\mathrm{PV}} \cdot \mathrm{LCOE}\right) / E^{\mathrm{L}} \tag{9}$$

Where the tariffs are set to :

- $c^{\mathrm{IMP}} = 20$ cts/kWh
- $c^{\mathrm{EXP}} = 8$ cts/kWh
- LCOE $= 15$ cts/kWh

Table 8 shows the main results without and with the flexible demand. The PV penetration could be increased by 20% with the flexibility and this without decreasing the share of the generation locally consumed (SC). The self-sufficiency also increases by 20% (relative) to reach 43.1%. With the tariffs set above, the electricity cost for the grid is not cheaper. However in the case of a PV penetration of 0.87, if the extra energy had been curtailed instead of using flexibility, the electricity cost would have reached 21.6 cts/kWh.

Table 8: **Scores without and with the flexibility**

	PVP	SC [%]	SS [%]	C [cts/kWh]
Without flex	0.73	49.8	36.1	20.7
With flex	0.87 (+20%)	49.6 (-0.4%)	43.1 (+20%)	20.9 (+0.9%)

Figure 25 shows the electricity cost evolution normalized by the import tariff c^{IMP} in function of the LCOE normalized by the export tariff c^{EXP}. It should be noted that flexibility becomes economically interesting if the LCOE goes below $1.75 \cdot c^{\mathrm{EXP}}$. With the tariffs defined above, the ratio LCOE/c^{EXP} is equal to 1.875 which is just higher than the profitability limit.

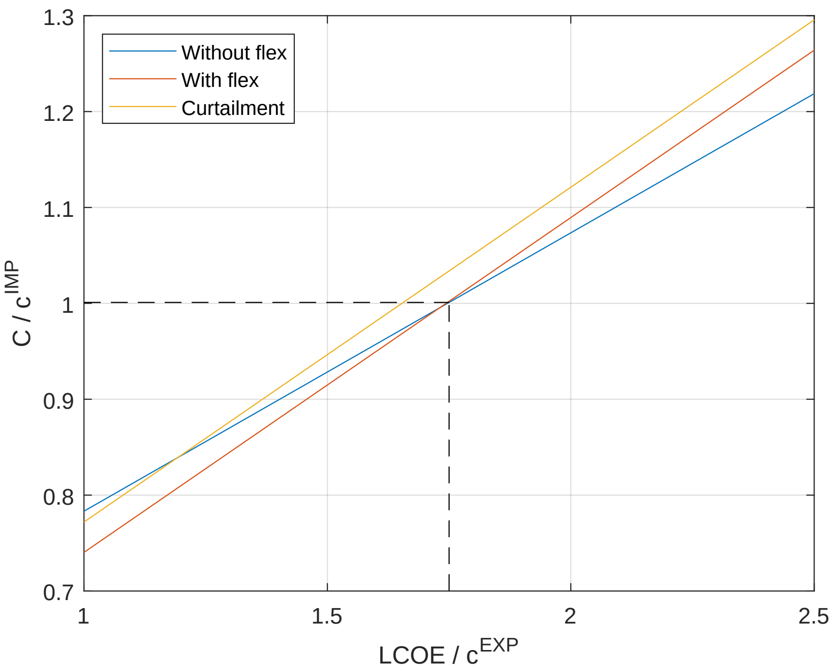


Figure 25: Electricity cost evolution normalized by the import tariff c^{IMP} in function of the LCOE normalized by the export tariff c^{EXP}

5.4 Demand behavioural theoretical and hot water flexibility

To give a reference to appreciate the theoretical behavioral flexibility of the demand, we propose to compare it to the theoretical flexibility that could be gather using domestic hot water heating (DHW). The daily mean of the theoretical demand flexibility (from behavioural change) over one year is about 150 kWh for the whole TR3716 grid.

Considering only the building B_{elecheat} with an electrical heating system for DHW, the total energy can be evaluated with the following equation.

$$E_{\text{DHW}} = \sum_{b \in B_{\text{elecheat}}} n_p(b) \cdot v_{dhw} \cdot c_p \cdot \Delta T \simeq 152\,\text{kWh} \tag{10}$$

Where n_p is the number of person in the building b, v_{dhw} the daily DHW consumption per person estimated at 50 l, c_p the specific heat of liquid water (4186 J/kg/°C) and ΔT the temperature difference estimated at 25 °C. So it is interesting to remark that both flexibility from potential behavioural change and flexibility from DHW heating have the same order of magnitude. The DHW one could be strongly increased in the future with a higher penetration of heat pumps, whereas the behavioural one is currently available with appropriated incentives.

6 Conclusions

A high level of penetration of distributed photovoltaic generation requires flexibility from the demand side in order to prevent high reverse power flow issues. First, this work showed a methodology to investigate the potential flexibility from behavioural change, i.e the flexibility in the energy consumption brought by a change in the behaviour of the people rather than any technical artefact. Second, the practical response of a panel of households was evaluated in the context of a demand-side management field experiment in the Jura area. Finally, the impact of the theoretical potential for a flexible demand is assessed on a use case network.

To evaluate the theoretical potential for flexibility, this work presents a methodology, based on a statistical approach to address the Non Intrusive Load Monitoring problem, to quantify the fraction of the consumed energy that could be shifted toward periods of high PV generation. Additionally, a score to evaluate the performance of the households to respond to demand-side management incentive is proposed. The results show that no significant difference is noticed between weekday and weekend as the fraction of potentially shiftable energy lays around 23 to 25% of the total energy consumption.

In order to practically assess the potential of households for demand-side management, a field experiment, the flexi project, has been conducted. Two different treatments were attempted: one double tariff at a fixed daily low rate period (1 am to 3 pm); the second treatment consisted in variable periods of low rate tariff either between 10am to 1pm, 1 pm to 4 pm or 4pm to 7pm, according to the insulation forecast. Both treatments had the same financial incentive, namely a bonus of 15 cts/kWh for the low rate period and a penalty of 4 cts/kWh during the remaining of the day, with respect to the standard 27.45 cts/kWh flat tariff. The results of the field experiment showed for both treatment a moderate response from the households. The variability of the individual households' response showed that some reacted very well to the incentives while others reacted at the opposite of what was expected. One reason to explain this is the voluntary nature of the experiment and the rather low financial incentive (possible monthly gains. Indeed, as the households had to pay at most the bill with the reference flat rate, some of them probably didn't feel any particular pressure to change their behaviour and didn't take the opportunity to achieve energy savings.
The moderate response of the households is put in perspective with the evolution of the theoretical potential for flexibility as the latter was decreasing between the period before the experiment and the period after the start of the experiment.

Finally, the effect of the theoretical potential of behavioural flexibility on the hosting capacity of a Rolle district is assessed. The low-voltage grid TR3716 is used as a test case for this assessment. As the annual energy consumption of each meter in the grid is known, the load profiles from the flexi field experiment are allocated to each meter in order to have the power measurement at this node. The disaggregation of the load profiles was used to assess the theoretical flexibility and a strategy was developed to efficiently reduce the exceeding PV generation. The main assumption here is the possibility to shift freely the energy. This approach allows to give an upper-bound of the effect of theoretical behavioural flexibility on the PV hosting capacity of a low voltage grid. The results show that PV penetration could be increased from 73% to 87% while the total cost of energy used only increases by 0.9%. A sensibility analysis on the levelized cost of the PV energy showed that flexibility is always a better solution than curtailing the excess PV generation. However, flexibility becomes profitable only if the levelized cost of PV is smaller than 175% of the cost at which the distribution grid operator buy the exceeding PV generation. For this same district, it has been estimated that the demand behavioural flexibility is currently of the same order of magnitude compared to the flexibility that could be gather from the domestic hot water heating

These results showed that flexibility is difficult to obtain from the households simply by providing financial incentives which are remaining small (due to the price of energy) compared to the effort to provide it. However, the impact on the PV hosting capacity, if the full potential was achieved is high enough to pursue investigation on this topic. Further studies will aim at evaluating the effect of the practical flexibility obtained with this experiment on the PV hosting capacity. Additionally, the combination of technical solutions with the behavioural incentives should be further studied.

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