BS 2021 1-3 SEPT BRUGES
INTERNATIONAL BUILDING PERFORMANCE SIMULATION ASSOCIATION

Designing and Experimenting Nudge Signals to Act on the Energy Signature of Households for Implementing Indirect Energy Flexibility

Muhammad Salman Shahid[1], Benoît Delinchant[1], Béatrice Roussillon[2], Frédéric Wurtz[1], Daniel Llerena[2], Adélaïde Fadhuile[2], Nils Artiges[1]
[1]Univ. Grenoble Alpes, CNRS, Grenoble INP, G2Elab, F-38000 Grenoble, France
[2]Univ. Grenoble Alpes, CNRS, INRAE, Grenoble INP, GAEL, F-38000 Grenoble, France

Abstract

To maintain energy balance in the grid, energy flexibility is entailed at consumer side. Generally, the participants of demand response experiments are offered economic incentive with historic or normative feedback on their energy consumption. In this article, we present an energy flexibility experiment concerning residential sector, which is based on nudge signals with indirect feedback and no monetary incentive. The results show that nudge signal can serve as an important tool to implement energy flexibility without hindering consumer's comfort. This study is effective to implement energy flexibility on local energy communities while offering no direct economic incentive.

Key Innovations

- Load curtailment and load shifting alerts are conceived for the residential buildings based on the day ahead forecasted condition of national grid.
- Nudge cocktail (a collection of nudge signals) is devised for sending alerts to the participants. The participants may respond to each alert according to their degree of flexibility without loss of comfort.
- Reference load curve is formulated for each participant. An image of reference load curve superposed on measured load curve is sent to the subjects as indirect feedback.

Practical Implications

The study is significant for energy flexibility of residential sector to mitigate forecasted day ahead energy imbalance in the grid. The load shifting alerts are based on the historic consumption of same sector, which enables the participant to implement energy flexibility according to their degree of flexibility without any loss of comfort.

Introduction

Electrical energy has become a necessity for mankind since its worldwide deployment through national grids in 20th century. However, the urge for decentralized renewable energy production leads to new challenges in the electric grid management. Constraints like network congestion and intermittent renewable production require energy flexibility to maintain balance in the grid. Network congestion may occur due to disconnection of a circuit or change in energy demand owing to the variation in temperature. This results in load shedding, therefore loss of comfort for residential consumers. The renewable energy production is intermittent in nature, therefore to avoid high cost energy storage, the renewable energy must be consumed during the period of production.

At consumer end, demand response serves to shift the demand pattern so that it can better match electricity supply. Direct load control enables the demand response operator to switch the shiftable loads at remote end. It can be effective for the industrial sector, however, the remote switching cause loss of comfort in residential sector.

Alternatively, sending occasional alerts prompt the residential consumer to manage energy consumption in accordance with their comfort and degree of flexibility. These alerts tend the consumer to either implement upward flexibility (valley filling during the interval of renewable production) or downward flexibility (curtailing partial load during peak hours). This article deals with an experiment regarding energy consumption behaviour of households. Several aspects can be studied to evaluate the efficiency of the nudge strategy, however this article only deals with the first aspect along with the statistical analysis of the results.

- Effectiveness of nudge cocktail to induce upward and downward flexibility.
- Degree of Flexibility in participant's household keeping in consideration equipments present in the house and the composition of the household.
- For each household, the distinct degree of flexibility (in terms of committed appliances) for upward modulation and download modulation.

State of the Art

This section presents state of the art of energy flexibility and nudge tool. In addition to that, it also presents suitable types of feedback of the earlier experiments conducted worldwide.

Energy Flexibility

The energy crisis in 1970s forced North America to start experimenting different modes of energy flexibility. Ehrhardt-Martinez & Donnelly (2010) classified the worldwide energy flexibility experiments into energy crisis era and climate change era. Residential sector remained as the focal energy consumption sector in these demand response experiments. Demand response is categorised into incentive based programs (e.g. direct load control, curtailable program) and price based programs (e.g. time of use, critical peak pricing, real time pricing etc.). Incentive based programs allow the operator to

https://doi.org/10.26868/25222708.2021.30962

remotely shut down consumer equipment; whereas the price based programs impel the consumers to manage their consumption according to the dynamic pricing (Albadi & El-Saadany, 2007). These programs achieve energy flexibility at the cost of consumer comfort. Hatton and Charpentier (2014) studied 20 energy flexibility experiments worldwide which were based on time of use (TOU), real time pricing (RTP) and critical peak pricing (CPP). EDF (Electricity of France) has introduced two colour coded critical peak pricing mechanisms and sends day ahead notifications to its residential subscribers (Bivas, 2011). The demand response is steered at the grid operator level while obliging the consumer to act upon it. It is intrusive, costly and takes from 10 seconds to 30 minutes to execute demand side management for the intended period (as illustrated in red box in figure 1).

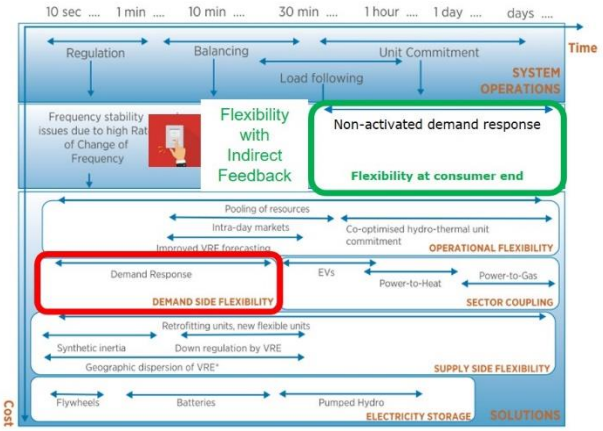

Figure 1 : Flexibility solutions relevant to intermittent renewable production (IRENA, 2018)

Another important aspect in energy flexibility is the type of feedback. In case of direct feedback, the demand response operator is obliged to give feedback to its customers in real time. Contrary to this, an indirect feedback is given to the consumer after the flexibility period is finished. It is either historic (comparing the consumption of household with the past consumption), or normative (comparing household energy consumption with that of a group of similar households) (Wang et al., 2018). It is normally presented in numerical form e.g. kWh, cost, CO_2 emissions (Fischer, 2008), in the form of clustered baseline load curve of identical households (Abreu et al., 2012) or as average daily load curve (Ozawa et al., 2016). Figure 2 presents a spectrum of different feedback mechanisms.

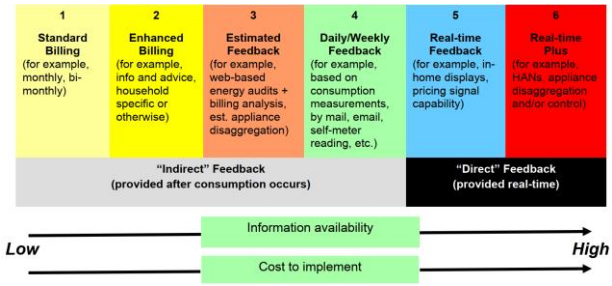

Figure 2: Feedback mechanisms (Neenan, 2009)

In a number of experiments, a control group is created with similar characteristics of treated group. "The control group is not subjected to any treatment and serves as a baseline to measure the effort of treated group" (Lesgards & Frachet, 2012). A matching method is used to place the individuals in control group and treated group based on the socio-economic characteristics of households. The matching method is not effective if the number of participants are unequal in both groups. Alternatively, a weight can be assigned to average load curve of control group with respect to each subject of treated group; The energy flexibility can be observed by difference of two load curves (Heckman et al., 1998).

"Difference in difference" is another method to measure the energy flexibility. With the assumption that the evolution of consumption in both groups is identical, the difference in difference method eliminates the temporal effects and bias selection between two groups (Bode et al., 2013). Another method is to create profile load curve for each subject. In this method, one selects the measured load curve of a number of previous days (of energy flexibility day 'D'), taking average of these load curves and then adjust the reference load curve with respect to a defined coefficient; the coefficient can be calculated by taking the difference or ratio of the average value of measured load curve and profile load curve (Goldberg & Agnew, 2003).

In this article, an alternative demand side management technique is presented, which is non-intrusive towards the end user, have low cost and takes from a few hours to certain days (as illustrated in the green box in figure 1). A reference load curve is created based on the historical consumption data of household and serves as indirect feedback to respective household of treated group.

Nudge

"Nudge is an aspect of the choice architecture that alters people's behaviour in a predictable way without forbidding any options or economic incentives." (Thaler & Sunstein, 2008). "The choice architecture refers to the practice of influencing choice by organizing the context in which people make decisions" (Shafir, 2013).

Social norms remained effective during the study of non-price based energy flexibility experiments. The pilot non-price nudge field study was performed in USA. In collaboration with energy utility companies, OPOWER analysed the energy consumption of households and sent Home Energy Reports (HER) to respective household consumers periodically. The energy consumption of a household for a period of time is compared with the energy consumption of energy efficient neighbours and all neighbours. This comparison is presented in graphical form along with energy conservation tips in the report, and is considered as the "descriptive norm".

An "injunctive norm" is also added in the report by giving a rating in the form of "efficiency standing". This efficiency standing categorized the household as "Great," "Good," or "Below Average". Multiple models predict that the social comparison module would nudge the households to decrease their energy consumption if they found in their home energy report that they have consumed more than the norm (i.e. their neighbours); and

the case is opposite for those households for whom the social comparison module would nudge to increase their energy consumption if they found in their home energy report that they have consumed less than their neighbours (Allcott, 2011). It has also been found that the provision of (indirect) feedback to customers on home energy usage with a focus on peer consumption decreased energy consumption by 1% to 2% (Ayres et al., 2013).

Through literature review, it has been observed that the nudges in the past experiments were price incentive (as in price based demand response programs, reward or penalty), competition based or environmental propagative. The price based nudges tend the consumer to either gain or avoid loss monetarily. The competition based nudges tend the consumer to win only and therefore are effective during the duration of the competition. In case of unlimited duration of competition, the consumer might abandon its efforts after a period of time. Thus these type of nudges does not remain sustainable. "The results suggest that environmental nudges are most effective in relatively liberal communities" (Costa & Kahn, 2013)

In this article, we coined a term "nudge cocktail". The reason for coining this term is that the conceived nudge for the experiment includes behavioural insight of the households and is a combination of multiple nudges. It is used to keep the households engaged within the experiment and measuring the effort of energy efficiency. This nudge cocktail does not include any social norm, rather it keeps a nudge based on the energy consumption of the household during alert period. It is presented in detail in the following section.

Experimental Design

This section demonstrates the experimental design. The experiment was conducted for a period of 1 year. The orange alerts were sent in winter during the months of November 2019 and March 2020. The green alerts were scheduled to be sent between April 2020 and September 2020. However due to the lockdown caused by COVID-19, the green alerts were rescheduled between July 2020 and September 2020.

Architecture

For this experiment, GAEL (Grenoble Applied Economics Laboratory) recruited 175 households (equipped with LINKY smart energy meter) in a French agglomeration. LINKY transmits the daily measured load curve of the consumer at a sampling period of 30 minutes to ENEDIS (French distribution system operator) server (Duplex et al., 2013). G2ELab (Grenoble electrical engineering lab) receives the daily measured load curve of each household from ENEDIS in encrypted form. An automatic script decrypts and anonymizes the data as per GDPR consent signed with each households.

The households are distributed into control group and treated group. The control group comprises of 79 households and treated group comprises of 96 households. The control group represents as a reference for electrical consumption of households in treated group. It ensures that the energy consumption of treated group is only influenced by the nudge during alert day. The treated group receives a set of SMS as nudge signal for each alert day. Alerts are not triggered for weekend and holidays. Two types of alerts are devised to send nudge signal towards treated group.

Green alert (GA): The purpose of this alert is to nudge the treated group for shifting their partial load from evening to the duration between noon and 3:00 PM on alert day 'D'. Following is the criteria to send a green alert:

- The nebulosity on alert day 'D' in the said French agglomeration should be zero. i.e. the sky will be clear and the solar production will be maximum.
- Based on the forecasted French national load curve of residential sector, a coefficient is calculated. The forecasting model is briefly discussed in next sub-section. To trigger a green alert, this coefficient should be greater than 1 i.e. the forecasted afternoon consumption of next day should be lower than the forecasted evening consumption. The coefficient is mathematically given in equation 1.

$$Coefficient_{GA} = \frac{\sum_{6\ PM}^{8\ PM} P_{consummed} / t_1}{\sum_{12\ PM}^{3\ PM} P_{consummed} / t_2} \quad (1)$$

Where t_1 and t_2 are number of hours during the considered period. Their values are 2 and 3 respectively.

Orange alert (OA): The purpose of this alert is to nudge the treated group for curtailing their partial load between 6:00 PM and 8:00 PM on alert day 'D'. The orange alert is based on the day ahead announcement of PP1/PP2 (Peak Period 1 and 2). These days correspond to high electricity consumption determined by RTE (French electric Transmission System Operator).

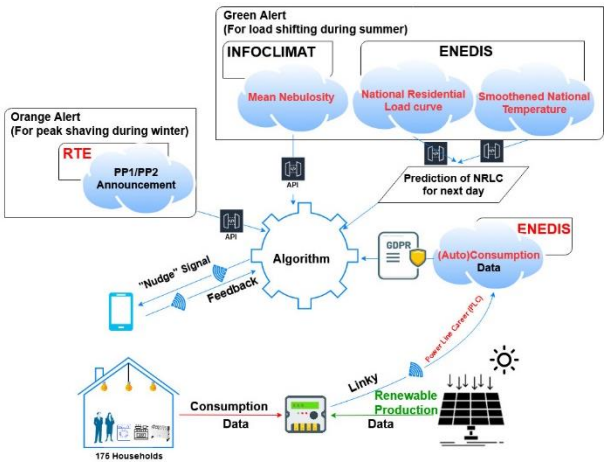

Figure 3: Schematic Diagram of project "EXPESIGNO"

Forecasting the French national load curve of residential sector

In order to forecast a day ahead French national load curve of residential sector, certain third party APIs are used to obtain daily updated data. Two of these APIs are related to ENEDIS. ENEDIS constructs national profiles of the energy consumption sectors in France. A profile represents average behaviour of a group of users and reflects how an average individual in the group consumes

https://doi.org/10.26868/25222708.2021.30962

electricity (RTE France, 2020). The data is sampled at 30 minutes and hereafter termed as national load curve. For our study, we selected "dynamic profile coefficient" of category "RES11_BASE". This category consists of the residential consumers which have contracted power ≤ 6 kVA. Most of the French households subscribes this contract and normally does not have electrical heating in their home. ENEDIS does not periodically update this data, therefore a prediction model is created that predicts the next day "D+1".

ENEDIS also provides the national temperature of France via another API. The national temperature is calculated by a weighted aggregation of measured temperature for 32 French cities (RTE France, 2020). Since we only have data until 'D-2' from ENEDIS API of temperature, therefore we need the weighted aggregation of forecasted temperature of 32 French weather stations. For this purpose, we use the API of CLIMACELL to gather the forecasted temperature data. The data is sampled by 1 hour. Using the method given in (RTE France, 2020), the aggregated temperature of 32 French cities is calculated.

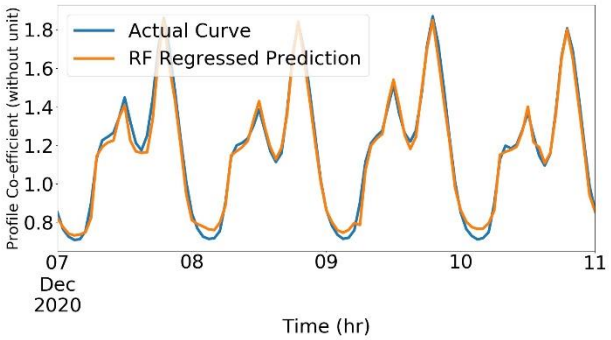

Figure 4: Prediction of 4 future days of French residential load curve by random forest regression

By using the data obtained from the APIs given above and adding certain lag features and temporal features (e.g. hour of day, day of week etc.), a random forest regression is performed on the French national load curve of residential sector. Figure 2 illustrates the prediction of French national load curve of residential sector versus the actual curve. The execution of model yields a mean absolute percentage error of 2.52%.

Elements of Nudge Cocktail

There are multiple elements of the nudge cocktail that are implemented for each alert day 'D'. For each alert day 'D', 4 sms are sent to each subject of treated group. The information in each type of sms is given below.

- Alert SMS: Energy production and its environmental impact i.e. elevated production of thermal power plants for orange alert and maximum use of renewable energy production for green alert.
- Commitment SMS: A customized set of advice for each subject of treated group about how to optimize energy consumption with his pre-defined commitment. The subject may change their pre-defined commitment for each alert.
- Reminder SMS: A reminder sms is sent in the morning of alert day 'D' to all the subjects of treated group.
- Image visualization SMS: An sms is sent to all the subjects of treated group so that they can view the result of their effort during the period of action on alert day 'D'.

The participants of treated group signed a commitment form, stating the appliances that they will use or not use in response to the alert. The commitment form consists of a list of all the appliances present in subject's household and the timeslots during which these appliances are used. For each alert day 'D', the subjects must commit the appliances that they will use (or not use) during period of action. For this purpose, a URL is added in the commitment message that permits the subjects to modify their default commitment on day 'D-1'.

Regular feedback to the subjects in the form of an image of the measured load curve superposed by reference load curve for alert day 'D' is sent to the subjects of treated group. The aim of this sms is to positively reinforce the subjects to continue acting on the nudge signals.

Timeline

- A potential alert is registered in database on day 'D-1' at 6:00 PM.
- At 6:45 PM on day 'D-1', alert sms is sent to treated group. Following this, customized commitment sms is also sent to each subject of treated group.
- The subjects of treated group are sent a reminder sms on alert day 'D' at 7:30 AM.
- The period of action on alert day 'D' depends upon the type of alert. For green alert, the period of action is from noon to 3:00 PM during which load shifting is expected. For orange alert, the period of action is from 6:00 PM to 8:00 PM during which load curtailment is expected.
- At 3:00 PM on day 'D+2', the measured load curve of all the subjects of both groups is received on G2ELab server. The measured load curve of each subject is anonymized with respective subject code as per GDPR consent and is stored in the database.

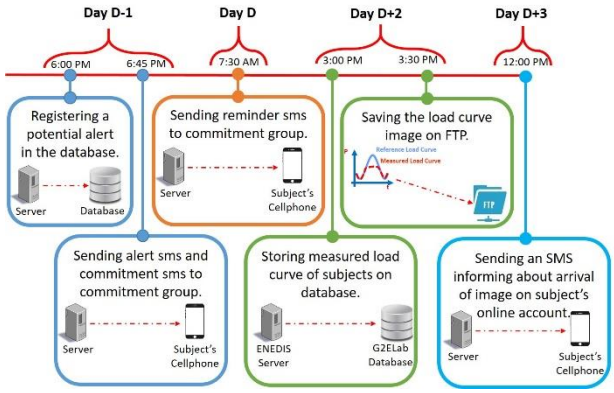

Figure 5: Timeline of each alert of experiment

- At 3:30 PM on day 'D+2', an image file is generated for each subject of treated group in which the measured load curve of alert day 'D' is superposed by reference load curve for alert day 'D' (reference load curve will be briefly discussed in a later section). These images are stored on a FTP server. The images

are picked up by GAEL later the same day and is placed on the personal account of each subject for visualization.

- At noon on day 'D+3', a sms is sent to all the subjects of treated group so that they can visualize their effort of alert day 'D' on their online account.

Reference Load Curve

A reference load curve has an important role in this study. It helps in scientific evaluation of the efficiency of nudge signal. Besides, the reference load curve is itself a nudge. A reference load curve is in fact an expected load curve on a normal day. The difference of reference load curve (i.e. expected load curve on non-alert-day) with flexibility driven measured load curve gives energy flexibility on alert day 'D'. Practically, it is important to select the method that does not underestimate or extremely overestimate the effort of energy flexibility on alert day "D". Currently, the following methods are used.

Mean [P_{D-1} & { Min (P_{D-2} : P_{D-5})}] : For an alert day 'D', a reference load curve is created by taking average of measured load curve of previous day 'D-1' and the measured load curve having lowest energy consumption between day 'D-2' and 'D-5'. This method is used for presenting the energy flexibility for load curtailment. Figure 6 illustrates the reference load curve superposed on measured load curve.

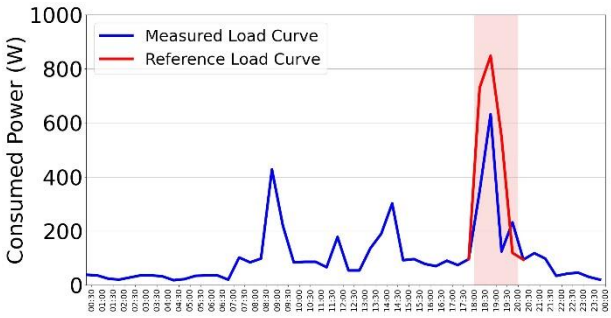

Figure 6: Superposition of reference load curve over measured load curve to visualize load curtailment

Mean [P_{D-1} & { Max (P_{D-2} : P_{D-5})}] : For an alert day 'D', a reference load curve is created by taking average of measured load curve of previous day 'D-1' and the measured load curve having highest energy consumption between day 'D-2' and 'D-5'. This method is used for presenting the energy flexibility for load shifting.

The selected methods take into account the temporal effect and indirectly take in to account the temperature factor for load curtailment alerts. The methods take into account the evolution of energy consumption with respect to time as it includes the energy consumption of day 'D-1'. Besides, it does not nullify the effect of minimum (or maximum) energy consumption occurred at any day D-n (where $2 \leq n \leq 5$).

Comparison of energy consumption of control group and treated group during normal days

A control group is created in order to find out if any external factor affect the experiment. The control group does not receive any treatment. Ideally, the average energy consumption of both group should be identical. For the sake of experiment, the period between noon and 3:00 PM is significant for load shifting on alert day 'D' (i.e. implementing green alert). Similarly, the period between 6:00 PM and 8:00 PM is significant for load curtailment on alert day 'D' (i.e. implementing orange alert). Therefore it is essential to compare the energy consumption of both groups during these periods on normal day (i.e. non alert day).

Figure 7 represents the distribution of energy consumption of both groups between noon and 3:00 PM during normal days, whereas figure 8 represents the distribution of energy consumption of both groups between 6:00 PM and 8:00 PM during normal days. It is interesting to see that the energy consumption pattern of both groups during the intended period of study is identical. The median difference between treated group and control group in figure 7 is 54 Wh, whereas the median difference between treated group and control group in figure 8 is 16 Wh; which is very small.

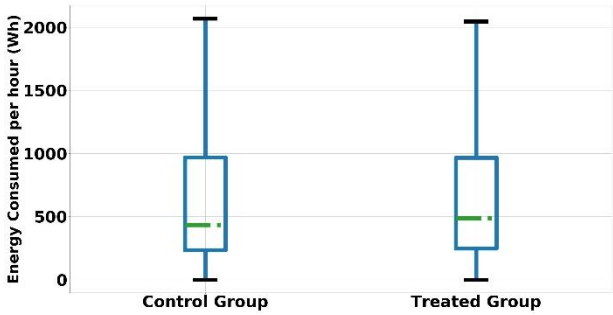

Figure 7: Distribution of energy consumption of both groups between noon and 3:00 PM

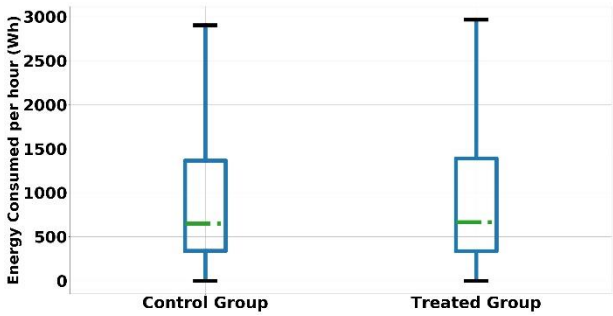

Figure 8: Distribution of energy consumption of both groups between 6:00 PM and 8:00 PM

Statistical comparison between the two groups

A statistical comparison of the data distribution of two groups gives us an idea whether the consumption of two groups is similar or different during the period of action. Through the visualization of data during the period of action on alert day 'D', it has been found that the data is asymmetric (i.e. not normally distributed) and is skewed towards left. Therefore a non parametric test called Mann-Whitney U test is chosen to find the statistical significance of each alert. The following hypothesis are tested using the Mann-Whitney U test.

- **Null Hypothesis**: The statistical distribution of energy consumption data of the treated group is same to the statistical distribution of energy consumption data of the control group during the period of action.
- **Alternate Hypothesis**: The statistical distribution of energy consumption data of the treated group is different to the statistical distribution of energy consumption data of the control group during the period of action.

The test was performed using the function of Python's SciPy package (scipy.stats.mannwhitneyu()). If the resulting p-value of any alert is less than α=0.05, the alternate hypothesis is validated (ie. both groups are statistically dissimilar over the period of action on alert day 'D').

Mann Whitney U Test for Orange Alerts

Table 1 presents the mean and standard deviation of both groups while table 2 presents the statistics, p-value and statistical significance (validation of the alternate hypothesis) of each orange alert by doing a comparison between control group and treated group. It has been found that for 7 orange alerts out of 9 orange alerts, the p-value is less than α, i.e. the difference between the population's mean of control group and treated group is statistically significant. In other words, the energy consumption of the treated group during the period of action on alert day is different than the energy consumption of control group for these 7 orange alerts. The aggregated result of both tables indicate that globally the orange alerts tended the subjects of treated group to implement load curtailment. The difference of the averages between control group and treated group in table 1 yields an average load curtailment of 133 W/30 minutes (or 266 W/h); which is significant if considered for a single household during peak hours of residential consumption. This is further validated with a 0 p-value for aggregated alerts in table 2.

Table 1 : Mean and standard deviation of energy consumption of control group and treated group for orange alerts

Orange Alert No.	Control Group		Treated Group	
	Mean	Standard Deviation	Mean	Standard Deviation
1	703	810	659	1263
2	623	818	460	443
3	825	1012	631	845
4	707	899	534	735
5	734	917	557	626
6	630	770	616	779
7	689	843	464	623
8	611	782	473	589
9	660	800	587	948
Aggregated	687	854	554	798

Table 2: Mann Whitney U Test between Control group and treated group for orange alerts

Orange Alert No.	Statistics	p-value	Significance
1	49266	0.001	True
2	52209.5	0.097	False
3	48381	0.001	True
4	49400.5	0.003	True
5	51403	0.015	True
6	53847.5	0.178	False
7	42789.5	0.000	True
8	50605.5	0.012	True
9	49106.5	0.005	True
Aggregated	4032969	0.000	True

Among these orange alerts, the 7th orange alert performed better as compared to the others. The difference of the averages between two groups for orange alert no. 7 is 225 W/30 minutes (or 450 W/h). The average consumption load curve of both groups for orange alert no. 7 is presented in figure 9. It can be observed that the average energy consumption of treated group during the period of action is less than control group. The case is inverse for day 'D-1' and day 'D+1'. It suggests that the nudge signal had an impact on the households to implement load curtailment during period of action on day 'D'.

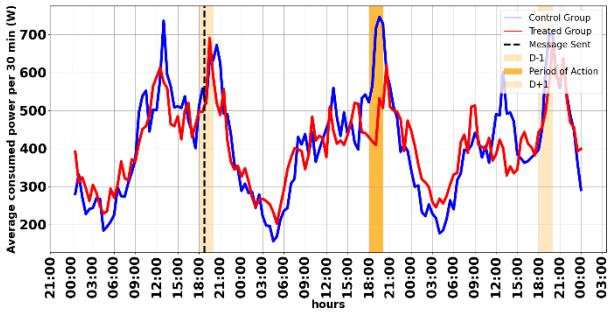

Figure 9: Average consumption load curve of both groups for 7th orange alert

Another important result to check is whether the subjects of treated group having electric heating have same or different energy consumption distributions as compared to the subjects having no electric heating. Except for orange alert no. 2, it is observed that there is a significant difference in the mean of both types of treated subjects.

Table 3: Mean and standard deviation of energy consumption of subjects having or not electrical heating for orange alerts

Orange Alert No.	Subjects having electrical heating		Subjects not having electrical heating	
	Mean	Standard Deviation	Mean	Standard Deviation
1	887	1676	431	535
2	450	397	470	481
3	758	840	513	835
4	698	831	387	601
5	733	724	388	457
6	803	943	444	537
7	645	806	303	318
8	624	698	338	430
9	811	1132	388	689
Aggregated	714	967	407	564

Table 4: Mann Whitney U Test between the subjects of treated group having electric heating and those who have not electrical heating in their house

Orange Alert No.	Statistics	p-value	Significance
1	12684,5	0	True
2	15424	0,225	False

3	13294	0,001	True
4	10722	0	True
5	10776	0	True
6	11536	0	False
7	11344	0	True
8	10748	0	True
9	9713	0	True
Aggregated	4032969	0	True

Mann Whitney U Test for Green Alerts

Table 5 presents the mean and standard deviation of both groups while table 6 presents the statistics, p-value and statistical significance of each green alert by doing a comparison between control group and treated group. It is observed that 3 green alerts out of 6 are statistically significant i.e. the treated group consumption is different than the control group consumption.

Table 5: Mean and standard deviation of energy consumption of control group and treated group for green alerts

Green Alert No.	Control Group		Treated Group	
	Mean	Standard Deviation	Mean	Standard Deviation
1	341	451	412	587
2	306	363	495	696
3	402	421	396	443
4	349	419	412	555
5	347	575	392	469
6	231	310	409	571
Aggregated	326	436	420	568

Table 6: Mann Whitney U Test between Control group and treated group for green alerts

Green Alert No.	Statistics	p-value	Significance
1	86783	0,07	False
2	65250,5	0,001	True
3	27909,5	0,243	False
4	92615,5	0,133	False
5	83942	0,004	True
6	76617	0	True
Aggregated	2571333	0	True

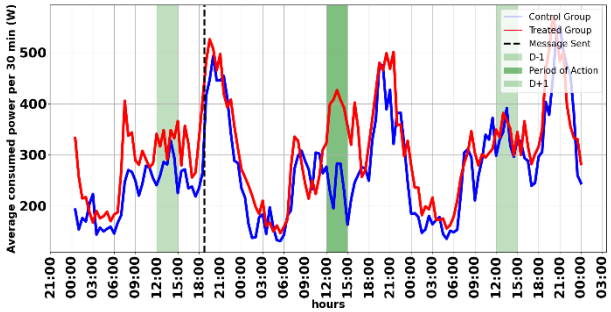

Figure 10: Average consumption load curve of both groups for 6th green alert

It should be noted that the results of some green alerts are affected with lack of retrieval of measured load curve of certain subjects due to expiration of annual GDPR consent signed with the subjects. However, most of the data is retrieved for 5th and 6th green alerts and the results of these two green alerts are less affected with the impact of lack of data. As given in table 5, the difference of mean of both groups is small except for green alert no. 6, in which we observe a difference of 178 W/30 minutes (or 356 W/h). Figure 10 presents the average load curve of control group and treated group for 6th green alert. It can be observed that the average energy consumption of treated group during the period of action is more than control group. However, it needs further investigation about which electrical loads remained significant for achieving load shifting.

Discussion and Conclusion

The traditional demand response techniques either ask for direct load control or offer price based incentives to the residential customer. These techniques are however intrusive and may be costly. The price based incentives keeps the consumer in loop as long as the offer is in place. Alternatively, demand side management can be achieved by social competition. The OPOWER experiment in USA is an example of social competition which induced a sense of load curtailment through self-evaluation and comparison of load consumption with neighbours. Yet, the impact of such experiments is for limited time. An alternative mechanism is proposed in this article, in which nudge signals are sent to the households of treated group with indirect feedback and no price incentive. The purpose of this experiment and specifically nudge signals is not to tend the subjects to implement energy flexibility for any monetary gain or competition, rather they are based on the forecasted condition of the electrical grid to avoid network congestion or consume elevated renewable energy production on day ‘D’.

In an experiment, a hypothesis is tested that whether the forecasted information of grid condition could nudge the residential consumers to implement indirect energy flexibility. The challenge of energy flexibility is connected with energy transition objectives, as it can leverage a better integration of intermittent production. Most of the subjects that are participating in this experiment are sensible about environment and react to nudges in this perspective. A comparison of the impact of nudge is done between control group and treated group. The comparison of energy consumption of both groups reveals that the proposed nudge signal cocktail has an impact on the households for most orange alert days demanding downward flexibility. The behavior for alert day is found different than the day ‘D-1’ and day ‘D+1’. The impact for upward modulation on alert day ‘D’ is not clear, possibly due to lack of sufficient data, and requires further investigation.

A similar procedure called “mon-ecowatt” is currently implemented by RTE. RTE sends SMS signal to the subscribers for curtailing load on peak consumption days. The future prospects of this work includes (but not limited to) measuring whether a habit of implementing energy flexibility is formed over the course of time. It is also interesting to measure how the socio-economic characteristics of each household affects their degree of implementing energy flexibility. Also, it will be interesting to know which time of the day is more impactful/reliable for implementing energy flexibility. Furthermore, the potential appliances for implementing

indirect energy flexibility could be explored by measuring the impact of individual appliances.

Acknowledgment

This work has been supported by the Auvergne Rhône-Alpes region, with *"Pack Ambition Recherche 2017 - Expesigno projet" (17 01110301)* and the *"OREBE"* project. This work has also been partially supported by the CDP Eco-SESA receiving fund from the French National Research Agency in the framework of the *"Investissements d'avenir"* program (ANR-15-IDEX-02).

References

Abreu, J. M., Câmara Pereira, F., & Ferrão, P. (2012). Using pattern recognition to identify habitual behavior in residential electricity consumption. Energy and Buildings, 49, 479–487. https://doi.org/10.1016/j.enbuild.2012.02.044

Albadi, M. H., & El-Saadany, E. F. (2007). Demand Response in Electricity Markets: An Overview. 2007 IEEE Power Engineering Society General Meeting, 1–5. https://doi.org/10.1109/PES.2007.385728

Allcott, H. (2011). Social norms and energy conservation. Journal of Public Economics, 95(9), 1082–1095. https://doi.org/10.1016/j.jpubeco.2011.03.003

Ayres, I., Raseman, S., & Shih, A. (2013). Evidence from Two Large Field Experiments that Peer Comparison Feedback Can Reduce Residential Energy Usage. The Journal of Law, Economics, and Organization, 29(5), 992–1022. https://doi.org/10.1093/jleo/ews020

Bivas, P. (2011). Load shedding production: how to offer electricity savings to millions of households (in french: La production d'effacement : comment offrir des économies d'électricité à des millions de foyers). Le journal de l'ecole de Paris du management, n°90(4), 8–14.

Bode, J. L., Sullivan, M. J., Berghman, D., & Eto, J. H. (2013). Incorporating residential AC load control into ancillary service markets: Measurement and settlement. Energy Policy, 56, 175–185. https://doi.org/10.1016/j.enpol.2012.12.024

Costa, D. L., & Kahn, M. E. (2013). Energy Conservation "Nudges" and Environmentalist Ideology: Evidence from a Randomized Residential Electricity Field Experiment. Journal of the European Economic Association, 11(3), 680–702. https://doi.org/10.1111/jeea.12011

Duplex, J., Gosswiller, S., & Fagnoni, S. (2013). A better knowledge of electricity consumption for residential customers through the Linky smart meter. 1333–1333. https://doi.org/10.1049/cp.2013.1188

Ehrhardt-Martinez, K., & Donnelly, K. A. (2010). Advanced Metering Initiatives and Residential Feedback Programs: A Meta-Review for Household Electricity-Saving Opportunities. 140.

Fischer, C. (2008). Feedback on household electricity consumption: a tool for saving energy? Energy Efficiency, 1(1), 79–104. https://doi.org/10.1007/s12053-008-9009-7

Goldberg, M. L., & Agnew, G. K. (2003). Goldberg, M. L., and G. Kennedy Agnew. "Protocol Development for Demand-Response Calculations: Findings and Recommendations (CEC 400-02-017F, KEMA Inc.).

Hatton, L., & Charpentier, P. (2014). French electricity system: estimation of residential customers' load shedding (in french: Système électrique français : estimation de l'effacement des clients résidentiels). 14.

Heckman, J. J., Ichimura, H., & Todd, P. (1998). Matching As An Econometric Evaluation Estimator. The Review of Economic Studies, 65(2), 261–294. https://doi.org/10.1111/1467-937X.00044

IRENA, I. R. E. A. (2018). Power system flexibility for the energy transition, Part 1: Overview for policy makers. 48.

Lesgards, V., & Frachet, L. (2012). Residential Electricity Demand Management: A Review of 30 Years of Global Experiments (in french :La gestion de la demande résidentielle d'électricité: retour sur 30 ans d'expérimentations mondiales)., 607, 162, 164, 192-210 [21 p.].

Neenan, B. (2009). Residential Electricity Use Feedback: A Research Synthesis and Economic Framework. 126.

Ozawa, A., Furusato, R., & Yoshida, Y. (2016). Determining the relationship between a household's lifestyle and its electricity consumption in Japan by analyzing measured electric load profiles. Energy and Buildings, 119, 200–210. https://doi.org/10.1016/j.enbuild.2016.03.047

RTE France. (2020). Relations between the DSO and the Balance Responsible Entity: Provisions applicable to the estimation of Load Curves (in french: Relations entre le GRD et Le Responsable d'equilibre : Dispositions Applicables Pour L'Estimation des Courbes de Charges).

Shafir, E. (2013). The Behavioral Foundations of Public Policy. Princeton University Press.

Thaler, R. H., & Sunstein, C. R. (2008). Nudge: Improving decisions about health, wealth, and happiness. Yale University Press.

Wang, F., Liu, L., Yu, Y., Li, G., Li, J., Shafie-khah, M., Catalão, J., Wang, F., Liu, L., Yu, Y., Li, G., Li, J., Shafie-khah, M., & Catalão, J. P. S. (2018). Impact Analysis of Customized Feedback Interventions on Residential Electricity Load Consumption Behavior for Demand Response. Energies, 11(4), 770. https://doi.org/10.3390/en11040770