From operating energy networks to managing energy systems: how electricity distribution firms are paving the way for new and innovative business models in energy distribution - a focus on the case of France

Author: Telman Azarmahd, Researcher, Paris-Sorbonne University

ENeC Laboratory, Maison de la Recherche, 28 rue Serpente - 75006 Paris, France
Phone: +33 6 42 99 35 94; E-mail: telman.azarmahd@paris-sorbonne.fr

Abstract

This paper aims to demonstrate the extent by which the electricity distribution network operator (DNO) may generate economic utility across a territory through the diversification of its core activity, from "pure" electricity distribution to new innovative services linked to the operation of the electric system. The paper reflects on the case study of Enedis, the French DNO, which operates on 95% of the continental territory.

By using a double-difference regression model, we first determine the impact of three innovative services implemented by Enedis on the price elasticity of power demand: deployment of smart meters; exploratory network impact studies performed for charging infrastructures dedicated to electric vehicles; and development of energy data platforms. Results show that these services seem to create a certain shift in elasticity and generate value and flexibility on the electric system, upon condition that end customers be provided with adequate signals (information about power price as well as their incumbent and historical consumption).

The second part of the paper gives insights on the sensitivity of certain types of French territories for several of the new services deployed by Enedis. We first cluster in three main groups a set of 224 urban areas in France, according to the growth of the different services implemented across their perimeter on the 2013-2015 period. We then use a discriminant analysis on a number of macroeconomic explanatory variables, in order to explain the underlying reasons for the deployment of these services. Results suggest that the growth of the main services of the DNO (data platforms and exploratory studies for electric vehicles) seem to be crystallized in large and highly attractive urban areas and metropolises, whereas more rural or remote areas are either more prone to services linked to their spatial and industrial development (urban planning or renewable energy studies), or are yet to be acquainted with the role of the DNO as an "enabler" of the energy transition on their territory.

Keywords: Business Models; Electricity system; Distributed Energy Resources (DERs); Distribution network operator (DNO); Distribution System Operator (DSO); Renewable Energies; Utility.

"We believe that electricity exists, because the electric company keeps sending us bills for it, but we cannot figure out how it travels inside wires."

- Dave Barry, American energy researcher and columnist[1].

Introduction: the distribution network in the wake of the game changers in the power industry

The traditional ubiquitous vision of the power utility business model, favoring large and integrated juggernaut-sized power firms subject to top-down political regulation across the whole electricity value chain, has literally gone the distance. In 2013, 94% of the senior power and utility executives surveyed did anticipate "a complete transformation or important changes" to this power utility business model by 2030[2]. Truth be told, one may not even have to wait until this far-fetched time horizon in order to realize that transformations in the electricity sector have been effective and under way for over a decade. The game changers in the power industry, and more generally public utilities, have been manifold.

The first change pertains to technological revolutions which have shaped the digitalization of the economy today: the world has become a connected mesh of binary data, instantly linking up thousands of data platforms capable of communicating with one another. Today, citizens do not only consume a certain number of electrons dispatched by the local or national power distribution company via medium and low-voltage cables. They now consume a specific service, which consists in receiving those electrons in exchange for the (close to) wireless smart metering of their consumption…with the ultimate goal for the distribution firms to use this data as an input for the improvement of their business as well as in the devising of new customized services for these citizens. In other words, your electric data is of great value for the world, and unraveling the patterns of your daily or even hourly use of power will contribute to the marketing of specific tailor-made solutions. These solutions will not only help your household make a step towards energy efficiency, they might also generate social utility for your neighbors, your residential district or community, and, well, even your city. The concept of social utility refers, in a nutshell, to the feature of a good or service addressing "needs that are not, or to a very low extent, taken into account neither by the State or the market" and which triggers a response to market distortions through the implementation of principles typical of the social economy (Rodet, 2008).

Let us go one step further and combine this generated potential for data analytics with the second game changer - the energetic transition - and we now have a powerful (literally speaking) bombshell ready to be dropped on the power utility sector. The inflows of distributed energy resources (DERs),

[1] D. Hunter, *Electricity is more than the bill*, Public Power blog, 28/07/2015.
[2] PwC, *Energy transformation: The impact on the power sector business model*. 2013.

which mainly include intermittent renewable energy sources such as solar and wind power that are being connected to the power distribution network 90% of the time[3], are the prime drivers of this transformation. Coupled with the rampant growth of battery density, and more generally electrical storage capacities, as well as the price-responsive management of electricity demand, these DERs have paved the way for a decentralized energy system.

The case of France is a testament to these industry transformations. The post-World War II era, which saw the rise of the power industry in France, especially with the advent of Electricité de France (EDF) in 1946 as a natural - albeit regulated - monopoly, favored a complex centralized system catalyzing the growth of the nuclear industry as the main source of power in the 1970s, nuclear power still accounting for almost 72% of the primary energy production in France in 2015[4]. The liberalization of the power sector in Europe, which started in the mid-90's, eventually led to the managerial unbundling of EDF in the early 2000's, thus clearly separating regulated activities within the electricity value chain (transport and distribution) with competitive ones (production and supply/marketing to end users). This unbundling scheme was completed with the creation of Enedis (back then ERDF) in 2008, as the main public distribution network operator, covering up close to 95% of the territory.

This paper aims to demonstrate the extent by which the electricity distribution network operator may generate economic utility across a national territory through the diversification of its core activity, from pure electricity distribution to new innovative services linked to the operation of the electric system. This generated utility will be more specifically analyzed via the case study of Enedis and its role on the French national perimeter.

Literature review

The academic literature describing current or potential future utility business models, especially in the case of power distribution, is fairly scarce. First off, the link between utility firms and their business models in general is far from being obvious, probably owing to the concept of "business model" not being an acknowledged component of a utility firm by nature (Newcomb et al., 2013; Lehr, 2013). Certain studies have analyzed the cost structure of the French electricity distribution sector, and provided an analysis over how economies of scale (Farsi et al., 2010) as well as the regulatory reforms and incentives in the distribution sector (Jamasb and Pollitt, 2003; Jamasb and Pollitt et al., 2005; Joskow and Schmalensee, 1983) were the main reasons why certain activities were re-structured across distribution units. The issue of the quality of service delivered by distributors has been thoroughly highlighted (Coelli et al., 2008) but solely put in the perspective of strict electricity

[3] RTE/Enedis/Syndicat des énergies renouvelables, ADEeF, *Panorama de l'électricité renouvelable au 30 juin 2016*, June 2016, p.31.
[4] RTE (Réseau de Transport d'Électricité), *Bilan électrique 2016*.

distribution. The efficiency issue of power distribution firms has been well-documented via panel data models in the case of several electricity concessions within a national territory in the cases of Switzerland (Filippini et al., 2006) and Algeria (Zeriouti and Belaid, 2016). Insights over the efficiency of power network costs have been provided via specific methods such as the statistical frontier analysis (Aigner, Lovell, and Schmidt, 1977) and combined with the issues of real-time electricity pricing (Borenstein, 2002). Jamasb and Pollit (2008; 2009) exhibit significant variations in efficiency scores among different econometric models applied to several European power distribution utilities. These efficiency scores give hints about the constraints created by regulation on the DSO's business model whenever it is a natural monopoly, and gives rationale about why a potential diversification in new services may not have been an option in the past, as it would have led to a high level of inefficiency in terms of costs for the DSO.

As regards the willingness-to-pay for a certain type of good – the parameter which helps in fact determine the social surplus generated by the economics of the good – the academic literature has put forward the importance of information in the case of residential electricity demand: the inhibition of full information may lead indeed to low price elasticity of power, and thus very little change in social surplus overtime (Reiss and White, 2005; Allcott, 2011; Ito, 2011). These results have been further analyzed in a case study experiment in the state of California (Jessoe and Rapson, 2013), and suggest that imperfect information leading to efficiency inhibition for residential power demand may be overcome with the provision of simple, low-cost information in the form of price signals. This information, in turn, shall entail a shift in power demand, and therefore generate new possibilities to increase the global social surplus for both the actors of the electric system and the customers.

This paper strives to combine the quantitative approach addressed by price elasticity models (as to the added-value derived from specific new services delivered by the power distribution firm) with a holistic spatial approach which introduces macroeconomic territorial parameters as full-fledged inputs and determinants of the value created by the DSO's new services.

Methodological overview

The first part of the paper consists in appraising the value of the price elasticity of power demand for three innovative services deployed by Enedis: smart metering, data platforms, and exploratory studies for electric vehicles. The methodology used in a double-differences model based on the impact of signals - or lack thereof - sent by Enedis to the different groups of customers in the experimentation. This analysis gives insight over how the new services may generate utility for the electric system via their impact on power demand.

The second part aims at classifying French territories according to their "sensitivity" regarding the delivery of certain services provided by the DSO, and at figuring the underlying reasons from an

economic and spatial standpoint behind this need for new services. The method used is a statistical multivariate analysis based on a hierarchical cluster analysis, a principal component analysis, and a discriminant analysis. This part strives to reveal what types of territories may contribute the most to the power demand reduction assessed in part 1.

1. Research experimentation on the impact of the DSO's new services on the price elasticity of power demand

1.1 Experimentation background and definition of customer groups

A transitory field experiment monitored by Enedis was launched in the summer of 2016 in order to assess the impact of three innovative services on the price elasticity of demand for a sample of residential customers scattered all across the French territory. The sample of consenting residential customers involved in this experiment stemmed from a total of 236 electricity concessions (out of a total of 580 in France at the beginning of 2016) and represented about 1,600 households altogether. The method used is a double-difference model described earlier. The three services proposed by Enedis on top of "pure" electricity distribution were, respectively:

(1) **Smart metering**: the deployment of Enedis' new smart meter called "Linky" and the ability for the customers to directly visualize the following data on the meter: their electricity consumption index via real time in-house display on the metering device, the incumbent electricity tariff in euro per kWh at which they were charged for their power consumption according to the time of the day, and the cumulated monthly power expenses they were incurring. No specific price signal mechanism was implemented (e.g. sending of text messages to notify the customers about a tariff change or an abnormal level of electricity consumption). To be eligible, customers simply were to have their main residence in a townhouse or a flat in which the smart meter had already been installed by Enedis. These customers were referred to as "Group A".

(2) **Data platform**: the development of a data platform for customers who already owned a smart Linky meter and who, on top of being able to get a glimpse on their real time consumption on the smart meter as in Group A, were given personal access codes to an online website in which they could follow their real time consumption index (global and for each main domestic appliance) as well as their historical data from the N-1 year, their power load curve and the aggregated consumed P_{max} (maximum capacity) at the IRIS area level[5]. Unlike Group A, these customers,

[5] IRIS ("Ilôt regroupé pour l'information statistique", which could be translated in english by "Grouped geographic area for statistical information") is an official geographical mesh used by INSEE, the French national

referred to as "Group B", were given signals by text messages whenever they could benefit from a decrease in kWh by postponing their household power consumption at a later time during the day, whenever the distribution network would experience a surge in capacity or power demand, or when their power consumption during a certain day would exceed the one of the previous year beyond a certain threshold variation[6]. These signals were delivered 60 minutes prior to the predicted surge in capacity, and invited customers to log in to their personal data platform via their smartphone or computer to get further information. These signals did not explicitly mention a variation in price in the message but simply raised customers' awareness about the urge to obtain new information on their individual account regarding their household power consumption. Customers from this group were made eligible on the basis of having a smart meter as well as full-fledged operating Internet access in their house.

(3) **Electric mobility development**: the delivery of "exploratory studies" for groups of customers located in a township where charging infrastructures for electric vehicles had already been installed. The overall purpose of this service deployed by Enedis was to determine if, through the analysis of price elasticity of demand, network reinforcement costs within a township in a specific concession could be avoided or reduced by raising global awareness as to the capacity constraints created by a surge of electric vehicles connecting at peak load. This service was implemented in three stages: first, local workers from Enedis would meet with customers in order to get acquainted with the charging patterns of their electric vehicle according to their daily routine (e.g. use of electric vehicle during the day and battery charging early in the evening). In order to ensure individual households' privacy and for Enedis to remain within the scope of the French regulation, the charging patterns of consenting customers were aggregated according to groups of at least 11 buildings. In a second stage, Enedis would conduct an exploratory study on the surrounding power distribution network to appraise the most vulnerable portions of the grid where potential reinforcement could be necessary due to the surge of electric vehicles recharging their batteries. Lastly, Enedis would commit to sending signals by text message and/or e-mail to those groups of customers as to when it would be more beneficial for them (from a financial standpoint) and for the distribution network (from a technical constraint standpoint) to have their electric vehicle charged. Each signal would be dispatched sixty minutes before the "critical" period and would explicitly recommend customers to charge at a later time. For instance, whenever Enedis predicted that the distribution network would sustain a capacity peak at a certain time of the day, it would dispatch a text message to the particular group of customers so they be notified about the possibility of postponing the charging of their vehicle at a subsequent time where the power tariff

institute for statistics. There are about 16,000 IRIS areas in continental France, each accounting for a district of about 1,800-5,000 inhabitants.

[6] The actual numbers for the range of variations were not made public.

would also be cheaper. To be eligible, customers from this group (referred to as "Group C") needed to have a smart meter installed in their home, own an exclusively electric vehicle (no hybrid engine), and have access to a charging infrastructure within a radius of 200 meters from their actual home building.

In order to test the experimentation, a fourth batch of customers, referred to as "Group D", was created as a "yardstick" control group. In this group, no particular new service was deployed and the status quo of Enedis as a "strict" operator of the public power distribution network was maintained.

1.2 Data collection and processing

The primary data source used for the experimentation consisted in the smart meter consumption indices on household power usage, collected at a 30-minute time interval by Enedis. Secondary data pertaining to specific household features stemmed from surveys conducted 1 month prior to the experimentation for all customers in all four groups. The data collected included information about home size in square meters, number of people living in the house, state of property (ownership or rental), age of house or flat, average time per day spent on the Internet, number of vehicles per household, and average income spent on mobility expenses per year for all kinds of vehicles (gasoline, electric charging, car maintenance…). All the data obtained for the power consumption indices was collected and processed from June 2016 till December 2016.

1.3 Descriptive statistics about the groups

Table 1: Summary of descriptive statistics by control and treatment group

	Group D (control): Power distribution only		**Group A: Smart meter only + no signal mechanism**			**Group B: Smart meter + data platform + signal**			**Group C: Smart meter + electric vehicle exploratory study + signal**		
	Mean	Obs.	Mean	Obs.	*Var.*	Mean	Obs.	*Var.*	Mean	Obs.	*Var.*
Peak use of power (kWh/h)	1.25	656	1.25	320	*0.00*	1.17	320	*-0.08*	1.02	296	*-0.22*
Off-peak use of power (kWh/h)	1.07	656	1.07	320	*-0.01*	1.00	320	*-0.07*	1.06	296	*-0.01*
Home size (sq. meters)	69.37	656	70.76	320	*1.40*	69.52	320	*0.15*	71.00	296	*1.63*
Number of people living in the house	2.92	656	3.42	320	*0.50*	3.47	320	*0.55*	3.25	296	*0.32*
State of property of the house (1=yes ; 0=no)	0.79	656	0.78	320	*-0.01*	0.79	320	*0.00*	0.80	296	*0.01*
Age of house or flat (years)	21.31	649	22.39	317	*1.08*	19.98	315	*-1.33*	18.70	292	*-2.61*
Average time spent on the Internet per day (min)	117.62	656	122.65	320	*5.03*	125.47	320	*7.85*	118.95	296	*1.33*
Number of vehicles in the household	0.89	656	0.83	320	*-0.06*	0.90	320	*0.00*	1.05	296	*0.16*
Average expenses in mobility per year (€)	234.76	638	252.39	309	*17.63*	243.20	311	*8.44*	285.48	275	*50.72*

Notes: The mean variations observed always refer to the difference between the treatment group and the control group.

Table (1) displays a set of descriptive statistics of observable features (consumption indices and household features) for all four groups surveyed in the experimentation. Aside from the age of house and the average annual expenses on mobility, which could not be obtained for all households surveyed, usually because of a lack of information regarding such feature, all the other data collected gather the same sample of observations for all features. Group D (control group) gathered about 41% of the total number of observations (656 observations), whereas groups A and B had exactly the same number (320 customers, about 20% of the total) and group C slightly less (296 observations). Group C's lesser amount of observations was due to the fact that all criteria necessary to carry out the experimentation were harder to meet for this group, mostly because the ownership of an electric vehicle, albeit growing, is still less prevalent than gas-fueled cars in France.

A comparison across control and treatment groups depicts evidence of statistical balance: the first figures seem to show that most household features do not differ across groups. Table (1) also indicates that, aside from Group C whose mobility expenses are slightly above the control group (group D), most households surveyed in Group A or Group B fell were not necessarily better-off or less precarious from a financial standpoint than the control group. A first assumption could possibly link electric vehicle ownership to higher earnings per household. However, this hypothesis is not supported by other features such access to house property or home size, as Group C's observations tend to be in the same range as all three other groups. Group C also has, by default, a number of cars per households higher than all three groups, which may explain the higher mobility expenses.

1.4 Test of robustness of randomization process

In order to test the robustness of the randomization of the experiment, we have assessed a linear regression model on mean peak power use and home size. The results of the Fisher test are displayed in Table (2) and show that both variables could not be deemed statistically significant in explaining the results obtained over the run of the 6-month experiment with respect to any of the three services deployed by Enedis. This further bolsters the random assignment of all households to the experiments.

Table 2: Fisher test on group assignments (test of robustness of randomization)

	Group A	Group B	Group C
Mean peak power use (kWh)	0.077	0.001	0.052
	(0.023)	(0.025)	(0.034)
Home size (sq. meters)	-0.034	0.035	0.042
	(0.091)	(0.089)	(0.092)
F-statistic	1.176	0.534	0.678
P-value	0.129	0.912	0.888
Obs.	976	976	952

1.5 Raw data results

Figure 1: Experimentation results, 27 August 2016

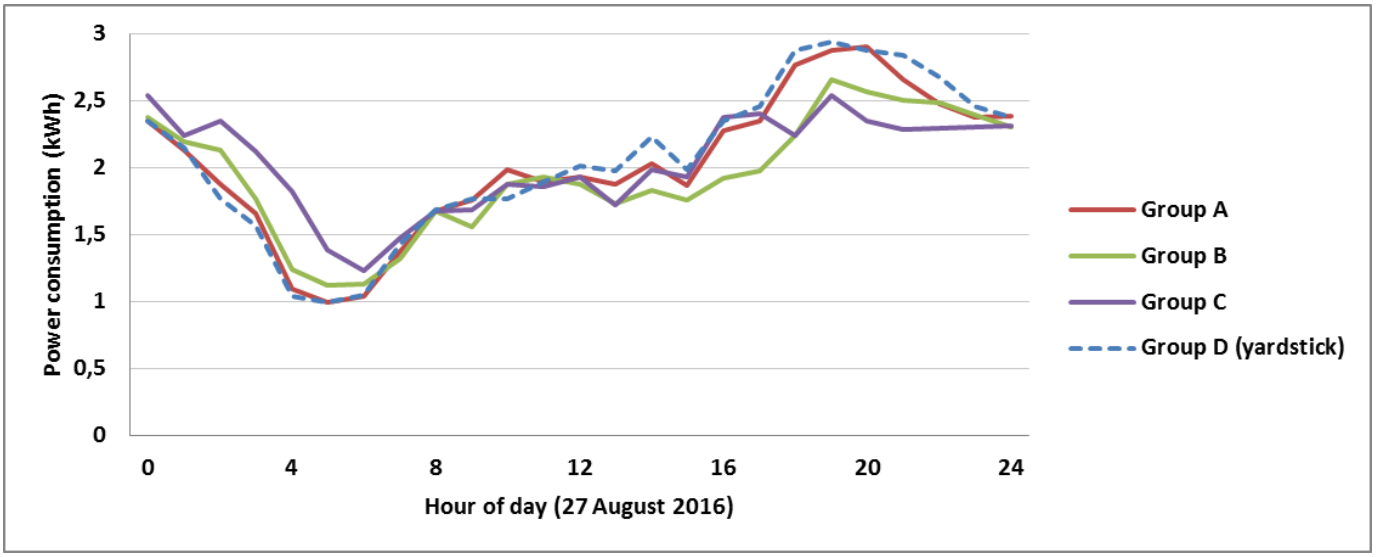
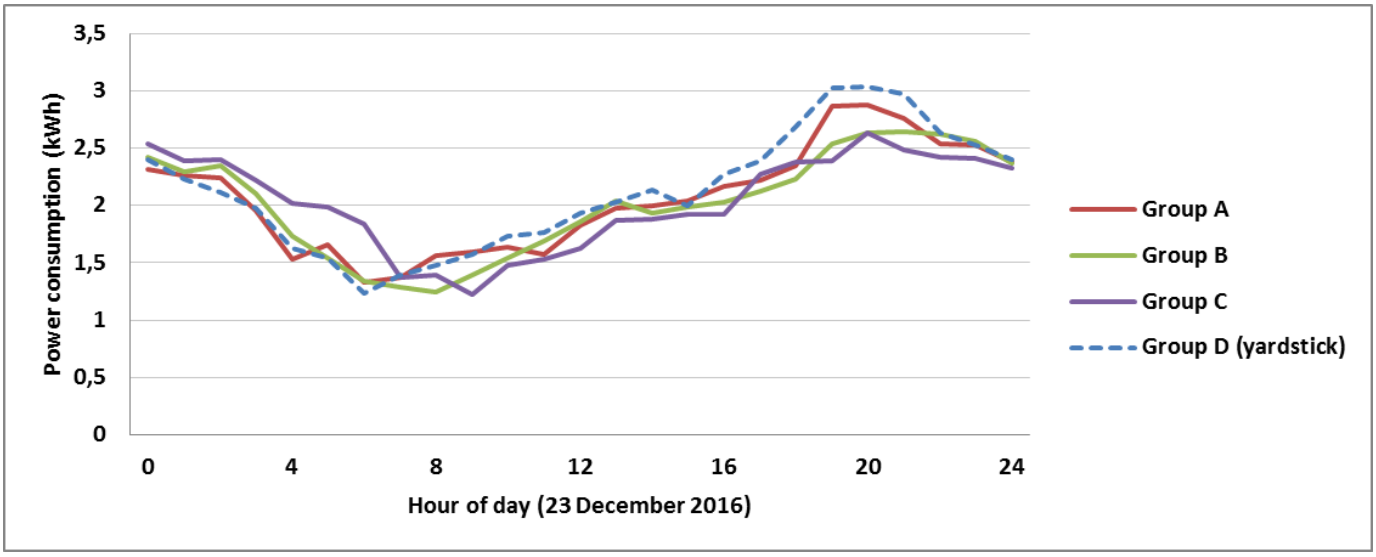


Figure 2: Experimentation results, 23 December 2016



The results of the experimentation are plotted on Figures (1) and (2) for 2 particular days in August and December 2016 respectively. The preliminary results indicate that groups A (smart meter with no signal) and B (smart meter + signal and data platform) seem to have relatively similar consumption patterns in both summer and winter up until peak hours (about 4pm-10pm) where group B's consumption strictly ends up under group A's, most likely owing to a price signal sent by Enedis to the customers[7]. An assumption could be made about the use of the data platform as a means for the

[7] Particulars regarding price signals and their components (time of the day, frequency of dispatching, average number per day) were not made public.

customers of Group B to monitor their consumption in order for the service to create a lower peak load and thus more flexibility for the power network. In any case, the use of a in-home display service such as the smart meter for Group A seems to diminish power consumption in the evening peak hours where the Group D's patterns always overlooks Group A and B's curves, although this is more ostentatious in winter than in summer between Groups A and D . Whether this peak load cut-off was catalyzed by the presence of the smart meter in the house still remains an assumption.

On the other hand, group C's consumption pattern is slightly more outstanding as there are obvious gaps at certain times of the day, namely early in the morning where Group C's consumption exceeds all three groups' but takes a dive in the evening peak hours (past 7pm). Interestingly enough, the gaps between Group C and the three other groups seem to be slightly more significant in the summer curve than in the winter one. Tentative assumptions could be made about electric vehicles being charged late throughout the night for a longer period of time in summer, as customers from Group C might tend to use their vehicle for errands other than the daily home-to-work back and forth commute. In any case, Figures (1) and (2) do seem to show statistical evidence of positive externalities generated by the DSO's new services on the power distribution network (lower constraints and more relative flexibility) and on the customers (incentives to benefit from more advantageous power consumption prices at a certain time during the day).

1.6 Detailed results on price elasticity of power demand

Price elasticity of power demand aims to quantify the evolution of customers' demand of power in response to a variation in the price of power. It is defined as:

$$e = \frac{\delta \ln c}{\delta \ln p} \tag{1}$$

where c represents the power consumption in kWh, p the price of power and δ the logarithmic differential operator. Whenever price is increased by 1%, power consumption varies by e%.

The methodology used is a double-difference (or difference-in-differences) model expressed as such:

$$\ln(c_{it}) = \sum_{g \in \{A;B;C\}} \beta_g D_{ht}^g + \gamma_g + \delta_e + \varepsilon_{ht} \tag{2}$$

where c_{it} represents the power consumption of the household h during the time interval t. D_{ht}^g is a binary variable {0;1} equal to 1 whenever h belongs to group g and if there is a price variation or an upcoming grid constraint on the distribution network which shall entail a subsequent price variation at time t. For instance, $D_{ht}^A = 1$ when h belongs to Group A (smart meter installed only) and t belongs to a time interval where there is a price variation or a surge of capacity to be observed on the grid which shall generate an imminent price variation. γ_g is a binary variable indicating the belonging to a

specific group {A; B; C} ; δ_e a binary variable equal to 1 whenever there is a power price variation resulting from a network constraint, and ε_{ht} is an idiosyncratic error term. β_g may be interpreted as the percentage variation in consumption between households in any of the groups {A; B; C} and Group D (control group). For instance, if β_A = 0.01, households in Group A consume 1% more power than households in Group D.

Table (3) summarizes the simplified results obtained in the regression model: column 1 shows the global variation from the double-difference model for all three groups {A; B; C}; columns 2 and 3 break down the fixed effects of time of day and households respectively. The results display that the estimations of β_A are comprised within the [-0.011; -0,019] interval, but that the null hypothesis according to which β_A equals zero may not be rejected (p-value over 0.05). As regards β_B, estimations are comprised within the [-0.018; -0.057] interval with the null hypothesis being possibly rejected for columns 1, 2, and 3. Regarding β_C, variations run within the [-0.112; -0.169] interval with again, the null hypothesis being possibly rejected.

Table 3: Treatment effects

	(1)	(2)	(3)	(4)
Group A (smart meter only, no signal)	-0.011	-0.019	-0.013	-0.012*
	(0.055)	(0.056)	(0.055)	(0.056)
Group B (data platform, signal)	-0.018**	-0.057**	-0.038**	-0.049*
	(0.032)	(0.032)	(0.034)	(0.032)
Group C (exploratory study, signal)	-0.147**	-0.112**	-0.169**	-0.151**
	(0.067)	(0.067)	(0.068)	(0.068)
Prob (A=B+C)	0.095**	0.085**	0.066**	0.024*
R-Sq.	0.00	0.09	0.15	0.26
Household effects fixed	NO	YES	NO	YES
Time effects fixed	NO	NO	YES	YES
Obs.	1592	1592	1592	1592

Notes: Column (1) displays the global variation from the double-difference model for all three groups {A; B; C}.Column (2) includes time fixed effects; Column (3) includes household fixed effects ; Column (4) includes both time and household fixed effects

,,*** indicate significance at 0.10, 0.05, and 0.01.*

These results indicate the following: first, there seems to be some sort of "incremental" effect on the price elasticity of power demand based on the level of service deployed by the DSO. This incremental effect more or less matches the consumption curves from Figures (1) and (2) in the evening peak hours where Groups B and C's consumptions did appear at a comparatively lower level than Group A's both in summer and winter, Group C always displaying the lowest figures out of the three groups. Based on Table (3), customers from Group A seem to slightly react to an overall variation of electricity prices, although their overall decrease in demand is not significantly different from the control group (the maximum elasticity with respect to the control group obtained does not exceed 2%).

Whether this decrease in demand may be attributed to the service of installing a smart meter with in-home display cannot be verified at this point according to the statistics (null hypothesis not rejected due to p-value). On the other hand, customers from Group B do appear more reactive than Group A to the price variations, though the reasons may be manifold: the higher decrease in power demand could be attributed to either the price signal per say (i.e. the reception of a text message) or to the new information acquired on the data platform. One could surmise here that, because the signal received by Group B customers did not *explicitly* indicate a variation in electricity prices but rather simply invited the customers to log in to their individual Internet platform to visualize "new electric data available about their household", those customers processed the information from their data platform service in order to understand that a network constraint and/or a rise in power prices would crop up in the next hour or so. Besides, they were not aware of the "60-minute timeframe rule" implemented by Enedis, meaning they could not automatically guess that a signal received by the DSO was systematically linked to an imminent change in prices. The fairly high confidence interval (p-value) for Group B customers may suggest that the deployment of the data platform on top of the smart meter may have contributed to a higher price elasticity of demand for that group. Finally, Group C's figures are clearly outstanding as the elasticity levels incurred by the experimentation are way higher than the other groups' in relative value, all of them being in the two-figure ranges for Group C. The rejection of the null hypothesis with quite a strong probability tends to conclude that the effects of the DSO's overall exploratory study with respect to electric vehicle charging behaviors were impactful. In this case, the parameter of the price signal (which did *explicitly* - contrary to Group B - recommend Group C to put off their battery charging process at a later time of the day) may have played a stronger role than for Group B by incentivizing Group C to reap the financial benefits of their behavioral change. As a result, these preliminary results seem to display an incremental relationship between the level of services deployed by the DSO and the impact on power demand reduction, which could, *ceteris paribus*, be indirectly linked to lower grid reinforcement costs for the DSO in the long-run.

The second observations resulting from Table (3) pertain to the fixed effects: according to columns {2; 3; 4}, time effects (responsiveness to power price variation following a signal sent 60 minutes before the "critical" event) entail a higher reaction on elasticity than household effects (responsiveness due to a household event or feature: presence of a person at home, ease of turning off already running electric appliances…) when compared to column 1 for Groups A and B. Conversely, household effects taken individually create the highest price elasticity for Group C. Both effects combined do not necessarily generate synergies to achieve the greatest possible variation of elasticity for all three groups: the highest variation is a result of the individual effect of time (Groups A and B) and household (Group C).

Therefore, Table (3) yields the following interpretations: at this stage, the deployment of a smart meter with in-home display only and no particular information signal related to the power network may not

necessarily end up in a significant change in consumer behavior as regards power consumption. On the other hand, the use of an individual data platform combined with information signal dispatched by the DSO turns to be more relevant in order to impact power demand. This relevance could be the result of higher customer engagement and control over their electricity behavior (and bill!) thanks to the DSO: ability to check his real-time consumption, ability to get acquainted with both daily and historical data related to the consumption of his domestic appliances, etc.). Finally, the delivery of exploratory studies with respect to electric vehicles charging infrastructure, again combined with information signal, seems to spur a significant decrease in power demand. An assumption around this result could be made here about the specific role played by the DSO as one of the "enablers" of the use of an electric vehicle, especially at a stage where gas-fueled cars are still the norm in France, and where political and economic incentives still remain some of the main drivers of the market growth for electric transportation. Those preliminary results should be nevertheless crossed over with other sociological parameters (e.g. capacity to obtain perfect and exhaustive information; individual sensitivity of electric vehicle owners to capacity surges on their local grid…) over the long-run in order to be deemed robust for the sample of households surveyed in the experiment, and avoid any bias.

2. Analysis of the impact of the DSO's new services from a spatial and macro-economic perspective in France

Although the aforementioned experimentation gives purely micro-economic perspectives on the value-added of the DSO's new services, it will not take into consideration the spatial and macro-economic dimensions related to the development of these solutions in a specific country (i.e. what type of service for what type of concessional territory). This is crucial in the case of France where Enedis covers about 95% of the continental country, and where local concessions for electricity distribution may not have the same time horizon or "appetite" for the deployment of the DSO's services.

2.1 Background of the spatial analysis

The analysis consists in investigating the deployment of four innovative types of services approved by the national regulator, and proposed by the DSO across the French territory at city-scale[8] level, and for which the contracting and delivery process is subject to the customer's specific need and discretion (i.e. the customers directly request and pay the DSO for the delivery of the service, as the service is not included within the concession contract signed between the DSO and the city or township). The four types of services investigated encompass two of the services studied in the first part of the paper:

[8] For convenience purposes, the terms "city" and "urban area" will be used interchangeably from this part of the paper onwards.

data platforms for industrial and residential customers and **exploratory studies for electric mobility**. The sole deployment of a smart meter with in-home display was not selected as a service per say in this investigation, as the European law has levied the compulsory deployment of smart meters to all households[9]. An extra two services were added to the list: **exploratory studies for the connection to the distribution grid of intermittent renewable energy technologies** (windpower, photovoltaic solar panels) for both industrial and residential customers, and **exploratory studies related to urban planning** for industrial customers (reconfiguration of specific areas in a town where there would be impacts on the low or medium-voltage power network, and where the expertise of the DSO might influence the spatial planning decision of an upcoming urban project : new district, renovation of certain buildings, etc.).

The idea behind the investigation was to determine a typology of territories which would be more "sensitive" - or not - to the delivery of these specific new services by the DSO, and, in such case, to give insight about the rationale for these territories to adopt these new services, i.e. explanatory variables which would condition or make eligible the positive deployment of certain services, rather than others, for certain types of territories.

2.2 Data collection

The analysis was performed on a set of 224 urban areas in continental France for which the total population is at least equal to 10,000 inhabitants in their urban center[10]. All these urban areas have contracted at least one of the four types of services proposed by the DSO in the 2013-2015 period[11]. Specific data about the area in which the DSO's services were deployed were collected at town level thanks to databases provided by Enedis, INSEE (French national institute for statistics), and AVERE (French association for the development of electric vehicles). All town-level inputs were later aggregated at the scale of the urban area they belonged to.

The following data, which was used as a set of explanatory variables, was collected for years 2013/2014/2015 and included: **overall area population**, **electricity consumption in kWh**, **level of employment rate** (defined as the ratio of people actually having a job over the total amount of people of working age), **penetration rate of rental properties** within the town (ratio of flats being rented out

[9] Directive 2009/72/CE of the European Parliament and Council release on July 13, 2009 regarding common rules for the domestic power market: *"The EU Member States should ensure the implementation of smart metering systems which favor the active participation of consumers to the electricity market […] In the case this implementation yields positive long-term economic evaluation regarding costs and benefits, 80% at least of all customers shall be equipped with smart metering systems by 2020 […]"*.

[10] An urban area, as defined by the French national institute of statistics, is referred to as a geographic perimeter made of an urban center of at least 10,000 inhabitants and a surrounding girth of peri-urban outskirts in which at least 40% of the residing population goes to work either in the urban center or in the other towns of the outskirts. This geographic scope of 224 urban areas is used as an intermediary mesh between regional level and city-level, thus covering about 80% of the French continental territory.

[11] The marketing of services dedicated to industrial and residential customers started in mid-2012 for Enedis, meaning that evidence of actual benefits could be seen only from 2013 onwards.

over total number of flats being occupied as a principal residence), **electric vehicle penetration** (ratio of number of electric vehicles over total number of vehicles bought), **renovation rate of buildings** (ratio of number of buildings renovated over total number of buildings), and **number of incumbent urban projects within a 1-year time horizon**.

Besides, the number of services deployed by the DSO in those areas was retrieved in absolute value: **number of data platform accounts opened**, **number of exploratory studies conducted for electric vehicles**, **number of studies conducted for renewable energy technologies**, and **number of studies conducted for urban planning projects.**

2.3 Methodology

The analysis is conducted in three stages. First, we use a divisive hierarchical cluster analysis, based on the number of services developed by the DSO. The annual evolution of the number of services "sold" to the city by Enedis (growth rate of the number of services deployed for a particular type of service) makes up a set of dependent variables in the statistical model. There are 8 dependent variables altogether: four types of services (DATA; MOB; REN; URBA) multiplied by two sets of growth rates: [2013-2014] and [2014-2015][12]. The hierarchical cluster analysis produces an exhaustive list of the 224 urban areas according to the group they "belong to", i.e. the cities with which each individual urban area shares the highest degree of resemblance in terms of the dependent variables used in the model.

The cluster analysis is then completed by a principal component analysis (PCA) which converts the correlated variables into a set of values of linearly uncorrelated variables (the principal components), thus reducing the projection of all 224 cities from an *n*-dimensional to a bi-dimensional vector space, allowing the emergence of specific characteristics for each city regarding the solutions deployed by the DSO.

Finally, a discriminant analysis (DA) is carried out with the set of explanatory variables in order to find out the optimal reclassification rate of cities among clusters for the typology of territories selected in the cluster analysis.

2.4 Descriptive statistics and independence of variables

Table (4) displays the results of the treatment for the dependent variables in the principal component analysis and Table (5) the Pearson correlation matrix between the 8 dependent variables.

[12] Each growth rate ratio constitutes a dependent variable of its own in the model, and is being preceded by the letter "g". The final 8 dependent variables are: {gDATA1314; gDATA1415; gMOB1314; gMOB1415; gREN1314; gREN1415; gURBA1314; gURBA1415}.

Table 4: Summary of descriptive statistics for the spatial analysis

Variable	Observations	Obs. with missing data	Obs. without missing data	Minimum	Maximum	Mean	Std. deviation
gDATA1314	224	0	224	-0.039228932	0.02690999	0.00195883	0.021058017
gDATA1415	224	0	224	-0.037077166	0.02839566	0.00739992	0.018267392
gMOB1314	224	0	224	-0.090460037	-0.01739695	-0.04588457	0.013699125
gMOB1415	224	0	224	-0.074670866	0.03533062	-0.01958101	0.016466131
gREN1314	224	0	224	-0.025817898	0.06054371	0.01574009	0.01385949
gREN1415	224	0	224	-0.074526549	0.03900705	-0.01715077	0.017762431
gURBA1314	224	0	224	-0.027315336	0.06405524	0.01665302	0.014663341
gURBA1415	224	0	224	-0.075420868	0.03947514	-0.01735658	0.017975581

Table 5: Pearson correlation matrix for set of dependent variables

Variables	gDATA1314	gDATA1415	gMOB1314	gMOB1415	gREN1314	gREN1415	gURBA1314	gURBA1415
gDATA1314	**1**	**0.687**	-0.125	0.134	0.074	-0.089	-0.059	-0.097
gDATA1415	**0.687**	**1**	-0.189	0.127	-0.171	-0.143	0.096	0.166
gMOB1314	-0.125	-0.189	**1**	**0.413**	**-0.235**	-0.178	**0.214**	0.201
gMOB1415	0.134	0.127	**0.413**	**1**	0.044	-0.172	-0.117	-0.189
gREN1314	0.074	-0.171	**-0.235**	0.044	**1**	**0.351**	-0.040	0.023
gREN1415	-0.089	-0.143	-0.178	-0.172	**0.351**	**1**	-0.016	0.098
gURBA1314	-0.059	0.096	**0.214**	-0.117	-0.040	-0.016	**1**	**0.665**
gURBA1415	-0.097	0.166	0.201	-0.189	0.023	0.098	**0.665**	**1**

Notes: values in bold are different from 0 with a significance level alpha=0,05

At first sight, there seems to be no relevant correlation among variables of different types, the higher correlation coefficient being valued at |0.235| between gMOB and gURBA. This shows evidence of relative statistical independence among the four types of dependent variables analyzed. However, correlation is fairly stronger for variables within the same category, with the correlations being in the [0.351-0.687] range, with the data platform services recording the maximum value. This would mean that urban areas which sustained a growth in the number of services during the first period seem to embark on a trend of capitalizing on this growth the following year.

2.5 Cluster analysis results

The cluster analysis reveals the classification of urban areas in up to seven main classes. Table (6) indicates the value of the within-class and of the between-class variances, and shows that the gap in variances is the highest between the typology in four and the typology in three clusters. As a result, we will concentrate here on the typology in three clusters.

Table 6: Variance decomposition for optimal classification in the hierarchical cluster analysis

Variance	Number of classes				
	3	4	5	6	7
Within-class	75.69%	61.83%	58.41%	53.47%	50.21%
Between-classes	24.31%	38.17%	41.59%	46.53%	49.79%
Total	100.00%	100.00%	100.00%	100.00%	100.00%

Table 7: Class centroids for each dependent variable in the 3-class typology

	gDATA1314	gDATA1415	gMOB1314	gMOB1415	gREN1314	gREN1415	gURBA1314	gURBA1415
Class 1	0.034	0.018	-0.020	0.017	-0.030	-0.026	-0.050	0.021
Class 2	0.052	0.041	-0.032	0.038	-0.015	-0.036	-0.001	0.015
Class 3	0.068	0.078	0.058	0.065	-0.015	-0.019	-0.034	0.013

Figure 3: Centroid profile plot

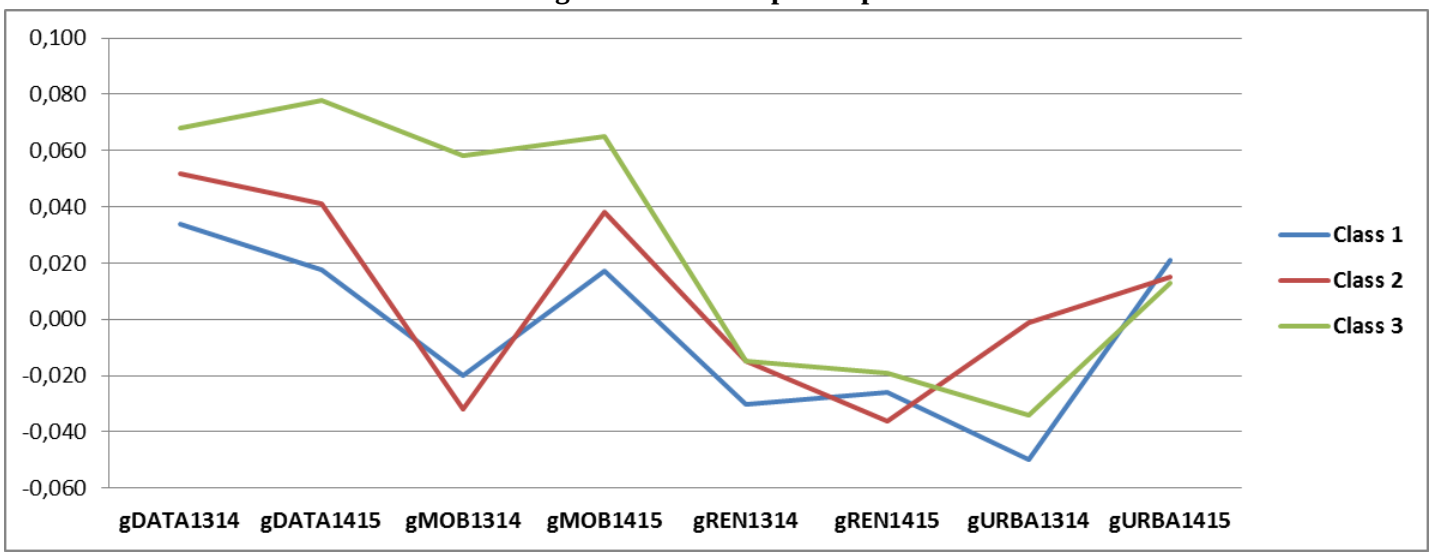


Table (7) displays the class centroids for each dependent variable in the 3-cluster typology and Figure (3) plots the profile of cluster centroids according to the dependent variable. The results seem to indicate that the most discriminating variables among all three clusters are the **growth rate of the data platform service (DATA)**, which is more pronounced during the [2014-2015] period between clusters {1; 2} and cluster 3; and the **growth rate of the electric mobility service (MOB)**, which is

more pronounced during the first period between clusters {1; 2} and cluster 3. The segmentation among clusters is less obvious for the two other services proposed by the DSO, although cluster 2 seems to break away for exploratory studies related to urban planning (URBA) during the first period [2013-2014].

The main preliminary conclusions, which could be drawn from the cluster analysis in a 3-cluster typology, is that certain urban areas in France seem to be more "receptive" to the delivery of data platform services by the DSO in the 2013-2015 period, whereas mobility studies, urban planning studies, and renewable studies seem to be less dependent on specific city features and could be perceived as more homogenously deliverable by the DSO across the French territory. The cluster analysis seems to favor higher relative "proximity" among cities in clusters 1 and 2.

2.6 Principal component analysis

According to Table (8), the cumulative variability of the model is summarized by the first two factors (F1 and F2) up to 69%, with the remaining factors F3 to F8 all having an individual variability of 10% or less. Therefore, and for simplification purposes in this paper, we shall focus here on F1 and F2 as the two principal components of the analysis.

Table 8: Eigenvalues of the principal component analysis

	F1	F2	F3	F4	F5	F6	F7	F8
Variability (%)	47.560	21.520	10.250	7.660	6.472	4.587	1.510	0.441
Cumulative %	47.560	69.080	79.330	86.990	93.462	98.049	99.559	100.000

Tables (9) and (10) indicate the correlations between variables and factors, and the contribution of each dependent variable to either axis, respectively. F1 seems to be relatively correlated to the growth of the data services and to a slightly lesser extent with the exploratory services for electric vehicles. On the other hand, F2 appears overall moderately correlated with the growth of data services on both periods [2013-2014] and [2014-2015] and the growth of the three other services in the second period [2014-2015]. According to Table (10), the contributions of gDATA and gMOB for both periods on F1 reach a total of 89%, meaning that F1 is mainly characterized by the growth in deployment of data platform services and electric mobility services. Regarding F2, the contributions of all four services deployed by the DSO during the second period amount to 74%, meaning that this axis characterizes the innovative service offering of the DSO in [2014-2015].

The definition of these axes sets a gauge in understanding how the 224 urban areas belong to a specific cluster: from a graphical standpoint, urban areas "close" to F1 in the bi-dimensional vector space were more prone to partnering with the DSO to use data platform or electric mobility services in 2013-2015, while those "close" to F2 were more likely to consider the DSO a partner of choice for the

implementation of various services dedicated to enhancing their energetic transition policy in [2014-2015].

Table 9: Correlation matrix between dependent variables and each factor)

	F1	F2	F3	F4	F5	F6	F7	F8
gDATA1314	0.661	0.389	0.014	0.141	0.348	-0.299	-0.104	0.296
gDATA1415	0.641	0.777	-0.078	0.177	-0.105	-0.156	0.023	-0.089
gMOB1314	0.541	-0.178	0.178	0.151	0.047	0.570	-0.056	0.040
gMOB1415	0.532	0.547	0.142	0.266	0.238	0.151	-0.208	-0.149
gREN1314	-0.174	0.146	0.314	0.231	-0.117	-0.209	-0.137	-0.172
gREN1415	-0.121	0.560	0.214	-0.363	0.297	0.021	0.465	0.253
gURBA1314	-0.162	-0.214	0.179	-0.201	0.350	0.011	-0.285	0.297
gURBA1415	-0.063	0.471	0.160	-0.165	0.513	-0.018	-0.052	0.436

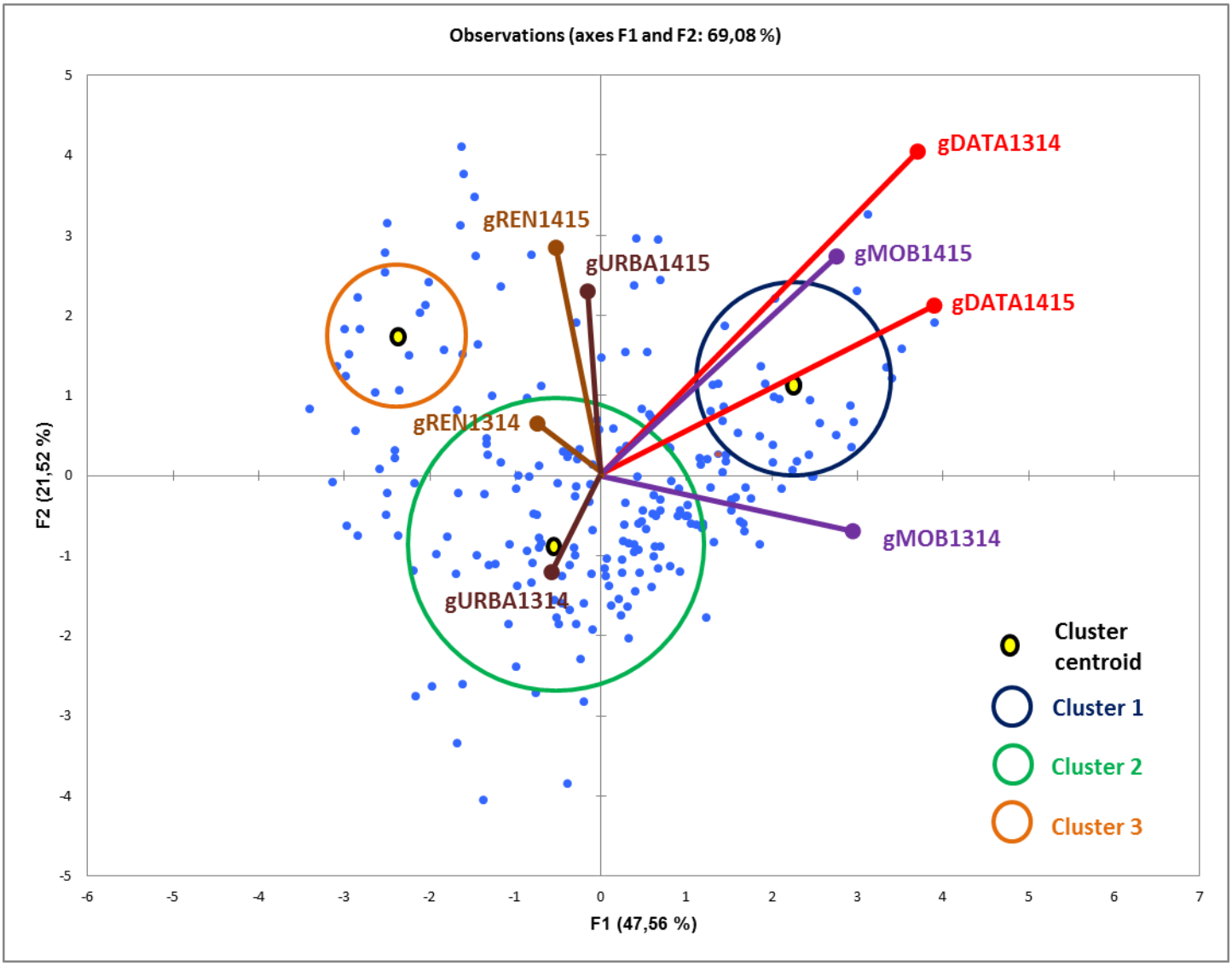
Table 10: Contribution of variables to factors (%)

	F1	F2	F3	F4	F5	F6	F7	F8
gDATA1314	**0.218**	**0.135**	0.031	0.078	0.001	0.140	0.078	0.172
gDATA1415	**0.204**	**0.248**	0.025	0.017	0.007	0.001	0.014	0.071
gMOB1314	**0.185**	0.049	0.061	0.022	0.021	0.843	0.055	0.093
gMOB1415	**0.169**	**0.166**	0.063	0.022	0.113	0.001	0.023	0.043
gREN1314	0.054	0.031	0.480	0.260	0.001	0.002	0.132	0.042
gREN1415	0.068	**0.181**	0.302	0.384	0.267	0.001	0.444	0.134
gURBA1314	0.013	0.047	0.034	0.214	0.280	0.011	0.237	0.147
gURBA1415	0.089	**0.143**	0.004	0.003	0.310	0.001	0.017	0.298

Notes: values in bold have been specifically highlighted for F1 and F2 whenever the contribution exceeded 10%.

Figure (4) plots the projection of all the 224 urban areas on the bi-dimensional vector space according to F1 and F2. The centroids of each of the three clusters defined by the cluster analysis are highlighted. The crossing-over between the cluster analysis and the principal component analysis leads to the following results: cities in cluster 1 (82 items) seem characterized by their relative proximity to data platforms and electric mobility services; cities in cluster 2 (124 items) seem to favor, again from a comparative standpoint, exploratory studies for renewable energies and urban planning ; cities in cluster 3 (18 items) stand out in the sense they do not seem prone to a particular type of service in the 2013-2015 period.

Figure 4: Projection of the 224 urban areas in the bi-dimensional vector space via the principal component analysis
(Dependent variables; F1/F2 axes)



2.7 Discriminant analysis (DA)

The purpose of the DA consists in using a set of explanatory quantitative variables which will be used to characterize cities the same way it was performed by the principal component analysis, the difference being that all 224 cities are now also characterized with a discrete qualitative variable: the group they belong to, i.e. clusters {1; 2; 3}. The DA will interpret the exploratory variables which "re-create" the existing city clusters in the best way possible, according to a rate of classification within a specific cluster as well as globally among clusters: the higher this global rate, the "more relevant" these explanatory variables shall be considered as underlying factors explaining the cluster analysis and thus the dependent variables used in the PCA.

The choice of explanatory variables used heeds both macroeconomic factors (demography, employment, property market, urban projects) and factors specific to the electricity sector and/or value chain (power consumption, renovation of buildings, penetration of electric vehicles), and aims at giving further insight on the type of cities characterizing each of the three clusters. The first iteration of the DA took into account all variables in order to test their independence.

Table 11: Correlation matrix between explanatory variables

	mPOP1315	mCONS1315	mEMPL1315	mRENT1315	mEVR1315	mRENO1315	mURBP1315
mPOP1315	1.000	0.452	0.138	-0.179	0.358	0.260	0.339
mCONS1315	0.452	1.000	-0.173	0.547	0.741	-0.241	0.274
mEMPL1315	0.138	-0.173	1.000	-0.660	0.543	-0.047	-0.143
mRENT1315	-0.179	0.547	-0.660	1.000	-0.321	-0.222	0.047
mEVR1315	0.358	0.741	0.543	-0.321	1.000	-0.016	0.298
mRENO1315	0.260	-0.241	-0.047	-0.222	-0.016	1.000	0.331
mURBP1315	-0.339	0.274	-0.143	0.047	0.298	0.331	1.000

Table (11) displays the simplified correlation matrix for each group of explanatory variables. Unlike the PCA and due to the high number of explanatory variables used (7 variables multiplied by 3 years for each = 21 variables altogether), we decided to take, for the sole purpose of releasing readable results in this paper, the arithmetic mean for years 2013/2014/2015 and for all 7 groups of variables in the model, and we plotted a second set of iterations of the DA to obtain the simplified correlation matrix. *[NB: for each group of variables, the standard deviation between the mean and the actual observations for each of the three years is under 5%, which makes the mean substitution method a sufficiently relevant proxy in order to pursue with the DA]*. The variables are now denoted with an *m* (for "mean") which precedes their code[13].Table (11) displays that all explanatory variables show moderate to very low correlation with one another. The highest correlations are between the rental property penetration rate (mRENT1315) and the employment rate (mEMPL1315), as well as between the power consumption (mCONS1315) and the electric vehicle penetration rate (mEVR1315), with respective correlations of |0.660| and |0.741|. For the latter case, we ended up rejecting mEVR1315 as an explanatory variable, as the absolute value of the penetration rate for electric vehicles retrieved for the group of 224 urban areas was quite low (under 10% of penetration rate for all cities included in the model), and because further iterations of the DA – as described below - did not actually characterize mEVR1315 as a significant discriminatory variable for groups of cities which, at first sight, seemed to be more prone to exploratory services for electric vehicles, based on the cluster analysis and the PCA.

[13] This gives us 7 variables altogether: {mPOP1315; mCONS1315; mEMPL1315; mRENT1315; mEVR1315; mRENO1315; mURBP1315}.

Table 12: Optimal confusion matrix obtained for the discriminant analysis

from \ to	1	2	3	Total	% correct
1	73	7	2	82	**89.02%**
2	19	85	20	124	**68.55%**
3	1	4	13	18	**72.22%**
Total	93	96	35	224	**76.34%**

Table (12) displays the confusion matrix obtained with the combination of explanatory variables which maximized the total reclassification rate of the 224 urban areas among the clusters defined by the 3-class typology. This rate is equal to over 76% with the following set of variables: {mPOP1315; mCONS1315; mEMPL1315; mRENT1315; mRENO1315}. As mentioned above, the successive iterations did not consider the relevance of the average penetration rate of electric vehicles (mEVR1315) or of the number of urban projects (mURBP1315) over the 2013-2015 period, as both variables lowered the global reclassification rate among clusters. The "one-by-one" addition of individual explanatory variables in the DA showed that {mPOP1315; mRENT1315; mEMPL1315} contributed to the global reclassification rate up to 68%, meaning that macroeconomic factors characterizing the 224 cities played in fact a more significant role than variables pertaining to the electricity sector (mCONSO1315; mRENO1315). Cluster 1 exhibits the highest inner reclassification rate (over 89%) whereas cluster 2 barely tops the same rate at 68%. This result is not surprising considering cluster 2 contains the highest number of cities. As a result, a potential identification of paragons (observations which are the most representative of this cluster's characteristics) could lead to the reclassification of several cities from cluster 2 to clusters 1 or 3. Although the analysis of paragons is not performed at this stage in the present paper, it is one of the limiting factors of the overall results obtained for both clusters 2 and 3 which exhibit the lowest inner reclassification rates.

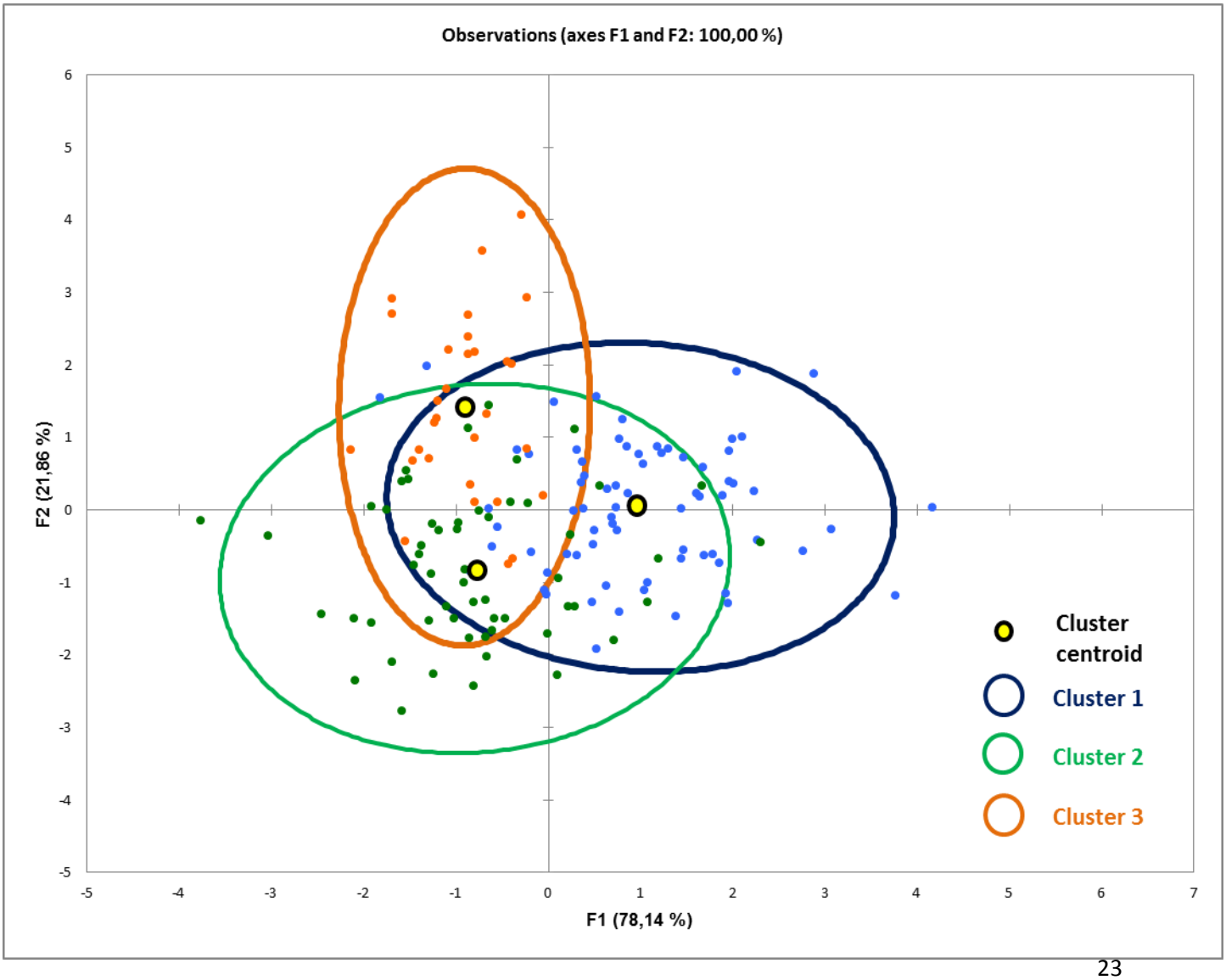
Table (13) shows the correlation between the set of explanatory variables and the two factors F1/F2 which contribute to 100% of the explained variance of the model, with respective sub-weights of 78% and 22%. F1 is mostly correlated to pure macroeconomic factors: average demography in the urban area, employment rate of the population, and share of properties that are being rented out (positive correlations in the [0.587-0.744] range). F2, on the other hand, seems to be correlated to variables linked to the electricity value chain: average power consumption and average number of building renovations within the urban area (positive correlations in the [0.659-0.704] range).

Table 13: Correlation between explanatory variables and factors in the discriminant analysis

	F1	F2
mPOP1315	**0.744**	0.223
mCONS1315	0.314	**0.704**
mEMPL1315	**0.694**	-0.137
mRENT1315	**0.587**	0.303
mRENO1315	-0.125	**0.659**

Notes: values in bold have been specifically highlighted for F1 and F2 whenever the correlation with the corresponding variable exceeded 50%.

Figure 5: Projection of the 224 urban areas in the bi-dimensional vector space via the discriminant analysis
(Explanatory variables; F1/F2 axes)



Finally, Figure (5) displays the projection of all 224 urban areas in the bi-dimensional vector space obtained through the DA. The position of each centroid and the approximate assessment of each cloud of observations seem to indicate that:

(1) Cluster 1 cities are mostly characterized by variables that are positively correlated to F1 (growth of demography, of employment rate, and of the share of rental properties in the urban area). A closer look at the observations within the cloud reveals that cluster 1 encompasses most of the biggest metropolises in France (Paris, Bordeaux, Aix-Marseille…) and a fair share of cities above 50,000 inhabitants.

(2) Cluster 2 cities are characterized by variables that are negatively correlated with F1 and F2 (though the negative positioning in the vector space remains relatively weak for both axes: certain cities do remain in the positive range for each factor). These cities seem to be prone to a slight recession for all explanatory variables. A closer glance reveals that cluster 2 cities are mainly medium-sized cities (usually between 20,000 and 50,000 inhabitants) located in suburban or semi-rural areas, which could also be a tentative argument for energy generation to be potentially decentralized in those areas (hence the higher need for renewable energy studies according to the PCA) which could serve as "prototypes" for the deployment of new solutions by the DSO.

(3) Cluster 3 cities seem to be characterized by variables that are negatively correlated to F1 and positively correlated to F2. These are basically cities with receding attractiveness and employment rate, but high energy consumption and rate of renovations. A look at the list of 18 cities composing this cluster reveals the presence of small-sized remote rural areas (between 10,000 and 20,000 inhabitants), which could be prone to higher energy precariousness and be hampered by weaker economic development. An assumption could be made about the DSO being strictly viewed as a provider of electricity for industrial and residential needs (and not an "enabler" of the energy transition), hence the absence of relative sensitivity to the deployment of innovative energy services.

Last but not least, the global reclassification rate obtained in the discriminant analysis leaves out an extra 24% which have not been explained by the selected explanatory variables. Several parameters, which could be part of the global equation, have not been tested for lack of accurate quantitative assessment tools at this stage: role of local governance in the urban area, impact of local energy policies implemented, etc.

Conclusions

In this paper, we explored the rationale behind the need for the DSO to expand its business model, from being a strict operator of the physical infrastructure to becoming a key actor of the whole electricity distribution system. This expansion goes hand-in-hand with the experimentation of new solutions for the DSO's markets (the territories on which it "physically" operates).

On one hand, the deployment of these solutions creates value for the electricity system as a whole, as it may generate a shift in price elasticity for power demand, provided end customers become fully-engaged actors of the system. Results show that he development of smart metering services, data platforms and exploratory studies for electric vehicles shall be accompanied by a strong involvement process where the final customer becomes aware of his energy consumption. The ability of pricing to influence power demand was confirmed through the experiment, as well as the one to use transparent information (via signals) as the main vector of involvement of these customers.

On the other hand, unlike the current business model which consists in delivering power as a commodity to all territories, the DSO must adapt the deployment of its innovative solutions. The spatial analysis seemed to show that, even though data platform services and mobility studies have paved the way as the prime game changers in the DSO's diversification process, other solutions in the form of exploratory studies for the implementation of renewable energies or urban planning schemes are slowly building up their nest. French urban areas which are, relatively speaking, more "sensitive" to data platform and electric vehicle services, seem to experience a decent level of attractiveness, a high level of employment, and a higher share of rental park in their real estate market. Therefore, these results emphasize a strong link between territorial development and business model evolution for public power utilities, which are dedicated to playing a more significant role in urban policies in the upcoming years if they ambition to fully adapt to the digital and the energetic transition.

References

[1] Aigner, D., Lovell, C. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. Journal of econometrics, 6(1), 21-37.

[2] Allcott, H. (2011). Rethinking real-time electricity pricing. *Resource and energy economics*, *33*(4), 820-842.

[3] Allcott, H. (2011). Social norms and energy conservation. *Journal of public Economics*, *95*(9), 1082-1095.

[4] Belaid, R., Zerouti, M. (2016). Analyse des déterminants de l'inefficience productive des concessions de distribution d'électricité en Algérie : étude empirique avec la méthode d'analyse par frontière stochastique "SFA", Revue d'économie et de statistique appliquée, ENSSEA, 25-2016.

[5] Borenstein, S. (2005). The long-run efficiency of real-time electricity pricing. *The Energy Journal*, 93-116.

[6] Christensen, L. R., Jorgenson, D. W., & Lau, L. J. (1973). Transcendental logarithmic production frontiers. *The review of economics and statistics*, 28-45.

[7] Coelli, T., Crespo, H., Plagnet, M. A., Romano, E., Perelman, S., & Paszukiewicz, A. (2007). Incorporating quality of service in a benchmarking model: an application to French electricity distribution operators. CIRED.

[8] Farsi, M., Filippini, M., & Greene, W. (2006). Application of panel data models in benchmarking analysis of the electricity distribution sector. *Annals of Public and cooperative Economics*, *77*(3), 271-290.

[9] Farsi, M., Filippini, M., Plagnet, M. A., & Saplacan, R. (2010, June). The economies of scale in the French power distribution utilities. In *Energy Market (EEM), 2010 7th International Conference on the European* (pp. 1-7). IEEE.

[10] Giannakis, D., Jamasb, T., & Pollitt, M. (2005). Benchmarking and incentive regulation of quality of service: an application to the UK electricity distribution networks. *Energy policy*, *33*(17), 2256-2271.

[11] Growitsch, C., Jamasb, T., & Pollitt, M. (2009). Quality of service, efficiency and scale in network industries: an analysis of European electricity distribution. *Applied Economics*, *41*(20), 2555-2570.

[12] Ito, K. (2014). Do consumers respond to marginal or average price? Evidence from nonlinear electricity pricing. *The American Economic Review*, *104*(2), 537-563.

[13] Jamasb, T., & Pollitt, M. (2003). International benchmarking and regulation: an application to European electricity distribution utilities. *Energy policy*, *31*(15), 1609-1622.

[14] Jamasb, T., & Pollitt, M. (2008). Reference models and incentive regulation of electricity distribution networks: An evaluation of Sweden's Network Performance Assessment Model (NPAM). *Energy Policy*, *36*(5), 1788-1801.

[15] Jessoe, K., & Rapson, D. (2014). Knowledge is (less) power: Experimental evidence from residential energy use. *The American Economic Review*, *104*(4), 1417-1438.

[16] Joskow, P. L., & Schmalensee, R. (1983). Markets for power: an analysis of electric utility deregulation.

[17] Lehr, R. L. (2013). New utility business models: utility and regulatory models for the modern era. *The Electricity Journal*, *26*(8), 35-53.

[18] Meeusen, W., & van Den Broeck, J. (1977). Efficiency estimation from Cobb-Douglas production functions with composed error. *International economic review*, 435-444.

[19] Newcomb, J., Lacy, V., Hansen, L., & Bell, M. (2013). Distributed energy resources: policy implications of decentralization. *The Electricity Journal*, *26*(8), 65-87.

[20] Reiss, P. C., & White, M. W. (2005). Household electricity demand, revisited. *The Review of Economic Studies*, *72*(3), 853-883.

[21] Rodet, D. (2008). Les définitions de la notion d'utilité sociale. *Économie et solidarités*, *39*(1), pp-164.