# Unfolding distributed demand-response through future-proof tariff design: Benefits and consumer reaction to future tariff design

Working paper

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**Abstract**

Relying on hourly consumption of electricity consumers, this paper examines the consumer reaction to dynamic electricity rates in the context of increasing renewable generation capacity and carbon price. We estimate power prices using a unit commitment model calibrated to France in 2018. We assess the bill savings from price responsive consumers under the Real-Time Prices (RTP) and Time-of-Use (ToU) scheme currently in place. We find that consumers under RTP have increasing electricity bill savings linked to the deployment of renewable capacity. However, estimated gains are small, with less than 10€ bill savings for the residential segment in the central assumption. Our results also suggest that the current ToU rates doesn't provide the right incentives with regards to generation scarcity in future power markets. These results call for a revision of the end-use rate design, and question the savings estimate used to justify more widespread adoption of real-time pricing.

**Keywords**: demand-side response, dynamic tariff, power market, retail prices

# 1. Introduction

Following the liberalization of power markets, the competition in retail activities has offered consumers an increasing choice of suppliers. Yet, unbundling of the market hasn't translated into diversification of billing schemes when it comes to rate design: a majority of consumers are still charged a flat tariff based on their energy consumption. This historical choice was driven by limited metering capabilities, as the infrastructure deployed only allowed for annual or bi-annual readings, and the inexistence of smart appliances.

Both the literature and fields experiment have however demonstrated tangible welfare gain from switching to dynamic pricing, by having a direct cost pass-through from wholesale market prices to end-users (Allcott, 2011; Faruqui and Sergici, 2010). Consumers were proved in those pilot projects to be statistically significantly price elastic, with peak lead reduction achieving between 10 and 50% depending on the incentives, contradicting the common assumption of inelastic load. There is therefore the opportunity to send price incentives to end-users that would better reflect the market situation, and notably enable them to manage their load to respond to grid congestion or scarcity on the supply side. If short-term benefits might be low, literature has demonstrated long-run welfare gains by delaying or avoiding investments in peaking capacity and network expansion that can be important (De Jonghe et al., 2012).

Those benefits are expected to be even more tangible now that most countries are on the verge of completing a national rollout of smart meters and that system variability starts to be supply-side driven due to the increase of wind and solar generation. The European Commission indicates an annual saving of 22-70% of the energy supply component in the annual bill for small consumers (European Commission, 2019). Notwithstanding the benefits, concerns exist as dynamic pricing results also in a pass-through of risks linked to price volatility towards end-users, that are less able than retailers to hedge against price volatility. Existing spot-index based tariffs in Texas have therefore lead during the 2021 winter to considerable increase in consumer bills (Blumsack, 2021). Mitigation options consist of second-best pricing schemes such as Time-Of-Use[1] or Critical Peak Pricing. However, the European Parliament directive 2019/944 (European Parliament, 2019) state that "[All consumers] should therefore have the possibility of benefiting from the full deployment of smart metering systems and, where such deployment has been negatively assessed, of choosing to have a smart metering system and a dynamic electricity price contract. This should allow them to adjust their consumption according to real-time price signals that reflect the value and cost of electricity or transportation in different time periods, while Member States should ensure the reasonable exposure of consumers to wholesale price risk." Such dynamic offer will be mandatory for supplier with more than 200 000 final costumers according to the same directive. There is therefore a need to assess to what extent the demand-response will represent an opportunity for reactive consumers.

This article contributes to the literature by exploring welfare gains of different time-differentiated electricity tariffs in the French future power market. With the joint increase of near-zero marginal price capacities of renewable power and the rise of the short-run marginal cost of remaining thermal units due to increasing price of CO2 allowances, electricity market prices are called to face increasing volatility in the near future. Lag in the adoption of new rate design could result in short-term welfare loss if current incentives proved to be inefficient.

[1] Time-Of-Use rates adjust the rate depending on a pre-defined time period. It usually incentivizes the electricity consumption at a time of low demand (price), during the night. Critical Peak Pricing defines a fixed annual number of days where the rate of electricity is higher.

We investigate in a first step how renewables and carbon price affects power price volatility in joint assemessment of France, the UK, and Germany. Given our interests, we focus on obtaining power prices from a unit commitment model. Then, bill impacts in the form of savings are estimated based on generated market prices under two tariff schemes: Time-of-use (ToU) and Real-time pricing (RTP). When accounting for risk exposure considerations, price volatility is an important factor to be considered for adoption of dynamic rate. Therefore, we assess the extent to which risk-averse end-users, opting out of RTP, could prevent welfare gains of dynamic pricing and if current incentives are aligned with ongoing change in power markets.

We find that under the current elasticity hypothesis, the bill impact in 2018 of switching to dynamic rate is only marginal, reaching at most 4% savings in the energy supply component of the annual electricity bill. Savings can reach as high as 17% considering higher price-elasticity. Moreover, we confirm that current incentives under time-of-use rates are efficient, yet limited, with savings reaching around 3% of the energy supply component. Those benefits however don’t hold with an increasing share of renewable generation, with incentives becoming mis-aligned with the power prices. The study also demonstrates an increasing value for real-time cost rate for end-users, but very limited gain should be expected for all consumer segment.

This paper is structured as follows. Section 2 introduces the methodology and data used in the paper. Section 3 describes the results. Section 4 discusses the results and concludes.

## 2. Methodology

Different methodologies have been used to assess the welfare gain of switching to real-time prices. A first segment of the literature represented by Borenstein and Holland (2003), Joskow and Tirole (2007), Léautier (2012), and Schweppe et al. (1985) analysis flat-tariff inefficiencies using a model of competitive wholesale and retail electricity markets. Results demonstrate that direct pass-through is optimal in most cases, even if expected gain appears marginal compare to the cost of smart meter rollout (Léautier, 2012). Yet, as the rollout is on the verge of being completed and as fields experiments (Allcott, 2011; Faruqui and Sergici, 2010) tend to demonstrate the effectiveness of dynamic pricing, the potential could easily be triggered. De Jonghe et al. (2012), Gambardella and Pahle (2018) and Wolak (2019) developed model-based methodologies to assess welfare gains from RTP implementation and underlined the reduction of required investment in peaking generation capacity with demand response deployment, with only slight change expected in the electricity bills.

Recent research shows that the underlying of the market power prices might be disregarded in some modeling framework. Blume-Werry et al. (2019) underline that most of the price-setting technologies are heavily linked with foreign markets, even in large countries such as Germany. This stressed the importance of considering multiple countries to approximate power prices, and lead us to include Germany, United Kingdom, and Austria in this study. Ward et al. (2019) builds on historical data to adjust a market model to better capture variability of prices, and acknowledge a widespread shortfall in current methodologies. We believe that model simplifications affecting the price formation could lead to undermining the market valuation of flexibility alternatives such as price-driven demand response, and include suggested methodology in our model framework.

### a. Unit commitment model

The model consist of a MILP partial equilibrium model of the power market, usually refered as a unit commitment (UC) model, based on Quoilin (2015) and Palmintier (2011) formulations to estimate market prices. Unit commitment models represent the day-ahead commitment of each power plant units based on their short-run marginal costs and technical constraints. The demand is considered in this first stage as inelastic and will be assessed in a second stage. Such simplification is representative of the current market structure, where consumers on dynamic rate received the information based on the day-ahead dispatch.
Clearing price divergences compared to historical could be explained notably by combined heat and power plants (CHP) (sector coupling), lack of unit by unit technical details, or non-competitive bidding. A price markup per unit has been added based on historical values (Ward et al., 2019).

The objective function is to minimize total costs of producing electricity (1):

$$\min\,(TotalCost) = \sum_{t,k,z} Prod_{t,k,z} * \left(Markup_{t,k,z} + SRMC_{t,k,z} + EF_k * ETS_{t,k}\right) + \sum_{t,k,z} UC_{t,k,z} + \sum_{t,\ k} LL_t * VoLL_t \qquad \forall k \in \kappa,\ \forall t \in \tau,\ \forall z \in Z \qquad (1)$$

$Prod_{t,k,z}$ is the hourly production of a given technology cluster of a market area;

$Markup_{t,k,z}$ is a calculated price mark-up based on historical data;

$SRMC_{t,k,z}$ is the short-run marginal cost of a unit, composed of fuel price and variable O&M;

$EF_k$ is the emission factor in tCO2(eq) of a given technology cluster.

$ETS_{t,k}$ is the market price of the carbon emission allowances. We assume a full pass-through of the carbon price;

$UC_{t,k,z}$ are costs related to technical costs. It encompasses startup costs, shutdown costs, ramping costs and technical constraint related to minimal uptime (downtime) and maximum ramping up (down) capabilities;

$LL_{t,k}$ is the lost load, which is the energy not served in a market area;

$VoLL_t$ is the value of the lost load, associated with the market price cap in the power market, set at 3000€/MWh;

The cost minimization objective function is subject to constraints to capture the specificities of each technology cluster. Technology cluster considered consist of a triplet of fuel used, turbine installed and vintage class[2]. Additional constraints are considered for renewables-based technology (wind, solar, or hydropower) limiting the availability of the natural resources and are based on 2018 historical production. Those are therefore modeled as an hourly availability

[2] Fuel considered are coal, lignite, gas, nuclear, and renewables power. Technology is mostly used to distinguish between OCGT and CCGT gas power plant. Vintage classes are representative of the commissioning year of the power plant, linked to efficiency values considered for SRMC calculation.

factor (in %) multiplied by the installed capacities, with the possibility to curtail in case of excessive generation, a hypothesis that we might reconsider especially in a highly renewable scenario, especially when considering feed-in premium scheme. Thermal units also are described with operational constraints reflecting their technical capabilities, as described in Palmintier (2011). Those are ramping capabilities constraint, minimum up, and downtime and minimum power generation. Hydropower and battery behavior are constrained by their operating range, storage capacities, and charging/discharging behavior.

The market price resulting from the UC model is deduced from the marginal value of the supply and demand constraint (2). A marginal increase of exogenous parameters, in this case the load, would result in an increase of the production variable, therefore of the objective function by an amount equal to the short-run marginal cost of the last unit called. Such value can be used as a proxy for the outcome of a day-ahead power market under perfect competition, to render the dispatch performed by ISO[3]s (Brent Eldridge et al., 2018).

$$\sum_{t,k,z} Prod_{t,k,z} + Import_{z,z} = Load_{t,z} + Export_{z,z} + \sum_{t,s,z} CH_{t,s,z} \qquad \begin{array}{l} \forall k \in \kappa, \\ \forall t \in \tau, \\ \forall z \in Z \end{array} \qquad (2)$$

$Load_{t,z}$ is the hourly demand of a market area, considered inelastic;

$Import_{z,z}$ and $Export_{z,z}$ are variables for power exchanges between different market area;

$CH_{t,s,z}$ is the variable used to denote the charging/discharging power flows of storage technologies;

ENTSO-E Transparency data (2020) is used for hourly data for load, renewables infeed, and power exchange capacities for each European market area. Technical parameters used for the Unit Commitment equations come from Schill et al. (2017). The power plant database used for the technology clustering comes from the open energy modeling initiative (2020). Table 1 summarize key power market metrics in terms of consumption for France, the UK, and Germany in 2018. Table 2 describes the scenario considered in this study and associated names. Increasing deployment of renewables has been considered, together with a progressive increase in carbon price. The situation anticipated is that near-zero marginal power prices occurrence will increase, linked to the renewable, as the thermal unit will have increasing generation prices, linked to the carbon price increase.

[3] Independent system operator, in charge of the coordination and monitoring of the power system. We don't distinguish with the European terms Transmission System Operator (TSO).

### b. Demand-side model

To account for how end-users might react to real-time price variations, we used a second stage system dynamic model. This framework applies to a market structure where consumers would be informed of day-ahead market prices and is similar to existing RTP rates as described by Faruqui and Sergici (2010). It is also the current market structure envisaged in France and already commercialized[4]. The demand-response model follows Doostizadeh and Ghasemi formulation (Aalami et al., 2010; Doostizadeh and Ghasemi, 2012) where end-user responds to the differences between market prices and their average energy tariff under a flat rate[5]:

$$d_c(t) = d_{0c}(t) * \left(1 + \varepsilon_c(t) * \frac{p(t) - p_{wg}(t)}{p_{wg}(t)} + \sum_{\substack{h \neq t}}^{h=t-x\ldots t+x} \varepsilon_c(t,h) * \frac{p(h) - p_{wg}(h)}{p_{wg}(h)}\right) \tag{3}$$

Where $d_{0c}(t)$ is the inelastic demand of a consumer considered in the UC, $\varepsilon_c(t)$ is the self elastic of the consumer considered, $p(t)$ is the day-ahead market prices, $p_{wg}(t)$ is the flat tariff proposed to the consumer, considered as being equal to the demand weighted average price of electricity of the consumer. The cross-elasticity[6] $\varepsilon_c(t,h)$ has not been considered as pilot projects show little evidence of energy shifting (Allcott, 2011; Borenstein, 2005).

Data used for inelastic demand at the consumer level comes from Enedis open data (2020). It provides aggregated consumption for load profile by segment (Residential, Professional and Industrial) and voltage level at a half-hourly granularity in France, including an average profile of sites equipped with smart meters. Consumers on flat rates that don't receive any price incentives have been considered for the inelastic demand, and are still representative of an important share of the draw-off points in France (see Table 3, Figures 1 and 2). Consumers currently under time-of-use rate have been used, with consumption pattern significantly different than consumer under flat rate. A heat-map of the hourly consumption pattern per day of the week is provided in Figure 3 for illustration. It underlines the efficiency of price incentives, even though lifestyle of the consumers opting in for time-differentiated tariff is not fully representative of their price elasticity.

As a first estimate, we distinguished elasticity per consumer segment according to the value provided by Burke and Abayasekara (2018) and presented in Table 4. An evident limitation of such values is that the study estimate short-term price elasticities of electricity demand in the U.S. Those values are however aligned with estimates used in the literature that consider RTP (De Jonghe et al., 2012; Gambardella and Pahle, 2018; Lijesen, 2007). We performed additional sensitivities to assess the robustness of the results for higher levels of short-term price elasticities.

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[4] See for reference, the Tempo tariff in France or new dynamic rate such as barry.

[5] We haven't considered an incentives or penalties that would have been contractualized beforehand with third parties, thus resulting in a simple time-based program.

[6] Cross-elasticity refer to inter-period elasticity of demand. In other words, price-reactive demand will consider for each timestep not only the distance to the average electricity price, but also the relative distance of the neighbouring hours.

The flat rate offered to consumers for this research considers only the supply component of the price offered by homogenous retail firms. Retail firms are assumed to buy and sell electricity at the wholesale market prices, with zero profit on this component. The flat rate can be therefore calculated as being the demand weighted average wholesale price captured by end-users. We assume consumers react to variation to this average price that would be offered by the retailer, and use the weighted average price as a benchmark to estimate bill rebate from switching to a dynamic price scheme. An example of price-reactive consumer load change is procured in Figure 4a for a 48-h period. The dashed load profile indicates the impact of demand response, and underlines both the valley filling and the peak load reduction potential of price-reactive consumers.

Overall market impact has been analyzed thanks to the unit commitment model representative for the intra-day dispatch, this time considering the short-term load adjustment of reactive consumers. Thus, it is representative of the situation where the price takers assumptions wouldn't hold for a high share of price-reactive consumers, resulting in a possible rebound effect on the market prices link to demand shifting.

*Table 4 – Elasticities considered per consumer segment*

| | Static price-elasticity of the demand |
|---|---|
| **Residential** | *-0.11* |
| **Professional** | *-0.05* |
| **Industrial** | *-0.11* |

# 3. Results

## 3.1 Current rate

Results based on the current rate schemes are presented in Table 5. The current Time-of-Use rate delivers proper incentives under the current operations across all segments, with an average price of electricity around 3% lower than under the flat rate in 2018. Users, therefore, consume electricity at a time with less generation scarcity, resulting in an increased consumer surplus. This however does not hold with an increasing share of renewables, neither under more important carbon price considered as in scenario RES100.3 (see scenario definition in Table 2 of appendix) for the consumer segment. The wholesale market prices evolve and become less correlated with the load. As a result, off-peak power consumption of the residential segment under a Time-of-Use tariff does not benefit from the solar generation, therefore are not beneficial from a system perspective (see Figure 3). Indeed, on-peak daytime consumption coincide in RES scenario with the increasing solar generation. From a system perspective, demand should be encouraged to be shifted toward noon, to benefit from the near-zero marginal cost of PV Panels and avoid reverse flow in the distribution grid. As the professional and the industrial segment are less subject to important load variability throughout the day, and are often already to some extent price reactive in the industrial segment, the effect is less pronounced for those consumer segments or appears even to stay profitable based on their current profile.

*Table 5 – Average price of electricity per consumer segment*

| | | Historic Price | Basecase | RES40 | RES80 | RES100 | RES100.3 |
|---|---|---|---|---|---|---|---|
| Residential | Flat rate | 51.76 | 48.88 | 38.37 | 30.96 | 27.72 | 38.46 |
| | ToU price difference (%) | -3% | 0% | 0% | 1% | 2% | 2% |
| | Consumer bill impact (€) | -7.5 | -0.9 | 0.3 | 1.6 | 2.4 | 3.3 |
| Professional | Flat rate | 52.63 | 48.62 | 38.05 | 30.43 | 27.07 | 37.83 |
| | ToU price difference (%) | -2% | -1% | -1% | -1% | -1% | -1% |
| | Consumer bill impact (€) | -11.6 | -6.6 | -5.3 | -4.0 | -3.4 | -5.0 |
| Enterprise | Flat rate | 52.81 | 48.78 | 38.24 | 30.64 | 27.30 | 38.10 |
| | ToU price difference (%) | -3% | -3% | -3% | -4% | -5% | -4% |
| | Consumer bill impact (€) | -54.6 | -47.0 | -37.0 | -36.9 | -39 | -45 |

One can observe that the bill savings, assuming similar consumption level, are little between the base rate and the time-of-use rate. Households indeed benefit in recent years from energy efficiency improvements of most appliances and heating systems. Therefore, the benefits of delaying those appliances in off-peak hours (at night) gradually erode as the energy efficiency improve, and result in some cases in a net loss for the consumer compared to a flat rate. Moreover, one should note that only the energy part of the bill is assessed in this framework, which represents only a third of the total bill. We didn't take into account consumer preferences of electricity consumption timing, neither private cost to switch from one rate to another, which would likely discard the benefits from switching rate. This cost might be non-negligible, as very low switching rates are seen in the current power market (less than 3% in 2020) (CRE, 2020).

## 3.1 Real-Time prices

Table 6 depicts the comparison between users under the base rate and RTP rate. As excepted, it results in an overall price decrease for the consumer, as they tend to under consume at peak price and overconsume when prices are low (Figure 4a). Gains are however less important than under the Time-of-Use rate in 2018, which might indicate we have under-estimated the elasticity of end-users and the possibility to shift a more important part of the consumption towards neighboring hours. Yet, and contrary to the current Time-Of-use rate, the savings increase with the increase in volatility of prices. As expected, price-reactive consumers react more as the prices reach more extreme values, as depicted by the difference between the RES100 and RES100.3 scenario. It is also important to note that the resulting annual load consumption level for each segment does not vary significantly. As the user reacts to its flat tariff, calculated as the demand weighted average price of the wholesale market for each customer segment, differences in annual consumption level are below 0.2% in all cases.

*Table 6 – Average price of electricity per consumer segment*

| | | Historic Price | Basecase | RES40 | RES80 | RES100 | RES100.3 |
|---|---|---|---|---|---|---|---|
| Residential | Flat rate | 51.76 | 48.88 | 38.37 | 30.96 | 27.72 | 38.46 |
| | RTP price difference (%) | -1.4% | -0.9% | -2.1% | -3.0% | -3.5% | -4.2% |
| | Non isoelastic RTP price difference (%) | -1.5% | -1.0% | -2.1% | -3.0% | -3.5% | -4.2% |
| | Consumer bill impact (€) | -3.75 | -2.28 | -3.87 | -4.48 | -4.63 | -7.86 |
| Professional | Flat rate | 52.63 | 48.62 | 38.05 | 30.43 | 27.07 | 37.83 |
| | RTP price difference (%) | -0.7% | -0.4% | -0.9% | -1.3% | -1.6% | -1.8% |
| | Consumer bill impact (€) | -3.78 | -2.33 | -3.75 | -4.45 | -4.70 | -7.69 |
| Enterprise | Flat rate | 52.81 | 48.78 | 38.24 | 30.64 | 27.30 | 38.10 |
| | RTP price difference (%) | -1.4% | -0.9% | -2.0% | -3.0% | -3.5% | -4.2% |
| | Consumer bill impact (€) | -8.09 | -4.99 | -8.29 | -9.81 | -10.29 | -17.10 |

We also investigate the case when residential have a time-differentiated elasticity (Figure 5), but results don't yield sensible differences. In the historical case, as the elasticity is higher when price peaks, it tends to slightly overperform the isoelastic case. Yet, as the prices decorrelated to the load, the differences are only marginal for the remaining scenarios.

To estimate the required price-elasticity of demand required to reach significant bill savings, we performed additional sensitivities on the price elasticity of demand. Results for the Historic and RES100.3 scenario are depicted in Table 7. As a reminder, The European Commission indicates an annual saving of 22-70% of the energy supply. Our results don't achieve such level of annual savings in the considered range of elasticity. Yet, the considered range for the residential and industrial segments is already quite large, with load variation between +58% and -50%. In other words, consumers would be in measure to half or twice their energy consumption given the price signals. We believe such results depict a situation where consumers are equipped with smart devices, that would automatically adjust their consumption pattern based on the price signals received. Indeed, the consumption pattern is heavily distorted compared to lower values of price-elasticity (see Figure 4b). Such demand-management smart operation is already considered by electric-intensive firms (Google, 2020). Yet, we believe the opportunities are lower for the residential segment, and would mostly rely on smart charging of EVs or personal home storage. It also to be noted that that framework for this research does not lead to significant energy savings, as the total consumption from the residential segment increase by 3.85% at most in RES100.3. Consumers have more opportunities to increase their consumption during a period of low prices (mostly linked to renewable or nuclear). This could be assimilated to a rebound effect linked to the prevalence of low prices in the day-ahead market.

*Table 7 – Average price of electricity per consumer segment for different price elasticity for Historic and RES100.3 scenario*

| | | Historic Price $\varepsilon_1$ | 1.5 * $\varepsilon_1$ | 2 * $\varepsilon_1$ | 3 * $\varepsilon_1$ | 4 * $\varepsilon_1$ |
|---|---|---|---|---|---|---|
| Residential | Flat rate (€/MWh) | 51.76 | | | | |
| | RTP price difference (%) | -1.4% | -3% | -3.9% | -5.8% | -7.7% |
| | Consumer bill impact (€) | -3.75 | -8.2 | -10.8 | -15.8 | -21 |
| Professional | Flat rate (€/MWh) | 52.63 | | | | |
| | RTP price difference (%) | -0.7% | -1.4% | -1.8% | -2.7% | -3.6% |
| | Consumer bill impact (€) | -3.78 | -7.56 | -9.72 | -14.62 | -19.35 |

| | | RES100.3 $\varepsilon_1$ | 1.5 * $\varepsilon_1$ | 2 * $\varepsilon_1$ | 3 * $\varepsilon_1$ | 4 * $\varepsilon_1$ |
|---|---|---|---|---|---|---|
| Residential | Flat rate (€/MWh) | 38.46 | | | | |
| | RTP price difference (%) | -4.2% | -6.3% | -8.4% | -12.4% | -16.4% |
| | Consumer bill impact (€) | -7.86 | -11.8 | -15.72 | -23.2 | -30.7 |
| Professional | Flat rate (€/MWh) | 37.83 | | | | |
| | RTP price difference (%) | -1.8% | -2.7% | -3.6% | -5.4% | -7.2% |
| | Consumer bill impact (€) | -7.69 | -11.5 | -15.38 | -23.1 | -30.8 |

## 3.1 Market impact

We finally assess the overall impact of having price-reactive consumers from a system perspective. Table 8 present the case where all consumers currently under flat tariff would opt-in to RTP. The peak load reduction level found around -1% is far from pilot projects value found, as we only consider a share of the consumers would be price responsive, undermining the potential at the system level. Testing higher share of real-time prices will likely increase the peak load reduction potential. However we believe the gain will stay marginal, and has little chance to materialize considering the low switching rate in the retail power market. We also believe that this indicates that the peak load won't necessarily benefit from providing day-ahead prices to end-users. Indeed, as prices are less and less correlated with the load, this event won't necessarily coincide with the peak prices faced by consumers. The result when considering the maximum load reduction observed throughout the year reach 2.9GW, and therefore corresponds to a total load decrease of 3%, more significant than the one observed at peak load. Moreover, for each consumer segment, load reduction reaches between -9% and -18% compared to the inelastic case, well-aligned with pilot projects and other studies (Faruqui and Sergici, 2010; Gambardella and Pahle, 2018). The fact that peak load hour and peak prices are to be more and more disconnected with increasing renewables might lead to grid congestion issues, and time dynamic rates under zonal pricing would have a very limited contribution to alleaviate this issue

*Table 8 – Price-reactive impact on wholesale market and load*

| | RES100 | RES100.3 |
|---|---|---|
| **Range of maximum load reduction (%)** | -8%-18% | -9%/-18% |
| **Market price difference (%)** | -3% | -1% |
| **Peak Load reduction (%)** | -0.8% | -1.0% |
| **Peak Load reduction (GW)** | -0.80 GW | -0.96 GW |
| **Max Load reduction (GW)** | -1.6 GW | -2.9 GW |

## 4. Conclusion

Our study suggests that gains from dynamic pricing are overestimated. When comparing the results to the bill reduction envisaged by the European Commission (2019) for RTP schemes of 22-70% of the energy supply component in the annual bill, the demand response would need to deliver more than six times the savings found. Indeed, we find that the yearly average price difference compared to inelastic load never exceeds 5%. Additionally, we performed sensitivities on the short-term price elasticity, with cases where consumers can curtail 50% of their energy consumption. In those cases, yearly results doesn't depict a situation where consumers bill would be reduced by more than 17%. The result of the European Commission would therefore likely go along with a net decrease of electricity consumption for the end-users. The utility function associated with electricity consumption is however not evaluated in pilot projects. Indeed, reducing load consumption level comes with comfort loss linked to reduced heating level for example. Considering the stability of the yearly consumption found under our demand-side response hypothesis, we believe that results would hold true when considering hourly cross-elasticities or load shifting potential that are already captured, even if not constraint explicitely. Changing the willingness to pay of a consumer to lower values would however allow capturing more benefit and would likely result in a lower annual energy consumption. This could be the subject of further research.

The gap found could come from the low estimate used for the price elasticity of demand, despite evidence that it triggers a reasonable amount of load reduction at peak prices (9-18%) compared to the literature. Yet, it has also been demonstrated that the real-time price rate envisaged (RTP) scarcely triggers the most significant price response. More targeted price signals like the ones envisaged in Critical Peak Pricing schemes usually perform better for peak shaving. RTP is however the most straightforward pass-through of wholesale market prices, and results demonstrate that this tariff gain interest with increasing price volatility. This would however require to increase price-elasticity, which we believe is likely given the current electrification policies (EV, Storage). On the contrary, evidence that a Time-Of-Use is well-suited in a context of high renewable generation and a high carbon price is not demonstrated in our research. It is likely that fixed timed tariff results in wrong price incentives. Fixed ToU are indeed unable to counter balance the weather-dependent variability of the net load and therefore lessen the interest of such rates.

The integration of demand-side response also results in a decrease of the system peak load. An interesting finding of the study is that the maximum load reduction resulting from end-users won't necessarily coincide with the system peak load. This could notably result in increasing risks in grid congestion, a dimension which scarcity is not currently priced in current markets. We believe that further research is required to understand to what extent grid and generation scarcity would require different signals to be conveyed to the end-users, and might conflict with each user. This issue relates to the TSO-DSO coordination research stream, where country-wide signals resulting from the wholesale market might go against local grid congestion flexibility requirements.

Finally, it is important to note that our study has some limitations. Market prices generated for different levels of renewable capacity and carbon price don't capture the full volatility of price bids, notably effects of strategic bidding and feed-in tariff, that would distort the merit order. This could result in stronger incentives for the end-users, and would likely results in more important bill savings. We however don't find significant change when using historical market prices. Then, the price elasticity of end-users is a highly debated measure, difficult to estimate, and depends highly on households. Also, the approximation that consumers react relatively to the flat rate that would have been offered to them is subject to discussion, as the consumer won't necessarily have access to this information.  Finally, considered consumption patterns are representative of only a fraction of the end-users, especially for the residential side. Different consumption patterns would result in different captured prices.

However, we believe that the trends depicted in our study for the relevance of the Time-of-use tariff and the low profits resulting from real-time pricing would still hold. This question the policy pursued, as there is little evidence of significant incentives for the consumers. Moreover, consumers have little possibility to hedge against prices in a period of sustained high power prices, contrary to a retailer that could secure power price contracts. We believe this would be another important issue to address if RTP would be generalized.

Finally, as next steps, we believe that the rapid cost decrease of batteries and the adoption of Electric Vehicles might result in more important benefits of RTP, an element that will be the be the subject of further research.

## 5. Appendix

*Table 1 - Summary statistics of French, UK, Germany electricity consumption in 2018*

| Country | **France** | **United Kingdom** | **Germany** | **Austria** |
|---|---|---|---|---|
| Annual electricity demand (TWh) | 305.05 | 475.70 | 498.90 | 70.98 |
| Average hourly consumption (GW) | 34.82 | 54.30 | 56.95 | 8.10 |
| Standard Deviation (GW) | 7.42 | 12.30 | 9.86 | 1.55 |
| Minimum consumption (GW) | 12.56 | 30.45 | 35.18 | 4.73 |
| Maximum consumption (GW) | 54.52 | 96.33 | 76.79 | 11.92 |

*Table 2 – Scenario considered in this study*

| Category | Description | Key figures[7] |
|---|---|---|
| **Historical** | 2018 historical market prices | 23.6 GW<br>16€/tCO2(eq) |
| **Basecase** | 2018 Model prices | 23.6 GW |
| **RES20** | +20% RES in France | 28.3 GW |
| **RES40** | +40% RES in France | 33 GW |
| **RES80** | +80% RES in France | 42.5 GW |
| **RES100** | +100% RES in France | 47.2 GW |
| **RES100.3** | +100% RES in France<br>Carbon price x3 | 47.2 GW<br>47 €/tCO2(eq) |

[7] Aggregated numbers of Wind and Solar PV installed capacities considered in the scenario.

*Table 3 – Consumer segment dictionary (Enedis, 2020)*

| Category | Segment | Description |
|---|---|---|
| **RES1** | Residential | Résidentiel Base ≤ 6 kVA |
| **RES11** | Residential | Résidentiel Base + WE |
| **RES2** | Residential | Résidentiel HP / HC - |
| **PRO1** | Professional | Professionnel Base |
| **PRO2** | Professional | Professionnel HP / HC |
| **ENT1** | Enterprise | Entreprise1 Basse Tension – avec Cadran |
| **ENT2** | Enterprise | Entreprise2 Basse Tension – avec Période Mobile |

*Figure 1 – Annual consumption in 2018 per consumer segment*

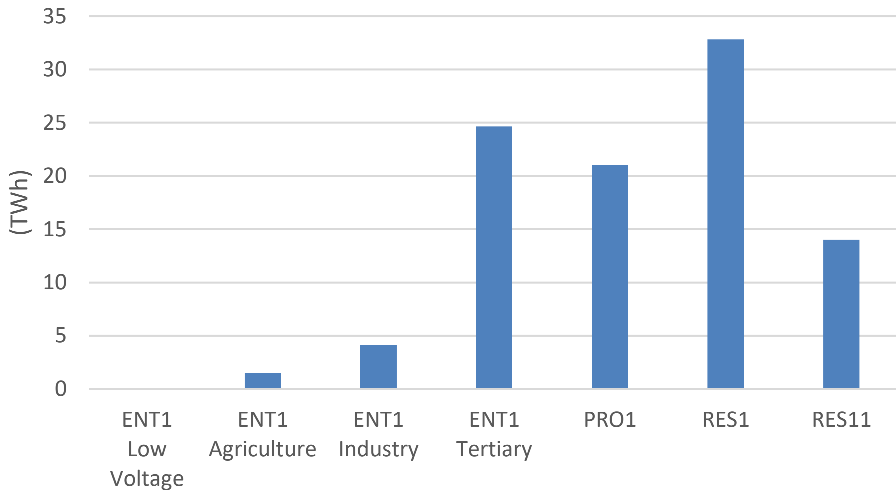



*Figure 2 – Average consumption in 2018 per draw-off point per consumer segment*

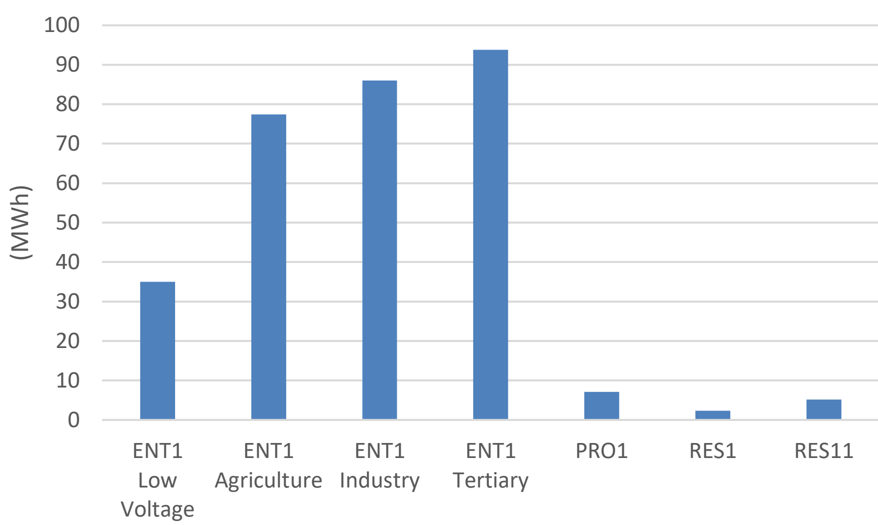
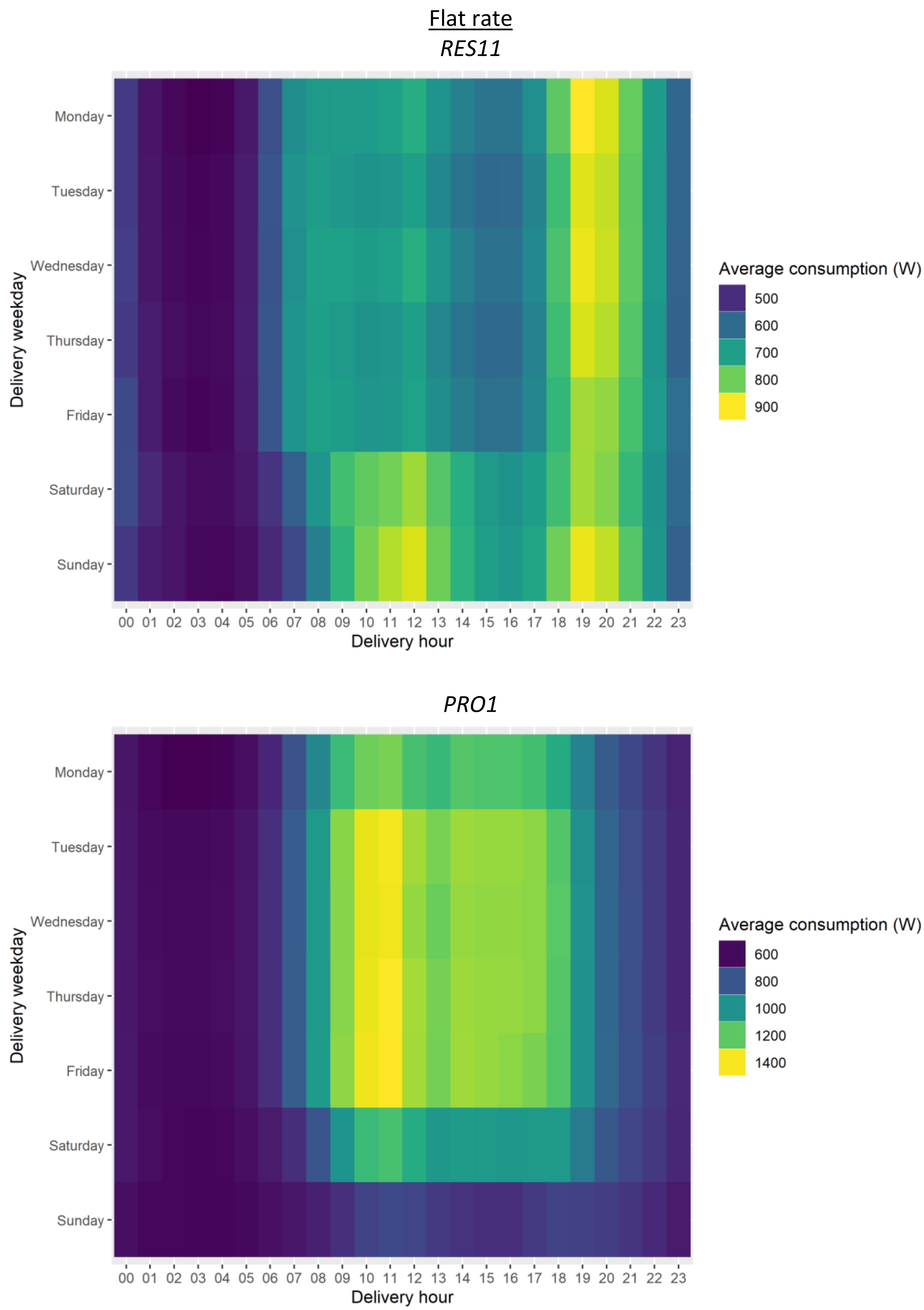
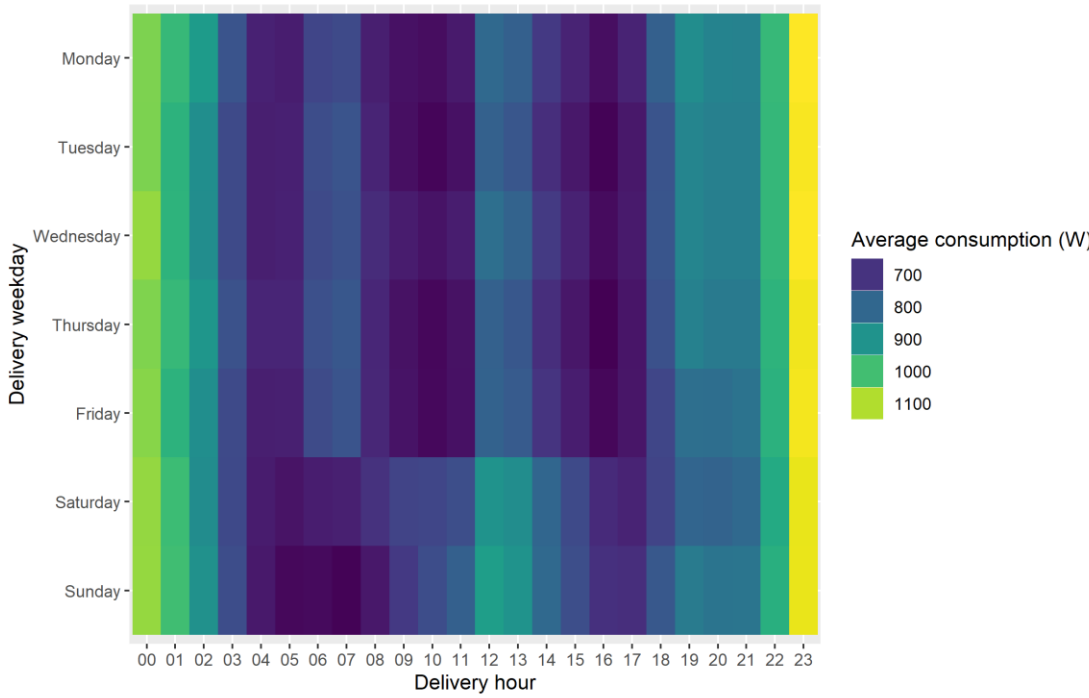


*Figure 3 - Average load profile for the residential base rate and time-of-use rate in 2018*



## Time-of-Use rate

*RES2*




*PRO2*

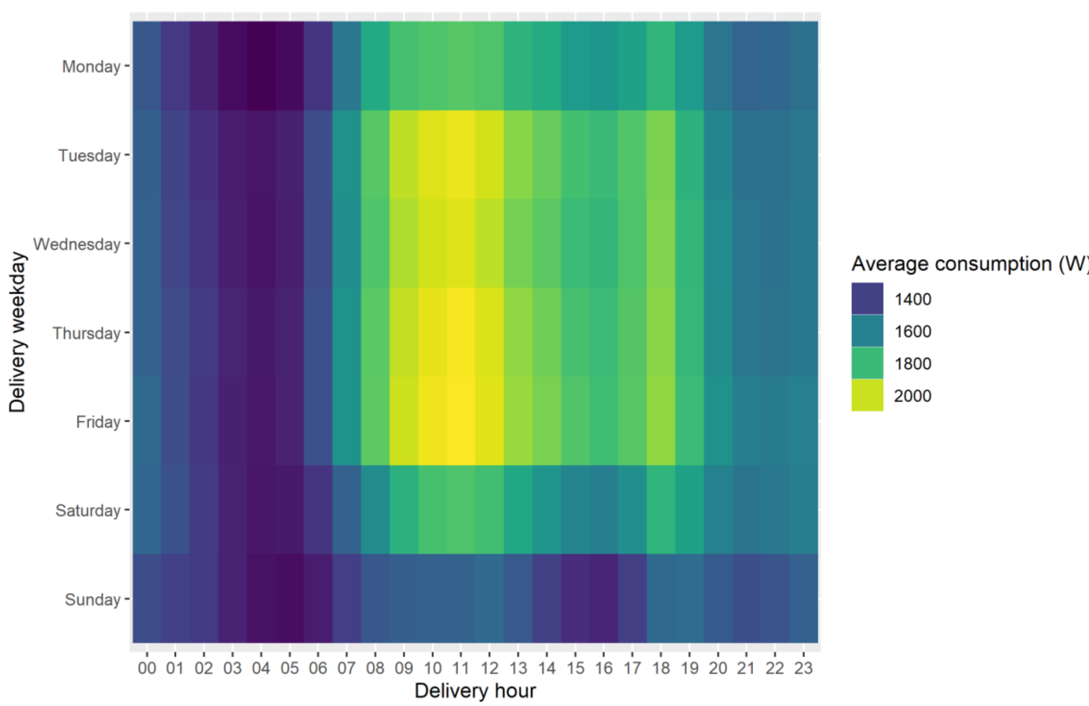


*Figure 4a – Load reduction for a residental consumer with short-term elasticity of -0.11 in RES100.3 scenario*

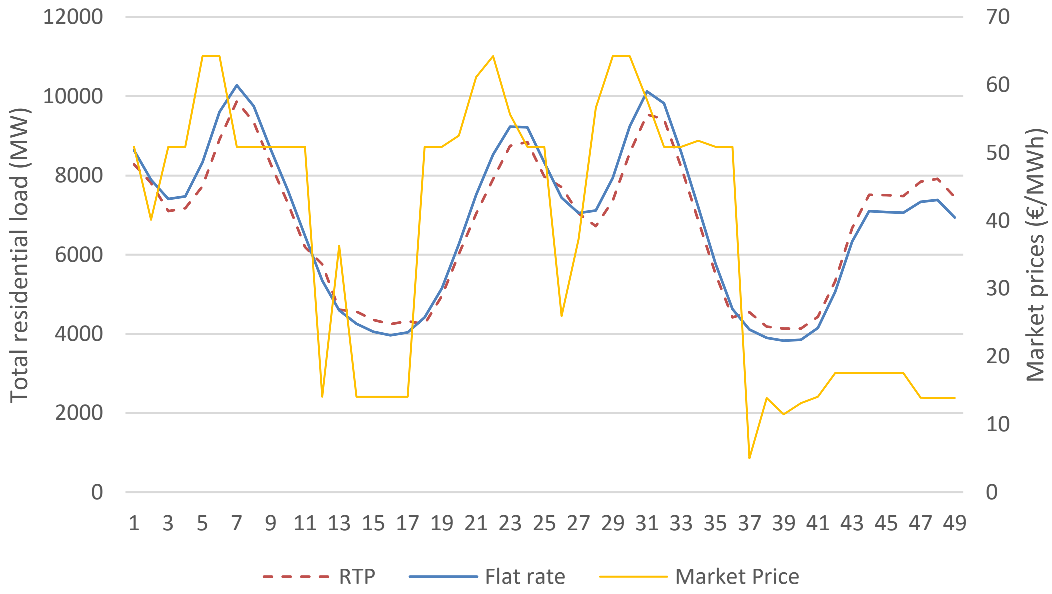



*Figure 4b – Load reduction for a residental consumer with short-term elasticity of -0.44 in RES100.3 scenario*

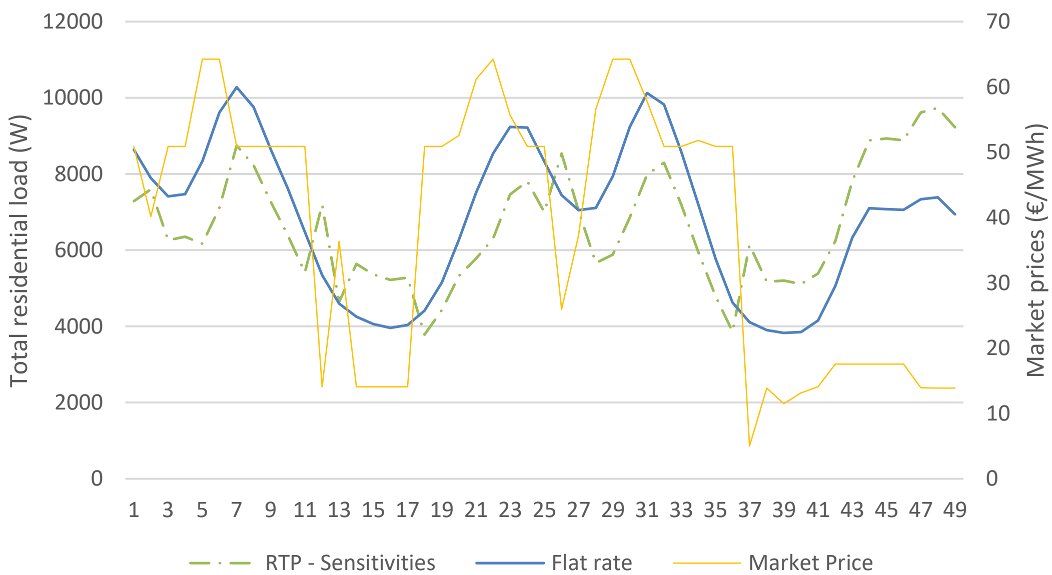
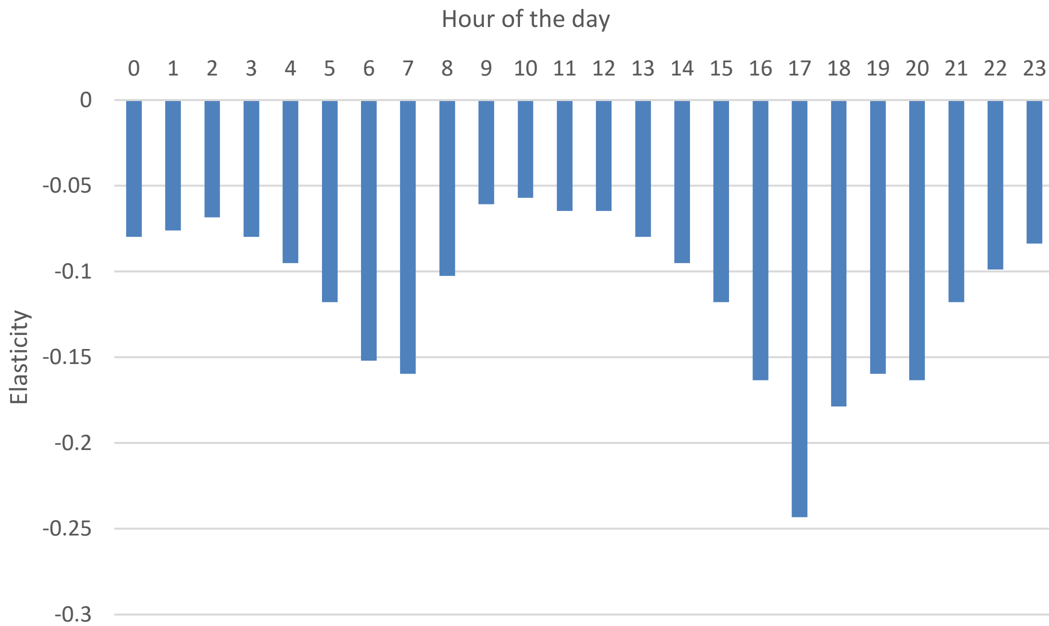


*Figure 5 – Nonconstant price elasticity of electricity demand* (Knaut and Paulus, 2016)



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