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ENSURING DISTRIBUTED DEMAND-RESPONSE THROUGH FUTURE-PROOF TARIFF DESIGN

Clément Cabot, Manuel Villavicencio

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Ensuring distributed demand-response through future-proof tariff design

Clément Cabot[1], Manuel Villavicencio[2]

Abstract

Relying on the 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) schemes 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 suggest that the current ToU rates do not provide the right incentives concerning 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: tariff design, power market, demand-side response, dynamic tariff, real-time prices

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Contact: Tel.: +33 6 69 01 11 76, E-mail adress: clement.cabot@mines-paristech.fr

I. INTRODUCTION

[1]MINES ParisTech, PSL University, Centre for industrial economics (CERNA), i3 UMR CNRS, 60 Bd St Michel 75006 Paris, France
[2]PSL Research University, LEDa [CGEMP], Place du Maréchal de Lattre de Tassigny, 75775 Paris, France

Following the liberalization of power markets, the competition in retail activities has offered consumers an increasing choice of suppliers. Nevertheless, unbundling of the market has not translated into the diversification of billing schemes regarding to rate design: most 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; Wolak, 2011). 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 (Borenstein, 2005; 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 in 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 in a pass-through of risks linked to price volatility towards end-users, who are less able than retailers to hedge against price volatility. Existing spot-index-based tariffs in Texas have led during the 2021 winter to a considerable increase in consumer bills (Blumsack, 2021). Mitigation options consist of second-best pricing schemes such as Time-Of-Use[3] or Critical Peak Pricing. However, the European Parliament directive 2019/944 (European Parliament, 2019) states 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." According to the same directive, such dynamic offers will be mandatory for suppliers with more than 200 000 final customers. There is, therefore, a need to assess to what extent the demand-response will represent an opportunity for reactive consumers.

This paper contributes to the literature by exploring the 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 the increasing price of CO2 allowances, electricity market prices are called to face increasing volatility in the near future. Lag in adopting new rate designs could result in short-term welfare loss if current incentives prove to be inefficient.

We investigate in a first step how renewables and carbon price affects power price volatility in joint assessment 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).

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

When accounting for risk exposure considerations, price volatility is an essential factor to be considered for the adoption of dynamic rates. 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 a real-time prices 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, do not hold with an increasing share of renewable generation, with incentives becoming misaligned with the power prices. The study also demonstrates an increasing value for real-time cost rate for end-users, but minimal gain should be expected for all consumer segments.

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.

II. 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 the expected gain appears marginal compared to the cost of smart meter rollout (Léautier, 2012). Yet, as the rollout is on the verge of being completed and as field 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 a slight change expected in the electricity bills.

Recent research shows that some modelling frameworks might disregard underlying market power prices. Blume-Werry et al. (2019) underline that most 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 led us to include Germany, the United Kingdom, and Austria in this study. Ward et al. (2019) build on historical data to adjust a market model to better capture variability of prices and acknowledge a widespread shortfall in current methodologies. We believe model simplifications affecting price formation could undermine the market valuation of flexibility alternatives such as price-driven demand response. Therefore we included the suggested methodology in our model framework.

2.1. Unit commitment model

The model consists of a MILP partial equilibrium model of the power market, usually referred to 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 unit 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 the second stage. Such simplification is representative of the current market structure, where consumers on a dynamic rate receive 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 the 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 clusters consist of a triplet of fuel used, turbine installed, and vintage class[4]. Additional constraints are considered for renewables-based technology (wind, solar, or hydropower), limiting the availability of natural resources and are based on 2018 historical production. Those are therefore modeled as an hourly availability 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 a feed-in premium scheme. Thermal units are also described with operational constraints reflecting their technical capabilities, as in Palmintier (2011). Those are ramping capabilities constraints, minimum up and downtime, and minimum power generation. Finally, hydropower and battery behaviour are constrained by their operating range, storage capacities, and charging/discharging behavior.

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

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 increase 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[5]s (Brent Eldridge et al., 2018).

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

$Load_{t,z}$ 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 modelling initiative (2020). Table 1 in appendix summarize key power market metrics in terms of consumption for France, the UK, and Germany in 2018. Table 2 describes the scenarios considered in this study and their associated names. Increasing deployment of renewables has been considered, together with a progressive increase in the carbon price. The anticipated situation is that near-zero marginal power prices occurrence will increase, linked to renewable energy sources, as the thermal unit will have increasing generation prices, linked to the carbon price increase.

Table 2 – Scenario considered in this study

Category	*Description*	*Key figures*[6]
Historical	2018 historical market prices	23.6 GW 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 Carbon price x3	47.2 GW 47 €/tCO2(eq)

[5] Independent system operator are in charge of the coordination and monitoring of the power system. We don't distinguish it from the European terms Transmission System Operator (TSO).
[6] Aggregated numbers of Wind and Solar PV installed capacities considered in the scenario.

2.2. Demand-side model

We used a second stage system dynamic model, to account for how end-users might react to real-time price variations. 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[7]. 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[8]:

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

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[9] $\varepsilon_c(t,h)$ 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 the voltage level at a half-hourly granularity in France, including an average profile of sites equipped with smart meters. Consumers on flat rates that do not 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 in appendix). Consumers currently under time-of-use rate have been used, with consumption patterns significantly different than consumers under flat rate. A heat map of the hourly consumption pattern per day of the week is provided in Figure 3 in appendix for illustration. It underlines the efficiency of price incentives, even though the lifestyle of the consumers opting in for time-differentiated tariffs 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 estimates short-run price elasticities of electricity demand in the U.S, but not RTP price elasticity. We believe this assumption can therefore be considered optimistic. 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.

This research's flat rate offered to consumers considers only the supply component of the price offered by homogenous retail firms. Retail firms are assumed to buy and sell electricity at wholesale market prices, with zero profit on this component. The flat rate can be therefore calculated as being

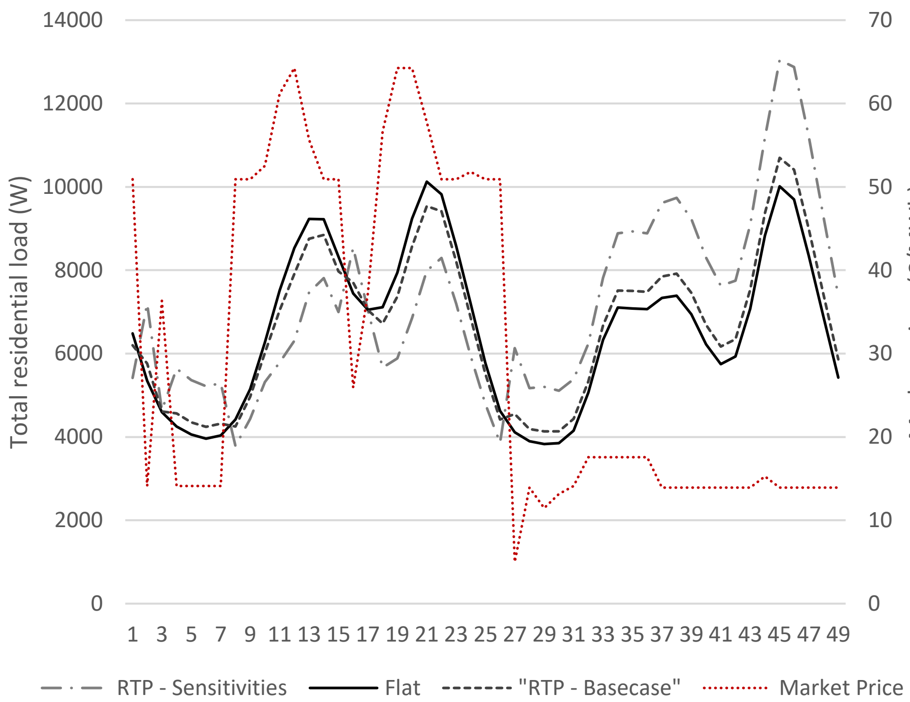
[7] See for reference, the Tempo tariff in France or new dynamic rate such as barry.

[8] 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.

[9] Cross-elasticity refers 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 neighboring hours.

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 rebates from switching to a dynamic price scheme. An example of price-reactive consumer load change is procured in Figure 4 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.

Figure 4 – Load reduction for a residental consumer with short-term elasticity of -0.11 and -0.44 in RES100.3 scenario



The overall market impact has been analyzed thanks to the unit commitment model representative for the intra-day dispatch, considering the short-term load adjustment of reactive consumers. Thus, it is representative of the situation where the price takers' assumptions would not hold for a high share of price-reactive consumers, resulting in a possible rebound effect on the market prices linked 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*

III. 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. However, this 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 in 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 solar generation, therefore is not beneficial from a system perspective (Figure 3 in appendix). Indeed, on-peak daytime consumption coincides 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 significant load variability throughout the day and are often already 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 levels, are little between the base rate and the time-of-use rate. Households indeed benefited 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 improves 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, representing only a third of the total bill. We did not consider consumer preferences of electricity consumption timing nor private cost to switch from one rate to another, which would likely discard the benefits of the 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).

3.2. 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 4). Gains are, however, less important than under the Time-of-Use rate in 2018, indicating we have underestimated end-users' elasticity and the possibility of shifting a more important part of the consumption towards neighbouring 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 scenarios. 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 in appendix), but the results do not yield sensible differences. In the historical case, as the elasticity is higher when price peaks, it tends to overperform the isoelastic case slightly. Yet, as the prices are decorrelating with the load, the differences are only marginal for the remaining scenarios.

To estimate the required price elasticity of demand to reach significant bill savings, we performed additional sensitivities on the price elasticity of demand. Results for the Historic and RES100.3 scenarios are depicted in Table 7. As a reminder, The European Commission indicates an annual saving of 22-70% of the energy supply. Our results do not achieve such a 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 (Figure 4). 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 mainly rely on smart charging of EVs or personal home storage. It is also to be noted that the framework for this research does not lead to significant energy savings, as the total consumption from the residential segment increased 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 ε_1	*1.5 * ε_1*	*2 * ε_1*	*3 * ε_1*	*4 * ε_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 ε_1	*1.5 * ε_1*	*2 * ε_1*	*3 * ε_1*	*4 * ε_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

3.3. Long-Term sensitivities

The first sets of results are performed using 2018 as a baseline scenario to assess the impact of an increasing share of renewable and carbon pricing, all things equal. In reality, all parameters considered in the day-ahead market model will evolve in the near future, notably the thermal unit capacities, the fuel prices and the demand level. We have therefore considered additional scenarios of long-term development of the French power sector to see to what extent results hold true considering wider power system evolution. We have considered three different scenarios based on the TYNDP 2020 scenario (ENTSOs, 2020). TYNDP is a joint effort led by the ENTSO-E based on recent announcements and development planned by both private and public actors. National Trends (NT) is a scenario aligned with the energy and climate policies of the European targets. Distributed Energy (DEn) depicts a situation with a higher European autonomy with a renewable and decentralized focus, while Global ambition (GA) represents a situation with a global economy with centralized low-carbon and RES options. Table 8, Table 9, and Figure 6 provide an overview of the variable changes in the three scenarios. We limit the study to 2040, as more dimensioning and uncertain market design can change above this time horizon.

Table 8 – Summary of load sensitivities considered for long-term scenario based on TYNDP20 for the year 2040

TYNDP20 - 2040		*FR*				*UK*				*DE*			
		2018	GA	DEn	NT	2018	DEn	GA	NT	2018	DEn	GA	NT
TWh	Annual load	475	502	560	502	305	380	397	336	517	788	571	625
%	Percentage increase from 2018	-	6%	18%	6%	-	25%	30%	10%	-	52%	10%	21%

Table 9 – Summary of fuel price sensitivities considered for long-term scenario based on TYNDP20 for the year 2040

	TYNDP20 - 2040	*2018*	*GA*	*DEn*	*NT*
€/GJ	Natural Gas price	6.2		7.31	
€/GJ	Coal price	2.65		6.91	
€/tCO2	CO2 price	15.7	80	100	75

Figure 6 – Summary of installed capacity considered for long-term scenario based on TYNDP20 for the year 2040

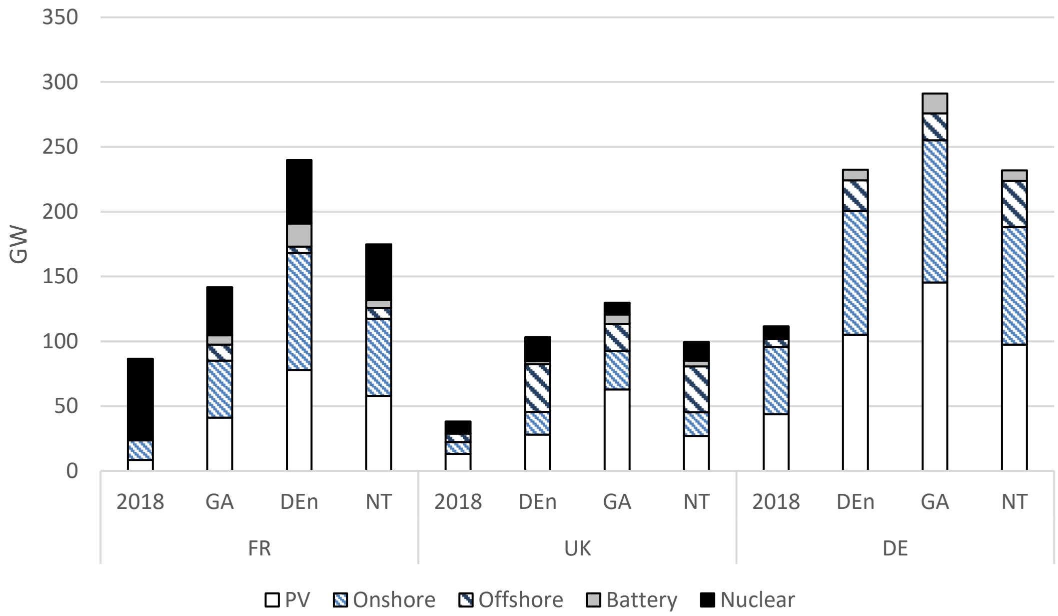


Table 11 – Average price of electricity per consumer segment for different TYNDP scenarios

		Historic Price	DE ε_1	DE $4 * \varepsilon_1$	GA ε_1	GA $4 * \varepsilon_1$	NT $\varepsilon 1$	NT $4 * \varepsilon 1$
Residential	Flat rate	51.76	92.6	92.6	100.9	100.9	90.5	90.5
	RTP price difference (%)	-1.4%	-1.1%	-4.7%	-1.2%	-5%	-1.1%	-4.6%
Professional	Flat rate	52.63	94.5	94.5	103	103	92.4	92.4
	RTP price difference (%)	-0.7%	-0.5%	-2%	-0.5%	-2.1%	-0.5%	-2%
Enterprise	Flat rate	52.81	92.8	92.8	101.2	101.2	90.7	90.7
	RTP price difference (%)	-1.4%	-1.1%	-4.5%	-1.2%	-4.8%	-1.1%	-4.4%

Table 11 depicts the savings resulting from an RTP for each scenario considered. Two different elasticities have been considered, the default assumption ε_1 and a situation with a fourfold increase in price elasticity. Results for each scenario are quite similar and are mostly driven by the slight changes in terms of the installed capacity of Renewables. Savings found in the long-term scenario are much lower than in the stylized scenario RES100.3 considered in Section 3.2, with a reduction of less than 5% compared to the 16% found previously. This is primarily due to the low occurrence of near-zero power prices in the three scenarios considered. Even if the considered renewable capacities (Table 10 in appendix) are much higher than in RES100.3, the load is now between 6 and 30% higher than in 2018, with a decrease in conventional capacities. Fossil-based power plants and, to a lesser extent, nuclear power plants are therefore still marginal most of the time to balance the load, which results in a net increase of the average power price. We can also underline that a delay in the deployment of renewable capacity would likely result in high market prices as the carbon price is increasing while the nuclear fleet is being dismantled in Germany, for example. Therefore, results from our long-term scenario don't indicate increased savings from the RTP rate adoption compared with historical results found in Section 3.2.

Note that we have considered a constant willingness to pay for electricity based on the flat rate that would have been offered, resulting in the use of the same consumption pattern and total demand level for each consumer segment. One can argue that with the power prices increasing, the long-term elasticity of the demand will likely result in a decreased annual consumption, especially when considering a doubling of power prices, as depicted in our results. Out of the market subsidy could however lower the phenomenon by providing financial support to avoid an energy poverty situation (République Francaise, 2021). This also holds for the industrial segment, where competitiveness could be negatively affected by rising energy prices and result in state subsidies too (Bureau et al., 2013).

3.4. Market impact

We finally assess the overall impact of having price-reactive consumers from a system perspective. Table 12 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 a 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 of materializing, considering the low switching rate in the retail power market. We also believe that this indicates that the peak load will not necessarily benefit from providing day-ahead prices to end-users. Indeed, as prices are less and less correlated with the load, this event will not necessarily coincide with the peak prices faced by consumers. When considering the maximum load reduction observed throughout the year, the result reaches 2.9GW, and therefore corresponds to a total load decrease of 3%, which is more significant than the one observed at peak load. Moreover, load reduction reaches between -9% and -18% for each consumer segment 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 hours 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 limited contribution to alleviating this issue

Table 12 – 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

IV. 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, 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 hourly energy consumption. In those cases, yearly results depict a situation where consumer bills would be reduced by more than 17%. However, the long-term scenarios aligned with prospective plans do not yield such considerable bill saving, even with increased short-term price elasticity, as the occurrence of near-zero marginal price remains scarce. The situation might change with an even more accelerated transition toward a high share of renewable in the power mix. We believe the result of the European Commission would, therefore, likely go along with a net decrease in electricity consumption for the end-users. However, the utility function associated with electricity consumption is not evaluated in pilot projects. Indeed, reducing power consumption comes with comfort loss linked to reduced heating levels, for example. We have considered stable yearly consumption under our demand-side response formulation and therefore did not assess long-term price elasticity. If we believe that our results would hold when considering hourly cross-elasticities or load shifting potential, changing the willingness to pay of a consumer to lower values would however allow capturing more benefit. It would likely result in 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. However, RTP is the most direct pass-through of wholesale market prices, and results demonstrate that this tariff gains interest with increasing price volatility. This would 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 the 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 cannot counterbalance the weather-dependent variability of the net load and therefore lessen the interest of such rates. It can, however, decrease the peak load hour, which does not necessarily reduce the need for peaking capacities to account for the risk of dark doldrums. It might lower the grid investments in the long run.

The integration of demand-side response also results in a decrease in the system's 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 in 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 other. This issue relates to the TSO-DSO coordination research stream, where country-wide signals 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 do not capture the full volatility of price bids, notably the effects of strategic bidding and feed-in tariff, which would distort the merit order. This could result in stronger incentives for the end-users and would likely results in more important bill savings. However, we do not 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 will not necessarily have access to this information. Finally, considered consumption patterns are representative of only a fraction of the end-users, especially on the residential side. Therefore, 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 were 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 subject of further research.

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Appendix

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

	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 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

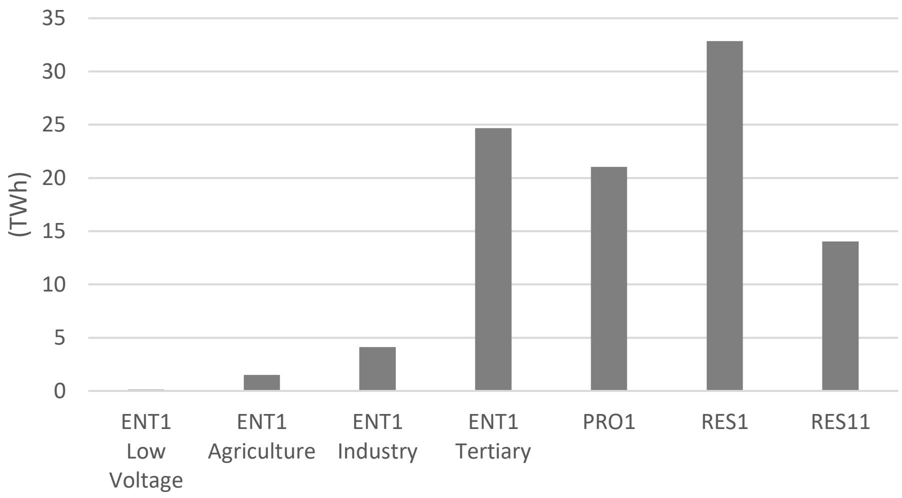


Figure 2 – Average consumption in 2018 per draw-off point per consumer segment

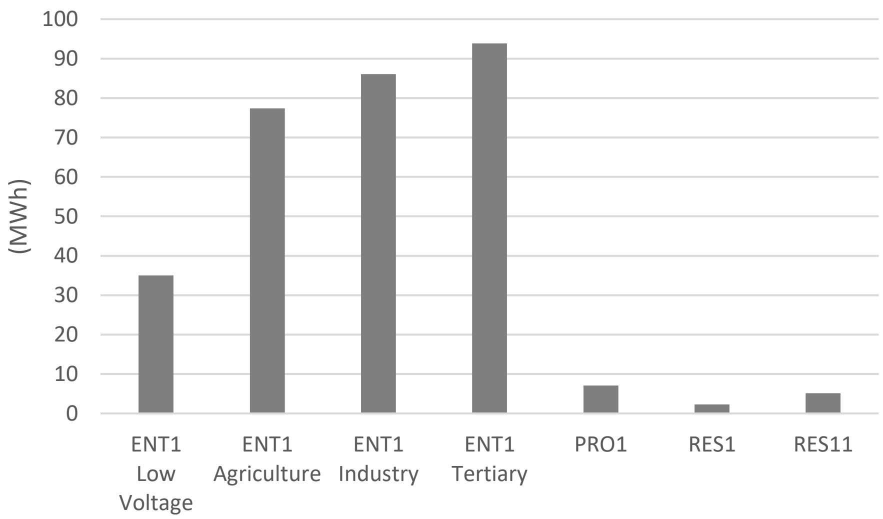
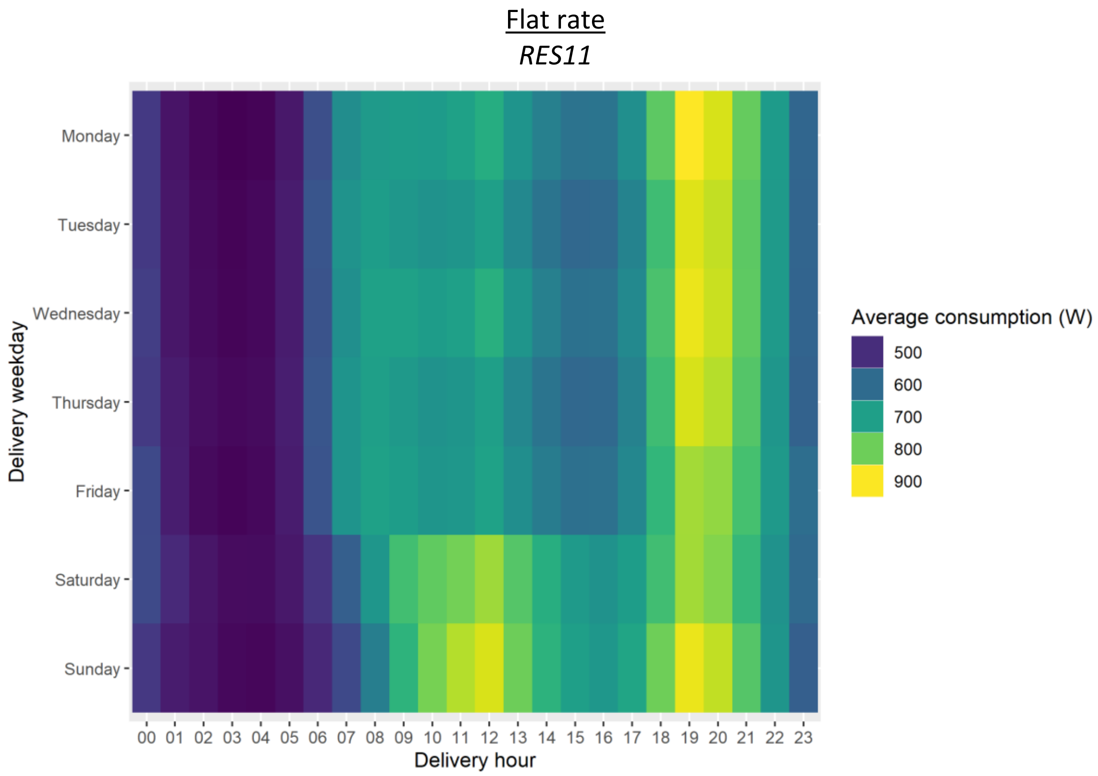
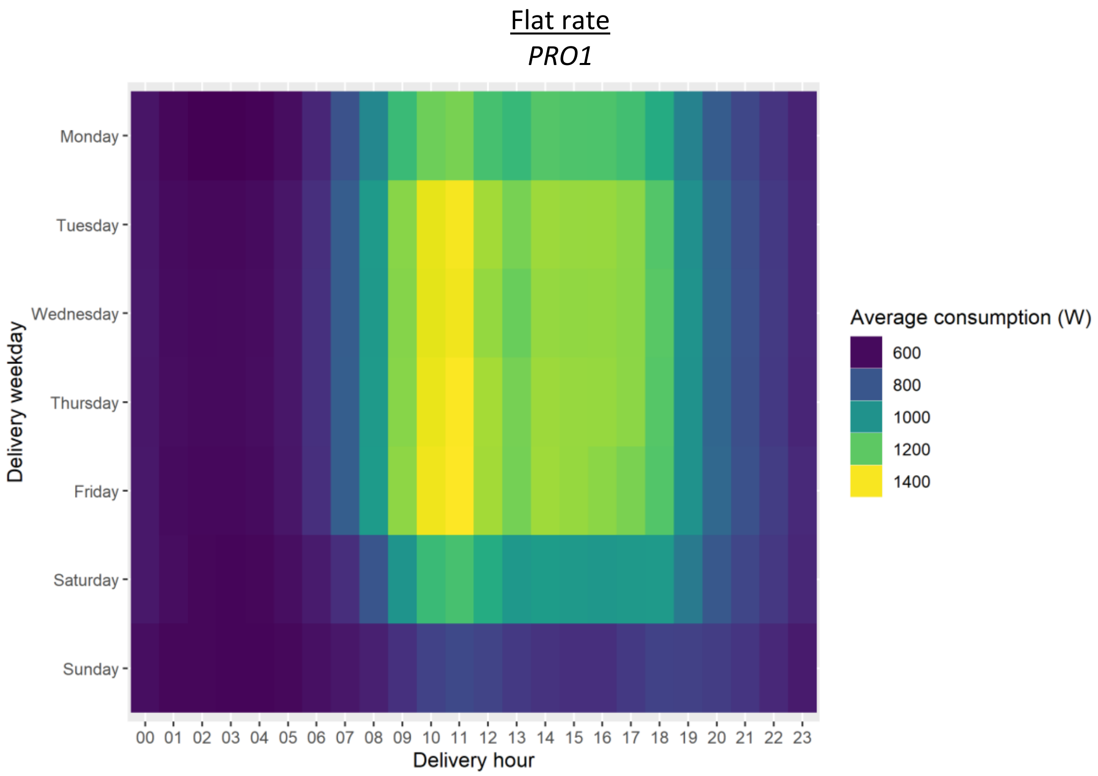


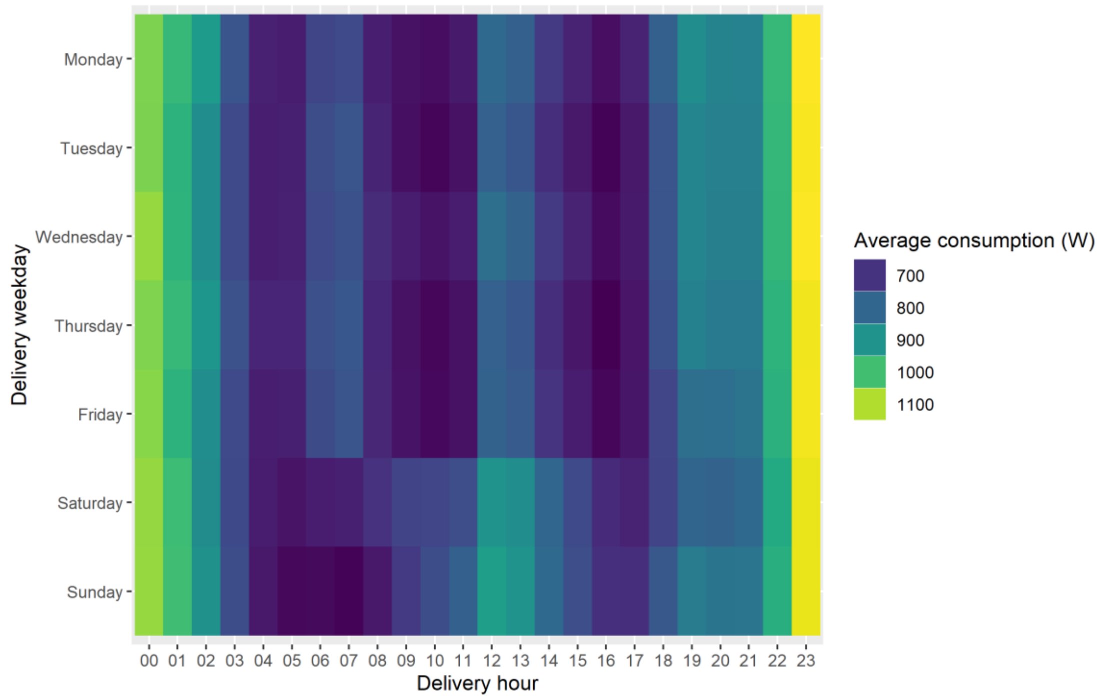
Figure 3 - Average load profile for the residential base rate and time-of-use rate in 2018





<u>Time-of-Use rate</u>

RES2



<u>Time-of-Use rate</u>

PRO2

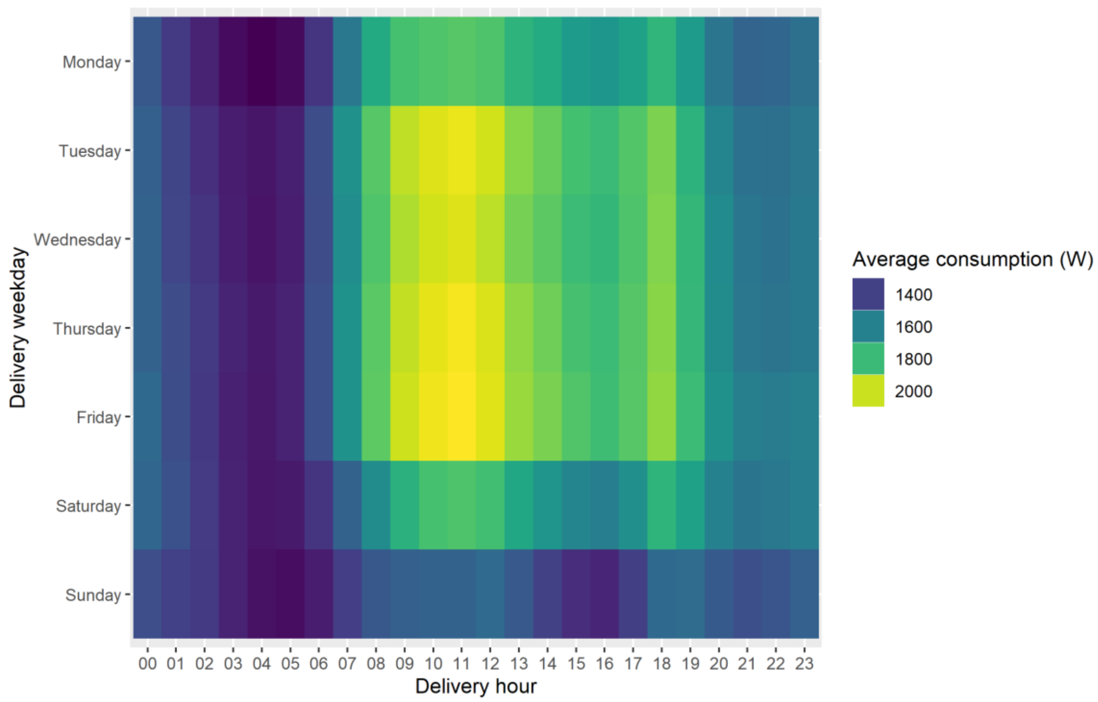


Figure 5 – Nonconstant price elasticity of electricity demand (Knaut and Paulus, 2016)

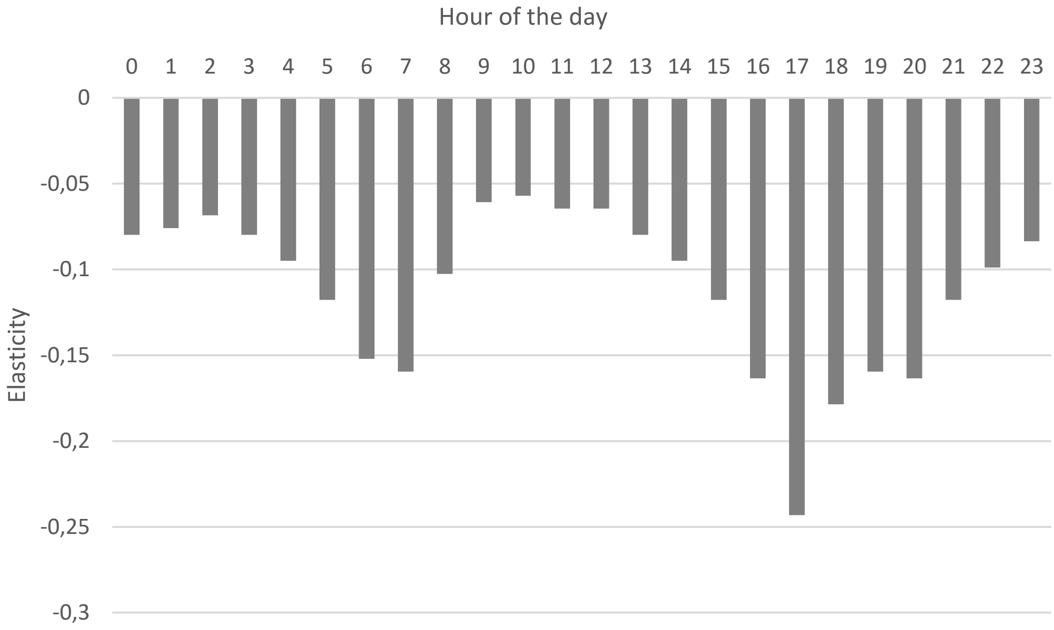


Table 10 – Summary of installed capacity considered for long-term scenario based on TYNDP20 for the year 2040

TYNDP 20 - 2040		*FR*				*UK*				*DE*			
		2018	GA	DEn	NT	2018	DEn	GA	NT	2018	DEn	GA	NT
Production Capacity (GW)	PV	8.5	41.2	77.9	57.9	13.1	27.9	62.9	26.9	43.9	105	145.3	97.4
	Onshore	15	43.9	90.3	59.6	9.1	17.6	29.6	18.3	51.8	95.4	109.9	90.8
	Offshore	0	12.4	5	8.4	6.6	36.8	21	35.5	6.3	23.9	20.6	35.5
	Battery	0	7.1	17.7	5.9	0	2.3	7.3	4.5	0	8.1	15.4	8.1
	Nuclear	63.1	37.2	48.9	43.1	9.3	18.5	9	14.3	9.5	0	0	0
Increase from 2018 (%)	PV	-	385%	816%	581%	-	113%	380%	105%	-	139%	231%	122%
	Onshore	-	193%	502%	297%	-	93%	225%	101%	-	84%	112%	75%
	Offshore	-	-	-	-	-	458%	218%	438%	-	279%	227%	463%
	Battery	-	-	-	-	-	-	-	-	-	-	-	-
	Nuclear	-	-41%	-23%	-32%	-	99%	-3%	54%	-	-100%	-100%	-100%