Harnessing implicit and explicit flexibility from residential customers' load profiles using grid tariffs

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***Abstract*—The energy transition is currently causing drastic changes in distribution network management. In their long-term planning of the grid, system operators need to account for the evolution of the distributed production, as well as new consumption patterns and magnitudes due to the electrification of usage. Both imply higher power going through a sometimes weak low-voltage network.**

To decrease the need for grid reinforcement, using implicit flexibility from grid users is considered. One way of achieving this is by designing adequate grid tariffs for energy consumption. This work explores the flexibility potential of residential customers and test different tariff mechanisms to assess their efficiency at decreasing grid stress.

This work uses load profiles with a flexibility component from a stochastic generator and determines the potential for optimal implicit flexibility using self-consumption and tarriff optimization, then the remaining flexibility is computed and proposed as reserve for automatic reaction to external explicit flexibility markets (FCR and aFRR). The impact on the customers' bills, DSO revenue and grid usage is computed at each step and for each scenario.

***Index Terms*—Flexible demand, Load profiles, Tariff response, Optimization, Distribution Grids**

I. Introduction

Distribution system operators are facing a bilateral paradigm change. On the one hand, the increasing penetration of distributed generation units, mostly composed of rooftop PV, is redefining the operating limits of their grid. The historical one-way transfer of energy is becoming bidirectional, causing high stress and overvoltages on the low-voltage level. This is already becoming a problem in some part of the grid where the so-called "duck curve" is becoming a "canyon curve" [1]. The energy transition will also have a high impact on the load profile of residential customers. In fact, low-carbon technologies (LCTs) often run on electricity that will also have to pass through the distribution grid. Causing drastic changes in both the pattern and the amplitude of the energy needs in residential areas.

Reacting to this changing environment is a key challenge for DSOs in the next decades. In Europe, the need to reinvest in an often aging, insufficient, or even forgotten network topology is certain [2]. This will bring an important extra cost to the DSO budget which will be borne by the end customer. Thus, it should be done efficiently to ensure reliable operation at optimal cost. This poses a tangible question about long-term forecasting load evolution scenarios and how to use them.

The project source of the results presented in this paper has received funding from the Belgian Energy Transition Fund (UNLEASH Project).

The impact of LCTs on the results of network planning problematics can be decreased by leveraging on their flexibility potential. In fact, most new loads also come with inherent control scheme. These schemes could be used to jointly optimize the usage of the appliance and the energy use in the house. This work will only consider the implicit flexibility potential of the residential areas. The implicit flexibility is unlocked by internal signal for energy or price efficiency. It will consists mainly on maximizing the self consumption, tariffs optimization with time of use or peak shaving in case of capacity tariff.

Interesting review work on flexibility include [3], [4].

Additional case studies on the quantification on this flexibility and impact on network investment are numerous [5]–[11]

Several works have studied the impact of incentivization on the demand of residential users and their willingness to adapt their usage in practice [12]–[15].

Our approach will try to compare grid tariffs by making customer perfectly react in day-ahead, then assess the effect of a fully-automatic activation for explicit flexibility (FCR and aFRR).

Section II presents how the profiles are generated and used, section III describes the case study, section IV develops the models used, and section V shows some results. Section VI summarizes and proposes potential further uses of this tool.

II. Load profiles generation

The load profiles used in this work should include a flexibility component. This can be problematic as such measurements need extra hardware and can be considered too intrusive regarding privacy. This is why synthetic load profiles are used here, generated from a customizable Python library [16]. This tool is based on a stochastic occupancy profile generator [17] which will create a base consumption depending on the occupation of the household members. The additional load profiles for flexible appliances are then appended depending on the same occupancy pattern.

A. Baseload

The base load is composed of all the non-flexible appliances (light, kitchen, computer, TV, etc.). These are activated by

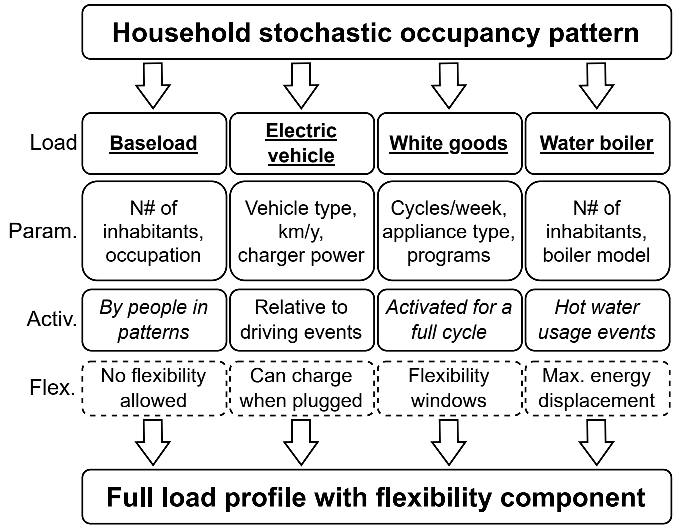

Fig. 1: Load profiles construction and resulting flexibility

house members when they are home according to the data from [17]. This part of the load profile consists of all essential uses of electricity. Thus, it cannot be modified.

B. White goods

These consist of programmable loads, also called wet appliances. Each home can be assigned a dishwasher, a washing machine, and a dryer. These will be launched for full programs for a fixed number of cycles per week. The starting time of the program can be delayed or advanced in a certain flexibility window around the initial starting point.

C. Electric vehicle

If the household uses an electric vehicle, it can be charged at home. This part of the electric load profile is determined from the occupancy profile of the household member who is the car user. After a leaving event that is longer than 30 minutes has high chance of generating a driving event. Depending on the driving duration, the number of events for the current week and the total yearly kilometers, the amount of kilometers is determined for each event. Using the car size, which includes the average consumption, the kilometers are converted to kWh. The consumption is then converted to a return state of charge for the EV battery, considering its capacity and its previous departure SoC.

A consumption that is too important and that brings the EV SoC below 50% has a chance of generating an outside charge event. This probability goes to 1 as the return SoC reaches 0%. In this case, the car consumption for this trip is simply divided by two, accounting for a full charging midway.

From the return SoC, the reference profiles just models a charge starting at the arrival time. This charges uses the full power of the charger until it reaches the departure time or the target state of charge.

Some flexibility can be obtained from the electric vehicle by delaying the start of this charge, making it intermittent and lowering the power reference. All these actions ultimately delay the charging of the EV, which incurs a risk of unmet target, thus a discomfort.

D. Water boiler

Electric water boilers can provide an important amount of flexibility in the residential load profile. They represent a large consumption in households and their thermal capacity can provide an efficient storage, facilitating load shifting.

The boiler model used in the generator is based on [18], with events of water use related to the home occupancy profile. To generate the exact flexibility provided by the water tank, the complete boiler model with consideration for losses and heat transfer should be included in the customer flexibilization process.

E. Heat pump

Similarly to the boiler, the heat pump uses a thermal capacity model. It considers three temperature levels: inside, walls and outside, the outside thermal capacity is infinite, the walls have a high thermal capacity that depends on the year of construction (*i.e.* the materials) and the inside has a very low, that accounts for the air volume.

Temperatures are computed from power exchanges that consists of losses due to temperature differences, irradiance and power incoming from the heatpump with a constant COP.

This gives a realistic temperature and power profile with fast dynamics for the inside of the house and slower dynamics for the walls temperature.

F. Aggregation

The model has been calibrated to match aggregated data from Fluvius [19], and will be further calibrated so the profiles match those that have been measured through the UNLEASH project (Belgian ETF).

III. Case study

A. Tariffs

Several incentivization mechanisms will be tested to see the effect both physically (on the grids), and financially (for the DSOs and users):

- Constant: Base case used to see what the improvements are due to the more complex tariffs, the customers have no incentive to shift loads;
- Day/night: Historically a two-period energy meter was installed to offer night discount (6-22, 22-6);
- Dynamic: The days are divided into 5 periods with three tariffs: high, medium, and low (1-7, 7-11, 11-17, 17-22, 22-1);
- Capacity: One of the previous cases, with additional fees for the peak power exchange value, this is tested for daily, weekly, monthly and yearly basis (base 3.33 €/kW each month);

For the sake of comparison, all the price profiles have the same average value. This does not correspond to a realistic

Name	EV	WB	HP	PV	BSS	%
Type 1						
Type 2						
Type 3						
Type 4						
Type 5						
Type 6						
Type 7						
Type 8						
Type 9						
Type 10						

TABLE I: Summary of the population of UNLEASH dataset

test case, but would provide a better comparison where the incentive does not depend on the risk for the retailer or the DSO.

Another way of efficiently activating flexibility with a local motive could be through local energy communities [11].

The prosumers are modeled as price takers which will react optimally to the tariffs they are offered. An optimization problem is defined for each of the houses and their optimal behavior will be computed depending on all the previously presented tariffs.

B. Distribution network

The result of the basecase, of th optimization problem and of the automatic activation are then used in a PowerFlow to assess impact of the distribution network. This is done for each timestep of each day through the P^{inj} variables that correspond to the injected power at each node using Pandapower [20].

A standart benchmark distribution network is used [21]. The parameters for this Dickert network are *long* range feeders, *multiple* customers, *cables* as line type, and the case type is *average* with a total of 122 buses, 120 of which are residential customer, the last one is the slack bus. The LV-MV transformer is removed, initial electrical loads are maintained, and static generators are added to represent PV system of discharging batteries.

C. Population

The considered population is considered to be representative of the dataset available from the unleash project with these 10 archetypes in the following proportions. Different users of the same archetype do not specifically have the same appliance model.

The load profiles for population are regenerated using ResFlex [16], in order to have the flexibility potential of the profiles. This however causes a small drift from the reality.

From this base population, a change in PV/BSS penetration is also possible in a longer term, or a change in the amount of flexible loads. The population is adapted to gradually increase both these until 100% of PV, BSS, EV, WB and HP, which corresponds to a complete electrification. This could correspond to a net zero objective.

IV. Models

A. Optimal implicit flexibility

$$
\begin{aligned}
\min \quad & \text{Cost and discomfort (2a)} \qquad (2)\\
\text{subject to} \quad & \textit{Objective definition } (2b), (2c)\\
& \textit{Exchange constraints } (2d) - (2f),\\
& \textit{Peak definition } (2g), (2h),\\
& \textit{PV and BSS constraints } (2i) - (2l),\\
& \textit{Electric vehicle model } (2m) - (2q),\\
& \textit{Water boiler model } (2r) - (2v),\\
& \textit{Heat pump model } (2w) - (2z),
\end{aligned}
$$

$$
\begin{aligned}
\min_{\Omega} \quad & B + J^{\text{flex}} && (2a)\\
\text{s.t.} \quad & && \\
B =& \Delta_T \textstyle\sum_{t\in\mathcal{T}} (\pi_t^{\text{i,ret}} i_t^{\text{gri}} - \pi_t^{\text{e,ret}} e_t^{\text{gri}}) && (2b)\\
& + \pi^{\text{peak}} \overline{P} && \\
J^{\text{flex}} =& \textstyle\sum_{t\in\mathcal{T}} (J_t^{\text{EV}} + J_t^{\text{WB}} + J_t^{\text{HP}}) && (2c)
\end{aligned}
$$

$$
\begin{aligned}
P_t^{\text{inj}} =& P_t^{\text{PV}} + P_t^{\text{dis}} - P_t^{\text{fix}} - P_t^{\text{flex}} - P_t^{\text{cha}} && \forall t \in \mathcal{T} \quad (2d)\\
P_t^{\text{inj}} =& e_t^{\text{gri}} + i_t^{\text{gri}} && \forall t \in \mathcal{T} \quad (2e)\\
P_t^{\text{flex}} =& P_t^{\text{EV}} + P_t^{\text{WB}} + P_t^{\text{HP}} && \forall t \in \mathcal{T} \quad (2f)\\
\overline{P} \geq& P_t^{\text{inj}} && \forall t \in \mathcal{T} \quad (2g)\\
-\overline{P} \leq& -P_t^{\text{inj}} && \forall t \in \mathcal{T} \quad (2h)\\
P_t^{\text{PV}} \leq& \gamma_t^{PV} \bar{P}^{\text{PV}} && \forall t \in \mathcal{T} \quad (2i)\\
P_t^{\text{cha}} \leq& \bar{P}^{\text{BSS}} && \forall t \in \mathcal{T} \quad (2j)\\
P_t^{\text{dis}} \leq& \bar{P}^{\text{BSS}} && \forall t \in \mathcal{T} \quad (2k)\\
s_t^{\text{BSS}} =& s_{t-1}^{\text{BSS}} && \forall t \in \mathcal{T} \quad (2l)\\
& + \Delta_T (\eta^{\text{BSS}} P_t^{\text{cha}} - P_t^{\text{dis}} / \eta^{\text{BSS}}) / C^{\text{BSS}} && \\
P_t^{\text{EV}} \leq& a_t^{\text{EV}} \bar{P}^{\text{EV}} && \forall t \in \mathcal{T} \quad (2m)\\
s_t^{\text{EV}} \geq& t_t^{\text{dep,EV}} \bar{s}^{\text{EV}} && \forall t \in \mathcal{T} \quad (2n)\\
s_t^{\text{EV}} =& t_t^{\text{arr,EV}} s_t^{\text{arr, EV}} + (1 - t_t^{\text{arr,EV}}) s_{t-1}^{\text{EV}} && \forall t \in \mathcal{T} \quad (2o)\\
& + \Delta_T \eta^{\text{EV}} P_t^{\text{EV}} / C^{\text{EV}} && \\
\textstyle\sum_{t\in\mathcal{T}} P_t^{\text{EV}} =& \textstyle\sum_{t\in\mathcal{T}} P_t^{\text{ref,EV}} && (2p)\\
J_t^{\text{EV}} \geq& \alpha^{\text{EV}} \left(s_t^{\text{ref,EV}} - s_t^{\text{EV}} \right) && \forall t \in \mathcal{T} \quad (2q)
\end{aligned}
$$

$$
\begin{aligned}
P_t^{\text{WB}} \leq& \bar{P}^{\text{WB}} && \forall t \in \mathcal{T} \quad (2r)\\
T_t^{\text{WB}} =& T_{t-1}^{\text{WB}} && \forall t \in \mathcal{T} \quad (2s)\\
& + \Delta_T (P_t^{\text{WB}} - P_t^{\text{use, WB}} - P_t^{\text{loss,WB}}) / C^{\text{WB}} && \\
T_t^{\text{WB}} \geq& t_t^{\text{use,WB}} \min\{T_t^{\text{ref,WB}}, T_t^{\text{set,WB}}\} && \forall t \in \mathcal{T} \quad (2t)\\
\textstyle\sum_{t\in\mathcal{T}} P_t^{\text{WB}} =& \textstyle\sum_{t\in\mathcal{T}} P_t^{\text{ref,WB}} && (2u)\\
J_t^{\text{WB}} \geq& \alpha^{\text{WB}} (\min\{T_t^{\text{ref,WB}}, T_t^{\text{set,WB}}\} - T_t^{\text{WB}}) && \forall t \in \mathcal{T} \quad (2v)
\end{aligned}
$$

$$
\begin{aligned}
P_t^{\text{HP}} \leq& \bar{P}^{\text{HP}} && \forall t \in \mathcal{T} \quad (2w)\\
T_t^{\text{HP}} =& T_{t-1}^{\text{HP}} && \forall t \in \mathcal{T} \quad (2x)\\
& + \Delta_T (COP^{\text{HP}} P^{\text{HP}} - P_t^{\text{loss,HP}}) / C^{\text{HP}} && \\
\textstyle\sum_{t\in\mathcal{T}} P_t^{\text{HP}} =& \textstyle\sum_{t\in\mathcal{T}} P_t^{\text{ref,HP}} && (2y)\\
J_t^{\text{HP}} \geq& \alpha^{\text{HP}} (\min\{T_t^{\text{ref,HP}}, T_t^{\text{set,HP}}\} - T_t^{\text{HP}}) && \forall t \in \mathcal{T} \quad (2z)
\end{aligned}
$$

TABLE II: Inputs or parameters of the model

	Dim	Dom	Unit	Description
P^{fix}	$\mathcal{U} \times \mathcal{T}$	$\mathbb{R}_+$	kW	Fixed power consumption
$\overline{P}^{\text{PV}}$	$\mathcal{U} \times \mathcal{T}$	$\mathbb{R}_+$	kW	Max PV power production
C^{PV}	$\mathcal{U}$	$\mathbb{R}_+$	kWp	PV nominal power
$s^{\text{init,BSS}}$	$\mathcal{U}$	$[0,1]$	-	Initial battery state of charge
C^{BSS}	$\mathcal{U}$	$\mathbb{R}_+$	kWh	Battery capacity
η^{BSS}	$\mathcal{U}$	$[0,1]$	-	Battery efficiency
$\pi^{\text{i,ret}}$	$\mathcal{T}$	$\mathbb{R}_+$	€/kWh	Retailer import price
$\pi^{\text{e,ret}}$	$\mathcal{T}$	$\mathbb{R}_+$	€/kWh	Retailer export revenue
π^{peak}	$\mathcal{T}$	$\mathbb{R}_+$	€/kW	Peak price
Electric Vehicle				
a^{EV}	$\mathcal{U} \times \mathcal{T}$	$\{0,1\}$	-	EV plugged
$t^{\text{arr,EV}}$	$\mathcal{U} \times \mathcal{T}$	$\{0,1\}$	-	EV arriving
$t^{\text{dep,EV}}$	$\mathcal{U} \times \mathcal{T}$	$\{0,1\}$	-	EV leaving
$s^{\text{arr,EV}}$	$\mathcal{U} \times \mathcal{T}$	$[0,1]$	-	EV state of charge at arrival
$s^{\text{ref,EV}}$	$\mathcal{U} \times \mathcal{T}$	$[0,1]$	-	EV reference state of charge
$P^{\text{ref,EV}}$	$\mathcal{U} \times \mathcal{T}$	$\mathbb{R}_+$	kW	Power from reference profile
$\bar{\mathbf{s}}^{\text{EV}}$	$\mathcal{U}$	$[0,1]$	-	Target state of charge
$s^{\text{init,EV}}$	$\mathcal{U}$	$[0,1]$	-	Initial state of charge
η^{EV}	$\mathcal{U}$	$[0,1]$	-	Battery efficiency
C^{EV}	$\mathcal{U}$	$\mathbb{R}_+$	kWh	Battery capacity
$\bar{P}^{\text{EV}}$	$\mathcal{U}$	$\mathbb{R}_+$	kW	Charger maximum power
$\boldsymbol{\alpha}^{\text{EV}}$	$\mathcal{U}$	$\mathbb{R}_+$	€/kWh^2	Discomfort reluctance
Water Boiler				
$T^{\text{ref,WB}}$	$\mathcal{U} \times \mathcal{T}$	$\mathbb{R}_+$	°C	Reference temperature
$T^{\text{set,WB}}$	$\mathcal{U} \times \mathcal{T}$	$\mathbb{R}_+$	°C	Setpoint temperature
$P^{\text{loss,WB}}$	$\mathcal{U} \times \mathcal{T}$	$\mathbb{R}_+$	kW	Losses through envelope
$P^{\text{use,WB}}$	$\mathcal{U} \times \mathcal{T}$	$\mathbb{R}_+$	kW	Losses from water use
$P^{\text{ref,WB}}$	$\mathcal{U} \times \mathcal{T}$	$\mathbb{R}_+$	kW	Power reference
$\mathbf{t}^{\text{use,WB}}$	$\mathcal{U} \times \mathcal{T}$	$\{0,1\}$	-	Water usage event
$T^{\text{init,WB}}$	$\mathcal{U}$	$[0,1]$	-	Initial temperature
$C^{\text{th,WB}}$	$\mathcal{U}$	$\mathbb{R}_+$	°/kWh	Thermal coefficient
$\bar{P}^{\text{WB}}$	$\mathcal{U}$	$\mathbb{R}_+$	kW	Water usage event
$\boldsymbol{\alpha}^{\text{WB}}$	$\mathcal{U}$	$\mathbb{R}_+$	€/°h	Discomfort reluctance
Heat Pump				
$T^{\text{ref,HP}}$	$\mathcal{U} \times \mathcal{T}$	$\mathbb{R}_+$	°C	Reference temperature
$T^{\text{set,HP}}$	$\mathcal{U} \times \mathcal{T}$	$\mathbb{R}_+$	°C	Setpoint temperature
$P^{\text{loss,HP}}$	$\mathcal{U} \times \mathcal{T}$	$\mathbb{R}_+$	kW	Power losses through walls
$P^{\text{ref,HP}}$	$\mathcal{U} \times \mathcal{T}$	$\mathbb{R}_+$	kW	Power from reference profile
$T^{\text{init,HO}}$	$\mathcal{U}$	$[0,1]$	-	Initial temperature
$C^{\text{th,HP}}$	$\mathcal{U}$	$\mathbb{R}_+$	°/kWh	Thermal coefficient
$\bar{P}^{\text{HP}}$	$\mathcal{U}$	$\mathbb{R}_+$	kW	Nominal thermic power
COP^{HP}	$\mathcal{U}$	$\mathbb{R}_+$	-	Coefficient of performance
$\boldsymbol{\alpha}^{\text{HP}}$	$\mathcal{U}$	$\mathbb{R}_+$	€/°h	Discomfort reluctance

TABLE III: Variables of the model

	Dim	Dom	Unit	Description
e^{gri}	$\mathcal{U} \times \mathcal{T}$	$\mathbb{R}_+$	kW	Retailer export power
i^{gri}	$\mathcal{U} \times \mathcal{T}$	$\mathbb{R}_+$	kW	Retailer import power
P^{PV}	$\mathcal{U} \times \mathcal{T}$	$\mathbb{R}_+$	kW	PV production power
P^{cha}	$\mathcal{U} \times \mathcal{T}$	$\mathbb{R}_+$	kW	BSS charging power
P^{dis}	$\mathcal{U} \times \mathcal{T}$	$\mathbb{R}_+$	kW	BSS discharging power
P^{inj}	$\mathcal{U} \times \mathcal{T}$	$\mathbb{R}_+$	kW	Node injection power
$\overline{P}$	$\mathcal{U} \times \mathcal{T}$	$\mathbb{R}_+$	kW	Peak power
P^{flex}	$\mathcal{U} \times \mathcal{T}$	$\mathbb{R}_+$	kW	Flexible load power
P^{EV}	$\mathcal{U} \times \mathcal{T}$	$\mathbb{R}_+$	kW	EV charging power
P^{WB}	$\mathcal{U} \times \mathcal{T}$	$\mathbb{R}_+$	kW	WB power setpoint
P^{HP}	$\mathcal{U} \times \mathcal{T}$	$\mathbb{R}_+$	kW	HP power setpoint
s^{EV}	$\mathcal{U} \times \mathcal{T}$	$[0,1]$	-	EV state of charge
T^{WB}	$\mathcal{U} \times \mathcal{T}$	$\mathbb{R}_+$	°C	WB tank temperature
T^{HP}	$\mathcal{U} \times \mathcal{T}$	$\mathbb{R}_+$	°C	HP indoor temperature
J^{EV}	$\mathcal{U} \times \mathcal{T}$	$\mathbb{R}_+$	€	Discomfort from EV flex
J^{WB}	$\mathcal{U} \times \mathcal{T}$	$\mathbb{R}_+$	€	Discomfort from WB flex
J^{HP}	$\mathcal{U} \times \mathcal{T}$	$\mathbb{R}_+$	€	Discomfort from HP flex

B. Automatic reserve for explicit flexibility activation

In this part, we can consider that some of the water boilers are part of a pool of flexibility. This aggregated pool can either react to a FCR or an aFRR market signal. The size of the pool is a parameter set to 1500 boilers, which is sufficient to get to the required 1 MW of power to bid in these markets. Depending on the penetration parameter, a specific amount of participating WB is randomly assigned, these are the ones whose profiles will be modified.

1) FCR: This bidding strategy is only for 4-hour time windows with a minimum of 1 MW. The signal consist of a relative setpoint. For this 1 MW and 1500 boilers pool, if we have 750 boilers, we have to react for 5 % of the signal (750 over 1500). For exemple, when a signal is 1.150, the complete pool has to consume 150 kW more, thus each boiler 0.1 kW of additional power. The 5% of the 150 kW could also be shared differently among the boilers, but preliminary simulation did not show any benefits from that, so the simpler sharing has been chosen.

2) aFRR: The data from Thermovault only contains downward flexibility. We will thus only model boiler activation. This new activation signal (divided by the number of boilers) will override the initial setpoint.

C. Power flow computation and key performance indicators

Each member is assigned to a node in the distribution grid, and its P_t^{inj} variables are used in the power flow simulation. The power flow simulation is computed for each timestep of each day in the scenario.

V. Results

A. Implicit flexibility

Table for users' costs in the different scenarios

Table for DSO KPIs and revenues

Show results on the grid for evolving penetration of PV and BSS

Show results on the grid for different amounts of households with EV/WB/HP

B. Explicit flexibility

Time of use tariff is used and we show the effect on the grid, users bills and discomfort (water temperature).

VI. Conclusion

This model and simulation highlight the unperfectness of standart billing tariffs, it also shows that a capacity tariff is profitable for DSOs.

Limitations of the work:

- Perfect reaction of customers
- No limit on how much they react
- No link between stochastic model of load and demand for FCR and aFRR

This model could also be used in a longer-term model, to assess potential needs for network reinforcement depending on the user's tariffs and their level of acceptance and reaction to those tariffs. A tariff incentive to reduce peak demand could be very efficient in minimizing LV grid congestion, if customers have automatic control over this peak.

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