Modeling the Impact of End-User Flexibility and Bill Structure on Future Transmission Grid Load

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***Abstract*—Demand-side flexibility is expected to play a key role during the transition towards renewable-dominated power systems and the electrification of transportation and heating sectors. Following this, massive investments in transmission capacities will be required, which may be reduced if end-users appropriately exploit their flexibility from the edge of the network. However, modeling the end-user flexible behavior and its impact on transmission grid load during the planning stage is not straightforward. The rationale behind this is that it results from the aggregation of atomistic loads and that it may be unlocked implicitly, i.e., via the structure of electricity bill. In this paper, assuming economically rational end-users, we develop an equilibrium model of end-users minimizing their electricity bill, while taking into account the elasticity of electricity prices. The proposed approach is used to derive updated transmission load projections, highlighting the benefits of considering end-user flexibility for transmission system planning.**

***Index Terms*—End-User Flexibility, Equilibrium Modeling, Load Shifting, Power System Planning.**

I. Introduction

The increasing share of renewable energy sources in the electricity generation mix, combined with the growing electrification of transportation and heating sectors call for massive investments in transmission capacities. While additional network investments are mainly driven by system peaks, making an optimal use of the existing infrastructure is paramount for achieving a cost-efficient transition. One way to do so is by unlocking end-user flexibility on the demand-side [1].

There are two main strands in the literature focusing on end-user flexibility for transmission system. The first refers to the explicit provision of balancing or ancillary services via demand response programs [2], involving direct load control by aggregators who bring small-scale flexibility to large-scale balancing markets [3]. The second refers to the flexible behavior of end-users in view of decreasing energy procurement cost, which would be implicitly encouraged via the structure of the electricity bill [4]. The focus of this paper is on the latter.

Economic studies have shown that end-users do respond to price variations [5]. Therefore, assuming economically rational end-users, the structure of their electricity bill (i.e., the way the utilization of both energy and network are charged) can have a significant impact on their consumption behavior. In that direction, different studies investigate the way end-user may change their consumption habits. In particular, authors in [6] investigate different electricity pricing schemes (such as time-varying and time-of-use electricity prices) and their impact on the procurement cost for end-users. Differently, authors in [7]-[8] estimate the level of flexibility provided by electric vehicles and show the willingness of end-users to change their attitude in front of time-varying prices. Other electric assets may bring flexibility to the grid. Heat pumps, for instance, are studied in [9]-[10] where the authors develop a tool for predicting the flexible behavior of end-users according to their target comfort temperature. Finally, authors in [11] develop an equilibrium problem that is capable of modeling the consumption behavior of several types of end-users in front of different network tariff schemes. Their focus is on the economic variations of yearly billing schemes under different bill structures.

All the aforementioned literature only studies the implicit flexibility and mainly its economic impacts on the end-user. A few additional contributions envisage the impact of flexibility on the network operation and planning. In particular, authors in [12]-[13] analyze the modeling of demand-side flexibility for planning purposes, while analyzing the costs and benefits of the modeling accuracy. In [14], authors take the economic point of view to establish the impact of flexibility on distribution system operator revenues, under different bill structures. They conclude that capacity-based network charges may help distribution grid operators shield their revenues. Finally, authors in [15] are interested in assessing whether grid tariffs should recover historical or future network cost (i.e., forward-looking cost accounting for future grid expansions).

The primary focus of all these scientific contributions is on distribution network and there exist few contributions in the literature that have a transmission-level, or nation-wide focus. Authors in [16] take a nation-wide point of view and derive an equilibrium problem for modeling the interactions between the electricity market, aggregators and demand response (i.e., with a special focus on heat pump flexibility unlocked via direct load control). Authors in [17] study the impact of local energy market integration on grid infrastructure. To the best of our knowledge, this is one of the only contributions in the literature making a link between energy exchanges at local level and transmission grid infrastructure. Their main findings show that exchanges at local level do have a (positive or negative) impact on transmission grid load.

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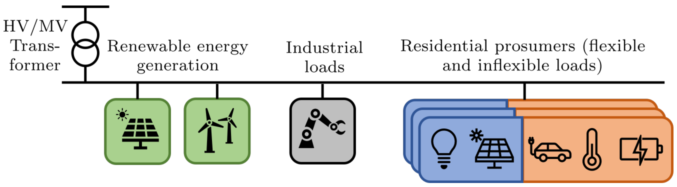


Fig. 1. The load at the transmission level is mainly composed of distributed renewable energy generation (green), industrial loads (grey), and residential prosumer loads, part of which is flexible (orange) or inflexible (blue).

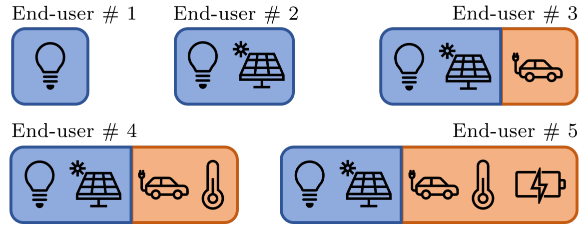


Fig. 2. The different types of end-users characterized by their assets.

In this paper, we are interested into modeling the impact of *implicit flexibility* (unlocked via the structure of electricity bill) on future transmission grid load. More particularly, we develop an equilibrium model of flexible end-users minimizing their electricity bill, taking into account the elasticity of electricity prices. The proposed approach enables transmission system operator to derive future load projections accounting for flexibility as well as to assess the remaining flexibility available, e.g., for other explicit programs. In addition, we perform several numerical analysis based on updated load projections, and are able to highlight the impacts of different electricity bill structures on transmission grid infrastructure. Our tool is dedicated to be parameterized and is useful for network studies for the future of transmission grid, for which the level of flexibility is uncertain (e.g., the number of electric vehicles or heat pumps deployed in a given area).

The rest of this paper is structured as follows. Section II introduces the proposed methodology in details. Section III derives a numerical analysis showing the potential of our tool. Finally, Section IV summarizes the main conclusions of this paper.

II. Methodology

In this section, we introduce the proposed methodology for modeling the impact of end-user flexibility on the transmission grid load. First, we describe how the load profiles at the transmission level are disaggregated into different components, and especially residential loads in Section II-A. Section II-B presents the bill minimization problem which models the flexible behavior of individual end-users. Section II-C introduces the different bill structures explored in the scope of this paper. Finally, the solution procedure is explained in Section II-D.

A. Disaggregation of Transmission-Level Load Profiles

We isolate the aggregate behavior of residential end-users at the Transmission/Distribution (T/D) interface, as depicted in Fig. 1. In particular, we retrieve synthetic profiles from the measured load at the T/D interface corresponding to the installed renewable energy generation (i.e., wind, solar and cogeneration) and to industrial loads. Next, loads from flexible assets are isolated, using future projections of, e.g., number of electric vehicles, heat pumps or home batteries associated to a T/D load profile. The residual load is mostly inflexible and is referred to as *aggregate load of residential end-users*.

Next, the aggregate residential load is broken down into different types of prosumers with different distributed energy resources (e.g., PV panels, electric vehicles, heat pumps, ...) and flexibility levels. The different types of prosumers are listed in Fig. 2. This helps us establishing an estimation of the number of individual end-users associated to a transmission load profile, using the following procedure. The number of end-user of type # 5 is determined via the estimated number of home batteries. Following the same direction, the number of end-users of type #3 and #4 can be trivially determined based on the projections for numbers of electric vehicles and heat pumps. Next, the number of end-users of type # 2 is determined by dividing the estimated and remaining[1] PV solar generation by the capacity of individual PV installations. Finally, the number end-users of type # 1 is determined as the remaining individuals[2].

B. End-User Consumption Behavior

We model the consumption behavior of end-users, via a bill minimization problem which applies for each type of end-user and writes as follows:

$$\min_{w_t^{\text{net}}, g_t^{\text{PV}}, ch_t, dc_t, e_t, w^{\text{bill}}} \sum_{t \in \mathcal{T}} \lambda_t w_t^{\text{net}} + f^{\text{NT}} w^{\text{bill}}, \tag{1a}$$

$$\text{s.t. } w_t^{\text{net}} = D_t^{\text{BL}} + ch_t^{\text{d}} - dc_t^{\text{d}} + ch_t^{\text{w}} - dc_t^{\text{w}} - g_t^{\text{PV}} \;\; \forall t \in \mathcal{T}, \tag{1b}$$

$$0 \leqslant g_t^{\text{PV}} \leqslant \text{LF}_t^{\text{pv}} \text{CAP}^{\text{pv}} \;\; \forall t \in \mathcal{T}, \tag{1c}$$

$$e_t^{\dagger} = e_{t-1}^{\dagger} + \eta^{\text{ch}} ch_t^{\dagger} - \frac{dc_t^{\dagger}}{\eta^{\text{dc}}}, \forall t \in \mathcal{T}_{\setminus 1}, \forall \dagger \in \{\text{d}, \text{w}\}, \tag{1d}$$

$$e_1^{\dagger} = E_0^{\dagger} + \eta^{\text{ch}} ch_1^{\dagger} - \frac{dc_1^{\dagger}}{\eta^{\text{dc}}}, \forall \dagger \in \{\text{d}, \text{w}\}, \tag{1e}$$

$$e_{24(d+1)}^{\text{d}} = e_{24d}^{\text{d}}, \forall d \in \mathcal{D}, \tag{1f}$$

$$e_{168(w+1)}^{\text{w}} = e_{168w}^{\text{w}}, \forall w \in \mathcal{W}, \tag{1g}$$

$$0 \leqslant e_t^{\dagger} \leqslant \text{CAP}^{\dagger} \;\; \forall t \in \mathcal{T}, \forall \dagger \in \{\text{d}, \text{w}\}, \tag{1h}$$

$$0 \leqslant ch_t^{\dagger} \leqslant \text{CR}^{\dagger} \;\; \forall t \in \mathcal{T}, \forall \dagger \in \{\text{d}, \text{w}\}, \tag{1i}$$

$$0 \leqslant dc_t^{\dagger} \leqslant \text{CR}^{\dagger} \;\; \forall t \in \mathcal{T}, \forall \dagger \in \{\text{d}, \text{w}\}, \tag{1j}$$

$$w^{\text{bill}} = f\left(w_t^{\text{net}}, \text{Network tariff}\right), \tag{1k}$$

$$\lambda_t = g\left(w_t^{\text{net}}\right), \tag{1l}$$

[1]End-users of types # 3, # 4 and # 5 already possess PV installations.

[2]Our procedure for disaggregating the residential load is perfectible. We highlight that an increased number of types of prosumer, with a more specific selection of flexible assets, would render a more detailed and representative local load. In the scope of this project, the suggested procedure is already sufficient for establishing an estimation of implicit flexibility and its benefits for the transmission system. In addition, the proposed tool is intended to be easily parameterized and to derive subsequent sensitivity analysis.

where set $\mathcal{T} = \{1, ..., |\mathcal{T}|\}$ is the set of all timesteps, sets $\mathcal{D} = \{1, ..., |\mathcal{D}|\}$ and $\mathcal{W} = \{1, ..., |\mathcal{W}|\}$ represent the corresponding sets for days and weeks and, set $\dagger \in \{\mathrm{d}, \mathrm{w}\}$ distinguishes daily or weekly variables. The objective function (1a) represents the total amount to be paid by the end-user yearly, where $\lambda_t \in \mathbb{R}$ is the retail electricity price in €/kWh, $w_t^{\mathrm{net}} \in \mathbb{R}$ is the net interaction in kWh (i.e., withdraw or injection) with the network, $f^{\mathrm{NT}} \in \mathbb{R}^+$ is the network tariff to be paid to the network operator and, $w^{\mathrm{bill}} \in \mathbb{R}^+$ is the billing parameter used to calculate the total network cost[3]. Equation (1b) calculates w_t^{net} for each timestep as the energy balance between the residential baseload $D_t^{\mathrm{BL}} \in \mathbb{R}^+$ (comprising of all domestic electric appliances, as well as electric vehicles and heat pumps), the upward and downward flexibility $ch_t \in \mathbb{R}^+$ and $dc_t \in \mathbb{R}^+$ provided by the end-user[4] and, PV curtailment $g_t^{\mathrm{PV}} \in \mathbb{R}^+$. Constraint (1c) entails that the PV curtailment lies within zero and the actual solar generation for each timestep. The actual solar generation at timestep t is defined via a time-dependent load factor parameter $\mathrm{LF}_t^{\mathrm{pv}} \in \mathbb{R}^+$ and the PV installation capacity $\mathrm{CAP}^{\mathrm{pv}} \in \mathbb{R}^+$. The flexible behavior of end-users is modeled via the operation of two virtual batteries, i.e., describing daily and weekly flexibility, in equations (1d)-(1g). Equation (1d) describes the battery state-of-charge $e_t^{\dagger} \in \mathbb{R}^+$, following the battery state-of-charge at the previous timestep $e_{t-1}^{\dagger}$, and charging and discharging actions during the current timestep, i.e., $ch_t^{\dagger}$ and $dc_t^{\dagger}$. Parameters η^{ch} and η^{dc} correspond to the battery efficiency in charging and discharging mode respectively[5]. Equation (1e) describes the state-of-charge after the first timestep, which depends on the initial battery state-of-charge $E_0^{\dagger} \in \mathbb{R}^+$. Constraints (1f) imposes that the state-of-charge at the end of the day equals that of the beginning of the day for the virtual battery mimicking the end-user daily flexibility. The same applies weekly in equation (1g) for weekly flexibility. Equations (1h) to (1j) set minimum and maximum operating conditions, i.e., maximum state-of-charge $\mathrm{CAP}^{\dagger}$ and maximum charging rate $\mathrm{CR}^{\dagger}$. Finally, constraint (1k) establishes the link between the consumption behavior (i.e., w_t^{net} for all timesteps), the network tariff and the actual billing parameter w^{bill} to be paid by the end-user. For the sake of clarity, this link is represented by function $f(.,.)$ in formulation (1), which will be further described in the following section. Similarly, equation (1l) introduces an elasticity model of electricity price that is also further described in Section II-C.

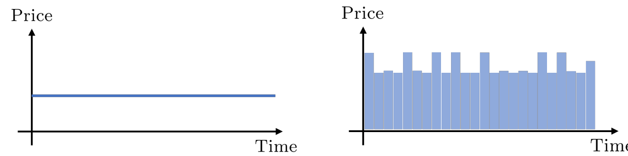
C. Modeling of Bill Structures

In this section, we introduce the different bill structures under investigation. Subsection II-C1 is devoted to retail electricity pricing scheme and subsection II-C2 is devoted to network tariff component.

[3]The units for f^{NT} and w^{bill} depend on the network tariff structure and will be described in the following paragraphs.

[4]It is worth mentioning that, in the scope of this paper, upward (resp., downward) flexibility refers to an increase (resp., decrease) in consumption.

[5]In this paper, the flexible behavior of end-user is modeled via the operation of two virtual batteries. In that direction, the battery efficiency parameter relates to a cost associated to the use of flexibility for the end-user. As end-users freely dispose of their own flexibility, battery efficiency parameters are usually set as high values.



(a) Flat electricity price. (b) Time-varying electricity price.

Fig. 3. Different types of retail electricity pricing schemes under investigation in this paper.

1) Retail Electricity Prices: We explore two main ways for charging retail electricity, namely, fixed electricity prices and time-varying electricity prices.

a) Fixed Electricity Prices: This first scheme corresponds to a flat price for electricity over the whole year (e.g., fixed 1-year contract), as represented on the left-hand side plot of Fig. 3. In that direction, the electricity price for each hour λ_t is constant and considered as a parameter in equation (1a).

b) Time-Varying Electricity Prices: A time-varying contract may be proposed to end-users (and requires smart-metering technology) which applies a different electricity price for each hour of the day, as depicted by the right-hand side plot of Fig. 3. Typically, the prices for each hour of the day are communicated in advance (e.g., the day before) which allows end-users to adapt their consumption.

In this work, we account for time-varying electricity prices via an elasticity model which is embedded within the bill minimization problem in equation (1l). Unlike using a fixed electricity price vector, this method allows to update the electricity prices according to the consumption behavior of end-users. The underlying assumption entails that all end-users associated to a load profile follows the same behavior, i.e., the aggregate behavior of all end-users may therefore have an impact on the electricity prices.

We derive a regression model of electricity prices λ_t versus the total load at T/D interface $W_t^{\mathrm{T/D}}$, as follows:

$$\lambda_t = a \cdot W_t^{\mathrm{T/D}} + b, \tag{2}$$

where $a \in \mathbb{R}$ and $b \in \mathbb{R}$ are the coefficients of the regression model and are related to the elasticity of prices with respect to the electricity demand. Using the optimal flexible behavior of end-users, one can reconstruct $W_t^{\mathrm{T/D}}$ by reaggregating the behavior of all end-users:

$$W_t^{\mathrm{T/D}} = \sum_{j \in \mathcal{J}} N_j w_{t,j}^{\mathrm{net}} + P_t^{\mathrm{Ind.}} - G_t^{\mathrm{Dec.}}, \tag{3}$$

where set $\mathcal{J}$ refers to the set of types of end-users, N_j is the number of end-users of type j, $P_t^{\mathrm{Ind.}}$ is the industrial load at timestep t and, $G_t^{\mathrm{Dec.}}$ is the decentralized generation at timestep t. The combination of (2) and (3) results in a regression model that can be incorporated in model (1).

Consequently, electricity prices λ_t are now part of the decision variables in model (1), resulting in a bilinear term $\lambda_t w_t^{\mathrm{net}}$ in the objective function (1a). Given proper bounds for these decision variables, we relax the bilinear term via McCormick [18], as described in equations (4), as follows

$$\min z_{j,t} \tag{4a}$$
$$\text{s.t.}\quad z_{j,t} \geqslant \underline{\lambda} w_{t,j} + \lambda_t \underline{w} - \underline{\lambda} * \underline{w}, \tag{4b}$$
$$z_{j,t} \geqslant \overline{\lambda} w_{t,j} + \lambda_t \overline{w} - \overline{\lambda} * \overline{w}, \tag{4c}$$
$$z_{j,t} \leqslant \underline{\lambda} w_{t,j} + \lambda_t \overline{w} - \underline{\lambda} * \overline{w}, \tag{4d}$$
$$z_{j,t} \leqslant \overline{\lambda} w_{t,j} + \lambda_t \underline{w} - \overline{\lambda} * \underline{w}, \tag{4e}$$

where variable $z_{j,t} = \lambda_t w_t^{\text{net}}$ and $\{\underline{\lambda}, \overline{\lambda}\}$ and $\{\underline{w}, \overline{w}\}$ are lower and upper bounds for electricity prices and net individual interaction of end-user j with the network, respectively.

2) Network Tariff: We focus on three main types of network tariff components, known as fixed, capacity-based and volumetric tariffs, which are encoded within constraint (1k). We would like to highlight that our tool can be extended to other types of network tariffs, however, this is out of the scope of the current paper.

a) Fixed Network Tariff: A fixed network tariff (in €/year) is charged once a year and is completely independent of the consumption behavior of end-users. It may usually depend on a contractual capacity (e.g., capacity of the electric meter). In that framework, equation (1k) takes the form of

$$w^{\text{bill}} = 1, \tag{5}$$

and f^{NT} is equal to the fixed network tariff in €.

b) Capacity-Based Network Tariff: The capacity-based network tariff (in €/kW) is a charge that is based on a measured capacity, e.g., annual peak consumption. In that case, equation (1k) becomes

$$w^{\text{bill}} = \max_{t \in \mathcal{T}} \; w_t^{\text{net}}, \tag{6}$$

with w_t^{bill} in kW and f^{NT} is equal to the network charge in €/kW.

c) Volumetric Network Tariff: The volumetric network tariff component in €/kWh is a charge that is based on energy consumed during a given period of time. Different measurement windows exist with different time granularity. For instance, annual net metering refers to a case where the net energy consumed is considered, while hourly net metering refers to a case where injections and withdraws are netted during each hour. The volumetric network charge under an annual net metering scheme modifies equation (1k) as follows:

$$w^{\text{bill}} = \sum_{t \in \mathcal{T}} \; w_t^{\text{net}}, \tag{7}$$

where w_t^{bill} is expressed in kWh and f^{NT} is the network tariff in €/kWh.

D. Network Cost Recovery and Solution Procedure

Problem (1) models the consumption behavior of each end-user individually. It is now important to ensure that the transmission system operator will recover its yearly network cost, independently of end-user behavior. This can be achieved by adjusting iteratively the network tariff as explained hereafter.

Algorithm 1 Solution procedure

Step 1: Set $k = 0$. Set a value for network cost to be recovered NC$^{\text{init.}}$ = 10^5 € and a value for network tariff $f_k^{\text{NT}} = 0.1$ €. Set the convergence threshold ϵ to, e.g., 10^{-2}.
Step 2: Solve the bill minimization problem (1) for each type of end-user j, given f_k^{NT}.
Step 3: Compute the total network cost NC = $\sum_{j \in \mathcal{J}} N_j f_k^{\text{NT}} w_j^{\text{bill},*}$, given $w_j^{\text{bill},*}$ the optimal value for decision variable w_j^{bill}.
Step 4: Check if the convergence criterion, i.e., $\frac{|\text{NC}^{\text{init.}} - \text{NC}|}{\text{NC}^{\text{init.}}} \leq \epsilon$, is ensured. If not, set $k \leftarrow k+1$, and $f_k^{\text{NT}} = \frac{\text{NC}^{\text{init.}}}{\sum_{j \in \mathcal{J}} N_j w_j^{\text{bill}}}$ and go to step 2.

Following the disaggregation procedure in Section II-A, the aggregate economic transactions may be cast as,

$$\text{EC} = \sum_{j \in \mathcal{J}} N_j \sum_{t \in \mathcal{T}} \lambda_t w_{t,j}^{\text{net}}, \tag{8}$$
$$\text{NC} = \sum_{j \in \mathcal{J}} N_j f^{\text{NT}} w_j^{\text{bill}}, \tag{9}$$

where EC is the total energy cost for all end-users associated with a load profile and, NC is the total network cost for all end-users. In addition, N_j is the number of end-users of type j.

Pursuing network cost recovery, it is important that the flexible behavior of end-users does not entail losses for the grid operator. Hence, we set an initial value for network cost and define a system operator agent that ensures a constant income from end-users. This modeling approach can be seen as an equilibrium problem between end-users and a transmission system operator ensuring network cost recovery. We solve the resulting problem to optimality using an iterative procedure based on *tâtonnement* [19]. The solution procedure[6] is described in Algorithm 1.

III. Numerical Study

Our numerical study is based on anonymized hourly load projections from the Belgian control zone for the year 2030. We focus on one load profile in an urban area for which detailed information is available as follows[7]. The estimated industrial load[8] equals 100 kW, the number of distribution-connected electric vehicles and heat pumps is 1106 EVs and 380 HPs, respectively. The capacity of decentralized renewable

[6]It is worth mentioning that solving an equilibrium problem can be achieved by deriving the KKTs of the underlying optimization problems and using dedicated solvers such as PATH. However, in the scope of this paper, the adaptability of the code (i.e., adding or removing optimization constraints in future steps of the project) was an important criteria which is less straightforward with equilibrium models.

[7]We have ran simulations on different types of load profiles, i.e., in different rural and urban areas, and have observed similar results for the electricity bill structures under investigation in this paper. Therefore, we derive a detailed analysis for one particular load profile.

[8]The industrial load is assumed to be constant over the year and is therefore given in kW.

TABLE I
INPUT PARAMETERS DEFINING THE 5 TYPES OF PROSUMERS.

Prosumer	#1	#2	#3	#4	#5
Inflexible load (Peak in kW)	4.0	4.0	4.0	4.0	4.0
PV installation [kW]	No	4.0	4.0	7.0	8.0
Electric vehicle	No	No	Yes	Yes	Yes
Heat pump	No	No	No	Yes	Yes
Home battery	No	No	No	No	Yes
Flexibility					
Charging rate (weekly) [kW]	0.4	0.4	1.8	1.8	2.8
Battery capacity (weekly) [kWh]	0.8	0.8	3.6	3.6	7.6
Charging rate (daily) [kW]	0.4	0.4	2.5	3.7	4.7
Battery capacity (daily) [kWh]	0.8	0.8	5.0	9.8	13.8
Battery efficiency [%]	99.9	99.9	99.9	99.9	99.9

TABLE II
IMPACT OF END-USER FLEXIBLE BEHAVIOR ON T/D LOAD PROFILES.

	Flat energy price			Time-varying energy price		
	Fix	Cap	Vol	Fix	Cap	Vol
Peak variation [%]	0 %	-4.9 %	0 %	-1.0 %	-5.1 %	-1.0 %
Peak to average ratio	1.63	1.55	1.63	1.61	1.54	1.61

energy generators is 5800 kW (of which 4700 kW of wind turbines capacity and 1100 kW of PV installations) and the capacity of residential PV installations is equal to 7000 kW. In addition, hourly profiles are obtained for electric vehicle load, heat pump load, as well as renewable energy generation (wind, solar, cogeneration).

We isolate the aggregate behavior of residential end-users at the T/D interface by setting apart the industrial loads, as well as the generation from distributed energy generators connected at the T/D interface. Next, we define different types of distribution-connected end-users following Section II-A. The detailed input parameters are provided in Table I. These are composed of the peak for inflexible residential load in kW, the capacity of PV installation in kW, as well as the binary information of end-user ownership for an electric vehicle, a heat pump or a home battery. In particular, those are assigned with an additional flexible load profile mimicking the load of an electric vehicle, heat pump or home battery. Table I also reports the level of flexibility for each end-user (which may depend on the owned assets), which are composed of the charging rate in kW and the battery capacity in kWh, for each type of virtual batteries, i.e., weekly and daily, as well as the battery efficiency. Following the input parameters at the T/D level, and the definition for the types of end-user, we calculate the number N_j of each type of end-user, and are able to derive individual end-user loads.

The individual loads of every type of end-user are then fed into the equilibrium model in Section II-D mimicking the flexible behavior of end-users. We explore several electricity bill structures (namely, flat and time-varying electricity prices, combined with fixed, capacity-based and volumetric network tariffs) and estimate the impact of end-user flexibility on the transmission system load profiles. In what follows, we analyze the impact on the load profile at T/D interfaces in Section III-A, the aggregate end-user behavior in Section III-B, and the remaining available flexibility in Section III-C.

A. *Impact on T/D Load Profile*

We solve the equilibrium model for all aforementioned structures of electricity bill and report the peak variation (in %) of the obtained load profile with respect to the case where end-users do not provide any flexibility as well as the peak to average ratio (indicating the flattening of a load profile) in Table II. We use a structure of electricity bill composed of a flat energy price and a fixed network tariff as a benchmark case (i.e., no incentive is given to end-user to unlock flexibility). We first observe that a flat energy price combined with an annual volumetric network tariff provides the same results with respect to flexibility compared to the benchmark case, hence, achieving no peak reduction. In addition, a capacity-based network tariff component is able to unlock flexibility in a beneficial manner for the transmission grid, as it achieves a 4.9% peak reduction, with a peak-to-average ratio equal to 1.55. The effect of time-varying electricity pricing is also beneficial as it achieves peak reduction for each network tariff component, with respect to the case where a flat electricity price is applied[9].

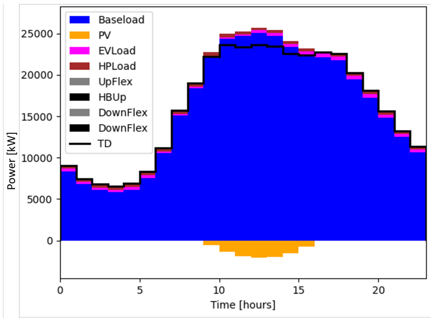
B. *End-User Behavior*

In this section, we study the aggregate consumption behavior of end-users during the day where the peak consumption (of the benchmark load profile) appears at T/D interface. The results are shown in Figures 4(a) to 4(c) for a flat electricity pricing scheme and in Figures 4(g) to 4(i) for a time-varying electricity pricing scheme. In these figures, we report the load components (i.e., residential inflexible load in blue, EV load in magenta, HP load in red, and PV generation in yellow), as well as the flexible (upward and downward) behavior of end-users in grey. The resulting interaction with the network is represented via a thick black line.

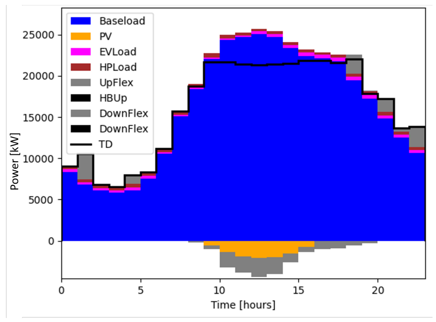
We begin with Figures 4(a) to 4(c), i.e., including a flat electricity pricing scheme. Similarly as in Section III-A, we use the case with a flat electricity price and a fixed network tariff component in Fig. 4(a) as a benchmark, and observe in Fig. 4(c) that a volumetric network tariff component does not increase the flexibility of end-users. Differently, the results in Fig. 4(b), i.e., electricity bill comprising of a capacity-based network tariff shows that end-users are using their flexibility to reduce their peak consumption. In particular, end-users reduce their consumption during the peak period (from 10 am to 2 pm, corresponding to the period of solar energy generation for this particular load profile) to consume rather in the morning, or in the evening.

We now describe Figures 4(g) to 4(i). As a general observation, in all cases, the electricity price arbitrage between the hours of the day has the most impact on the end-user consumption behavior, i.e., end-users are most likely to consume during low-price hours and decrease consumption

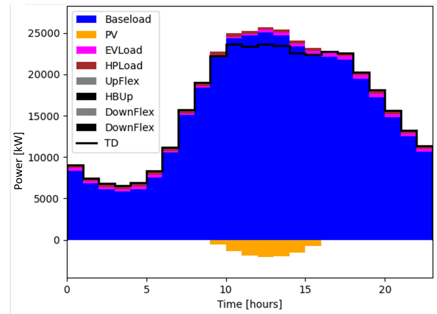
[9]We would like to highlight that this outcome is dependent on the modeling approach used in the scope of this paper, which assumes that the prosumer knows in advance the yearly variations of price, and optimizes his behavior for the whole year at once. More detailed modeling approaches (e.g., with a day-ahead revelation of electricity prices for the next day) would not necessarily achieves the same results, though we believe our approach is able to capture an approximate behavior of end-user.



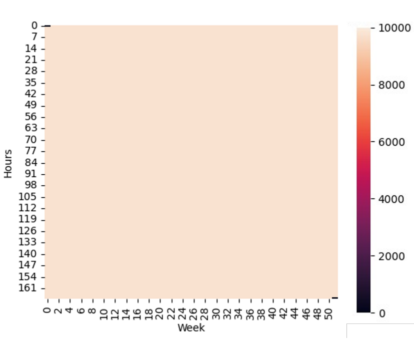
(a) Aggregate end-user behavior during peak consumption day: Constant energy price and fixed network tariff.



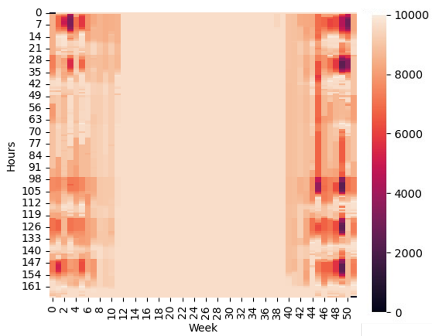
(b) Aggregate end-user behavior during peak consumption day: Constant energy price and capacity-based network tariff.



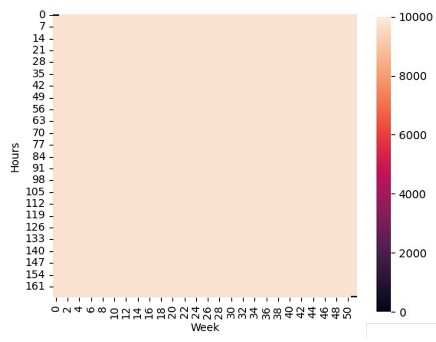
(c) Aggregate end-user behavior during peak consumption day: Constant energy price and volumetric network tariff.



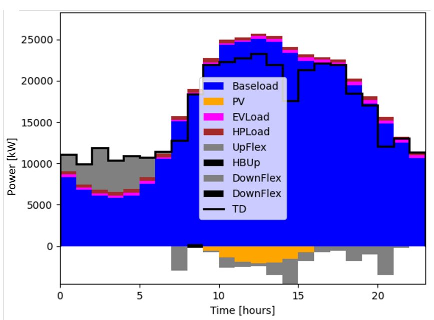
(d) Remaining upward flexibility: Constant energy price and fixed network tariff.



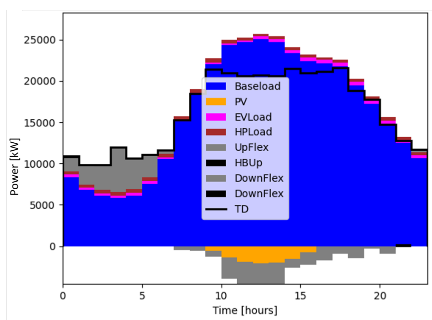
(e) Remaining upward flexibility: Constant energy price and capacity-based network tariff.



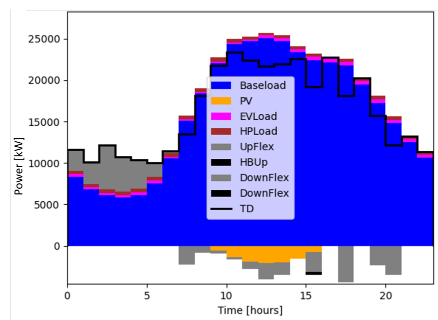
(f) Remaining upward flexibility: Constant energy price and volumetric network tariff.



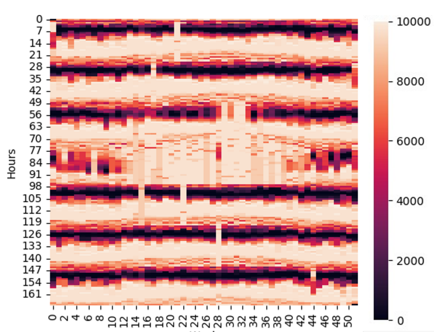
(g) Aggregate end-user behavior during peak consumption day: Constant energy price and fixed network tariff.



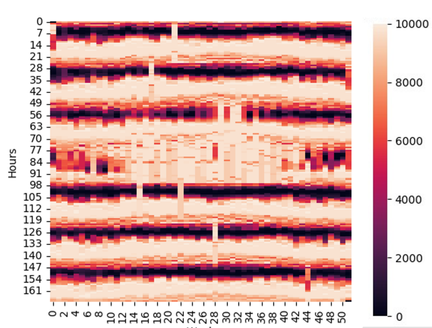
(h) Aggregate end-user behavior during peak consumption day: Constant energy price and capacity-based network tariff.



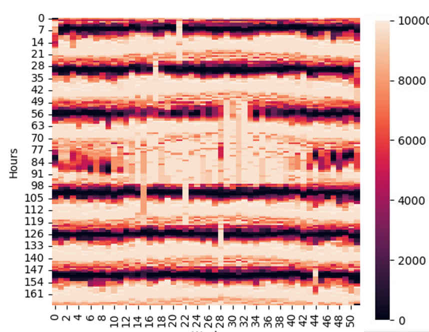
(i) Aggregate end-user behavior during peak consumption day: Constant energy price and volumetric network tariff.



(j) Remaining upward flexibility: Constant energy price and fixed network tariff.



(k) Remaining upward flexibility: Constant energy price and capacity-based network tariff.



(l) Remaining upward flexibility: Constant energy price and volumetric network tariff.

Fig. 4. Simulation results.

during high-price hours. As an additional impact on load profile, a capacity-based network tariff component (see Fig. 4(h)) allows to reduce peak consumption during the peak periods. Similar to Section III-A, the combination between time-varying electricity pricing and capacity-based network tariff achieves the highest decrease in peak consumption.

C. Utilization of Flexibility

In this section, we are interested in describing the manner end-users use their flexibility along the year, from the T/D interface viewpoint. To do so, we calculate the residual upward flexibility[10], i.e., the residual capacity in kW that could be called by the system operator via, e.g., explicit programs, as follows:

$$\mathrm{RF}_t^{\mathrm{UP},\dagger} = \begin{cases} \mathrm{CAP}^\dagger - e_t^\dagger & \text{if } e_t^\dagger + \eta^{\mathrm{ch},\dagger}\mathrm{CR}^\dagger \geqslant \mathrm{CAP}^\dagger, \\ \mathrm{CR}^\dagger - ch_t^\dagger & \text{otherwise,} \end{cases} \tag{10}$$

for each type of flexibility, i.e., $\dagger = \{\mathrm{d}, \mathrm{w}\}$. In equation (10), if the battery state-of-charge is close to the battery capacity (i.e., first assertion), the residual upward flexibility for the following hour is the difference between the battery capacity and its state-of-charge. Otherwise, the residual upward flexibility is the difference between the charging rate and actual charging happening during timestep t, i.e., second assertion.

We report in Figures 4(d) to 4(f) (for flat electricity prices) and Figures 4(j) to 4(l) (for time-varying electricity prices), the remaining flexibility available $\mathrm{RF}_t^{\mathrm{UP,d}} + \mathrm{RF}_t^{\mathrm{UP,w}}$. The figures correspond to a matrix plot where each pixel corresponds to one hour of the year (y-axis represents the hour of the week, x-axis represents the weeks in a year), and for which a darker pixel significates less residual flexibility available.

We begin with Figures 4(d) to 4(f) for a flat electricity pricing scheme. We observe that a fixed network tariff component (Fig. 4(d)) entails that the residual flexibility is always maximum, meaning that flexibility has not been used throughout the year. Similar results are obtained for a volumetric network tariff component, see Fig. 4(f). Differently, a capacity-based network tariff component (Fig. 4(e)) incentivizes the end-users to reduce their peak consumption, which mainly occurs during the winter days. Hence, the residual upward flexibility is less available during mornings and evenings of winter months.

Figures 4(j) to 4(l) report the residual flexibility obtained with a time-varying electricity pricing scheme. The utilization of flexibility seems similar among the three bill structures explored, i.e., fixed, capacity-based and volumetric network tariff. Indeed, the flexibility is mainly used here to do arbitrage on the electricity prices. This is also true for capacity-based tariff where only a few hours of additional flexibility are required to reduce the peak consumption.

IV. Conclusion

In this paper, we have derived a tool that is capable of accounting for the impact of end-user flexible behavior on load profile at the T/D interface. The flexible behavior of end-users is based on economic signals and is implicitly incentivized by the structure of electricity bill, while accounting for the elasticity of electricity prices. We were able to produce updated load profiles at the T/D interfaces, showing that a capacity-based network tariff component is the most beneficial for transmission grid operation.

As future work, we highlight the modeling of other types of electricity bills, e.g., for transmission-connected consumers. In addition, linking real residential load profiles with load profiles at T/D interfaces, via a disaggregation technique would help generate more accurate profiles at the end-user level.

[10]For the sake of clarity, we omit residual downward flexibility, for which equations (10) only requires slight adaptations.

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