

# End Users Flexibility Potential Estimation Under Differing Prosumers' Characteristics and Constraints

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**Keywords:** FLEXIBILITY, ELECTRIC VEHICLES, DISTRIBUTION SYSTEMS, GRID SERVICES.

## Abstract

The flexibility requirements for the grid are expected to increase with the increased share of variable renewable energy sources (VRES) and the increased electrification of the consumer space. Flexibility provision from end-users is expected to play a key role in relieving congested grid conditions and helping balance the fluctuations in VRES outputs, thus complementing other solutions such as storage and controllable forms of generation. The estimation of the flexibility potential of end-users is of crucial importance in planning and operational decisions to maintain the reliable operation of the grid. An accurate flexibility potential calculation requires not only including the technical constraints of the flexibility assets, but also the behavioural constraints imposed by the users' behaviour and preferences as well as the manufacturer's recommended usage. This paper focuses on estimating the impact that such constraints can have on the overall flexibility potential of residential Electric Vehicles (EVs). To this end, a mathematical residential flexibility model is first developed, in which a set of key user parameters and constraints are included, which have a direct impact on the availability of the EV and its flexibility potential – combining driving requirements, differing charging options (e.g., at home vs. at work), preference on state of charge status/ranges, among others. To quantify the impact of these constraints, a case study is developed based on residential profiles from Flanders (Belgium).

## 1 Introduction

Recent years have ushered in an unprecedented transformation of the residential end-users' energy landscape driven by three key technological advancements: electrification, integration of distributed energy resources (DERs), and digitization of the end-user sphere [1]. Indeed, with the electrification of heat and mobility, electric vehicles (EVs) and heat-pumps (HPs) are constituting a growing proportion of residential end-users' energy needs. The decreasing costs and increased performance of photovoltaic (PV) systems and batteries have increasingly enabled their uptake, thus endowing end-users with unprecedented generation and storage capabilities. Digitization – empowered by smart (sub-)metering and energy management systems – has enabled smart energy control of residential flexible assets, thus optimizing their use. These three advancements not only lead to a fundamental change of energy consumption patterns but also enable users to act flexibly, i.e., to actively control their consumption, generation, and storage profiles to achieve financial benefits while supporting the reliable operation of the distribution grid. This flexibility is essential in supporting the integration of variable renewables in the system and in enabling the active system management of the distribution and transmission grids. Indeed, this flexibility can be leveraged by distribution system operators (DSOs) for essential grid services such as congestion management and voltage control, and for complementing distribution network investment plans [2], [3].

The potential scale of such flexibility has been attested in various studies. For example, the 2024 – 2035 flexibility and adequacy study by the Belgian transmission system operator (Elia) puts a potential of 2GW of flexibility in Belgium by 2035 [4]. In this respect, different works in the literature have analysed how different assets can be used flexibly and the flexibility volumes they can deliver. However, to adequately quantify this flexibility, user behaviour aspects (and its possible evolution) must be fundamentally integrated in the analysis as abstractions of these dimensions would lead to a mischaracterization of the flexibility potential.

Indeed, various works in the literature [5], [6], when considering, e.g., EV flexibility, even though often consider driving behaviour (and thus, charging requirements and unavailability of the EV at home), they abstract a range of other behavioural and manufacturer's constraints (e.g., with respect to the state of charge preferences and limitations thereon, potential of charging elsewhere at supported prices, limit on the charging power modulation, among others) that can significantly impact the flexibility potential of the EV. Neglecting such constraints and limitations can potentially lead to a skewed estimation of the residential flexibility potential, at times underestimating it and at others overestimating it, as will be shown in the current work.

This paper aims at investigating the practical flexibility potential of residential end-users, by focusing on the flexibility potentially unlocked from EVs. In this respect, we consider not only the technical flexibility potential of EVs but also key

prosumers' behavioural and manufacturer's constraints, including driving behaviour, preferences on state of charge (SoC), possibilities of charging elsewhere, among others, which impact the flexibility potential of the EV as compared to a generic benchmark setting that assumes the EV being largely at home, always plugged in, and can be used (charged, or discharged in case of vehicle-to-grid (V2G) applications) with limited behavioural and technical constraints.

Towards this end, we first develop a residential flexibility model, consisting of an optimization model that allows end-users to optimally schedule their consumption and charging activities when faced with dynamic price profiles (dynamic retail pricing and network tariffs, with capacity and volumetric components) while considering the technical operational characteristics of the assets available (e.g., EVs and PVs). Then, key additional behavioural and technical EV characteristics are identified and integrated in the developed flexibility model to allow formulating informed constraints on the potential flexible use of the EVs. This model is then used to quantify the flexibility that can be offered by different users focusing on a Belgian case study from Flanders, where the analysis considers a set of real consumption profiles made available by the Flemish DSO, Fluvius [7]. The generated results highlight the impact that behavioural and technical constraints induce on the flexibility potential of EVs, the costs incurred by the consumers, the self-consumption potential of end-users, and their simultaneity of consumption and peak load trends, which directly impact grid operation.

The paper is organized as follows. Section 2 presents the flexibility model and methodology admitted. The case study is presented in Section 3, while Section 4 concludes the paper providing a future outlook.

## 2. Methodology and Model Development

### 2.1 Residential flexibility model

For calculating the residential flexibility potential from EVs, an optimization framework has been developed. This optimization framework, dubbed the residential flexibility model, optimizes the electricity consumption of a household, following an hourly or quarter hourly resolution for a given period of time (e.g., a year) – where the optimization is done on a daily basis following a rolling horizon technique (i.e., optimizing over 36 hours for each day) – considering the households base energy demand, self-generation, and demand and technical constraints of the flexible assets (e.g., EVs). This model allows each household to adapt their power offtake and injection at different times of the day to minimize the cost of meeting their demand / maximize their revenues in case of net injections. These costs are governed by electricity retail pricing and network tariffs to which the household is subjected. Electricity retail prices can be dynamic (e.g., reflecting variations in wholesale market prices) [8] incentivizing dynamic consumption/injection reactions

thereto, as compared to the traditional static retail contracts. Similarly, distribution and transmission network tariffs can have a time-varying component (known as time-of-use tariffs, as has been discussed, e.g., in the Walloon [9] and Brussels [10] regions in Belgium) and can have volumetric and capacity components, thus applying network tariffs not only to cumulative kWh consumptions but also to maximum power consumption levels (kW), as is the case, e.g., in Flanders [11], [12]. The model can then be run iteratively for each day.

Thus, the flexibility potential of a household is calculated as the difference in household consumption when subjected to fixed prices as compared to dynamic (and capacity-based, in the case of network tariffs) pricing. This flexibility potential can be directly computed based on the developed flexibility model by comparing the outcomes under different pricing structures. The flexibility model can be formulated as follows (this is a formulation in abstract form focusing on EVs and PVs; an extended formulation including other assets can be found in our extended reports available in [5] and [11]).

$$\min_{o,t,s} \sum_{t \in \mathcal{T}} [c_t^o o_t + c_t^i i_t] + v^{cap} \hat{\delta}_d^m, \quad (1)$$

subject to:

$$o_t = D_t + o_t^{EV} \quad \forall t \in \mathcal{T}, \quad i_t = i_t^{PV} + i_t^{EV} \quad \forall t \in \mathcal{T}, \quad (2)$$

$$c_t^o = \lambda_t^o + v_t^{TSO,o} + v_t^{DSO,o} \quad \forall t \in \mathcal{T}, \quad (3)$$

$$c_t^i = \lambda_t^i + v_t^{TSO,i} + v_t^{DSO,i} \quad \forall t \in \mathcal{T}, \quad (4)$$

$$i_t^{PV} = \kappa_t^{PV} \bar{P}^{PV} \quad \forall t \in \mathcal{T}, \quad (5)$$

$$0 \leq o_t^{EV} \leq \bar{P}^{EV,o} \quad \forall t \in \mathcal{T}, \quad 0 \leq i_t^{EV} \leq \bar{P}^{EV,i} \quad \forall t \in \mathcal{T}, \quad (6)$$

$$0 \leq s_t^{EV} \leq \bar{E}^{EV} \quad \forall t \in \mathcal{T}, \quad (7)$$

$$s_t^{EV} = s_{t-1}^{EV} + \eta^{EV} o_t^{EV} - i_t^{EV} / \eta^{EV} \quad \forall t \in \mathcal{T}, \quad (8)$$

$$0 \leq o_t \leq \bar{P}^o \quad \forall t \in \mathcal{T}, \quad 0 \leq i_t \leq \bar{P}^i \quad \forall t \in \mathcal{T}, \quad (9)$$

$$\hat{\delta}_d^m \geq o_t \quad \forall t \in d, \forall d \in m, \forall m \in \mathcal{M}, \quad (10)$$

$$\hat{\delta}_d^m \geq \hat{\delta}_{d-1}^m, \forall d \in m, \forall m \in \mathcal{M}, \quad (11)$$

$$\hat{\delta}_0^m = 0, \forall m \in \mathcal{M}, s_0^{EV} = s^{EV,init}. \quad (12)$$

The formulation considers three time resolutions:  $t \in \mathcal{T}$  is intraday resolution (e.g., hourly), where those hours span day  $d \in m$ , where  $m \in \mathcal{M}$  is within the set of months  $\mathcal{M}$ , and where  $\mathcal{M}$  spans any number of years considered. As such, this formulation can be run successively on a daily basis to span the full time horizon. The objective function (1) minimizes the daily cost of the user, where the offtake/injection cost parameters ( $c_t^o/c_t^i$ ) are composed of the electricity offtake/injection prices ( $\lambda_t^o/\lambda_t^i$ ), the TSO network offtake/injection tariffs ( $v_t^{TSO,o}/v_t^{TSO,i}$ ), and the DSO volumetric network offtake/injection tariffs ( $v_t^{DSO,o}/v_t^{DSO,i}$ ), as defined in (3) and (4).  $v^{cap}$  is the capacity tariff and  $\hat{\delta}_d^m$  is the monthly peak experienced at day  $d \in m$ , where  $t \in d$ . (2) computes the net injection and offtake ( $o_t/i_t$ ) of the household at time  $t$ , based on the household base net load ( $D_t$ ), EV offtake ( $o_t^{EV}$ ), PV injection ( $i_t^{PV}$ ), and EV injection ( $i_t^{EV}$ ) in case V2G is permitted.  $i_t^{PV}$  is computed in (5), based on the PV instantaneous capacity factor ( $\kappa_t^{PV}$ ), and the PV rated capacity

( $\bar{P}^{PV}$ ), both of which are known parameters. The EV maximum offtake and injection are within the rated power limits as defined in (6). Here, setting  $\bar{P}^{EV,i}$  to 0 would prevent the use of V2G. The SoC of the EV ( $s_t^{EV}$ ) is constrained by the energy capacity ( $\bar{E}^{EV}$ ) of the battery in (7). The dynamic evolution of  $s_t^{EV}$  based on charge/discharge actions is governed by (8), where  $\eta^{EV}$  is the battery efficiency. (9) limits the offtake and injection of the household based on its connection capacity limits. (10) and (11) recursively compute the daily peak load for a day ( $d$ ) as the maximum between the peak achieved so far in a month (11) and the peak consumption in  $d$  (10). This method is a proxy for the Flemish capacity tariffs (which are computed based on the average of monthly defined peaks) to enable the optimizer to optimize on a daily basis (as compared to needing to optimize for a full month, which is impractical as it assumes knowledge of all required parameters at the beginning of the month). (12) resets the monthly peak demand at the beginning of each month to 0 and initializes the SoC of the EV at the start of the time horizon.

## 2.2 Behavioural and Technical Constraints

The formulation presented in Section 2.1 is a fundamental formulation that considers the EV to act as a shiftable load (under smart charging) or as a battery under V2G, which allows changing its charging behaviour through time in reaction to the dynamically changing price signals. This formulation is the starting basis on which further adaptations can be built. Indeed, the EV flexible behaviour is governed by a myriad of *user behavioural constraints*, as well as *EV manufacturer's constraints*, which impact the availability of the EV and the flexibility of its charging behaviour (and discharging in case of V2G). The EV may not always be available at the location of residence and may not always be plugged in when available. It has options to charge elsewhere (at possibly reduced/supported rates, e.g., at work) impacting its SoC and charging needs. The energy consumption of EVs, and thus their charging needs, are also dependent on the user's driving behaviour, while its SoC limits are governed by the user's preferences and manufacturer's recommendations for preserving battery life. All these aspects, among others, impact the flexibility potential of residential-connected EVs.

We next define a concrete number of key factors, which we have integrated in our model (to complement the formulation in Section 2.1) and whose impacts we aim to investigate in the case study presented in Section 3. These key factors are the following: (1) **Expected Consumption**: expectations on the energy needs of an EV based on its driving behaviour. (2) **Charging Session**: The time range during which the EV is expected to be at home in a certain day and plugged in. This is also based on expected **Leave Times**, **Return Times**, and **Commute Times**, which are considered in the model set-up. (3) **Target SoC**: the target SoC the user would like to have at the end of the charging session, e.g., before leaving home. (4) **Expected SoC**: as many users are expected to have supported charging options (e.g., reduced charging costs at work), this

dimension captures the expected SoC when the EV returns home (e.g., from work) based on the expected charging behaviour at work. (5) **Preferred SoC range**: this parameter captures the range in which the user prefers the SoC to stay, either due to personal preferences or due to manufacturer's recommendations (e.g., in the 20% to 80% range of full capacity). (6) **V2G Capability**: this indicator captures whether V2G is possible. (7) **Min SoC power rating**: an SoC rating below which the EV will always be charged at full power. In addition to other EV parameters such as **maximum charging power** (as specified by the EV and/or the charging station), **energy capacity**, **charging and discharging efficiencies**, which are part of the formulation in Section 2.1, these parameters and associated constraints enable refining the flexibility feasibility space of the EV, which is significantly different from the setting in which the EV is assumed to always be at home and always be plugged in (enabling smart charging or V2G availability for the full time period).

Instantiation of those parameters, in addition to the base consumption profiles, PV time series outputs, and applicable electricity prices and tariffs constitute the complete numerical setting under which the potential of EV flexibility can be explored, as will be carried out in the case study of Section 3.

## 3 Case Study and Results

### 3.1. Simulation set up and scenarios

We consider a set of residential consumers in Flanders, whose case consumption data is available in [7]. The consumption data is from 2022, where we focus on households that did not at the time have an EV or PV installed. We focus on 20 households with the highest peak demand. To assess self-consumption potential, we consider that consumers with an EV also have PV installed at their home. The consumers are exposed to a dynamic energy retail price and applicable tariffs for 2022 for Belgium based on [11].

EV flexibility behaviour is influenced by both user behaviour and manufacturer constraints. To address these factors, additional scenarios are analysed. These are categorized as the **base scenario**, **reference scenario**, and **behavioural scenario**. The base scenario is one in which EV users do not respond to dynamic price signals (tariffs or retail prices). Instead, they charge their EVs at their convenience without worrying about the cost of charging. For the reference scenario, EV users respond to dynamic tariffs and retail prices. However, user behavioural and technical constraints (highlighted in Section 2.2), are not considered. In the behavioural scenario, on the other hand, we incorporate the behavioural and technical constraints introduced in Section 2.2. For the user behavioural constraints, we consider a daily energy consumption need (induced by average driving distance) of 10kWh [13]. The driving time is drawn from a uniform distribution between 6–9 AM for leaving home and 4–7 PM for returning home. It is also assumed that users

follow a consistent daily driving profile. To assess the impact of having the possibility of charging away from home at significantly reduced rates on the total EV flexibility potential at the home connection level (i.e., impacting the household consumption profile), we consider that 50% of users have access to charging facilities away from home at a lower or no cost. The SoC preferred minimum and maximum limits are set to 20% and 80%, respectively. We consider a target SoC when charging elsewhere of 80%, and a minimum SoC preference of 30% before leaving home. We consider an average battery capacity of 62 kWh as per [13], a maximum power rating of 11 kW, and an efficiency of 90%.

The following key performance indicators (KPIs) have been considered to compare the EV flexibility potential for the described scenarios. The flexibility unlocked by the EV in the reference and behavioural scenarios are computed with respect to the base scenario. The KPIs are then computed as the percentage difference between the results achieved in the behavioural scenario as compared to the reference scenario. An example KPI calculation is presented in (11), where  $\sigma$  is a generic representation of one of the computed quantities defined next, i.e.  $\sigma \in \{f^u, f^d, C, SC\}$ .

$$KPI_{\alpha} = \frac{\sigma^{behavioral} - \sigma^{ref}}{\sigma^{ref}} \times 100. \quad (13)$$

The computed KPIs are the following:

- i. **Volume of unlocked upward and downward flexibility ( $f^u, f^d$ ):** The cumulative volume of upward and downward flexibility provided by the EV during the considered time horizon.
- ii. **Cumulative consumer cost (C):** The financial savings achieved by users in response to varying prices and EV constraints.
- iii. **Self-consumption levels (SC):** SC reflects how price signals and the availability of EVs influence a user's consumption of household PV generation.

SC is computed as the portion of the total energy offtake of a household that took place during times of PV generation as compared to the total yearly energy demand. SC can be computed as follows, where  $\mathcal{T}^{PV}$  is the set of time instances  $t \in \tilde{\mathcal{T}}$  such that  $i^{PV} > 0$ .

$$SC = \frac{\sum_{t \in \mathcal{T}^{PV}} o_t}{\sum_{t \in \tilde{\mathcal{T}}} o_t}. \quad (14)$$

### 3.2. Quantitative Results

A summary of the computed KPIs is illustrated in Fig. 1. As can be seen in Fig. 1, the total volume of provided upward flexibility increased by 37.18% when introducing the behavioural considerations to the use of EVs. The reason for that is that due to having the capability of charging elsewhere at reduced rates, the residential load decreases significantly. This will be naturally balanced out by an increase of load elsewhere (at the location of charging). However, here the

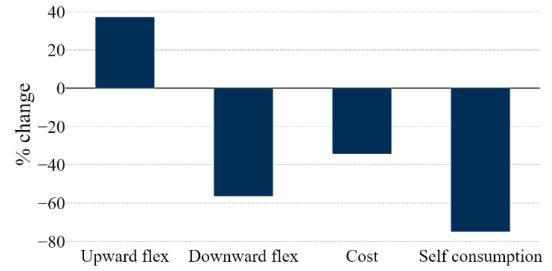


Figure 1 KPI Calculation.

focus is on the load of the residential unit, as its flexibility is being assessed. A natural next step of research is to explore the flexibility potential at all charging locations to have a holistic quantification. Fig. 1 shows, on the other hand, that the level of provided downward flexibility has decreased by 56.5% when including the behavioural and technical considerations. This reduction is due to the limited availability of EVs at the household location during significant portions of the day, which leads to different SoC requirements and different charging needs at home. Indeed, the availability of workplace or other external charging facilities at a lower cost significantly impacts the residential flexibility potential of EVs, as when aiming to minimize their charging costs, users would have little incentive to charge at home. The charging behaviours of the users lead to a reduction of total costs experienced by the studied users of 34.38%, under the behavioural scenario. In terms of self-consumption levels, Fig 1 shows a decrease in SC by 75% under the behavioural scenario. In this scenario, the users have limited capacity to capitalize on their self-generated PV energy for their charging behaviour, and resort to injecting any surplus energy they have to the grid. This reduction occurs due to unavailability of EV at the household location during peak PV power production periods. This highlights the importance of analysing cases with shiftable loads and home battery management systems for optimizing the use of self-generated energy.

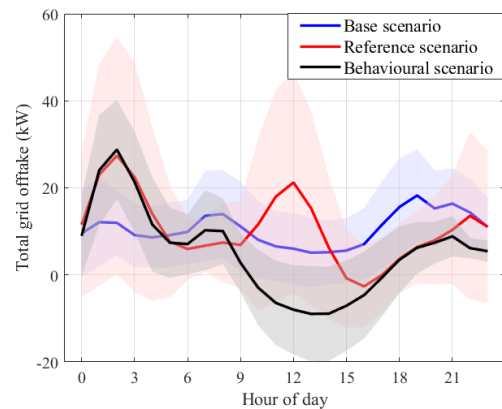


Figure 2 Cumulative hourly load (average +/- 1 standard deviation).

The reaction to dynamic prices and the constraints thereon impacts the consumption profiles of the users and the simultaneity of their consumptions. This is highlighted in Fig.

2, showing the average cumulative load under each scenario at each hour of the day in the studied year, along with a band (in shaded colour) representing a one standard deviation (+/-) band from the average. The results show that the reference scenario led to generally higher peaks than the base scenario, as users concurrently shift their consumptions to lower-priced hours. The behavioural scenario leads, however, to a reduction of this peak, and even a reduction of the cumulative load (compared to the base scenario), as users charge elsewhere (load reduction) and have limited downward flexibility at the home connection to capitalize on lower-priced hours.

#### 4 Conclusion

EV flexibility potential is expected to play a key role in meeting the increasing power system flexibility requirements in support of network planning. This study has showcased the importance of accounting for different behavioural and technical requirements when estimating the flexibility potential of residential EVs. The case study shows the scale of the impact that these constraints can introduce on the available volumes of flexibility (upward and downward), the costs to the user, the potential of self-consumption, and the resulting cumulative peak loads. A natural extension of the current study lies in two dimensions: (1) expanding the case study for the Belgian scale, and (2) considering other flexible assets (such as HPs and batteries). These extensions are currently being addressed as part of the ETF Reinvent project.

#### 5 Acknowledgements

This work is conducted within the Reinvent project. Reinvent has received funding from the Energy Transition Fund 2023 granted by the Belgian FPS Economy, SMEs, Self-employed and Energy.

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