Residential flexible load profile generator to estimate the impact of tariffs and demand response on distribution grids and energy bills

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Abstract

The flexibility of residential loads must be considered to reach an optimal long-term development strategy in distribution networks. However, due to privacy and logistic obstacles, real data for this is not yet available.
This work proposes a tool for generating synthetic behaviors of the households' members. It stochastically constructs a load profile by generating occupancy patterns inside the home and random appliance usage events depending on the attendance, to construct a baseload for the home. In addition to this fixed load, several types of flexible appliances with adapted flexibility boundaries.
These load profiles are used to model neighborhoods or small villages, to represent the reaction of a complete low-voltage grid to different tariffs. Users change their consumption patterns within the defined boundaries to react optimally to varying energy and grid prices. This allows to evaluate the effects of the regulations for grid tariffs on the customers' energy bills, the grid congestion and the DSO revenues.

1 Introduction

The energy transition brings a lot of challenges for the electric distribution networks. Due to both the electrification of usages and the development of distributed energy resources (DERs):

- The consumption patterns of residential users are going through a total change. In addition to the classical home appliances a roll-out of electric vehicles (EVs), controllable thermoelectric appliances Water boilers (WBs), Heat pumps (HPs), and other time-shiftable loads, also called White Goods(WGs) is progressively happening. This is drastically changing the power and energy consumption in residential area.
- The energy transition fosters new investment in less CO_2 intensive generation units. Many are directly connected to the distribution grids and can cause deleterious reverse power flows.

This work mainly emerges from the needs of the first category, by proposing a way to model the end-users' loads and to allow to quantify their flexibility potential. Indeed, the second category does not necessitate more models. It mainly consists of PV generation which is completely weather-determined, Wind turbines, which are often not possible for residential areas, and battery storage systems (BSSs) whose profiles are completely control-dependent.

On the other hand, load profiles in residential areas are increasingly uncertain and hard to predict. This constitutes a challenge for DSOs, the low-voltage network monitoring is still incomplete or nearly absent in certain regions. Moreover, where it is present, assessing the evolution of electricity use and how it affects individual profiles is not possible without intrusive pieces of equipment.

Such forecasts, especially in the long-term for planning future distribution systems, are highly important to quantify and activate this flexibility potential.

We propose a tool to generate residential electric load profiles stochastically, this includes a baseload on which controllable appliances can be added. Some boundaries for the flexibility of said appliances are also provided to assess the possibility of demand response mechanisms. All the data is synthetic, coming from stochastic occupancy of the houses, and designed to match statistical data when aggregated.

A few projects already managed to measure real-world data that includes some separation of the households' appliances [1, 2]. However, these are limited in the amount of homes and do not allow the modeling of different populations.

There have also been some projects for district energy demand modeling [3, 4]. Those tools provide efficient but opaque solution to generate load profiles, they also include district heating needs and other types of customers, to model complete cities. This project needed a completely customizable tool where appliances could be added with a flexibility component. Opensource libraries such as [5, 6] were more relevant in these conditions.

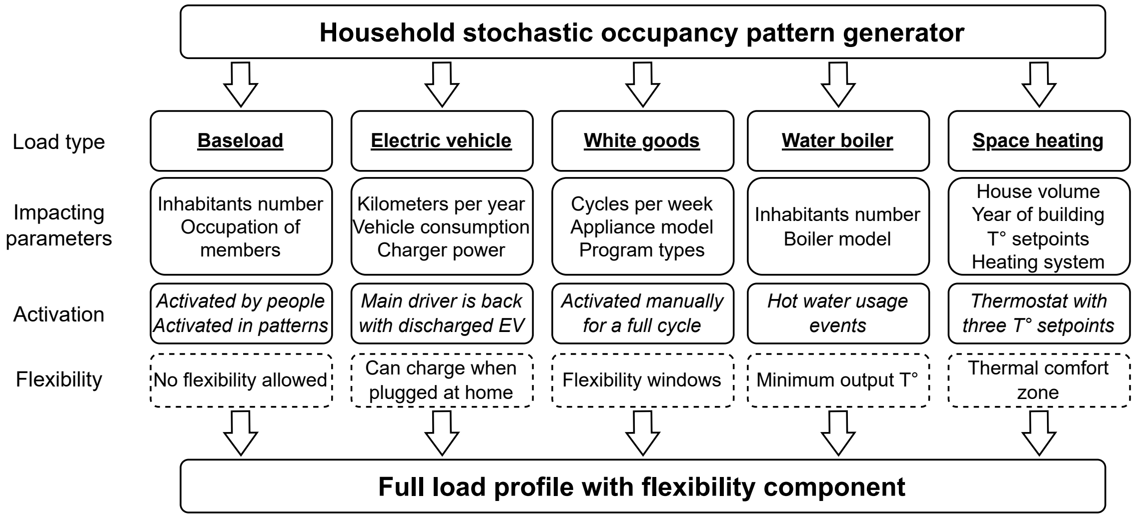

Fig. 1. Load profile generator organization

Another approach involves a machine learning technique to detect and cluster the appliances in measured complete household load profiles [7–9]. This method has given decent results, but still needs real data and proves that customers can be concerned about privacy issues for data coming from smart meters.

This work tackles the problem from the opposite side. Considering a population for which the aggregated load is measured at the transformer, it is possible to rebuild plausible individual profiles. This can done using population data and some other socio-economic factors that are converted into penetration for distributed energy resources (DERs): photovoltaic (PV) systems, electric vehicles (EVs), electric water boilers (WB), direct electrical heating or heat pumps (HPs).

Section 2 presents how the generator has been constructed and how the profiles are generated, section 3 describes how it can be used to evaluate the potential impact of some new regulations in end-customer behaviors and grid congestion. Section 4 summarizes and proposes potential further uses of this tool.

2 Flexible load profile generator

As shown in Figure 1, the output load consists of five terms representing each type of appliances, with a corresponding flexibility component. These terms depend on the input parameters, the occupancy pattern generated by [6], and some random parameters.

2.1 Stochastic occupancy

The base of this generator is a stochastic occupancy behavior simulation tool [6], which generates occupancy profiles for the members of the house. This occupancy depends on the type of inhabitant (Working hours, student, unemployed, etc.) and is repeated over the full year. This will be the base data for generating all the different appliances' energy needs.

2.2 Baseload

The baseload is comprised of all non-programmable appliances. This can be considered as the household's fixed load. Indeed, it would be unrealistic to consider consumers who will adapt their usage of base appliances to external signals. This category includes fridges, kitchen appliances, computers, televisions, lights, etc.

All data for appliance activation and power needs comes from [6], this provides a realistic load profile. This can be modified by using a scaling factor. When specified, the yearly baseload input parameter is converted to scale the load accordingly.

2.3 White goods

The white goods, also called wet appliances are time-shiftable controllable loads (washing machines, driers, and dishwashers). Depending on the family size, an amount of weekly cycles is assigned, an input can override this number for each appliance. The cycles can vary in profile and length according to the appliance model and program, respectively. The program type is randomly selected among predefined data [10].

2.4 EV

To generate car usage patterns, a main driver attribute is first assigned to one of the household's members. Then, the car owner leaving home is detected on the occupancy pattern which creates a "driving event". This driving event will last until the driver is back. Vehicle usage data is taken from [11].

Depending on the duration of the trip and the annual mileage input parameter, a length in kilometers is assigned to each driving event. Then, this length is converted to an energy need according to the size of the vehicle and converted to a return state of charge (SoC).

Charging outside the house is also considered, and this energy usage is removed from the load profile. When the battery charge is getting low throughout the travel, the probability of charging the EV on the road is computed. When this happens, the initial vehicle discharge is divided by two. This represents a charging event happening halfway through the trip (*i.e.* at the destination).

This probability is equal to 1 the return SoC is lower or equal to 0 and null when it is above 50%. It evolves linearly between those two points.

When the EV returns home, it is directly plugged and charged at full power until the maximum SoC is reached, this represents the initial fixed load, which mimics a standard use of an EV without smart-charging.

2.5 Space Heating

A complete house thermal model is considered. Based on the occupancy profile, three temperature setpoints are defined:

- High when someone is present.
- Medium when everybody present is sleeping.
- Low when no-one is home.

The exact temperature level for each setpoint depends on the input parameters.

A simple control strategy with temperature dead bands around the setpoint is then used to convert the temperature profile to energy needs. When running, the thermal unit only operates at full power.

2.6 Water boiler

The load profile generator includes a full thermal model of the water tank and boiler [12].

The internal temperature evolution is computed using this thermal model and the stochastic water usage events depend on the occupancy. The resulting temperature drop is compensated by activating the boiler at nominal power until the setpoint is reached again.

2.7 Flexibility windows output

The described consumptions are considered as the initial fixed profile of the household. If we want to model flexibility capacity and reactions, some plausible flexibility boundaries must be provided with this profile.

This is defined per type of appliance:

- *Baseload:* No flexibility is possible, this is the basic usage of non-controllable appliances.
- *EV:* The EV charging starting time can be delayed and the power magnitude decreased. By knowing the necessary energy and the power rating of the charger, the flexibility window can be computed, with the a full-charge constraint at EV departure. Vehicle to grid or vehicle to home can also be considered.
- *White goods:* The white good are time-shiftable loads, a maximum (in hours) can be set to define the maximum shit in delay or advance for each cycle. Once launched, the program profile will have to stay identical.
- *Water boiler* and *Space heating:* The thermal appliances can be modeled using a larger deadband on the thermostatic control. Using flexibility the nominal power activation constraint can also be relaxed and the system can be operated at any power level below. The thermal model of the appliance is still needed for this flexibility component.
- *Water boiler* and *Space heating* (variant): A less demanding option for flexibility is also available. This simplifies and avoids the need for the thermal model *a posteriori*. It has a constant daily energy constraint, with a maximum time for energy displacement.

2.8 Inputs description

Table 1 summarizes all generator inputs for a single load profile sorted by appliance types.

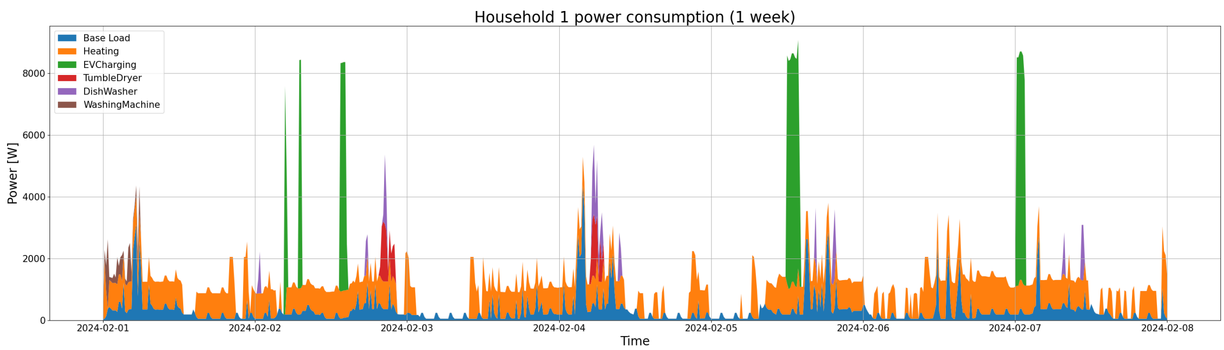

Fig. 2. Example of a weekly load profile

	Name	Description
General	Timestep	Granularity of the output, minimum 1 minute (min)
	Duration	Number of weeks to be generated
	Starting date	The day of the year at which simulation is starting (for seasonality)
Base	Family size	Number of people in the house
	Occupation	Unemployed, Full/Part-time job, Student or Child, for each person
	Baseload	Yearly baseload can be overridden (kWh/y)
Electric Vehicle	Annual use	Kilometers per year
	EV type	Small, medium or big: converted to a consumption (kWh/100km) and battery size (kWh)
	Charger	Maximal power output of the car charger (kW)
WG	Washing	Number of cycles per week (optional)
	Drier	Number of cycles per week (optional)
	Dishwash	Number of cycles per week (optional)
Boiler	Boiler type	None, Electrical or Thermodynamic boiler
	Boiler size	Water tank volume (L)
	T° setpoint	Output temperature setpoint (°C)
Space Heating	T° setpoints	Low, medium and high temperature setpoints (°C)
	Surface	Ground surface of the house(m^2)
	Height	Height of the house (m)
	Construction	Decade of construction, to be converted to insulation layers
	Outside T°	Yearly temperature profile to compute heat exchanges (°C)
	Power	Nominal input power of the heating system
	COP	Equal to 1 for direct heating and above for HPs

Table 1 Inputs of the generator for a single household

2.9 Aggregation

The tool is also designed to output multiple load profiles, to model a whole population, and to see impact on the grid infrastructure. This way, a neighborhood, a city, or even a full country can be modeled quickly with varying penetration and proportions for each appliance. To this end, the input values in table 1 have to be replaced by lists with associated proportions, which will be interpreted as probabilities by the generator.

The additional parameters for population modeling are presented in Table 2. All parameters in Table 1 should also be provided, converted to lists of values with corresponding probabilities except for the "General" inputs, common for all profiles.

The penetration parameters are optional, as this can be achieved by selecting a portion of appliances with zero nominal power. However, they can become relevant for multi-year studies by making these parameters vary without changing the other probability inputs.

	Name	Description
	Number	Amount of profiles to be generated
Penetration	EV	Portion of household profiles which include with an EV
	Direct WB	Portion of household equipped with electrical boiler
	Therm. WB	Portion of household equipped with thermodynamic boiler
	HP	Portion of profiles equipped with HP
	Direct heating	Portion of profiles equipped with direct heating

Table 2 Additional inputs of the generator for a population

3 Impact assessment of different tariff methods

Quantifying further need for power distribution is one of the main challenges that DSOs will have to face in the upcoming years. This tool could efficiently assess the impact of energy transition and grid tariff evolution on the energy grid.

One of the solutions proposed to unlock this potential is to create new tariffs to activate implicit flexibility. By reducing the grid fees when the energy is abundant, users are pushed to increase their consumption, the reciprocal is also true.

The profile generator is thus to able to estimate the maximal efficiency of different grid tariffs under varying hypotheses on the profiles;

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 to see what the improvements are due to the more complex tariffs;
- Day/night: Historically a two-period energy meter was installed to offer night discount;
- Dynamic: The days are divided into 5 periods with three tariffs: high, medium, and low;
- Capacity: One of the previous cases, with additional fees for the peak power exchange value;

Apart from grid tariffs, other structures such as energy community could emerge and coordinate the use of DER and residential load flexibility [13]

B. Penetration:

These results are dependent on many aspects:

- Type of grid: urban, suburban, rural;
- PV penetration;
- BSS deployment;
- Evolution of heating needs and technologies.

According to Belgian scenarios for the evolution of energy usage, a representative multi-year study can be conducted to determine if the previously ideal tariff method will remain optimal.

4 Conclusion

This work showed the need to have an appliance-dependent load profile for households to model the possibilities for demand side management at the residential low voltage level.

It proposes a fully functional and customizable tool that avoids taking intrusive and long-lasting measurements. By aggregating multiple profiles, modeling larger-scale systems is made possible with simple input parameters adaptation. These results can also be used for longer-term planning by generating the same population over multiple years with scenarios for evolving penetrations of low-carbon appliances, PV, and battery systems that have to be considered and included in the residential energy management system.

The result of this generator is realistic in a bottom-up approach using appliance-based individual load profiles and can be aggregated to be statistically representative for populations with defined load magnitude and patterns as well as low-carbon technologies penetration features.

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