ResFlex: a residential load profile generator to model individual demand response in distribution grids

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Abstract

To reach an optimal long-term development strategy in distribution networks, the flexibility of residential loads must be considered. However, due to privacy and hardware obstacles, real residential electrical demand data is usually incomplete, outdated or not available.

This work proposes a tool for generating synthetic load profiles dependent on the behavior of the households' members. Based on that, 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 are also considered, with suitable flexibility limits.

These load profiles can model neighborhoods or small villages to represent the reaction of a complete low-voltage grid to different tariffs. Users will change their consumption patterns within the defined boundaries, reacting optimally to different energy and grid prices. This could allow the evaluation of the effects of different regulations to the customers' energy bills, the grid congestion, and the system operator revenues.

1 Introduction

The energy transition brings multiple challenges for electric distribution networks, induced by both the electrification of usages and the development of distributed energy resources (DERs):

- The consumption patterns of residential users are undergoing a complete transformation. 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 areas.
- 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 addresses the first challenge by proposing a method to model end-user loads, enabling the quantification of their flexibility potential. In contrast, the second category does not require new models. These typically include PV units, which are entirely weather-dependent; wind turbines, which are generally unsuitable for residential areas; and battery storage systems (BSSs), whose profiles are completely control-dependent.

Moreover, residential load profiles are becoming increasingly variable and hard to predict. This constitutes a challenge for distributed system operators (DSOs), because low-voltage network monitoring is still limited or nearly absent in some regions. Moreover, even where such monitoring is implemented, assessing the evolution of electricity demand and how it affects individual profiles is not possible without intrusive equipment, raising concerns about consumer privacy. However, forecasting such loads, especially in the long term, is essential for planning future distribution systems and accurately quantifying and activating this flexibility potential.

The proposed tool aims to generate residential electric load profiles stochastically. These profiles are composed of 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 data is synthetic, coming from a stochastic occupancy pattern for the houses, and designed to match statistical data when aggregated.

A few projects measured real-world data and included some separation of the households' appliances [1, 2]. However, these are limited in the number of homes and do not allow the modeling of extensive populations.

Other projects for district energy demand modeling [3, 4] exist. However, despite providing efficient solutions to generate load profiles, those tools are opaque solutions. They include district heating needs and other types of customers to model complete cities.

The work presented here is a fully customizable tool where appliances can include a flexibility component. Open source libraries such as [5, 6] are more relevant in this work due to

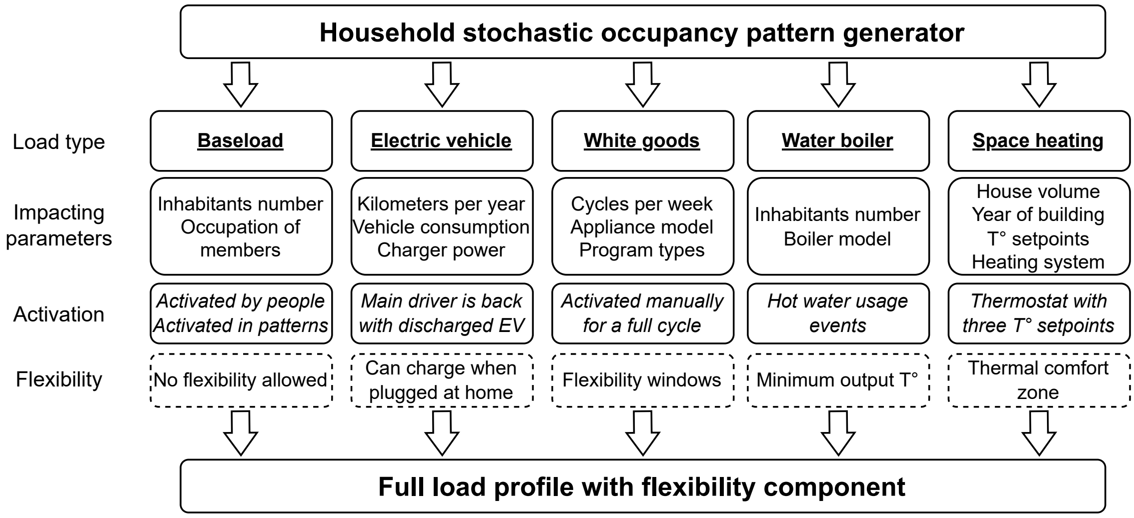

Fig. 1. Load profile generator organization overview.

their accessibility and configurability, and this work is built upon them.

Another approach involves a machine learning technique to detect and cluster the appliances activation in measured household load profiles [7–9]. This method has given decent results but still requires real data, which induces customer concerns about privacy issues for data coming from smart meters.

This work tackles the problem differently. Starting from individual plausible profiles, a population for which the aggregated load is measured at the transformer can be approached. This is done using population data and some other socioeconomic factors that are converted into penetration for DERs: EVs, electric WBs, and direct electrical heating or HPs.

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

2 Flexible load profile generator

As shown in Figure 1, the output load is composed of five terms that represent each type of appliance, with a corresponding flexibility component. These components depend on the input parameters, the occupancy pattern generated by [6], and some external parameters detailed below.

2.1 Stochastic occupancy

The base of this generator is a stochastic occupancy behavior simulation tool [6], which generates occupancy profiles for each member of the house. This occupancy depends on the type of resident (Working hours, student, unemployed) 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 load component can be considered as the fixed house demand. It would not be realistic to consider consumers who will adapt their baseload to external signals. This category includes most plugged-in appliances: fridges, kitchen appliances, computers, televisions, lights, etc.

All data for the activation of the appliance and power profiles come from [6], which 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

White goods, also called wet appliances, can act as time-shiftable controllable loads (washing machines, driers, and dishwashers). Depending on the family size, a number of weekly cycles is assigned for each appliance; this number can be overwritten by an input. Cycles can vary in profile and length according to the appliance model and program. The type of program is randomly selected from 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 owner of the car leaving the home for more than 15 minutes is detected in the occupancy pattern, creating 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 stochastic length in kilometers is assigned to each driving event. Then, this length is converted to an energy need according to the vehicle's size and then to a return state of charge (SoC).

The possibility of charging outside the house is also modeled, and this energy usage is removed from the load profile. The probability of a charging event outside the home P(ch,out) increases when the ratio between the required and available energy decreases. The probability P(ch,out) is mathematically defined as:

$$r = \frac{E_{\mathrm{j}}}{E_{\mathrm{l}}} \tag{1}$$

$$\mathtt{P}(\text{ch,out}) = \begin{cases} 1, & \text{if } r > 1.0 \\ 0, & \text{if } r < 0.05 \\ r, & \text{otherwise.} \end{cases} \tag{2}$$

Where the dimensionless ratio r is defined by the energy required for the considered journey E_j in kWh, divided by the available energy in the EV's battery E_l in kWh.

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). The charged amount is also stochastically computed based on the journey length, battery size, and power station type.

When the EV returns home, it is directly plugged in and charged at full power until the maximum SoC is reached; this represents the initial fixed load, which mimics the 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 is one of the input parameters. Based on previous work [12], each house is classified into one of the five construction year ranges (from before 1945 to after 2008). The corresponding thermal and sizing properties are then stochastically determined: ground surface and air volume, windows surface and wall insulation.

The space heating model can be summarized in four equations:

$$T_{t+1}^{in} = T_t^{in} + k^{th} \cdot \left(P_t^{HP,th} - P_t^{loss}\right) \tag{3}$$

$$k^{th} = k_{air}^{th} + k_{env}^{th} \tag{4}$$

$$P_t^{loss} = P_t^{exf} + P_t^{cond} - P_t^{irr} \tag{5}$$

where t is the considered time step. The subscripts air and env refer to the modeling of the house, which is considered as 4 walls (with windows), a floor, and a ceiling constituting the envelope of a paralellepiped filled with air. Furthermore,

- T^{in} and T^{set} are the indoor actual and desired temperatures,
- k^{th} is the thermal coefficient expressed in K/J,
- $P^{HP,nom}$ are the nominal power of the HP and P^{HP} its instantaneous setpoint.
- P^{loss} are the total thermal losses composed of P^{exf} (air exfiltration), P^{cond} (conduction of the envelope), and P^{irr} (irradiation).

A simple control strategy with temperature dead bands around the setpoint is then used to convert the temperature profile to energy needs.

In a nutshell, the model simulates indoor air temperature dynamics based on a simplified thermal representation of a dwelling, where the building is treated as a cube composed of air and an envelope (walls, floor, ceiling). Considered heat gains and losses are walls conduction, air exfiltration, and solar irradiation. The energy demand associated to the space heating is then derived from this control behavior.

2.6 Water boiler

The load profile generator includes a complete thermal model of the water tank and boiler [13].

$$T_{t+1}^{wb} = T_t^{wb} + k^w(P_t^{wb} - P_t^{loss} - P_t^{w,use})$$

The internal temperature evolution is computed using this thermal capacity of the water volume k^w. The stochastic water usage events depend on the occupancy, they cause power losses due to water inlet at lower temperature $P^{w,use}$. The losses through the tank envelope P^{loss} are proportional to the difference between the water temperature and the room temperature, which is assumed constant.

The water boiler is either activated at nominal power or deactivated. When it is below a temperature threshold, it activates until the setpoint is reached again.

2.7 Flexibility windows output

The described consumptions are considered as the initial fixed profile of the household. Some plausible flexibility boundaries must be provided along this profile to model flexibility capacity and reactions. This flexibility depends on the appliance type:

- *Baseload:* No flexibility is possible, this is the basic usage of non-controllable appliances.
- *EV:* EV charge 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 could also be considered.
- *White goods:* A maximum (in hours) can be set to define the maximum shift in delay or advance for each cycle of each wet appliance. Once launched, the program profile will have to stay identical.
- *Water boiler* and *Space heating:* The thermal appliances can be modeled using a larger temperature deadband on the thermostatic control, or a discomfort measure can be defined. The thermal model of the appliance is still needed for this flexibility component.

	Name	Description
General	Timestep	Granularity of the output, minimum 1 minute (min)
	Duration	Number of days to be generated (day)
	Starting date	Time of the year at which simulation is starting (day)
Base	Family size	Number of people in the house (pers.)
	Occupation	Unemployed, Full/Part-time job, Student or Child, for each person
	Baseload	Yearly baseload can be overwritten (kWh/y)
Electric Vehicle	Annual use	Average yearly use of the EV (km/y)
	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	Year of construction, converted to different insulation layers affecting heating dynamics (years)
	Outside T°	Yearly temperature profile to compute heat exchanges (°C)
	Power	Nominal input power of the heating system (kW)

Table 1 Inputs of the generator for a single household.

2.8 *Inputs description*

Table 1 summarizes all generator inputs 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 the impact on the grid infrastructure. This way, a neighborhood, a city, or even a representation of an entire country can be modeled quickly. To this end, the input values in Table 1 have to be replaced by lists with associated proportions, which the generator will interpret as probabilities.

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.

	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

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 choosing a given proportion for each type of appliance and then slowly increasing their penetration.

3 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

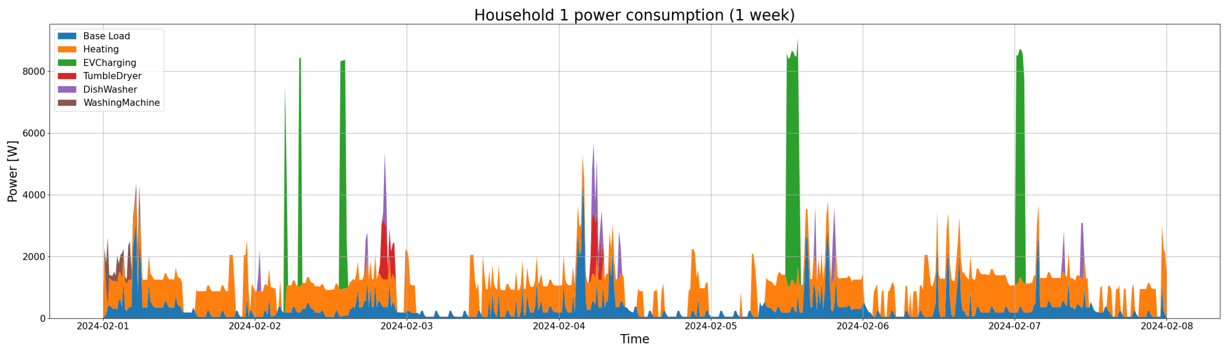

Fig. 2. Example of a weekly load profile

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.

The aggregated output results have been validated on Belgian data [14]. The first natural use of this tool could be to model a population reaction to various electricity tariffs or to model the impact of flexibility in a residential energy community [15].

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