RESIDENTIAL DEMAND MANAGEMENT AND DISTRIBUTION GRID IMPACT ASSESSMENT

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ABSTRACT

Demand Response in the residential sector has the potential to help future energy systems to balance variable power generation with electric demand. Harnessing its flexibility is however a challenge. We study in this article a day-ahead planning optimization and a stochastic appliance scheduling procedure that could serve different objectives. The aim of the study is twofold. In a first step, we develop a bottom-up consumption model and a flexibility model in which users set preferences on the flexibility that each load is capable to deliver. The model both accounts for the active and reactive part of the power exchanged with the grid. In a second step, the impact of control decisions on the distribution grid is assessed. It is shown that voltage imbalance factor is likely to exhibit larger extreme values when demand response is used to fulfill external objective, especially in feeders where clients are single phase connected.

I. INTRODUCTION

Residential Demand response is believed to be the largest source of flexibility in EU systems [1]. However, this potential is hardly exploitable today. Both market design and regulatory issues make the access to such potential either expensive or risky [2]. The foremost challenge is to create a stable and reassuring framework for massive participation of residential consumers. This supposes that external interventions on end-users appliances are non-disruptive. Control algorithms should take user's preferences into account and limit comfort disagreements. Furthermore, energy contracts should reflect short-term opportunity for consumers in order to foster participation while at the same time limit risk exposure to high prices. Finally, grid constraints also have to be considered, what enhance control complexity.

In this direction, this study presents a residential consumption model, load control algorithm and their impact on the low voltage electricity network. In section II, a residential consumption model is built. Section III presents control algorithms with associated results in Section IV. Section V discusses reactive power modeling in low voltage grids while Section VI highlights the impact of algorithm neglecting load localization.

II. RESIDENTIAL CONSUMPTION MODEL

A consumption model is built and simulates the active and reactive power consumption of the different appliances. The model details are to be found in [3]. We present in this section a bottom-up approach for active power consumption modelling.

There are four kinds of appliance models (Table 1): lighting and service, regulated and passive appliances.

Table 1: Considered appliances

Appliance Type	***Appliance list***
Service appliance	Dishwasher, washing machine, tumble dryer, kettle, oven, cooking plates, Television
Regulated appliance	Refrigerator, freezer, electric Boiler, Heat pumps, electric heating.
Passive appliance	Multimedia (internet routers, clocks, television boxes),
Lighting	-

Service appliances are end-uses starting at a certain time, delivering a service before shut down (e.g., dishwasher, kettle). Their behavior is simulated from a database of consumption profiles and their schedule is extracted from a statistical analysis of user's behavior.

Regulated appliances are equipped with sensors and control elements that manage their running cycles. This group encompasses fridges or heat pumps. Their consumption profiles follow control laws based on physical characteristics and statistically distributed preference set-points. Some consumption profiles of the service appliances are generated using similar principles.

Passive appliances are considered as an aggregated consumption: multimedia, monitoring, standby behavior of diverse appliances. Passive elements are reproduced similarly in all simulated houses due to lack of knowledge, and follow an average profile.

Lighting is also modeled as a unique appliance. Its consumption profile is generated from average consumption data. This is certainly the strongest weakness of the proposed model. Lighting should preferably be modeled in a more discrete way, on a load-by-load basis, especially to study distribution grid impacts. However, there is no evidence that a refined model would change our conclusions.

Measurements and general consumption profiles.

The consumption profile database is filled by measured appliances. We show here below some examples.

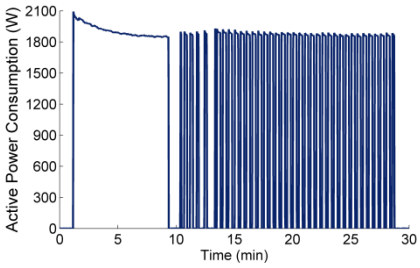

Figure 1: Active power measurement (plate) [3].

End-user's habits: appliance functioning statistics.

The average power consumption differs both in its hourly profile and in magnitude. These statistics will help us to generate different consumption profiles to represent household behavior.

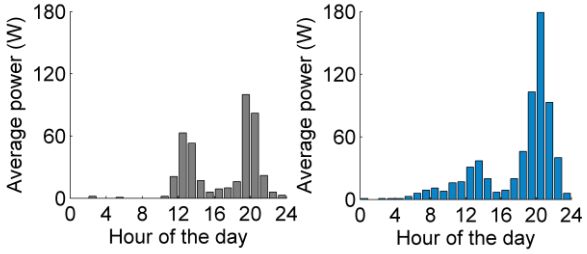

Figure 2: Average hourly power consumption of two different users (adapted from ECUEL[1]).

Regulated loads: physical parameters and energy balance.

The regulated loads are modeled with the use of mass and energy balance equations as well as control laws.

The following equations represent the evolution of temperature in the inner mass of an electric oven (T_f) and of the heating coils (T_r).

$$C_r \frac{dT_r(t)}{dt} = \frac{V^2}{R(T_r(t))} - a\left(T_r(t) - T_f(t)\right) \quad (1)$$

$$C_f \frac{dT_f(t)}{dt} = a\left(T_r(t) - T_f(t)\right) - b\left(T_f(t) - T_{amb}\right) \quad (2)$$

The electric resistance of the coils R is itself dependent on these temperatures. The resistance temperature dependence is supposed to be linear and described by a unique parameter α. The initial resistance value R_0 is known at the initial temperature T_0.

$$R(T_r(t)) = R_0\left(1 + \alpha(T_r(t) - T_0)\right) \quad (3)$$

There are two heat exchange parameters a (resistance to oven's thermal mass) and b (heat losses to ambiance). The inner mass and resistance have thermal capacitance of C_f and C_r respectively. An Illustration of these equations is presented on Figure 3. the active power consumption $\frac{V^2}{R(T_r)}$ (blue) and the oven's inner-mass temperature T_f (red). Three independent coils can be activated with different initial resistance. A timer regulates the duration for which each coils consumes energy. A thermostat selects the regulation mode. There are three modes: pre-warming (one coils stays on, another one alternates on and off), steady state (two coils are controlled on-off), on hold (no consumption).

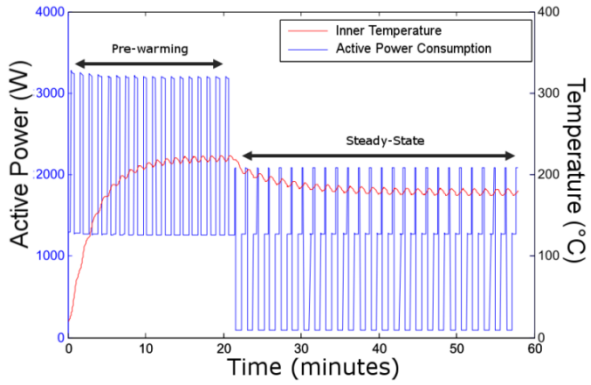

Figure 3: Active power and inner temperature (T_f) in an electric oven. $a = 15\ W/°C$, $b = 4.8\ W/°C$, $\alpha = 10^{-4}\ W/°C$, $R_0 = 16\Omega, T_{amb} = 20°C, C_r = 300J/°C, C_f = 1500J/°C$.

Refrigerators are modeled in a similar way. A thermostatically controlled cooling circuit is turned on and off in order to regulate the inner mass temperature. *Figure 4* shows a 5 hours example of power consumption profile.

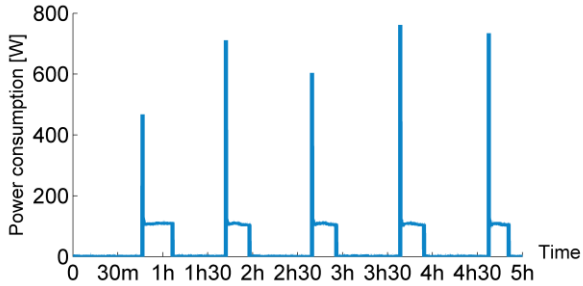

Figure 4: Active Power consumption measurement (fridge)

Passive appliances and lighting

The major weakness of the chosen approach is certainly to model both passive appliances and lighting as unique average profiles per households. Profiles are extracted from a 2008 study [4] and adapted to the household type treated here.

Household model and micro-grid

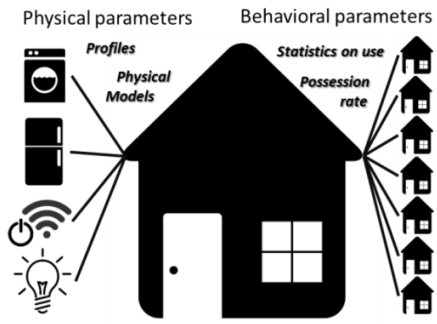

Figure 5: Household model, µ-grid generation principle.

1 http://www.enertech.fr

The household model gathers physical and behavioral parameters to generate second-by-second consumption profiles for each modeled load. A micro-grid of multiple houses with different appliances and behavioral patterns can be thereby generated as represented on Figure 5.

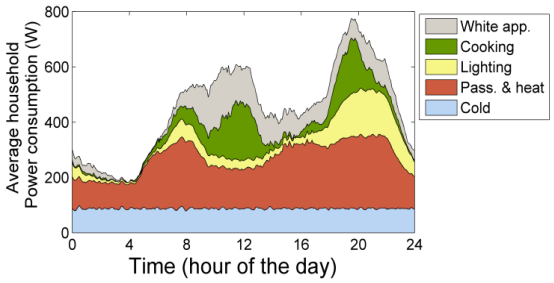

Figure 6: 5-minutes average power consumption per household by appliance type (1000 households group).

The average per-household consumption of a group of 1000 households is simulated for every 5 minutes during a single day. Results are presented on Figure 6, where the consumption is disaggregated by appliance type.

III. CONTROL ALGORITHMS

Certain types of electric loads are considered flexible. For instance, starting times of service appliances may be postponed and preference set-points of regulated appliances may be externally controlled. Two kinds of control algorithms are used in this summarized study where only some service loads (white appliances) are controlled. More detailed control is presented in [5].

Centralized control optimization heuristic.

In a first step, a centralized optimization is performed. The objective is to adapt the consumption profile of the whole micro-grid in order to be as close as possible to a reference profile. A scheduling heuristic is used. Each controlled load i starts initially at some defined time s_i during the simulation, which can be postponed with a certain delay d_i. We suppose in this centralized optimization that each delay d_i can be imposed externally. Each load will accept a maximum delay d_M^i (e.g. 6 hours) such that the optimization can choose d_i being anywhere in the interval $[0, d_M^i]$. Results are shown on *Figure 7* and more details may be found in [5].

Optimally biased random decisions on delays.

This second algorithm is a two-step decision process.

Day-ahead planning and statistics.

The first step consists in a static linear optimization, applied separately by appliance type and performing the day-ahead planning of the different load delays. Each day is divided into N time periods (5-min, 15-min, 1h, etc.). What differs from the previous algorithm is that we will define starting probability functions rather than controlling load on an individual basis.

The optimization exploits three important parameters: (1) the number of appliances a_k starting at each period k$\in [1, N]$ (2) the probability distribution function $p_k(d)$ that a load starting at time k will accept a maximum delay $d \in [0, N_d]$ (typically, N_d is the number of time periods in a day) and (3) the average consumption profile C_t, $t \in [1, T]$ of the related appliance type. The convolution of the average profile C_t with the number of starts a_k at each time k gives the initial consumption profile P_k^i at time k of the group of appliances: $P_k^i = \sum_{t=1}^{T} C_t\, a_{(k-t+1)}$.

The planning must compute *repartition variables* $x_{k,d}$. These variables represent, for each time k, a repartition of the starts a_k into the following time periods that respects the initial (statistical) requirements $p_k(d)$. Indeed, the probability distribution $p_k(d)$ suggests that *at least* a certain proportion of the load starts a_k initially occurring at time k will need to be scheduled before period (k+d). The product $a_{k-d}x_{k-d,d}$ is the number of loads initially starting at time k-d that are delayed up to time k. The final optimal profile P_k^f thereby takes preferences into account : $P_k^f = \sum_{d=1}^{N_d} \sum_{t=1}^{T} C_t a_{(k-t-d+1)} x_{(k-t-d+1,d)}$. The objective of finding the repartition variables is to spread the load starts across time in order for the final profile to be as close as possible to a reference one.

Real-time (biased) random decision

In real-time, the delay imposed to each appliance is randomly selected among a series of possible delays, with a probability that depends on the previous step results. Real-time decisions are made autonomously with conditionnal probabilities broadcasted once a day or more to each load. Results are shown on *Figure 8*. Other control strategies exists (e.g. [6]).

IV. RESULTS: SOLAR POWER BALANCE

The two above control algorithms are exploited in a simple test case. Each of the simulated houses is assumed to be equipped with a 3kWp PV installation. A PV generation profile is simulated to which the optimization adapts the households consumption. On *Figure 7*, the centralized algorithm (heuristic) is used.

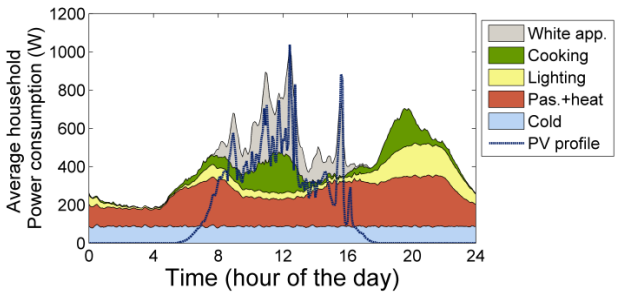

Figure 7: Centralized control heuristic. 5-minutes average power per household by appliance type (1000 households) with control on all white appliances. Identical maximum load delays : $d_M^i = 18h$ (optimistic).

Secondly, the *stochastic real-time scheduling* algorithm is used. Results are shown on Figure 8. As may be observed, this scheduling algorithm is not able to gather all white appliances at the time where PV panels are

generating power. This is actually imposed in the optimization, as some white appliances stay uncontrolled. Indeed, according to [7], an average of 60% of the dishwashers' cycles will be actually flexible and selected so by the user. Furthermore, only 30% of dryers and washing machine cycles dispose of some flexibility. Finally, the distribution of allowable delays ($p_k(d)$) is used (from [7]) limiting the amount of energy consumption that can be moved across the day.

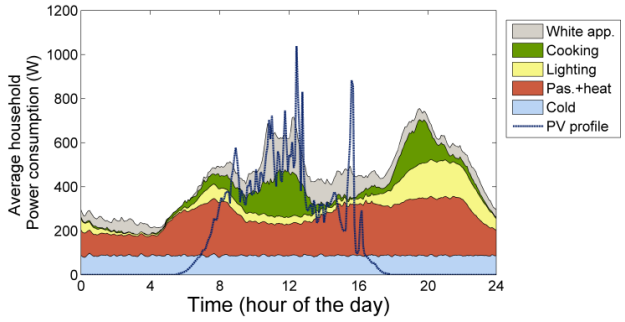

Figure 8: Optimally biased decisions. 5-minutes average power per household by appliance type (10^3 households).

V. REACTIVE POWER EXCHANGE

Appliances differ both in the physical phenomena at use (light, heat) and in the way the electric voltages/currents at their connection points are conditioned. Both of these elements influence reactive power exchanges [8].

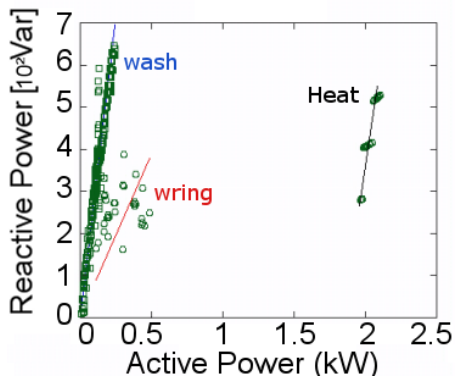

Figure 9: Active to Reactive power mapping of a washing machine. Modes: heat, wash, wring.

It is possible to map reactive power behavior with the active power consumption depending on the appliance's functioning mode (*Figure 9*). In this example, a washing machine uses different elements (heating coils, motors, etc.) with specific power factors. Active power consumption profiles give clues on the elements at use. At LEMCKO[2] lab (University of Ghent, Belgium), detailed measurements were conducted on typical appliances. Analyses performed on these measurements and on power conditioning elements (e.g. AC/DC converters) of each appliance were used to model reactive power exchanges.

VI. GRID IMPACT: VOLTAGE BALANCE

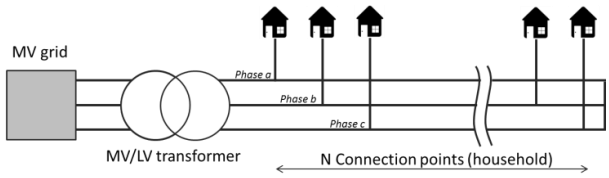

Figure 10: Micro-grid representation.

The N modeled households are connected to a 3-phase low voltage (LV) feeder. Some households (PV-houses) are equipped with photovoltaic panels. Some (DM-houses) participate in a demand management program in which they offer their flexibility to an external operator. Any connected household can be a PV-house, a DM-house or both. Solar panels and control algorithms impact two important power quality criteria : (1) the RMS value of the different phase voltage, and (2) the Voltage balance.

The RMS Voltage value should be maintained within a bounded interval p.u. [0.85;1.1]. PV power generation may increase the voltage level along LV feeders. In some cases, DR may help reducing this effect.

Furthermore, the 3-phase voltage system must stay balanced. All Currents and voltages magnitude should stay close to each other while their phase angles have to be shifted apart of $\pm 120°$. The EN50160 standard defines that the voltage unbalance factor must stay below a threshold of 2% for 95% of the time.

$$vuf = \frac{V_{ab} + a^2 V_{bc} + a V_{ca}}{V_{ab} + a V_{bc} + a^2 V_{ca}} 100$$

EN50160 standard: $x \leq 2\%$ s.t. $Prob(vuf \leq x) = 95\%$

Voltage unbalance is likely to be the most impacted by PV generation or DR actions. A simulation of a 600 meter long feeder with 60 connected houses is performed. Different scenarios are built. Scenarios define the kinds of houses (PV/DR) in the feeder, their connection type (phase to neutral, phase to phase) and their distribution on the feeder. Reactive power (Q) impact is also highlighted.

Single-phase equally distributed households.

Scenarios definitions are shown on *Table 2*. For instance, in the "Base+DR" scenario, single-phase connected DR houses are equally distributed along the feeder's phases.

Table 2 : Scenario definitions

Scenario	*DR ?*	*PV ?*	*Q ?*
Base	-	-	-
Base + DR	$3\times 1\varphi$	-	-
PV	-	$3\times 1\varphi$	-
PV + DR	$3\times 1\varphi$	$3\times 1\varphi$	-
PV + Q	-	$3\times 1\varphi$	✓

2 http://www.lemcko.be

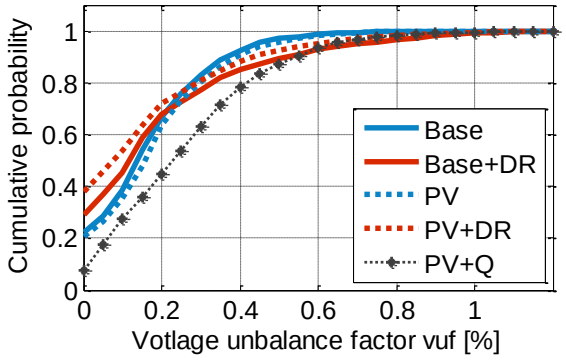

Figure 11: Cumulative probability distribution of observed voltage unbalance factor in a 60 houses, 600m feeder in different scenarios.

Firstly, one may easily observe reactive power should not be neglected (comparing the 95 percentile of "PV" and "PV+Q"). Secondly, demand response actions impact the unbalance factor. However, consequences are lower when DR's objective is to balance PV generation injected on the same feeder. Indeed, comparing "Base" and "Base+DR" scenarios shows that demand response acting for external purpose (there is no PV installed on the feeder) increase the unbalance factor. On the other hand, the comparison between "Base", "PV" and "PV+DR" shows (1) that PV generation is likely to degrade power quality, (2) that demand response used for local balancing will further degrade the situation but (3) to a lower extend than when DR is used for external purpose.

Single-phase unequally distributed households.

Two additional scenarios (*Table 3*) are considered, where houses are single-phase connected and unequally distributed among the different phases.

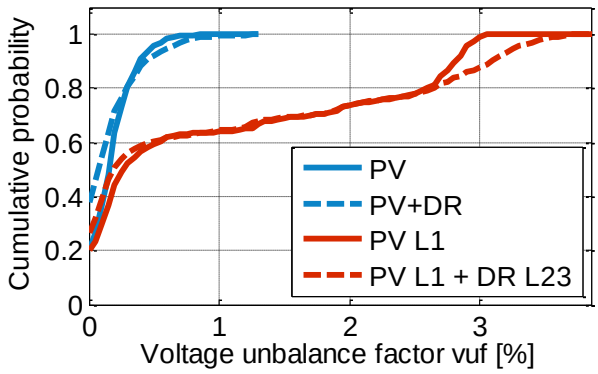

Figure 12: Cumulative probability distribution of vuf in a 60 houses, 600m feeder in different scenarios.

For illustrative purpose, let's consider extreme scenarios in which all houses with photovoltaic power (1/3rd of all houses) are connected to phase 1. Also, all flexible consumers (DR) are connected to the two other phases. This increases largely the vuf, as shown in *Figure 12*.

Table 3: Scenario definitions (2)

Scenario	***DR ?***	***PV?***	***Q ?***
PV L1	-	$1\times 1\varphi$	-
Base + DR	$2\times 1\varphi$	$1\times 1\varphi$	-

CONCLUSION

Residential power consumption is considered as a future source of flexibility, able to serve different purposes. However controlling demand at the residential level will likely impact quality criteria of the distributed power. We've shown in this study that it will be important to consider local connection information when demand response is used for external or local balancing. The article proposes a model of household active and reactive power exchange and performs several simulations. It is shown that neglecting local connection conditions of the controlled loads participating to demand response has large consequences on the voltage unbalance factor in feeders were houses are single-phase connected. We've also shown that multiple load control programs may reach similar objectives. However, some programs will be better suited to integrate local information. Furthermore, considering users preferences decreases largely the flexibility potential. Finally, reactive power should be considered in simulation models.

ACKNOWLEDGMENT

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