MODELING AND SIMULATION OF A RESIDENTIAL NEIGHBORHOOD WITH PHOTOVOLTAIC SYSTEMS COUPLED TO ENERGY STORAGE SYSTEMS

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ABSTRACT: The diffusion of the photovoltaic installations is reaching significant levels in the low voltage electric grid, therefore the need of effective energy management strategies increases. Within the Swiss2Grid (S2G) pilot project we are designing and testing a tool that allows the decentralized management of the distributed generation and consumption by controlling local energy storage systems and shifting the activation of households loads. In order to assess the effects of higher levels of diffusion of photovoltaic and storage system into the low voltage grid, we modeled the pilot residential neighborhood in Modelica, a multi-domain, open-source modeling language. In this paper we describe the components and the selected penetration scenarios. We finally present the results of the simulations, analyzing the effects of the chosen scenarios on neighborhood overall power, voltage instabilities and self-consumption.
Keyword: battery storage and control, demand-side, grid management, grid stability, modelling, simulation

1 INTRODUCTION

The increasing diffusion of generation and storage capabilities in the low voltage (LV) grid leads to new opportunities for development of decentralized control strategies in a system traditionally characterized by a lack of active control systems. In the Swiss2Grid project [1] we studied the performance of these novel hardware and software components in selected pilot households in a low voltage grid in Southern Switzerland. The scope of the pilot study is however constrained by the limited number of installed devices. It is therefore important to setup a simulation environment allowing to test high penetration scenarios. This paper describes the components we developed in Modelica language and the results of the first simulated scenarios. Figure 1 shows the modeled pilot residential neighborhood. We selected a LV branch line powering 39 single-family households.

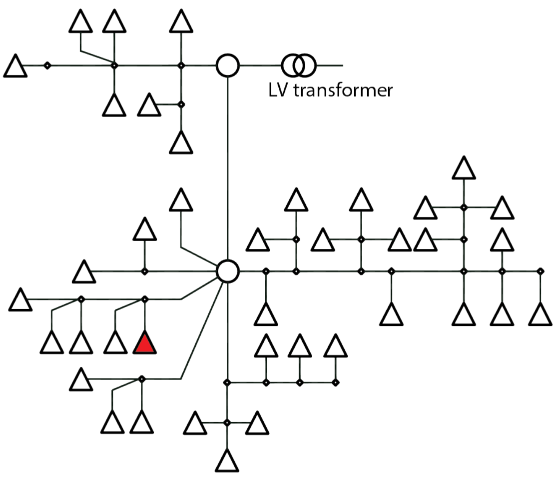

Figure 1: Layout of the modeled low voltage distribution grid branch. Triangles: houses, circles: electrical cabinets. The red house denotes the position of the example case of figure 4.

We acquired the data necessary for the simulation setup and validation in close cooperation with the local distribution system operator (DSO), setting up a long-term electric measurement campaign at both the transformer branch and the households' main electric panel.

In section 2 we describe the developed components and present the main design choices; section 3 describes the simulation setup with the results and in the final section the conclusions are drawn.

2 COMPONENTS

We built the model of the neighborhood using Dymola (Dynasim AB, Lund, Sweden), a modeling and simulation environment based on the multi-domain, open-source modeling language Modelica. In Dymola, we modeled a number of components for the PV generators, battery-to-grid systems, uncontrolled loads and the low voltage grid network simulation. The simulation performance was a primary goal, for this reason we developed low-order models that enable to test large-scale diffusion scenarios with a limited computational effort.

2.1 Photovoltaic system

Since many years, in our outdoor facility we are carrying on different test stands in which several PV modules are tested, focusing on their electrical and thermal behaviors. These measurements are performed with the MPPT3000, an electronic tracker with data logging developed internally [2], which collects voltage and current at maximum power point, temperature at the back of the module and acquires periodically the full I-V curve. These data are coupled with synchronized meteorological measures, namely the irradiance, the ambient temperature and the wind speed and direction.

After filtering the collected data, our software classifies the days basing on irradiance and clusters them into the following four groups: VERY-CLEAR, CLEAR, CLOUDY and OVERCAST [3]. As first step to have a reasonable PV profile as input for the model, we considered the power curve of a c-Si module during a VERY-CLEAR day. The test facility, to which the open air modules belong, has a tilt angle of 45° and an azimuth of -4°C.

The analysis of the measured trend shows a correlation higher than 99% with a sine-fit in the interval 9 AM – 4 PM, as shown in Figure 2. For this reason the sine-fit, truncated to zero when negative, was chosen as input for the model of the study. The different behaviors at sunrise (approximately 07 AM) and at sunset (approximately 5 PM) are due to the shadowing effect of mountains near the test facility.

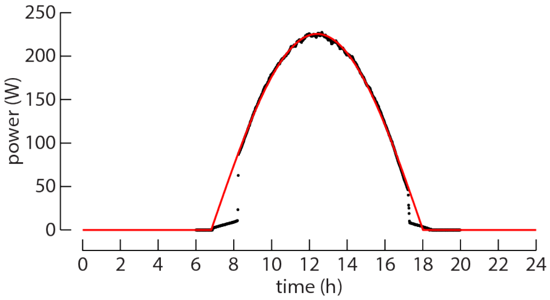

Figure 2: PV power's trend during a VERY CLEAR day (black dots) and its sine fit (red line).

PV field nominal power was randomly selected to lie between 3kWp and 5kWp. An additional 10% power loss was considered to take into account inverter efficiency and mismatch losses, while temperature losses were already taken into account by the module output. We equally divided the resulting AC power from PV into the three phases in order to model a balanced triphase PV system.

2.2 Battery-to-grid system

We modeled a Lithium-ion storage system, representing the most used battery application for home storage. This type of batteries is also used in the pilot part of the project. The implemented battery model is a simple energy storage with a fixed charging and discharging efficiency, the modeling of DC voltage and current profile behaviour has not been included because this level of details is not necessary for the simulation scenarios. In contrast, cyclic and calendaric aging and self-discharge of the battery have been considered.

The cycling aging is modeled in [4] with a linear expression as:

$$C_{loss} = 1 + kcQ_{abs} \cdot Q_{abs} \qquad (1)$$

$$Z_{inc} = 1 + kzQ_{abs} \cdot Q_{abs} \qquad (2)$$

where the linear cycling aging coefficient kcQ_{abs} represents the relative loss of capacity in function of the total transferred charge Q_{abs}. Similarly, the coefficient kzQ_{abs} represents the increase of the internal impedance.

To consider the calendaric aging or the battery, Ecker et al. [5] developed the following semi-empirical models for the loss of capacity and increase of internal impedance:

$$C_{loss} = 1 + c_a \cdot c_V^{\left(\frac{V-V_0}{\Delta V}\right)} \cdot c_T^{\left(\frac{T-T_0}{\Delta T}\right)} \cdot \sqrt{t} \qquad (3)$$

$$Z_{inc} = 1 + c_a \cdot c_T^{\left(\frac{T-T_0}{\Delta T}\right)} \cdot \left[c_V \cdot \left(\frac{V-V_0}{\Delta V}\right)^2 + 1\right] \cdot \sqrt{t}) \qquad (4)$$

where the loss of capacity C_{loss} and the increase of impedance Z_{inc} are determined by the elapsed time t, battery temperature T and voltage V.

The state of health (SOH) represents the condition of a battery (or a cell, or a battery pack), compared to its ideal conditions. The units of SOH are percent points, indicating the actual battery's conditions in respect to the manufacturer specifications. Typically, a battery's SOH will decrease over time and with use. The SOH is calculated by using the following formula described in [4] as:

$$SOH = \left(\frac{\frac{C}{C_0} - x_c}{1 - x_c}\right) \cdot \left(\frac{\frac{Z}{Z_0} - x_z}{1 - x_z}\right) \qquad (5)$$

where C and Z are the current capacity and internal impedance determined by the previous equations, C_0 is the initial capacity and Z_0 the initial impedance. The x_c coefficient indicates the capacity of the battery at end of life and the x_z coefficient indicates the internal impedance at the end of life of the battery.

The self-discharge is another phenomenon that influences the battery's performances. It acts simultaneously with the aging phenomenon but, contrariwise, it is reversible. In our model we applied a linear self-discharge expressed as a percent of total capacity loss per month.

We then modeled the battery inverter by using a DC/AC conversion efficiency curve defined in [6] and expressed as:

$$\eta = \frac{u}{a + b \cdot u + c \cdot u^2} \qquad (5)$$

where η is efficiency and u is the input power ratio of the AC inverter. The a, b, c coefficients are determined by fitting the efficiency curve given by the inverter's manufacturer [6].

The sizing of the modeled battery capacity, expressed in kWh, is determined by multiplying the nominal power of the PV field of the corresponding house (kWp) by a constant factor uniformly distributed between 2.5 and 3.5.

2.3 Battery control system

We implemented a simple way to control the battery that consists of charging the battery when the PV power is above 20% of the PV field nominal power and discharging it when it is below, according to:

$$\begin{cases} P_{Lim} = 0.2 \cdot P_{PVn} \\ \gamma = 1/(1 + e^{P_{PV} - P_{Lim}}) \\ P^* = (P_{PV} - P_{Lim}) \cdot (\gamma \cdot k_{dis} + (1-\gamma) \cdot k_{cha}) \end{cases} \qquad (6)$$

where P_{PVn} is the nominal power of the PV field, P_{PV} is the instantaneous power produced by the PV (positive when producing), P_{Lim} is the switching point from charge to discharge, P^* the desired battery power, negative when discharging, positive when charging. k_{cha} and k_{dis} are the charging and discharging gains, which in our simulations were set to 0.7±0.05 and 1.1±0.05. γ is a sigmoidal function used to avoid discontinuities when switching from charging to discharging. This fuzzy logic was introduced to reduce the simulation time.

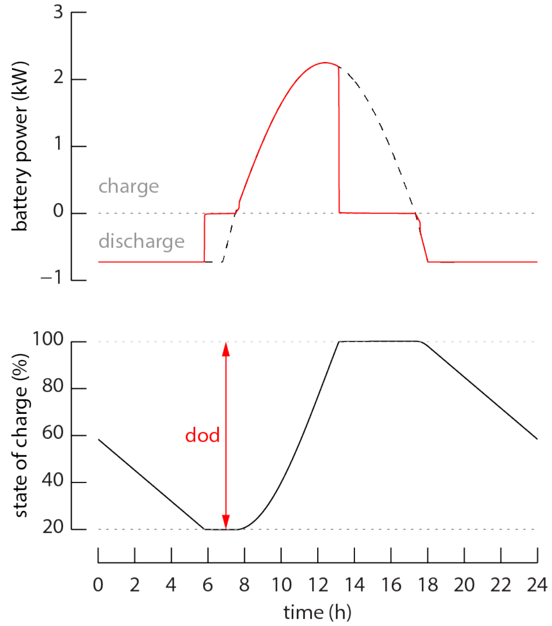

Figure 3: Example of battery control system behavior

2.4 Uncontrolled loads

The uncontrolled loads are modelled based on real data measured in the context of the Swiss2Grid pilot project [1]. We analyzed 11 houses and computed the distribution power consumption as a function of the day time for the month of April 2013, using intervals of 10 minutes. For each analyzed house, synthetic power consumption profiles with time steps of 10 seconds were generated in the following way: At each time step there is a 99% chance to retain the power used in the previous time step and a 1% probability randomly pick from the measured power distribution for the respective day time. A change in power is forced if the simulated value does not lie between the minimum and maximum power measured for the corresponding time of day. This allows to force synchronization when a ripple control signal is sent. Each phase is analyzed separately and when generating the synthetic signals the order of the phases is randomly shuffled. Synthetized reactive power is computed from the synthetized active power so as to keep $0.958<\cos(\varphi)<0.981$ ($Q=U(0.2,0.3)*P$), which is in line with what we observed in the real data.

In our simulations we randomly generated synthetic profiles uniformly distributed between the 11 house types. This resulted in 17 houses with ripple controlled water heaters, out of 39.

2.5 Low voltage distribution grid

We simulated a 4-bus unbalanced grid with fixed 50Hz frequency using the Modelica quasi-stationary electrical package [7]. The feeder transformer was modeled with a capacity of 250 kVA and a core loss of 0.26 kW. Iron losses were calculated for a short-circuit voltage of 4% of the nominal voltage. We simulated one branch of the transformer of the Swiss2Grid project, consisting of 39 houses and 66 nodes.

3 RESULTS

We defined 7 simulation scenarios: the first is without PV and battery (used as baseline). The other scenarios include PV generation with and without battery-to-grid systems (B2G) under several penetration rates in the neighborhood.

Table I: Description of the simulated scenarios.

Scenario	Active Houses	PV	B2G	Pen. Rate
1	0/39	-	-	0%
2	10/39	x	-	~25%
3	10/39	x	x	~25%
4	20/39	x	-	~50%
5	20/39	x	x	~50%
6	39/39	x	-	100%
7	39/39	x	x	100%

The example of figure 4 corresponds to the 39/39 PV with battery case. In A, the power profile in the example house is shown. The battery is able to absorb the PV power until around 2pm when it reaches 100% SOC; the charged energy is then injected back at a lower power rate after the end of PV production. In blue we see the uncontrolled loads.

The simulated voltages on the three phases (B) have a similar behavior but they present irregularities introduced by the phase imbalance. We notice two peaks in the voltage profile. The first, at around 2pm, is generated by the reach of full capacity of the battery systems. The seconds, at 10pm, is caused by simultaneous change in power due to the ripple controlled electrical water heaters. The power profile at the transformer (C) shows a similar but inversed behavior, with respect to the voltage.

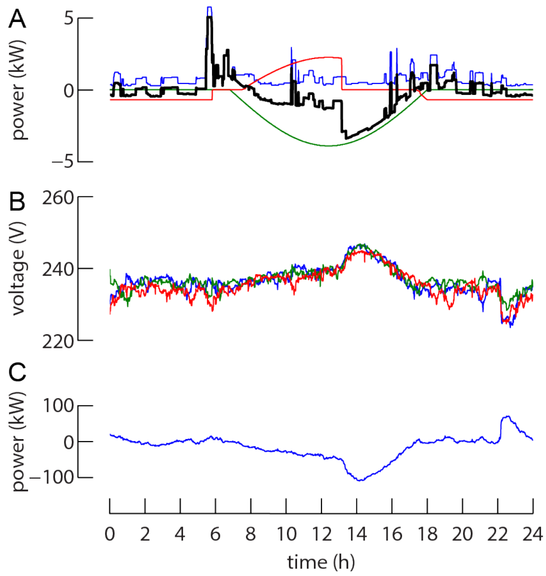

Figure 4: Example of simulation. A: household power consumption. Blue: uncontrolled loads, green: PV, red: battery, black: total. B: Voltage and the main panel for the three phases. Blue: phase 1, green: phase 2, red: phase 3. C: total power consumption at the LV transformer.

In order to assess the effect of the presence of PV and battery on the grid stability, we computed the variance of the total active power at the transformer σ^2_{PTrafo} and calculated the relative instability $\sigma^2_{PTrafoRel}$ as the difference between the minimum power variance, which corresponds to the 0% PV case, and the variance excursion within the different scenarios.

$$\sigma^2_{PTrafoRel} = 100 \cdot \frac{\sigma^2_{PTrafo} - \sigma^2_{PTrafoMin}}{\sigma^2_{PTrafoMax} - \sigma^2_{PTrafoMin}} \quad (7)$$

The same applies to the voltage relative instability. For each scenario, the median of the voltage variance between the 39 houses σ^2_V is calculated and the relative instability calculated according to:

$$\sigma^2_{VRel} = 100 \cdot \frac{\sigma^2_V - \sigma^2_{VMin}}{\sigma^2_{VMax} - \sigma^2_{VMin}} \quad (8)$$

The self-consumption is computed as the percent of the energy produced by the PV consumed within the neighborhood.

In figure 5 we show the simulation results for the defined scenarios, with respect to the baseline.

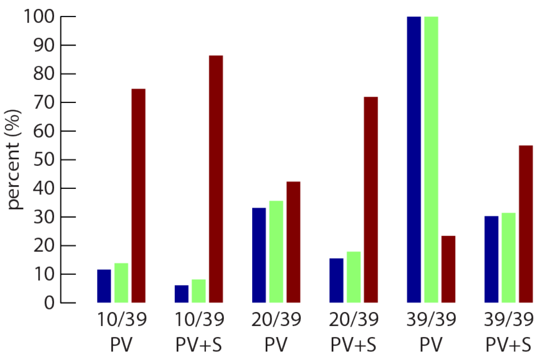

Figure 5: Simulations results: Blue: Relative instability of transformer power, green: relative median instability of local V, red: neighborhood self-consumption.

If we consider the scenarios in which the battery is not present, we see that the diffusion of PV generation progressively increases the relative instability of the transformer power. This is also confirmed by the neighborhood self-consumption rate. In case of low penetration of PV a high percentage of generated power is absorbed by the existing loads. The increase of PV generation reduces the self-consumption, increasing therefore the power instabilities on the LV transformer. The generated PV power also affects the voltage values in the grid; the relative median voltage instability shows a behavior similar to the power instability.

The introduction of local storage systems has a strong impact on the performance indexes. We notice that in the 10/39 case the impact of storage in not very high, because the PV power is already absorbed by the existing loads. However in the high penetration scenarios the benefits of a local storage is visible, reaching a threefold reduction of voltage and power instabilities and a twofold increase of self-consumption in the 39/39 case.

4 CONCLUSIONS

We implemented in Modelica a working model of the pilot residential neighborhood with photovoltaic installations coupled with storage systems. We generated random synthetic load and generation profiles based on the monitoring data from our pilot plants and test facilities. We also developed a low-order battery model, which considers calendaric and cycle aging and takes into account the battery self-discharge. We devised a simple battery control strategy for the increase of the PV self-consumption.

We defined multiple simulation PV generation scenarios with and without battery-to-grid systems under several penetration rates in the neighborhood.

The simulation results show that the increase of PV generation enhances the power and voltage instabilities and decreases the neighborhood PV self-consumption rate. The introduction of decentralized battery systems reduces the instabilities and increases the self-consumption, especially in the high diffusion scenarios. This is achieved by a very simple rule based battery control strategy.

Future work will focus on improving the existing components and introducing additional components, e.g., detailed photovoltaic models, electric cars, heat pumps and water heater models. We also plan to add an external software interface in order to be able to setup a co-simulation environment for advanced control algorithms.

5 ACKNOWLEDGMENTS

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