DEMAND RESPONSE BASED ON SMART METERING INFRASTRUCTURE TO FACILITATE PV INTEGRATION IN LOW VOLTAGE GRIDS

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ABSTRACT

Increasing penetration of distributed generation in combination with an aging grid infrastructure calls for a more flexible and efficient utilization of grid assets. Demand response is well suited to absorb peaks from local generation, but typically requires augmentation of the existing communication infrastructure to an extent that renders this option uneconomical in the context of low-voltage grids. In this paper we describe a pilot project where existing electric water heaters are controlled in dependence of local photovoltaic generation via the Advanced Metering Infrastructure.

INTRODUCTION

Most European countries have set ambitious goals to increase the penetration of renewable energy in the generation mix. An important fraction of this new generation, especially photovoltaic (PV) generation, is and will be installed in the low-voltage grid. Nowadays, some distribution grids are already facing problems such as overvoltage and line overloading due to the local PV generation. The traditional approach to these problems is grid reinforcement. However, more recently, alternative approaches such as demand response, distributed storage, control of active and/or reactive PV power and tap changing transformers are receiving increased attention [1] [2]. Demand response is attractive because it makes use of the existing load flexibility in the system. However, it might require an expensive communication and control infrastructure. While such a dedicated infrastructure might not be cost-effective, the use of Advanced Metering Infrastructure (AMI) for demand response can be very attractive, since it is being rolled out in many distribution grids.

The Utility of the Canton of Zurich (EKZ), Landis+Gyr and the ETH Zurich partnered in 2011 to develop concepts for AMI-based demand response with electric water heaters (EWHs). Contrary to other thermal storage devices, EWHs are a source of flexibility which is also available during periods of peak PV infeed in the spring and summer. In January 2016, a pilot project was launched to test the concepts developed during the research phase. In this project, an Advanced Load Controller computes optimal switching commands for existing EWHs, based on load and PV power predictions and the estimated state of the EWHs. These commands are sent to the EWHs via the AMI.

COMMUNICATION INFRASTRUCTURE

In Switzerland, EWHs are traditionally switched on during low load hours at night using ripple control signals sent from the medium-voltage transformers. This system was meant to maintain a high enough baseload during nighttime, in order for the nuclear power plants in the system to run continuously. Since EWHs are only allowed to run around 4 to 6 hours per day during nighttime, they have a large storage capacity in order to be able to provide enough warm water throughout the day. Ripple control only allows to control load groups with unidirectional top-down communication. Currently, EKZ is rolling out Smart Meters to all its customers. Thanks to the AMI put in place, ripple control can be replaced with a combination of communication over mobile networks and power line. The AMI, see Figure 1, consists of two centralized remote control systems:

- Advanced Metering Management, whose role is to record, process and administer the Smart Meter data, and which provides downward communication to field devices and upward communication to application systems,
- Load Management System, in charge of the load management applications, e.g. definition of activation and blocking times for switchable loads,

and field devices:

- Smart Meters at metering points,
- Load Switching Devices connected to controllable loads,
- Data Concentrators at low-voltage transformers, which are the local interfaces between the Advanced Metering Management and Smart Meters as well as Load Switching Devices.

Communication between the Advanced Metering Management and the Data Concentrators is through the mobile network, while communication between Data Concentrators and Smart Meters and Load Switching Devices is over power line.

As shown in Figure 1, the Advanced Load Controller computing the switching actions makes use of the AMI infrastructure via an interface to the Load Management System. In order to compute the switching actions, the load controller receives real-time measurements of the distribution transformer power, as well as PV power forecasts, and can access a database of past load and production data. In the pilot project, real-time measurements of a large PV power plant are also available.

In contrast to the ripple control infrastructure, the AMI allows for bidirectional communication and possesses the possibility to control each device individually. Moreover, the AMI-based system has a higher spatial resolution, as the signals are fed into the grid at the low-voltage rather than the medium-voltage level. For these reasons, the AMI allows to use a different control strategy for each low-voltage grid depending on the characteristics of local distributed generation and local weather conditions.

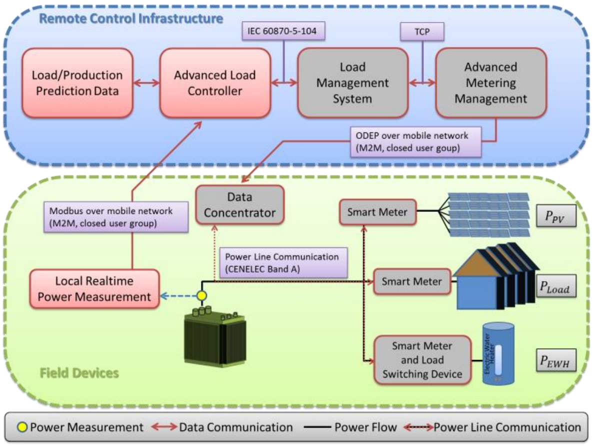

Figure 1: Communication network for demand response based on standard Advanced Metering Infrastructure (in grey).

ADVANCED LOAD CONTROLLER

The basic idea behind demand response for PV integration is to make EWHs consume power locally when there is excess PV generation and thereby minimize rising voltages close to the connection points of the distributed PV plants and limit the power flow into the medium-voltage grid. While voltages in the low-voltage grid are not directly monitored, the presence of reverse power flows acts as an effective proxy in the controller concept, which dramatically reduces the number of required live measurement points. The Advanced Load Controller schedules the EWHs autonomously, based on local PV and load predictions and a real time power measurement on the low-voltage side of the transformer. If a high PV generation is expected, the EWHs are partially or fully switched on during the PV generation peaks. Otherwise, the EWHs are charged during the night only, as in the traditional ripple control setting.

EWHs model

The EWHs are modeled as an energy storage device with rated power P and storage capacity C whose state of charge SOC evolves over time according to

$SOC^{t+1} = SOC^{t} + \frac{P}{C} SOO^{t} - D^{t}$,

where D^{t} represents the hot water draw and the heat losses at time step t, and SOO^{t} the state of operation (on or off). The SOC is a normalized parameter that can take values between 0 and 1.

Since the term D^{t} is not known a priori and is stochastic in nature, an estimation technique will be developed during the course of the project, based on the communicated switching signals and the data collected from the EWH Smart Meters. The Smart Meter data are not received in real-time, but only transmitted once a day. It is not strictly necessary to have dedicated EWH Smart Meters for the proposed control concept to work, but it was important at this pilot project stage, in order to validate and improve the deployed models.
While EWHs are used as controllable devices in this pilot project, since they are the most commonly available flexible load in the pilot grid, the controller concept described here could be applied to other controllable loads with appropriate load modeling.

Control concept

Two control concepts were developed for this project [3] [4]: a heuristic control concept and a model predictive control (MPC) approach [5]. The controller was implemented in the programming language python and runs every 5 minutes.

Heuristic control
In this case, EWHs start being switched on as soon as a reverse power flow is forecasted for the immediate time step. The EWHs are switched on according to a priority list based on the estimated charging time, i.e. the time they would remain consuming power once switched on. The number of EWHs to be switched on depends on the magnitude of the forecasted reverse power flow. As soon as there is no forecasted reverse power flow, the EWHs start being switched off, starting by those who have the lowest estimated charging time. During the night, the EWHs are switched on at predefined times.

Model predictive control
In this approach, at each given time step, an optimization problem with a given horizon (24 hours in this case) is solved. In this optimization the evolution of the state of charge of the EWHs is explicitly modeled and therefore the intertemporal limitations of their flexibility are taken into account. After the optimization problem is solved, the switch on/off control actions computed for the immediate time step are implemented. Then, the state of charge of the EWHs and the load and PV forecasts are updated, and the optimization horizon is shifted by one time step.

In the optimization problem a costs is assigned to:
- switching actions (to avoid performing those actions too frequently),
- electricity consumption, where consumption during night hours has a lower cost than during daytime,
- violations of the maximum transformer power,
- reverse power flows

and the following constraints are considered:
- EWH model,
- transformer power constraints,
- SOC constraints.

PV forecasts

The controller uses commercial PV power forecasts from the company SteadySun. The forecasts combine satellite image processing (for an horizon up to 6 hours) and numerical weather models (for an horizon of up to 48 hours), and are updated every 15 minutes. Based on the measured PV production data, a self-learning algorithm is used to improve the prediction quality.

Load forecasts

Several machine learning techniques were implemented to forecast non-controllable load based on historical data and, optionally, also temperature forecasts: support vector regression, k-nearest neighbor and regression trees [6]. The practical advantage of these machine learning techniques compared to traditional time series models is that they do not require a pre-processing of the input data.

TEST GRID

Table 1 summarizes the most important properties of the test grid. Given the large installed PV capacity, reverse power flows can be observed frequently (around 9% of the time), see Figure 2.

There are 63 customers with EWHs in the test grid, out of which 27 volunteered to participate in the pilot project. Regular customers face a two-level time-of-use tariff, while the pilot customers are always charged with the low tariff. Hence, any economic disadvantage from participating in the pilot project, due to the shift of EWH consumption from nighttime to daytime, is eliminated.

Table 1: Properties of the low-voltage test grid.

Property	Value	Remarks
Transformer	630 kVA	
Installed PV capacity	466 kW	
Load	350 kW summer peak	75 customers
Electric Water Heaters	128 kW controllable, 314 kW in total	27 controllable devices, 63 devices in total

LESSONS LEARNT

Demand Response for PV integration over an existing AMI offers large potential savings. However, the initial IT-integration efforts should not be underestimated. Future deployments of the aforementioned concepts need to be carried out in a standardized process in order to avoid IT costs that overcompensate the savings from grid upgrade deferral. To achieve high reliability for the communication of switching commands, the CENELEC A Band needs to be relatively free of interference. DSOs should therefore have the capability to monitor emissions in that frequency band and be able to implement corrective measures.

Apart from the technical lessons, EKZ was quite positively surprised by customers' enthusiasm to participate in such a pilot project for improved PV integration, which itself speaks for the case of increased customer inclusion.

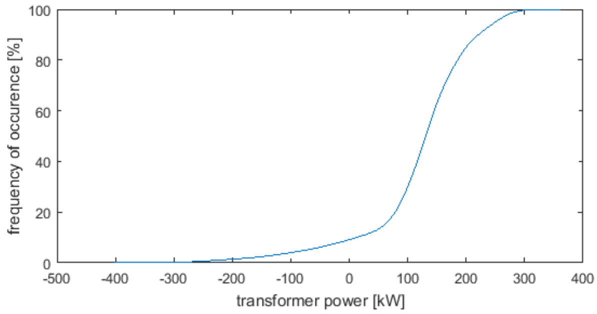

Figure 2 Empirical cumulative distribution function of the test grid transformer power for the period from 25.8.2015 to 10.3.2016.

RESULTS

Simulation results for the test grid assuming a perfect forecast are shown in Figure 3 to Figure 6 for an horizon of 48 hours. In this simulation the 27 EWHs were grouped into five clusters of similar characteristics. On the less sunny first day, where no reverse power flows are expected, the EWHs are charged during the night only. On the second day, as reverse power flows are expected, both the heuristic controller and the MPC controller avoid these by activating EWHs. Both methods achieve a satisfactory performance in this case.

In general, while the heuristic method is simple and might be more robust against modeling errors, it is not forward looking. Therefore, it might activate EWHs too early, using up their flexibility before the critical time of maximum reverse power flow arrives. This is especially relevant on days where the EWH charging capacity is not sufficient to absorb all excess generation from PV – the heuristic would exhibit quite poor performance in those cases, while the MPC can make a best effort in limiting the worst case violations. However, this latter concept may lead to suboptimal results if the predictions and modeling assumptions are not sufficiently accurate. During the pilot project, the performance of both options will be monitored and assessed based on the real life performance.

CONCLUSIONS AND OUTLOOK

This paper presented a pilot project whose goal is to leverage the Advanced Metering Infrastructure currently being rolled out to increase the PV hosting capacity of distribution grids by means of demand response, more specifically by controlling electric water heaters.

During the course of the project different control approaches will be tested, compared and further developed. Therefore, for monitoring and assessment purposes, additional meters were also deployed in the pilot project, in particular dedicated Smart Meters for the electric water heaters. However, the control concept has been conceived in a way that it could also be deployed in other distribution networks in the future, relying solely on the standard Advanced Metering Infrastructure at each household and live measurements at the distribution transformer. Moreover, the concept is not limited to controlling electric water heaters, but can be readily extended to control other flexible loads by introducing appropriate load models.

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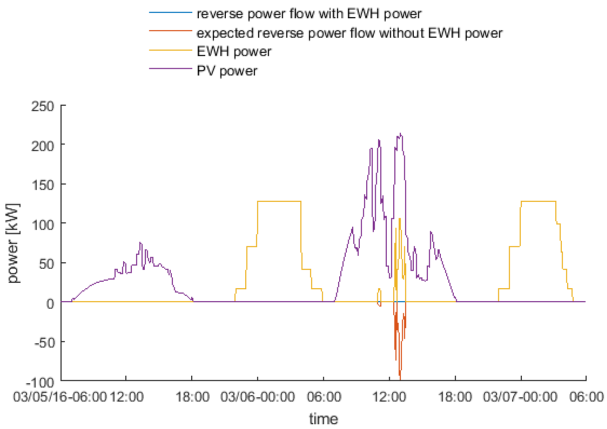

Figure 3 Power profiles with heuristic.

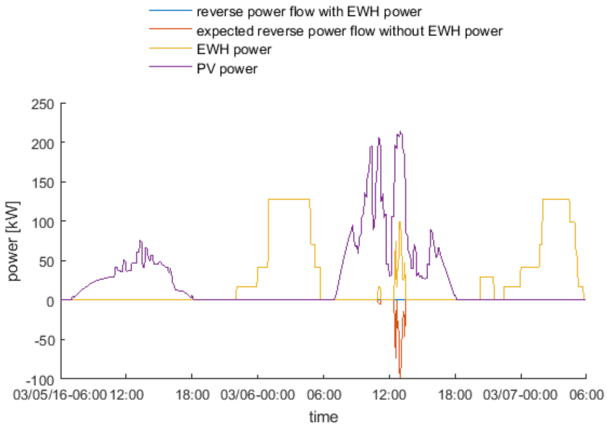

Figure 4 Power profiles with MPC controller.

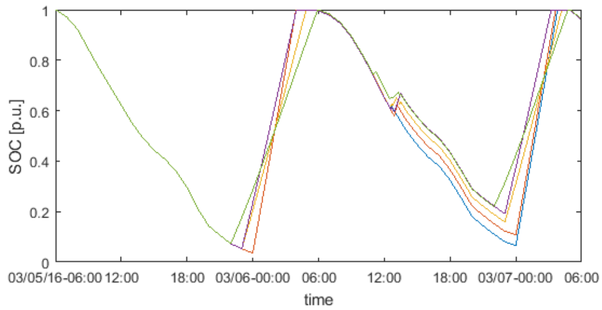

Figure 5 EWH groups' SOC with heuristic.

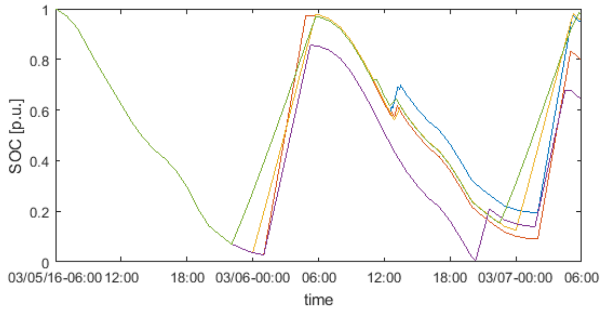

Figure 6 EWH groups' SOC with MPC controller.