Flexible Scheduling of Residential Energy Loads, the Optiflex concept

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Abstract

In the context of the Optiflex project, we consider the problem of dispatching grid loads in presence of energy production coming from renewable sources. As renewables are mostly weather-dependent and therefore massively and quickly fluctuating, the imbalance between production and consumption, the over voltage and overload of grid components are just a few of implications. One of the technical measures for mastering these challenges is the intelligent management of available flexibilities in the grid. In order to let the distribution system operators face this challenge, a concept aimed to actively control heat pumps and electric heaters is proposed. This concept is concretised in four main steps: power profile disaggregation of the controllable flexibilities, photovoltaic power prediction, power demand estimation of the controllable loads, and loads actuation scheduling.

Keywords

Smart Grid, Algorithms, Disaggregation, Demand, Forecast, Scheduling, Optimization

1. Introduction

Production of energy from renewable sources has been growing constantly in the past few years. Today, renewables constitute a substantial part of the electric energy production in Switzerland and in several other European countries and will continue to grow in the coming years and probably even decades (e.g., in Switzerland refer to the "Energy Strategy 2050" [1]).

Since the energy production from renewable sources is mostly weather-dependent and therefore massively and quickly fluctuating, various challenges arise. Unbalance between production and consumption, overvoltage and overload of grid components are just a few of them. One of the technical measures for mastering these challenges is the intelligent management of available flexibilities in the grid. With the OptiFlex project (Innosuisse, 43383.1 IP-EE) we want to use the already installed Smart Metering base as measurement, communication and switching infrastructure, without the need of any additional hardware, containing investments for Smart Grid use cases. In a first step we want to control flexibilities for distribution grid purposes only.

The general approach and a description of the algorithms will be presented in the next sections.

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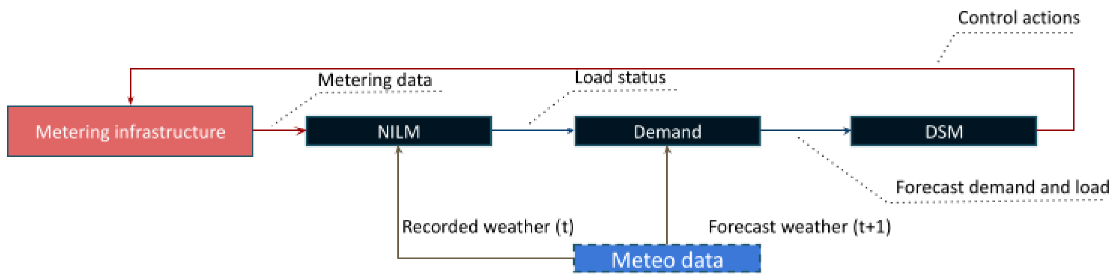

Figure 1: Schematic representation of Optiflex.

2. Methodology

Distribution System Operators (DSO) can adopt two different approaches in order to control household flexibilities: decentralized or centralized. Both having pros and cons.

The decentralized approach consists of controlling the loads in a distributed way, installing additional plug-on electronic units which measure electrical parameters of the controllable loads, such as voltage, current and frequency, calculate energy needs and production forecasts, and according to the best possible scheduling, controls the household devices autonomously [2]. This approach allows for a direct interface with the device, and very detailed measurements (in the order of 1Hz), allowing the status (on/off) of the device to be known. Disadvantages arise when this solution has to be scaled up: the installation can not always be executed in one step (i.e. one visit), the mounting is not everywhere easily possible (e.g., old buildings), the production of a wide range of devices and the unit maintenance are costly, since hardware failure and necessary replacements may occur. Furthermore, a sort of coordination mechanism is still needed to mitigate network unbalances, overvoltages and overloads. This coordination requires a telecommunication network to be in-place.

These disadvantages could be overcome by a centralized approach, since there is no need to install further hardware components. Indeed, current smart-meter technology is able to communicate detailed enough power measurements and act on local switches. Centralized algorithms are able to orchestrate the flexibilities to meet the goals of grid stability. On the side of disadvantages, managing the massive data flow generated by all smart meters deployed in a grid and collect them in a centralized database is a challenge which may hinder the success of centralized approaches.

3. Algorithms

A simplified representation of the Optiflex suite of modules and their interaction is reported in "Figure 1".

The metering infrastructure feeds metering data into the system, data is processed to understand loads' behavior with the Non-Intrusive Load Monitoring (NILM) component according to past weather data. Load behavior is then used to train a demand model able to forecast future needs according to future weather forecasts. Finally, grid loads are steered by a Demand Side Management (DSM) component and the process is continuously iterated.

3.1. Non-Intrusive Load Monitoring (NILM)

NILM is necessary when electrical loads are not directly monitored but an estimate of their use is needed. Commonly, the smart-metering infrastructure provides the necessary measurements at the Point of Common Coupling (PCC) of each household, that are composed of active and reactive power measurements as well as voltages and currents. The purpose of NILM is to detect the activation of major controllable loads (normally heat pumps and domestic water heaters) that can be steered via the actuators installed at the smart-meter and separate their power foot-print from the other loads that are considered as uncontrollable.

Non intrusive load monitoring has been studied since the 90s [3]. Extensive reviews of such algorithms are provided, for instance, by Zoha et al. [4] and by Zeifman & Roth [5].

The main issue to implement effective disaggregation algorithms is the sampling frequency. While the majority of the approaches rely on sampling rates in the range from 0.1 Hz to 1 Hz, in Optiflex we deal with much lower sampling frequencies in the order of one sample per minute.

In this context, our purpose is to control a pre-defined set of flexibilities, in particular heat pumps and electric heaters, for which we know the nominal power and the relay status with a 5 minutes resolution, in addition to the meter power profile.

Given these data, the disaggregation algorithm aims to detect whether a flexibility has been absorbing power or not during a given time interval. The approach is described in detail in [6], it builds on previous work [7], [8], [9] and it is also inspired by recent research from Bu et al. [10].

3.2. Irradiance estimator - Photovoltaic production forecaster

The irradiance estimation algorithm has been designed and implemented to tackle the issue of missing direct monitoring of photovoltaic (PV) installations and the presence of inaccurate weather data (global irradiance measurements). In presence of either direct PV monitoring or accurate weather data, the algorithms infrastructure is designed in order to use the real data.

The irradiance estimation algorithm has been inspired by the approaches presented in previous works [11], [12]. Differently than our approach, in these studies, the PV production is generated from a set of reference PV installations under clear sky conditions.

The basic idea of our approach is to exploit the (negative portion of the) power reading of a set of meters in a *neighborhood* monitoring PV installations together with domestic loads exploiting the assumption that PVs are exposed to similar irradiation conditions. The methodology uses a popular software library (PvLib, a community supported tool that provides a set of functions and classes for simulating the performance of PV energy systems).

Irradiance estimation is obtained with the following procedure:

- Compute the Global Horizontal Irradiance (GHI) in clear sky conditions (GHI*) of the considered neighborhood over a defined period of time discretized in time steps (e.g., the past 24 hours).

- For each PV installation, compute a scaling factor of GHI*, for each time step, so that the estimated production matches the power reading of the meter.
- For each time steps, among the scaling factors of all PV installations, retain the maximum.
- Use the retained scaling factors to estimate the irradiance from GHI*.

The rationale behind this approach is that not all major loads are absorbing power simultaneously and the effect of PV installations is directly visible in the metering data. The approach is detailed in [6].

3.3. Demand estimation

With demand estimation it is intended the task of predicting the time-dependent needs of a flexibility to be connected to the grid, that is the amount of time a flexibility must be allowed to drain power from the grid in different moments of the day. More formally, we aim to predict the future power usages of a flexibility $y_t, y_{t+1}, ..., y_{N-1}$ using the output of the disaggregation algorithm that estimates past power usages $y_{t-m}, y_{t-m+1}, ..., y_{t-1}$, where M is the number of historical data used to forecast, and N is the number of future values being forecast.

There are several forecasting methods available, namely: moving average, seasonal method with error correction, autoregressive model, autoregressive integrated moving average model, function fitting neural network, and nonlinear autoregressive neural network. In the current implementation of Optiflex, we devised a software architecture capable of using different techniques with minor implementation effort. We currently provide a demand estimation algorithm which hybridizes a seasonal method with a simple classification method.

Seasonal method: we assume that demand has daily-seasonal patterns. Thus, this method predicts the future demand values by computing statistical distributions for the values at the same time point in previous days. Let m be the period of the seasonality $l = \frac{M}{m}$ be the number of available seasonal data, and the future values.

As an example, average values can be then computed by:

$$\hat{y}'_{t+i} = \frac{\sum_{j=1}^{l} y_{t+i-jm}}{l}, \quad i = 0, 1, ..., N-1 \tag{1}$$

Classification method: the output of the disaggregation is a data sample that is used to calibrate a seasonal model, we hybridize the seasonal method with a simple classification method, thus obtaining multiple seasonal models, one for each class. Fundamentally:

- We define a set of classes $C \cup \{c_0\}$, where c_0 is a base class
- We classify the sampling data as belonging to two classes c_j and c_0
- We update the seasonal data of classes c_j and c_0
- We predict the class of the future power usages and predict using the appropriate seasonal model

The method is generic (classes can be defined in several ways) but in the current implementation of Optiflex we use four classes + the base class (class 0).

The classification method is based on aggregated daily weather data: average daily temperature, average daily irradiance. To classify samples, we use static data associated to the location

Table 1
Classification rules

	Daily T avg $\geq$ Monthly T avg	**Daily T avg $<$ Monthly T avg**
Daily I avg $\geq$ Monthly I avg	Hot – Sunny day	Cold – Sunny day
Daily I avg $<$ Monthly I avg	Hot – Cloudy day	Cold – Cloudy day

of the pilot site: average monthly temperature, average monthly irradiance. The four classes intuitively correspond to "Hot - Sunny", "Hot - Cloudy", "Cold - Sunny", and "Cold - Cloudy" days.

Classification is then performed as in "Table 1" where letter I stands for Irradiance and letter T stands for Temperature.

3.4. Scheduler

Scheduling is the final component of the Optiflex algorithmic pipeline. Its basic purpose is to steer controllable flexibilities in order to optimize some objective functions (peak shaving in the current implementation). Flexibility steering is subject to some functional constraints that must be respected.

The scheduling algorithm (scheduler in short) is centralized. It means that it simultaneously considers the entire set of controllable flexibilities. It implements a Model Predictive Control scheme, in summary, it considers the control actions over a future period of time called planning horizon and it actually implements only a smaller portion of the control actions called control horizon and the process repeats when the control horizon is elapsed. The planning horizon is defined as a discretized time interval T divided in timeslots (24h, discretized in 288 timeslots of 5 minutes each in the current implementation of Optiflex) and the control horizon is 1 timeslot. The control actions are therefore discretized and assumed constant during each timeslot. Control actions can be categorized as follows:

- Binary control actions: related to the control of a power switch. 1: flexibility connected to the grid, 0: otherwise.
- Continuous control action: this is normally related to a power setpoint of the flexibility (commonly associated with storages or chargers), values are bound to operational constraints of the flexibility.

The scheduler has to respect some constraints operating the flexibilities. In particular for binary flexibilities, the amount of time the flexibility is connected to the grid must be sufficient to ensure that the flexibility can satisfy the energy demand. Furthermore the flexibility should not change its state too frequently and too many times during period T in order to preserve the lifetime of the physical switch.

For continuous flexibilities, the scheduler must maintain the state of the flexibility within bounds and reach the desired state at time t.

The scheduler considers the behavior of the rest of the grid in order to account for the uncontrollable portion of the power the model considers an aggregated signal. The software architecture of Optiflex, as done for demand estimation, allows to use modular implementations of the scheduler. For moderate sized pilot sites (hundreds of flexibilities) an exact approach based on a MILP formulation is used. For larger pilot sites (thousands of flexibilities) a fast optimizer based on local search heuristics is used.

4. Results

The challenges tackled and solved by the Optiflex project are manifold:

- Manage the massive data flow generated by all smart meters deployed in a grid, by collecting them in a centralized database, along with the metadata of each flexibilities (i.e. nominal power).
- Analyse the measurements to determine the behavior of the flexibilities present in the grid and proactively control them to meet the goals of grid stability, by developing a set of algorithms able to identify the power profile of each controlled flexibility, estimate the power consumption of the next 24 hours and steer the loads by meeting the energy demand.
- Integrate weather forecasting data to predict future behavior of the loads and power generation in the grid, especially due to PV production, in order to take proactive measures to compensate excess of power production or power consumption.
- Provide grid managers a functional environment to monitor and control the behavior of the grid.

These results have been achieved by testing this concept in distribution network of a local DSO in Massagno, Ticino, Switzerland. The algorithms have been designed in order to be exploited on different size of the network and to be deployed in the entire grid or even in one or more subregions in parallel. The pipeline has been firstly tested with the help of a comprehensive low voltage simulation framework called OPTISIM and developed within SUPSI [13], in order to validate the robustness over long periods and to compare the test-set without algorithms and with algorithms acting on controllable loads. The designed test-set is calibrated on a district of the local DSO grid. The community includes the following characteristics:

- A 30 kWp public PV plant (on the kindergarten)
- 18 single family houses with:
  - 3 PV plants (32.76 kWp)
  - 10 heat-pumps
  - 26kW of electrical heater
- A 50 kWh battery installed at the public PV plant location

In “Figure 2” we report the overall active power of the test-set. It ranges approximately from -20kW to 80kW. In the top sub-plot we report the overall power when all loads are not controlled and can freely absorb power when necessary. In the bottom sub-plot we report the overall power when all flexibilities are controlled by Optiflex. We observe a pattern for the uncontrolled case where loads tend to accumulate during morning and evening hours forming power peaks.

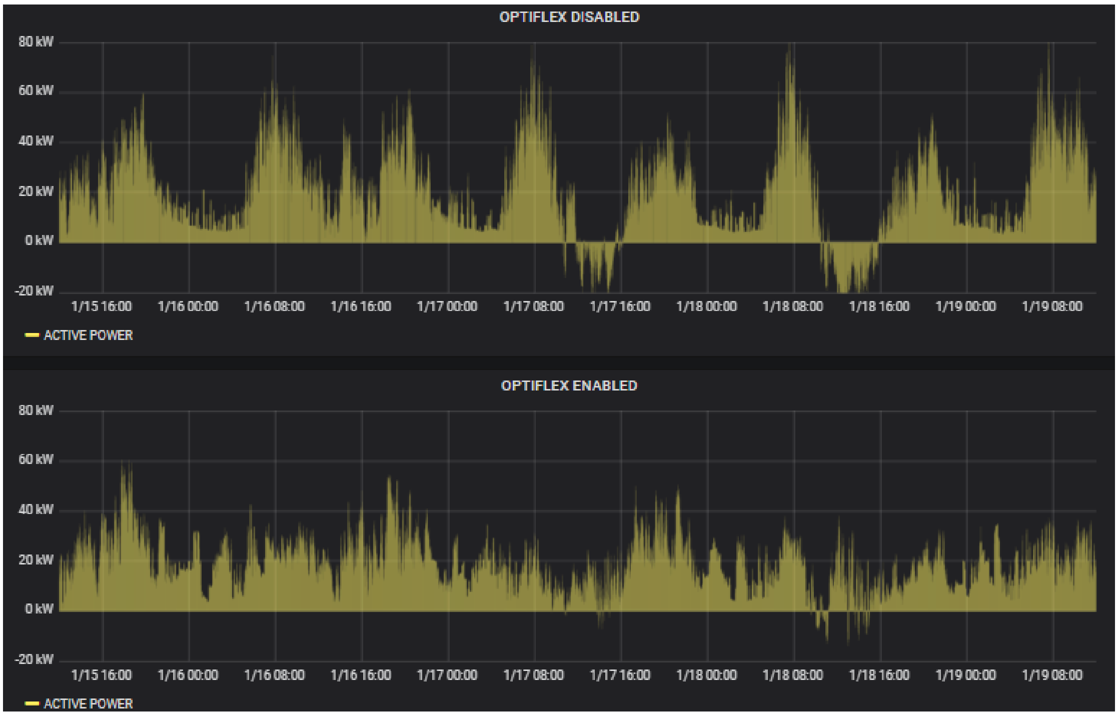

Figure 2: Simulation results.

We then observe that Optiflex is capable to prevent the formation of such high peaks by spreading loads along the day. We report that the overall energy provided on a daily basis for the test-set does not differ between the two settings, that is all loads are absorbing the same amount of energy. From a preliminary analysis of the test-set we observe KPI peak reductions of 30-40% with cases of peak reduction of up to 50%.

Simulation was followed by deploying the algorithms in the field, where a test phase on the same simulated grid is still running. In parallel, scale up tests are being carried out in wider regions. The first region is composed of 2 transformer stations, 373 meters and 155 flexibilities (73 heat pumps, 60 boilers and 22 PVs), and the second matches the entire DSO network, where the data available in the database at this time are 72 transformer stations, 9526 meters and 1481 flexibilities (388 heat pumps, 828 boilers and 265 PVs).

5. Conclusions

The Optiflex solution aims at the exploitation of Smart Metering technology, i.e. the possibility of modern energy meters to communicate detailed measurements of the energy flow and the capability of acting on local switches, to intelligently manage the available flexibilities in the grid such as electrical loads and energy storages in a centralized way, to make the electrical grid more robust, smoothly integrate distributed energy production and minimize energy losses due to high power peaks. This centralized implementation allows a lower investment by the DSO to meet the goals of grid stability, as it is not necessary to install and maintain distributed hardware components, making deployment on different pilots less wasteful.

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