

# Using Flexibility Information for Energy Demand Optimization in the Low Voltage Grid

Sandfordf Bessler<sup>1</sup>, Domagoj Drenjanac<sup>1</sup>, Eduard Hasenleithner<sup>1</sup>, Suhail Ahmed-Khan<sup>1</sup>  
and Nuno Silva<sup>2</sup>

<sup>1</sup>FTW Telecommunications Research Center, Donau-City 1, A-1220 Vienna, Austria

<sup>2</sup>EFACEC Energia Máquinas e Equipamentos Eléctricos, S.A, PO Box 3078, 4471-907 Moreira Maia, Portugal

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**Abstract:** Flexibility information that characterizes the energy consumption of certain loads with electric or thermal storage has been recently proposed as a means for energy management in the electric grid. In this paper we propose an energy management architecture that allows the grid operator to learn and use the consumption flexibility of its users. Starting on the home asset level, we describe flexibility models for EV charging and HVAC and their aggregation at the household and low voltage grid level. Here, the aggregated energy controller determines power references (set points) for each household controller. Since voltage limits might be violated by the energy balancing actions, we include a power flow calculation in the optimization model to keep the voltages and currents within the limits. In simulation experiments with a 42 bus radial grid, we are able to support higher household loads by individual scheduling, without falling below voltage limits.

## 1 INTRODUCTION

The intensive deployment of photovoltaic based power generation modules in private homes has caused the most Distribution System Operators (DSO) to come out with rules to limit installations that would otherwise further increase the voltage and the power injection into the grid during the sunny hours. In the same time, a number of flexible loads such as HVAC for heating, air conditioning, combined heat pumps, and electric vehicles multiply the actual peak household consumption from 2kW to 7 kW, a level which, if reached simultaneously by many consumers, would create overload problems in the grid.

At the basis of this work, we use the concept of power and energy flexibility for consumption, generation or storage, as valuable information to be exchanged between the grid actors. In this way, the flexibility information reported by a distributed energy resource (DER) can be used for direct control by a DSO, a utility or a third party aggregator. For allowing this kind of remote intervention, the DER owner would benefit monetarily, however the contract and tariff aspects are beyond the scope of this paper.

The main objective of this work is to investigate the feasibility of a (low voltage) grid environment,

in which flexible assets report (future) flexibility information to a grid level controller, which uses it to schedule the power level of those assets optimally. Flexibility information and actuation form a demand response closed loop in which asset models are used to predict the load, see (Palensky and Dietrich, 2011) for a comparison of demand response schemes.

The major contributions of this work are:

- to define flexibility models for EV charging, heating ventilation and air conditioning (HVAC) and aggregate them to home or customer energy management system (CEMS) flexibility,
- to formulate a CEMS optimization model that uses the flexibility to control its flexible assets,
- to formulate the optimization model of an aggregation controller,
- to build and evaluate a system of communicating controllers that optimally schedule the consumption/generation in a low voltage grid.

### 1.1 Previous Work on Flexibility

With the emergence of Distributed Energy Resources (DER) in the last two decades, the decentralization of

the energy network has started. Within their work to integrate the DER into the energy network, the M490 Working Group (SG-CG/RA and SG-CG/SP) introduced the concept of flexibility, which combines the consumption, production and storage into one flexibility entity. Within the five layer Reference Architecture specified in the Smart Grids Architecture Model (SGAM) (SGAM, 2012), the flexibility interfaces are situated in the Information layer (where the data models are situated) and the Communication layer (where the protocols for interoperability are situated) (Orda et al., 2013). The flexibility interface conveys the characteristics that a DER exposes to an aggregator or virtual power plant. DERs are equipped with local controllers that follow also local goals, (Biegel et al., 2013). An aggregator manages multiple DERs.

Flexibility concepts have been used in the context of electric vehicle charging (Lopes et al., 2011) and flexible home consumption. (Sundström and Binding) use the energy stored in the EV fleet and the bounds of this energy to optimize the charging schedules at the fleet (aggregator) level. In (Binding et al., 2013) the authors present FlexLast, a solution for management the consumption of power for cooling in supermarkets, based on the flexibility reporting and control. Energy prices together with flexibility information have been used in a scheduling model in (Tušar et al., 2011). The Danish project iPower, see (Harbo and Biegel, 2013), goes a step further by defining flexibility services contracted between players in which the aggregator manages a portfolio with flexible consumers with low marginal flexibility costs.

The rest of the paper is organized as follows: in Section 2 we define the flexibility of a charging EV, an HVAC used for house heating and aggregate them to household flexibility. In Section 3 we describe the system architecture and introduce the optimization problem at the household level. In Section 4 we introduce the LV aggregation controller and formulate the scheduling problem at the LV grid level. In Section 5 we report on numeric experiments in the simulation environment and discuss the results. Finally we conclude and present directions for further research.

## 2 FLEXIBLE ASSET MODELS

A DER exposes flexibility information in order to allow a planning and scheduling algorithm to control by means of setpoints the amount of energy in time that flows from or to that asset. The time is discretized to  $N$  periods of duration  $T$ , where  $N = 0, 1, \dots, N-1$  is the set of periods defining a forecast time horizon of duration  $NT$ . In order to calculate the asset flexibility,

a model of consumption and storage of energy will be used. It is important to mention that the considered processes are relatively slow, they do not "see" transients, abrupt voltage or power changes, therefore the mechanisms proposed are not suitable for voltage control. If the period  $T$  is set to 15 minutes, the consumed power of an asset during this period is the average power in this interval, etc.

In the next subsection we present simple asset models: the electric vehicle and the HVAC used here for heating a house. In the rest of the paper we will use the following notation for the energy flexibility  $\underline{E}_j^{asset}$  and  $\overline{E}_j^{asset}$ , and for the power flexibility  $\underline{P}_j^{asset}$  and  $\overline{P}_j^{asset}$ , where  $j$  is the time period index, and the underline/overline notation means the minimum respectively maximum flexibility.

### 2.1 The Electric Vehicle (EV) Predictive Load Model

In a simplified world, an EV  $i$  that is charged at a charging point is a load which can be activated from the plug-in time until the leave-time. In a residential scenario the plug-in and plug-out/leave time at the charging point can be individually configured or gained from history data, whereas in case of public charging stations, reservations can provide in advance information about the expected load. In this paper we will restrict to the residential case in which the EV is controlled by the Customer Energy Management System (CEMS).

The charging power varies from period to period,  $p \in [0, P_{max}]$ , but is constant during a period. At the end of the stay, the total charged energy amount should be between a minimum demand and a maximum demand value (full charged):  $E^{EV} \in [D_{min}, D_{max}]$ . This provides additional freedom in the charging process and expresses the fact that users do not have to fully charge the battery.

The energy flexibility is initially zero and represents the *cummulative* energy charged by the EV. The convention used is that the power consumed during period  $i$  corresponds to the cummulative energy at the end of this period. Figure 1 illustrates the flexibility of a charging load with  $P_{max}^{EV} = 8$  kW,  $D_{min} = 4$  kWh and  $D_{max} = 8$  kWh. In Figure 1 we depict the minimum and maximum energy for the next eight periods, calculated one period before EV arrival and 2 periods later, where 2.5 kWh have been actually charged.

If we denote the already charged energy with  $D_c$ , the arrival period with  $a$  and the leave period with  $l$ , then the maximum power and energy flexibility are

$$\bar{P}_j^{EV} = \begin{cases} P_{max}, & \text{if } \bar{E}_{j-1}^{EV} + TP_{max} < D_{max} - D_c. \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

$$\bar{E}_j^{EV} = \bar{E}_{j-1}^{EV} + T\bar{P}_j^{EV}, j = a, \dots, l \quad (2)$$

The minimum flexibility represents the latest time to start charging in order to satisfy the remaining demand  $D_{min} - D_c$

$$\underline{P}_j^{EV} = \begin{cases} P_{max}, & \text{if } l - [(D_{min} - D_c)/T/P_{max}] \leq j < l. \\ 0, & \text{otherwise.} \end{cases} \quad (3)$$

$$\underline{E}_j^{EV} = \underline{E}_{j-1}^{EV} + T\underline{P}_j^{EV}, j = a, \dots, l \quad (4)$$

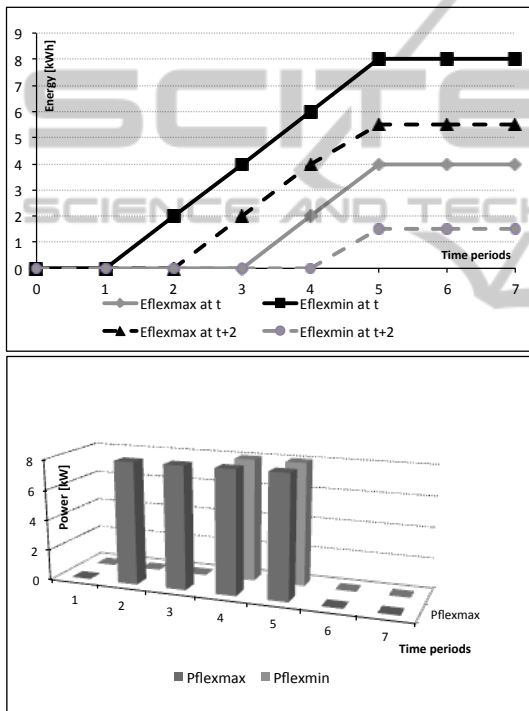


Figure 1: EV energy flexibility at time  $t$  and  $t+2$  (top) and power flexibility (bottom).

## 2.2 The HVAC Predictive Load Model

Heating, ventilation and air condition are good examples of thermal storage. Since a house is a complex thermal system, a complete theoretical approach of formulating the model is impractical. We use however the first law of thermodynamics to describe energy consumption and storage capacity of a simple house that consists of a two floors detached house placed in Austria with a total size of  $128 \text{ m}^2$ . Moreover, the house is well isolated and the majority of windows are facing south resulting in a total annual energy demand of around  $60 \text{ kWh/m}^2$ . The mathematical equation,

based on the first law of thermodynamics, describing the major thermal effects in the house is:

$$E^P + E^a + E^s + E_i^h - E^v - E_i^{trans} = mc\Delta Temp_i \quad (5)$$

where

- the heating energy at time  $i$  is  $E_i^h = z_i P^{HVAC} T$ , where  $z_i \in \{0, 1\}$  is the control signal in period  $i$ ,
- $E^P$  is the energy (heat) generated by the presence of people in the house, in our case 256 Wh,
- $E^a$  is the caloric energy generated by appliances and lights; for  $3 \text{ W/m}^2$ , we obtain  $E^a = 384 \text{ Wh}$ ,
- $E^s$  is the energy received from sun (assuming 40% glass surface, south orientation), in our case 560 Wh.
- $E^v$  is the energy lost via ventilation that depends on the temperature difference between inside and outside,  $E^v = 45 \text{ Wh}$ ,
- $E^{trans} = UP\Delta Temp_i$  is the energy lost due to window and wall conductivity at time  $i$ .  $U[\text{W/m}^2/\text{K}]$  is a measure of the thermal resistance and  $P[\text{m}^2]$  is the surface of the specific material,  $\Delta Temp_i$  is the temperature difference to outside.

Using the equation (5), the model estimates the inside temperature for the planning horizon, based on a heating schedule. A temperature range of e.g 18 – 22°C determines the point in which heating has to be switched on, respectively has to be switched off.

In order to calculate the flexibility, the HVAC uses the current state: for the maximum flexibility it can heat continuously up to the maximum temperature, then keep the upper limit. For the minimum, it can remain off, until the lowest temperature is reached, then it must heat for a minimum time. The energy flexibility is shown in Figure 2:

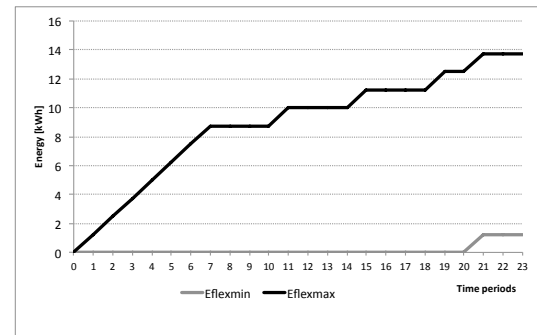


Figure 2: 5kW HVAC energy flexibility.

Given the ON-OFF operation of the HVAC heating in this example, the power flexibility is straightforward:  $\underline{P}_j^{HVAC} = 0$  and  $\bar{P}_j^{HVAC} = P^{HVAC}$ , the heating power.

In the considered smart households, photovoltaic power generation is also available. Although this energy cannot be stored, the generated active power can be derated and/or curtailed. For a simple active power control, the ideal photovoltaic output  $p$  is first limited by the inverter maximum power,  $P_{rated}$ .  $P^{gen} = \min(P_{rated}, \eta AI_{solar})$ , where  $\eta$  is the efficiency of the solar cells and  $A$  is their area in  $m^2$ . To control a certain range of this power output, we introduce the generation factor  $gf \in [gf_{min}, 1]$  with  $gf_{min} < 1$ . For an available power  $P^{gen}$ , the PV generates therefore the power  $p = gf P^{gen}$  with  $gf_{min} P^{gen} \leq p \leq P^{gen} \leq P_{rated}$ . This model can be easily mapped to the industrial modes of control using derated power and curtailing (Pedersen et al., 2014).

Finally, in the household there is also the non-flexible consumption, which is characterized by an individual profile  $P^{load}$ . In order to calculate the aggregated energy flexibility, we define the aggregated power flexibility of the household (here identified at the level of the customer energy management system, CEMS) at the time period  $i$  as follows:

$$\underline{P}_i^{CEMS} = \max(-P_M^{CEMS}, P_i^{load} + \underline{P}_i^{EV} + \underline{P}_i^{HVAC} - P_i^{gen}) \quad (6)$$

$$\bar{P}_i^{CEMS} = \min(P_M^{CEMS}, P_i^{load} + \bar{P}_i^{EV} + \bar{P}_i^{HVAC}), i \in N \quad (7)$$

where  $P_M^{CEMS}$  is the maximum allowed consumed/generated power by the household, for instance 6.9 kW.

For the energy flexibility, the following recurrence is used

$$\underline{E}_i^{CEMS} = \underline{E}_{i-1}^{CEMS} + \underline{P}_i^{CEMS}, i \in N - \{0\} \quad (8)$$

$$\bar{E}_i^{CEMS} = \bar{E}_{i-1}^{CEMS} + \bar{P}_i^{CEMS}, i \in N - \{0\} \quad (9)$$

with initial  $\underline{E}_0^{CEMS} = \underline{P}_0^{CEMS}$ , and  $\bar{E}_0^{CEMS} = \bar{P}_0^{CEMS}$

### 3 ENERGY MANAGEMENT ARCHITECTURE

We consider a radial low voltage grid supplying a residential area, where each home is configured with the assets described in the previous sections: an HVAC used for heating, an EV charging point, PV generation and non-flexible loads. These assets are connected to a local controller, the CEMS, via a bidirectional data interface. The assets deliver flexibility information to the controller, and the controller calculates a control signal, specific for each asset type, as will be presented in detail in the modeling section. In a further aggregation step, the CEMS controllers communicate

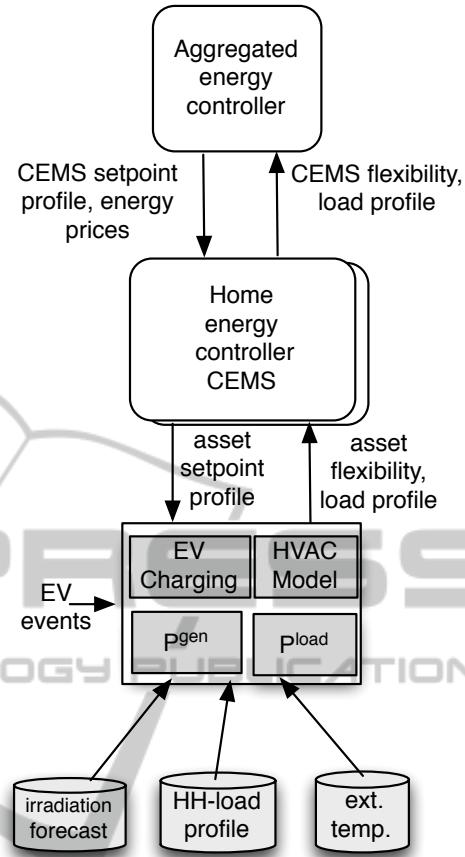


Figure 3: Energy Management Architecture.

with an aggregation controller, as depicted in Figure 3.

The bidirectional interface between the LV energy controller and the CEMS controller consists of following pieces of information:

- power flexibility and energy flexibility profile (from CEMS)
- preferred load trajectory (from CEMS)
- setpoint trajectory (to CEMS)
- market clearing energy prices (to CEMS)

#### 3.1 CEMS Energy Optimization

As mentioned at the beginning, the basic idea of reporting flexibility is to transfer the control of the house energy management up to a certain extend to the DSO or to an entity that participates in the energy market, but in the same time to follow local management goals.

The result is a multi-objective function with three terms which can be weighted differently in order to investigate the solution properties. The first term in

(10) makes the CEMS to follow the setpoints imposed at the LV grid level, and does so by minimizing the deviation between the CEMS net consumption (or injection in the grid) and the CEMS setpoint reference  $P^{ref}$ , similarly to the objective used in (Sundström and Binding),(Molderink et al., 2010). The second term maximize the own generated power  $gfP^{gen}$  over the prediction time horizon, so that more energy is locally stored. Finally the third term uses the day-ahead prices to minimize energy cost. The MCP (market clearing prices)  $c_j$  are published and available the day before, for the whole grid. Even if the household does not have an immediate monetary advantage for consuming more when the price is low, high prices correlate to peak demand that we want to penalize in the objective function. As the prices are positive, the minimization goal in (10) will cause the reduction of total energy consumption, an effect that is not always desired. For instance in the EV case, this would cause that the charging will stop once the minimum demand  $D_{min}$  is reached. To solve this problem we have to bias the price values around an average (the base value), leading to positive and negative values of  $c_j$ . The state variables and control signals are defined as follows:

Table 1: Notation summary.

Notation	Description
$y_j$	charging power in kW during j
$z_j$	HVAC heating binary control in j
$gf_j$	generation factor
$E_j^{EV}$	EV charged energy until j
$E_j^{HVAC}$	energy (thermic) stored at time j
$P_j^{in}$	net power from or to the grid
$P_j^{in+}$	$P_j^{in+} = P_j^{in}$ if $P_j^{in} > 0$ and zero else.
$P_j^{load}$	the non-flexible load
$E_j^{trans}$	lost energy through walls see (5)
$c_j$	MCP energy prices every 15 minutes

The optimization program in Equations (10) - (18) is quadratic and has integer (binary) variables. The constraint (11) expresses the power flows balance at the house grid connecting point. The constraints (14) and (15) express the accumulation of energy in the battery, such that it has to be within the flexibility limits. Similarly, the HVAC in constraints (13) and (17).

minimize

$$K_1 \left( \sum_{j \in N} (P_j^{in} - P_j^{ref})^2 \right) - K_2 \sum_{j \in N} gf_j P_j^{gen} + K_3 \sum_{j \in N} c_j P_j^{in+} \quad (10)$$

subject to:

$$P_j^{in} + gf_j P_j^{gen} - y_j - P_j^{load} - z_j P^{HVAC} = 0, j \in N \quad (11)$$

$$0 \leq y_j \leq P_{max}^{EV}, j \in N \quad (12)$$

$$z_j \in \{0, 1\}, j \in N \quad (13)$$

$$E_j^{EV} = E_{j-1}^{EV} + y_{j-1} T, j \in N - \{0\} \quad (14)$$

$$\underline{E}_j^{EV} \leq E_j^{EV} \leq \bar{E}_j^{EV}, j \in N \quad (15)$$

$$E_j^{HVAC} = E_{j-1}^{HVAC} - E_{j-1}^{trans} + E^{pasv} + z_{j-1} P^{HVAC} T \quad (16)$$

$j \in N - \{0\}$

$$\underline{E}_j^{HVAC} \leq E_j^{HVAC} \leq \bar{E}_j^{HVAC}, \quad j \in N \quad (17)$$

$$gf_{min} \leq gf_j \leq 1, j \in N \quad (18)$$

The results of the CEMS optimization are:

- a plan of the preferred net power consumption or power injection in the grid  $P_j^{in}, j \in N$ .
- a plan for the control actions: a)  $z_j, j \in N$  towards the HVAC, b)  $y_j, j \in N$  towards the EV charging point, c)  $gf_j, j \in N$  towards the PV inverter.

## 4 AGGREGATED ENERGY MANAGEMENT IN THE LV GRID

In this section we describe the model of the aggregated energy controller, see Figure 3. Its main role is to schedule the house loads, i.e. to decide which of the houses require high consumption during each time period. The problem is that, the knowledge of the total load alone does not guarantee that the voltage limits at the buses and the current limits in the feeders and at the transformer are respected. This is the reason for including information of the grid topology and the optimal power flow calculation in the optimization model.

The key idea is to take the total power and to distribute it in such a way that the resulting CEMS *setpoints* correspond to allowed voltages and currents. The assumption that also the real loads on the households lead to admissible voltages is of course only true, if the setpoints are closely followed by the household actual loads.

The proposed OPF (optimal power flow) optimization is repeated for each period j of the planning time horizon. We assume for the sake of simplicity

that a single household is attached to a bus in the radial LV grid. In practice, we assign to each bus several households (or CEMS controllers) to be individually controlled. Let  $B$  be the set of buses (households). Based on the preferred load trajectory  $P_i^{in}, i \in B$  received from the CEMS, we define the variable  $\beta_i$ , as the additional power required to obtain the setpoint for bus  $i$ , therefore  $P_i^{ref} = P_i^{in} + \beta_i$ .

As for the CEMS, the objective (19) of the optimization problem has two terms: a) to minimize the total squared error between offered loads on the buses and the estimated setpoint values, and b) to minimize the setpoint fluctuation between subsequent time periods. For the latter goal, we store the setpoint calculated for  $j-1$  and use it in period  $j$  as  $P_i^{ref-}$ .  $\alpha$  is a parameter to tune the relative importance of the goals. For each period  $j$  we solve therefore the following problem:

minimize

$$\alpha \sum_{i \in B} \beta_i^2 + (1 - \alpha) \sum_{i \in B} (P_i^{in} + \beta_i - P_i^{ref-})^2; \quad (19)$$

subject to:

$$P_i^s - (P_i^{in} + \beta_i) - \left( \sum_{(i,j) \in Y} V_i V_j (G_{ij} \cos(\phi_i - \phi_j) + B_{ij} \sin(\phi_i - \phi_j)) \right) = 0, i \in B \quad (20)$$

$$Q_i^s - Q_i^{in} - \left( \sum_{(i,j) \in Y} V_i V_j (G_{ij} \cos(\phi_i - \phi_j) + B_{ij} \sin(\phi_i - \phi_j)) \right) = 0, i \in B \quad (21)$$

$$V_{min} \leq V_i \leq V_{max}, i \in B \quad (22)$$

$$\beta_i \leq \bar{E}_i^{CEMS} / T - \sum_{k \in N | k \leq j} P_{ki}^{in}, i \in B \quad (23)$$

$$\beta_i \geq \underline{E}_i^{CEMS} / T - \sum_{k \in N | k \leq j} P_{ki}^{in}, i \in B \quad (24)$$

In the Kirchoff equations (17) and (21), the voltages  $V_i$  and the angles  $\phi$  are variables, in addition to  $\beta_i$ .  $Y$  is the set of index pairs required for the admittance matrix, of which  $G$  and  $B$  are the real respectively imaginary parts. For the sake of simplicity in the presentation, we omit the current limitation constraints and the apparent power limitation of the transformer (see (Andersson,2012) for a tutorial on power flow equations).  $P_i^s$  is the power generated by the bus  $i$ , besides households (where generation is included in  $P_i^{in}$ ). Therefore  $P_i^s = 0$  except for the reference bus which supplies power to the LV grid.

The flexibility constraints (23) and (24) can be better explained with the diagram in Figure 4. Assume  $\beta_i > 0$ . For the selected period (e.g.  $j=2$ ) the setpoint  $P_i^{in} + \beta_i$  should correspond to the point B, and should be less than the flexibility value  $\bar{E}_i^{CEMS}$ , as expressed in Equation (23). Similarly, if  $\beta_i < 0$ , the setpoint value B' should be larger than  $\underline{E}_i^{CEMS}$ , expressed by Equation (24).

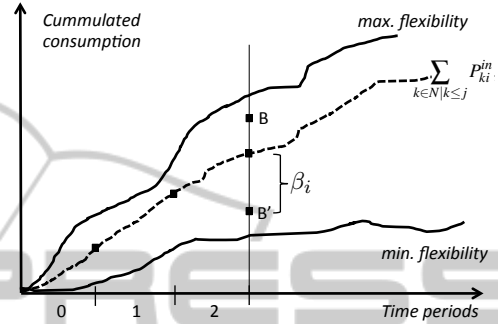


Figure 4: Graphical interpretation of constraints (23) and (24). The planned load curve is situated between the flexibility limiting curves.

## 5 SIMULATION EXPERIMENTS

### 5.1 Scenario

Within the FP7 project SmartC2net (SmartC2Net) we used a scaled down version benchmark residential LV grid in a rural area in Denmark with 53 buses, to which a number of 38 households are connected. The measured load has been used to derive the non-flexible load for each household. The original grid was already in the winter evening hours quite loaded, as the voltages at some buses reached a low of 95%. In the simulation, all the households have been enhanced with 5kW HVACs used for heating, and with PV panels with  $P_{rated} = 4$  kW. Ten houses have been configured with EV charging points associated to various parking periods and  $P_{max} = 8$  kW. The HVACs' starting inside temperature was randomly distributed between 18.1 and 21.9 degrees, the outside temperature is 1°C (January).

The simulation experiments have been performed for a duration of 72 periods (18 hours) with a planning horizon of 6 hours. The system in Figure 3 has been implemented in java, using for the optimization tasks the MIP solver (Gurobi) and for the nonlinear power flows the AMPL/minos (AMPL) environment. The 18 hours simulation was run on a MacBook Pro machine (2GHz Inter core i7) and lasted around five minutes.

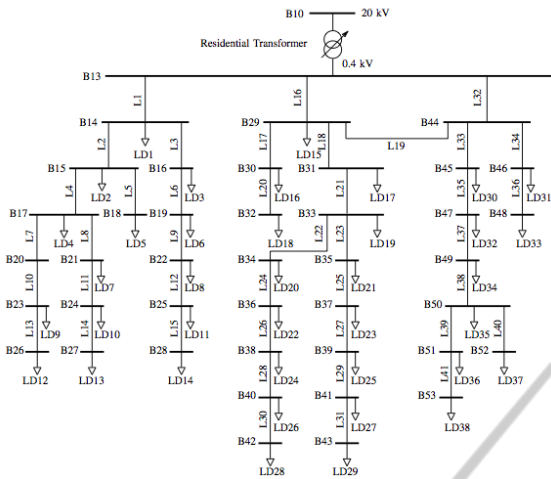


Figure 5: Low voltage benchmark grid.

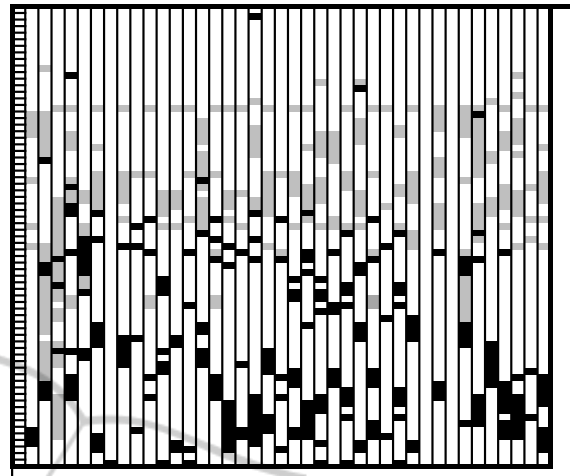


Figure 6: Schedule of consumption load among the CEMS during the simulation.

### 5.2 Simulation Results

The simulation of the controller operation shows that we can schedule higher loads than in the current grid in such a way, that the grid infrastructure needs not be enhanced.

We associated one house per bus, in total 38 houses and started the simulation at 6 AM during the month of January. Because of the lower number of houses in the experiment, the voltage limits have been tightened from 10% down to 5% around the nominal voltage.

In Figure 6 we illustrate the distribution of the loads on the buses: the black colored heating periods (more than 5kW) are alternating among the households represented on the columns of the diagram. The light grey regions correspond to loads between 1 and 4.9 kW and are mainly caused by EV charging. The uncolored rest is background load. Heating is more frequent in the evening (towards the bottom of the figure)

The overall system operation in energy closed loop is illustrated in Figure 7, in which we plot the sum of the bus loads and the sum of power setpoints in the time from 6am to 12pm. We observe that loads and setpoints follow each other. On the same axis are shown the energy prices  $c_j$ , relative to the base price of 44,23 Euro/MW, and the effect of negative prices on the consumption increase.

Considering a certain bus in detail, the load and setpoint values converge as well. The load and setpoints of household LD2 are shown in Figure 8. EV charging occurs from periods 12 to 28 and from 40 to 64). Heating takes place in period 28 and from 62 to 64. Note that the setpoint that is limited by the voltage and current limits is only partially followed by actual CEMS load.

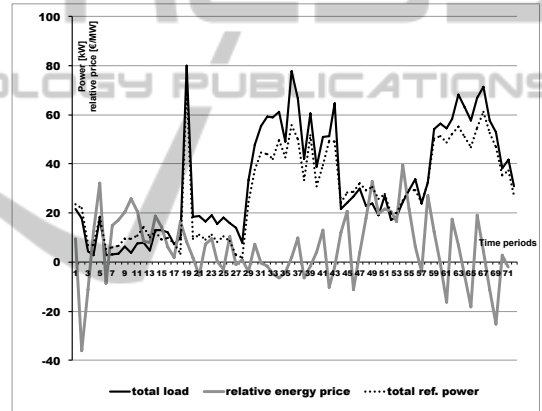


Figure 7: Total load and total reference power (setpoint) during the simulation. Prices are relative to the base price.

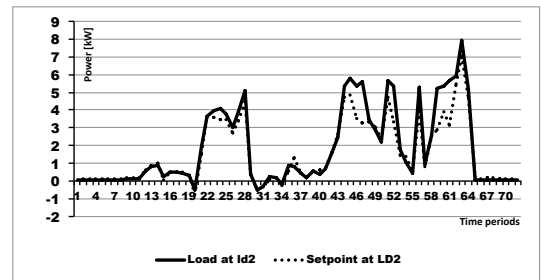


Figure 8: Load and setpoint at LD2 during the simulation.

In correlation with the setpoint (and the load) we depict in Figure 9 the voltage evolution at LD38, which is situated at the end of a feeder. The voltage constraint in (19)  $V_{min} = .95$  is often hit during lunch time and in the evening.

In a further series of simulations, we examine the performance of the EV charging. Several factors have

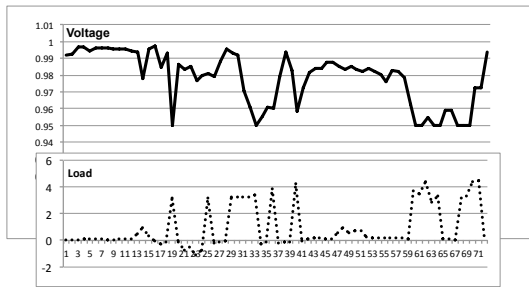


Figure 9: Setpoint and voltage at the household LD38 during the simulation.

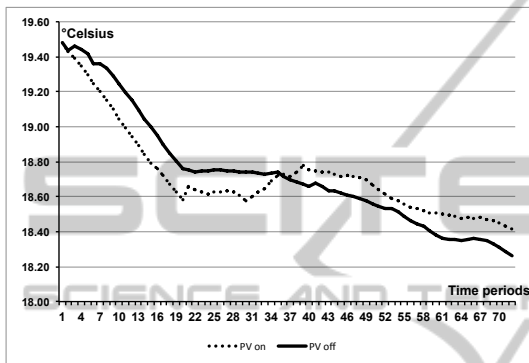


Figure 10: Comparison of average inside temperature during the simulation with and without PV.

an impact, such as the local generated power from PV and the energy price, both a function of the charging time of day.

The local generation does not appear in the power flows in the grid, but has an impact on the inside house temperature and on the energy stored in the batteries.

Figure 10 compares the inside temperature, averaged over the houses: if PVs are on, the temperature increases during the sunny hours. The same effect is observed with the charged energy  $E^{EV}$ , in Table 2. In general (during sunny hours) the PV generation adds energy to the battery (not much because of the low PV generation in winter).

Table 2: Comparison of EV charged energy in percent from  $D_{max}$  during the day hours, with and without PV, (\*\* in [kWh], \* in % of  $D_{max}$ ).

BUS	EV parking	$E^{EV}$ * noPV	$E^{EV}$ * PV	$D_{min}$ *	$D_{max}$ **
LD1	8am-12am	19	21.3	19	8.8
LD2	4pm-7pm	55	55	47	11.6
LD3	1pm-11pm	67	62	45	8.6
LD5	3pm-6pm	45.6	45.6	45.6	8.0
LD13	11am-4pm	37	43	37	6.8
LD30	9am-3pm	60.5	73	60.5	7.2
LD32	4pm-8pm	78	78	78	5.9
LD33	11am-4pm	45	47	45	8.4
LD34	6pm-9pm	22	22	22	6.8

### 5.3 Discussion

The described system is complex as it includes several load models and a lot of constraints that stabilize its operation, such as energy prices, limitation of currents and voltages, flexibility limits, to consider only a part. For the sake of a comparison, we assume that prices have no influence and that the aggregation controller provides each household with the energy it asks for. Note that, even in this particular case, a six hours load plan exists both at the aggregator and the CEMS side, and that correct heating and charging functionality are not affected. One evaluation criterium is the power quality, e.g. the frequency of the under-voltage occurrences, in our case voltages under 95% of the nominal value. The simulation creates peak loads as expected, such that 8.4% of the voltage measurements are below the limit, compared to zero occurrences, if the aforementioned constraints were active, see Figure 11.

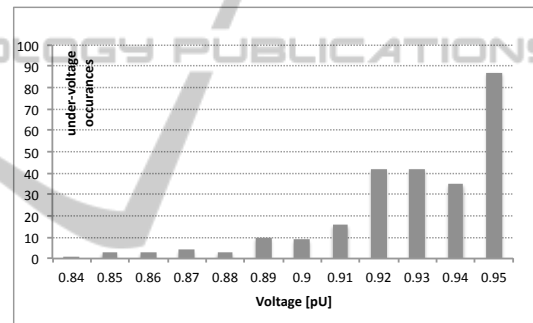


Figure 11: Simulation without price information and without voltage limit checks. Histogram of under-voltage occurrences.

## 6 CONCLUDING REMARKS AND FURTHER RESEARCH

In this work we address the energy management of distributed energy resources using power and energy flexibility information. In the selected residential scenario, we define two interconnected controller entities, the CEMS controller and the aggregated energy controller, and the appropriate energy optimization models. The approach is based on forward planning and optimized scheduling. Load predictive models are crucial for the demand side management mechanism presented. Day ahead prices are used to penalize or encourage demand at certain times of the day. Eventual congestion is avoided by limiting the power flows (voltages and currents). If we relax the conditions above, the power quality deteriorates drastically. In an experiment with a moderately loaded grid we



obtained 8.4% under voltage events from a total number of 3024 voltage measurements in the whole LV grid.

The benefit of using the flexibility information to control the assets is difficult to quantify in normal operation conditions: the EVs are charged to the required amount and the temperature in the houses remains within limits. We think that the real benefits of this architecture will be better visible in real world and failure cases, to be studied in the future:

- errors in the prediction of charging activities parameters such as plugin and leaving time, demand, of heating requirements, of non-flexible load, of the solar irradiation, etc.
- failure through the temporary disconnection of the communication network between the controllers, or failure of the metering data collection. Normal operation of loads and generators would continue for longer time in our proposed system than in a system without flexibility information exchange.

Finally, in this work it has been assumed that the aggregated energy management is done by the DSO, with input from the market actors (prices, available energy, etc.). However, if this functionality is implemented by a third party as part of a demand response system, then the grid topology information might not be available at the third party. In such a case a future system architecture should provide better interactions between DSO and market actors, and in the same time it should provide cooperative decisions vis-a-vis the consumers, similarly to the joint optimization problem solved by the aggregator.

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