A decentralized approach to demand side load management: the Swiss2Grid project

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***Abstract*—We present the Swiss2Grid project, a pilot and demonstration aimed at evaluating the impact of different distributed demand management policies in Smart Grids. The increasing diffusion of decentralised energy generation, especially photovoltaics, can lead to severe imbalances on the electric grid, which could require huge investments in grid infrastructures. The approach proposed by the Swiss2Grid project is to adopt a decentralised approach to load management at the local level. Single households use a local algorithm that, based only on local voltage and frequency measures, shifts the pre-emptible loads in time in order to minimise the costs for the consumer and to maximise the grid stability. In this paper we present the project set-up in Mendrisio, a city in Southern Switzerland, we describe the algorithm principles, and finally we present some preliminary results showing the impact of the Swiss2Grid algorithm on the Low Voltage grid.**

I. Introduction

The rapid diffusion of small scale and decentralized renewable energy sources poses a considerable challenge to the electric energy generation and distribution companies. The intermittent and decentralized production of electric energy represents a disruptive change in the technical, organizational and economic development of the electricity sector [1]. The combination of the electric grid with the massive use of information and communication technologies in the so called *smart grids* offers a promising solution to the increasing problem to integrate different renewable energy resources, to control and manage the balance between generation, consumption and storage and to optimize the use of the present infrastructure.

The need to develop smart grids to achieve common goals for secure energy supply, economic development and for a mitigation of the impact of the global climate change is a widely shared opinion[2]. However the complexity of the electricity system and the tremendous investments in new communication infrastructures supposed to centrally control and manage the load over the whole grid are creating a high barrier to the expansion of smart grids. Although there is a wide range of projects on smart grid going on[3], the exact design and the appropriate technologies for smart grids needs still much of research and tests in pilot studies.

In Switzerland, the diffusion of decentralized energy generation by photovoltaics or wind is still very low compared to the neighboring countries and represents less than 1% of the overall electricity production [4]. This is why the debate on smart grids is still in its beginning. However during the last two years, the impact of the rapid increase of PV in Southern Germany attracted the attention of various Swiss stakeholders and seriously questions their business model. The new Swiss energy policy strategy for 2050, decided after the Fukushima accident, fosters the increase of renewable energy resources and gives decentralized energy generation a relevant role [5].

Until now Swiss utilities were rather reluctant to approach the problem of the potential impact of renewables since the distribution network and the grid are still over-dimensioned. Yet, recent experience in Germany demonstrates that evolution in this field is fast and uncontrolled growth could lead to grid instabilities. Moreover, distributed power generation and an expected widespread adoption of electric vehicles might require major investments in transmission and distribution grid infrastructures, which have been estimated to be 18 billions Swiss Francs [6] for Switzerland. It is expected that the application of intelligent smart grid technologies has a potential to reduce those investments [7] and therefore the Swiss government asked the the Federal Office for Energy to steer a large group of experts to produce a Swiss road map for smart grids development [8].

Given this context, in 2010 the *Swiss2Grid* (S2G) pilot and demonstration project was started. The fundamental idea of the project is to optimize the load management of the low voltage distribution grid by a fully-decentralized decision making algorithm. The algorithm makes decisions on load shifting simply based on local information on voltage and frequency. The overall status of the network is therefore estimated and forecasted with local information and limited communication.

The S2G project follows an approach based on local and decentralized decision management for load shifting. The main goal of the project is to assess the real need of a two - way communication system and coordination scheme deputed to control the network load and to overcome the problems related to the transmission and elaboration of huge amounts of data. The second related goal is to understand to which extent local sources of energy generation can be connected to the grid without requiring new investments in the grid infrastructure.

Being deployed in a real-world setting in the city of Mendrisio (Canton Ticino, Switzerland), the project features comprehensive real data collection and opens the possibility of ad-hoc controlled experiments. Real data allows for the calibration of an accurate and realistic simulator to be used for scaling up experiments.

The paper is structured as follows. In Section II we introduce the project set-up and the measurement infrastructure.

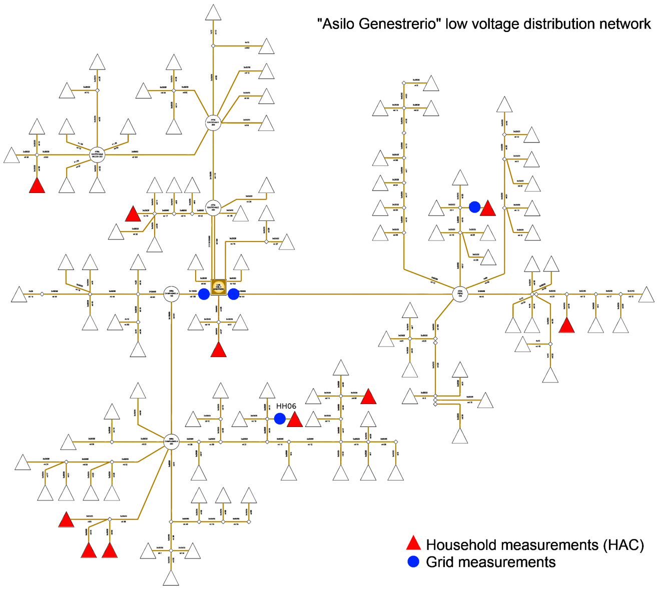

Fig. 1. Representation of the distribution network connected to the Asilo-Genestrerio MV-LV transformer in Mendrisio; the 10 pertecipating households under this transformer are depicted as filled red triangles. Grid measurements are acquired at blue dots.

Section III describes the rationale and the principles underlying the algorithm and the simulation environment we have developed to test the algorithm *in silico*. Section IV introduces some experiments designed to validate the algorithm and then in Section V the S2G project infrastructure is used to evaluate different policies and strategies for smart grid management such as the impact of the communication infrastructure and the effect of volatile energy prices. In the last section some preliminary conclusions are drawn.

II. The Swiss2Grid Pilot and Demonstration Project

A. The project set up

The Swiss2Grid project is a pilot and demonstration project. It involves 20 private households selected among 134 candidates in the region of Mendrisio. The energy supply is provided by local electricity distributor AIM (Aziende Industriali Mendrisio).

The selection of users was aimed at creating various clusters of households, where each cluster was grouped under the same medium voltage to low voltage (MV-LV) transformer. The most numerous cluster is composed of ten users, representing more than 10% of the total customers connected to that MV-LV transformer (see Figure 1). The selected users accepted to participate actively in the demonstration phase as every participating household was rewarded with the installation of a photovoltaics (PV) plant of 1.5kWp. House owners were keen to add their own contribution adding more installed generation power in total the sum of installed power was about 88kWp.

In each house was also installed a Household Appliance Controller (HAC). The HAC reads the grid state, measured as voltage, current and frequency over the three phases, and controls up to eight load sources thanks to the implementation

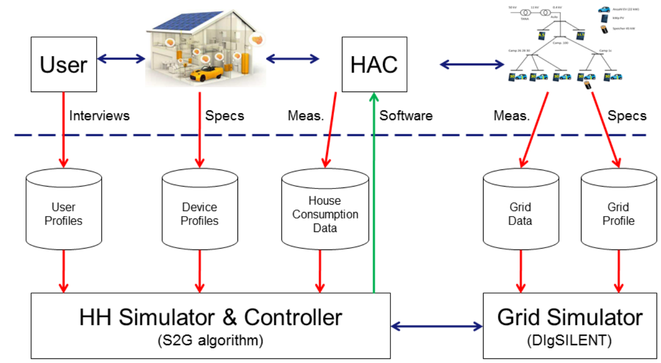

Fig. 2. Layout of the Swiss2Grid project components.

of the algorithm. Each HAC is connected over a powerline communication (Echelon) with a touch panel by which the user can set his/her preferences and visualise relevant information. The touch panel also works as a data gateway for all the information collected in one single household and transmits it over the internet to a central server. All data are verified and alarms are automatically raised in case of problems, e.g. with inverters or with monitoring equipment. It must be noted that this centralized data collection is intended for data analysis only as no centralized communication is expected for the final deployment of the Swiss2Grid concept. In Figure 2 we describe the overall structure of the Swiss2Grid system. The top layer contains the physical components (users, households, measurement devices and the grid network), while the bottom one lists the software components (the household simulator and controller, and the grid simulator). The software layer is used to design the algorithm to optimise the load shifting. The algorithm is then deployed in the HAC at the physical level.

B. Grid measurements

In order to investigate the impact of renewable sources on the grid, different measurement campaigns were and are still carried out at the level of the house connection point and the MV-LV transformers with highly sensitive measurement equipments. All the data from the monitoring equipment are time-stamped via the Network Time Protocol (NTP) to be ready for parallel and dependency analysis with the goal to get a full picture for the critical states of the grid in very short-term intervals. The required time accuracy has been achieved and verified by using a combination of GPS time signals and NTP signals.

C. The project team

Swiss2Grid is a project requiring interdisciplinary knowledge as it delivers a hardware and software solution for local load management in a smart grid. The measurement infrastructure was a joint effort of SUPSI - ISAAC and Bacher Energie AG, the algorithm development was provided by SUPSI - IDSIA, as well as the household simulator while the low voltage grid simulations were developed by BFH. SUPSI ISEA developed the HAC prototypes while the touch panel software and the data communication protocol for domestics (DomoML) were assigned to SUPSI ISIN. SUPSI - ISAAC coordinates the whole project. In summary, two Schools of

Applied Sciences (SUPSI - University of Applied Sciences of Southern Switzerland with four different institutes and BFH, the Bern University of Applied Sciences) and one industrial partner (Bacher Energie) teamed up to make Swiss2Grid possible.

III. MODELS, ALGORITHMS AND SIMULATION

The S2G algorithm has been designed in order to minimise the user costs and to maintain the local grid stability by shifting user loads when the price for energy is convenient and when the grid load is not excessive. Note that these objectives may be contrasting. The control algorithm implemented at each node is able to deal with multiple objectives and implements a two-level lexicographic scheme [9], [10]. In other words, each node can be configured to optimize a primary objective function and successively a secondary objective function subject to the constraint that the optimal value of the primary objective is not worsened more than a certain percentage. For example, because control actions for distributed smart grid management are implemented at residential level on end user's appliances [11], the primary objective we commonly use is related to the end user's energy costs. Secondary objectives can be the network stability or the aggregated network load.

This control mechanism is implemented through a *distributed algorithm* [12]. Each intelligent node (*controller*) is based on a mathematical model that includes variables representing the current and future states for one or more controllable devices (such as home appliances or electric vehicles) up to a temporal horizon of 24 hours, which is divided in a set T of 96 time slots, each with the same duration $\Delta t = 15\text{min}$. The system implements the *model predictive control* [13] paradigm: after the model is solved, one can determine the desired state of each appliance for each time slot. In the mathematical model (see [14] for details), the operational constraints of all devices are accounted for: for example, a water heater's temperature must always stay within a given temperature range, and the program of a washing machine must be finished before a given deadline previously defined by the resident.

The approach is validated through a comprehensive micro-simulation of households and their interconnecting grid. Some of the loads in each household are controlled by means of the distributed algorithm described above. The controller in each household takes as input the voltage measured at the plug, which is computed by simulating the relevant portion of the LV network.

The following appliance classes are simulated, using discrete 10-seconds time steps.

Energy buffers model appliances such as water heaters, air conditioning/heating systems, and fridges. Electrical energy used by the appliances keeps the system in a defined operational state (e.g., a given temperature range). Because such appliance class accounts to the largest portion of household loads, its intelligent control has been discussed in several works [15], [16], [17], [18]. For each energy buffer, we consider an unpredictable use its energy as well as the following characteristics: heat/energy capacity, a self-discharge rate, and thermal efficiencies.

Batteries for energy storage behave similarly to energy buffers. We simulate the evolution of their state of charge accounting for the self-discharge rate, maximum charge, maximum charging/discharging power, and charging/discharging efficiency.

Electric vehicle chargers consider the same characteristics outlined above for batteries. In addition, simulated residents define realistic release (plug) and due (unplug) times for the electric vehicles. After use, some fraction of the battery charge is depleted. Smart control of EV charging is subject to significant attention by researchers [19], [20], due to its easy controllability and foreseen increase in EV penetration rates.

Non-preemptible loads include washing machines, dishwashers, and all appliances operating according to a predetermined working program which can not normally be interrupted. Such appliances are normally idle: when started, they draw a pre-defined electrical load profile. Jobs to be executed are generated through realistic patterns and are characterized by a release time (e.g. when a dishwasher is loaded) and a due time (e.g. when the user wants the program to be over). Algorithms schedule the appropriate starting time in order to meet such strict requirements.

Non-controllable loads model appliances like TV sets, house lighting, and kitchen appliances, which are driven uniquely by simulated residents. Therefore, they are not subject to controllers.

Household residents are simulated as stochastic finite state machines: their behavior is driven by probabilistic models, which, every day, instantiate a different variation of a baseline routine, which is different for each resident, and accounts for the time of day. Residents interact with appliances in several ways: they use electric vehicles during working hours, and set feasible due dates when plugging for recharge; residents use hot water at reasonable hours, which results in mixing cold water in the water heater; they program non-preemptible load jobs at regular intervals for dishwashers and washing machines and define feasible due dates. Finally, residents trigger non-controllable loads at appropriate times, such as electric cooking appliances, lighting and entertainment appliances.

LV network voltage drop is evaluated by using the DIgSILENT grid simulator [21]: for each time step, the household simulator determines the load imposed on the grid at the point of common coupling (PCC) of each household. Such data is automatically imported in DIgSILENT, and a power-flow computation is triggered. As a result, voltage drop measurements at the PCC of each household are available and will be considered in the following time step.

IV. EXPERIMENTAL VALIDATION OF FULLY-DECENTRALIZED ALGORITHMS

In this section we present an experiment demonstrating the effectiveness of the proposed fully-decentralized algorithm when no communication infrastructure is available. In particular, we consider the problem of controlling a simple domestic water heater with a capacity of 200 liters and a 3kW heating element. The task is to maintain the water temperature in the tank within the temperature range $[58 - 62]C$ (at this temperature, the tank's thermal dispersion is roughly 40W), by

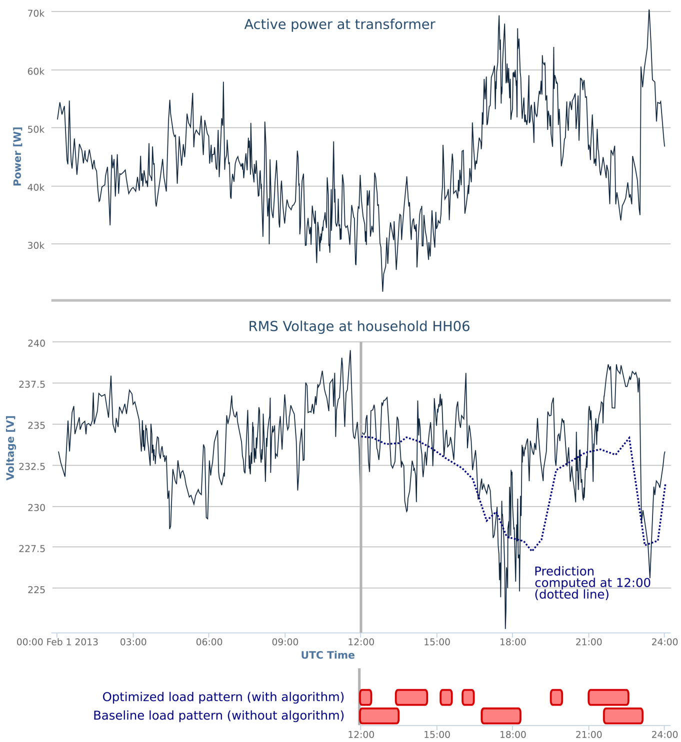

Fig. 3. Top: aggregate load profile (one phase only) for a given branch of the Asilo transformer, for whole day of Feb, 1 2013. Middle: measured voltage profile at household HH06 (which is downstream the same branch) for the corresponding period; note that voltage drop is clearly correlated to the aggregate load. We further illustrate the algorithm's behavior when run at 12:00 the same day (vertical gray line). First, the algorithm estimates the future voltage profile (dotted blue line) according only to measurements taken in the previous days; then, the algorithm schedules boiler loads using Model Predictive Control (first row of red boxes): compared to the baseline control (second row), such loads tend to be shifted to periods where transformer load (unknown to the algorithm) will be low.

controlling an heating element which can be switched on and off at different times (control variable). The baseline control method – which is commonly implemented in appliances – consists in turning the heater on as soon as the temperature drops below the lower limit, and turning it off as soon as the temperature exceeds the upper limit (threshold with hysteresis). This results in a regular energy use pattern which is normally observed in household load profiles also for other energy-buffer appliances like freezers and air conditioners.

The algorithm takes control of such activity pattern, and adjusts it in order to optimize energy loads while still meeting the user requirements. In particular, in this experiment the algorithm aims at shifting loads from periods where the LV transformer is heavily loaded, to periods where the transformer has a lighter load. However, in absence of an explicit communication infrastructure, the algorithm is never aware of the actual transformer load: therefore, we use the locally-measured voltage drop as a rough estimation of transformer load, under the assumption that the amount of measured voltage drop is correlated to the transformer load. Therefore, the algorithm will exploit the water's attempt to shift the heating from periods where the measured voltage is low, to periods where it is higher (see Figure 3).

A. Correlation Between Measured Voltage Drop and Transformer Load

We tested this assumption in a separate experiment, where we observed that voltage drop measured at the plug is in fact correlated with transformer load. In general, we observed that such correlation is maximized for households farther away from the transformer (correlation coefficient larger than $|\rho| = 0.74$), whereas it is reduced as the considered household gets closer to the transformer (down to a still significant correlation coefficient $|\rho| = 0.21$)

In the following, we consider the behavior of the algorithm in a typical situation (household HH06) where the household is at an average distance from the transformer ($|\rho| = 0.35$).

B. Algorithm Settings and Quantitative Behavior

We consider a period of three months, from Jan, 1 2013 to March, 31 2013. In each household, the algorithm is configured to ignore energy price and generate a 12-hour schedule for the heating pattern, in order to optimize the grid stability objective. In our simulation, the voltage is played back from the data logged in the actual households in the same period. Future voltages are predicted as follows: each day is divided in 15-minute slots, and for each slot the voltage is predicted as the average voltage measured in the same slot of the previous 5 days. No distinction is made between working days and holidays, although this is going to be considered in future work.

Every 30 minutes, the algorithm runs and generates a new schedule which overrides the previously-computed one. This is necessary in order to account for unpredicted events, such as deviations from the predicted voltage, or e.g. the user consuming some of the hot water, thus mixing cold water and thus increasing the requirements for the future heating.

We now compare the load pattern generated by the algorithm with the load pattern generated by the baseline control mechanism. Both approaches draw the same total amount of energy during the three considered months (i.e., approximately 86.3 kWh): we want to see how this energy is distributed in time. By analyzing the aggregate load profile at the transformer, we observe that for one third of the time, the relevant branch of the transformer was delivering less than 9.5kW; for another third, it was delivering more than 14.2kW; and for the remaining third, it was delivering an intermediate amount of energy. Therefore, we define E_{low} as the total energy drawn by the boiler during time periods when the transformer load was less than 9.5 kW; E_{high} as the total energy drawn by the boiler during time periods when the transformer aggregate load was more than 14.2 kW; E_{med} otherwise.

For the boiler controlled by the baseline controller, $E_{\text{low}} \approx E_{\text{med}} \approx E_{\text{high load}} \approx 28.8$ kWh, i.e. a similar amount of energy is drawn when the transformer is under low or high load. On the contrary, the algorithm is able to shift these loads in such a way that $E_{\text{low}} = 36.8$ kW, $E_{\text{med}} = 31.4$ kW, and $E_{\text{high}} = 18.1$ kW. This shows that the proposed demand side management algorithm, which relies only on measured voltage drops at the plug, is able to shift most loads towards period with low aggregate load at the transformer.

V. S2G AS A LABORATORY FOR SMART GRID EXPERIMENTS

The experiment we described above only represents one of the many possible tests made possible by the S2G infrastructure. Below, we report two examples of other ongoing activities, which yielded interesting and counterintuitive results.

A. What is the Advantage of a Communication Infrastructure?

One of the objectives of the S2G project consists in quantifying the advantages of a communication infrastructure which allows explicit coordination among different energy users. In order to investigate this issue, we designed a simulated testbed with 120 households, each of which is equipped with an algorithm controlling its largest energy users (EV charging, water and space heating, washing machine and dishwasher). In this setup, algorithms are not provided with voltage measurements: instead, they optimize energy use through communication with controllers in neighboring households. After scheduling its own loads, a controller shares its forcast load profile with neighbors, which will take that into account during their own optimization; the process is iterated as the algorithms periodically reschedule their own loads accounting for the loads of all known neighbors [22]. In particular, each controller attempts to shift its loads from periods when the aggregate loads of known neighbors is large, to periods when such aggregate load is low; in this setting, the aggregate load of known neighbors represents an approximation of the load at the transformer.

Of course, the infrastructural investments for enabling bidirectional communication among all controllers downstream a given LV transformer is significant: we want to investigate whether more limited (thus cheaper and more easily implemented) communication infrastructure would still allow algorithms to effectively flatten the aggregate load. In order to test the effects of limited communication infrastructures, we partition the 120 households in groups composed by few households each (named *communication neighborhoods*), and assume that all households within the same neighborhood can communicate with each other, whereas no communication can occur across neighborhoods borders: then, small communication neighborhoods can be provided by very simple and inexpensive communication technologies (like low-bandwidth ad-hoc wireless networks). How small can we make the neighborhoods without compromising the algorithms' performance? Experimental results show that, suprisingly, communication neighborhoods composed by as few as 2 or 3 households already yield a significant improvement in terms of load flattening at the transformer, with very low bitrate requirements over the communication channel. Larger communication neighborhoods, which would require significant infrastructure, yield comparively negligible improvements.

Figure 4 reports quantitative simulation results supporting such conclusion: the leftmost bar represents the baseline case, in which controllers have no communication ability nor can exploit local voltage measurements: a sample daily aggregate load profile is represented below as a gray line. Bidirectional communication within small neighborhoods can improve this situation significantly (sample daily load profile reported below as black line for neighborhoods composed by three households). Enabling larger groups of households to communicate

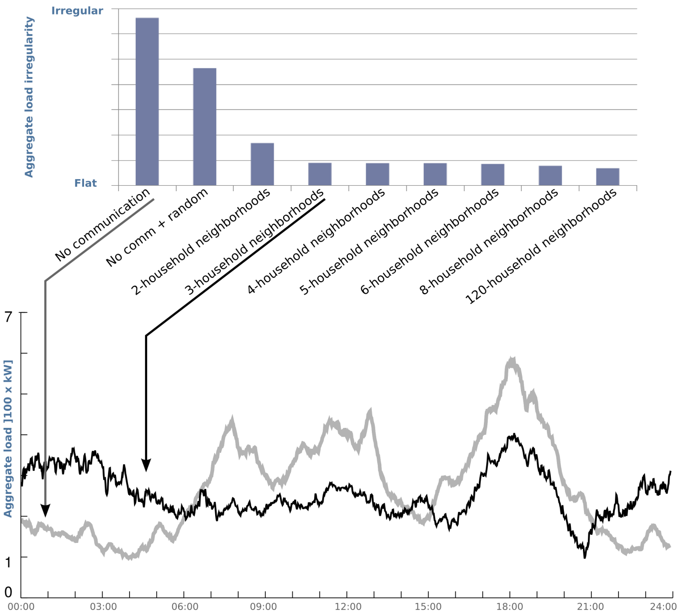

Fig. 4. Top bar chart: effects of different amounts of communication pervasiveness on the instability of the aggregate load (measured as in [22]). Below: sample daily aggregate load profile for the baseline case (gray line) and 3-neighborhood case (black line).

(which requires significant infrastructure investments) yields comparatively negligible improvements.

Note that in this set of experiments, controllers could only use explicitly communicated information in order to optimize loads, and were not provided with voltage measurements. Comparing voltage-driven and communication-driven optimization is planned in future work.

B. Effects of Volatile Pricing Profiles

As we previously introduced, when multiple objectives must be optimized, the S2G algorithm implements a lexicographic approach in which one objective is optimized with more priority than others. Then, the system designer only needs to determine the priority of each objective. Consider the following example: a load could be shifted to any of two time periods t_1 or t_2; energy price is higher in t_1 than in t_2, but a higher transformer load is predicted in t_2 than in t_1. Where should the algorithm place the load in this case?

In the following we investigate the case in which the primary objective is price of energy for the user, and the secondary objective is load flattening. Then, once the optimal price is determined, the algorithm attempts to also optimize the load, *as soon as the resulting energy price is not increased more than a given percentage* η. This controls a tradeoff between the interests of different stakeholders: for instance, if we set $\eta = 0$, the user is sure that any schedules produced by the algorithm will be optimal in terms of energy cost – while load stability will still be optimized as soon as it comes for free. In the example outlined above, if $\eta = 0$ the algorithm would always choose t_1, because placing the load in t_2, although beneficial for the network, would cost more. Instaed, in case $\eta = 10\%$, the algorithm would place the load in t_2 if and only if the price in t_2 was at most 10% higher than in t_1.

When such mechanism is implemented, how do algorithms behave when different pricing profiles are in place? We explored the issue in [14], studying the collective behavior of 100 households under different penetration rates of smart households. We observed that, if algorithms control a large fraction of all loads, volatile pricing profiles yield destabilizing collective behaviors, unless we allow for a large deviation η from the optimal price. This phenomenon is easily explained: with $\eta = 0$, algorithms are *greedy* since they attempt to shift all loads to lower-cost timeslots: then, peaks are created in such timeslots, as all algorithms attempt to optimize energy price.

From this point of view, the Swiss bi-level energy pricing profile has very desirable characteristics. In this case, any load placed within the low-tariff period can be shifted to any other time within such period without any change in cost to the user: then, once the energy cost is optimized, algorithms retain a large amount of freedom for optimizing the secondary objective without any change in costfor the user. Our experiments show that under the swiss bi-level energy tariff, algorithms can very effectively optimize energy costs while at the same time flatting the aggregate load at the transformer.

VI. Conclusions

We presented the Swiss2Grid pilot and demonstration project, aimed at investigating, from a practical perspective, whether decentralized demand-side load management can limit the infrastructure investments predicted in the next years to accommodate renewable resources and electrical vehicles.

We outlined the main components of the project, which involves a large effort in terms of data collection, concentrated in a pilot site in Mendrisio (Ticino) where 20 households were involved.

We described how decentralized decision making algorithms, only exploiting information available locally, can shift household loads in order to optimize multiple objectives at once, namely energy costs for the user, and flattening of aggregate loads at the transformer. Algorithms can be configured by the system designer in order to handle in a meaningful and predictable way the cases in which such objectives are conflicting.

Preliminary results reported in this paper show that voltage drops measured at the plug represent an useful piece of information for optimizing loads, which limits the need for an explicit two-way communication infrastructure. The voltage measurement can be achieved with very simple electronic circuits allowing the realization of cost-effective solutions. Moreover, even when explicit coordination through communication is desired, we showed that very limited communication infrastructures are sufficient. Finally, we reported results which warn against the dangers of very volatile energy pricing schemes, in case cost-optimizing algorithms are controlling a large fraction of the total load.

Future work will focus on the investigation of the effect of the algorithm to higher grid levels, the evaluation of impact on present grid control processes and strategies and the development of tariffs scenarios suitable for a decentralized algorithm.

VII. Acknowledgements

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