Comput Sci Res Dev
DOI 10.1007/s00450-017-0347-6

SPECIAL ISSUE PAPER

Shaping aggregated load profiles based on optimized local scheduling of home appliances

Christoph Hunziker[1] · Nicola Schulz[1] · Holger Wache[2]

Abstract We present a new method to control an aggregated electric load profile by exploiting the flexibilities provided by residential homes. The method is based on a common energy price combined with inclining block rates, broadcasted to all households allowing them to minimize their energy provisioning cost. The distributed home energy management systems receive the price signal and use mixed integer linear programming for optimal scheduling of load, storage, and generation devices. The method provides excellent scalability as well as autonomy for home owners and avoids load synchronization effects. As proof of concept, an optimization algorithm for determining a day-ahead price is applied in two case studies. An excellent conformance between a given reference load profile and the resulting aggregated load profile of all households is demonstrated.

Keywords HEMS · Real-time price · Inclining block rates · Demand response · Distributed load management · MILP

1 Introduction

The electric power demand in traditional grids with constant energy tariffs shows quite large variations between peak load and off-peak periods. Such load curves generally do not coincide with typical production profiles of power plants, especially if there is a large share of regenerative, fluctuating energy resources present. Due to this reason, in future, a better adherence of the electricity demand to the production profile is required. Therefore, one of the major aims of smart grids is the reduction of the gap between demand and supply [10].

Home energy management systems (HEMS) constitute an essential part of future smart grids. HEMS enable efficient demand response (DR) and demand side management (DSM) programs since they are capable of intelligently managing and altering electricity consumption of residential households [11]. In [20], a management strategy is proposed minimizing electricity costs based on a day-ahead electricity tariff. Recently, various approaches for the coordinated use of flexible loads have gained attention that include network constraints into their optimization targets. [1] proposes a three-phase model with constraints on voltages, currents and powers in the network. In [12], the peak-to-average ratio (PAR) of distribution transformer load is included into the target function for minimization. In [26], the problem of optimal load scheduling is combined in a single framework with the optimal power dispatch problem. This work investigates the possibility that the aggregated load profile of all residential customers of a utility company follows a given reference schedule. This enables a more cost effective energy procurement as well as it allows to prevent overload situations in the distribution grid by constraining load peaks in the desired reference schedule.

Various pricing schemes have been employed for billing purposes by utility companies with the aim of finding the most efficient energy management method. The pricing schemes proposed so far for smart grids are real-time pricing (RTP) [2,6], time-of-use pricing (ToU) [7], critical-peak pricing (CPP) [8], day-ahead pricing (DAP) [4], inclining block rates (IBR) [21] etc. In RTP scheme, consumers are informed about the pricing rates on hourly basis as the rates may change

✉ Christoph Hunziker
christoph.hunziker@fhnw.ch

1 School of Engineering, University of Applied Sciences Northwestern Switzerland, Klosterzelgstrasse 2, CH-5210 Windisch, Switzerland

2 School of Business, University of Applied Sciences Northwestern Switzerland, Windisch, Switzerland

Published online: 21 August 2017

hourly. In ToU pricing scheme a consumer is charged least during off-peak, less during mid-peak and more during peak periods. IBR represents a pricing regime, where the energy price rises progressively based on the current power level (furtheron called *tier*) [11,21].

In this paper we follow the approaches of Mohsenian-Rad and Leon-Garcia [14] as well as Zhao et al. [27] who propose a combination of RTP with IBR. Based on this tariff scheme, households are able to optimize their energy provisioning cost by scheduling their appliances which consume or produce energy (therefore called energy devices further on) accordingly. But neither Mohsenian-Rad and Leon-Garcia [14] nor Zhao et al. [27] showed how to optimize the schedule of different energy devices with different characteristics for particular households. Further it is not yet known if the combination of RTP and IBR can be used to adapt the demand to the supply, i.e. to adhere to a collective reference schedule.

Mixed integer linear programming (MILP) has been highlighted as a powerful optimization method for DSM within HEMS in recent years [3,12,17,18]. In various studies, a day-ahead pricing scheme has been used to minimize the electricity charges of the consumer. In this paper we show that MILP can also be used to schedule the energy devices of households receiving a RTP & IBR price scheme.

Furthermore, we show with an iterative method, that it is possible to determine the electricity tariff in such a way, that the aggregated load of a reasonable number of households follows a given reference schedule with good precision.

The paper is organized as follows: Sect. 2 motivates and explains the system architecture and the chosen pricing scheme for residential load management. Section 3 defines the optimization problem and explains the MILP approach for finding load schedules with minimal energy provisioning cost for individual households. Section 4 illustrates the potential of the method by demonstrating the adherence of aggregated load profiles to a given reference at the example of two case studies. Section 5 contains a conclusion.

2 Pricing scheme and system architecture

In this work we propose a method how utility companies can control the aggregated load profile of their customers. Surveys [23] have shown that households prefer to retain control of their own devices and do not favor direct remote control by the utility company. Therefore, only approaches which leave autonomy to the households are to be considered: the households receive incentives (price signal) letting them decide on their own how to react considering the local degrees of freedom.

All price schemes require a signal generator which sends the current prices to the households. In the proposed approach the price signal is broadcasted from the regional utility company to the households' HEMS which schedule local energy devices with respect to minimal cost while not affecting the home-owners comfort. The system architecture is shown in Fig. 1. The architecture involves an additional communication channel in return direction for billing purposes. This channel is not described in more detail, since it conforms with widely applied smart metering practice today. The approach described in this work, however, assumes an established metering infrastructure allowing the utility company to periodically collect (e.g. daily) measured load profiles of each household.

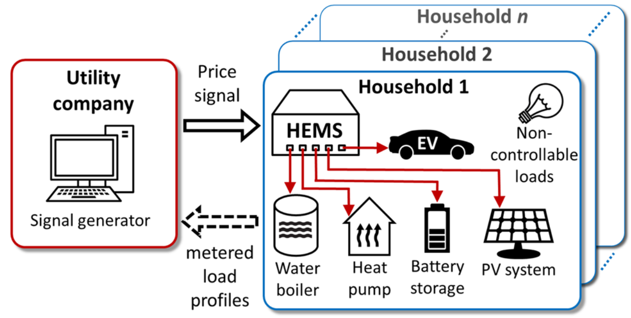

Fig. 1 Proposed system architecture

The analysis of [2,6] shows that RTP is the more economically useful price model in contrast to the others. Therefore, a RTP scheme has been adopted in this work as well.

For an efficient device scheduling price information of a future time window is necessary. In environments with real-time pricing (RTP), households will start forecasting the prices in order to optimally schedule their devices. Whether households perform their own price forecasts or receive it from an external service provider does not change the outcome of collective load management, since reliable forecasts will converge with real prices of the future time window either way. The approach described in this work is based on a common price forecast directly distributed by the utility company as part of the price signal shown in Fig. 1. The forecasted time window has been chosen to cover the period of one day. Such a tariff scheme is also known as day-ahead real-time pricing (DA-RTP) in literature. How price forecasts are calculated is not content of this work.

Mohsenian-Rad and Leon-Garcia [14] as well as Zhao et al. [27] argue that DA-RTP leads to load synchronisation because all electric devices with the possibility to be turned on are activated when the prices are low—and vice versa. Instead of distributing the load over the day it leads to concentrated peaks in short time intervals. This behaviour prevents good adherence to a reference load profile and can lead to overloaded grids. To avoid this load synchronisation Mohsenian-Rad and Leon-Garcia [14] and Zhao et al. [27] propose to combine DA-RTP with IBR.

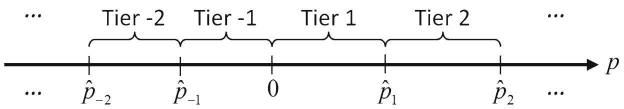

Fig. 2 Definition of power levels corresponding to price tiers. The point $p = 0$ divides the power axis into positive and negative tiers (tier zero does not exist)

The price signal generator does not provide one price but several price bands, so-called *tiers*. Price tiers are defined with respect to the level of electric power p. Figure 2 shows several price tiers specified by $\hat{p}_k$. The energy price τ_t for a household at a certain time depends on its momentary power drawn ($k > 0$) or provided ($k < 0$) by the household. In case of power drawn, higher power levels lead to higher energy prices; in case of power provision, higher power levels lead to lower energy refunds (see Fig. 8 for an example). Thus, households try to remain in the lowest possible price tier and keep their power consumption low. This leads to a wider temporal distribution of their loads and thus prevents load synchronization effects.

In order to treat different households with different load characteristics in a fair way, the power levels $\hat{p}_k$ locating the tiers can be defined with respect to average load in consumption or production direction for each individual household. The process of determining these power levels can take place periodically, e.g. once a month, and does not necessarily require communication between the utility company and the corresponding household, as long as the calculation base is transparent. The HEMS can potentially determine the power levels by itself based on communicated, normalized signals valid for all customers.

In summary, we employ a rather complex price signal with several tiers. The advantages of this approach (DA-RTP & IBR) are:

Scalability Due to one-way communication of the price signal, DA-RTP & IBR is scalable while the amount of data sent per day might be larger than in other approaches.

Autonomy The decision autonomy is completely given to the households, including the management of their comfort requirements.

Privacy Beyond disclosure of their net load profile for billing purposes which is already widely applied smart metering practice, home owners do not need to disclose any information about the existence or assignment of local energy devices. Load profiles do not need to be collected in real time and can be communicated daily or weekly.

Load synchronisation Load synchronisation effects can be eliminated.

Flexibility provision The approach enables the utility company to benefit from flexibilities provided by the households. With adequate price signals, the aggregated load profile can be shaped to the utility company's needs (as shown in Sect. 4.3).

Economic incentives Households have the possibility to operate their energy devices in a more economic way. They can profit from their capability of supporting the grid.

Interoperability The price based interface is technology independent and allows otherwise all HEMS-types to be applied by the households.

3 Local optimization problem for residential homes

The proposed method for regional load management is based on a price interface common to all residential homes. This turns the complex optimization problem with a large number of homes and corresponding flexible devices into a distributed and much simpler optimization problem with the scope of one customer or one household, respectively. The primary objective is to minimize the cost for energy procurement on the level of each household.

3.1 Energy device model

For an efficient scheduling of heterogeneous load and generation devices in residential homes, device models which can be handled in a homogeneous manner are useful. Furthermore, they shall represent the flexibility offered by the individual energy devices as accurately as possible. For this purpose, the framework of power nodes has been adopted [9]. This approach is based on the idea, that an energy device in general converts electric energy between the grid and the demand- or supply side (see also Fig. 3). We use a simplified version in which a linear description of device behaviour is used in order to apply it with MILP. Often, there is some energy storage capacity available, connecting the demand-

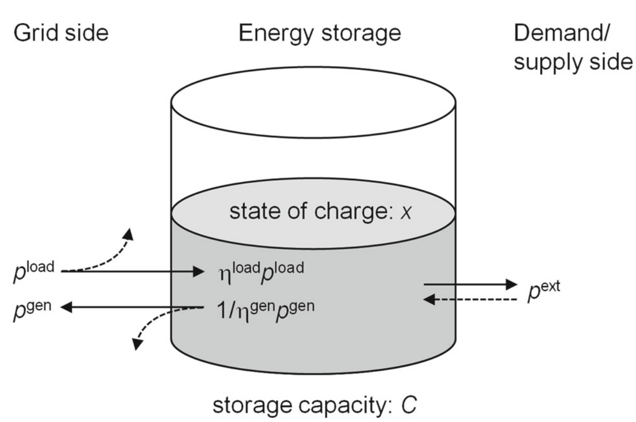

Fig. 3 Dynamic model of an energy device

Table 1 Configuration of the device model for the energy devices considered in this work

Device	C (kWh)	η^{load} [25]	η^{gen} [25]	p^{ext} (kW)
Boiler	Storage capacity for heat	1: electr. boiler >1: heat pump boiler	–	Hot water usage (including heat losses)
PV	0	–	Converter efficiency	Produced DC power (including potential power curtailment)
Electric vehicle	Battery capacity	Charging efficiency	V2G discharging efficiency	Battery power consumed by vehicle
Uncontrollable load	0	1	–	Sum of uncontrollable electrical loads
Heat pump	Total heat capacity of building	COP> 1	–	Total heat losses of building
Battery	Usable battery capacity	Converter efficiency	Converter efficiency	Losses of battery modules

or supply side with the electrical installation or grid side. In case of an electric load, electric power $p^{\text{load}} > 0$ charges the local storage capacity C, while the demand $p^{\text{ext}} > 0$ is served from the storage. In case of a generation device, the local storage is supplied by $p^{\text{ext}} < 0$ and the stored energy is converted into electric energy on grid side $p^{\text{gen}} > 0$. In this model, p^{ext} primarily represents the energy demand or supply by the external process, however, it also includes storage losses or potentially wasted energy due to curtailing. The dynamics of an arbitrary energy device can be described by the power node equation:

$$C\dot{x} = \eta^{\text{load}} p^{\text{load}} - 1/\eta^{\text{gen}} p^{\text{gen}} - p^{\text{ext}} \tag{1}$$

$\dot{x}$ denotes the derivative of the state-of-charge (SoC) of the corresponding device with respect to time. η^{load} and η^{gen} denote the conversion efficiency in either direction, respectively. The equation describes the energy balance between the energy which is generated or consumed by a device on one hand, and the energy which is drawn or fed back to the grid. The devices flexibility is given by its buffering capability, i.e. by its storage capacity C. The interpretation of the mentioned parameters in the context of the different energy devices is described in Table 1.

3.2 Definition of scheduling problem

The minimization of the energy procurement cost being performed by the HEMS is formulated as an optimization problem using MILP. The generic form of the problem is given by

$$\min_{\mathbf{p}} \mathbf{f}^T \cdot \mathbf{p} \quad \text{subject to} \quad \begin{cases} A \cdot \mathbf{p} \leq \mathbf{b} \\ A_{\text{eq}} \cdot \mathbf{p} = \mathbf{b}_{\text{eq}} \\ \mathbf{l}_{\text{b}} \leq \mathbf{p} \leq \mathbf{u}_{\text{b}} \end{cases} \tag{2}$$

The vector $\mathbf{p}$ holds a combination of either integer or continuous variables to be optimized. In the present case, these are the discrete time vectors p_t^{load} and p_t^{gen} for each energy device and time $t \in [1, T]$. $\mathbf{f}^T \cdot \mathbf{p}$ represents the linear target function of the problem to be minimized, written as the scalar product of a vector $\mathbf{f}$ with $\mathbf{p}$. The first two rows on the right of Eq. 2 represent linear inequality and equality constraints, respectively, that define the space of possible solutions (see also Sect. 3.2.2). $\mathbf{l}_{\text{b}}$ and $\mathbf{u}_{\text{b}}$ define further limitations on $\mathbf{p}$ directly.

The full MILP formulation includes several hundred variables (for each time step and for each device) to be optimized and a similar number of constraint equations representable in the form given above in Eq. 2. The specification of the full problem is omitted at this point, since the approach has been used in similar frameworks and is not new in the context of HEMS [12,26]. In the subsections below, the underlying concept applied in this work is described.

The optimization is carried out in a time window of 24 h. The demand or supply p_t^{ext} of the individual energy devices needs to be forecasted for this time window. The performance of the scheduler, therefore, depends on the quality of this forecast. The chosen duration of 24 h allows to use weather forecasts with good precision on one hand. On the other hand, time constants of the energy devices' storage capabilities are typically shorter or of the same order of magnitude, allowing the scheduler to exploit the full flexibility potential of the household.

3.2.1 Target function

The target function $\mathbf{f}^T \cdot \mathbf{p}$ in Eq. 2 to be minimized as a result of the MILP algorithm represents the total energy cost K in the time interval $t \in [1, T]$ optimized by the scheduler:

$$K = \sum_{t=1}^{T} \left(\sum_{k=1}^{N} p_{k,t}^{+} \cdot \tau_{k,t} \cdot \Delta t - \sum_{k=-N}^{1} p_{k,t}^{-} \cdot \tau_{k,t} \cdot \Delta t \right) \tag{3}$$

$p_{k,t}^{\pm}$ is the total electric power in tier k either in consumer $(+)$ or in producer $(-)$ direction. $\tau_{k,t}$ is the energy price valid for tier k at time t. Δt is the duration of one discrete time step.

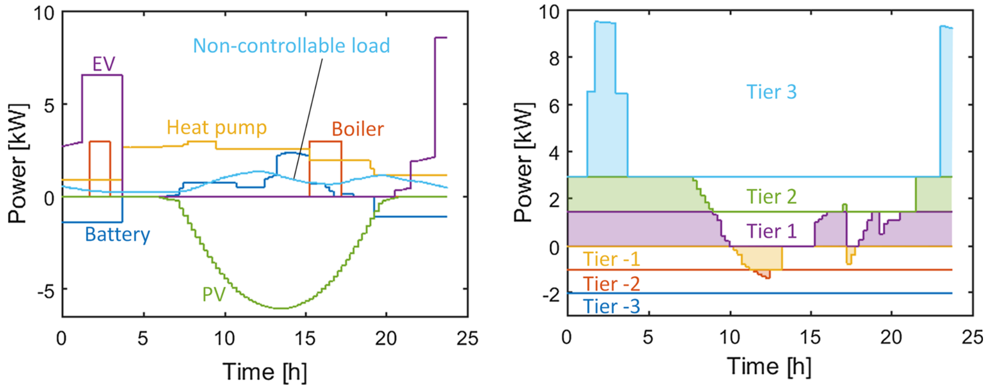

Fig. 4 Device schedules for minimal cost at the example of one household. *Left* schedules for the individual energy devices. *Right* break down of total load p_t^{grid} in the household onto the defined tariff tiers $\tau_{k,t}$. The schedule corresponds to tariff structure of case study B

The total electric power at the grid connection point at time t is given by the sum over all tiers as

$$p_t^{\text{grid}} = \sum_{k=1}^{N} p_{k,t}^{+} - \sum_{k=-N}^{1} p_{k,t}^{-} = \sum_{\#\text{ devices}} p_t^{\text{load}} - p_t^{\text{gen}} \tag{4}$$

3.2.2 *Energy device scheduling*

Each energy device exhibits constraints that must be fulfilled by the optimization algorithm. These constraints have to be formulated in linear dependence with the unknown vector $\mathbf{p}$ of the optimization problem (see also Eq. 2). The dominant constraint for each device providing some storage between energy demand and electric energy on grid side is to keep the state-of-charge (SoC) x_t in the allowed range $0 \leq x_t \leq 1$ for $t \in [1, T]$. The SoC can be derived from Eq. 1 and is given by

$$x_t = x_0 + \frac{\Delta t}{C} \sum_{i=1}^{t} \left(\eta^{\text{load}} p_i^{\text{load}} - \frac{1}{\eta^{\text{gen}}} p_i^{\text{gen}} - p_i^{\text{ext}} \right). \tag{5}$$

x_0 ist the current SoC at time $t = 0$ (beginning of time window for optimization). The limitations of x_t can be transformed into inequality equations of the form $A \cdot \mathbf{p} \leq \mathbf{b}$, constituting the optimization problem in Eq. 2. In addition, each energy device has constraints on minimum and maximum allowed schedulable electrical power p_t^{load} and p_t^{gen}, again represantable within Eq. 2. The MILP algorithms can also handle devices of type *on/off* represented as integer or binary constraints of schedulable power. Furthermore it is possible to introduce extra constraints of the form $x_t > X^*$ valid at a specific point in time t, ensuring that SoC x_t is larger than a user defined value X^*. This type of constraint has been used in this work to specify a minimum SoC of hot-water boilers in the morning and a minimum SoC of an electric car at a specified time of disconnection from the charging station.

Figure 4 shows the results of the MILP algorithm for an exemplary household. The plot on the left contains the device schedules for all managed devices. The sum of the device loads defines the total load of the household p_t^{grid} which is broken down onto the defined tariff tiers $\tau_{k,t}$ according to Eq. 4 (plot on the right). The tariff used in this example corresponds to case study B introduced below in Sect. 4 (see also Figs. 7 and 8). The following energy devices are managed by the HEMS:

EV: Required battery recharge of 32 kWh between 20.15 and 03.45 o'clock (battery capacity: 40 kWh).
Heat pump: Average heat losses in the house 6 kW (provided storage capacity: 24 kWh).
Boiler: hot water usage is 9.6 kW scattered throughout the day (capacity of boiler: 12 kWh).
Battery: maximum power ±4 kW (capacity 10 kWh).
PV: production profile for a clear day (produced peak power: 6 kW).
Non-controllable load: Sum of all other loads, not influenced by HEMS (a standard load profile (SLP) H0 [25] has been applied as statistical forecast).

The optimization algorithm determines the optimum device schedules for minimal energy provisioning costs within the time window of 24 h, considering all degrees of freedom provided by the controllable energy devices. Three tiers in either direction of power flow are considered according to the right side of Fig. 4. The power intervals of tiers +3 and −3 are bounded on one side by the upper end of tiers ±2 and unbounded towards higher power on the other side.

4 Case study

In order to prove our approach for shaping the aggregated load profile, a case study has been carried out. Basis for the

Table 2 Randomized parameterization of energy devices for 100 simulated households

Device	Penetration	Demand/ supply	Efficiency	Schedulable electrical power	Available device capacity
Boiler [15]	100%: if heat pump (HP) present 40%: if no HP present	[4.8, 9.6] kWh (randomly distributed)	1 or 3 (electrical or HP boiler)	3 or 4 kW: electr. boiler 1 or 2 kW: HP boiler	$C \in [6, 12]$ kWh
PV [24]	50%	[1, 6] kW peak power (typical PV profile)	$\eta^{\text{gen}} = 1$	100% curtailable	0
EV [5,19]	25%	[5, 15] kWh (at charging station for 8 h a day)	$\eta^{\text{load}} = 1$	11 kW (50% with vehicle-to-grid (V2G) functionality)	$C \in [20, 80]$ kWh
Uncontrollable load [16]	100%	Dynamized standard load profile H0 [25], (household: [3.55, 5.2] MWh/a)	–	–	0
Heat pump [13,22]	50%	$p^{\text{ext}} \in [4, 8]$ kW	$\eta^{\text{load}} \in [2.5, 4]$	$2 \cdot p^{\text{ext}}/\eta^{\text{load}}$	$C \in [12, 24]$ kWh
Battery	40% if PV present	–	$\eta^{\text{load}} = \eta^{\text{gen}} = 1$	$0 < p^{\text{load}} < C/2.5$ h $0 < p^{\text{gen}} < C/2.5$ h	$C \in [5, 15]$ kWh

The specified parameter intervals define ranges of uniform probability density for the corresponding parameter. Detailed explanation: See Sect. 4.1

case study is a winter day with energy devices in households of a future scenario in Switzerland.

4.1 Simulation setup

The simulation includes 100 households with a random configuration of energy devices according to Table 2. The chosen configuration has been elaborated in workshops together with two local utility companies and resembles a future scenario for Switzerland. References have been specified that put the data into perspective. For each household, the device parametrization has been determined according to the following steps:

1. The specified penetration in column 2 defines the probability whether the corresponding device is available in the household.
2. Column 3 defines how the external demand or supply p^{ext} has been constructed. In case of the boiler, an energy demand has been chosen from the specified interval, assuming a uniform distribution. The maximum value of 9.6 kWh corresponds to a four person household with a daily hot water usage of 40 l per person [15]. The daily hot water consumption has been randomly distributed to the simulated time slots throughout the day time. In case of the PV system, a peak power has been chosen from the specified interval, again assuming a uniform distribution. The size of such systems is confined by the available rooftop area and can be considered representative for family home buildings [24]. An ideal production profile has been chosen as shown in Fig. 4 (left). In case of the electric vehicle (EV), the time of of plugging the EV into the charging station has been randomly determined between 6.00 and 23.00 o'clock. A connection time of 8 h after plugging in was assumed. The energy demand during charging has been randomly chosen from the specified interval. 10 kWh correspond to a travel distance between 40 and 90 km depending on the type of car [5]. These travel distances seem high compared to the average daily traveling distance of 37 km in Switzerland [19]. However, the performance values reported by the car manufacturers have to be considered ideal (no heating, no air conditioning, ideal operating points etc.). In case of the uncontrollable load, a standard load profile [25] was used based on a yearly energy usage which has been randomly chosen from the specified interval (average energy consumption of a household with two or four persons) [16]. In case of the heat pump, constant heat losses throughout the day have been assumed, again randomly chosen from the specified interval. Depending on the size of the house, temperature difference and insulation standard, heat losses can vary strongly. The distribution represents

a winter day. For the battery device, p^{ext} is set equal to zero.
3. The efficiency of the devices are set according to column 4. In case of the heat pump, a coefficient of performance >1 has been randomly chosen from the specified interval, assuming a uniform distribution (see e.g. [13]).
4. Column 5 describes the limitations imposed on the schedulable electrical power. In case of the boiler, only an on or off state is allowed with the specified power depending on a randomly chosen boiler type. In case of the PV system, the production is allowed to be curtailed continuously between 0 and 100 %. In case of the electric vehicle, the power is assumed to be continuously controllable between 0 and the specified maximum value. 50% of the charging stations have been assumed to allow to discharge the traction battery into the grid. In case of the heat pump, the maximum electrical power was assumed to be continuously controllable between zero and twice the demanded heating power currently required by p^{ext}. The premise for such controllability is an rpm-regulated device. The battery device is assumed to be capable of changing over the full storage capacity within 2.5 h.
5. The last column 6 specifies the device capacities (where available). The capacities have been randomly chosen from the specified intervals, assuming a uniform distribution. The storage capacity relevant for the heat pump is the total, effective heat capacity of the building. The specified interval has been chosen to represent a variety of buildings of light or heavy construction type. In [22] the effective heat storage capacity C has been calculated for a typical single-family dwelling with two floors according to EN ISO 13786, resulting in a heat storage capacity of 157 Wh/(m^{2}K). With a ground area of 170 m^2 and a temperature comfort zone of ± 1 °C, C results to 53 kWh. However, this value is valid for a storage period of 24 h only. The effective heat capacity reduces for shorter periods. The mean value of the interval considered in our simulation has been estimated to approx. 1/3 of this result. The storage capacities assumed for the battery and electric vehicle conform with existing solutions on the market.

4.2 Price signal optimization

The goal of the case study is to show that with moderate price based incentives, the regional load can be influenced in such a way as to follow a given reference load profile. For this purpose, a price vector $\tau_{0,t}$ has been iteratively determined for minimal deviation between the aggregated load of 100 simulated households p_t^{tot} and a reference load p_t^{ref}. The price structure contains 3 tiers for net production or consumption, respectively:

$$\tau_{k,t}^{\pm} = a_k \pm \tau_{0,t} \qquad \text{with} \quad \sum_{t=1}^{T} \tau_{0,t} = 0 \tag{6}$$

a_k specifies a price offset for each tier k. Each iteration n for price improvement includes the following three steps:

1. The net load p_t^{grid} is determined for each household based on price $\tau_{0,t}^n$.
2. The aggregated regional load p_t^{tot} is determined as the sum over all simulated households.
3. An improved price $\tau_{0,t}^{n+1}$ is calculated based on the deviation $\Delta p_t = p_t^{\text{tot}} - p_t^{\text{ref}}$ between regional load and its reference.

The last step determines a new price signal with the aim of minimizing the deviation from an arbitrary reference load p_t^{ref}. The calculation involves five parameters (k_p, k_i, k_d, k_0, and k_t), see also Fig. 5. Primarily, the price adaption

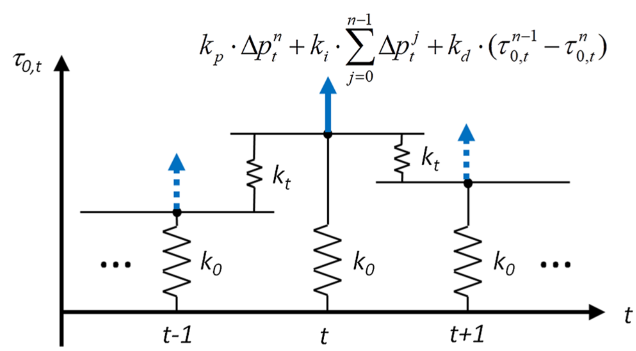

Fig. 5 Method for iterative improvement of price structure for regional load management

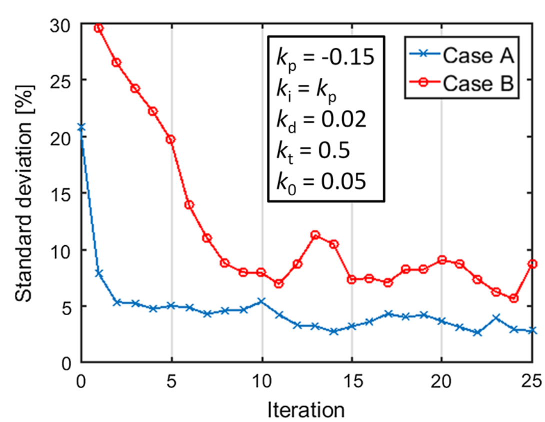

Fig. 6 Evolution of the standard deviation of Δp_t^i between the aggregated load and its reference as a function of iteration n. The *two curves* represent two different reference load profiles of case studies A and B introduced in Sect. 4.3 below. The parameters used for the price optimization are given in the box

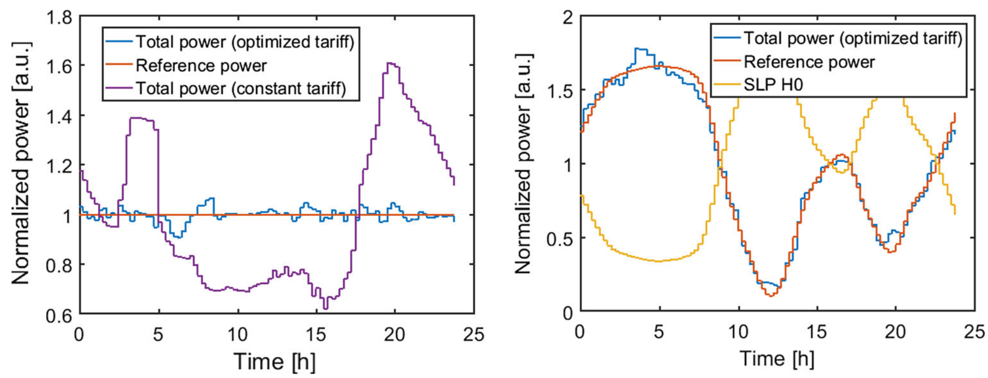

Fig. 7 Aggregated load profiles for optimized price structures. *Left* case study A (flat reference load profile); *right* case study B (reference profile: inverted standard load profile H0 [25]). The standard deviation from the reference load profile is A: 2.7% and B: 5.7%

is proportional to the deviation from the reference load at the corresponding time t (parameter k_p). However, also the history of past iterations is considered (k_i), the tariff change rate from one iteration to the other (k_d) as well as the adjacent time steps (k_t). τ_t^{n+1} is calculated as the solution of the set of equations for each t:

$$k_p \cdot \Delta p_t^n + k_i \cdot \sum_{j=1}^{n-1} \Delta p_t^j + k_t \cdot \left(\tau_{t-1}^{n+1} - \tau_t^{n+1}\right)$$
$$+ k_t \cdot \left(\tau_{t+1}^{n+1} - \tau_t^{n+1}\right) + k_d \cdot \left(\tau_t^n - \tau_t^{n+1}\right)$$
$$- k_0 \cdot \tau_t^{n+1} = 0 \tag{7}$$

For the simulations carried out in this work, the price signal converged after typically 10 to 15 iterations. For more iterations none or only minor improvements have been observed (see also Fig. 6). Since an iterative approach for price determination is not directly applicable in reality, finding more practicable methods must be subject of further research. The results presented in this work, however, demonstrate the possibility of collective load management based on the proposed tariff scheme.

4.3 Results on regional load shaping

The aggregated load has been calculated for two different reference load profiles. In order to demonstrate the potential of our proposed method two rather extreme reference load profiles have been chosen: Case study A represents a price structure optimized for a constant reference load whereas case study B has been optimized for an inverted standard load profile H0 as shown in Figs. 7 and 8. The total power with optimized tariff shown in Fig. 7 on the left is compared to a reference scenario resulting from a constant tariff of 20 rp/kWh[1] for consumed and −10 rp/kWh for generated energy, respectively. The difference between cases A and B is solely due to a different price function $\tau_{0,t}$. The scenario for the simulated households and its corresponding energy devices as well as all other price and simulation parameters have not been altered. The good adherence between reference load and resulting aggregated load (standard deviation with respect to average daily load is 2.7 and 5.7% for case studies A and B, respectively) demonstrates the effectivity of this method in utilizing the flexibility provided by its households. The statistical basis with 100 simulated households can be considered small compared to the foreseen number of households belonging to a managed region. It can be expected that even better results can be obtained with larger numbers of households participating in the same program.

4.4 Cost savings for residential homes

Figure 9 shows the distribution of cost savings for 100 households taken into account for case study B. Cost savings are determined by comparing cost of the optimized load profiles of each household with corresponding reference load profiles established as follows: The reference load profiles have been optimized with the same algorithm using a constant tariff scenario given by 20 rp/kWh for consumed and −10 rp/kWh for generated energy (see also Fig. 7, left). Such a tariff favours internal consumption, however, does not give any incentives when to draw energy from the grid nor on limiting power.

31% of the households do not profit at all or only very little from HEMS, since these households are not at all or only to a small amount capable of providing flexibility towards the grid – according to the randomly selected device penetration defined in Table 2. This result is plausible, since according to the specified device penetration probabilities (column 2), 30% of the households do not contain devices which offer a large flexibility potential such as the heat pump, the electric vehicle, and the battery. All other homes are capable of

[1] *rp* is the subunit of the Swiss franc (100 rp = 1 CHF).

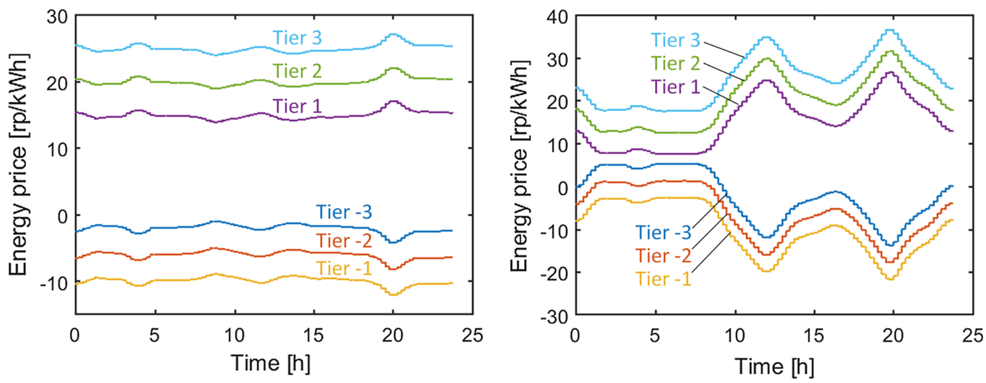

Fig. 8 Optimized price signals for aggregated load profile shaping over 24 h. *Left* case study A; *right* case study B. For case study A very moderate price variations suffice to yield a constant load profile in the time interval

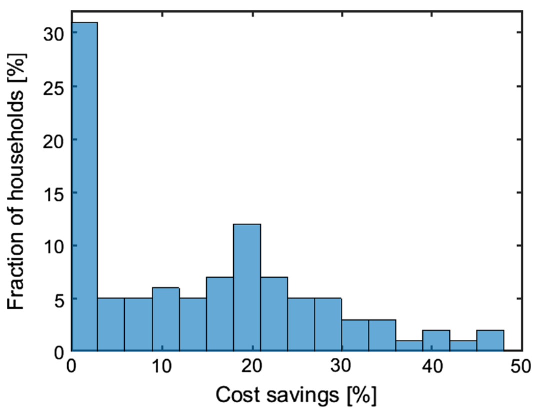

Fig. 9 Distribution of cost savings in case study B with respect to a reference scenario with maximum internal consumption, but otherwise without incentives on when and how much power is used (constant tariff situation). Relative cost savings refer to average costs of all households resulting from the reference scenario. The average saving for the individual households is 14.2%

optimizing their energy cost by supporting the grid with their flexibility. On average, overall cost savings of 14.2% can be obtained.

5 Conclusion

Case studies A and B presented in Sect. 4 demonstrate high controllability of the aggregated load profile solely based on common price incentives for a statistical sample of households. The flexibility required for load management is provided by HEMS which schedule local energy devices with the aim of minimizing energy cost in households. Stability of control is ensured and load synchronization is avoided by applying a price structure consisting of several progressive price tiers in dependence of consumed or generated power. The method is based on distributed control algorithms in each household, therefore leaving full freedom of control on the side of the home owner. Furthermore, the method is just in the sense that the power levels of the price tiers can be defined relative to average consumption and/or production of the household. Another advantage is the technology independent, price based interface between the energy provider and the supplied households. The common day-ahead energy tariff can be processed by any HEMS enabling interoperability between various HEMS manufacturers.

Acknowledgements This work has been supported by the *Strategic Initiative 'Energy Chance'* funded by the University of Applied Sciences Northwestern Switzerland.

References

1. Baccino F, Massucco S, Silvestro F, Grillo S (2014) Management strategy for unbalanced lv distribution network with electric vehicles, heat pumps and domestic photovoltaic penetration. In: 2014 IEEE PES general meeting | conference exposition, pp 1–5. doi:10.1109/PESGM.2014.6939158
2. Borenstein S (2005) The long-run efficiency of real-time electricity pricing. Energy J 26(3), 93–116. http://www.jstor.org/stable/41319500
3. Chen X, Wei T, Hu S (2013) Uncertainty-aware household appliance scheduling considering dynamic electricity pricing in smart home. IEEE Trans Smart Grid 4(2):932–941. doi:10.1109/TSG.2012.2226065
4. Doostizadeh M., Ghasemi H (2012) A day-ahead electricity pricing model based on smart metering and demand-side management. Energy 46(1): 221–230 . http://www.sciencedirect.com/science/article/pii/S0360544212006603
5. Elektroautos im Vergleich (2017) Website. http://www.elektroauto-news.net/wiki/elektroauto-vergleich
6. Faruqui A, Sergici S (2009) Household response to dynamic pricing: a survey of the experimental evidence. Brattle Group. doi:10.1016/j.energy.2009.07.042
7. Gyamfi S, Krumdieck S, Urmee T (2013) Residential peak electricity demand response-Highlights of some behavioural issues. Renew Sustain Energy Rev 25:71–77. doi:10.1016/j.rser.2013.04.006. http://linkinghub.elsevier.com/retrieve/pii/S1364032113002578
8. Herter K, Wayland S (2010) Residential response to critical-peak pricing of electricity: California evidence. Energy

35(4):1561–1567. doi:10.1016/j.energy.2009.07.022. http://www.sciencedirect.com/science/article/pii/S0360544209003016

9. Heussen K, Koch S, Ulbig A, Andersson G (2012) Unified system-level modeling of intermittent renewable energy sources and energy storage for power system operation. IEEE Syst J 6(1):140–151. doi:10.1109/JSYST.2011.2163020
10. Ipakchi A, Albuyeh F (2009) Grid of the future. IEEE Power Energy Mag 7(2):52–62. doi:10.1109/MPE.2008.931384
11. Javaid N, Khan I, Ullah MN, Mahmood A, Farooq MU (2013) A survey of home energy management systems in future smart grid communications. In: 2013 eighth international conference on broadband and wireless computing, communication and applications, pp 459–464. doi:10.1109/BWCCA.2013.80
12. Mattlet B, Maun JC (2016) Assessing the benefits for the distribution system of a scheduling of flexible residential loads. In: 2016 IEEE international energy conference (ENERGYCON), pp 1–6. doi:10.1109/ENERGYCON.2016.7513932
13. Milelli A (2012) Wärmepumpe: Worauf es ankommt. Online article. http://www.fws.ch/news/items/waermepumpe-worauf-es-ankommt.html
14. Mohsenian-Rad AH, Leon-Garcia A (2010) Optimal residential load control with price prediction in real-time electricity pricing environments. IEEE Trans Smart Grid 1(2):120–133. doi:10.1109/TSG.2010.2055903. http://ieeexplore.ieee.org/document/5540263/
15. Nipkow J (2013) Elektrische Wassererwärmung in der Schweiz—Statistische Daten, Abschtzung des Elektrizitätsverbrauchs, Ersatzmechanismen, Potenzial Wärmepumpenboiler. Tech rep, Swiss Federal Office of Energy SFOE. http://www.bfe.admin.ch/dokumentation/00459/index.html?lang=en
16. Nipkow J (2013) Typischer Haushalt-Stromverbrauch. Tech rep, Swiss Federal Office of Energy SFOE. http://www.bfe.admin.ch/dokumentation/00459/index.html?lang=en
17. Paterakis NG, Pappi IN, Catalo JPS, Erdinc O (2015) Optimal operational and economical coordination strategy for a smart neighborhood. In: 2015 IEEE eindhoven powertech, pp 1–6. doi:10.1109/PTC.2015.7232511
18. Paterakis NG, Erdin O, Bakirtzis AG, Catalo JPS (2015) Optimal household appliances scheduling under day-ahead pricing and load-shaping demand response strategies. IEEE Trans Ind Inform 11(6):1509–1519. doi:10.1109/TII.2015.2438534
19. Pendlermobilität in der Schweiz. Tech rep, Swiss Federal Statistical Office (2016). https://www.bfs.admin.ch/bfs/en/home/statistics/mobility-transport/passenger-transport/commuting.assetdetail.1351-1400.html
20. Qayyum FA, Naeem M, Khwaja AS, Anpalagan A (2015) Appliance scheduling optimization in smart home networks comprising of smart appliances and a photovoltaic panel. In: 2015 IEEE electrical power and energy conference (EPEC), pp 457–462. doi:10.1109/EPEC.2015.7379994
21. Reiss PC, White MW (2005) Household electricity demand. Revisited. Rev Exonomic Stud 72(3):853–883. doi:10.1111/0034-6527.00354. https://academic.oup.com/restud/article/72/3/853/1557538/Household-Electricity-Demand-Revisited
22. Schulz N, Bichsel J, Wache H, Farooq AA, Hoffmann C, Lammel B, Mettler F (2015) Smart stability–market-economic interaction of smart hhome for improved power network stability. In: Proceedings of international conference CISBAT 2015—future buildings and districts—sustainability from nano to urban scale, pp 487–492. doi:10.5075/epfl-cisbat2015-487-492
23. Soland M, Loosli S, Koch J, Christ O (2017) Acceptance among residential electricity consumers regarding scenarios of a transformed energy system in switzerland–a focus group study. Energy Effic. doi:10.1007/s12053-017-9548-x
24. Solardachrechner (2017) Onlinetool. http://www.swissolar.ch/fuer-bauherren/planungshilfsmittel/solardachrechner/
25. Standard load profiles: German association of energy and water industries (BDEW) (2011). https://www.bdew.de/
26. Yao L, Damiran Z, Lim WH (2017) Energy management optimization scheme for smart home considering different types of appliances. In: 2017 IEEE international conference on environment and electrical engineering and 2017 IEEE industrial and commercial power systems Europe (EEEIC / I CPS Europe), pp 1–6. doi:10.1109/EEEIC.2017.7977565
27. Zhao Z, Lee WC, Shin Y, Song KB (2013) An optimal power scheduling method for demand response in home energy management system. IEEE Trans Smart Grid 4(3):1391–1400. doi:10.1109/TSG.2013.2251018