Cooperative Energy Management Approach for Short-term Compensation of Demand and Generation Variations

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***Abstract*— In this work, we introduce the short-term phase of a cooperative energy management algorithm, which exploits the flexibilities arising from the shifted switching of heating systems and charging and discharging of thermal storage. The cooperative approach does not follow any financial gain optimization for individual households but rather targets a solution that is beneficial for all parties involved. We introduce profile deviation categories based on previous studies and define the concept of flexibility provided by the heating systems according to operational boundaries and the capacity of the thermal storage. Within this short-term phase of the energy management algorithm, the switching of the heating systems is coordinated in order to avoid transient effects due to simultaneous switching. Furthermore, occurring deviations from a day-ahead schedule are detected, evaluated and analyzed, and an adequate combination of resources to dispatch is calculated in order to compensate the deviations. The method evaluates short-term weather forecasts and user behavior forecasts, statistical data and signals from the upper grid level. The short-term load compensation is based on local state estimation and includes grid aspects. We present here preliminary results from a case study for a radial grid segment from the model region, in which the combination of dispatch resources is calculated such that their distance from the location of the primary cause of the deviation is minimized.**

Keywords—energy management; demand side management; load variations; flexibilities; realtime control

I. INTRODUCTION

InnovationCity Ruhr [1] is a set of projects, which aims to demonstrate the potential of an average city in Germany to integrate renewable energy generation and to achieve significant reduction of its CO_2 emissions in a limited period of time. Dual Demand Side Management (2DSM) is a project in InnovationCity Ruhr, which exploits the flexibility arising from the coupling of thermal and electrical supply systems, and storage technologies [2][3]. Major outcomes are: a multi-energy simulation platform and a novel control strategy, based on planning algorithms and short-term control actions.

In this paper, the short-term phase of a cooperative energy management approach is introduced and demonstrated on a sample residential area. In Section II, studies related to the background of the paper and to the modeling and control approaches are presented. Section III describes the system, the assumptions and constraints for the application of the algorithm. The overall energy management approach is presented in Section IV. The short-term compensation algorithm and the results from the case study are introduced in Sections V and VI.

II. RELATED STUDIES

A very mature energy management concept, Triana, is described in [4]. This concept is organized in three phases, prediction, planning and real-time control, similarly to the 2DSM concept. The real-time control is based on an optimization for the balancing of energy flows between pools in the sense of energy sources and sinks. In a further step, an algorithm for model-predictive control is included, in order to reduce negative effects of decisions on later time periods. In Triana, the real-time control operates on the single-device level for every building. Grid aspects are neglected except for the option to account for import and export of energy in the cost functions.

Reference [5] presents a concept for the compensation of solar variations by load-shifting for smart appliances and electric vehicles. The authors suggest the aggregation of negative and positive reserve capacity to smooth PV variations. However, the authors focus on electric vehicles and household devices and do not consider thermal storage.

The approach in [6] suggests the use of aggregated populations of thermostatically controlled loads to manage frequency and energy imbalances. The work is based on state estimation of the electric loads for different levels of real-time communication and available information.

In [7], the authors present an online and offline demand side management optimization models for the control of household appliances and energy storage. Further, a set of heuristics is presented, in order to properly react in real time to unexpected events.

The contribution of this work is to include the consideration of grid aspects and local state estimation in a cooperative setup for the short-term load compensation. The proposed approach

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abstracts the control from individual household appliances and focuses on the flexibilities of heating systems and thermal storage, while minimizing the effect on residents' comfort. Furthermore, deviations from the schedule are analyzed individually by every household based on statistics on residents' behavior and forecasts and classified according to the expected duration. The short-term load compensation method is designed as a cooperative approach, which follows global goals beneficial for all participants rather than the individual goals of the particular household.

III. System Description

A. Framework

For the development of the 2DSM solution, we focused on a scenario with cooperative agents realized within a multi-agent system framework, neglecting financial incentives. The functions and the interaction of the agents are described in Section III.B. The energy management approach is based solely on the flexibilities allowed for by the shifted switching of the heating devices and the installed thermal storage. This is explained in more detail in the following.

All households are equipped with a heating system, which can be an electric heater, a heat pump (HP), or a micro Combined Heat and Power (µCHP). Households with a HP or with a µCHP have additionally a thermal storage, which is charged when the heating systems are running. Some households are equipped with photovoltaic modules (PV). Generated PV energy is used to supply the household demand in the first place. In case the generated energy exceeds the household demand, the energy is fed into the grid.

The energy management approach presented here is cooperative and does not follow any financial gain optimization for the individual households. This approach, contrary to the approaches focused on the financial gains of the individual customer, is beneficial for all market participants. On the one hand, customers' monthly expenses can be reduced with increasing amount of installed flexibilities. On the other hand, grid stability is secured and the integration of energy from renewable sources is increased, which saves costs for the grid operator.

For the implementation of the cooperative algorithm, we assume that the customers are willing to switch their heating systems and to feed the surplus of PV generation into the grid as long as their comfort is not penalized. We expect that this scenario is acceptable only if customers do not experience financial disadvantages. An option to solve the financial issues is a flat rate energy tariff similar to internet tariffs, in which the customer pays a basic fee per month, irrespective of their consumption, and accepts requests from the grid operator as far as possible. Such tariff should account for the consumption and offer various basic fees, according to the average power range needed in the household or to the flexibilities the household has actually provided. The tariff could include for example an extra power range for a limited number of hours to cover occasional higher energy consumption, possibly not guaranteed in the peak time. An option for addressing the additional maintenance costs and the reduced life time of the heating systems is that the devices are owned and installed by the energy provider, who keeps the right to switch them when the needs of the household are satisfied, similarly to [9]. However, these billing aspects constitute the viability of the proposed energy management concept in a future energy management structure, which still has to be designed and developed. They are beyond the scope of this work and, therefore, not discussed further.

At the current stage of the project, the 2DSM control algorithm is implemented in a simple hierarchical structure, where the agents aggregate the data received from the lower level, filter relevant data and forward them to the higher level. This structure is not an essential part of the control approach and could be easily replaced by a decentralized structure, in which any of the participants could act as master, for example the building with the highest flexibility in this hour.

B. 2DSM Control Approach

The control approach is organized in two phases. In the first phase, the planning phase, day-ahead schedules are negotiated between the households, represented by Building Agents, and a higher instance, referred to as an Aggregator Agent. The area for which the Aggregator Agent is responsible is referred to as its cluster. In the second phase, the short-term compensation phase, main topic of this paper, the switching of the heating systems is coordinated, and deviations from the schedules are compensated for. Both phases are schematically in Fig. 1 and introduced briefly in the following.

Within the planning phase, which is introduced in the top half of Fig. 1, the Building Agents communicate with an Aggregator Agent, negotiate and agree upon a schedule for the next day in resolution of one hour. The negotiation process is based on forecasts for generation of renewable energy and expected residents' behavior.

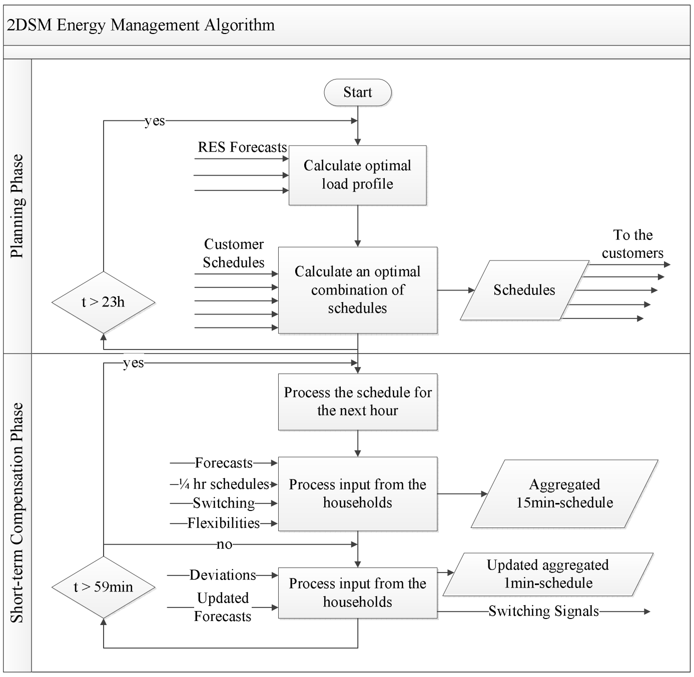

Fig. 1. 2DSM Algorithm: Planning phase and short-term compensation phase

Within the short-term phase (described in the bottom part of Fig. 1), occurring deviations from the negotiated schedule are detected and compensated so that the aggregated schedule for the controlled area is kept within certain limits. At the beginning of every hour, in the coordination phase, the schedules for this hour are defined in resolution of 15 minutes by every household. Furthermore, switching of the heating systems is coordinated to avoid transient effects due to simultaneous switching. The compensation algorithm accepts continuously signals for occurring or expected deviations. It is triggered every minute in presence of deviations to find an adequate combination of dispatch resources to compensate the deviations, according to the representation in Fig. 1. The approach is presented in detail in the next chapter.

IV. Short-term Compensation of Deviations

In this section, we introduce deviation categories according to their duration and magnitude and define the concept of provided flexibilities. Deviation categories based on statistical data are useful in systems with limited real-time information and communication, as they can be used to estimate the expected duration and magnitude of the occurring deviations. Even though the deviation categories are based on statistical data, they are grouped by season, week day and time of the day and allow a differentiated view of the detected deviations. For the short-term compensation of deviations, the categories are used to simulate realistic input from a system, for which solely reference values such as the number of residents and socio-economic data are known.

Based on the deviation categories and the flexibility definition, the coordination of switching processes and the compensation of deviations are introduced as key functions of the algorithm.

A. Deviations

According to previous studies, the duration and magnitude of deviations depends on the investigated time interval [10]. They occur more often and with larger magnitudes in the evening hours on weekdays and around noon on weekends. Possibly, this can be explained with the residents' presence and the stochastic nature of consumer behavior. Depending on the region, the demand is subject to specific seasonal variations, such as heating and lights in winter and air conditioning in summer. The study in [11] states an average duration of deviations between 15 and 45 minutes around noon and between 30 and 90 minutes on evenings for weekdays. For weekends, the average duration of deviations is between 15 and 90 minutes around noon and on the early afternoon, and between 15 and 60 minutes in the evening hours. Furthermore, numerous randomly occurring deviations below 5 minutes were detected. In regard to PV variations, studies show that 99% last less than 20 minutes [11] [12].

Based on these considerations, the short-term compensation algorithm is triggered in intervals of one minute in order to update the demand and generation forecasts for the next minute. Deviation signals from the Building Agents are processed and included to the aggregated demand curve for the next m intervals for a deviation with expected duration of m minutes.

B. Flexibilities

In order to maintain awareness of the available flexibilities in the cluster, the heating devices update their flexibility and notify the Aggregator Agent in the coordination phase.

From the operative point of view, the flexibility limits of a heating system are defined by technical constraints and by operational boundaries. This is depicted in Fig. 2 for a μCHP, where the operating area of the heating system is defined by the temperature limits of the thermal storage (on and off areas in the figure). For example, the lower temperature limit is usually around 20°-25°C, and the upper limit could reach 95°C. The operating line expresses the relation of thermal and electrical energy generation for this device, also referred to as its Coefficient of Performance (COP). Depending on the current operating point of the heating system, its flexibility potential is described by the operating line. The operating line is the trajectory of the operating point. The direction in which the operating point moves along its trajectory depends on the state of the device (on or off).

Based on these considerations, the flexibility of a household is defined as follows:

$$FL_{rangeN} = \{t_L, t_H \in \mathbb{N}_0 \mid t_L < t_H, 0 \leq t \leq 60\} \quad (1)$$

$$FL_{magnN} = \{P_L, P_H \in \mathbb{R} \mid |P_L| \leq |P_H|, \\ 0 \leq |P| \leq P_{HSmax}\} \quad (2)$$

In (1) and (2), FL_{rangeN} and FL_{magnN} are the time and power ranges of the flexibility of household N. P_{HSmax} denotes the upper limit for generation or consumption for the flexible device from operational point of view. t_L and t_H, and P_L and P_H denote the lower and upper limits of the time and the power range of flexibility, respectively. P_H could be less or equal to P_{HSmax}. P_H is equal to P_{HSmax} in case the device offers the flexibility to generate or consume energy in its full capacity. However, in rare cases it is possible that the device offers flexibility less than P_{HSmax}, for example according to slow-charging settings for electric vehicles. Positive FL_{magn} denotes the capability of the household to increase its consumption, for example by switching on a HP, between minutes t_L and t_H of the following hour. Power dispatch could be a range ($P_L \neq P_H$, e.g. in case of device capable of modulated operation), or a fixed value ($P_L = P_H$).

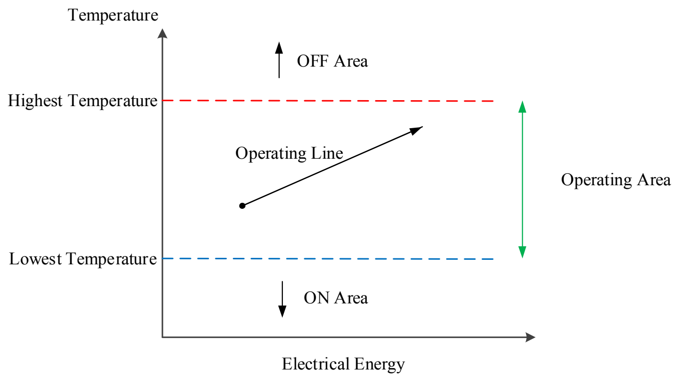

Fig. 2. Flexibility of a μCHP according to the operation area of the device

C. Coordination

As the schedules negotiated upon in the planning phase are in a resolution of one hour, the coordination algorithm is executed in the beginning of every hour.

In the coordination phase, the day-ahead forecasts for the generation from regional resources are updated according to short-term weather forecasts. Assuming that the increased share of renewables requires frequent short-term updates at the upper grid level too, the algorithm provides the possibility to distribute the additional energy among the clusters which detected severe deviations. Therefore, in the coordination phase input from the upper grid level is taken into account, so updated generation trends can be adequately addressed and integrated into the grid if possible.

To avoid simultaneous switching and the resulting grid instabilities due to transient switching effects, the switching order of the heating systems is defined in the coordination phase. For the demonstration of 2DSM, a random algorithm inspired by the carrier sense multiple access (CSMA) in communication networks is planned, in order to avoid simultaneous switching of several heating systems. CSMA was developed as an advanced method to overcome the problem of collisions of data frames sent through a communication channel [9]. In CSMA, the sender senses the channel and sends if the channel is idle. If the channel is busy, several strategies are possible:

- 1-persistent CSMA: the sender continuously senses the channel and sends as soon as the channel is idle
- non-persistent CSMA: the sender waits a random amount of time until it senses the channel again
- p-persistent CSMA: the sender waits for the next time slot and sends the frame with (chosen) probability p or waits for the next time slot with probability *q=1-p*

For the proposed energy management approach and the time non-critical applications, such as switching of heating devices and charging of thermal storage, the non-persistent method was chosen. However, in order to implement the method adapted to the coordination of devices, the measuring unit, say, a smart meter, should be able to sense the line and detect if there are transient effects, meaning that another device has just been switched. This solution reduces communication cycles and traffic, but requires units capable of high-resolution measurements. This aspect will be investigated further in future works.

As the performance of the described method cannot be tested in real conditions until the demonstration phase of the project, an alternative method is implemented for the preliminary version of the algorithm. For the validation in simulation, the input of the households which will switch their heating system within the following hour is artificially created by a random generation of a number in the range between 1 and 60, which is considered as their switching time.

Despite its simplicity, the alternative approach is viable as a back-up of the described CSMA-based approach in the demonstration phase. As the transient phase of the considered heating systems is in the range of 1-2 minutes, in systems with limited number of HPs and μCHPs the values should be chosen around the beginning of the 15-minutes intervals, for example ±2 minutes. In case the random switching points interfere, the households receive an alternative switching point such, that there are no two devices switching at the same time.

With a growing number of heating systems in the cluster, the Building Agents will receive more often alternative switching points. As the next project phase foresees their implementation as self-learning systems, they will correct their suggestion range according to the alternative switching points which they received.

D. Compensation Approach

In case of deviations which have to be compensated for, several options are possible for the combination of devices to deliver the dispatch energy. In the following, the principle and the steps are explained schematically for an assumed positive deviation, which means demand higher than expected. The steps are: update of the PV generation forecasts, reduction of the consumption by switching off heating systems which consume energy and increased generation by switching on μCHP. The same procedure is followed for negative deviations, with opposite considerations of generation and consumption.

1) Prediction and estimation of PV generation

In the first step, the deviation is compared with the short-term updates for PV generation, assuming that these would increase or decrease the magnitude of the demand deviation.

In order to forecast the PV generation for the next time interval, the parameters initial voltage-current curve, which is calculated analytically, are estimated based on forecast updates, using a linear regression model with a Kalman filter based on [14].

First, the PV characteristics are calculated according to the current weather conditions. We distinguish three weather categories, sunny, cloudy, and variably cloudy as in [12]. The weather categories influence the PV voltage-current curve to a varying degree, according to the different ambient temperature and, therefore, the efficiency factor, and to the generation variability.

For the prediction of the PV generation based on the semi-empirical relations, the current efficiency for the weather conditions and measured values from the last n intervals are employed in the regression model in (3).

$$y_k = a_0 + \sum_{i=1}^{n} a_{k-i} y_{k-i} \frac{\eta_k}{\eta_{k-i}} + v_k \tag{3}$$

In equation (3), y_k is the predicted value for the PV generation for time interval k, based on previous measurements from time intervals from 1 to n; a_0 represents an error model; and η_k and v_k describe the efficiency and the measurement noise at time interval k.

In order to improve the accuracy of the prediction and minimize errors due to unknown modeling parameters in the state-space representation of the system, we implemented a Kalman filter to estimate the state space model and to predict the state transitions in the model based on measurements from the last time intervals.

Based on the PV generation update for the considered interval, the deviation magnitude is updated. In case the PV generation is more than expected, this compensates the higher demand. In case the net total deviation is still outside the predefined limits, the deviation has to be compensated by switching the heating devices. In the following, three possible criteria for the choice of a combination of devices are presented.

2) Compensation of deviations by switching off HPs

Due to technical constraints and issues with the lifetime of the devices, heating systems are blocked for some time after switching. Maximum 3-4 switching actions per hour are technically possible; however, frequent switching should be avoided. If the thermal storage is charged from low to full state of charge (SoC) in one cycle, without interrupting the heating systems, their efficiency and lifetime are increased significantly. Therefore, from the operational point of view, the SoC of the thermal storage is a good criterion for the choice of devices which should be switched. However, this approach is focused on the individual household and is not conform to the cooperative strategy outline. Besides, we expect it to have long-term effects on the energy management algorithm, as it could lead to additional deviations.

Another option is to follow the scheduled SoC in order to keep the demand curve as close as possible to the schedule. This is important for the stability of the overall control algorithm, as the use of flexibilities changes the operation parameters of the addressed households and, therefore, the demand profiles. For example, HPs which are addressed as additional loads, charge their thermal storage during the operation cycle and would be a source of deviations when the storage is fully charged. In this way, the random use of flexibilities increases the level of uncertainty and the probability that approaching the end of the schedule (at 24:00), the allocation of flexibilities does not converge. Therefore, the scheduled SoC is included in the decision process for the addressed devices. This aspect of the short-term compensation algorithm will be a subject of further investigations, as the range of influence of flexibilities use in relation to the installed flexibilities is a part of the validation of the overall algorithm.

The other relevant criterion for the choice of dispatch resources is their physical distance from the cause of the deviation, in order to minimize losses in the system and to avoid congestions. The implemented algorithm searches for the optimal solution for the compensation of the deviation, distributing the excess energy inversely proportional to the distance to the deviation cause. This strategy is interesting for rural areas due to the long distances between the customers, but also for advanced billing options, such as the option for a group of customers to install a near-district heating system and a combination of generation units and share the energy costs.

For the case study in this paper we assume positive deviation due to higher demand and minimization of losses as a compensation criterion. Therefore, the first compensation step is to switch off energy consuming heating devices, HP, as a zero-loss solution according to [5] and [6].

Reference [5] and [6] describe a coordination method for the control of aggregations of thermostatically controlled loads (TCLs), such as refrigerators and heat pumps. The authors use Markov chain models to describe the temperature evolution of populations of TCLs and a Kalman filtering for state estimation in case of limited information from the system. The authors offer different control options based on the computation of power from devices likely to switch on and off in the next time step due to environment and operational parameters, such as the outside temperature and the operation settings.

Based on the work in [5] and [6], for this work we implemented a simplified state transition model for the HP, as illustrated in Fig. 3, where the possible states are on/off and satisfied/unsatisfied.

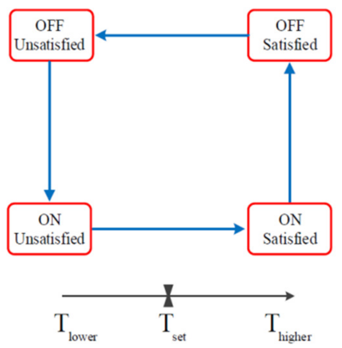

Fig. 3. State transition model for the HP

In order to compensate the occurred deviation, the total amount of power from devices with high probability to be switched in the next time interval is computed; these are the devices in the on and unsatisfied state. According to the deviation magnitude, 5%, 10%, 15% or 20% of the best and good possible combinations of HPs are addressed. In case of a deviation residual, the flexibilities offered by µCHPs are evaluated.

3) Compensation of deviations by switching on µCHPs

The dispatch of generation according to the physical distance to the cause of deviation is based on the principle introduced in [15] and described by equation (4). In (4), loads are indicated with m, and distributed energy sources with n. Accordingly, a deviation at node m due to higher demand is indicated with ΔP_m:

$$P_m^n = \Delta P_m \frac{P_n^{flex}}{d_m^n} \left(\sum_{n=1}^{N} \frac{P_n^{flex}}{d_m^n} \right)^{-1} \tag{4}$$

In (4), the contribution P_m^n of node n is calculated according to its distance to the deviation d_m^n and its flexibility P_n^{flex}. The consideration of the distance to the deviation for all distributed energy sources introduces an optimal dispatch solution for the compensation of the deviation.

In the discussed case of higher demand than scheduled, the procedure is applied to the µCHPs that offered flexibility for the considered time interval. In the last step of the compensation procedure, deviation residuals are offered to neighborhood areas or announced to the upper grid level.

Further development of the algorithm will include the consideration of several criteria; for which both steps will be combined and weighted.

V. CASE STUDY

In this section, results from a case study are presented for a radial grid segment from the model region. In order to illustrate the performance of the presented algorithm, two scenarios are studied for a realistic deviation vector, according to the level of penetration of flexible heating systems in the residential area. The tests are focused on the potential for the compensation of deviations at local level. In particular, we study the reduction of losses with the implemented algorithm which was described in the previous section. The level of penetration of flexible heating systems is modeled by simulating different combinations of HPs and µCHPs in the residential area.

The tests were done on a radial grid segment in a residential area, as illustrated in Fig. 4. The test scenario maps an existing area within the model region. The grid characteristics, the modeled buildings and the geographical relations reflect the real circumstances in the area.

Both test scenarios are illustrated in Fig. 4, where the flexible resources (HPs and µCHPs) are illustrated as additional load or generation at the corresponding nodes. The distance between the nodes is given in meters. The additional resources considered only for the advanced test scenario are indexed with "$_2$". All households with flexible heating devices have thermal storage, which allows them to generate (µCHPs) or consume energy (HPs) when addressed with a corresponding request.

The grid segment consists of 19 nodes, each corresponding to a building. Many buildings are apartment buildings with up to eight households. There are 62 households in total, with one to five residents. We used the average values calculated in the study on load variations in residential areas in [11], and scaled them according to the characteristics of the test scenario for the time 11:00-12:00 on a Sunday in winter. The deviation categories scaled for a household of four residents are illustrated in TABLE I.

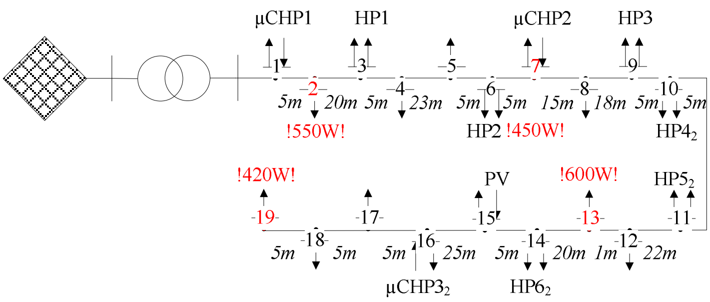

Fig. 4. Grid segment of the case study

TABLE I. DEVIATION CATEGORIES FOR A HOUSEHOLD OF FOUR PEOPLE

	Weekday			
	Summer		***Winter***	
Time slot	**Magnitude**	**Duration**	**Magnitude**	**Duration**
07:30-09:30	Up to 125W	Up to 20min	Up to 175W	Up to 15min
11:30-14:30	Up to 250W	15-45 min	Up to 300W	15-35 min
17:30-22:00	Up to 425W	45-90 min	Up to 425W	30-70 min
	Saturday			
	Summer		***Winter***	
Time slot	***Magnitude***	***Duration***	***Magnitude***	***Duration***
10:00-12:00	Up to 200W	Up to 45min	Up to 100W	Up to 20min
12:30-16:00	Up to 550W	20-60 min	Up to 500W	20-60 min
19:30-22:00	Up to 175W	Up to 20min	Up to 500W	15-70 min
	Sunday			
	Summer		***Winter***	
Time slot	***Magnitude***	***Duration***	***Magnitude***	***Duration***
9:00-15:00	Up to 500W	30-90 min	Up to 425W	15-90 min
18:00-22:30	Up to 375W	15-70 min	Up to 325W	15-60 min

According to the frequency of occurrence of deviations in [11], we implemented following four deviations:

- Node 19, a 3-person household: deviation with a magnitude of 420 W and a duration of 45 minutes
- Node 13, a 5-person household: deviation with a magnitude of 600 W and a duration of 40 minutes
- Node 2, a 5-person household: deviation with a magnitude of 550 W and a duration of 30 minutes
- Node 7, a 4-person household: deviation with a magnitude of 450 W and a duration of 35 minutes.

A. Basic Scenario

In the basic scenario flexible heating systems are modeled at node 3, 16 and 17 (HP1, HP2, HP3), and at nodes 1 and 7 (µCHP1 and µCHP2). Their scheduled operation modes, SoC and flexibility for the time 10:00-13:00 are listed in TABLE II.

The scheduled operation mode, listed as "Schedule" in Table II, is 0 for devices, which are off within this hour, 1 for devices running and consuming electrical energy, and -1 for devices running and generating energy. As described in Section IV.B, positive flexibility power range denotes the possibility of the household to increase its energy demand. For example, according to the schedule for the time slot 11:00-12:00, the thermal storage of HP1 is charged to 33% at the beginning of the time slot. HP1 is scheduled to be running between 11:00 and 12:00. It offers flexibility to reduce its consumption by 400 W ($FL_{magn} = -0.4$ kW) at any time if necessary ($FL_{range} = \{0, 60\}$min). Further negative flexibilities are provided by µCHP1 and µCHP2, which could increase their generation by 370 W and 540 W, respectively.

TABLE II. SCHEDULES AND FLEXIBILITIES FOR THE RESOURCE IN THE BASIC SCENARIO

Time Slot	Parameters	HP1	HP2	HP3	µCHP1	µCHP2
10:00 - 11:00	***Schedule***	1	0	0	-1	-1
	SoC	37%	35%	70%	46%	55%
	FL_{range} *[min]*	$\{0,60\}$	$\{0,60\}$	$\{0,60\}$	$\{0,60\}$	$\{0,60\}$
	FL_{magn} *[kW]*	$\{-0.4\}$	$\{1.0,5.0\}$	$\{1.0,3.0\}$	$\{-0.37\}$	$\{-0.54\}$
11:00 - 12:00	***Schedule***	1	1	0	-1	-1
	SoC	43%	30%	69%	53%	64%
	FL_{range} *[min]*	$\{0,60\}$	$\{0,60\}$	$\{0,60\}$	$\{0,60\}$	$\{0,60\}$
	FL_{magn} *[kW]*	$\{-0.4\}$	$\{0\}$	$\{1.0,3.0\}$	$\{-0.37\}$	$\{-0.54\}$
12:00 - 13:00	***Schedule***	1	1	0	-1	-1
	SoC	49%	41%	68%	60%	73%
	FL_{range} *[min]*	$\{0,60\}$	$\{0,60\}$	$\{0,60\}$	$\{0,60\}$	$\{0,60\}$
	FL_{magn} *[kW]*	$\{-0.4\}$	$\{0\}$	$\{1.0,3.0\}$	$\{-0.37\}$	$\{-0.54\}$

1) Coordination

HP2 is scheduled to be off in the time slot 10:00-11:00, and to be running in the next time slot due to the low SoC of the thermal storage (30%). The device generates a random number for its preferred starting time (minute 42) and sends a signal to the Aggregator Agent.

The short-term PV forecast updates indicate expected generation increase by 400 W.

2) Deviation processing and compensation

The deviations described above are illustrated in Fig. 5. The increased PV generation reduces the net total deviation to 1620 W.

The distance between the µCHPs and the loads are illustrated in Fig. 6. According to the distance to the deviations and equation (4), Fig. 6 shows the optimal solution for loss-efficient energy dispatch from both µCHPs among the deviations. The µCHP1 would be the most efficient option to compensate the deviation at node 2 due to the very short distance of 5m between the nodes. The adequacy of µCHP1 for the compensation of the other deviations decreases with the distance to nodes 7, 13 and 19.

This conclusion is confirmed by the compensation adequacy of µCHP2 at node 7. As there is a detected deviation at the same node, the most efficient solution is to assign the same resource for its compensation.

By switching HP1 and both µCHPs, the initial aggregated deviation of 1620 W was reduced to 310 W. In this case, the signal for a deviation would be announced to the upper grid level or communicated with neighbor clusters as described in Section IV.

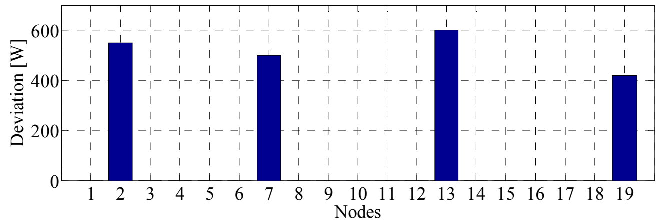

Fig. 5. Deviations in the time 11:15-11:50

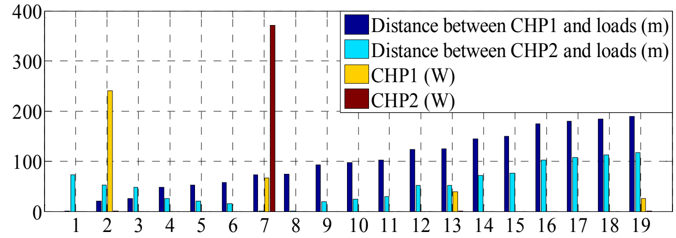

Fig. 6. Distance to the loads and corresponding adequacy for compensation of the deviations in the basic scenario

B. Advanced Scenario

For the advanced scenario, further 3 HPs (HP4, HP5 and HP6 at nodes 10, 11 and 14), and µCHP3 at node 16 were included. The schedules and flexibilities for the resources introduced in the basic scenario are considered the same. The parameters of the additional resources are listed in TABLE III.

TABLE III. SCHEDULES AND FLEXIBILITIES FOR THE RESOURCES ADDED FOR THE ADVANCED SCENARIO

Time Slot	Parameters	HP4	HP5	HP6	µCHP3
10:00 - 11:00	***Schedule***	0	1	0	-1
	SoC	62%	44%	70%	46%
	FL_{range} *[min]*	$\{0,60\}$	$\{0,60\}$	$\{0,60\}$	$\{0,60\}$
	FL_{magn} *[kW]*	$\{1.2,3.6\}$	$\{-0.3\}$	$\{0\}$	$\{-0.54\}$
11:00 - 12:00	***Schedule***	0	1	1	-1
	SoC	61%	47%	68%	53%
	FL_{range} *[min]*	$\{0,60\}$	$\{0,60\}$	$\{0,60\}$	$\{0,60\}$
	FL_{magn} *[kW]*	$\{1.2,3.6\}$	$\{-0.3\}$	$\{0\}$	$\{-0.54\}$
12:00 - 13:00	***Schedule***	0	1	1	-1
	SoC	60%	50%	72%	60%
	FL_{range} *[min]*	$\{0,60\}$	$\{0,60\}$	$\{0,60\}$	$\{0,60\}$
	FL_{magn} *[kW]*	$\{1.2,3.6\}$	$\{-0.3\}$	$\{0\}$	$\{-0.54\}$

1) Coordination

Within the coordination phase, the Aggregator Agent receives the signal from HP2 as described in the basic scenario, and a signal from HP6 that it will switch on at minute 21 of the current hour. As the switching times do not interfere, no further actions are required from the Aggregator Agent.

The short-term PV updates indicate generation increase by 400 W.

2) *Deviation processing and compensation*

The deviation vector is the same as for the tests with the basic scenario. The distance from the µCHPs to the nodes is illustrated in Fig. 7. Again, µCHP1 is the most efficient option to compensate the deviation at node 2. µCHP2 is the optimal compensation resource for the deviation at the same node. µCHP3 at node 16 should be addressed as first resource for the compensation at node 19 and, to a limited extent, for the deviation at node 13.

The three µCHPs offer flexibility potential of ca. 1450 W, which compensates completely the deviation residual of 920 W after the PV update and after switching off HP1 and HP5. According to Fig. 7, the most adequate combination of resources for the deviation compensation with minimal losses is µCHP2 and µCHP3. This assumption is validated by simulation of the optimal combination and of random switching combinations, which are µCHP1 and µCHP2 or µCHP3. The simulation results are listed in TABLE IV.

We assume that the deviation residuals of 10 W and -160 W are both within the preset limits. The grid losses of 752 W and 750 W for random switching are higher than the calculated losses of 736 W for the optimal resource combination, which confirms that the calculated optimal combination of dispatch resources performs better than the option to switch resources in a random manner.

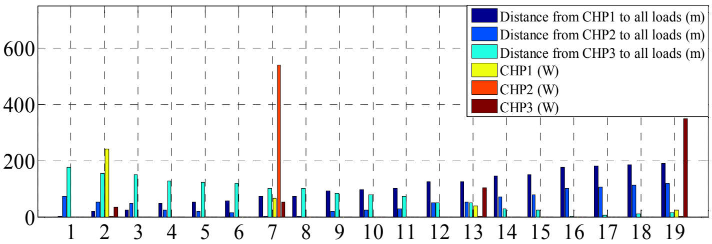

Fig. 7. Distance to the loads and corresponding adequacy for compensation of the deviations in the advanced scenario

TABLE IV. NETWORK LOSSES AND DEVIATION RESIDUAL FOR THE COMBINATIONS OF RESOURCES

Combination	Network Losses	Deviation Residual
µCHP1 and µCHP2	752 W; 536 Var	10 W
µCHP1 and µCHP3	750 W; 541 Var	10 W
µCHP2 and µCHP3	738 W; 536 Var	-160 W

VI. CONCLUSIONS

In this work, an approach for the short-term compensation of deviations is presented as a part of a two-phase energy management algorithm. We define the concept of provided flexibilities and introduce statistical deviation categories.

The short-term compensation approach starts with the coordination of heating devices in order to avoid transient effects due to simultaneous switching. The compensation of deviations can follow different priorities. Here we calculate the combination of dispatch resources such that the physical distance to the deviation cause and, therefore, the losses are minimal.

We demonstrate the presented algorithm on a grid segment with 19 nodes and 62 households which reflects the real conditions in an area in the model region of the project. The generation of the deviation signal is based on statistical studies and shows the applicability of statistical load-deviation data in systems with minimal real-time information exchange.

The simulation confirms the applicability of the compensation approach for realistic conditions. The decreased grid losses for the optimal combination of dispatch resources compared to random switching confirm the adequacy of the implemented loss minimization algorithm.

REFERENCES

[1] InnovationCity Ruhr [Online]. Available: http://www.bottrop.de/microsite/ic/, last visited: Sept. 2013

[2] C. Molitor et al., "New energy concepts and related information technologies: Dual Demand Side Management," in *Proc. Innovative Smart Grid Technologies (ISGT), 2012 IEEE PES* , pp.1,6, 2012

[3] I. Stoyanova et al., "Challenges in modeling a multi-energy system at city quarter level," in *Proc. COMPENG 2012, IEEE Workshop on Complexity in Engineering*.

[4] A. Molderink, "On the three-step control methodology for Smart Grids," PhD thesis, University of Twente, 2011. ISBN 978-90-365-3170-2

[5] J.L. Mathieu, S. Koch, D.S. Callaway, "State Estimation and Control of Electric Loads to manage real-time energy imbalance," *Power Systems, 2013 IEEE Transactions on* , vol. 28, no. 1, pp.430-440, Feb. 2013

[6] Mathieu, J.L.; Callaway, D.S., "State Estimation and Control of Heterogeneous Thermostatically Controlled Loads for Load Following," *System Science (HICSS), 2012 45th Hawaii International Conference on* , vol., no., pp.2002,2011, 4-7 Jan. 2012

[7] A. Schuelke, K. Erickson, "Serving solar variations with consumption control of smart appliances and electric vehicles," *Innovative Smart Grid Technologies (ISGT Europe), 2011 2nd IEEE PES International Conference and Exhibition on* , vol., no., pp.1,8, 5-7 Dec. 2011

[8] A Barbato, G. Carpentieri, "Model and algorithms for the real time management of residential electricity demand," in *Proc. IEEE International Conference and Exhibition, ENERGYCON '12*, 2012.

[9] Lichtblick – die Zukunft der Energie [Online]. Available: http://www.lichtblick.de/, last visited: Sept. 2013

[10] IEEE 802.15.4-2006, Chapter 7.5.1.4 CSMA-CA algorithm.

[11] I. Stoyanova, M. Marin, A. Monti, "Characterization of load profile deviations for residential buildings," in *Proc. Innovative Smart Grid Technologies (ISGT), 2013 IEEE PES*, 2013

[12] G. Kerber, "Aufnahmefähigkeit von Niederspannungsverteilnetzen für die Einspeisung aus Photovoltaikanlagen," Ph.D. dissertation, Dept. Of El. Eng. and Inf. Techn., Technische Universität München, 2011

[13] W. Jewell, "Issues in utility-interactive photovoltaic generation", IEEE Power Engineering Review, April 1994

[14] Y. Hosoda, T. Namerikawa, "Short-Term Photovoltaic Prediction By Using H ∞ Filtering And Clustering,", *SICE Annual Conference (SICE), 2012 Proceedings of* , vol., no., pp.119,124, 20-23 Aug. 2012.

[15] A. Costabeber, P. Tenti, and P. Mattavelli, "Distributed cooperative control of low-voltage residential microgrids," 2012 3rd IEEE International Symposium on Power Electronics for Distributed Generation Systems (PEDG), pp. 457–463, Jun. 2012.