Management and control of domestic smart grid technology

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***Abstract*—Emerging new technologies like distributed generation, distributed storage, and demand side load management will change the way we consume and produce energy. These techniques enable the possibility to reduce the greenhouse effect and improve grid stability by optimizing energy streams. By smartly applying future energy production, consumption and storage techniques, a more energy efficient electricity supply chain can be achieved. In this paper a three-step control methodology is proposed to manage the cooperation between these technologies, focused on domestic energy streams. In this approach, (global) objectives like peak shaving or forming a Virtual Power Plant can be achieved without harming the comfort of residents. As shown in this work, using good predictions, in advance planning and realtime control of domestic appliances, a better matching of demand and supply can be achieved.**

***Index Terms*—Micro-generation, Energy efficiency, Microgrid, Virtual Power Plant, Smart grid**

I. INTRODUCTION

In the last decades, more and more stress is put on the electricity supply and infrastructure. On the one hand, electricity usage increased significantly and became very fluctuating. Demand peaks have to be generated and transmitted, and they define the minimal requirements in the chain. Thus, due to the fluctuating demand, minimal grid requirements have increased. Another effect of fluctuations in demand is a decrease in generation efficiency [1].

On the other hand, the reduction in the CO_2 emissions and the introduction of generation based on renewable sources become important topics today. However, these renewable resources are mainly given by very fluctuating and uncontrollable sun-, water- and wind power. The generation patterns resulting from these renewable sources may have some similarities with the electricity demand patterns, but they are in general far from being equal. For this reason, supplemental production is required to keep the demand and supply in balance, resulting in an even more fluctuating generation pattern for the conventional power plants. Finally, the introduction of new, energy efficient technologies such as electrical cars can result in a even further fluctuating electricity demand. Uncontrolled charging of electrical cars will result in a high peak demands of electricity since these vehicles need to be charged fast to ensure enough capacity for the upcoming trip. Lowering the peaks in demand is desirable to prolong the usage of the available grid capacity.

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A solution for these problems may be to transform domestic customers from static consumer into active participants in the production process. Consumers participation can be achieved due to the development of new (domestic) appliances with controllable load, microgeneration and domestic energy storage of both heat and electricity. These devices have potential to shift electricity consumption in time without harming the comfort of the residents. Examples of devices with optimization potential are (smart) freezers and fridges which can adjust their cooling cycles to shift their electricity load or batteries that can temporarily store excess electricity. How to improve energy efficiency using this domestic potential is still not well studied and needs to be a topic of further research.

It is, in general, agreed that it is both desirable and necessary to manage Distributed Generation (DG) and to optimize its efficiency. In [2] it is stated that a fit-and-forget introduction of domestic DG will cause stability problems. Furthermore, the large scale introduction of renewables requires a new grid design and management. A study of the International Energy Agency concludes that, although DG has higher capital costs than power plants, it has potential and that it is possible with DG to supply all demand with the same reliability, but with lower capacity margins [3]. The study foresees that the supply can change to decentralized generation in three steps: 1) accommodation in the current grid, 2) introduction of a decentralized system cooperating with the central system and 3) supplying most demand by DG. However, both [2] and [3] indicate that commercial attainability and legislation are important factors for the success of the introduction of DG.

The goal of our research is to determine a methodology to use the domestic optimization potential to 1) optimize efficiency of current power plants, 2) support the introduction of a large penetration level of renewable sources (and thereby facilitate the means that are needed for CO_2 reduction) and 3) optimize usage of the current grid capacity.

In this work we give a more detailed description of the control strategy presented in [4] to exploit domestic optimization potential. This control strategy consists of (local) profile prediction, in advance global planning and realtime local control. Here, these individual steps, the choices made and the idea behind the methodology are expounded. Furthermore, results of a new realistic use case simulated using a simulator [5] are given. Furthermore, lessons learned from our prototype with first versions of our algorithms to study controllability of the devices in the real world are given.

The remaining of this paper is structured as follows. The following section introduces the domestic optimization potential. Section III gives an overview of related work and ends with a general management and control concept based on the related work. Section IV describes our approach and the proposed three-step methodology. Next, sections V to VII describe the details of the three steps. In section VIII the results of two case studies are given. We conclude this paper with a discussion of the results.

II. Optimization potential

The goal of our control methodology is to exploit the optimization potential of domestic technologies. Although some of these technologies themselves may lead to a decreased domestic energy usage (electricity and heat), the initial goal of this method is not to decrease domestic energy usage, but to optimize the electricity import/export by reshaping the energy profiles of the houses. The energy profiles are reshaped such that they can be supplied more efficiently or by a higher share of renewable sources. Besides improving efficiency, optimization can (and has to) enhance the reliability of supply [2], [3].

The primary functionality of the system is to control the domestic generation and buffering technologies in such a way that they are used properly. Furthermore, the required heat and electricity supply and the comfort for the residents should be guaranteed. Some devices have some scheduling freedom in how to meet these requirements. This scheduling freedom of the domestic devices is limited by the comfort and technical constraints and can be used for optimizations. More scheduling freedom can be gained when residents are willing to decrease their comfort level leading to less restrictive constraints for the scheduling. This (small) decrease in comfort should lead to benefits for the residents, e.g. a reduced electricity bill.

The optimization objective can differ, depending on the stakeholder of the control systems. The objective for residents or utilities can be earning/saving money and therefore the goal is to generate electricity when prices are high and consume electricity when prices are low. For network operators the goal can be to maintain grid stability and decrease the required capacity while an environmental goal can be to improve the efficiency of power plants. Therefore, an optimization methodology should be able to work towards different objectives.

Next to different objectives, control methodologies can have different scopes for optimization: a local scope (within the house), a scope of a group of houses e.g. a neighborhood (microgrid) or a global scope (Virtual Power Plant). Every scope again might result in different optimization objectives.

1) Local scope: On a local scope the import from and export into the grid can be optimized, without cooperation with other houses. Possible optimization objectives are shifting electricity demand to more beneficial periods (e.g. nights) and peak shaving. The ultimate goal can be to create an independent house, which implies no net import from or net export into the grid. A house that is physically isolated from the grid is called an islanded house.

The advantages of a local scope is that it is relatively easy to realize; there is no communication with others (privacy) and there is no external entity deciding which appliances are switched on or off (social acceptance).

2) Microgrid: In a microgrid a group of houses together optimize their combined import from and export into the grid, optionally combined with larger scale DG (e.g. windturbines). The objectives of a microgrid can be shifting loads and shaving peaks such that demand and supply can be matched better internally. The ultimate goal is perfect matching within the microgrid, resulting in an islanded microgrid. Advantage of a group of houses is that their joint optimization potential is higher than that of individual houses since the load profile is less dynamic (e.g. startup peaks of appliances disappear in the combined load). Furthermore, multiple microgenerators working together can match more demand than individual microgenerators since better distribution in time of the production is possible [6]. However, for a microgrid a more complex optimization methodology is required.

3) Virtual Power Plant (VPP): The original VPP concept is to manage a large group of micro-generators with a total capacity comparable to a conventional power plant. Such a VPP can replace a power plant while having a higher efficiency, and moreover, it is much more flexible than a normal power plant. Especially this last point is interesting since it expresses the usability to react on fluctuations. This original idea of a VPP can of course be extended to all domestic technologies. Again, for a VPP also a complex optimization methodology is required. Furthermore, communication with every individual house is required and privacy and acceptance issues may occur.

III. Related work

Most research projects in first instance focus on *introducing and managing (domestic) DG*. In [7] the impact of DG on the stability of the grid itself is studied, i.e. whether the oscillatory stability of the grid and transformers can be improved with DG. Their conclusion is that it is possible to improve the stability when the generators are managed correctly. The authors of [8] conclude, based on UK energy demand data, that it is attractive to install microCHPs to reduce CO_2 emission significantly.

Next to DG, energy storage and demand side load management are also relevant research topics. One of the options is to combine windturbines with electricity storage to level out the fluctuations by predicting the expected production and planning the amount of electricity exported to the grid exploiting the electricity buffer [9]. In [10] and [11] Grid Friendly Appliances are described. These appliances switch (parts of) their load off when the frequency of the grid deviates too much. This frequency deviation is a measure for the stress of the grid.

A lot of *control methodologies* for DG, energy storage and/or demand side load management are described in literature, mostly using an agent-based solution. Most agent based methodologies propose one agent per device placing bids at the agent one level higher [12]. This higher level agent aggregates the bids and sends them upwards. The top level agent determines a market clearing price based on the bids and the objective. In [13] multiple domestic technologies are combined: they conclude that demand side load management offers 50% of the potential. However, there have to be incentives for the residents to allow some discomfort (e.g. a reduced energy bill to allow a deviation on the room temperature).

The PowerMatcher described in [14] and [15] uses a similar agent based approach but also takes the network capacity into account. Field tests showed a peak reduction of 30% when a temperature deviation of one degree of the thermostat is allowed [16].

In [17] the results of individual (local) and overall (global) optimizations are compared. They conclude that global optimizations lead to better results. Next, they claim that agent based methodologies outperform non-agent based methodologies since agent based methodologies take more (domestic) information into account.

Next to agent based methodologies, there are also *non-agent based methodologies*. The research described in [18] proposes a method that is capable to aim for different objectives. The methodology is based on a cost function for every device and using a Non Linear Problem definition the optimal schedule is found. The authors of [19] address the problems of both agent and non-agent based solutions: non-agent based solution are less scalable and agent based solutions need local intelligence and are not transparent. Therefore, they propose a combination: aggregate data on multiple levels, while these levels contain some intelligence. In [20] a methodology is proposed using Stochastic Dynamic Programming (SDP). The stochastic part of the methodology considers the uncertainty in predictions and the stochastic nature of (renewable) production and demand.

Most methodologies use prediction of demand and/or production. Both can be predicted rather good with neural networks, as described in [21] and [22].

Summary: Most of the researchers propose a hierarchical structured, agent based solution. The hierarchical structure ensures the scalability of the solution. Although a lot of approaches claim to be distributed without a central algorithm, all approaches found have one decision-making element.

The similarities between the described approaches and our approach is the control up to an appliance level and the hierarchical structure with aggregation on each level (local and global control). The main differences are the prediction/planning and the lack of agents. Although some agent-based approaches use prediction and planning on a device level, this is utilized for profit raising of the agent itself. The latter is also the main difference between our approach and an agent-based approach: agents are greedy and try to optimize their own profit where our optimization methodology tries to reach a global objective for the whole fleet. As stated in [17], global optimization algorithms lead to better results. Furthermore, our approach can address each household individually using different steering signals instead of using the same signal (price) for everyone.

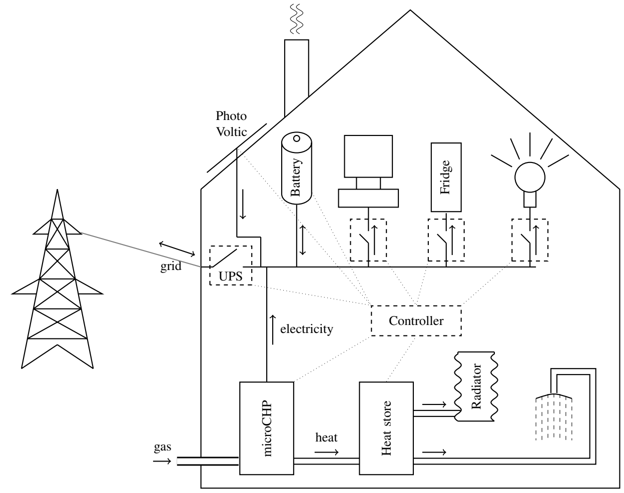

Fig. 1. Model of domestic energy streams

IV. Approach

Our research focuses on the development of algorithms for the control of energy streams in (a group of) houses. These algorithm are verified using a simulator. This simulator can simulate the complete methodology for a large fleet of houses on a device level incorporating local and global controllers. A detailed description of the simulator can be found in [5]. Furthermore, the validity of assumptions made during development of our models have been verified with a prototype. This prototype consists of a microCHP appliance, a heatstore, controllable appliances (both heat and electricity) and control algorithms implemented in software. A detailed description of this prototype can be found in [23].

The remainder of this section describes the underlying model of a house on which the algorithms and also the simulator are based. Next, the basic idea and a general description of the proposed control methodology are given.

A. Model

The model of a single house is shown in Fig. 1. Every house consists of (several) micro-generators, heat and electricity buffers, appliances and a local controller. Multiple houses are combined into a (micro)grid, exchanging electricity and information between the houses. Electricity can be imported from and exported into the grid. Heat is produced, stored and used only within the house.

All domestic heat and electricity devices are divided into three groups: 1) *producers* producing heat and/or electricity, 2) *buffers* temporarily storing heat or electricity and 3) *consumers* consuming heat and/or electricity. Every producer, buffer and consumer is called a device. Heat and electricity production can be coupled on device level. For example, a microCHP produces either heat and electricity or nothing at all. The same holds for some consuming devices, e.g. a hot fill washing machine. A more detailed description of the model can be found in [5].

Within the model, the planning horizon is discretisized resulting in a set of consecutive time intervals. The number of intervals depends on the length of the planning horizon and the length of the intervals. We often use a 6 minute time interval since such an interval length is a good trade off between accuracy and amount of data [24]. Furthermore, 6 minute time interval calculate easy since it is $\frac{1}{10}$ of an hour.

B. Methodology

The goal of the energy management methodology is to introduce a generic solution for different (future) domestic technologies and house configurations. Furthermore, within the methodology multiple objectives are possible and the scope of the methodology can differ. As a consequence, the methodology needs to be very flexible and generic. Since there can be global objectives (e.g. in case of a VPP) and the actual control of devices is on domestic level, both a global and a local controller are needed. Furthermore, the methodology should be able to optimize for a single house up to a large group of houses. So, the algorithms used in the control system should be scalable and the amount of required communication limited. The goal of the methodology is to exploit as much potential as possible while respecting the comfort constraints of the residents and the technical constraints of the devices.

One of the applications of the control methodology is to act actively on an electricity market. To trade on such a market, an electricity profile must be specified one day in advance. Therefore, it should be possible to determine a planning one day in advance for the next day.

Another application can be to react on fluctuations in the grid. Reacting on fluctuations requires a realtime control and sufficient generation capacity must be available at every moment. To achieve this available capacity, again a planning must be determined in advance.

Therefore, the proposed control strategy consists of three steps. A schematic representation of the method is given in Figure 2. In the first step, a system located at the consumers predicts the production and consumption pattern for all appliances for the upcoming day. For each appliance, based on the historical usage pattern of the residents and external factors like the weather, a predicted energy profile is generated. The local controller aggregates these profiles and sends them to the global controller. The aggregated energy profile determines the potential of all appliances located in the houses.

In the second step, these optimization potentials can be used by a central planner to exploit the potential to reach a global objective. The global controller consists of multiple nodes connected in a tree structure. Each house sends its profile to its parent node, this node aggregates all received profiles and sends the aggregated profile upwards in the tree, etc. Based on the received profile and the objective, the root node determines steering signals for its children to work towards the global objective. Each node in the tree determines steering signals for its children based on the received steering signals. The house controllers can determine an adjusted profile, incorporating the steering signals. This profile is sent upwards in the tree and when necessary the root node can adjust the steering signals. So, the planning is an iterative, distributed algorithm lead by the global controller. The position of the uppermost node and

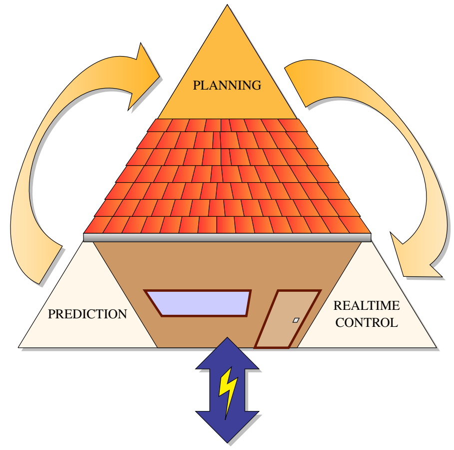

Fig. 2. Three step methododolgy

therefore the global controller determines the scope of the optimization (within the house, a neighborhood node, etc.). The result of the second step is a planning for each household for the upcoming day.

In the final step, a realtime control algorithm decides at which times appliances are switched on/off, when and how much energy flows from or to the buffers and when and which generators are switched on. This realtime control algorithm uses steering signals from the global planning as input, but preserves the comfort of the residents in conflict situations. Furthermore, the local controller has to work around prediction errors.

The combination of prediction, planning and real-time control exploits all potential on the most beneficial times. The hierarchical structure with intelligence on the different levels ensures scalability, reduces the amount of communication and decreases the computation time of the planning.

This three-step approach is discussed in more detail in the following sections. The combination of prediction, local controllers and global controllers can be extended to a Smart Grid [2] solution, controlling non-domestic DG, non-domestic buffers and domestic imports/exports optimizing efficiency of central power plants. Since the use case described in the Results section is based on a microCHP, the description of the first two steps focus on the optimization of a fleet of microCHP devices.

V. Step 1: Local prediction

The optimization potential of micro-generators is based on their scheduling freedom. While PV or microwindturbine are solely dependent on renewable resources and thus have no scheduling freedom, a microCHP appliance is controllable. When a heat buffer is added to the system, the production and the consumption of heat can be decoupled, within the limits of the heat buffer. This freedom can be used to schedule the microCHP to produce heat, and thus electricity, on more beneficial periods. Using a heat buffer enables the possibility to have an electricity steered control of a microCHP appliance instead of a heat steered control. The scheduling freedom of a microCHP appliances is limited by the heat demand of the household and size/level of the heat buffer. By predicting the heat demand in advance, a better schedule can be determined for heat-driven generators, improving its optimization potential. Since the use case described in the Results section is based on a microCHP, the rest of this section focuses on heat demand prediction.

In our approach, the heat demand for each individual household is predicted using neural network techniques. The goal is to predict the heat profile for the next day as accurately as possible. Based on the prediction, a schedule for the microCHP can be calculated. The value of this schedule depends on the accuracy of the predictions.

There are several reasons why individual heat demand prediction is used. The first and most important reason is that the schedules of the generators are made locally. A second reason is that when our approach is used for optimization of a group of households. The group might consists of hundreds of thousands up to a million of households. It is then infeasible to do a prediction per house centrally. It might be possible to do a prediction of a whole group, but eventually all individual generators must be scheduled, based on local heat demand. By moving the prediction to a local control system in the house, a scalable system is achieved.

The heat demand (of a household) is dependent on factors like weather, insulation and human behavior. The prediction model should be able to predict the heat demand one day ahead, based on recent observations. In other words, based on recent heat demand data and information about external factors like weather and insulation, the model should learn the relation between these factors and the heat demand.

The relation between external factors, behavior and the corresponding heat demand might be different for each house and household. Each house is different and has different insulation characteristics. Every household is different and has different behavioral patterns. By predicting the heat demand per house locally, local information about the specific environmental and behavioral characteristics can be used to improve the prediction.

One important factor in the heat demand is the behavior of the household. However, due to human nature, this behavior is not static. People have different behavior on different days of the week, thus the model has to be flexible. Changes in behavior should be learned quickly in order to cope with changes, e.g. holidays.

A. Prediction Model

For our prediction model, neural networks techniques are used. Neural networks are computational models based on biological neurons [25]. They are able to learn, to generalize, or to cluster data. A network has to be configured (trained) such that the application of the network to a set of given inputs produces the desired outputs (which are also given).

The output of our prediction model is the heat demand per hour. We assume the most relevant factors for the heat demand are the behavior of the residents, the weather and the characteristics of the house. Therefore, information about these factors are thus candidates as input for our prediction model.

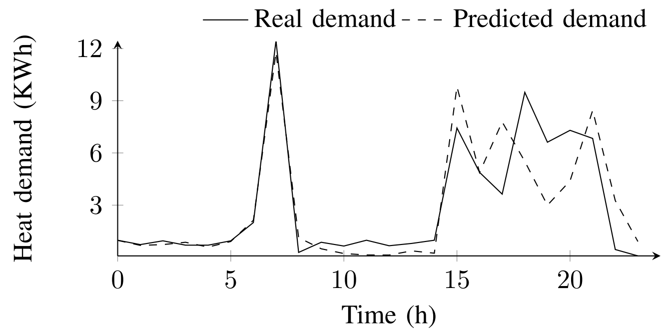

Fig. 3. Heat demand prediction for a household on Nov. 22, 2007

To learn the behavior of the residents, historical heat demand is used as an input. Information about the weather can for example be represented with outdoor temperatures, wind speeds and solar radiation. Since houses do not change that often, we consider the characteristics of the house static. Because of this, the neural network should be able to learn these characteristics since they are present in all other input data used. In [22] and [26] multiple possible combinations of input sets and their influence on the predictions are presented. Furthermore, in [26] a different way of constructing the training set is presented. Common use, when generating a training set for neural network applications, is to select a large, randomly selected set used for training. In our case, this translated to giving the network many samples to find as much general behavior as possible. However, since behavior is changing during the year, [26] shows that this is not the best way. Using only information of the last weeks as training information gives better prediction.

B. Results

An example of a good prediction is depicted in Figure 3. Here, a prediction is done for a household on November 22, 2007 using historical heat demand data and outdoor temperatures as input. As can be seen in the figure, the trend is followed quite good. As expected, due to human nature and unmeasurable influences, there is some deviation from the real heat demand.

VI. Step 2: Global planning

The planning described in this section focuses on a large fleet of houses combined into a VPP, all equipped with a microCHP and heat buffer.

Based on the heat demand prediction for a single house we plan the runs of the corresponding microCHP. This means that the exact periods in time are specified during which the microCHP should be switched on. This planning takes into account that the complete heat demand of the house has to be guaranteed, while using a heat buffer. Furthermore, the planning is restricted by technical constraints of the microCHP like minimal runtime. An complete explanation of these constraints can be found in [27].

Based on the heat demand prediction, each house of a group of houses (of size N) makes a production plan, satisfying the domestic, or local, constraints (i.e. the heat demand constraints plus the technical, microCHP related constraints). Considering the generators in these houses as a Virtual Power Plant (VPP) introduces a new dimension in the planning problem, since we now have to focus on the total electricity production of this group of houses. As a consequence, the planning does not only need to satisfy local constraints, also a global constraint on the total electricity production is added. More precisely, the group of houses should satisfy a predefined production plan P, that is based on the role the VPP wants to play.

The problem of realizing the production planning for the group of houses is based on a discretisation of time, as noticed in Section IV-A. The planning horizon of a single day is divided into N_T intervals for which a decision must be made for each microCHP in each house. Since a simplified version of the problem is known to be NP-complete in the strong sense [27], we develop heuristics which find in reasonable time a planning for the group of houses that is 'good enough'. In this context, we mean by 'good enough' that we approximate the predefined (discrete) production plan $P = (P_1, \ldots, P_{N_T})$. As objective, we use the squared mismatch ms to this plan P, which should be minimized:

$$ms = \sum_{j=1}^{N_T} (\sum_{n=1}^{N} e_{n,j} - P_j)^2, \quad (1)$$

where $e_{n,j}$ is the produced electricity in house n during time period j.

Since we deal with an NP-complete problem, in the next subsection we propose a heuristic method that works in reasonable time. This method makes use of fast locally optimizing methods, which, in the presence of a hierarchical structure, results in a scalable planning method from a global perspective.

A. Iterative Distributed Dynamic Programming

The problem is to find production plans for local households which are subject to local constraints, whereas we want to minimize the global deviation of the total electricity production, measured by the squared mismatch ms. In this subsection we describe a heuristic that solves this problem by separating the two elements that make the problem difficult:

1) finding a local plan satisfying local constraints;
2) minimizing the squared mismatch from the global production plan.

Next, these two elements are combined in an Iterative Distributed Dynamic Programming approach. This approach is explained in more detail by tackling the two single elements.

1) Finding a local plan satisfying local constraints: A local production plan that satisfies both technical (microCHP related) and domestic (heat demand) constraints can be found by using a Dynamic Programming approach. This approach uses a state s to describe the household situation in each interval. For more detail we refer to [28]. Over time, the state s changes based on the decision x_j to have the microCHP running or not. From the state the run history and the total production until the current time period are deducted. So, technical constraints of the microCHP and heat buffer constraints can be met by only allowing feasible states and state changes in the corresponding time periods. Since the global production plan P often is based on the electricity market (e.g. the Dutch APX market [29]), the costs in the Dynamic Programming formulation are chosen to also be electricity price related. More formally, if p_j denotes the price on the electricity market in period j, we define the market related costs c_j for state changes in time period j by

$$c_j = (\max_i p_i) - p_j. \quad (2)$$

since the steering signal for production should be low when the price is high (steering signals are costs, the objective is cost reduction). The costs of a state change from period j to period $j+1$ depend on the related decision x_j and are given by $x_j c_j$. Now, for each interval j and state s we define the cost function $F_j(s)$, which expresses the minimal costs needed from interval j until the end of the planning horizon, N_T, assuming that the current situation is characterized by the state s.

In practice the number of states is not too large, if the time periods are chosen larger than or equal to five minutes. Via a backtracking algorithm the value of $F_0(s_0)$ can be calculated, which minimizes the total costs from the start of the planning period (indicated by state (s_0) in period 0) until the end of the planning period. The path(s) corresponding to this value give the state changes and, thus, the corresponding decision values x_j to switch the microCHP on or off, i.e. it gives a production plan for the house.

2) Minimizing the squared mismatch from the global production plan: By sending all local production plans to a global planner, the sum of all production plans of the group of houses can be calculated and can be calculated and gives a global electricity output of the VPP, leading to a squared mismatch ms from the production plan P. In an iterative approach we aim to minimize this mismatch by iteratively steering the local production plans in a mismatch-reducing direction. As a consequence, most of the computation is still done locally at the houses. On a central level the steering of the plans in a certain direction is calculated. To allow for scalability, the group of houses is divided into a hierarchical structure. In this way a limited number of houses can be regarded as a sub group, which is steered into the right direction independently from other sub groups. For simplicity we refer in the following to the plan P as the production plan for a sub group of houses.

In combination with the use of the local Dynamic Programming approach, we adapt the steering signals in the following way. Artificial additional costs a_j^i are added to the state change costs c_j for time period j in iteration i, if:

- the electricity output of the VPP is larger than the plan P_j, and
- in the local house plan the microCHP is running at time period j.

The values of a_j^i are sent to the local planner and a new planning is determined by the local planner. In this way, microCHPs that are running in periods where the sub group plan is exceeded are stimulated to produce at other time periods. In the steering method, the additional cost a_j^i that is used in the steering process, decreases with each iteration i, to minimize negative overshooting effects and guarantee a convergence.

VII. Step 3: Local scheduling

This section presents the scheduling algorithm that controls the devices in a single house. The decisions of the algorithm are based on the current situation in the house and optionally on the steering signals from the global controller. The most important requirement of the algorithm is to guarantee the comfort for the residents and the proper usage of devices. Within this requirement, the goal is to optimize the electricity import/export.

The basic idea is that there is a certain demand and this demand should be matched. The demand is defined as the sum of the heat and electricity demand of all consumers. This demand is given as an input parameter and can be matched with 1) import from the grid, 2) production by generators, 3) the buffers and 4) switching off consumers (not providing them). When the sum of the four possibilities gives more heat and/or electricity than the demand, the corresponding energy flows to a buffer and/or into the grid. However, some matching is more desirable than others: e.g. it might be allowed to switch off a fridge temporarily but a TV set should stay on. Therefore, for every matching costs are defined.

As stated above, every device (in the house) and the grid can match a certain amount of energy demand (optionally zero). Furthermore, energy flowing to a buffer or to the grid is seen as negative matching. Via this generic model, matching costs of all devices, independent of technology, can be expressed with linear cost functions. The cost function can express 1) the costs of the matching, 2) the costs of state transitions (e.g. startup costs) and 3) costs to steer the behavior and reach global objectives.

Following this setup, the algorithm has to find an optimal combination of matching sources using for all devices cost functions of the same structure. The algorithm is executed for each time interval. The matching cost for each device is determined at the beginning of the time interval, based on the status of the device. The status of the devices cannot be determined on beforehand, since the status may depend on decisions in former time intervals. In the current implementation, the costs only depend on the current status without taking future states into account.

The optimization problem considers a given set of devices Dev. Decision variables x_i are introduced which express the amount of matching of device $i \in Dev$. Since these variables are used for both heat and electricity, two multiplication factors are introduced, one for heat (H_i) and one for electricity (E_i), e.g. the heat/electricity ratio of a microCHP is $8:1$ thus possible choices are $H_i = 8$ and $E_i = 1$.

The possible values for the variables x_i may be restricted. For example, a consuming device can be switched off ($x_i = demand$ or $x_i = 0$) and a certain amount of electricity can be import/exported ($-2000 \leq x_i \leq 5000$). Furthermore, the cost function parameters may rely on the concrete value of x_i, i.e. the cost function is a non-continuous stepwise

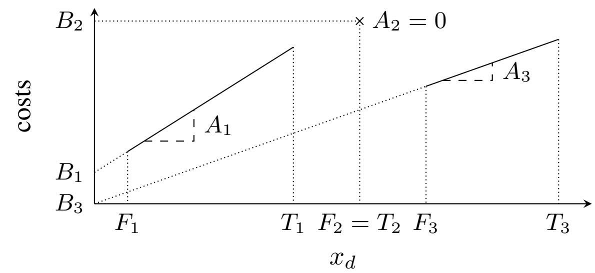

Fig. 4. Example intervals and costs for x_i

function. To model this, for each device $i \in Dev$ a set S_i of intervals is specified and the variable x_i is allowed to take only values from one of these disjoint intervals. Each interval $I_{ij} = [F_{ij}, T_{ij}] \in S_i$ specifies a uniform area for the variable x_i, in the sense that the costs associated with $x_i \in I_{ij}$ can be expressed by $A_{ij} \times x_i + B_{ij}$. The value A_{ij} expresses the matching costs and B_{ij} the startup costs if x_i is chosen from the interval I_{ij}. An example of intervals and associated costs is shown in Figure 4.

The problem of finding a best solution is modeled as an Integer Linear Program (ILP). The objective of the ILP is to minimize the costs while all given heat demand D^h and electricity demand D^e is matched. This is ensured with the constraints in (5) and (6) given below. Furthermore, all values of x_i must be valid, i.e. chosen on one of the intervals I_{ij}. To ensure this, extra binary decision variables c_{ij} are introduced and every x_i is split up into variables x_{ij} for every interval $j \in S_i$. Via (7) is forced that for every device only one of the c_{ij} is one, i.e. the variable c_{ij} specifies the interval from which x_i is chosen. Constraint (8) ensures that only the x_{ij} corresponding to the nonzero c_{ij} is nonzero and lies within the specified interval. The value of x_i of a device gets defined as the sum of all x_{ij} for that device (see (4)).

$$min \qquad \sum_{i,j} A_{ij} \times x_{ij} + c_{ij} \times B_{ij} \tag{3}$$

$$s.t. \qquad x_i = \sum_j x_{ij} \; \forall i \in Dev \tag{4}$$

$$D^h = \sum_i H_i \times x_i \tag{5}$$

$$D^e = \sum_i E_i \times x_i \tag{6}$$

$$\sum_j c_{ij} = 1 \; \forall i \in Dev \tag{7}$$

$$c_{ij} \times F_{ij} \leq x_{ij} \leq c_{ij} \times T_{ij} \; \forall i \in Dev, j \in S_i \tag{8}$$

VIII. Case studies

To verify the methodology, two case studies are used. The first case study is a simulation of a group of houses using real heat demand data and real prediction to verify whether it is possible to make a planning based on prediction. Furthermore, it is verified how well the actual scheduler follows the planning. The second case study is a test with a single house

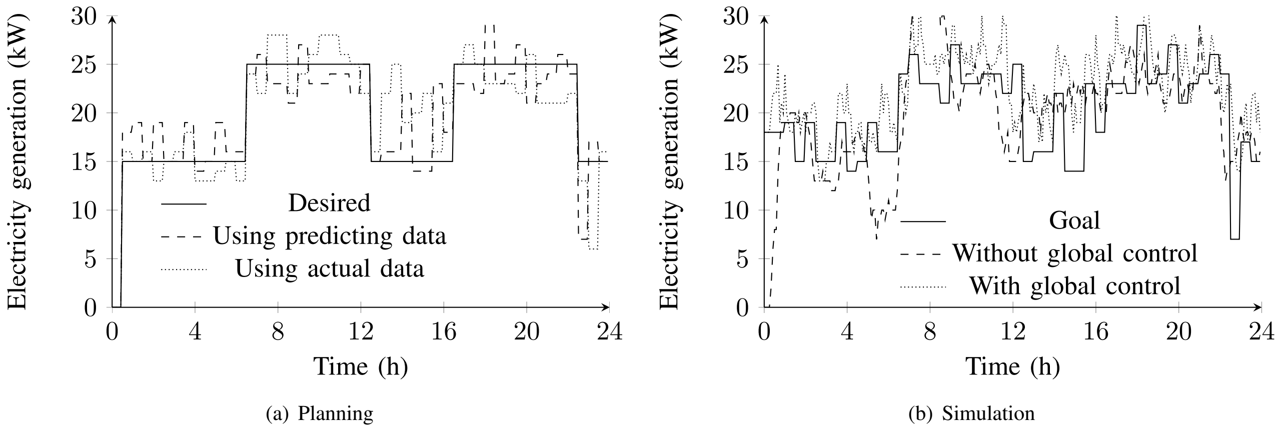

Fig. 5. Planning and simulation using the three-step methodology for 39 houses

prototype to verify whether the methodology is also applicable in a real world situation.

A. Simulation

A neighborhood consisting of 39 houses has been simulated with our simulator using the three-step-approach. From our database with real heat demand data of Dutch households, 39 heat profiles between Nov. 19, 2007 until Nov. 31, 2007 have been extracted and used as input for the simulations.

1) Planning: For all houses, a prediction is made using the above described method. Using the heat demand predictions, the global planner schedules the runtime of the generators in these houses. The objective of the planning is a combination of flattening the electricity production and to produce during periods when electricity is expensive. Since it is the winter season, there is quite some heat demand. The high heat demand results in less scheduling freedom, making the scheduling more difficult.

The results of the scheduler are depicted in Figure 5(a). The solid line gives production plan P, the preferred production pattern. However, this objective cannot be reached due to limited schedulingsfreedom. Two different plannings are made: one using the predicted heat demand (dashed line) and one using the actual heat demand (dotted line). As can be seen, both plannings cannot reach the objective and there quite a difference between both plannings. The total electricity production of both plannings is almost equal, 475 kWh using the prediction and 477 kWh using the actual demand. However, the periods the electricity is produced differs; the sum of the absolute difference per time interval (SAD) between both plannings is 82 kWh, 17% of the total production. So, the total heat demand is predicted quite accurate (2 kWh difference), but the prediction of the heat demand pattern during the day is less accurate. Since the actual heat demand is not known one day in advance, the planning based on the predicted heat demand is used.

2) Realtime control: Within the simulation, the houses are controlled using the local controller which receives steering signals from the global controller. For the simulation the real heat demand is used, so the determined planning can probably not exactly be followed due to prediction errors. The results of the simulations are depicted in Figure 5(b). The solid line depicts the planning made by the global planner. The dotted line depicts the actual number of microCHPs running (i.e. the production pattern). The dashed line depicts the production pattern when no optimization was used, i.e. if the microCHPs were only heat-led. The production pattern using optimization deviates 96 kWh from the schedule without optimization (SAD); the optimization methodology shifted 17% of the production, while there was limited optimization potential due to high heat demand.

The total electricity production in the optimized pattern was 540 kWh, more than planned; all free capacity of the heat buffers is used to enable more production capacity to follow the planning as good as possible. The optimized pattern deviates 77 kWh (14%) from the planning (SAD), roughly equal to the prediction error of 82 kWh. From this 77 kWh, only 10 kWh was under production, the rest was overproduction. So, in the actual schedule almost all electricity we promised to produce based on the planning is produced. However, the deviation caused imbalance due to overproduction. So, the scheduler did not efficiently worked around prediction errors but tried to reach the promised production by producing more electricity. This drawback might be overcome by taking not only the current state into account in the scheduler but also some future state.

Determining the global planning by the iterative approach using our simulator took a couple of minutes on a single PC (using local TCP/IP connection between the nodes). In a real situation the computational time will decrease since the computations are distributed while the communication time will slightly increase. The expectation is that the total time will be in the order of minutes due to the hierarchical structure, which is acceptable for a one-day planning for 24 hours. The computation of the local controller can be done within a second for a five minute time frame.

B. Field test

In [30] we showed that peak shaving and shifting of demand in time using only a realtime scheduler is possible using a single house prototype. In this case study also the possibility to actually switch on/off the appliance on the preferred times

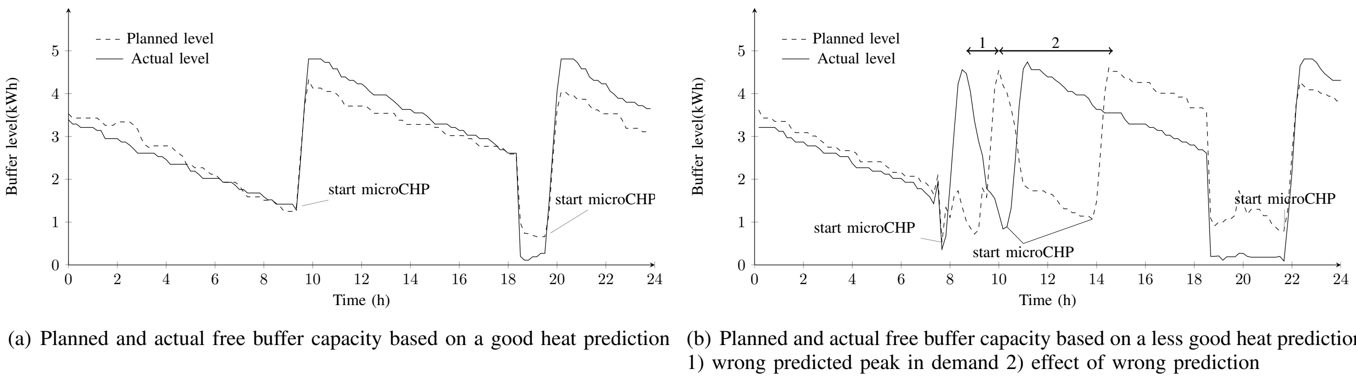

Fig. 6. Results lab tests local planning and scheduling of a microCHP

by the local scheduler is verified. The house prototype consists of a Whispergen microCHP, a Gledhill heat buffer, a computer controllable hot water tap and a controllable thermostat in combination with a heat exchanger.

The objective is to shift production as much as possible to daylight hours (prevent noise at night). Furthermore, short runs are avoided (wearing of the machine). The generator runs until the buffer is filled, so only switch on signals are given. The planned and actual level in the Gledhill for two different days is given in Figure 6.

The heat demand prediction for the day in Figure 6(a) was accurate. Therefore, the planned and actual level in Figure 6(a) are similar and, more important, the planned and actual runtimes of the microCHP are also equal. Furthermore, the microCHP is started on initiative of the scheduler and not as a natural reaction on the buffer level at $t = 9.3$.

The planning for the second day was to switch on the microCHP at $t = 7.5$ and stay on until $t = 10$, supplying the peak demand at $t = 8.5$. However, the peak demand came a few minutes later, the buffer was full before the peak and the microCHP had to be switched off. Therefore, the peak was supplied by heat from the heat buffer and the actual and scheduled buffer level deviate for multiple hours. This shows the long term effect of small differences between prediction and actual heat demand. However, re-planning some moment later in time in Figure 6(b) (e.g. at $t = 8.5$) might have prevented a non-scheduled start at $t = 10.2$ and the planning might have been followed better.

IX. Conclusion and Future work

The three step methodology proposed in this paper using a hierarchical planning is a scalable solution with limited communication requirements. The local prediction and scheduler result in a generic solution supporting different technologies and houses with different optimization potential.

The first case study shows that it is possible to make a planning for a group of houses based on predicted heat demand using an objective. Furthermore, the local scheduler is capable of following this planning up to a certain level. The schedule deviates from the planning due to prediction errors. The local controller is not capable of coping with prediction errors well enough. The promised production is reached by producing more heat than necessary (by filling the heat buffers), resulting in a overproduction on other times. Therefore, improved methods for the local scheduler to work around prediction errors are needed.

The second case study shows that it is possible to determine a planning based on a prediction one day ahead. The models are accurate enough to determine a planning and it is possible to control the microCHP. However, when the heat demand deviates from the prediction, the planned and actual runtimes of the microCHP deviate as well. A wrongly predicted peak (for only a few minutes!) can have a severe impact on the runtime. However, if a new planning is determined, the buffer levels and therefore the runtimes of the microCHP converge earlier.

Current and future work focuses on working around prediction errors. On one hand, the local controller should take future states into account to prevent decisions that influence future states very negatively. On the other hand, when the local controller cannot deal with the prediction errors anymore, re-planning on a higher level is required. Due to the hierarchical structure of the planning, re-planning can be done on different levels.

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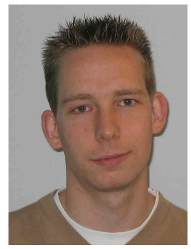
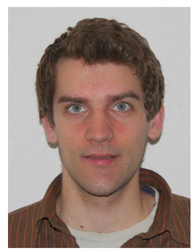
X. Biographies

Albert Molderink was born in Heerenveen (The Netherlands) in 1983. He received his B.Sc and M.Sc. degree in Computer Science from the University of Twente, Enschede, The Netherlands, in respectively 2004 and 2007. In addition, he received an Electrical Engineering minor certificate. When he completed his study he started working towards a Ph.D. degree at the University of Twente under supervision of Prof. dr. ir. G.J.M. Smit. He is working in a research group that investigates the possibilities of increasing energy efficiency using embedded control, mainly via optimization and control algorithms. His research focus is on algorithms to optimize energy streams within a house.



Vincent Bakker received his M.Sc. degree in Computer Science from the University of Twente in 2007, with a minor certificate in Entrepreneurship. Currently he is working on his Ph.D. thesis researching domestic demand prediction for in home optimizations. Currently his interest are: machine learning, optimization modeling and large scale distributed (intelligent) systems.



Maurice G.C. Bosman received his M.Sc. degree in Applied Mathematics from the University of Twente in February 2008. Currently he is a PhD student in the CAES and DMMP groups at the faculty of Electrical Engineering, Mathematics and Computer Science at the University of Twente. His research interests include energy efficiency, scheduling and online algorithms.

Johann L. Hurink received a Ph.D. degree at the University of Osnabrueck (Germany) in 1992 for a thesis on a scheduling problem occurring in the area of public transport. From 1992 until 1998 he has been an assistant professor at the same university working on local search methods and complex scheduling problems. From 1998 until 2005 he has been an assistant professor and from 2005 until 2009 an associated professor in the group Discrete Mathematics and Mathematical Programming at the department of Applied Mathematics at the University of Twente. Since 2009 he is a full professor of the same group.

Current work includes the application of optimization techniques and scheduling models to problems from logistics, health care, and telecommunication.

Gerard J.M. Smit received his M.Sc. degree in electrical engineering from the University of Twente. He then worked for four years in the research and development laboratory of Océ in Venlo. He finished his Ph.D. thesis entitled "the design of Central Switch communication systems for Multimedia Applications" in 1994. He has been a visiting researcher at the Computer Lab of the Cambridge University in 1994, and a visiting researcher at Lucent Technologies Bell Labs Innovations, New Jersey in 1998. Since 1999 he works in the Chameleon project, which investigates new hardware and software architectures for battery-powered hand-held computers. Currently his interests are: low-power communication, wireless multimedia communication, and reconfigurable architectures for energy reduction. Since 2006 he is full professor in the CAES chair (Computer Architectures for Embedded Systems) at the faculty EEMCS of the University of Twente. Prof. Smit has been and still is responsible of a number of research projects sponsored by the EC, industry and Dutch government in the field of multimedia and reconfigurable systems.