Planning Based Real-Time Control Using DEMKit

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Abstract—There is a trend towards local energy markets in order to integrate renewable energy sources and controllable devices into the energy system. As a result the market size is getting smaller and making an accurate day-ahead planning as base for acting on these markets is getting harder. As a consequence, deviations from the offered planning are more likely to occur. In this paper, we propose a planning-based real-time control method to deal with such deviations on device level in order to follow the submitted planning as good as possible. The proposed method controls the devices in each house sequentially, ordered by their flexibility (from least flexible to most flexible) and aims to realize the planned profile as good as possible without deviating too much from the individual planning for the devices.

Index Terms—Real-Time control, Day-ahead Planning, local capacity market

I. INTRODUCTION

Trading of electricity is organized via different markets. In the past, energy suppliers traded for large groups of customers on these markets. Due to the integration of renewables on decentralized places in the grid, also local capacity markets will emerge in the future (e.g. [10], [1]). These new markets and also the existing markets have a day-head and intraday time horizon. The time horizon of these markets is subdivided into smaller time intervals of e.g. 15 minutes or 1 hour.

For acting on day-ahead markets one has to specify the amount of energy to be consumed or produced for specific time intervals. Therefore it is important to have a forecast of production and consumption (prosumption) for each time interval of the time horizon of the given market. In the past energy suppliers did this for large groups of customers, and therefore this task was easier due to the law of large numbers and the independent behavior of customers. With the upcoming of local markets the size of the involved group of customers for which a supplier or aggregator acts on the market gets much smaller. Furthermore, more controllable appliances like heat pumps or electrical vehicles enter the scene and more synchronization of appliances (e.g. for PV production via the sun) will occur. As a consequence predicting the energy profiles gets harder. To improve this process it is suggested to perform the forecast based on more detailed day ahead plannings of appliances on house level [7] [8]. These plannings can be updated up to an hour before delivery time on the intraday market [10]. As soon as the market is closed, prosumers are expected to produce/consume based on the offered

planning in the market. However, since the planning is based on forecasts, deviations will likely occur. This can be the result of wrong predictions (e.g. inaccurate weather forecast) or a change in consumers behavior. Therefore it is not always possible to follow precisely the offered planning. However, prosumers may have some flexibility on using some devices, and therefore they may be able to correct the wrong predictions by themselves.

The goal of this paper is to introduce a method that controls the flexible devices in a house in real-time to compensate for deviations from planning. The real-time control uses the available flexibility of appliances in each house and makes decisions on a smaller time slices that helps to adapt the planning of appliances in such a way that the overall profile of the house stays close to the original planning.

In this paper, we first briefly explain the day-ahead planning in Section I-A. Then some of the related works in this area is discussed in Section II. The main contribution of this paper which is the planning based real-time control is explained in Section III. Finally, in Section IV we explain a developed simulation tool and the test case that we use to validate our method.

A. Day-ahead planning

In the context of this paper we assume that a day-ahead planning is given, which is a 15 minutes based power profile for the next 24 hours (96 time intervals). This planning is based on predictions of the power profiles for the usage of each device in the houses and also on the flexibility that users have to use these devices. For example, if a washing machine is supposed to be used on a given day, there is information providing the first possible starting time and the time it should be finished. According to this information individual plannings for each device are determined for the next day such that the overall profile follows some objective as good as possible. Hereby the profile is specified as average demand values for each of the 96 time intervals of 15 minutes length.

II. RELATED WORK

There are already existing real-time control approaches. One well-known example is the PowerMatcher [4], [5], where the controller makes online decisions without taking consumption and production in future time intervals into account. This may result in using the flexibility at an improper time (e.g. earlier than it is needed). To partially solve this problem, in [6] a

method is proposed which does a multi-objective optimization and takes into account some actual measured load of the flexible devices.

Another attempt to combine planning and real-time control is presented in [9]. The difference with our approach is that we try to solve the deviation from the planning as local as possible, whereas [9] tries to solve it in more global level. Furthermore, in [2] the authors try to solve the above problem by presenting an approach that is based on easy to predict characteristics and not house level power profile predictions which may be hard to predict. This approach takes the real-time control up to some extent into account already in the planning phase. However, this approach is limited to specific device classes.

III. PLANNING-BASED REAL-TIME CONTROL

Our planning-based real-time control uses the day-ahead planning as an input, together with real-time measurements from a smart meter and other updated data such as weather conditions or state updates of appliances upto the current time. Note that not only the overall day ahead profile, but also the plannings of individual devices are part of the input. The goal is to determine based on these inputs, a detailed planning for smaller intervals (e.g. one minute time slots) for a short time period in the future (e.g. the next 15 minutes). Hereby the goal is to follow the day-ahead planning as close as possible but also to take in to account future time intervals. The latter implies that it is important that current decisions do not block the exploitation of flexibility within future time intervals.

During each 15-minutes time interval a finer grained profile should be determined using smaller sub-intervals, whereby the average power value over all 15 sub-intervals should stay as close as possible to the predicted overall day-ahead planning. We use one minute as length for these smaller time periods, which we call time slots. In other words, each 15 minute time interval splits into a set $T = \{1, \dots, 15\}$ of time slots, where each time slot $t \in T$ represents a time period of one minute.

In the following, we use a specific but quite generic model of a house and its devices to explain the basic idea of our real-time control. However, the developed approach can be used also when other devices become available and it can also be adapted on a neighborhood level or some other upper level in the grid.

A. House Model

In our model each house has a set Dev of devices, where every device $d \in Dev$ is of one of the following Types $D_{types} = \{bl, pv, tsh, hp, ev, eb\}$. Baseloads (bl) is a device in which all uncontrollable devices without any flexibility are collected, e.g. lighting. Photo voltaic panels (pv) are devices that produce an uncontrollable amount of energy and are dependent on the weather (sun). Time shiftable (tsh) devices, like washing machine and dishwasher, are devices of which the starting time is controllable, but they are uncontrollable as soon as they are started. The fourth type of devices is called heat pump (hp). This type represents a device that uses electricity to produce heat and which has a heat buffer of limited capacity where it can store produced heat. Electrical

vehicles (ev) are devices which have to be charged a certain amount of electricity within a given time limit, whereby the load of charging the ev can be chosen from some pre-defined charging levels. The last type, which is also the most flexible one is electrical battery (eb). An eb can be charged or discharged and its state of charge and power limitation have to be taken into account.

Furthermore, for each house a predicted profile p_p with 15 minutes time intervals results from the planning, whereby $p_p(i)$ represents the total predicted consumption (kWh) of the house for time interval $i \in I = \{1, \dots, 96\}$. Next to this overall profile, the device profiles $p_d(d, i)$ resulting from the made planning are given, whereby $p_d(d, i)$ represents for each device $d \in Dev$ the consumption (kWh) of the device for time intervals $i \in I$.

B. Real-Time Control of Devices

At the beginning of time interval i the predicted profiles of uncontrollable devices (these are devices of type bl, pv, tsh) for the time interval i are updated according to the received real-time measurements until the end of time interval $i-1$. This short term predicted profiles for time interval i and for device d are denoted by $p_{sd}(d, i)$. If we sum up the deviations of these device profiles from their original profile in the planning, we have the amount of energy which should be compensated by the controllable devices in time interval i .

The possible flexibility of (a controllable) device d is used to specify a decision set $ds(d, t, i)$, which represents the set of its possible states in time slot t . This set is determined based on the definition of the device and its constraints, but also the decisions made upto time slot $t-1$. The selected state for device d in time slot t is denoted by $\bar{ds}(d, t, i)$.

The objective of the real-time control is to make decisions for the controllable devices in such a way that the sum of the real-time profiles $p_r(d, t, i)$ over all devices d and all time slots of time interval i is such that it follows the predicted profile $p_p(i)$ using the least possible flexibility. Following the predicted profile means that there should be preferably no difference between the total real profile at the end of time interval i and the planned profile for that time interval. Besides, the deviation by the end of each interval will not take into account in the next intervals, since it is already paid in the market. This leads to the following objective:

$$\min |\sum_{d,t} p_r(d, t, i) - 15p_p(i)|.$$

In addition to this, the flexibility should be used in such a way that it does not restrict the flexibility for the next time intervals too much.

In the following paragraphs we describe this process in more detail for different device classes in the order of their flexibility (from low to high) and discuss how to control them according to the received real measurements.

1) *Baseloads, PV*: The part of the load within the house which is without any flexibility and can therefore not be controlled is summarized in a single device called the baseload (bl). This device should be treated first in the real-time planning, as it is not controllable, but the total load is based on new information/measurements which has become available

via the short term predicted profile p_{sd} of this device. Another device that should also be considered is the PV panel (pv), this device has also no flexibility, but can deviate from the profile predicted during the planning phase as a result of imprecise weather predictions.

Since baseload and PV are not controllable, there is no choice (i.e. the decision set for the real-time profile contains only one element), and the remaining appliances have to adapt their behavior to compensate for deviations introduced by these two devices compared to the original planning. In this paper we do not consider curtailment of PV system.

2) *Time Shiftables*: Time shiftable devices (tsh) like a washing machine offer flexibility usually only through the starting time. This flexibility is constraint by the time at which the device is activated (the user pushes the start button) and the time before the device has to be finished. Depending on the state of the device at the beginning of a time interval, the decision set $ds(tsh, t, i)$ of a time shiftable device tsh can have the following options.

- **The device tsh is either already started or supposed to be kept off in time interval i .** In this case tsh is uncontrollable and can be treated the same way as baseloads; i.e. the predicted profile may be updated at the beginning of the time interval, and the decision set has only one option.
- **The device is supposed to start in time interval i based on the predicted profile $p_d(tsh, i)$.** In this case we force that the real-time control starts the device in one of the time slots of time interval i . Thus, $ds(tsh, t, i)$ has two options as long as the device has not been started up to time slot $t - 1$. If $t = 15$ and the device has not been started or if the device has been started before t , the decision set has only one option left and the load is uncontrollable.

The choice in which time slot the start option is chosen, depends on the deviation of all devices upto time slot t , in addition to deviation of the baseload and PV from the predicted profile at time slot t . The time shiftable will be turned on at time slot t , if the total consumption by them is less than expected by time slot t , and the difference can be compensated by starting the time shiftable device. More precisely, if the total deviation up to now is less than a given threshold $\Delta_{min} < 0$, then the device is started immediately. However, if this total difference upto time slot t is more than a given threshold $\Delta_{max} > 0$, the device is kept off in time slot t . If the difference stays between these bounds, the device is started somewhere at the middle of the time interval i , more precisely at time slot 8.

To formalize this, we denote $Diff(d, t, i)$ the total difference between the real-time and the predicted profile for all time slots up to $t - 1$ and for the deviation of devices d' in time slot t which are considered before device d . More precisely it includes three parts: 1. The deviation of all devices in time slots $1, \dots, t - 1$. 2. The deviation of devices for that already decisions for time slot t have been made. 3. The difference between the short-term predicted profile and the original profile of the considered device.

Fig. 1: Real-Time decision for a heat pump, in current situation 'OFF' leads to a violation of $f_{min}(i)$.

If we denote the difference between the power consumption when starting the device d at time slot t until the end of the time interval and the predicted profile (i.e. $p_d(d, i) * (15 - t)$), by $C(d, t)$, the above condition can be implemented by Algorithm 1.

Algorithm 1 Control of a time shiftable device

- 1: **if** $Diff(tsh, t, i) + C(tsh, t) < \Delta_{min}$ **then**
 - 2: $\bar{ds}(tsh, t, i) = \text{ON}$
 - 3: **else if** $Diff(tsh, t, i) > \Delta_{max}$ **then**
 - 4: $\bar{ds}(tsh, t, i) = \text{OFF}$
 - 5: **else if** $t < 15/2$ **then**
 - 6: $\bar{ds}(tsh, t, i) = \text{OFF}$
 - 7: **else** $\bar{ds}(tsh, t, i) = \text{ON}$
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3) *Heat Pumps*: Heat pumps (hp) in combination with a heat buffer have more flexibility in comparison with the previous devices, since both starting and ending times are controllable assuming that the buffer is not full. We assume that the heat pump is not modulated and can only be turned on and off. The produced heat in a time slot, when the heat pump is on, is a given constant. Furthermore, due to technical reasons the use of the heat pump is restricted by minimum on and off times denoted by Min_{on} and Min_{off} , respectively.

The decision set $ds(hp, t, i)$ of a heat pump has in general two options (on/off) but has to consider the given constraints. Furthermore, the heat pump has to ensure that the requested heat demand is fulfilled and that the capacity of the attached heat storage is respected. Using the short term predicted profile this can be expressed by flexibility variables $f_{min}(i)$ and $f_{max}(i)$, which represent the minimum and maximum amount of heat that the heat pump is allowed to generate during time interval i , respectively. For the real-time control we adapt these variables to take into account also the desired state of charge ($SoC_{hp}(i)$) the heat buffer should have at the end of the time interval i based on the given planning $p_p(hp, i)$. More precisely, we allow a certain deviation $\Delta_{SoC}(hp)$ from the goal state of charge $SoC_{hp}(i)$. Based on these constraints, the variables $f_{min}(i)$ and $f_{max}(i)$ are adapted accordingly. Figure 1 indicates that the decision at time slot t is based on these two variables and the generated heat $f(d, t, i)$ upto time slot $t - 1$. In the other words, the decisions should ensure that at the end of the time interval we have

$$f_{min}(i) \leq f(d, 15, i) \leq f_{max}(i).$$

Together with the minimum on and off times these con-

straints determine which options are still in the decision set $ds(hp, t, i)$. If this set contains both options, we again use the deviation $Diff(hp, t, i)$ (this variable is defined in the same manner as in Section III-B2) to make a choice. More precisely, if the decision set $ds(hp, t, i)$ still allows both options, we again use Algorithm 1 to determine the choice between on and off. However, for hp we have no information on $C(hp, t)$ and therefore we set this value to the minimum consumption of the hp if we have it on in time slot t .

4) *Electrical vehicles*: An electrical vehicle (ev) has to be charged until a given time interval i_e upto a given level. The charging of the ev can be done at given load levels $L = \{l_1, \dots, l_n\}$. Furthermore, flexibility variables $f_{min}(i)$ and $f_{max}(i)$ are given, which represent the minimum and maximum allowed state of charge of ev at the end of time interval i . The decision set $ds(ev, t, i)$ has $n + 1$ options which are the different levels of charging the ev including the option to turn it off. The decision which charging level to use in the next time slot, depends on the deviation upto now ($Diff(ev, t, i)$), and constraints caused by variables $f_{min}(i)$, $f_{max}(i)$, and i_e . Again, let $ds(ev, t, i)$ denote the set of charging level, which still are allowed based on the given constraints and let $C(ev, t)$ denote the minimum amount ev gets charged if we select the minimum allowed charging level. Using this data, Algorithm 2 can be used to decide which charging level to use in time slot t .

Algorithm 2 Control of electrical vehicle

- 1: **if** $Diff(ev, t, i) + C(ev, t) < \Delta_{min}$ **then**
 - 2: $\overline{ds}(ev, t, i) =$ lowest charging level from $ds(ev, t, i)$ which brings $Diff(ev, t, i) + C(ev, t)$ above Δ_{min}
 - 3: **else if** $Diff(ev, t, i) > \Delta_{max}$ **then**
 - 4: $\overline{ds}(ev, t, i) =$ minimum allowed charging level from $ds(ev, t, i)$
 - 5: **else if** $t < 15/2$ **then**
 - 6: $\overline{ds}(ev, t, i) =$ minimum allowed charging level from $ds(ev, t, i)$
 - 7: **else**
 - 8: $\overline{ds}(ev, t, i) =$ minimum charging level from $ds(ev, t, i)$ which brings $Diff(ev, t, i) + C(ev, t)$ closest to 0
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5) *Electrical battery*: The most flexible device in this model is the electrical battery. It can be charged or discharged at given load levels $L = \{l_1, \dots, l_n\}$. Again, flexibility variables $f_{min}(i)$ and $f_{max}(i)$, which represent the minimum and maximum state of charge the battery may have at the end of time interval i , are given. The decision set $ds(eb, t, i)$ denotes the different levels of charging or discharging which do not lead to a violation of constraints caused by variables $f_{min}(i)$ and $f_{max}(i)$. The selection of a decision from this set again depends on deviations upto the current time $Diff(eb, t, i)$. The resulting algorithm is a slight modification of Algorithm 2, which results from the fact that also discharging is possible.

IV. SIMULATION

To validate the potential of the proposed real-time control, we conduct a simulation. In this section we first explain

Fig. 2: Baseload profile (per interval)

— Real-time profile (generated by profile generator [3])
— Predicted profile (using history)

the simulator we are using to validate our method. Then in Section IV-B the used test case is described, followed by the results in Section IV-C.

A. DEMKit

DEMKit is a platform developed at the University of Twente, to simulate and demonstrate control in smart grids, see [11]. It is based on the TRIANA concept ([7], [8]) consisting of the three steps: prediction, planning and real-time control. DEMKit has device components that model the behavior and the flexibility of devices. In addition, devices can have optional controller component for device specific prediction, scheduling and online control algorithms. We integrated the represented real-time control method of this paper as the third step in DEMKit.

B. The Test Case

In order to validate the proposed real-time method, a house equipped with some baseload, a washing machine, an EV and an electrical battery is modeled in DEMKit. For this house first, as starting point the day-head planning of this house is generated. In our scenario the start and end time of washing machine, and the availability of the EV are generated using the profile generator introduced in [3]. This generated data is used as input for the planning but also for the real-time control. In contrast to this, for the baseload of the house we used different profiles for the planning and real-time control to introduce prediction errors. For the planning, we predicted the baseload profile using the history of the last four weeks, and for the real-time data we used the profile generator. Therefore the baseload is the only source of deviation in this test case. Our goal is to investigate how the planning gets affected by deviations and how we can compensate for it using the real-time control. Moreover, in this simulation the objective for the day-ahead planning was creating a flat profile. This in general implies that the flexible devices are used quite a lot in the planning.

Figure 2 represents the predicted and realized baseload profile. The difference is the deviation from the day-ahead planning due to prediction errors. The total deviation is 1.24 kWh.

C. Results

In Figure 3, we presented the planned profile for the house and the profile realized by the real-time control. As can be seen, the flexible devices have enough potential to flatten the

Fig. 3: Total power demand of a house (per interval)
— real-time profile (p_r), — planned profile (p_p)

	$> p_p(d, i)$	$< p_p(d, i)$	total
Baseload	2.55	-1.31	1.24
Time Shiftable	0.03	-0.03	0
Electrical vehicle	0.62	-0.64	-0.02
Electrical battery	0.73	-1.75	-1.02

TABLE I: Deviations of the real-time control from the predicted planning for Test case 1 (kWh).

overall profile in the planning. However, also the real-time control is able to follow almost all the time the planned profile and thereby able to compensate the prediction errors, except for a short large peak in the evening. Compensating for this large prediction error would imply devices would deviate more than the allowed threshold from their planning. As a result, the real-time control reduces the deviations as much as possible within the allowed range.

To see how the realized real-time profile look like, in Figures 4a-4c the planned and realized profile of devices are given. The time shiftable device in Figure 4a is delayed for couple of minutes to reduce the deviation at the start of time interval. The figure also shows that postponing of the device starting time will change the power profile in other time intervals, as the profile of the time shiftable in general is not flat,. Therefore the structure of the profile should be taken into account as well in the real-time control, to avoid larger deviation in future time intervals.

Figures 4b and 4c show that most of the deviations are managed by the electrical battery, but the EV also compensates for them during its availability. This is also confirmed by Table I which represents the total volume of energy for the time slots where the real-time profile was above the planning ($> p_p(d, i)$) and was below the planning ($< p_p(d, i)$). Furthermore the sum of these two values is given. As indicated in the table the time shiftable can only shift and has no deviation in total since the profile is not controllable. The EV is deviating in both direction for around 0.63 kWh from its planning, but the overall volume has to stay (almost) the same (upto a small deviation of 0.02 kWh) as the EV has the constraint to be charges upto a given level. As a result a large amount of deviations, especially the deviation in total volume, is taken care of by the electrical battery.

To investigate the capability of the real-time control and how much deviation it can tolerate, we used a second test case with more deviation and less flexibility. In this test case we used both PV and baseload as the source of deviation with a total volume of the deviation of -3.54 kWh and the electrical

(a) profiles of time shiftable (per interval)

(b) profiles of EV (per interval)

(c) profiles of electrical battery (per interval)

Fig. 4: — real-time profile, — planned profile

battery as the only flexible device. We used the same method as for the first test case to generate the profiles, except for the PV, day-ahead and real-time measurement data of the PV production for each time interval are obtained from [12] (DSO Regie de Wavre). In this test case the deviation of the total volume is in the other direction, which means that less energy is used than expected.

Figure 5 represents the deviation for PV and baseload, which is less than expected especially during the afternoon. Figure 6 represents the total planned and realized profile of the house. As it is shown in this figure the battery can no longer compensate all the deviations due to the used threshold for the deviation and therefore some deviations stays in the realized profile.

The compensation and deviations realized by the different devices in this test case are shown in Table II. As it can be seen although the only flexible device is the electrical battery it compensate quite good for the deviations, and the deviation is reduced about 73% using the real-time control.

V. CONCLUSION

The developed real-time control method determines decisions for controllable devices using finer granulated time slots with the goal to follow a given day-ahead planning. The

Fig. 5: Baseload+PV profile for test case 2 (per interval)
— real-time profile — planned profile

Fig. 6: Total power demand of a house for test case 2 (per interval)
— real-time profile (p_r), — planned profile (p_p)

usage of devices in each time slot is decided based on the deviations up to that time and constraints for the devices. The method uses the flexibility of devices like electrical vehicles and batteries to compensate for the occurring deviations from the planning like changes in baseload and PV prediction.

The method has been evaluated in a simulation study and the results show that the real-time control can compensate for the deviations unless there is a huge difference between the planning and the real data. The real-time control does not compensate such large deviations as it aims to keep device profiles as close as possible to their predicted profile, since otherwise there is risk of having larger deviation in future time intervals. Due to the used constraints for time shiftables, heat pumps and EVs, the electrical batteries deal with most of the deviations. However, also the other devices compensate as much as they are allowed. It is also shown that even without having a lot of devices with flexibility, e.g. by using only the electrical batteries, the proposed method is able to compensate for prediction errors and allows to follow a day-ahead planning quite well.

VI. FUTURE WORK

Although the method in principle is working fine and reduces the deviations, a closer look at the behavior of some devices shows that still some refinements should be done. For

	$> p_p(d, i)$	$< p_p(d, i)$	total
Baseload	0.29	-4.45	-4.16
PV	0.65	-0.04	0.61
Electrical battery	3.21	-0.65	2.56

TABLE II: Deviations from the predicted planning using the real-time control for Test case 2 (kWh).

Fig. 7: Electrical battery profile (per minute)
— real-time profile, — planned profile

example, at the beginning of each time interval the baseload profile gets updated and as a reaction of this, the electrical battery reacts quite fast and extreme on these deviations. This results in an eager profile, as can be seen from Figure 7, where the profile of the battery on a minute scale is given. One of the future work is to avoid these extreme changes by taking into account also the state used in the previous time slots and react more smoothly.

Moreover, as a future work, the flexibility boundaries can be adapted depending on the reason of the deviation. If the deviation happened as a result of a postponed event, the boundaries should be wider. However, for a structural change in the planning, like sunnier weather or more heat demand, narrower boundaries should be used. Moreover, if deviation can not be avoided, the decision should be in a way that we take benefit from it or at least that our control method does not create grid problems.

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