Asynchronous Event Driven Distributed Energy Management using Profile Steering

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***Abstract*—Distributed Energy Management methodologies with a scheduling approach based on predictions require means to avoid problems related to prediction errors. Various approaches deal with such prediction errors by applying a different online control mechanism, such as a double-sided auction. However, this results in two separate control mechanisms for the planning phase and the real-time control phase. In this paper, we present a two-phase approach with profile steering based control in both phases. The first phase is synchronous and uses predictions to create a planning. The second phase uses profile steering to schedule individual devices in an event driven and asynchronous manner. Simulation results show that this methodology results in an improved power quality and follows the planning better with a RMSE reduction of up to 34%. In addition, it provides more robustness to failure of connection and improves transparency of its actions to prosumers.**

***Index Terms*—load management, demand side management**

I. Introduction

With the increasing penetration of renewable energy sources in the distribution grid, flexibility from the loads in this distribution grid becomes increasingly important to maintain balance between consumption and production. At the same time, the electrification of energy demand by adoption of battery electric vehicles (BEVs) and heat pumps also challenges the grid from a capacity perspective. As a reaction, distributed Energy Management (DEM) methodologies such as [1], [2] are developed to control the flexibility that these assets bring. To guarantee feasibility of future control actions, proactive DEM methodologies use predictions and planning algorithms. These proactive methodologies aim to manage energy both in *time* (e.g., plan for future events) and *space* (e.g., spread the power over several assets).

Compared to pure reactive control methods such as [3], proactive DEM has to deal with prediction errors. These can be both in the energy domain (e.g., underestimates of the energy production by PV) and the time domain (e.g., late arrival of a BEV). Events in real-time therefore may change the constraints that were considered during the planning phase, resulting in invalid or undesired device schedules. Hence, proactive DEM requires additional real-time control methods to resolve these prediction errors in order to follow the planning as good as possible. Most proactive DEM methods therefore employ an online control method such as e.g., a double-sided auction [3] to control devices in real-time.

The downside of such an approach is that two different control strategies must be developed. Therefore, we propose a two-phase approach in which we use one optimization model in both the offline planning phase and online realization phase. More specifically, we use the profile steering algorithm by Gerards et al. [4]. Furthermore, we use an event based approach where devices are scheduled asynchronously during the realization phase. The main advantage is that only one method needs to be developed. Another advantage is that updated predictions can be incorporated in the optimization model, resulting in a model predictive control (MPC) approach that spreads its flexibility in time and thereby avoids extreme behaviour. Furthermore, we show that this approach also adds transparency to the prosumers, which enhances the user-acceptance of the proposed system. The main contributions of this paper are:

- a planning based approach for online control, that is
- robust to prediction errors and communication failure,
- while being transparent to enhance user acceptance.

The remainder of this paper is organized as follows. The next section covers related work on DEM methodologies that employ a planning based strategy and related work on user-acceptance of such systems. Section III unveils the proposed two-step methodology. A use-case is presented and simulation results are evaluated in Section IV. Subsequently, further benefits and possible applications are discussed in Section V. Section VI draws conclusions and presents future work.

II. Background

Siano [5] has published a comprehensive survey of DEM approaches with different underlying ideas. Among those approaches are many online control mechanisms, often with price incentives to change the behaviour of a fleet of devices. Within the PowerMatcher [3] approach, a double-sided auction is used to steer devices in real-time with the advantage of knowing the response of the fleet to a new price incentive. Furthermore, it enables the system to act fast on energy balancing market with e.g., 15 minute intervals. The TRIANA approach by Molderink et al. [1] performs offline forecasts and planning to optimize the energy usage of a fleet of households. The usage of forecasts allows the system to avoid the problem of running out of flexibility as it can balance usage of flexibility for both the short term and longer term. However, predictions are never completely accurate. Events in real-time therefore may change the constraints that were considered during the planning phase,

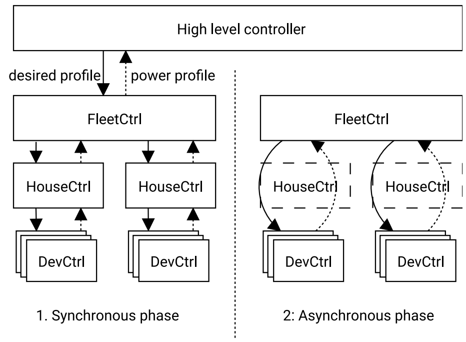

Fig. 1. Illustration of the control structure and signals in both phases.

resulting in invalid device schedules. Hence, planning based methodologies require additional real-time control to resolve these prediction errors in order to follow the planning as good as possible. However, executing a synchronous replanning that considers all devices for several intervals in the future for each deviation is computationally too expensive and may not give answers in time. Thus a different lighter approach is required.

Molderink et al. [6], [7] have therefore evaluated different real-time control mechanisms to resolve prediction errors and follow the initial plan as good as possible. In their evaluation, the best performing solution is to combine the scheduling approach with a double-sided auction to resolve prediction errors. This auction method considers all available devices to redistribute the planned power value for the current interval and can therefore be seen as a synchronous approach. The approach is further extended by Toersche [8].

Another approach is the three-step approach by Vandael et al. [2]. Here forecasts are done at a central level such that prediction errors can cancel out. Claessens et al. [9], [10] show that a self-learning approach can be used on the central level within this approach. Ruelens et al. [11] use the three-step approach to control a fleet of BEVs with uncertain arrival and departure times. Herein a fleet controller, which is in charge of the charging process of BEVs, aggregates all constraints and optimizes the overall charging process over the considered time span. Charging rates of the electrical vehicles are updated in real-time using a priority signal, which is comparable to the double-sided auction. To ease the amount of communicated data during the real-time operation, an event-driven approach improvement is proposed by de Craemer et al. [12]. Herein the devices respond asynchronously based on major events, such as the arrival or departure of a BEV. Significant reductions in communicated data are observed with comparable performance.

However, for a DEM system to be effective in residential areas, end-users need to accept the system as well. Research on user-acceptance of DEM systems is done by Paetz et al. [13] where interviews with consumers were held, whereby a part of the participants were living in a smart home during the research. Their findings are that users are willing to accept smart appliances and control when the system provides cost-saving potential in a transparent manner without loss of comfort. Mert et al. [14] draw similar conclusions after interviews and questionnaires throughout Europe. A reward for each individual smart operation is seen as a good motivator to encourage end-users to provide flexibility.

III. Two-phase Approach

As indicated, previous studies do not find an adequate solution to prediction errors of the total energy demand and production for a given optimization horizon. In an auction based approach the market is cleared at the scheduled demand for each time interval, and therefore may use too much flexibility at times to stick to the plan. This often results in peak load or generation of energy as it forces devices into a ”must-run” state to meet the constraints set by end users. Another effect is early filled battery storage that can therefore no longer shave PV peaks. Furthermore, the system lacks transparency to end-users as it is unknown on beforehand at what price the auctioneer clears the market and therefore how and when their devices will operate.

Therefore we present a two-phase approach that is inspired by the DEM methodologies [1] and [12]. The first step is a synchronous prediction and planning phase that forecasts future flexibility in the given fleet of devices. This forecasted flexibility is then used to optimize the profile towards a *desired profile* for the next day. The second phase is concerned with the realization of this *planned profile*. For this we use an event driven approach to schedule devices asynchronously. This results in an evolutionary realization of the planning that continuously incorporates updated predictions. Hereby, the controller structure is the same as in related work (e.g., [1]): a hierarchical tree managing energy as locally as possible in a distributed fashion. Fig. 1 shows the interaction between controllers in the two steps. The following two subsections present the details of these two phases.

A. Phase 1: Synchronous Planning

The first phase is the synchronous planning phase and is similar to the prediction and planning steps used in [1]. This phase is synchronous in the sense that a planning is created on a regular basis and considers all devices for a given planning time horizon, thus the planning takes place in both time and space. The resulting schedule and profile can be used to verify that physical grid constraints are met. The created schedules are still based on predicted profiles and flexibility.

In the current implementation we build further on the profile steering algorithm as presented by Gerards et al. [4]. Profile steering works by sending an explicit *desired profile* to lower level controllers and devices, which expresses exactly what we want them to achieve. Such a *desired profile* $\vec{p} = [p_1, \ldots, p_N]^T$, with N being the number of intervals, could for instance be a zero-profile (i.e. $[0_1, \ldots, 0_N]^T$) which expresses that a balance of production and consumption of energy is desired. The objective is to minimize the distance between this *desired profile* and the aggregated *power profile* $\vec{x} = [x_1, \ldots, x_N]^T$ of a set M of devices using some vector norm. In our case, we minimize the distance using the Euclidean distance (i.e. minimize $||\vec{x} - \vec{p}||_2$). This process is coordinated by a *fleet controller* that manages a fleet devices.

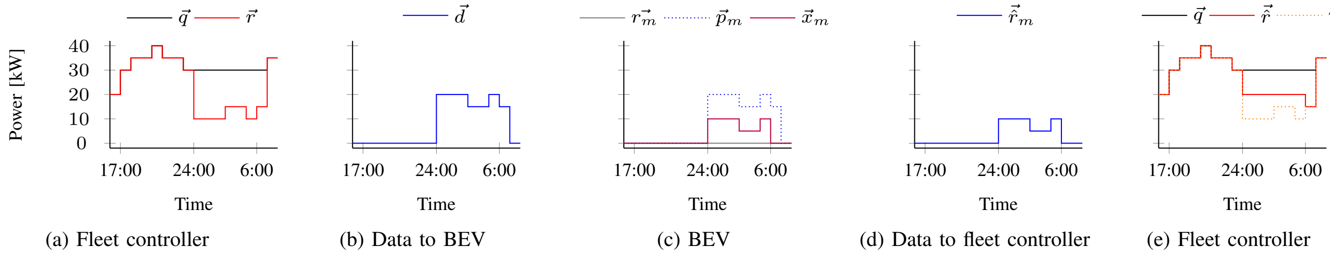

Fig. 2. Example of event-based scheduling with a BEV arriving at 17:00 that has a charging deadline at 6:00 the next day and energy demand of 50 kWh

Initially, each device $m \in M$ receives this *desired profile* $\vec{p}$ and is asked to minimize the distance between this *desired profile* and its own *power profile* $\vec{x}_m = [x_{m,1}, \ldots, x_{m,N}]^T$. The higher level controller receives all *power profiles* from devices connected, resulting in an aggregated *power profile* $\vec{x} = [x_1, \ldots, x_N]^T$. Then, in an iterative method, the controller sends out the *difference profile* $\vec{d} = \vec{x} - \vec{p}$, the devices obtain a new local desired profile $\vec{p}_m = \vec{x}_m - \vec{d}$ and respond with a new optimized candidate *power profile* $\vec{\hat{x}}_m$ that minimizes $||\vec{\hat{x}}_m - \vec{p}_m||_2$. Subsequently, the controller selects the device m with the largest improvement in the objective and calculates a new *difference profile* $\vec{d}$. The chosen device m commits its own candidate profile (i.e. $\vec{x}_m := \vec{\hat{x}}_m$). This process continues until no significant improvement is made or the maximum number of iterations is reached. The result of the algorithm is a schedule $\vec{x}_m = [x_{m,1}, \ldots, x_{m,N}]^T$ for each device m and a *planned profile* $\vec{q} = \vec{x}$ at the *fleet controller*. We refer the reader to [4] for more background on profile steering.

Our approach differs from the three-step approach presented in [1] in the sense that it does not rely on a local, device level, planning. Instead, we only use this first phase as a speculative phase to estimate the available flexibility of the fleet of devices. The *planned profile* $\vec{q}$ is used as input for the second phase of the methodology. On the fleet controller level, the law of large numbers applies and therefore there is sufficient confidence that this profile can actually be (almost) realized the next day.

The law of large numbers does not apply to the lower controller levels, such as house and devices controllers. Hence we discard device schedules from devices with a high uncertainty, such as individual BEVs, while we keep predictions from uncontrollable loads (of which the sum is predictable) and planned schedules of batteries (which we assume are available throughout the day). The device schedules that are kept are stored as *committed profile* $\vec{r}_m = \vec{x}_m$. Schedules for uncertain devices are created at run-time, when there is enough confidence that these schedules are actually feasible for these devices. Note that the local devised schedule in this phase may still be kept locally for fall back strategies when communications fail. Therefore these profiles are cleared in this phase (e.g., $\vec{r}_m = [0, \ldots, 0]^T$). Likewise, the *fleet controller* stores the aggregated *committed profile* $\vec{r} = \sum_{m \in M} \vec{r}_m$.

B. Phase 2: Asynchronous Realization

The second phase of the methodology is concerned with realizing the planned power consumption $\vec{q}$ of the fleet using active control. As argued, we do not want to resort to different control approaches and optimization algorithms for this process. Instead, we re-use the concepts of profile steering and existing device optimization algorithms to realize this. However, we switch to an event based approach in which devices initiate control actions asynchronously from each other and only for themselves. Thus, devices are not all controlled at the same time in our approach. Furthermore, devices create a schedule for an upcoming time horizon. Note that this approach differs from other approaches, such as auctions, where the central controller is able to initiate actions to change the demand at any given time. Based on this we do not refer to the term real-time control in our approach.

1) Scheduling individual devices: The basic idea behind our approach is to schedule a device when there is enough confidence that constraints and parameters will not (significantly) change anymore. A schedule is reliable when constraints, e.g., a deadline for a washing machine, and parameters, e.g., the requested charge of a BEV, are unlikely to change. For example, a reliable schedule for a BEV can be created upon the event of arrival. From that moment on, the start time, end time and requested charge, as well as the capabilities of the device, are known and unlikely to change. White goods may be scheduled in the same way. Other devices, such as a battery, may trigger other events, for example when they are nearly full or on a regular timed basis. Events are not limited to those mentioned here.

Scheduling of a single device is done via the so-called *fleet controller*. We use an example (Fig. 2) with a BEV m arriving at 17:00 and departing at 6:00 the next day, with a total demand of 50 kWh. Upon arrival, device m triggers an event and requests an updated *desired profile* $\vec{d}$ from the *fleet controller*. The objective of this *fleet controller* is to realize the *planned profile* $\vec{q} = [q_1, \ldots, q_K]^T$ as good as possible, where K indicates the amount of remaining planned intervals ($1 \leq K \leq N$). To keep track of the confirmed device schedules a *committed overall profile* $\vec{r}$ is kept locally at the *fleet controller* (Fig. 2a). The objective is to minimize the Euclidean distance between this *committed overall profile* and the *planned profile* ($||\vec{q} - \vec{r}||_2$) in order to follow the original planning. Hence we send $\vec{d} = \vec{q} - \vec{r}$ to the device m as *desired profile* since it exactly expresses the gap in the profile that needs to be filled (Fig. 2b). In this example, there is still a large valley to be filled in the night.

Device m first adds its own *committed profile* $\vec{r}_m$ =

$[r_{m,1}, \ldots, r_{m,K}]^T$ to the received signal, resulting in $\vec{p}_m = \vec{d} + \vec{r}_m$. Note that the local *committed profile* may be zero (such as in the example) or filled with a (partial) profile as a result from previous events (e.g., a previously planned battery). The device then minimizes the Euclidean distance between its own *power profile* $\vec{x}_m = [x_{m,1}, \ldots, x_{m,K}]^T$ and $\vec{p}_m$ (i.e. minimize $||\vec{x}_m - \vec{p}_m||_2$) while satisfying the (updated) user constraints (Fig. 2c). Since constraints are unlikely to change, the resulting schedule is considered reliable and realized. Hence the device commits the update on the *committed profile* $\vec{\hat{r}}_m = \vec{x}_m - \vec{r}_m$. This $\vec{\hat{r}}_m$ is then send back to the fleet controller (Fig. 2d). The *fleet controller* now obtains a new *committed profile*: $\vec{\hat{r}} = \vec{r} + \vec{\hat{r}}_m$ (Fig. 2e). Finally, the device and fleet controler update their *committed profile*: $\vec{r}_m := \vec{x}_m$ and $\vec{r} := \vec{\hat{r}}$.

All device events are handled in order and only one single device is considered at a time. Also, scheduling a single device in our methodology is a "single shot" operation that does not require several iterations and, depending on the device type, only one to few of these events are expected on a daily basis. Furthermore, the resulting device schedule to be followed spans multiple time intervals and thus improves the robustness against loss of connection in the time between events.

2) Updating predictions: In addition to the control over the flexible assets, we are left with the inflexible load and generation. Since there is nothing to be controlled, we consider their respective predicted profiles to be realized (confirmed) immediately in the first phase of our method. Load and production forecasting controllers may update their predicted profiles in the meantime. So these controllers regularly send an updated $\vec{r}_m$ to the *fleet controller* which expresses the difference between the new prediction and the previous prediction. In that way, more accurate predictions for, e.g., solar production can be incorporated. Flexible devices that request a new planning after such updates can then directly incorporate these predictions in their own optimized profiles. This approach is also applicable to devices that would like to cancel their planning, such as an earlier departing BEV.

3) Incremental realization of the planned profile: As time elapses, other devices trigger events as well and create a schedule based on the newly received *desired profile*. A further advantage of this approach, next to using the same algorithms for planning and realization, is that this scheduling based approach is proactive and takes the future into account. Therefore, by its very design, prediction errors in the energy domain are spread out in time, which prevents the creation of synchronized peaks. Furthermore, the used device level algorithms, such as presented by van der Klauw et al. [15], have low complexity and therefore can communicate the devised schedule to end-users nearly instantaneously. If there is enough diversity in the event times, new device schedules, triggered by new events, can resolve open problems. This leads to an incremental realization of the *planned profile*. The major drawback, compared to the auction approach, is that there is no direct online control to accurately distribute the problem to the devices on a short time scale. Therefore it is expected to see more smaller deviations from the planning as the result of prediction errors in the time-domain.

IV. Evaluation

The performance of the presented DEM methodology (referred to as *Event*) is evaluated using two cases. The results are compared to a synchronous approach, which uses a double-sided auction as control mechanism to follow the planning achieved in the first phase (referred to as *Sync*). The latter approach is similar to the one taken in [6].

A. Case studies

The first case that we consider is an office building with rooftop solar panels installed and several BEV charging stations for both employees and visitors. Real measurement data of an office is used as the static load, whereas PV production data of 2016 is obtained from [16] (DSO Regie de Wavre) given in 15 minute intervals. The PV data consists of real measurements, day-ahead predictions and intraday predictions as provided by the DSO. Note that this DSO has a small service area (15.236 connections) and was one of the few available datasets that fits the need for both PV predictions and measurements. However, it is unknown how the PV production is predicted. To resemble the size of the office building, the PV data is scaled by $\frac{39}{1000}$ to obtain a realistic PV production profile given the size of the building. Arrival, deadline and energy demand information of the BEVs are generated. A part of the BEV load resembles a normal 9-to-5 working pattern, whereas other BEVs arrive and leave randomly during working hours. We refer to this case as *Off* and we simulate a total of four weeks starting March 30, 2016.

The second case is a neighbourhood of 81 households of which the profiles are generated using an artificial load profile generator [17]. We refer to this case as *Res*. Each household is equipped with PV panels using the same PV data as in the *Off* case, but now multiplied by $\frac{1}{1000}$. Furthermore, 16 randomly selected houses are equipped with a 12kWh battery and a 20 households own a BEV. Furthermore, a network model for this neighbourhood is available for load-flow calculations. The batteries randomly trigger an event every 90 to 180 minutes. In this case we simulate a week starting at June 23, 2016.

In both cases the size of simulation intervals is set to 1 minute, whilst data is analysed using 15 minute averages. Day-ahead predictions for the base-load and BEV flexibility are made using a simple weighted averages method based on the observations of the same weekdays for the past 4 weeks. For PV, we use the day-ahead data [16] in the planning phase. We update the PV and base-load predictions on run-time using the last measured value and adjust the short term predictions (the next 3 hours) with a linear combination of the current deviation from the prediction and the prediction itself.

To evaluate the influence of prediction errors, we also run simulations where the day-ahead PV predictions are replaced by the more accurate intraday predictions from [16], denoted by *Event+* and *Sync+*. The objective is to balance production and consumption in the grid by setting the target profile to $\mathbf{0}$ ($\vec{p} = [0, \ldots, 0]^T$). The planning horizon is set to 2 days ($N = 192$) and a new planning is executed every day (96 intervals).

TABLE I
NUMERICAL RESULTS OF THE SIMULATION CASE STUDIES

	MAE-P	RMSE-P	MAE-I	RMSE-I
Off-Sync (kW)	6.65	11.96	2.77	7.84
Off-Event (kW)	7.73	11.75	2.41	6.23
Off-Sync+ (kW)	6.65	11.94	2.77	7.84
Off-Event+ (kW)	7.71	11.70	2.41	6.19
Res-Sync (kW)	3.40	8.20	3.51	7.98
Res-Event (kW)	4.11	5.81	3.40	4.83
Res-Sync+ (kW)	2.53	5.41	2.60	5.80
Res-Event+ (kW)	3.26	4.44	2.17	4.31

TABLE II
NUMERICAL RESULTS OF LOAD-FLOW STUDIES

	$V_{\min}$ (V)	$V_{\max}$ (V)	Loss (kWh)	Util (%)
Res-Sync	207.7	244.1	31.5	76.5
Res-Event	212.9	237.3	31.5	66.0
Res-Sync+	206.4	243.3	30.8	75.8
Res-Event+	218.9	236.2	28.8	61.7

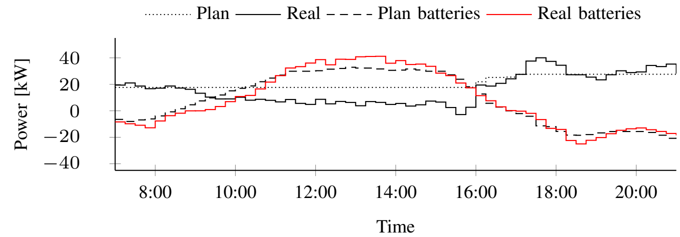

Fig. 3. Usage of batteries to peak-shave PV with the event-based approach.

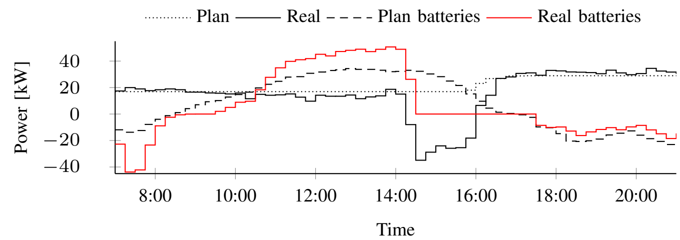

Fig. 4. Usage of batteries to peak-shave PV with the synchronous approach.

B. Results

The performance of the systems is evaluated using the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) between the planned and realized profile (referred to as MAE-P/RMSE-P). The MAE indicates the total average deviation from the planning and the RMSE value penalizes large deviations from this planning. Furthermore, we also evaluate the MAE and RMSE from a planning based on perfect predictions (referred to as MAE-I/RMSE-I), which shows how far the methodologies are off from the solution obtained using the profile steering heuristic in the ideal case.

Table I presents the numerical results for the considered cases. Overall, it can be concluded that the *Sync* approach does indeed perform better at minimizing the absolute distance from the planned value with a MAE-P of 6.65kW for the *Off* case and 3.40kW for the *Res* case due to the nearly continuous control over all flexible loads. The *Event*-based approach presented in this work revises the device plannings less often and hence it can not follow short term fluctuations as accurate as the *Sync* approach. However, it incorporates updated predictions, which result in reduced load and generation peaks compared to the *Sync* approach. This effect is also reflected in the RMSE-P for both cases. In the *Res* case an improvement of 34% is achieved on RMSE-P. Better predictions improve the performance of both approaches and the main observations stay the same. The results indicate that the proposed approach is able to perform closer to the near optimal solution obtained with perfect predictions (MAE-I/RMSE-I).

We also compared simulation times with optimization and control, excluding database writes and load-flow calculations for the approaches. Within the *Off*-case, the event-based approach completes the simulation in 53.6 seconds versus 303.5 seconds for the synchronized approach. For the *Res*-case, these numbers are 264.1 and 404.1 seconds respectively. The relative difference between the two cases can be explained by the number of events, which is significantly higher in the *Res*-case with the 16 batteries spawning timed events.

In table II the results of load-flow analysis of the *Res*-case indicate that *Event* scores better on voltage levels ($U_{\min}$ and $U_{\max}$). Also the maximum cable capacity usage (Util) is lower, whilst the total energy losses in the distribution network are equal for both approaches with the normal predictions. Therefore, the event-based approach puts down a good performance on the electricity grid as well, whereas *Sync* performs significantly worse for a few hours in the obtained dataset.

The major difference between the two approaches is how they deal with prediction errors. Here the event-based approach has an advantage to prediction errors in the energy domain. A day with significantly more PV production than forecasted is depicted in Fig. 3 for *Event* and Fig. 4 for *Sync* in the *Res*-case. Herein, it is clear to see that the event-based approach adapts its measured power consumption (Real, red line) by deviating from the planning (Plan, black line). It spreads the forecasted error nicely over the afternoon, but still ensured that batteries are nearly full at the end of the afternoon and thus optimize local energy storage. In contrast, the synchronized auction approach sticks to the plan, resulting in a significant higher power consumption by the batteries (Real batteries, blue line) than planned for them (Plan batteries, grey line). The batteries are full around 14:30 and can therefore no longer compensate for the PV peak, resulting in a sudden drop of the overall measured power consumption. It is also clear that the *Sync* approach is indeed better in resolving prediction errors in the time domain at the global level. This is clearly seen by the smaller deviation from the planning around 17:30.

V. DISCUSSION

The results show that this initial attempt at using profile steering to realize a *planned profile* is very promising. Overall, the presented event-based approach performs better on predictions errors of the amount of produced/consumed energy. In contrast, *Sync* deals better with prediction errors in the time domain, as expected. More quantitative studies on this are required to find out which approach works better in which case. Possible improvements to the event-based methodology may be to add weights to the objective function such that deviations from the planning in the first, more urgent, upcoming intervals are resolved more than those in the later intervals. In such a case, the algorithm speculates that other devices, triggering events later in time, may solve these problems. Also the rate of events triggered by batteries may be increased, which is perfectly possible considering the simulation time differences. Last but not least, the current implementation relies on the amount of events triggered by the devices. It is possible to use events originating from the fleet controller to also replan devices (if allowed) as well.

The method was also proposed to fulfil wishes from prospective end-users. In that sense, the proposed method provides transparency to end-users as it can give a clear device schedule and incentive to the end-user for each smart operation. The latter can be a fixed incentive for given flexibility, but also based on the calculated improvement as described in [4]. Since the scheduling is nearly instant, the prosumer will directly receive an offer for the flexibility, which can be accepted or refused. This makes the smart operation of devices clear, tangible and allows prosumers to plan other activities based on the schedule. If the end user refuses the offer, the device can run directly and be considered as an inflexible device and hence no data on the profile has to be send.

The proposed control methodology is a technical solution to manage energy streams and is therefore not targeted for a specific market or use-case at this stage of development. However, the concept or parts of it are applicable to energy markets (with or without minor modifications). As an example, the methodology can be used by an aggregator within an energy flexibility market concept such as defined in the USEF framework [18]. However, the system may also be used in other frameworks or stand-alone systems such as the management of energy within a large building. Furthermore, Toersche [8] stated that profile steering, and the event based approach as presented, can be easily extended with linearly scaling multi-commodity support. Hence we see applicability of the concept for more complex hybrid energy systems.

VI. Conclusion

This paper has presented a new control methodology for distributed energy management. The basis of the methodology is to use planning based algorithms to asynchronously schedule individual devices for multiple time intervals. This in contrast to synchronized online control approaches that consider all devices for only the next time interval. The advantage of the presented approach is that the same algorithms can be used for both day ahead planning and the realization of this planning. This method also increases the robustness of the system against prediction errors in the energy domain and loss of communication technology. Furthermore, it also allows for clear communication to prosumers, which will likely improve the acceptance of the system by prosumers.

Results show that the performance of the proposed methodology is similar to that of auction control. The proposed method performs slightly better on the RMSE from the planned value and significant reductions in computation time are achieved. Therefore, the methodology is suitable for peak-shaving objectives or markets where deviations from a planning are penalized quadratically. Future work lies in incorporating better predictions and bi-directional events. The addition of multi-commodity support for emerging hybrid energy systems is also left for future work.

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