Abstract—Demand Response (DR) is widely considered to be an integral part of future energy systems with high renewable energy penetration. Fast and reliable DR schemes require appropriate communication infrastructure. By limiting both the data sent and the measurements taken, the marginal cost of adding a load unit to the DR scheme can be reduced so that it becomes economically viable to utilize small loads such as hot-water boilers for DR.

This paper presents an estimation and control topology for DR relying only on measurements of aggregated power and one-way communication. By using a state observer based on particle filtering and by switching individual loads based on comparing a drawn random number to a broadcast switching signal, accurate tracking of a reference signal can be achieved.

In a case study it is shown that employing the proposed algorithms on a basic Smart Meter infrastructure enables the utility to significantly reduce overall cost by avoiding consumption of balancing energy.

I. INTRODUCTION

In-feed of renewable energy is rapidly increasing. As curtailment of renewable generation should be minimized, this leads to an increased demand for flexibility in the power system. This flexibility can be offered by demand side management. Most current research and pilot projects regarding ancillary services using demand side management focus on tertiary control and on large customers. However, there exists also considerable potential to shift demand in small household loads, especially in loads with thermal storage. This group of loads includes refrigerators, freezers and air-conditioning as well as space and water heating. It was shown in [1], [2] that small loads can be used for tracking an arbitrary reference signal. In this paper, we focus on hot-water boilers as they are the dominant group of thermostatically controlled loads in Switzerland, as well as in most of central and northern Europe.

In order not to alienate customers from such load management schemes, three requirements must be fulfilled: customer end-use of the device must not be impeded, customer interaction must not be required and no additional cost shall be incurred by the customer. Such a scheme could be combined with a suitable incentive for participation, which could be a monetary reward, or be enforced by regulation.

In [2], the topic of using boilers for Demand Response (DR) was already addressed, however, it was assumed that all, or a subset of, the loads can be measured. To reduce this limitation, state estimation techniques for a population of air conditioners were introduced in [3]. This recent work is extended by introducing a more advanced observer based on particle filtering which can handle forecast errors more effectively and therefore yields improved tracking results. The performance of the implemented control scheme is assessed using real measurements from a Swiss substation.

A. Hot-Water Boilers as Flexible Load

Hot-water production accounts for roughly 16% of the total residential electric energy consumption in Switzerland [4]. In the service area of the utility of the Kanton Zurich (EKZ) which serves around 285,000 customers, 105,000 water boilers with a combined nominal power of 440 MW are installed. The associated energy consumption can be shifted within a 24 hour window. In Switzerland, hot-water boilers are currently shifted to low-load hours using ripple control, minimizing the loading of lines and transformers, while customers profit from reduced night-time tariffs. We propose a scheme that allows utilizing the load-shifting potential of hot water boilers for fast and accurate tracking of a reference signal.

B. Communication Infrastructure and State Estimation

Deployment cost is a major issue when discussing the implementation of DR schemes. Most schemes are not financially viable when comparing the low expected profit that a single hot water boiler can generate with the cost of the measuring and communication infrastructure needed. Especially retrofitting installed boilers might prove to be cost-prohibitive. Our approach is therefore (a) to use the Smart Meter infrastructure and (b) to minimize communication by using advanced state estimation techniques. The reasoning is as follows:

(a) Many countries in Europe are considering a Smart Meter roll-out until the end of the decade [5]. They are expected to replace ripple control and to additionally provide Advanced Meter Reading. Therefore they can switch loads and additionally offer basic bidirectional communication capabilities. The main advantage over ripple control is the increased bandwidth and higher frequency with which control signals can be sent.

(b) In the proposed approach, temperature constraints of the loads are ensured locally and the system operator is not aware of the state of a specific load. Therefore, unidirectional communication is sufficient. As in [2], broadcasts are used to minimize forward communication. Measuring the resulting change in power at the substation can be used to estimate the...
number of units that are able to respond for up- or down-regulation. This concept also inherently guarantees privacy to the customer.

Section II describes the system modeling, observer design and controller design in detail. In Section III the described methodology is applied in a case study and detailed results are given. Conclusions are drawn in Section IV.

II. SYSTEM DESCRIPTION

Figure 1 shows the proposed control topology. The numbers indicate in which section the particular blocks are described. Our primary goal is to closely track a given power reference \( r \) at substation level by employing switchable loads. That is, with the tracking control we want to achieve minimal deviation between the reference \( r \) and the load at the substation \( P_{\text{tot}} \).

Different use cases for the tracking can be identified, e.g., provision of ancillary services or integration of distributed, stochastic generation. In this paper we aim at minimizing consumption of balancing energy, which is the task of the 15 min E-control, see II-D.

If the state of all participating loads, or even just the aggregated states, are known, and if each unit could be addressed directly, this would be straightforward. However, it is assumed that due to communication restrictions only \( P_{\text{tot}} \), but no states, can be measured and only few commands can be sent. Further, the loads must adhere to local thermal constraints, see II-B, leading to switching that appears stochastic from an aggregated point of view.

A particle filter was designed to estimate the system states, see II-C. From these estimates the control signal \( u_{\text{sw}} \) is computed and broadcast to all units. Depending on whether load is to be reduced or increased, \( u_{\text{sw}} \) is either the probability \( u_{\triangledown} \) for switching from on to off, or \( u_{\triangle} \) for switching from off to on.

\[
 u_{\text{sw}} = \begin{cases} 
 u_{\triangledown} \in [0,1], & u_{\triangle} = 0, \quad \text{if } e < 0 \\
 u_{\triangle} \in [0,1], & u_{\triangledown} = 0, \quad \text{if } e > 0 
\end{cases}
\]

By measuring the change in power at the substation, it is now possible to update the estimate of the aggregated states.

A. Communication Infrastructure

In Switzerland and most of Europe, ripple control is used for load-switching. Ripple control consists of a powerful transmitter in the substation, which emits a high-energy signal with a frequency in the range of 200 Hz to 1.5 kHz, which passes through low-voltage transformers. Sending of a signal takes only a few seconds, but to prevent overheating of the sender such a signal can only be sent every two minutes. Therefore, ripple control is not well suited for those DR schemes where a fast update rate is desired.

In order to avoid these limitations, the proposed scheme is based on the Smart Meter infrastructure. In Europe, Smart Meters communicate via Power Line Communication (PLC), usually using the PRIME standard [6]. As PLC signals cannot pass through transformers, a base node has to be installed at each low voltage transformer. As not all Smart Meters in a feeder can be reached by the base node, the signals are repeated by service nodes. The bandwidth, which is rather limited, and the time delay introduced due to the multi-hop architecture, which is in the order of a few hundred milliseconds [7], are sufficient for our purpose. As Smart Meters are expected to replace ripple control, hot water boilers are connected to circuits separate from other loads which can be switched by the Smart Meter.

B. Plant Model

The boilers are bang-bang controlled with an acceptable operating band limited by \( T_{\text{min}} \) and \( T_{\text{max}} \). The temperature losses to the environment are neglected. There are four operation states which the boilers may assume, see Figure 2. Boilers are either in the acceptable range, termed ON or OFF, or in hysteresis range. If they are in hysteresis range, they are not controllable, and represented by COLD or HOT, respectively. The total number of participating boilers \( n \) is known, as is for each boiler \( i \) the capacity \( C_i \), i.e. the product of temperature band and water volume, and nominal heating power \( P_{N_i} \). It is also assumed that an estimate of the mean hot water consumption \( P_c \) of the participating boiler population is available. For the proposed control scheme, only the aggregated behavior is relevant.

The following aggregated states are introduced: the number
of boilers that are available for switching and are ON, \( n_1 \), or OFF, \( n_0 \), and the number of locked units that are HOT, \( n_h \), or COLD, \( n_c \). The output of the boiler subsystem, see Figure 1, is the power consumed by the boiler population \( P_B \). It can be approximated by the mean nominal power \( P_N \) times the sum of ON and COLD units.

\[
x = [n_1 \ n_0 \ n_h \ n_c]^T \quad (2)
\]

\[
y = P_B \approx P_N(n_1 + n_c) \quad (3)
\]

The tracking control sends a broadcast containing a switching probability, termed \( u_{\Delta} \) for increasing load (units switching from OFF to ON) and \( u_{\nabla} \) for load reduction. Each boiler performs a Bernoulli trial to decide how to react to the input signal, the probability density function for the population after propagating by one time step is therefore described by a binomial distribution. \( B(n, p) \) denotes a binomial distribution with number of trials \( n \) and probability \( p \). We now look at the time evolution of the system and introduce the discretized time step \( k \), \( t = t_0 + k \Delta t \). For brevity \( k \) is noted as superscript.

The dynamics of the system evolve as

\[
n_{1}^{k+1} = n_{1}^{k} - B(n_{1}^{k}, u_{\Delta}^{k}) + B(n_{0}^{k}, u_{\nabla}^{k}) + B(n_{1}^{k}, \mu_{\Delta}) - B(n_{1}^{k}, \mu_{\nabla})
\]

\[
n_{0}^{k+1} = n_{0}^{k} - B(n_{0}^{k}, u_{\nabla}^{k}) + B(n_{1}^{k}, u_{\Delta}^{k}) + B(n_{0}^{k}, \mu_{\nabla}) - B(n_{0}^{k}, \mu_{\Delta})
\]

\[
n_{h}^{k+1} = n_{h}^{k} + B(n_{h}^{k}, \mu_{h}) - B(n_{h}^{k}, \mu_{h})
\]

\[
n_{c}^{k+1} = n_{c}^{k} + B(n_{c}^{k}, \mu_{c}) - B(n_{c}^{k}, \mu_{c}) \quad (4)
\]

Since \( E[B(n_0, u_{\Delta})] \) is known to be \( n_0 u_{\Delta} \), (4) is a bi-linear model. The last two terms in each equation describe the local switching of loads. As each term appears twice with opposite sign, it is clear that the total number of units is conserved when advancing from \( k \) to \( k + 1 \). The probabilities \( \mu_h \) and \( \mu_c \) describe the mean likelihood of a unit going from switchable to locked, while \( \mu_{\Delta} \) and \( \mu_{\nabla} \) are the mean likelihoods for leaving a locked state. If the state of charge (SoC) of the boilers is uniformly distributed, they are given by

\[
\mu_{h} = \frac{P_h - P_c}{C} \Delta t \quad \mu_{\nabla} = \frac{P_c}{C_d} \Delta t
\]

\[
\mu_{c} = \frac{P_c}{C_d} \Delta t \quad \mu_{\Delta} = \frac{P_N - P_c}{C_d} \Delta t \quad (5)
\]

where \( P_h = \frac{1}{n} \sum_{i=1}^{n} P_{N_i} \) is the mean nominal heating power, \( P_c \) is the cooling (in our model, the mean water draw at a given time of day), \( C = \frac{1}{n} \sum_{i=1}^{n} C_i \) is the mean capacity of the boiler population and \( d \) is the proportion of the dead-band against the total temperature band. Most of the time, the SoC of the boiler population is not uniformly distributed and the values above are only approximations.

The substation power \( P_{tot} \) is composed of the demand of the switchable loads \( P_B \), as in (3), and all passive loads \( P_p \).

\[
P_{tot}^k = P_B(n_{1}^{k} + n_{c}^{k}) + P_p + n_{h}^{k} + e_{h}^{k}
\]

\[
P_{tot}^{k+1} = \beta_{z}^{k+1} \cdot P_{tot}^{k} \quad (6)
\]

The passive loads can be described as the forecast \( P_t \) and some offset. This offset can again be split in two parts: a Gaussian distributed, zero mean noise \( w_p \) from switching of passive loads, and a forecast error \( e_f \). Neither \( P_B \) nor \( P_p \) can be measured separately, \( e_f \) can therefore not be determined directly. Furthermore, the forecast error is strongly auto-correlated. However, an analysis of historic data showed that the change in forecast error \( \Delta e_f^{k} = e_f^{k} - e_f^{k-1} \) can be assumed to be zero mean.

The current state of a specific boiler is unknown, and so is the total number of boilers that have the relevant states of switchable ON and switchable OFF. The aim of the observer described in the next section is to find the state estimate \( \hat{x} \).

C. Observer Design

Estimating the states \( n_1, n_0 \) is not trivial. One reason being that the temperature constraints of the individual loads are ensured locally, meaning that loads may turn on or off when reaching their limits. Second, the noise \( w_p \) is substantial. Third, the process model is bilinear. Finally, the probability density functions (PDF) of the state estimates may assume a multimodal distribution. Therefore, a particle filter was implemented, which can handle non-linear, non-Gaussian distributed noise and arbitrary state PDF.

Like the Kalman filter, particle filtering is based on Bayesian tracking. A detailed introduction on particle filtering is given in [8]. Here the general formulation is briefly repeated and its application explained. A particle filter uses \( n_t \) representations of the system states, each called a particle. This number must not be confused with the \( n_t \) boilers used by the DR scheme. In a first stage, a prediction is performed for each particle using the process model \( q \).

\[
x_{p,i}^{k+1} = q(x_{m,i}^{k}, u^{k}) \quad \forall i \in \{1,...,n_t\} \quad (7)
\]

The index \( m \) denotes a particle or state after a measurement update and the index \( p \) after a prediction step. In the measurement update, a measurement \( z \) is taken and for each particle the probability \( \beta_z^{k+1} \) of measuring that particular value is computed.

\[
\beta_z^{k+1} = \Pr(z^{k+1} | x_{p,i}^{k+1}) \quad (8)
\]
The $\beta^*_i$ are then normalized and $n_r$ new particles are sampled. Using this method, particles that do not agree with the measurement are discarded, and particles in good agreement with the measurement are sampled more often [8].

In our case, the prediction is done according to the process model in (4), where the binomial probabilities are evaluated explicitly for each particle. From this, $\Delta P_{\text{tot}}^{k+1}$ is computed for each particle. We choose our measurement $z$ as

$$z^{k+1} = \Delta P_{\text{tot}}^{k+1} = P_{\text{tot}}^{k+1} - P_{\text{tot}}^k = \Delta P_B^{k+1} + \Delta P_f^{k+1} + \Delta e_f^{k+1} + \Delta w_p^{k+1}.$$  \hspace{1cm} (9)

Using the measurement taken at the substation and knowledge about the distribution of noise $w_p$, the particles can be resampled according to their likelihood.

Thereby, the particles for which $\Delta P_{\text{tot}}^{k+1}$ is in good agreement with $\Delta P_{\text{tot}}^{k+1}$ are selected. These particles are the ones that held a good estimate about the number of loads that were switchable at time step $k$, and assuming that the process model (4) is correct, the state of these particles at the current time step $k+1$ is in good agreement with $x^{k+1}$. The notion that a signal $u_{\Delta}^k$ to increase demand leads to a good estimate of the number of loads that were OFF when receiving this signal, and vice versa for decreasing demand, is intuitive.

Using measurement of $\Delta P_{\text{tot}}$ rather than $P_{\text{tot}}$ also improves the resilience against forecast errors, as the auto-correlation inherent to $e_f$ is avoided and the well-behaved $\Delta e_f$ is used instead. This detail in formulation is an important improvement over [3].

### D. Controller Design

To test the proposed setup a simple controller for tracking and an outer control loop improving schedule compliance were implemented.

The tracking controller is a proportional controller. The aim is to minimize the difference $e$ between the reference signal $r$ and the total demand $y$. The switching probability is computed by

$$u_{\text{sw}}^k = \begin{cases} u^{-} & e^k > 0 \\ u^{+} = |e^k|, & e^k < 0 \end{cases}$$  \hspace{1cm} (10)

where $P_N$ is the mean nominal heating power. More sophisticated controllers can be implemented to achieve a more desirable trade-off between tracking accuracy and load switching, but this is beyond the scope of this paper.

The deviation between forecast and actual energy consumption within each period, usually a quarter of an hour, is penalized by the TSO. With the ability to track an arbitrary reference, we now aim to minimize the balancing energy cost. If there was a deviation from the schedule during the first few minutes of a period, this can be canceled out in the remaining time. For example, if during the first five minutes 20 kW h too much were consumed, it is desirable to consume 20 kW h less than forecast during the time left. The 15 min E-control adjusts the reference for the tracking control in such a way, that

$$\left| \int_{t_{15}}^{t_{15}+15 \text{min}} (P_f - P_{\text{tot}}) \, dt \right|$$  \hspace{1cm} (11)

is minimized. $t_{15}$ denotes the start of the current period.

### III. Case Studies

In III-A we explain how the performance of the proposed setup was tested. The results are discussed in III-B.

#### A. Setup

Real measurements from a substation that is providing power to a small city close to Zurich in Switzerland were used. The data is depicted in Figure 4a. The load at the substation varies between 1 MVA and 7 MVA. The power measurements were taken with 10 s resolution. Load steps of 100 kW and more in up and down direction are observed in the time series. Minimization of the balancing energy costs of the system is set as the control target. A simple forecast for one day was
created by taking the 15 minute average values of the previous day. As reference input for the controller a smoothed version of the 15 minute forecast was used. The smoothing was done by cubic interpolation.

The boilers were modeled as simple point sources, that is constant temperature in the whole boiler was assumed. Furthermore, it was assumed that 450 boilers are taking part in the DR scheme. To get a realistic distribution of the heating powers \( P_{N_i} \), 450 samples were taken from the total of 105 000 boilers served by EKZ. The energy capacity is rated at 8 h \( P_{N_i} \), meaning that it takes 8 h to heat up a cold boiler. The average duty cycle is assumed to be 0.25, meaning that each boilers runs for 6 h per day. Thus, the average power consumption of the switchable loads is around 0.5 MW, which is about one tenth of the total mean power consumption at the substation. Due to regulation, data about nominal size and heating power of the installed boilers are known to the utility. Table I shows the nominal parameters used.

There is always an uncertainty associated with the nominal values. To include this plant-model mismatch, beta distributed noise is added to the parameters of the boilers used in the simulation while the particle filter uses the nominal values for the prediction step. A realistic water draw model based on [9] was used.

The boiler population was simulated with a 10 s time step, while the time step between control signals was varied from 10 s to 300 s. The detailed discussion focuses on a control time step of 30 s. In the following section we discuss the results of the case study. First we look at the quality of estimation, then we investigate tracking accuracy and finally we discuss the economic benefits.

### B. Results

#### a) Estimation Accuracy

In Figure 5 a comparison of the estimated and actual states is depicted. The estimates are in good agreement with the actual values. These good estimation results can be achieved with as few as 200 particles. However, the states \( n_h \) and \( n_c \) (\( n_c \) not shown) cannot be observed sufficiently, as there is too much uncertainty in the local load switching and no direct way to observe the locked states.

Another effect can be observed at 19 h. As the consumption exceeds the forecast, the controller continuously reduces the number of boilers that are ON, until \( n_1 \) reaches zero. As the control is saturated, only switch-off signals \( u_{\neg \neg} \) and no switch-on signals \( u_{\neg \neg} \) are sent, therefore no direct information about \( n_0 \) can be collected. The error in the estimation of \( n_0 \) is corrected at 20 h, when the system returns to a normal state. However, \( n_1 \), which is of most interest during this period, is well estimated.

The quality of the estimates also depends on the number of measurements taken and therefore on the control time step. Table II shows the mean signed difference (MSD) and the root mean square error (RMSE). As expected, longer update times result in decreased estimation accuracy.

#### b) Tracking Accuracy

Figure 4a shows the day ahead forecast and the uncontrolled demand at the substation. Note that the errors deviate considerably from zero. Using the proposed DR scheme, it is possible to reduce this deviation, as can be seen in Figure 4b. The loads closely follow the reference signal, and the errors are not only smaller in magnitude, but they are close to zero mean. A histogram of the integrated difference between realization and 15-minute forecast according to (11) is depicted in Figure 6. The height of the bars describes the frequency a certain amount of balancing energy was consumed. Clearly, using DR considerably reduces the deviations and thus the cost for balancing energy incurred by the balancing group. At the same time, switching of the loads is considerably increased.

### TABLE I  
**Nominal Parameters of the 450 Boilers Used**

<table>
<thead>
<tr>
<th></th>
<th>mean</th>
<th>min</th>
<th>max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capacity ( C ) [\text{kW h}]</td>
<td>35.4</td>
<td>8.00</td>
<td>160</td>
</tr>
<tr>
<td>Heating power ( P_{h} ) [\text{kW}]</td>
<td>4.42</td>
<td>1.00</td>
<td>20.0</td>
</tr>
<tr>
<td>Cooling / water draws ( P_{c} ) [\text{kW}]</td>
<td>-1.11</td>
<td>-0.25</td>
<td>-5.00</td>
</tr>
<tr>
<td>Substation demand [\text{kW}]</td>
<td>4570</td>
<td>900</td>
<td>7330</td>
</tr>
</tbody>
</table>

\(^{1}\) The water draws are modeled as stochastic time series. The given values are the mean consumption of the household.

### TABLE II  
**Evaluation of the Estimation Accuracy**

<table>
<thead>
<tr>
<th>control time step [\text{s}]</th>
<th>( \hat{n}_1 - n_1 ) MSD</th>
<th>RMSE</th>
<th>( \hat{n}_0 - n_0 ) MSD</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>-2.93</td>
<td>19.95</td>
<td>3.30</td>
<td>30.69</td>
</tr>
<tr>
<td>30</td>
<td>-2.58</td>
<td>26.42</td>
<td>6.43</td>
<td>34.62</td>
</tr>
<tr>
<td>60</td>
<td>0.81</td>
<td>29.13</td>
<td>13.72</td>
<td>40.77</td>
</tr>
<tr>
<td>120</td>
<td>4.38</td>
<td>39.62</td>
<td>20.68</td>
<td>44.92</td>
</tr>
<tr>
<td>300</td>
<td>9.70</td>
<td>44.87</td>
<td>24.58</td>
<td>48.88</td>
</tr>
</tbody>
</table>
controller. 2) Stability issues might arise with loads that do not react immediately, either due to latency or load characteristics, and/or have a more complex step response than hot water boilers. This issue needs consideration in the design of the tracking controller. 3) The finite energy capacity and resulting constraints has been modeled, but not investigated in this paper. A model-predictive controller could be used to take care of storage constraints.

IV. CONCLUSION

This paper presents a control strategy for Demand Response (DR) which relies only on measurements of aggregated power at a substation and on a basic Smart Meter infrastructure. By employing state estimation techniques, measurements of individual loads can be avoided. This significantly reduces the cost for sensing and communication infrastructure while offering excellent scalability. Furthermore, this approach inherently protects the privacy of customers.

The proposed control scheme offers good tracking of a reference signal and thus enables the utility to comply with the day-ahead schedule and effectively minimize consumption of balancing energy. It was shown that this leads to a considerable overall cost reduction, promising an economically viable DR scheme.

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