Evaluation of the Performance of Indirect Control of many DSRs Using Hardware-in-the-loop Simulations

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Abstract— **Controlling the power consumption of many Demand Side Resources, DSRs, will be required in the future power system where a big share of the electric energy will be produced using stochastic renewable sources and the conventional power plants might not have the flexibility of providing all the regulating power. Indirect control of demand side resources is supposed to shift the electric power consumption of each single unit through broadcasting of a control signal; the flexibility in the aggregated power consumption can be used for supplying balancing power to the electric power system. Indirect control approach is convenient from communication point of view since the real-time data flow is only in one direction because the decision is computed locally according to user preferences. On the other hand, this approach results in an open loop control scheme, since it is assumed that no real-time power readings from the units can be performed. The aim of the paper is to discuss the performance of an emulated closed loop control using an estimator for predicting the aggregate power response and a regulator. By using these components it is possible to produce a control signal to broadcast to distributed demand side resources. A population of DSRs, buildings with electric space heating, is indeed simulated in a software simulation platform using an hardware in the loop approach, that allows to feedback the real heat dynamics of SYSLAB FlexHouse into the simulations for pretending more realistic result.**

I. INTRODUCTION

Demand side resources, or DSRs, are electric loads whose electric power consumption can be shifted or controlled for a while without having a big impact on the quality of the services they are providing to the final users. Examples of DSR devices are space or water heating, electric vehicles or also fully deferrable load such as washing machine or dishwashers. In the case of water or space heating, the flexibility is given both by the thermal inertia, that prevent instantaneous changes in the temperature, and by the fact that it is possible to vary the set point by a fraction without deteriorating user comfort.

Because of their flexibility, DSRs are suitable to be controlled in order to provide power system services respecting their constraints, physical limits and local user preferences [1]. The power system ancillary services that could exploit demand side resources capabilities are frequency regulation [2] and spinning reserve restoration or regulating power. DSR units could also support voltage control, if they are connected to the grid through an inverter with the possibility of regulating the reactive power [3].

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With rapid increase of the share of energy produced from variable renewable sources, the most severe challenges for the power system ancillary services are the ones related to the management of the regulating power.

From the power system point view, the response from a single DSR unit is not relevant because the small amount of power it involves. Therefore it is important to control an high number of electric loads to produce an aggregated response with some significance, and in order to impact the operation of the grid. Controlling a big number of demand side resources requires a wide ICT infrastructure and computational power, both local and centralized, for implementing decision algorithms and for actuating the decisions.

Control approaches for DSRs can be classified in direct and indirect. The former has the aim of controlling the amount of power that each single unit should use while the latter should be able to induce a shift in the power usage with broadcasting a control signal: this could be a price signal [4], such as in the Flexpower project [5], where the final users have a directly quantifiable economic advantage when they decide to shift the power consumption of their devices.

Direct control could give the possibility of driving precisely the consumption of DSRs but it is a very demanding real-time process both from communication and computational power point of view: information (*i.e.* local conditions or user preferences) has to travel from each device up to an aggregator which has to elaborate it, to produce and propagate decisions back to all units.

Indirect control can be realized with a simpler one way real-time communication (the price or control signal) and since all the decisions are computed locally, the computational load for the aggregator is not extensive.

[6] presents a scalable and hierarchical implementation of direct control with using a *control-by-price* approach. Such solution has the advantage of embedding all the electric power needs in a demand curve but it requires two-way real-time communication as conventional direct control.

In this paper, an indirect control architecture for providing regulating power to the electric power system is presented. The aim of the proposed work is to test if indirect control can be used for driving a population of DSR units (electric space heating) following a given reference signal of the electric power to consume. The control loop has been closed with a regulator and using an estimator, whose parameters are updated on-line, for predicting the aggregated power response.

The control signal is directly produced by the control loop, so it does not have a market meaning; therefore in the presented work, the concept of price signal does not apply because there is no interaction with the electric market.

The proposed architecture has been implemented and tested in a Java based simulation platform that allows to feedback into the simulations the thermal dynamics of a real office building for introducing more realism.

Detailed descriptions of the simulation setup, the control approach and a comparison with Flexpower project approach are given in Section II.

Section III presents and discusses the results of the simulations.

Conclusions are provided in Section IV.

II. METHODS

The overall overview of the control approach is shown in Figure 1. The quantity ΔP_i expresses the amount of regulating power needed by the power system at the discretized time instant $t = i$. The quantity ΔP_i acts as a reference for the closed loop regulated system which is composed by a regulator and an estimator of the aggregated power response of the DSR units.

The control signal p_i, that is the output of the regulator *R* at time $t = i$, is then sent to the population of demand side resources that should react as predicted by the estimator.

It is worth to notice that the signal ΔP_i does not express the absolute value of the electric power the units are required to consume, but it is a reference for the variation in consumed electric power to achieve; this means, for example, that if the grid needs demand side resources to consume 1 MW of electric power more then $\Delta P_i = +1MW$. The aim of the proposed control loop is then to require to the population of demand side resources a variation in the consumed power: if the model is able to predict correctly the aggregate response of the DSRs population, the closed loop regulator takes care of producing the adeguate control signal to broadcast to the units in order to get from the them the required consumption variation.

The control signal, which is common to all the units, is broadcasted to the DSRs once every five minutes. As Figure 1 shows, the quantity p_i is a classic control signal as intended in systems theory; the control signal does not have an energy price meaning because there are no interactions with the electric market.

In the proposed approach, the regulator R is a proportional-integral and the gains have been chosen in order to stabilize the closed loop system; a better solution could be defining a quadratic cost function and defining a LQ regulator because it assures stability of the loop if the system is stabilizable.

A. Aggregate response simulation

Figure 2 shows the structure of the simulation setup. The box with the gray dots represents the population of the simulated demand side resources which, in this setup, is composed by 1200 buildings each of them equipped with 10 kW electric space heating. Each building m is controlled by its control algorithm that decides the heating power P_i^m for every instant of time $t = i$. Each building m has a temperature evolution T_i^m where subscript i still refers to a time instant. Input signals p_i and W_i of Figure 2 are respectively the closed loop control signal (introduced in Figure 1) and local weather information which are required for computing time evolution of the thermal models.

The simulation platform also controls the electric space heating of a real office building, FlexHouse[7]. Applying the same control signal both to FlexHouse and its thermal model allows computing a prediction error $\Delta T_i = T_i^f - T_i^{fm}$ (*i.e.* FlexHouse temperature minus FlexHouse thermal model temperature) that is used for perturbing in real-time the behavior of the population of buildings. This *hardware-in-the-loop* approach allows both testing control algorithms on a real building and obtaining more realistic simulations of buildings thermal dynamics because it feeds back into the simulations uncertainties and disturbances that are not taken into account while modeling (such as wind that might have considerable cooling effect). Simulations are carried out in real-time for allowing the real building to react to control signal. All the buildings are subject to same weather

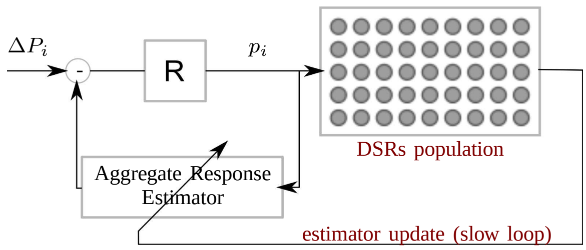

Fig. 1. The proposed control approach. A model is used for predicting the aggregated power response from all DSRs; a closed control loop with a regulator is used for producing the control signal to send to the population of buildings. Subscripts i refers to the discretized time interval $t = i$.

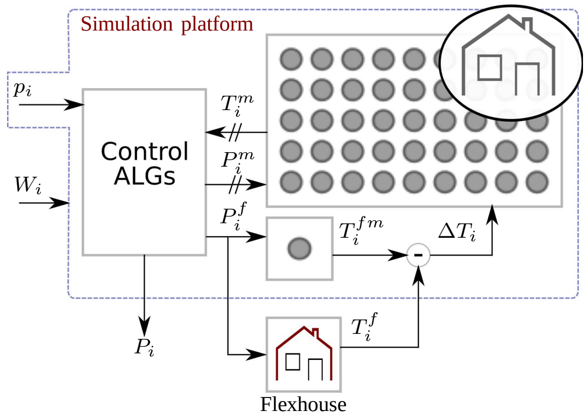

Fig. 2. The setup used for simulating the aggregate power response of a population of buildings. A real office building, FlexHouse, is used as the *hardware-in-the-loop* for feeding back into the simulations real environmental conditions. W_i signal is for weather data, P_i is for electric heating power and T_i is for indoor temperature. Quantity p_i is the control signal introduced in Figure 1. Superscripts m, f, fm are respectively for buildings index, *FlexHouse*, and FlexHouse thermal model. ΔT_i is the prediction error of FlexHouse thermal model.

condtions.

Outputs of the simulation platform are the aggregate power response of all DSRs, the power consumption and temperature profiles of each single building and FlexHouse.

FlexHouse is a small automated office building which is heated by ten 1 kW electric heaters that can be controlled. Flexhouse is part of SYSLAB[8], the DTU distributed power system facility located in Risø campus. The simulation has been realized with a Java platform that allows to perform dynamic simulations of generic model and it is linked with SYSLAB.

The models for the population of buildings are derived from FlexHouse thermal model, where relevant parameters (thermal resistance and capacity) have been modified following a normal distribution. Equations 1 and 2 show the second order system of continuous time linear differential equations used for describing thermal behavior of Flexhouse [9] (time dependency is omitted).

$$\begin{aligned} \dot{\underline{x}} &= \begin{pmatrix} -2.73{\times}10^{-5} & 9.15{\times}10^{-6} \\ 1.48{\times}10^{-3} & -1.48{\times}10^{-3} \end{pmatrix} \underline{x} \qquad (1) \\ &+ \begin{pmatrix} 0 & 1.81{\times}10^{-5} & 7.38{\times}10^{-4} \\ 1.48{\times}10^{-2} & 0 & 0 \end{pmatrix} \begin{pmatrix} P \\ T^{\text{out}} \\ S \end{pmatrix} \\ T^{\text{in}} &= \begin{pmatrix} 1 & 0 \end{pmatrix} \underline{x} \qquad (2) \end{aligned}$$

where T^{in} is the indoor temperature and the input quantities P, T^{out}, S are respectively the heating power, the outside temperature and the solar radiation. Temperatures are expressed in [°C], electric power in [kW] and sun radiation in [kW/m^2]. Continuous time model is discretized with a time step of $20s$ for simulations.

The algorithm chosen for controlling the space heating for all the buildings is proposed in [10],[11]. It was originally used for controlling DSRs with a price signal. In this context, the price signal is replaced by a generic control signal. Algorithm is described by Equations 3 and 4:

$$\Delta T_i = -k\ \hat{p}_i \qquad (3)$$

$$\hat{p}_i = \frac{p_i - \overline{p}_i}{\sigma_i} \qquad (4)$$

where p_i, $\overline{p}_i$ and σ_i in Equation 4 are respectively the current value of the control signal, the average and standard deviation of the control signal history. Coefficient k is a positive constant and sets the price responsiveness capability of the algorithm by producing the offset ΔT_i for the indoor comfort temperature. Virtually, every time $t = i$ a new control signal is received, a new offset ΔT is computed and it is used for producing the indoor temperature set point $T_i^{\text{in ref}}$ according following Equation:

$$T_i^{\text{in ref}} = 23°C + \Delta T_i$$

The set point $T_i^{\text{in ref}}$ is then achieved using a traditional thermostat controller with an interval of $\pm 2.5°C$

B. Estimation of the aggregated response

The transfer function $F(s)$ (with s Laplace operator) of the model used for estimating the aggregated response of the population of demand side resources has the form that is shown in Equation 5.

$$F(s) = \frac{\Delta P(s)}{p(s)} = \frac{b_0 s + b_1}{s^2 + a_1 s + a_2} \qquad (5)$$

The symbols $\Delta P(s)$ and $p(s)$ in Equation 5 are for the deviation in electric power consumption and the control signal respectively; coefficients a_1,a_2, b_0, b_1 are the parameters that have to be identified.

The numerator of the transfer function is a pure derivative when $b_1 = 0$ and that is to expect because the step response of the demand side control algorithm does not give any steady state contribution (this comes from Equation 4), therefore it must be the same for the aggregated response.

The parameters of the transfer function are identified with using standard least squares. An observation matrix H and column $\underline{b}$ are built with observing the past realizations of the aggregated response for a given control history; the vector $\underline{p}$, that contains the parameters that need to be estimated, is indeed obtained using Equation 6 that allows to minimize the 2-norm of the difference among real measurements and the estimated values[12].

$$\underline{p} = (H^T H)^{-1} H^T \underline{b} \qquad (6)$$

Because the simulations are performed in discrete time steps, the transfer function that is really estimated it is the *z*-domain version of Equation 5.

The estimation process is repeated on-line during the simulations once every six hours; the periodic update of the estimator is required because the aggregated response of DSR units is not time invariant and it could change, for example because some DSR units stop working, because of communications problems or correlated changes to algorithm sensitivity to control signal (k coefficients in Equation 4) operated by users.

The time constants of the estimator are also affected, in the case of space heating, by variation in weather conditions (outdoor temperature and solar radiation for example); this means that the estimator could easily have different values for the parameters depending if it is night or day time.

The estimator is estimated also at the beginning of the simulations with a training signal: DSR units are exposed to several step variations of the control signal p_i for six hours.

As mentioned before, indirect control uses only one way real-time communication for broadcasting the control signal p_i to all the distributed units. In this proposed setup, it is required also to read the power consumption of DSR units in order to update the parameters of the estimator; identification process does not have strict real-time constraints and, besides, it is not repeated with the same frequnecy as the control signal is sent. Furthermore, since the estimator uses only information about the aggregate response, it is not even necessary to communicate with each single unit because it possible to use readings from the SCADA system of the distribution system operator. Because the model for estimation predicts the deviation in the aggregate power consumption given a control signal $\left(F(s) = \frac{\Delta P(s)}{p(s)}\right)$, the readings from the SCADA system can be used without distinguishing between the electric load that provides support to regulating power and the one that does not: in fact the power that does not have sensitivity to control signal is automatically discarded by the parameters estimation process because it does not react to any variation of it.

It is noting that the single contribution from each single DSR unit is strongly non linear with respect the control signal; non linearities are introduced both by the demand side control algorithm discussed before and by the thermostatic controller that takes care of maintaining the computed indoor temperature in each building. In this proposed setup, the linear transfer function of Equation 5 is used to predict the dynamics of the aggregated response because the relative high number of DSR units can mitigate the effects of non linearities.

Non linearities are also introduced in the simulation by the hardware-in-loop-approach because non linear effects act on Flexhouse (convection for example).

C. A comparison with Flexpower project approach

Flexpower is a Danish national research project whose aim is to develop a five minutes real-time electric market that is able to attract a large number of small scale resources for contributing to regulating power provision. The current markets, day-ahead and hour ahead, are maintained as the basis of the normal power system operation. Regulating power market will be extended with using a one way price signal propagated to all subscribed market participants that will react according their needs and user settings. The one way price signal is calculated using the current regulating market and it is the most expensive selected bid; an estimator of the aggregate power response computes the amount of power that DSRs can consume with the given price; then the system operator should take into account also this amount of power when it will select the bids to activate, and it will send the price signal to all market participants.

The first difference between Flexpower approach and the setup proposed here is in Flexpower, the control signal is the price for the electric energy and the mechanism for building it follows conventional electric market rules.

The estimator is used in the same way in both approaches, that is predicting DSRs power consumption given a control or a price signal. The difference in the estimation process, it is that, in Flexpower, a prediction on the absolute value of the global consumption is required while, in the proposed approach, variations in power consumption are treated; this allows to simplify the estimator form since it does not need to take into account information such as outdoor temperature, in the case of space heating for example, because it is assumed that the unit commitment scheduled is aware of the energetic needs of DSRs.

Finally the proposed approach is a closed control loop: this means that is possible to define the performance of the regulation loop with choosing a suitable values for the regulator R. This can be useful because in this way it is possible to modify the dynamics of the aggregate response and for example deciding if having a fast but brief contribution from DSRs or the opposite. In the case of Flexpower, producing a price for defining an appropriate dynamic response of the DSRs would require to override the bids market mechanism.

III. Results and Discussion

As explained in Section II, simulations here presented are obtained with sending a control signal p_i to a population of 1200 building warmed using electric heating and with 10 kW as nominal power for a maximum total power consumption capability of 12 MW. Buildings are modeled using second order models with uniformly distributed parameters; the hardware in the loop approach, discussed in Section II, requires that the simulations are carried out in real-time. Each DSR unit is controlled with an algorithm that is able to move the power consumption according to a control signal. Control signal p_i comes from a regulator driven by the difference between a power reference deviation ΔP and the prediction of DSRs aggregated power response computed by an estimator (Figure 1).

In the following plots, the time values on the x-axis does not refer to the absolute time of the day but it is the incremental time of the experiment.

Plot (*a*) of Figure 3 compares the power consumption of the population of buildings when they are required to support the power system (blue line) and when they are not (red line). Plot (*b*) of Figure 3 shows the indoor temperature profiles of one of the building randomly selected from the population. Red line is the temperature profile when the heating power is controlled by a traditional thermostatic controller; blue line is the temperature profile when the heating is managed by the algorithm with price responsiveness capability discussed in Section II.

The blue temperature profile of the plot (*b*) of Figure 3 exhibits a certain time delay compared with the red one and that is obtained by the control algorithm with slightly changing the indoor temperature set point (Section II); this small time delay allows shifting power consumption and obtaining an important difference in the aggregated power response without compromising individual user comfort.

It is worth noting that plot (*b*) of Figure 3, even if it shows the temperature behavior of just one random building of the population, is a good indication of the

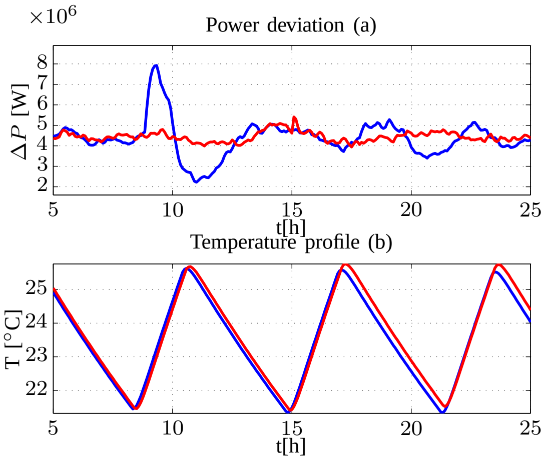

Fig. 3. Plot (*a*) shows the different profiles of the aggregated power response of the population of demand side resources when they are required to support the grid (blue line) and when not (red line). Plot (*b*) shows the indoor temperature behavior of one of the building of the population both when its thermostat is controlled by the demand side algorithm and when the set point is the optimal indoor comfort level.

comfort level for all the buildings because all of them use the same algorithm for controlling their indoor space heating.

Plots in Figure 3 and 4 refer to an experiment carried out in a cloudy winter period (no solar irradiation) and with no significative differences in temperature during hours; this explains why the red line of Figure 3 is nearly flat, *i.e.* the demand for electric heating power was similar for all the period. Besides, the red line is nearly flat even if the buildings are using thermostatic based control (*i.e.* ON/OFF control) because the high number of units in the population of DSRs.

Figure 4 reports the deviation in the aggregated power consumption of DSR units together with its requested reference signal (ΔP_i, as reported in Figure 1) respectively with the blue and red lines; the green line is the prediction of the aggregated power response computed by the estimator.

Two step variations for the consumed power are required to the aggregated response of the population of DSR units; the amplitude of the variations are respectively 2 MW and 500 kW (+44% and +11% with respect to power that was consumed) and the length is one hour for both.

The negative peaks of the blue line of Figure 4, just after the two step variations of the reference, were expected because DSR management algorithm receives a new control value that is suddenly greater than the previous ones and then it starts to bring the indoor temperature set point to the optimal one; this causes a rapid decrease in the consumed power. In order to avoid this effect, a control algorithm for DSRs with a steady state response different than zero would be necessary; this could provide benefits from power system point of view but it can override local user preferences because that equals to add a memory effect to the demand side control algorithm: for example in the case of space heating, the indoor temperature set point would have a

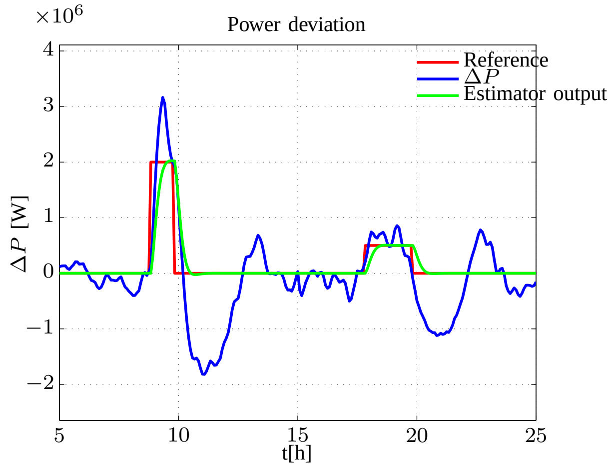

Fig. 4. The blue line shows the response of the aggregated power consumption of DSR units to multiple steps variation of the power reference which is the red line; the green line is response of the estimator.

component that depends on the history of the control signal.

Plots in Figure 5 refer to two other experiments and they both show, as for Figure 4, the profiles of the variation of the aggregated power response when a reference ΔP with multiple steps variation is applied.

The green line of plot 5 (*a*) shows a different behavior than the one in Figure 4 because the parameters of the estimator, that are updated on-line, have changed.

Plot (*b*) in Figure 5, which is obtained with a simulation without hardware-in-the-loop and using constant values for weather data, shows that the control loop is not able to induce a deviation in the aggregated power response closed to its reference. This is because the outdoor temperature has been chosen close to the indoor comfort one; this produces the effect of reducing the number of DSR units that need electric power concurrently. With lower number of units then the non linearities, introduced by the control algorithm and the thermostatic cycles, starts to become evident and to degrade the capability of the regulator to produce a deviation in the aggregated power response similar to the power deviation reference signal ΔP.

IV. Conclusion and Future Work

In this paper, an indirect control strategy with the aim of providing regulating power to the electric power system is presented.

The proposed setup allows to set a reference for a deviation in electric power to consume that is required to the demand side aggregated response; then, a feedback regulation loop with a regulator produces the control signal that is broadcasted to the demand side resources.

The loop is closed with an estimator that predicts the aggregated power response of DSRs. The parameters of the (linear) estimator are identified on-line every six hours using least squares; identification process does not have strict real-time constraints on the communication and is not as frequent as the the real-time control signal, that is delivered every

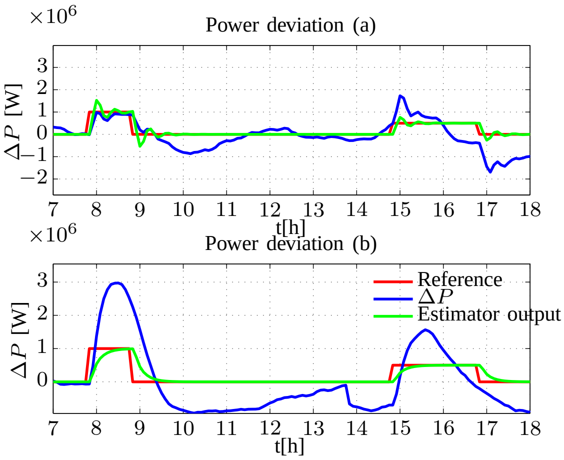

Fig. 5. Power deviation reference, DSRs aggregated power response and estimated power response for two different experiments. Control loop does not perform well in plot (*b*) because non linearities introduced by the control algorithm and thermostatic cycle starts to emerge because a low number of units is using electric power in the same time.

five minutes; furthermore identification does not need to retrieve information about power consumption from each single unit but it can use power readings from distribution system operator SCADA systems.

For these reasons the proposed approach satisfies the main requirement of indirect control, that is requiring only one way real-time communications.

The control signal produced by this setup does not have any economic meaning so it cannot be intended as a price signal.

Demand side resources are simulated with using a population of 1200 buildings warmed with electric heating for a maximum total power consumption of 12 MW. An hardware-the-loop approach has been used for performing the simulations: this feature allows feeding back into the simulation platform the thermal dynamics of a real office building together with all the uncertainties related to models identification and disturbances. Weather data used for the simulations are also real.

Simulations show that the proposed setup can move the power consumption of the aggregated power response following a reference signal; there are limitations that are mainly given by the fact that the demand side control algorithms cannot offer a steady state contribution different than zero when a step in the reference signal is applied.

When the number of units that are using electric power concurrently decreases (and this happens in the case of space heating when the differences between the indoor temperature set point and the outdoor temperature is small or the sun is providing most of the thermal energy for maintaining the set point), then the non linear effects starts to be visible in behavior of the aggregate power response. Non linearities between power response and price signal are due to both the non linear demand side control algorithm and the thermostatic controller that is used for maintaining the indoor temperature reference produced by the algorithm.

Future work in the proposed control approach will be in the direction of improving the overall control performances; this can be done with looking for a better estimation of the aggregated power response, for example by increasing the frequency of the estimator identification process. Also the closed loop regulator could be improved in terms of stability and in order to get out of the aggregated power response the most useful dynamics for the power system.

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