Providing ancillary service with commercial buildings: the Swiss perspective ⋆

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Abstract:
Ancillary services constitute the cornerstone of the power grid. They allow for an efficient system operation, provide resilience to uncertainties and establish safeguards against unprecedented events. Their importance is growing due to the rise of grid decentralisation and integration of intermittent, renewable power sources, which lead to more variability and uncertainty in the system. Today, the vast share of ancillary services is provided by large generating units. An ongoing effort by research and business entities focuses on using variation of loads connected to the power grid in order to increase significantly the provision of such services, hopefully at a reduced cost. We examine here, from an economic perspective, the use of commercial buildings as ancillary service providers based on real prices from the Swiss electricity market. We calculate the effect of retail electrical prices on the economic performance of a building and find that for the rates charged in the least expensive cantons a single building can reduce its overall energy costs, when participating in the ancillary services market. For the high end of prices this gradually becomes prohibitive but can be alleviated for a building that has a need for electricity during nighttime hours, as well as daytime. Finally, we show, the counter-intuitive result that providing ancillary services can increase the comfort levels of a building at a decreased cost.

Keywords: Ancillary services, stochastic programming, buildings

1. INTRODUCTION

Accommodating for the fluctuating mismatch between electrical consumption and generation, either because of operational uncertainties or large irregular events, is performed at different hierarchical levels. A spot market, usually operated on an hourly basis (but also cleared a day in advance), matches or alters the generation schedule of power plants to meet the projected demand of load serving entities (LSE). The power grid operator, due to the inherent unpredictabilities in the actual delivery of this transaction, procures additional generation capacity as a backup to meet the mismatch at faster time scales, when required. These services are named ancillary services (AS) and are commonly procured from large generation units, operated at lower than nominal capacity at all times to accommodate for the fluctuating regulation signal of the grid operator.

Commercial buildings are large consumers of electrical power and are moving to more sophisticated levels of automation in order to increase oversight, comfort levels and reduce energy costs. For this reason, they are also being envisioned as storage elements that could increase the performance and the robustness of the power grid by becoming ancillary service providers (ASP), without the need for investing in new generation capacity (or underutilising the existing one).

A building accumulates energy through its thermal capacity. This slowly dissipating energy can be employed to shift the electrical load of the HVAC (Heating, Ventilation and Air-Conditioning) system to more beneficial time windows (a demand response service) or to absorb fluctuations arising from tracking a regulation signal that fulfils an AS obligation towards the grid operator. The critical constraint is to ensure a comfortable environment to the occupants while providing the promised service.

Several studies have explored the benefits of buildings participating in electricity markets, usually by adapting to the variations of electrical price to achieve a less costly operation by shifting load. Qureshi et al. (2014) investigate participation in the New York demand response (DR) program using model predictive control (MPC), Vrettos et al. (2013) study DR for residential buildings coupled with extra storage. These approaches mostly optimise the operation of the building without a priori promises to the grid operator.

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ASPs have to commit before being able to provide a service to the power grid (e.g. increasing or decreasing consumption at request) that is determined in advance (here weekly). Based on this commitment the grid operator sends a high frequency regulation signal, according to his needs, that the ASP has to follow while also fulfilling his primary operational objectives (for a building that would be delivering comfort to occupants at a low cost). Buildings providing AS have been explored in Maasoumy et al. (2014), Maasoumy et al. (2013), Vrettos et al. (2014), Pavlak et al. (2014), Hao et al. (2013) and Balandat et al. (2014). These studies examine the capacity for providing such services with artificial economic criteria and for a limited prediction horizon (at most daily).

We use here real economic data from the Swiss EPEX market (from 2013) and explore commitments that have a weekly horizon. We employ a two stage stochastic formulation, that allows us to exploit certain statistical properties of the regulation signal. We find this approach to be effective while also satisfying constraints when tested against real regulation signals. Moreover, we try to assess the economic feasibility, of a building providing AS. For this, we study how the retail price of electricity plays a significant role in the decision for participation. For a single unit this is due to variable constraints (night setback), between working and non-working hours, that create a requirement for the procurement of electricity even at times that the building might not usually need it. We find that a building, or an aggregation, that requires some energy consumption at all times during the week would always have an incentive to participate in the secondary control market for even the highest, realistic, prices of electricity.

Finally, we evaluate the comfort levels attained, by using standard long-term satisfaction metrics and find that participation in AS improves the average comfort satisfaction levels compared to operating the building to minimise costs without AS participation.

In Section 2 we introduce the Swiss AS market and present some of the statistical qualities of the frequency regulation signal. In Section 3 we present the methodology for acquiring a simulation model for the building, while in Section 4 we examine how a commercial bidding can bid in the AS market while operating inside its comfort constraints. Finally, in Section 5 we present our simulation set-up, describe the long term comfort metric we use and explain our results.

2. SECONDARY ANCILLARY SERVICES IN SWITZERLAND

According to The European Network of Transmission System Operators for Electricity (ENTSO-E) definition, three levels of frequency control are generally used to maintain the real-time balance between load and generation.

Frequency Containment Reserve (FCR) control is a local and decentralized proportional controller that contains the system frequency within a maximum deviation bound following large generation or load outages in a synchronous area of continental Europe. Note that FCR is only activated in the case of contingency when the system frequency is outside of a deadband, which is set ± 10 mHz in continental Europe.

Frequency Restoration Reserve (FRR) control is a centralized and continuous control (i.e., is used in both normal operation and in contingency cases) to restore the frequency and exchanges with other control areas to their target values. Such an indispensable frequency control can be implemented automatically (aFRR) with a central proportional-integral (PI) controller, or manually (mFRR) by directly calling providers.

Replacement Reserve (RR) is a manually activated product that is used i) for further imbalances in the case FRR has already been activated and is unable to restore the frequency to its target value, ii) to release FRR in the case of large disturbances and iii) to anticipate expected imbalances.

In this paper, we focus on the Swiss Ancillary Services market and an aFRR product, which is known as the Secondary Control Reserve (SCR). SwissGrid, the operator of Swiss electrical grid, procures about ± 400 MW SCR in a weekly auction for every hour of the following week from a set of pre-qualified Ancillary Service Providers (ASPs), which can be either loads or generators.

During real-time operation, SwissGrid activates the procured SCR through an Automatic Generation Controller (AGC) by sending each second an activation signal in parallel to all ASPs that have been accepted in the secondary control market. Note that the activation signal, which is called the Area Control Signal (ACS) in this paper, is proportional to the awarded capacities of all accepted ASPs.

We detail the operational and financial structures of the Swiss secondary ancillary services system in the following sections.

2.1 Swiss Secondary Ancillary Services Market

At the start of each week, the provider of ancillary services (the building) must submit a *capacity bid*, α MW, and a *baseline* energy schedule $\bar{e} = \{\bar{e}_k\}$, where $\bar{e}_k$ is measured in units of MWh and is provided in 15min time increments for the entire week.

Throughout the paper we take the perspective of the service provider, and adopt the convention that energy is positive when it flows into the service provider and that monetary values are positive when they flow out from the provider.

If the baseline is negative (the service provider is a generator), then the baseline is a production schedule, and is sold on the spot market at the hourly spot rate. However, if the service provider is a consumer, as we assume throughout this paper, then the baseline energy is purchased from the retail market, at fixed retail rates. As a result, we can define the cost to the service provider for the baseline schedule $\bar{e}$ as

$$C_{\text{baseline}}(\bar{e}) := c_{\text{retail}} \sum \bar{e}_k$$

where c_{retail} is the retail price of electricity.

The financial reward paid to the provider for offering a capacity of α MW is based on the bid price of the provider

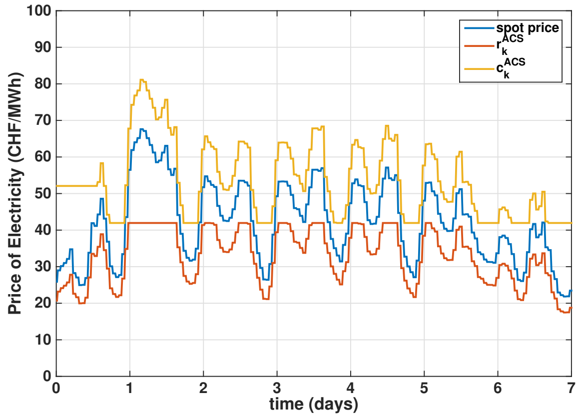

Fig. 1. Incentives for tracking the ACS.

(pay-as-bid), and is proportional to α.

$$R_{\text{capacity}}(\alpha) := c_{\text{capacity}} \cdot \alpha \tag{1}$$

For the purposes of the study in this paper, we fix the bid price of the provider c_{capacity} to be the average of accepted bids in the market, measured in CHF / MW.

2.2 Real-time Operation

Each 15 minute period, SwissGrid measures the error in energy between the ACS a_k and the energy consumed / produced by the provider e_k, and a financial remuneration / penalty is paid / imposed with a price that is coupled to the Swiss spot market price (SwissIX). This financial adjustment is based on two components: An incentivisation price for energy consumed / produced as a result of tracking the ACS, and a penalty price for deviations against this signal.

Incentivisation If the ACS a_k is positive, then the provider is being asked to consume more energy, and so this energy is sold at a discount. If the signal a_k is negative, then the request is for a reduction in consumption. However, the provider has already purchased this energy at retail rates in the form of its baseline schedule and as a result, SwissGrid returns a rebate to the provider for the energy not used. The reward for tracking an ACS $\{a_k\}$ is therefore

$$R_{\text{ACS}}(a) := \sum -c_k^{\text{ACS}} \max\{a_k, 0\} + r_k^{\text{ACS}} \max\{-a_k, 0\} \tag{2}$$

where c_k^{ACS} and r_k^{ACS} are the cost and rebate paid for energy respectively. Figure 1 shows the relationship between these various prices for the 30^{th} week of 2013.

Note that the reward for ACS tracking may be either positive or negative, depending on whether the service provider gains energy as a result of tracking the signal, or produces it.

Imbalance Penalties The tracking imbalance ϵ_k between the ACS a_k, and the energy consumed / produced by the provider e_k at time k is

$$\epsilon_k = e_k - \bar{e}_k - a_k \tag{3}$$

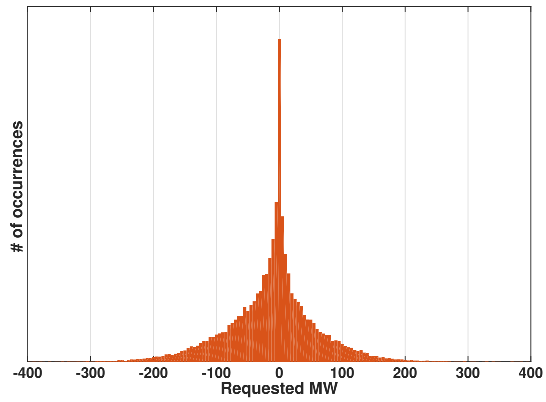

Fig. 2. Distribution of the averaged 15 min ACS for 2013

SwissGrid levies a penalty against providers for tracking imbalances. Using a similar argument to the previous section, different penalties are paid for positive and negative deviation:

$$C_{\text{penalty}}(\epsilon) = \sum c_k^{\text{penalty}} \max\{\epsilon_k, 0\} - r_k^{\text{penalty}} \max\{-\epsilon_k, 0\} \tag{4}$$

where c_k^{penalty} and r_k^{penalty} are the cost and rebate paid for tracking deviations.

The reader is referred to the SwissGrid website [1] for full details on the incentivisation and imbalance penalties involved.

2.3 Statistical Properties of the ACS

Important elements of the ACS can be captured by analysing the statistics of the signal provided by Swissgrid. We restrict our analysis here to the average ACS over a 15 min period (the actual signal comes every 1 sec with a clearing of 15 min), since we assume that a lower level controller captures the high frequency deviations, while our optimization scheme provides the mean level of power at each time period. We also find that the time correlation of the ACS is strong for this time period (0.55 after 15 min), so that the signals do not differ excessively.

The distribution of the ACS throughout 2013 can be observed in Figure 2. The maximum absolute magnitude of the ACS is 400 MW, however the mean of the absolute magnitude is roughly 50 MW. The ACS is almost zero mean, with a small negative bias of almost -11 MW, however this varies per week and especially per day (there exist days for which the ACS is almost entirely positive or entirely negative).

From the probability density distribution of the signal we can deduce that there exist only a few significant outliers, while the mass of the signal is concentrated close to zero. The standard deviation of the ACS is almost 70 MW, while the kurtosis of the distribution is higher (~ 5) than that of the normal distribution.

By saturating tracking for very extreme outliers (track an outlier up to a portion of its full magnitude) we can protect

[1] `http://www.swissgrid.ch/swissgrid/en/home/experts/topics/ancillary_services.html`

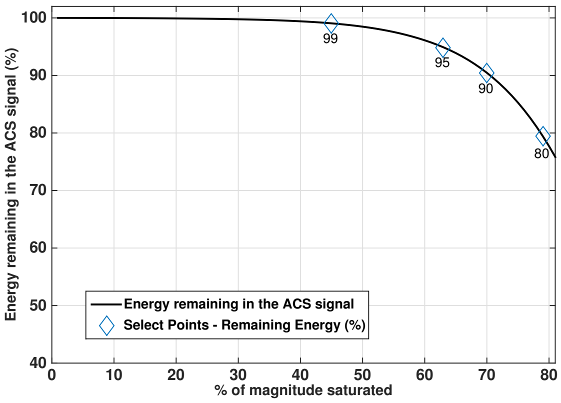

Fig. 3. Power Remaining in the ACS after truncating outliers at different saturation levels

the equipment, facilitate larger bids while also fulfilling the AS obligation at an acceptably high level of compliance. We track $a_k^{sat} = min(a_k, (1 - sat) \cdot a_k)$, where a_k is the original ACS and $sat \in [0, 1]$ the saturation level.

In Figure 3, we observe that shaving 60% of the magnitude of outliers preserves more than 96% of the energy in the ACS. This means that tracking is still effective for a very large portion of the requests. Here, we restrict to a 40% saturation level that allows for tracking more than 99% of the energy contained in the ACS. This results on average to only one to three 15 min periods in a week where the tracking is suboptimal. Most operators (including SwissGrid) allow a small percentage of time where the tracking can be suboptimal. Thus, the tracking capacity (and the revenue) is increased by tracking truncated ACS and taking advantage of the allowed tracking suboptimality.

3. BUILDING MODEL

We use the MATLAB toolbox OpenBuild, see Gorecki et al. (2014), to extract a linear state-space model from a detailed EnergyPlus building model. EnergyPlus, Crawley et al. (2001), is a tool for comprehensive modeling of building thermodynamics and HVAC systems. However, this representation is highly detailed, and not suitable as a prediction model in an optimization-based control scheme. OpenBuild extracts all the required data (material properties, orientation of different surfaces, etc.) from an EnergyPlus model and uses it to automatically construct a first principles linear model of the building thermodynamics. Moreover, EnergyPlus is also used to compute the effect of the external weather conditions and the internal gains on the linear model. Once constructed, the linear model is again validated against EnergyPlus. For more details see Gorecki et al. (2014) .

The linear model obtained from OpenBuild has 70 states and is reduced in order to 20 states using the Hankel-Norm based balanced truncation method. The reduced linear model is discretized with a sampling time of 15 min. to obtain a linear dynamic model

$$\begin{aligned} x_{k+1} &= Ax_k + B_u u_k + B_d d_k \\ y_k &= Cx_k \end{aligned} \tag{5}$$

where $x_k \in \mathbb{R}^n$ is the state, $u_k \in \mathbb{R}^m$ is the thermal energy input to each of the m zones, $d_k \in \mathbb{R}^p$ is the disturbance input (external air temperature, sky temperature, solar radiation on each building surface, long-wave radiation, internal gain, etc.), and $y_k \in \mathbb{R}^q$ is the room air temperature at time step k. The total thermal energy input for the building e_k is then given by

$$e_k = \eta(\mathbf{1}^T u_k) \tag{6}$$

where we assume a constant electrical to thermal conversion efficiently of $\eta = 1$.

The building is deemed satisfactorily comfortable if certain temperature constraints are satisfied. This is used throughout our simulations and imposes linear constraints on the optimization problem. We define the comfort constraints at a level $\delta\,°C$ as $|y_k - T_{\text{ideal}}| \leq \delta$, where $T_{\text{ideal}}\,°C$ is the ideal temperature provided by the occupants (set to $24\,°C$ in the simulations).

As has been reported several times in the literature, a minimum cost approach, with no ACS tracking, would tend to follow the upper or lower temperature constraints in order to minimize energy spend. However, an ACS tracking approach would attempt to place the temperature somewhere between the upper and lower constraints in order to provide a greater flexibility for ACS tracking, which will result in a greater comfort for the occupants. This counter-intuitive behaviour can be observed in Section 5.

The building model, coupled with a forecast of weather and occupancy, allows the characterization of the set of all energy signals that the building is able to consume throughout the coming week, while still ensuring the comfort of its occupants. This *comfort set* is given as

$$B_{\text{comfort}}(\delta) := \left\{ \{e_k\} \;\middle|\; \begin{array}{l} x_{k+1} = Ax_k + B_u u_k + B_d d_k \\ |Cx_k - T_{ideal}| \leq \delta \\ u_k \in \mathcal{U} \\ e_k = \eta(\mathbf{1}^T u_k) \end{array} \right\} \tag{7}$$

4. THE BIDDING PROBLEM FOR COMMERCIAL BUILDINGS

In this section, we formulate the weekly bidding problem that a building faces when participating in the secondary ancillary services market of Switzerland. The goal is to characterize the weekly set of capacity bids α and baseline energy consumptions $\bar{e}$ such that the building can ensure comfort of its occupants with a high probability. Amongst this set, the building can then select the element that minimizes its expected cost of operation.

From Section 2, the total financial cost of the service provider can be summarized as

$$\begin{aligned} C(\alpha, \bar{e}, a, e) := \; & C_{\text{baseline}}(\bar{e}) - R_{\text{capacity}}(\alpha) \\ & + C_{\text{penalty}}(e - \bar{e} - a) - R_{\text{ACS}}(a) \end{aligned}$$

We can see that given an ACS a to track and a baseline schedule $\bar{e}$, the optimal action of the building is to minimize any imbalance penalty C_{penalty}. We define the function $C^{\circ}_{\text{penalty}}$ as the minimum penalty that can be obtained subject to comfort of the building's occupants

$$\begin{aligned} C^{\circ}_{\text{penalty}}(\gamma) := \; & \min_{e} C_{\text{penalty}}(e - \gamma) \\ & \text{s.t. } e \in B_{\text{comfort}}(\delta) \end{aligned}$$

We can now formally define the bidding problem as

$$\min_{\bar{e},\alpha} C_{\text{baseline}}(\bar{e}) - R_{\text{capacity}}(\alpha) \qquad (8)$$
$$+ \mathbb{E}_{\hat{a}} \left[C^{\circ}_{\text{penalty}}(\bar{e} + \alpha\hat{a}) - R_{\text{ACS}}(\alpha\hat{a})\right]$$

where the expectation is taken over the distribution of the normalized ACS $\hat{a}$.

The optimizer $(\bar{e}^{\star}, \alpha^{\star})$ of (8) is then the baseline schedule and capacity bid that will result in lowest expected operating costs of the building, subject to the occupants of the building remaining comfortable.

4.1 Computation : Two Stage Stochastic Programming

The bidding problem (8) can be solved using a two-stage stochastic programming approach. The first stage variables are those that must be provided to SwissGrid at the start of the week : the capacity bid α, and the baseline schedule $\bar{e}$. The second stage variables are then the response of the building e^j to the randomly drawn samples $\hat{a}^j$ of the normalized ACS.

We can now pose the two-stage stochastic optimization problem approximating (8)

$$\min_{\bar{e},\alpha} C_{\text{baseline}}(\bar{e}) - R_{\text{capacity}}(\alpha) \qquad (9)$$
$$+ \frac{1}{N_s}\sum_{j=1}^{N_s}\left[-R_{\text{ACS}}(\alpha\hat{a}^j)\right]$$
$$\begin{aligned} \text{s.t.}\ & x^j_{k+1} = Ax^j_k + B_u u^j_k + B_d d_k \\ & |Cx^j_k - T_{ideal}| \leq \delta \\ & u^j_k \in \mathcal{U} \\ & e^j_k = \eta(\mathbf{1}^T u^j_k) \\ & e^j_k - \bar{e}_k = \alpha\hat{a}^j_k \\ & \alpha \geq 0 \end{aligned}$$

where N_s is the number of samples drawn from the normalized distributed of the ACS. The horizon length of the optimization problem (9) is one week with a time step of 15 min. Note that a tracking constraint is added to ensure perfect tracking of the samples $\hat{a}^j$ of the normalized ACS. Thus, the imbalance penalty C_{penalty} term is removed from the cost function.

We highlight that problem (9) can be re-cast as a linear programming problem, enabling the solution of very large-scale problems. The constraints are clearly linear, and the functions C_{baseline} and R_{capacity} are also linear functions. From equations (2) and (4), we see that the functions C_{penalty} and R_{ACS} are convex piecewise affine functions of their arguments, and can therefore be re-formulated as linear functions subject to linear constraints using a standard epigraph formulation.

5. SIMULATION RESULTS

5.1 Simulation Setup

We employ an EnergyPlus model of a five zone commercial building from the reference building database of US DoE: Office of Energy Efficiency and Renewable Energy (2011), with a total surface of 500 m^2. The optimization is run during the cooling season (mainly the summer months) on a week long basis. Weather and occupancy disturbances are assumed to be perfectly forecast, while the ACS (provided by Swissgrid) is revealed causally and is unknown at the time of the bid. For the ACS scenarios we use the recorded ACS from the previous weeks.

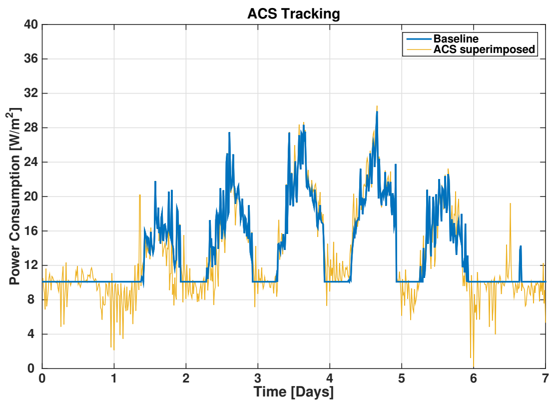

Fig. 4. Baseline consumption declared for a week and the ACS superimposed when it is realised.

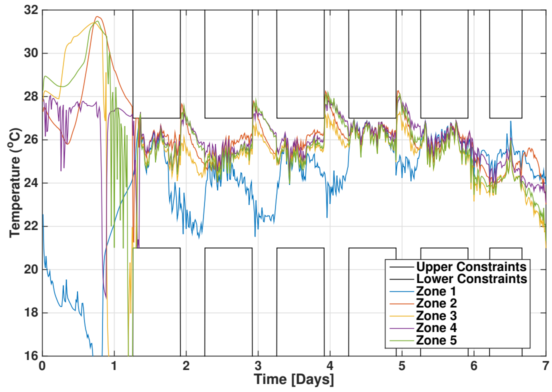

Fig. 5. Zones temperature profile for time varying comfort constraint (night setback).

For the financial variables, we use spot prices from the 2013 Swiss market, bonus and penalties for tracking (or deviating from ACS) from Swissgrid for the same year and the average capacity bid per week as published.

The building model is run with a 15 min time step and the problem is solved using a YALMIP interface, Löfberg (2004), to the Gurobi numerical solver. The number of ACS scenarios is quite limited (14 to 15) due to the extreme memory requirements from the numerous constraints generated for a week long simulation. Sensitivity studies suggest that this small number of scenarios is still representative in this case. The average time required for a single week optimization is approximately 5 min.

5.2 Comfort Metrics

We evaluate comfort levels using the Predicted Percentage of Dissatisfied (PPD) index which is the predicted percentage of people among a large group who will be dissatisfied with the thermal environment, based on ASHRAE (2009). PPD is a function of deviations from an ideal temperature.

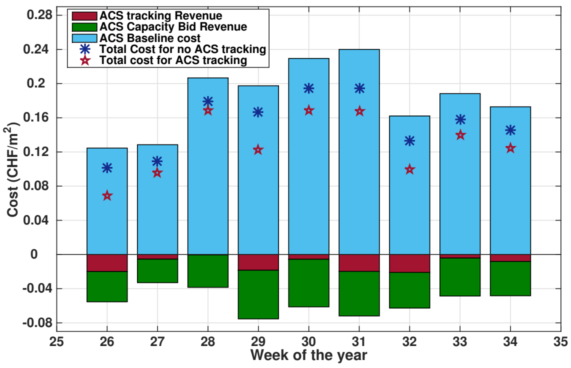

Fig. 6. Overall cost of AS vs no AS participation, per week.

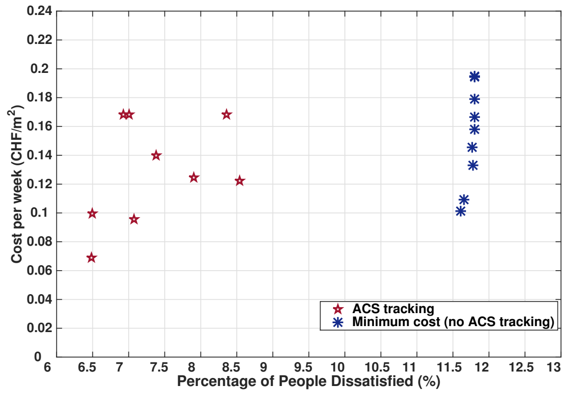

Fig. 7. Pareto curve of comfort vs cost for the same weeks.

The metric depends also on many other comfort quantities (such as humidity, irradiation, metabolic rate, etc) which we consider fixed. This provides the PPD for each zone of the building at every time period. To acquire a metric for the total building comfort throughout a week we resort to the long-termed percentage of dissatisfied (LPD) as recommended in Carlucci (2013)

$$\text{LPD} = \frac{\sum_{k=1}^{N}\sum_{z=1}^{Z} p_{z,k}\text{PPD}_{z,k}}{\sum_{k=1}^{N}\sum_{z=1}^{Z} p_{z,k}} \tag{10}$$

where k is the time step, z is the zone index, and $p_{z,k}$ is the occupancy rate. We use this quantity only as an output metric to evaluate comfort levels and do not impose it as a constraint.

5.3 Results

Our objective is to determine under which conditions it is preferable for a building to participate in ACS tracking and what is the expected benefit. We compare against the situation where the building attempts to minimise energy costs without ACS tracking, a scheme studied extensively in the literature. The result is assessed both in terms of comfort and cost.

We run our algorithm for a specific summer week (30th of 2013). The baseline declared by the algorithm, displayed in Figure 4, allows it to bid a capacity of 16 W/m^2 for the following week (which is more than 140% of the

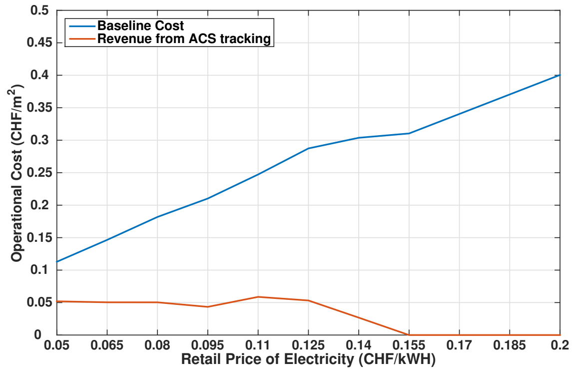

Fig. 8. Tracking revenues and cost of energy for different electricity prices for variable constraints (night set-back).

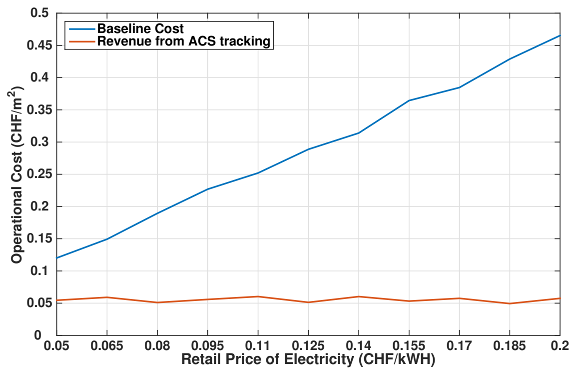

Fig. 9. Tracking revenues and cost of energy for different electricity prices for constant constraints.

average and 50% of the maximum power consumption of the building). The resulting temperature profile for all zones, when the actual ACS is received, seen in Figure 5, rarely violate constraints and when it does the violation is usually not significant.

We compare the overall energy cost of operating this building (0.168 CHF/m^2) for a specific week to minimum cost without ACS tracking (0.192 CHF/m^2), for a retail electricity price of 0.10 CHF/kWh (close to the minimum price of electricity in Switzerland for a commercial building). The overall savings are in the order of 13% with the capacity bid resulting in a revenue of approximately 0.054 CHF/m^2 and the tracking bonus in 0.0055 CHF/m^2. To provide AS the building had to consume 13.2 W/m^2 of power on average compared to 11.4 W/m^2 when no tracking was involved. This is mainly due to procuring energy during non-working hours in order to provide a feasible baseline for the magnitude of the ACS bid.

Similar results are obtained for all the summer weeks of 2013. In Figure 6 we observe the variation in revenue and cost for nine different summer weeks (for a retail price of electricity of 0.10 CHF/kWh). On average ACS tracking has an overall cost of 0.126CHF/m^2 compared to 0.154 CHF/m^2 for minimum cost without ACS tracking, an average improvement of 18%. Most of the revenue comes from the capacity bid rather than the bonus for tracking the real-time signal. A Pareto curve of the comfort attained vs cost is depicted in Figure 7. We see that ACS tracking can provide better comfort levels for the same temperature constraints at a reduced cost.

As we have mentioned, the retail price of electricity plays a crucial role in the participation of the building in the secondary control market. In Figure 8 we can see the sensitivity of the ACS revenue as the price increases. At approximately 0.155 CHF/kWh the algorithm considers tracking ACS not profitable enough compared to the costs of procuring an expensive baseline and decides to bid zero capacity in the market. Alternatively, if we consider a building with comfort constraints at all times, then we always have to buy a minimum of power. This allows ACS tracking without significant sensitivity on the price of electricity since the building is not using much more power on average (for most cases up to 5% more). In Figure 9 we observe that for a building with active constraints throughout the week the optimization algorithm will always choose participation in the AS market. The benefit of participation, as a percentage of overall costs is diminishing because the cost of electricity is becoming very large, but the absolute value of the revenue remains virtually the same.

It should be noted, that the building is buying energy at a very high price compared to the actual spot market because Swiss regulations currently require the baseline schedule to be purchased at retail rates. Access to the price levels of the spot market could provide considerable benefits for AS participation. Moreover, the building is being incentivized for tracking the ACS on a bonus calculated on the spot market (while purchasing electricity at higher rates).

Finally, we compare the LPD comfort levels offered by ACS tracking versus no ACS tracking by performing the following simulation test: we gradually tighten the temperature constraints towards the ideal temperature. This way the minimum cost approach creates better comfort levels (but at an increased cost) and the ACS tracking is forced to declare its baseline close to where the ideal temperature is manifested (with less room for large ACS signals). The results are depicted in Figure 10. We can observe that ACS tracking achieves the same level of LPD with considerably lower costs, except when the temperature constraints are very tight around the ideal level (where ACS tracking is not operationally possible).

6. CONCLUSION

Participation of buildings in the secondary AS market is highly sensitive on the price at which they procure electricity. For the lowest of the prices for commercial buildings, currently seen in Switzerland, ACS tracking improves the comfort levels considerably and the overall costs modestly. For price levels close to the spot market the economical benefits could be also significant. The two stage stochastic optimization algorithm can produce both the optimal bid (in terms of economic performance) and the suitable baseline consumption to be able to track the ACS as it arrives.

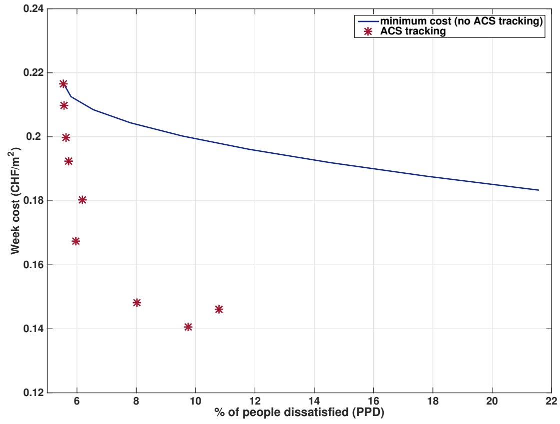

Fig. 10. Pareto curve of comfort levels vs cost for ACS tracking and no ACS tracking.

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