Reducing Peak Electricity Demand in Building Climate Control using Real-Time Pricing and Model Predictive Control

Frauke Oldewurtel, Andreas Ulbig, Alessandra Parisio, Göran Andersson, Manfred Morari

***Abstract*— A method to reduce peak electricity demand in building climate control by using real-time electricity pricing and applying *model predictive control* (MPC) is investigated. We propose to use a newly developed time-varying, hourly-based electricity tariff for end-consumers, that has been designed to truly reflect marginal costs of electricity provision, based on spot market prices as well as on electricity grid load levels, which is directly incorporated into the MPC cost function. Since this electricity tariff is only available for a limited time window into the future we use least-squares support vector machines for electricity tariff price forecasting and thus provide the MPC controller with the necessary estimated time-varying costs for the whole prediction horizon. In the given context, the hourly pricing provides an economic incentive for a building controller to react sensitively with respect to high spot market electricity prices and high grid loading, respectively. Within the proposed tariff regime, grid-friendly behaviour is rewarded. It can be shown that peak electricity demand of buildings can be significantly reduced. The here presented study is an example for the successful implementation of demand response (DR) in the field of building climate control.**

I. INTRODUCTION

A. Electricity Demand in Buildings

The aim in building climate control for office buildings is to keep the room's temperature, illuminance and CO_2 levels within a given comfort range, and to do so with minimum energy. In this work we assume that all consumed energy is in the form of electricity, which makes sense especially for the considered case, Switzerland, where in recent years heat pumps have become very popular [17]. Intuitively, the goal to minimize total electricity consumption seems to be well-chosen. In practice, however, such an optimization strategy can lead to remarkable peaks in electricity demand that can, and in light of grid stability, should preferably be avoided. Furthermore, electricity is consumed at times when, in the context of liberalized electricity markets, it is most expensive. The evolution of electricity prices is, however, external information that is not known to a conventional building controller. Since the building envelope itself constitutes a thermal storage, there inherently exists the possibility to shift electricity demand from high price to low price times or from high loading to low loading times, respectively. The controller should therefore be enabled to take advantage of demand shifting. This is possible, if information on both electricity spot prices and grid load levels can be incorporated directly in building climate control. Please note, that time-series for spot prices and grid loading levels should, fundamentally, be well correlated over time. Electricity demand for a given hour is strongly linked to grid load levels. And a high electricity demand will act as a driver towards high spot market prices, whereas low electricity demand has the opposite effect. However, this correlation, based on the fundamental linking of electricity demand and supply, does not hold if, for example, speculation is driving the spot market price (see also 3). Thus, using only the spot market price as tariff can induce negative effects, i.e. increasing already existing peak load levels in the electricity grid.

We therefore propose to use model predictive control (MPC) and a time-varying tariff scheme that is based both on spot market prices as well as on actual electricity grid load levels. This proposed tariff truly reflects the marginal costs of electricity provision for the end-user.

B. Model Predictive Control for Building Climate Control

MPC for building climate control has been investigated in several works before [9], [10], [14], [15], mainly with the goal of increasing the energy efficiency. Advantages of MPC are reported as resulting from readily incorporating time-varying constraints, e.g. varying the allowed room temperature range depending on occupancy or non-occupancy, from using weather predictions and occupancy predictions. In [15] a stochastic MPC controller to deal with uncertainties in weather predictions is proposed. In this paper we also use weather and occupancy predictions, but they are assumed to be perfect, i.e. the realization is equal to the prediction. Instead, the focus is on the question how the proposed time-varying tariff can be used for load shifting and the reduction of peak demand. Clearly, being price-optimal comes at the cost of not being energy-optimal. Thus, the question arises how much additional energy is needed to achieve the load shifting, i.e. how sensitive is the building to electricity prices.

C. Support Vector Regressor for Spot Price Forecasting

The knowledge of electricity price patterns based on what happened on the electricity spot market and with electricity grid load levels during previous days allows to improve the performance of demand response (DR) initiatives. In essence this means to help the customer in his decisions when and how to change their energy demand in light of varying

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electricity prices. Since the electricity tariff is only available for a limited time window into the future we need to forecast the hourly prices in order to provide the MPC controller with the necessary estimated time-varying electricity costs for the whole prediction horizon. The tariff time series is generally non-stationary with an hourly sampling time; it exhibits high-frequency fluctuations and peak shifting, also influenced by calendar effects, i.e. weekends and holidays. Therefore it is a relatively hard task to capture the dynamics of the tariff time series and fit a model out of the given data set. Several methodologies have been adopted for electricity price forecasting: broadly exploited approaches are time series models, such as Autoregressive Integrated Moving Average (ARIMA) [2], Artificial Neural Network (ANN) [21] and Support Vector Machine (SVM) [16]. In this paper we use the Least-Square Support Vector Machines (LS-SVM) method to forecast day-ahead electricity tariff prices based on past spot market prices and grid load levels.

D. Notation

The real number set is denoted by $\mathbb{R}$, the set of non-negative integers by $\mathbb{N}$ ($\mathbb{N}_+ := \mathbb{N}\backslash\{0\}$), the set of consecutive non-negative integers $\{j, \dots, k\}$ by $\mathbb{N}_j^k$.

II. PROBLEM SETUP

A. Building Model and Automation System

For our predictions we use a building model from [12], [15], given as

$$\begin{aligned} x_{k+1} &= Ax_k + Bu_k + \dots \\ &\quad \dots + B_v v_k + \sum_{i=1}^{m} [(B_{vu,i} v_k + B_{xu,i} x_k) u_{k,i}] \\ y_k &= Cx_k + Du_k + D_v v_k + \sum_{i=1}^{m} [(D_{vu,i} v_k) u_i], \end{aligned} \tag{1}$$

where $x_k \in \mathbb{R}^n$ is the state representing the room temperature and temperatures in the walls, floor and ceiling, $u_k \in \mathbb{R}^m$ is the input, and $v_k \in \mathbb{R}^p$ is the weather and internal gains (people, equipment) at time step k, and the matrices $A, B, B_v, B_{vu,i}$, and $B_{xu,i}$ are of appropriate sizes, $y_k \in \mathbb{R}^q$ is the output and the matrices C, D, D_v, and $D_{vu,i}$ are of appropriate sizes. The numerical values for the considered building example can be found in [12]. We consider a Swiss average building, with heavy construction, a low window area fraction facing south and high internal gains, which is a common building type in Switzerland. The sampling time is 1 hour. The automation system has the following actuators $u_k := \begin{bmatrix} u_{k,1} & u_{k,2} & u_{k,3} & u_{k,4} & u_{k,5} \end{bmatrix}^T$:

$$\begin{aligned} u_{k,1} &= \text{blind positioning } [-] \\ u_{k,2} &= \text{electrical lighting } \left[W/m^2\right] \\ u_{k,3} &= \text{chiller } \left[W/m^2\right] \\ u_{k,4} &= \text{cooling tower } [-] \\ u_{k,5} &= \text{radiators } \left[W/m^2\right]. \end{aligned} \tag{2}$$

The output $y_k := \begin{bmatrix} y_{k,1} & y_{k,2} & u_{k,3} \end{bmatrix}^T$ is given as

$$\begin{aligned} y_{k,1} &= \text{room temperature } [^\circ C] \\ y_{k,2} &= \text{room illuminance } [lux] \\ y_{k,3} &= \text{ceiling surface temperature } [^\circ C]. \end{aligned} \tag{3}$$

We take into account the following disturbances $v_k := \begin{bmatrix} v_{k,1} & v_{k,2} & v_{k,3} & v_{k,4} & v_{k,5} \end{bmatrix}^T$:

$$\begin{aligned} v_{k,1} &= \text{solar radiation } \left[W/m^2\right] \\ v_{k,2} &= \text{outside air temperature } [^\circ C] \\ v_{k,3} &= \text{wetbulb temperature } [^\circ C] \\ v_{k,4} &= \text{internal gains persons } \left[W/m^2\right] \\ v_{k,5} &= \text{internal gains equipment } \left[W/m^2\right]. \end{aligned} \tag{4}$$

The weather data are real weather measurements of Zurich from 2007. The internal gains are average values taken from Swiss building standards [20]. Since the actuators have a different efficiency, we need to multiply the input vector u with an appropriate scaling factor, which is given as:

$$\xi := \begin{bmatrix} 0 & 3.32 & 0.976 & 7.47 & 1.107 \end{bmatrix}^T. \tag{5}$$

The constraints on the control inputs are given as follows:

$$\begin{aligned} 0 &\le u_{k,1} \le 1 \\ 0 &\le u_{k,2} \le 1000000 \\ 0 &\le u_{k,3} \le 40.653 \\ 0 &\le u_{k,4} \le 1 \\ 0 &\le u_{k,5} \le 22.075. \end{aligned} \tag{6}$$

The constraints on the output are defined as:

$$\begin{array}{llll} \text{if occupied} & 21 \le y_{k,1} \le 26 & \text{else} & 5 \le y_{k,1} \le 40 \\ \text{if occupied} & 500 \le y_{k,2} & \text{else} & 0 \le y_{k,2} \\ & 18 \le y_{k,3}. & & \end{array} \tag{7}$$

Remark 1: Please note that the upper limit for electrical lightning $u_{k,2}$ has been chosen only for numerical reasons.

With the above inequalities, all constraints and dynamics of the MPC problem are defined. Next we describe the proposed electricity tariff scheme, which will be needed when formulating the MPC objective.

B. Real Time Pricing

A time-varying, hourly electricity tariff is proposed that truly reflects marginal costs of electricity provision, based on spot market prices, and electricity transmission and distribution grid loading, based on actual grid measurements. This is a general benchmark for evaluating demand response effects of price-responsive loads on the end-consumer side [22]. Our example case is the city of Zurich, Switzerland, using time-series of Swiss spot market prices from the European Energy Exchange (EEX), a generic yet realistic electricity load curve for Zurich and the existing tariff structure of Zurich's public electricity utility (ewz) for the year 2007 [3], [4]. All public holidays have been neglected in the constructed time-series.

The construction of the proposed time-varying, hourly end-consumer tariff is as follows:

1) Time-series of spot market prices and load curves are used to calculate the average spot price and average grid load level for the given time-period.
2) The relative weights of the individual cost components of electricity consumption, e.g. α, β and γ, are calculated using tariff data from ewz [4]. The average electricity price for the constructed time-series is $\mathsf{c}_{\mathsf{avg}}^{\mathsf{tariff}}$ =CHF 0.1465 /kWh.
3) The construction of the spot/load-based tariff is then accomplished using Eq. (8). (Index k corresponds to any hour of a given time period for which a tariff price vector is to be calculated). More details on the tariff construction can be found in [22].

Definition 1: Let the hourly electricity tariff $\mathsf{c}_{\mathsf{k}}^{\mathsf{tariff}}$ for time step k be defined as

$$\mathsf{c}_{\mathsf{k}}^{\mathsf{tariff}} := \left(\begin{array}{cc} & \alpha \cdot \frac{\mathsf{Spot\ price(k)}}{\mathsf{Spot\ price_{avg}}} \\ + & \beta \cdot \frac{\mathsf{Load\ level(k)}}{\mathsf{Load\ level_{avg}}} \\ + & \gamma \end{array} \right) \cdot \mathsf{c}_{\mathsf{avg}}^{\mathsf{tariff}} \quad , \tag{8}$$

$$\mathsf{with} \left\| \begin{array}{ccl} \alpha & := & \%\,\mathsf{Electricity_{avg}} \\ \beta & := & \%\,\mathsf{Grid\ utilisation_{avg}} \\ \gamma & := & \%\,\mathsf{City\ concession_{avg}} \end{array} \right\|$$

where $\mathsf{c}_{\mathsf{avg}}^{\mathsf{tariff}}$ is the average tariff price. For the considered case, α, β, and γ are 41.0%, 53.7%, and 5.4%, respectively.

Remark 2: By construction, Eq. (8) involves a normalization, i.e. an electrical load which is constant throughout the whole time period will incur the same costs with the time-varying tariff scheme as if the constant average electricity price would be applied.

The tariff construction is implemented here in a day-ahead fashion: Next day's EEX spot market prices are announced shortly after noon on weekdays. An exact day-ahead variable tariff price vector can then be constructed in line with the announcements of day-ahead EEX spot prices. This leads to a varying prediction horizon for the variable tariff's day-ahead prices of a 12 h minimum, just before the announcement of the next day's EEX spot prices, to a 36 h maximum, just after the announcement. Since our MPC optimization approach uses a $24h$ prediction horizon, the missing tariff prices of the first 12 hours of the next day have to be estimated, which we do via SVM, see Section III-B.

The proposed spot/load-based tariff scheme exhibits a good correlation, measured via the coefficient of determination (R^2), with both spot price and grid load time-series for the whole year 2007 ($R^2 = 0.91$ and $R^2 = 0.54$, respectively). In contrast, the direct correlation between spot price and grid load is remarkably low ($R^2 = 0.25$). An illustration of the correlation is shown in Fig. 1. The spot/load-based tariff is compared to the currently existing ewz day/night tariff scheme, in which electricity prices during night time (Mon.-Sat. 22h–6h, Sun. 0h–24h) are only about half that of prices during day time (Mon.-Sat. 6h–22h) [4], see Table I.

Remark 3: When considering only the first three quarters of 2007, the correlation with the load time-series are actually significantly higher: tariff–load $R^2 = 0.86$ and spot–load $R^2 = 0.54$. This remarkable difference is due to significant spot price peaks towards the end of 2007, shown in the inlay of Fig. 1, which distort the otherwise very good correlation.

The results from the correlation analysis are a strong indication that the spot/load-based tariff price signal acts as a communication signal for price-responsive end-consumers, truly relaying information on spot market price and grid load levels. It provides the necessary price information and economic incentive for end-consumers to react accordingly. This creates an important feedback in the system, acting against both peak grid loading and peak electricity demand, as grid-friendly consumer behaviour is rewarded.

The spot/load-based tariff scheme allows to find a consensus between the end-consumer's individual goal of minimising the cost for electricity and the superordinate goal of reducing peak electricity demand and peak grid load levels.

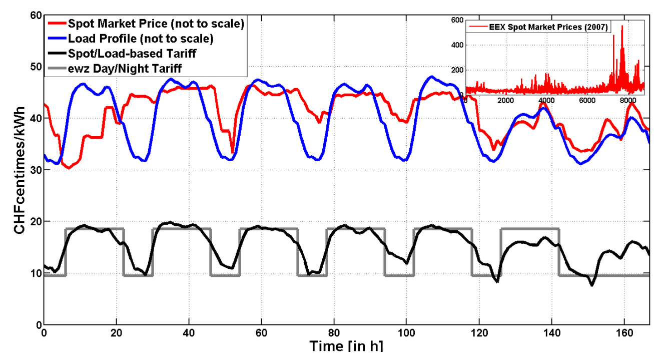

Fig. 1. Evolution of spot prices, grid load and spot/load-based tariff.

Tariff scheme	Spot time-series	Load time-series
	$R^2 =$	$R^2 =$
Day/Night	0.13 (0.30)	0.63 (0.63)
Spot-based	1.00 (1.00)	0.25 (0.54)
Spot/Load-based	0.91 (0.88)	0.54 (0.86)

TABLE I

CORRELATION OF VARIABLE TARIFF SCHEMES WITH SPOT PRICE AND GRID LOAD TIME-SERIES FOR THE YEAR 2007 (Q1-Q3 2007).

III. CONTROL DESIGN

A. MPC Formulation

For the initial state x_0 the control objective is to minimize a linear cost function

$$V(x_0) := \sum_{k=0}^{\infty} c_k \cdot \xi^T \cdot u_k, \tag{9}$$

where c_k is the electricity price at time k.

The electricity tariff is in the focus of our investigation. We will investigate four cases, the case when it is constant over time (constant tariff), when we have two different prices for day and night (day/night tariff), when it is time-varying but perfectly predicted (variable-perfect) - which is an artificial assumption, since we do not always have the 24h of the control prediction available from this tariff - and when it is time-varying and predicted via SVM methods (variable-regression).

The building model in (1) is nonlinear; in this case bilinear between inputs, states and weather parameters. Nonlinearities in the dynamic equations of an MPC problem will generally result in a non-convex optimization problem. The approach that we take here is a form of Sequential Linear Programming (SLP) for solving nonlinear problems in which we iteratively linearize the non-convex constraints around the current solution, solve the optimization problem and repeat until a convergence condition is met [7]. To keep formulations simple, we will assume for the remainder of the paper that we do the linearization at each hourly time step k, which results in the new matrices $B_{u,k}$ and $D_{u,k}$ and formulate the problem for the linear system of the form

$$\begin{aligned} x_{k+1} &= Ax_k + B_{u,k}u_k + B_v v_k \\ y_k &= Cx_k + D_{u,k}u_k + D_v v_k \quad . \end{aligned} \tag{10}$$

The polytopic constraints on the inputs and states as defined in (6) and (7) can be written as

$$\begin{aligned} & u_k \in \mathcal{U}, \quad \mathcal{U} := \{u_k \in \mathbb{R}^m | Su \leq s\} \\ \wedge \;\; & y_k \in \mathcal{Y}, \quad \mathcal{Y} := \{y_k \in \mathbb{R}^q | Gy \leq g\}. \end{aligned} \tag{11}$$

Consider the prediction horizon $N \in \mathbb{N}_+$ and define

$$\mathbf{u} \;\; := \;\; \left[u_0^{\mathrm{T}}, \ldots, u_{N-1}^{\mathrm{T}}\right]^{\mathrm{T}} \in \mathbb{R}^{Nm}.$$

The optimal control input u over the prediction horizon N is determined by solving MPC Problem 1.

Problem 1:

$$\begin{aligned} u^*(x_0) := \arg\,\min_{\mathbf{u}} \;\; & \sum_{k=0}^{N} {c_k}^T \cdot \xi^T \cdot u_k \\ s.t. \quad & u_k \in \mathcal{U} \\ & y_k \in \mathcal{Y} \\ & x_{k+1} = Ax_k + B_{u,k}u_k + B_v v_k \\ & y_k = Cx_k + D_{u,k}u_k + D_v v_k \\ & \forall k \in \mathbb{N}_0^{N-1} \end{aligned} \tag{12}$$

B. Support Vector Regression

Hourly pricing forecasting is a challenging task and a crucial aspect in a competitive electricity market. SVM is a powerful statistical method used for statistical classification and regression analysis. Recently the SVM technique is being successfully applied to find price patterns in the energy market [6], [13], [19]. The training algorithm of a SVM involves a quadratic optimization program, which provides an unique solution and does not require the random initialization of weights, as in ANN training. We apply Least-Square Support Vector Machines (LS-SVM) for regression (LS-SVR, Support Vector Regression) [16] to compute short-term tariff forecasts. Given N_s samples of system input patterns, E_i and the associated output values S_i, where i represents the sample, LS-SVR approximates the relationship between the outputs and inputs using the following equation:

Definition 2:

$$S_i = \sum_{i=1}^{N_s} w_i \phi(E_i) + b_i \ , \tag{13}$$

where $\phi(E_i)$ is a nonlinear mapping of the input data to a higher-dimensional feature space, b_i is the scalar threshold and w_i is the weight coefficient. Then the parameters w_i and b_i are estimated solving a linear regression problem in this feature space, which requires the assignment of the *kernel function* $K(E_i, E_j) = \phi(E_i)^T \phi(E_j)$ and the tuning of a predefined set of parameters. Then the SVR can avoid under- and over- fitting by tuning the parameter set. We apply formulas for parameter selection based on statistics research which are provided in [1]. More information regarding SVMs can be also obtained from the *kernel machines* web site [11].

C. Numerical Results for Short-Term Tariff Forecasting

We apply the LS-SVR method described above to compute tariff forecasts. The hourly spot market prices and grid loading levels for Zurich 2007 are considered for the training of the LS-SVR. Then the training data set is defined as follows: at each hour, the input patterns are based on the spot market prices, the load level data and the electricity tariffs 4 months back into the past, and the corresponding outputs are the electricity tariff one hour ahead. To improve the training accuracy and prevent over-fitting and under-fitting, we applied statistical analysis of studentized residuals to remove the outliers [5]. Then the nonlinear regressor is trained and used to predict the hourly electricity prices for the next day. Figure 2 shows forecasted and actual hourly electricity prices of the first three weeks of July 2007.

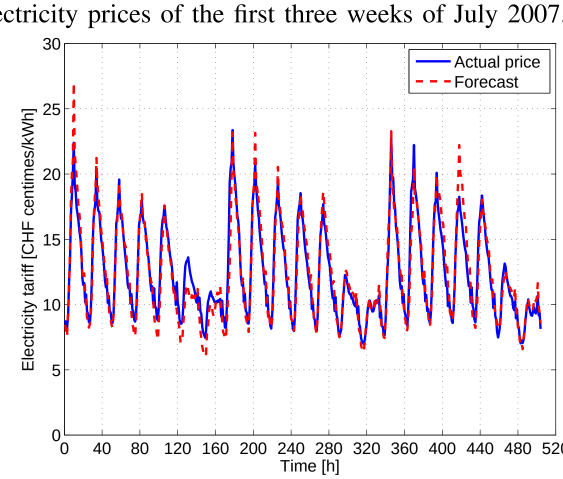

Fig. 2. Hourly electricity tariff forecasts for Zurich, 1-22 July 2007.

The value of the coefficient of determination R^2 for the three weeks presented is 0.94, proving the goodness of fit.

All the numerical results presented in this subsection are obtained by Matlab's SVM (Support Vector Machine) toolbox, a LS-SVM training and simulation environment written in C-code [18].

IV. Analysis

A. *Qualitative Differences*

A qualitative graphical depiction of the electricity consumption for the considered office room is given in Fig. 3. The time frame is the third week of December 2007. The evolution of room temperature for three different cases is presented: MPC optimization using a constant electricity tariff and MPC optimization using the variable tariff assuming either perfect information or using the regression estimation. In all cases, the *a priori* defined room temperature constraints are respected. However, significantly differing temperature patterns appear during night time: the variable tariff regime leads to a pre-heating of the office room during the early morning hours, when electricity prices are lowest. There exist slight differences between the cases of perfect information and estimation of tariff prices. When the MPC setup uses tariff estimations, the pre-heating during nighttime occurs 1-2 hours earlier and is on some mornings sub-optimal.

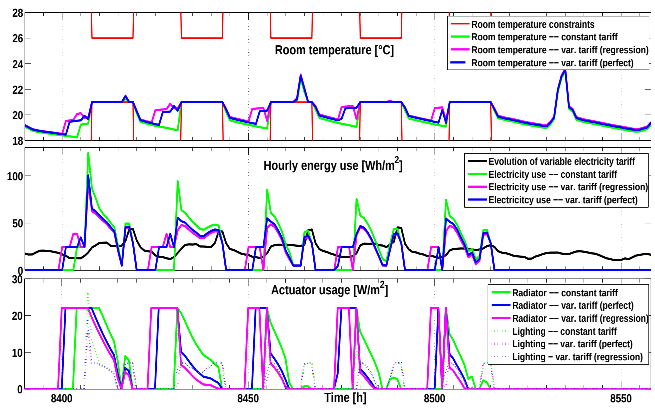

Fig. 3. Reducing peak electricity demand by shifting radiator usage in winter time.

The shift of electricity demand is accomplished mostly by a partial shift of radiator usage from day time to night time. This shift can only be partial as the temperature constraints need to be respected. The MPC optimizer clearly takes advantage of the office room's thermal inertia for its optimization. The demand of other appliances, such as lighting can mostly not be shifted in time. Some variations and an overall slight reduction in the office lighting's peak usage are noticeable nevertheless. This is accomplished by the control of the window blinds that adds an additional albeit small degree of freedom for the lighting.

B. *Quantitative Differences*

A quantitative analysis of the electricity consumption over the whole year 2007 for altogether 16 different room configurations [8] (Building insulation level: Swiss average / passive house, construction type: heavy / light, window area fraction: high / low, internal gains level: high / low) indeed shows interesting results, Fig. 4. First of all, a noticeable reduction in overall peak electricity demand as compared to the constant tariff: The daily maximum peak electricity demand, i.e the highest load event per day, is on average reduced by 7.9% (day/night tariff), by 5.2% (variable tariff – perfect information) and by 6.1% (variable tariff – regression). These aggregated consumption figures, however, are obscured by two facts: First, only a fraction of total electricity consumption can be shifted in time. Demand such as lighting is only barely shiftable, whereas thermal loads (chillers, cooling tower, radiator) are well shiftable in time. Second, the peak demand of the rooms should be compared with the given load curve for Zurich since only peak consumption occurring when grid load levels are already high is critical. When comparing directly the peak demand of the different rooms' thermal appliances with the given load curve, the peak shifting is remarkable: The thermal appliances daily maximum peak demand is on average reduced by 31.5% (day/night tariff), by 38.9% (variable tariff – perfect information) and by 39.0% (variable tariff – regression). Total electricity consumption stays the same for all Swiss average buildings and is marginally reduced for all passive houses, by -1%, when using an MPC setup with any of the given variable electricity tariffs. A rather unexpected result occurred when looking at electricity costs: Total costs for the whole year were significantly lower when using a constant tariff that simply charges the average cost of the variable tariff (CHF $0.1465/kWh$). When using and optimizing over the variable tariffs, costs are 11.6% (day/night tariff) and 26.3% (variable tariff – perfect/regression) higher. At first this result comes as a surprise. However, only a part of the office room's electric consumption can be shifted in time. Lighting can almost not be shifted and occurs when the office is by definition occupied, i.e. during the expensive day time. By construction (see Remark 2) the prices during the day are much higher than with the constant tariff. So if a significant amount of the load cannot be shifted to less expensive times, then the electricity costs will increase. When looking at the costs incurred by the given thermal appliances, significant cost reductions can be seen: On average 15% (day/night tariff) and $7-9\%$ (variable tariff – perfect/regression) lower. Depending on building type, differing trends can be seen: Swiss average buildings see increasing costs: by 0.3% (day/night tariff) and by $12.2-14.1\%$ (variable tariff – perfect/regression). This is due to the specifically high cooling/heating demand of such buildings and comparatively low thermal inertia. In contrast, the costs for passive houses decline steeply: by 29.5% (day/night tariff) and by $28.4-31.2\%$ (variable tariff – perfect/regression). This economic disadvantage for Swiss average houses could however be addressed by a scaling of the proposed tariff structure, such that e.g. an average household would under a variable tariff scheme pay the same as before, but would have the opportunity to pay considerably less if he behaves price-responsive. This way, an economic incentive would be created to use building-control schemes and behave grid-friendly. Additionally, it is expected that the positive effect on the peak demand reduction that was observed can be further exploited by considering buildings with more storage devices (e.g. a hot water boiler which can be heated during night) as well as systems with thermally activated building systems (the concrete is heated/cooled by a liquid in the slabs, which has long time constants. This is expected to enable further load shifting and consequently also result in lower electricity consumption costs.

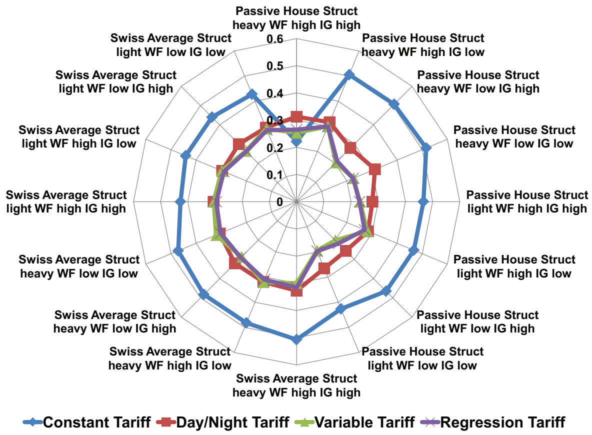

Fig. 4. Relative Peak Demand Reduction for different Room Setups.

V. CONCLUSIONS

This study shows that peak electricity demand in building climate control relative to a given reference load curve can effectively be reduced by incorporating an appropriately designed variable electricity tariff directly into the cost function of an MPC setup. This load shifting effort for thermal loads comes at the cost of higher electricity consumption. Overall electricity costs are however clearly increased for the given 16 test cases, as thermal loads here do not represent the majority of electricity consumption. Electricity costs only for the thermal loads, fall steeply for passive houses and increase slightly for Swiss average houses.

The proposed scheme is well suited to reach the goal of load shifting and decreasing of peak electricity demand with respect to a given load profile. The scaling of the tariff needs however to be tuned, such that an average household is not paying more than before; plus an economic incentive is given for adhering to such demand response (DR) schemes.

VI. ACKNOWLEDGMENTS

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