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CONTROL THEORY

Predictive smart thermostat controller for heating, ventilation, and air-conditioning systems

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Abstract. The paper suggests a simple energy saving controller for heating, ventilation, and air-conditioning (HVAC) systems that combines information on occupancy and weather with predictive control to save energy in buildings. The controller uses a pulse width modulation strategy and turns on/off the HVAC system based on the optimal decisions of the model predictive controller. The suggested controller is simple yet optimal (in a certain sense), and therefore suitable for residential and small commercial buildings where the cost of the controller is a key factor. The effectiveness of the proposed scheme is illustrated using simulations, whereas the model of the building thermal dynamics was identified based on data from experiments.

Key words: pulse-width modulation, on/off controller, HVAC, model predictive control

1. INTRODUCTION

Optimized consumption of energy in buildings helps to reduce energy costs and the carbon footprint. Recent research proved that information on climate forecasts, human occupancy, energy costs, and thermal storage can be employed in heating, ventilation, and air-conditioning (HVAC) control for improving the energy efficiency and reducing the costs [3,9,14–19,21,23,25,26]. To the best of the authors' knowledge the first effort to use climate forecasts to increase the efficiency of energy consumption in a HVAC system was addressed in [21] for integrated building automation systems. Industrial implementation of the HVAC control with prior information can be traced back to rule-based controllers from Siemens Automation [13]. The available results on the HVAC control can be grouped into two categories: (i) proactive controllers that employ prior information on climate, occupancy, building conditions, and storage [3,16–19,23,25,26], and (ii) reactive controllers that use measurements from a building [28,31]. The model predictive controller (MPC) is a widely used proactive controller (see [2] and the references therein); significant contributions in this direction are given in [8,17–19,21,25,26,29]. The simplest proactive controller is the smart thermostat (ST), proposed in [15], which uses occupancy predictions for reducing energy consumption in residential buildings. Although the results in [15] show a significant reduction in energy consumption, optimality of the solution is not guaranteed.

More recently, a simple controller that switches on/off depending on the minimum error between the average temperature and the desired temperature, the minimum temperature deviation from the desired temperature, and the minimum number of compressor starts per hour for a HVAC system was proposed in [32]. This approach solved a multi-objective optimization problem for computing the switching times. The obtained

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results proved that by properly selecting the on/off strategy, a cheap and optimal controller that can save energy in buildings can be designed. Although the proposed controller combines desirable features such as optimality and simplicity, the method does not accommodate occupancy and ambient temperature forecast information, which has been proved to reduce energy consumption. Furthermore, the controller lacks predictive capabilities, which are essential for dealing with unforeseen disturbances. Actually, no controller that combines the on/off strategy, the MPC, and predictions on weather and occupancy has been reported in the literature. The goal of this paper is to suggest a simple, yet optimal controller for HVAC systems that integrates prediction on weather and occupancy to save energy in buildings. Such controllers are required for residential and small commercial buildings, where the cost of a controller is a key factor.

Our controller incorporates (i) a modified one-dimensional Kalman filter (MODKF) for numerical temperature prediction, (ii) a Hidden Markov Model (HMM) based occupancy prediction algorithm, (iii) a Predictive Smart Thermostat Controller (PSTC) that combines the features of the MPC and pulse-width modulation (PWM) technique to design a simple on/off controller for a HVAC system in buildings.

The paper is organized as follows. The HVAC model and problem formulation are presented in Section 2. Temperature prediction using the MODKF and occupancy prediction using the HMM are presented in Section 3. The PSTC algorithm is presented in Section 4. The approach suggested in this paper is compared regarding energy savings with the simple conventional thermostat controller in Section 5 using simulations on a building thermal model. The model itself was developed based on data from experiments. The future course of the study together with the conclusions are presented in Section 6.

2. PROBLEM FORMULATION

2.1. HVAC system

The HVAC system consists of a heater and an air conditioner with a single speed compressor that consumes full power when turned on and no power otherwise. Although a heater is a conventional part of HVAC systems, we do not take it into account as in this paper only the process of cooling is considered. The air conditioner consists of internal and external units. The external unit houses the compressor and condenser coils, and the internal unit has the blower. To simplify the analysis, we ignore the power consumed by the blower because the energy input to the air conditioner is mainly used by the compressor. The air conditioner is controlled using a thermostat. A small dead zone is given in the thermostat to avoid frequent switchings. The thermostat is the cheapest HVAC controller and our goal is to modify this simple controller in such a way that the designed controller also accommodates climate and occupancy forecasts in its design. This is achieved by modifications shown in Fig. 1. The control computer turns on and off the compressor using a relay circuit, and the thermostat is used for maintaining the temperature within the comfort range defined by the consumer. Door firings and the temperature sensor are used to measure occupancy and temperature, respectively, and the database (DB) stores the historical information on occupancy and the weather information from the Internet.

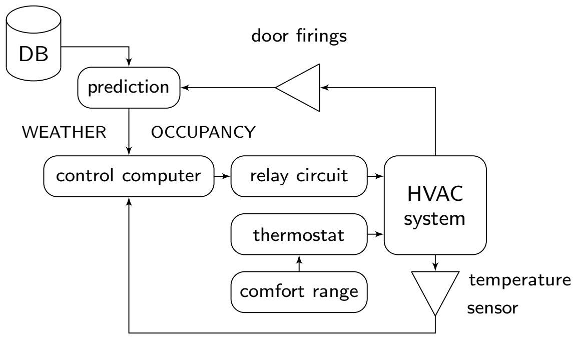

Fig. 1. Pulse-width modulation control of a HVAC system.

2.2. The model of building thermal dynamics

In our analysis, we employ the linearized sampled data model of the HVAC system, proposed in [5,20],

$$x(k+1) = ax(k) - bu(k) + k_1 w(k) + k_2 v(k), \quad (1)$$

where k indicates the discrete time instant, $x(k)$ is the building temperature at the time instant k in degrees of Celsius. We use the sampling time $T = 15$ min. The parameter $a > 0$ denotes the building thermal time constant; the parameter b denotes the temperature change over the period T due to the control input $u(k)$, i.e. models the effect of control input on the building temperature; the parameters k_1 and k_2 capture the effect of weather and occupancy on the building temperature; the variables $w(k)$ and $v(k)$ model the heating effects of weather and occupancy on the building thermal model, respectively [20]. Model (1) describes the thermal dynamics of the building following Newton's law of cooling. A similar model is employed in [3] for the HVAC control. A comprehensive review of modelling methods for HVAC systems can be found in [1].

2.3. Estimation of model parameters

To estimate the parameters of the building model (1), data were collected from a laboratory building for over 12 different working days from 8:30 a.m. to 10:00 p.m. by placing sensors in the four corners of the building. The occupancy level changed during the working hours and in the evenings; also data were collected on different days of the week to capture possible scenarios. The lab is actively used by students during regular working hours, after which the room has fewer students without much noticeable change in temperature. To model the system, a pseudo-random binary sequence input, generated from MATLAB, was used as the switching function and the HVAC was switched on and off manually depending on the generated sequence to record temperature values (see Fig. 2 for a typical period of 24 hours and 28 °C as the setpoint).

Observe that in (1) only the variables x, w, and u are measurable or known and the model is linear with respect to the parameters a, b, and k_1. The disturbance term v models the heating due to occupancy and other equipment in the building. Although $v(k)$ varies non-linearly in time, a non-linear model would make the MPC difficult to apply [20]. Therefore, we first estimate the parameters a, b, and k_1 using the least absolute shrinkage and selection operator (LASSO). Then, the difference between the actual (measured) and estimated temperatures gives $v(k)$. Figure 3 shows the estimated and the actual building temperature along with the model error. One can see from Fig. 3b that the error with the LASSO estimated building model is within ± 1 °C, which is a reasonable estimate considering the working temperature of the building. The error term is then used as the measurement of v to determine the parameter k_2 in the model. Since the disturbance term v behaves non-linearly in time, estimating the parameter k_2 is not straightforward. Analysis of data obtained from the experiment in the building and variation of weights in the weighted least squares suggested the existence of threshold values of the parameters k_1 and k_2 below which a linear thermal model of the building provides a reasonable prediction error. As a result, this modified estimates of the parameters a and b as well. The important outcome of this modification is that the linear model can be used in the MPC, thereby significantly reducing the computation complexity. Further, with the linear model, the MPC computations can be simplified by computing the prediction matrices off-line.

LASSO is a regression analysis method that performs regularization to enhance the accuracy of estimation via shrinking large regression coefficients to reduce overfitting. The LASSO estimate of the building model parameters can be formulated as an optimization problem

$$\min_z \frac{1}{N} \|Az - \beta\|^2 \tag{2}$$

subject to

$$|a| + |b| + |k_1| \leq t, \tag{3}$$

where t is a prespecified free parameter that determines the amount of regularization, $z = (a, b, k_1)^\mathsf{T}$ is the vector of parameters in (1) to be estimated, A is the $N \times 3$ regression matrix, and β stands for the measurement vector. In this paper we reformulate the constrained optimization problem (2) as a quadratic programming problem with the cost function

$$J(z) = z^\mathsf{T} A^\mathsf{T} Az - 2\beta^\mathsf{T} Az \tag{4}$$

subject to (3).

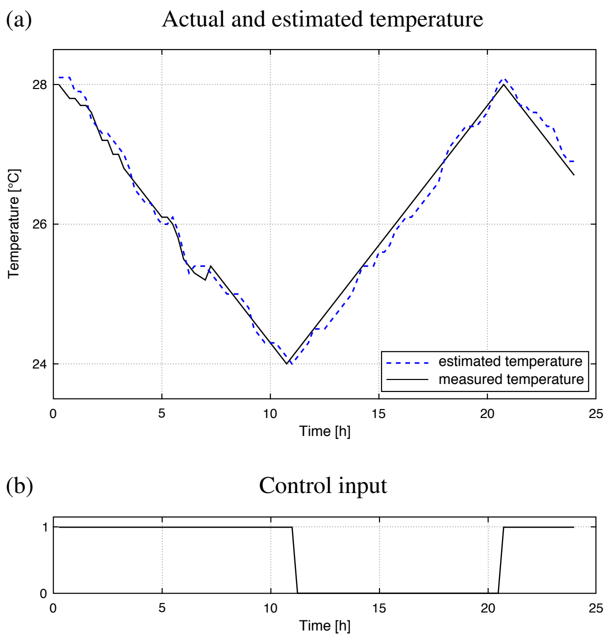

Fig. 2. Room temperature response to the HVAC.

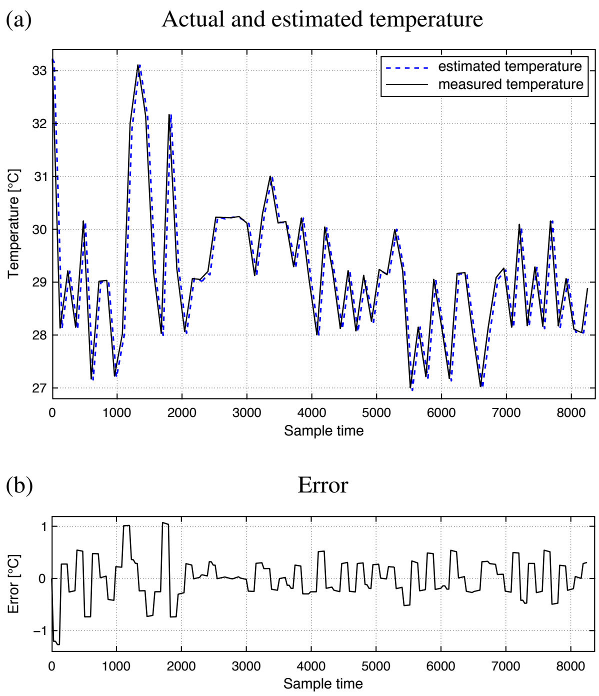

Fig. 3. Room temperature estimation with LASSO.

3. TEMPERATURE AND OCCUPANCY PREDICTION

3.1. Temperature prediction

Our controller needs the estimate of temperature $w(k)$ in (1) for computing the control input $u(k)$. The one-dimensional Kalman filter has proved to be a good tool for that purpose [10,11,22,23,27]. Note that in this subsection the sampling time T is not the same as in the model of building thermal dynamics (1). The Kalman filter actually works at a lower frequency (time step 1 h) because the outside temperature is not expected to vary significantly within one hour, or at least not to influence the building thermal dynamics. Moreover, in the Metropolis–Hastings (MH) sampler the discrete time step is 12 hours. We assume, like in [10], that the dynamics of temperature is random, yielding the system and observation (measurement) equations as

$$w(k) = w(k-1) + \varepsilon(k)$$

and

$$y(k) = w(k) + \mu(k),$$

respectively. The Kalman filter estimates recursively the unknown variable $w(k)$, based on observations y up to the time instant k. The prediction equations of the one-dimensional Kalman algorithm have the form

$$\hat{w}(k \mid k-1) = \hat{w}(k-1)$$

and

$$\mathscr{P}(k \mid k-1) = \mathscr{P}(k-1) + s^2_{\varepsilon(k)}. \tag{5}$$

The updating equations are given as

$$\begin{aligned} \hat{w}(k) &= \hat{w}(k \mid k-1) + \alpha(k)\left[y(k) - \hat{w}(k \mid k-1)\right], \\ \alpha(k) &= \frac{\mathscr{P}(k \mid k-1)}{\mathscr{P}(k \mid k-1) + s^2_{\mu(k)}}, \\ \mathscr{P}(k) &= [1-\alpha(k)]\,\mathscr{P}(k \mid k-1). \end{aligned} \tag{6}$$

Note that the variances of the noise terms $\varepsilon(k)$ and $\mu(k)$, i.e. $s^2_{\varepsilon(k)}$ and $s^2_{\mu(k)}$, affect crucially the outcome of the Kalman algorithm whereas the choice of the initial values $w(0)$ and $\mathscr{P}(0)$ does not. We update the variances once in every 12 hours using the 72 hour climate forecast, i.e. the computation of $s^2_{\varepsilon(k)}$ and $s^2_{\mu(k)}$ is based on the samples of 7 values of ε and μ, respectively. Then these values are used in equations (5) and (6) until the next update.

To get the samples of ε and μ, we rely on the MH sampler (see [30] and references therein). The MH sampler is an algorithm that generates a random sample from a distribution for which direct sampling is difficult. The key idea is to construct a Markov chain that converges to the given target distribution (in our case Gaussian), starting with simulating a ‘candidate’ sample from a proposal distribution (in our case uniform).

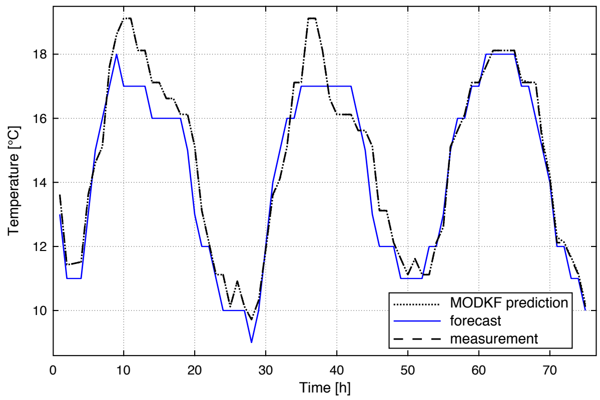

Fig. 4. Temperature estimation based on MODKF.

The Kalman filter combined with a MH sampler is called the modified Kalman filter (MODKF). To illustrate the accuracy of the MODKF, temperature profiles obtained from the forecast, the MODKF prediction, and the measurements for a period of three days in Tallinn are shown in Fig. 4.

3.2. Occupancy prediction

Another estimate one needs is that of occupancy [6,24], denoted by $v(k)$ in (1). Recently HMM, first proposed in [7], has emerged as a promising tool for modelling occupancy. For this purpose the forward HMM method was employed in [6]. In this investigation, we use the backward HMM method to compute the probability of occupancy being in *low*, *medium*, and *high* states, based on observations (door firings, historical occupancy rates, type of working day, time of day with 6 h window, etc.).

The HMM is described by the triplet $\Pi = \{T_{\mathrm{tr}}, X, Y\}$, where T_{tr} denotes the transition probability matrix, X denotes the observations, and Y the states. For a period of one day we used

$$T_{\mathrm{tr}} = \begin{bmatrix} 0.3 & 0.7 & 0 \\ 0.2 & 0.3 & 0.5 \\ 0.1 & 0.2 & 0.7 \end{bmatrix},$$

$$X = \begin{bmatrix} \textit{low} & \textit{low} & \textit{medium} & \textit{high} & \textit{high} \\ \textit{high} & \textit{high} & \textit{high} & \textit{high} & \textit{medium} \end{bmatrix}.$$

Given the HMM and an observation sequence, the most probable occupancy state is computed. The observed variables are type of working day (classified as *Fat*, *Normal*, *Vacant*, and *Vacate* based on historical information), the time of the day, type of the day, and occupation measurements via door firings (see more in [29]).

4. PREDICTIVE SMART THERMOSTAT CONTROL

4.1. PSTC description

We combine the MPC and the PWM and refer to the resulting controller as a *predictive smart thermostat controller* (PSTC). In principle, the PSTC is a controller whose on/off decisions are computed from the solution of an optimization problem. Additionally, the controller integrates predictions on outside temperature and occupancy forecast from the MODKF and the HMM, respectively, proposed in Section 3. The PSTC is shown schematically in Fig. 5. Measurements on inside temperature and door firings, necessary for occupancy prediction, are obtained from sensors in a building. In implementation, the PSTC algorithm has four steps: measure, update, compute, and apply. The variables $w(k)$ and $v(k)$ in the building model (1) are updated using the MODKF and the HMM.

The MPC is based on model (1) and the predictions $\hat{w}(k)$ and $\hat{v}(k)$. The optimization problem for a given prediction horizon is then solved under constraints imposed on the HVAC system.

4.2. PSTC algorithm

In principle, the PSTC (in implementation) is a PWM controller whose on/off decisions are computed from the solution of an optimization problem. Therefore, formulation of the optimization problem defines the energy saving capability of the PSTC. In order to implement the PSTC, first the prediction horizon N is defined. The MPC is a control strategy that solves an on-line optimal control problem in a receding horizon manner. The approach can be summarized in the following steps [12]:

(i) At time k and for given state $x(k)$, the open-loop optimal control problem is solved over the N-step prediction horizon, taking into account the *current* and *future* constraints.
(ii) The first element $u(k)$ in the optimal solution $U = (u(k),\ldots,u(k+N-1))$ is applied.
(iii) The procedure is repeated at the time instant $k+1$ using the state $x(k+1)$.

Given model (1), compute $\min_U J_1(N,x(k),U)$, where

$$J_1(N,x(k),U) = \sum_{l=k}^{k+N-1} \left(\hat{x}(l)^\top F\hat{x}(l) + u(l)^\top Hu(l)\right) \quad (7)$$

subject to

$$\hat{x}(l+1) = a\hat{x}(l) - bu(l) + k_1\hat{w}(l) + k_2\hat{v}(l) \quad (8)$$

and

$$X_{\min} \leq \hat{x}(l) \leq X_{\max}, \quad (9a)$$
$$U_{\min} \leq u(l) \leq U_{\max}, \quad (9b)$$

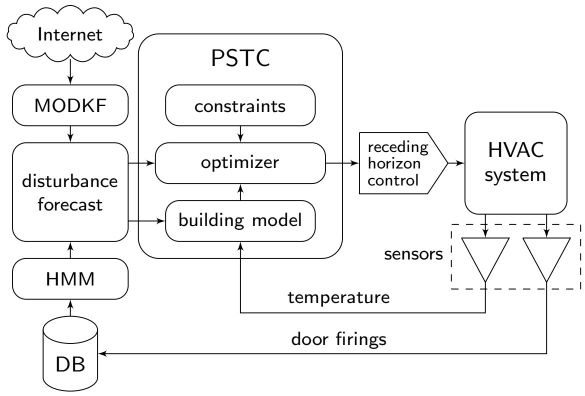

Fig. 5. Predictive smart thermostat controller.

where H and F are positive definite matrices, $\hat{x}(k)$ is the temperature estimated from (1) by using the estimate of the temperature $\hat{w}(k)^{-1}$ from the MODKF and occupancy estimate $\hat{v}(k)^{-1}$ from the HMM. The PSTC with the cost function (7) is referred to as PSTC 1. Such controller leads, unfortunately, to a severe computation load. A penalty method replaces a constrained optimization problem (7)–(9) by a series of unconstrained optimization problems, whose solutions (ideally) converge to the solution of the original problem. The measure of violation is non-zero when the constraints are violated and zero otherwise. For that, penalty functions (i.e. special terms consisting of a penalty parameter multiplied by a measure of violation of the constraint) are added to $J_1(N,x(k),U)$. We rewrite constraint (9a) as

$$\begin{aligned} \Upsilon_1(l) &:= X_{\max} \\ &\quad - (ax(l) - bu(l) + k_1\hat{w}(l) + k_2\hat{v}(l)) \geq 0, \\ \Upsilon_2(l) &:= -X_{\min} \\ &\quad + ax(l) - bu(l) + k_1\hat{w}(l) + k_2\hat{v}(l) \geq 0. \end{aligned} \quad (10)$$

Then, using the penalty function approach, proposed in [4], PSTC 1 can be reformulated as

$$\begin{aligned} \mathscr{J} &:= J_1(N,x(k),U) + \sum_{l=k}^{k+N-1} \big(\lambda_1(l)\max(\Upsilon_1(l),0)^2 \\ &+ \lambda_2(l)\max(\Upsilon_2(l),0)^2 + \lambda_3(l)\max(U_{\max}-u(l),0)^2 \\ &+ \lambda_4(l)\max(-U_{\min}+u(l),0)^2\big), \end{aligned} \quad (11)$$

where λ_i's are penalty parameters.

Assumption 1. *The optimization problem with the cost function* (11) *has a solution for all positive values of* λ_i*'s.*

Under Assumption 1 one can solve the optimization problem in three steps: (i) initialization of the penalty parameters $\lambda_i(l)$, (ii) solution of the unconstrained optimization problem, (iii) updating the penalty parameter $\lambda_i(l+1)$ that violates the constraint in (10).

The limitation of PSTC 1 is that the user preferences during different hours of the day are not taken into account. The optimizer tries to save energy throughout the day and even during periods of low energy consumption in grids (when the price of electricity is low), which is also undesirable from the grid perspective. The user preferences can be incorporated in the controller by adding into the cost function (11) a 'comfort term' $J_C(k)$, defined by

$$J_C(k) := e(k)^{\mathsf{T}} e(k),$$

where $e(k) = x_r - x(k)$ models the temperature variation from the setpoint x_r. In addition to $J_C(k)$, two weights α and β can be tuned by the consumer up to the restriction $\alpha + \beta = 1$. The resulting optimization problem, called PSTC 2, is defined as $\min_U J_2(N, x(k), U)$, where

$$J_2(N, x(k), U) = \beta J_1(N, x(k), U) + \alpha J_C(k) \tag{12}$$

subject to (8) and (9). The constrained optimization problem can again be solved using the penalty method.

The objective of the PSTC was to combine the existing thermostat controller to the MPC without affecting the existing hardware. This requires that the final control element, the thermostat, should not be modified and that we be only left with the option of changing the on and off time of the air conditioner. The PWM is a technique that generates continuous signals using on/off actuation signals and is an effective method for obtaining a quasi-continuous output, suitable for an on/off type actuator such as the single speed compressor. Hence, we are motivated to use a PWM controller that varies the power based on the duty cycle $\delta(k) := T_{\mathrm{on}}(k)/T = u(k)/u_{\mathrm{m}}$, where $0 \leq T_{\mathrm{on}} \leq T$ is the period when the continuous output is delivered, T is the total period considered, T_{on} corresponds to the period of cooling, $u(k)$ is the input signal obtained by the MPC, and u_{m} is the maximum value of the applied input. The control input from the PWM is determined by

$$u(t) = \begin{cases} u_{\mathrm{m}} \operatorname{sgn}(\delta(k)), & k \leq t < k + |\delta(k)| T, \\ 0, & k + |\delta(k)| T \leq t < k + T, \end{cases} \tag{13}$$

where $\operatorname{sgn}(\delta(k))$ indicates the direction of the signal ('+' for cooling and '−' for heating). Usually in HVAC systems the compressor cycle time (the time required for the compressor to complete one cycle) is used for computing T. The control input $u(t)$ thus models the duty cycle of the PWM controller. The PWM is implemented using a simple relay circuit that turns on/off, based on the signals generated by the control computer. Since frequent switching will lead to reliability issues due to chattering and incomplete compression, the sampling rate of T = 15 min as in [3,5] was chosen for reliability.

5. RESULTS AND DISCUSSION

In illustrating the proposed approach, for simplicity we consider only the cooling of the building. The performance of the controllers PSTC 1 and PSTC 2 was compared with the conventional thermostat controller based on MATLAB simulations, and climate forecasts were obtained from the Internet. Forecasts were entered to the data-log computer and transmitted to the control computer. Door sensor firings were used for occupancy predictions, while occupancy measurements were done manually by counting the people entering and leaving the building. The setpoint temperature of 22 °C was used in the simulation with an upper comfort margin of 25 °C and lower margin of 20 °C.

The performance of the PSTC 1 algorithm for 10 hours on a normal day is shown in Fig. 6. Predicted and measured occupancy are shown in Fig. 6b. One may observe that the occupancy predicted by the HMM is accurate enough and the predictions improve in time as the HMM uses the occupancy measurements. The status of the HVAC unit shown in Fig. 6a indicates whether it is on or off, the number 1 corresponds to on and 0 to off. When both the temperature and occupancy of the building are low, the length of the cooling period T_{on} is short, and as occupancy increases its length increases. This indicates the energy saving performance of the PSTC 1. Temperature variation in the room with the PSTC 1 for 24 hours is shown in Fig. 6c. It illustrates that the PSTC 1 not only maintains the temperature within the comfort region but also uses it effectively for minimizing energy costs, i.e. uses the lower comfort margin to cool the building at a low occupancy and uses the upper margin for a high occupancy level.

Performance of the PSTC 2 for 10 hours on a normal day is shown in Fig. 7. Energy savings can be observed from the status of the HVAC system, shown in Fig. 7a. The additional comfort term in (12) improves the temperature profile significantly as shown in Fig. 7c. The

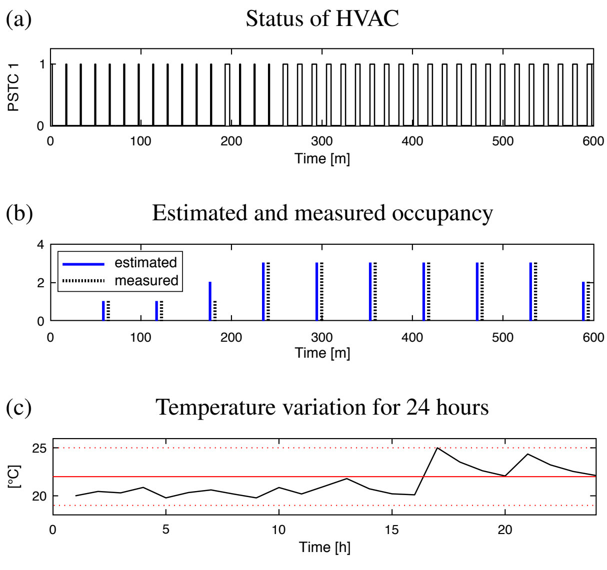

Fig. 6. Performance of the PSTC 1 algorithm for a normal day.

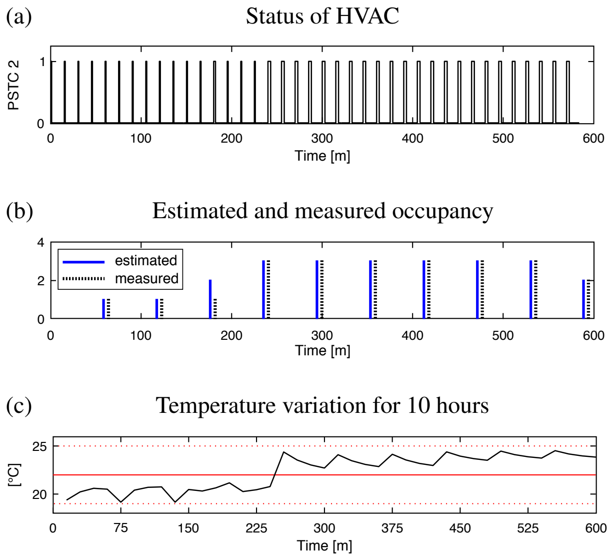

Fig. 7. Performance of the PSTC 2 algorithm for a normal day.

simulation points to the fact that when in (12) $\beta > \alpha$, the energy savings and predictive performance of the PSTC 2 are better than those of the PSTC 1. This can also be seen in Fig. 7a: the occupancy is predicted to be medium, and so there is a reduction in the length of T_{on} with the PSTC 2, whereas the PSTC 1 continues to apply the input during this time period, as shown in Fig. 6a. Comparison of the PSTC 1 and PSTC 2 control inputs by increasing α in (12) is shown in Fig. 8. One may observe that the energy savings and predictive behaviour of the PSTC 2 are significantly reduced. This is an expected behaviour as a greater impact of the comfort level increases energy consumption. Thus, the choice of α determines the performance of the PSTC 2.

The energy consumed in a HVAC system can be expressed via the following equation:

$$E \approx E_{\text{ss}} + E_{\text{tr}},$$

where E_{ss} and E_{tr} represent the steady-state and transient energy consumption in the compressor motor, respectively. The HVAC system consists of a water-cooled 10 horsepower single speed compressor (tonnage 10 TR, 380–415 V, 50 Hz, 16 A, COP 3.15–3.35). Denoting the power rating (nominal power) of the compressor motor by P, the steady-state energy consumption in kWh is

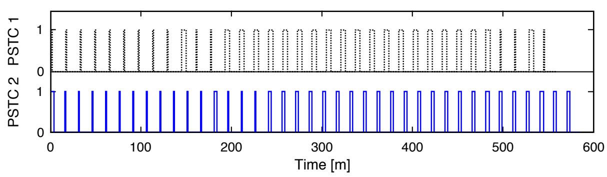

Fig. 8. Comparison of the PSTC 1 and PSTC 2 inputs.

Table 1. Energy consuption in the PSTC 1 and PSTC 2 for 1 h in kWh

Day	Thermostat	PSTC 1	PSTC 2
Fat	5.8	3.8	3.72
Normal	4.6	2.93	2.86
Vacant	2.8	1.24	1.02
Vacate	1.5	0.95	0.88

$E_{\text{ss}} = P \times 0.746 \times \delta_a \times \tilde{T}$, where δ_a is the average duty cycle for the time period $\tilde{T}$. The energy consumption is high for a short transient period at the beginning and is computed as $E_{\text{tr}} = 1.25 \times P \times 0.746 \times \delta_{\text{tr}} \times \tilde{T}$, where δ_{tr} is the ratio of the transient period (computed from the mechanical time constant of the motor) to the total period considered (T). In order to compute the total energy, we need to remove the component of the transient part accounted in the steady state part. This is done by using a compensation term $\chi = 0.25 \times P \times 0.746 \times (\delta_a - \delta_{\text{tr}}) \times \tilde{T}$. Thus, the total energy consumed in the HVAC system is

$$E_{\text{total}} \approx E_{\text{ss}} + E_{\text{tr}} - \chi. \tag{14}$$

Using (14), we compute the energy consumed by the PSTC 1 and PSTC 2 for a period $\tilde{T}$ = 1 h in the room (a laboratory with a ground floor, a mezzanine, and a first floor) of the size 12 m × 10 m × 10 m for different kinds of days in our repository with a high occupancy during the period for which the energy consumption is calculated and record the energy consumption in Table 1.

6. CONCLUSIONS

In this paper, a simple yet optimal controller for the HVAC control is proposed, called the predictive smart thermostat controller (PSTC). This controller combines the MPC with the PWM approach, leading to a simple on/off implementation. Furthermore, it integrates information on occupancy and weather forecasts to save energy. The controller does not require modification of the hardware.

To obtain the parameters of the building model, data collected from the test building were used. The data collected during the experiments showed that due to occupancy, the heating varies non-linearly in time. The presence of parameter threshold values models the disturbance below which the model is linear. To obtain the linear model, the parameter identification task was treated as a LASSO problem, and solved using a quadratic programming approach. The resulting model showed reasonable accuracy and was used in the MPC.

Next, since the implementation of the MPC requires accurate estimates of outside temperature, i.e $w(k)$ in (1), a modified one-dimensional Kalman filter (MODKF) was designed to predict the outside temperature using the weather forecasts. Our simulation results showed that the MODKF leads to a significant improvement in the numerical weather prediction accuracy. Occupancy was predicted using the Hidden Markov Model, which predicts the future state using the current measurements and information on the building occupancy for different days. As a result, an information updating mechanism was introduced in the occupancy prediction and the proposed model showed good prediction accuracy of occupancy.

Finally, two Predictive Smart Thermostat Controllers, denoted as PSTC 1 and PSTC 2, were proposed to optimize the control inputs based on a constrained optimization problem, using the building model and disturbance estimation to reduce the energy consumption. The PSTC 1 optimizes a quadratic cost function under the constraints. Although the controller shows significant energy savings, it does not enable taking into consideration user preferences. To overcome this shortcoming, the cost function of the PSTC 2 includes an additional comfort term and two weights that can be tuned by the user. Both controllers showed energy savings compared with the traditional thermostat controller.

The results further demonstrated that the PSTC 1 and PSTC 2 were not only able to save energy, but their implementation was also simple. As a result, the proposed controllers can be implemented in residential buildings where the controller cost is a major obstacle to the adaptation of energy saving controllers.

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Ennustava nutitermostaadiga kontroller kliimasüsteemide jaoks

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On leitud lihtne ja energiasäästlik kontroller kliimasüsteemide jaoks. Kontroller kombineerib ruumi hõivatuse ja välistemperatuuri hinnanguid mudelipõhise ennustava optimaaljuhtimisega. Kliimasüsteemi sisse- ja väljalülitamiseks kasutatakse pulsilaiusmodulatsiooni lähenemist, mis põhineb ennustava kontrolleri optimaalsel lahendil. Viimane võimaldab saada lihtsa kontrolleri, mis ei vaja riistvara väljavahetamist. Pakutud kontroller on teatud mõttes optimaalne, aga vaatamata sellele lihtne, mistõttu sobib nii elu- kui ka keskmise suurusega ärihoonete jaoks, kus kontolleri madal hind on oluline. Kontrolleri efektiivsust illustreeritakse simulatsioonide abil ja hoone soojusdünaamika mudeli identifitseerimine põhineb eksperimentaalsetel andmetel.