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Predictive Control for Heating Applications

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ABSTRACT

Siemens Building Technologies Landis & Staefa Division in Zug, Switzerland developed a predictive control algorithm that was first tested with simulations using historical weather data and then has been implemented in field tests that are currently running. The control algorithm makes use of numerical optimization technique for a linear dynamic model with input, rate of input change and state constraints. The algorithm computes periodically (every 20 minutes) the set point of the flow temperature control loop of the hot water heating system in such a way that the comfort temperature in the rooms can be maintained over a moving optimization horizon of fixed length (3 days) with minimum energy (receding horizon strategy). In order to achieve this goal, the control algorithm uses predictions of the behavior of the disturbances that act during the optimization horizon on the rooms under control. These predictions are generated using either past information or forecast information from an external weather forecast service or both.
The algorithm is an alternative to the classic outside temperature compensated control of heating systems with a heating curve, an optimum start stop control (OSSC) and a heat release algorithm, taking into account the dynamics and the practical limitations in a more natural way. Benefits of the algorithm are: comfort with minimum energy, easy to tune, easy to understand and possibility of straightforward extensions to other applications. Experiences with the algorithm in real buildings were very promising. The program runs currently on a PC that is connected to a Siemens Building Energy Management System. It is written in MATLAB and C.
The paper describes the algorithm and shows some results of simulations and of field tests

1. INTRODUCTION

Predictive controllers are controllers that somehow account for future behavior. The predictive controller considered in this paper belongs to a specific class of predictive controllers that are based on optimal control in a deterministic sense. A controller of this class continually, periodically, or at selected time points, looks ahead for a specific time horizon, predicts the disturbances over the time horizon, determines the control variable's optimal behavior during this time horizon, and applies the determined behavior until the next time point is reached when the controller again looks ahead. Although the evolution of the unknown disturbances is random, the controllers assume that the predicted disturbance is true, and therefore deterministic optimal control methods can be applied for the determination of the control's variable optimal behavior (certainty equivalence control). It helps the understanding, to think of the behavior of the control or other variable over the mentioned time horizon as a "profile" of the variable. The time horizon is called the prediction or optimization horizon. The different controllers of this class differ in the predictors, the models (state space models or input/output models) and the performance indices (choice of norms and of variables to be optimized) that are used.

Many predictive controllers belong to this class: the general predictive control (GPC) and model based predictive control (MBPC) methods [T.J.J.van den Boom 1996, H. Demircioglu et al. 2000]. Furthermore the following special purpose predictive controllers belong also to this class: all the predicted controllers presented at the CLIMA 2000 Conference in Brussels [J.Tödtli 1997], the GPC approach with a linear system model in [H.Erker 1992] and the NEUROBAT controller [NEUROBAT 1998]. The NEUROBAT controller solves the deterministic optimization problem by applying the deterministic dynamic programming method with the argument that a nonlinear neural net based system model and a nonlinear, not quadratic objective function was used.

A different approach to the certainty equivalence based controllers is possible if for the optimization one takes the uncertainty of the predicted disturbances explicitly into account. Probabilistic models of the disturbances are needed for this approach. This leads to stochastic optimization methods where probabilistic quantities influence the control action [D. Bertsekas 1987, J.Tödtli 2000].

We concentrate us here on one control application: the outside temperature compensated control of heating systems with a heating curve, an optimum start stop control (OSSC) and a heat release algorithm. The new algorithm was developed for two cases and are alternatives for the following classical solutions:

1. We assume that in a multi-room building one north oriented room (little heat gains) is used as a reference room and is equipped with a room temperature sensor that at least is used for the adaptation of one of the room models. All the other rooms are equipped with thermostatic valves and fed with hot water from the same heating circuit. The flow temperature set point is mainly determined by a feed forward control of the outdoor air temperature via the heating curve
2. The situation is the same as in 1) except for the fact that no room temperature sensor is available for the control. Therefore no automatic adaptation of a room model is possible.

In this paper we will only consider case 1). Instead of determining the flow temperature set point via the heating curve, it will be found by the predictive controller.

The goals that can be achieved by the predictive control method presented in this paper are at least threefold:

1. Current advanced devices for outside temperature compensated control of heating plants have integrated among other functions three specific functions that either rely on predictions of future behavior and/or use some kind of room (building) model. These three functions are:
   - Flow temperature control by outdoor temperature feed forward control via heating curve. This method uses a static model (heating curve) of the room expanded by a dynamic model for capturing the delay caused by the outside wall.

- Optimum start- stop control (OSSC) for reaching the indoor temperature set point profile in an economic way. This method uses a dynamic model for the prediction of the indoor temperature.
- The heat release algorithm (the algorithm that switches the heating plant on and off) uses a different dynamic model of the building.

The predictive control method has the capability to replace the three above algorithms by one function. This function uses one model with one set of parameters. It is expected that this fact makes the tuning of the parameters easier and the general concept easy to explain.

2. The predictive controller controls the heating plant such that the required comfort is achieved with minimum energy. Energy savings are achieved by minimization of an objective function that penalizes the energy consumption. The objective function is linear in the energy consumption. The comfort is not part of the objective function. Its specifications are formulated as inequality constraints as will be seen later.

3. The new method opens up opportunities for straightforward extensions of the algorithm to new applications. These are for instance:
- The influence of the user behavior on comfort and energy use can be estimated by model based predictive computation
- Warnings based on predicted calculations can be generated, for instance for frost alert.
- Display of different quantities like estimated heat gains and heating curve parameters are possible.
- If all rooms that are supplied by water with the same flow temperature are influenced by solar gains (single family homes, one heating circuit for south oriented rooms in office buildings) and a solar sensor is available, the weather forecast block can be extended by solar gain prediction.
- For systems with heat storage, general heat storage and energy management methods combined with different pricing policies can be treated similarly.

2. BASIC CONTROL CONCEPT

The basic control concept is shown in Figure 1. The system to be controlled consists of the flow temperature control loop including the room to be controlled. The control input to this system is the set point of the flow temperature and the output is the room temperature. An additional control input is the pump control signal that is activated by a control logic. Disturbances to this system are typically the outdoor air temperature, and solar and internal heat gains. It is assumed that this system can be described by a set of differential and algebraic equations. For many heating applications, the room temperature set point is a function of time that can be presented by a room temperature set point profile over time. It is assumed that at a given time this profile is known in advance at least for a time period of fixed length L. The predictive controller works now as follows: at a given time t=kT, where T is the sampling time, the following steps are carried out:

1) A profile of predicted disturbances (here outdoor air temperature) over the optimization horizon of length L is computed in the forecast block by using measured disturbance data up to kT and possible forecast information from an external weather forecast service (supplied over the Internet).

2) The room temperature set point profile is generated by using for instance information from the occupancy scheduler.
3) The elements of the state of the system to be controlled have to be measured or determined by an observer mechanism if not all are measured.
4) The controller, after having obtained these three different input vectors – the two profiles and the state - by performing step 1), 2) and 3) at time kT, will compute in step 5) the future behavior of the output of the controlled system over the time horizon of length L. To do that the predictive controller needs a model of the system to be controlled. If the parameters of this model are not known, an adaptive mechanism is used to estimate these parameters.

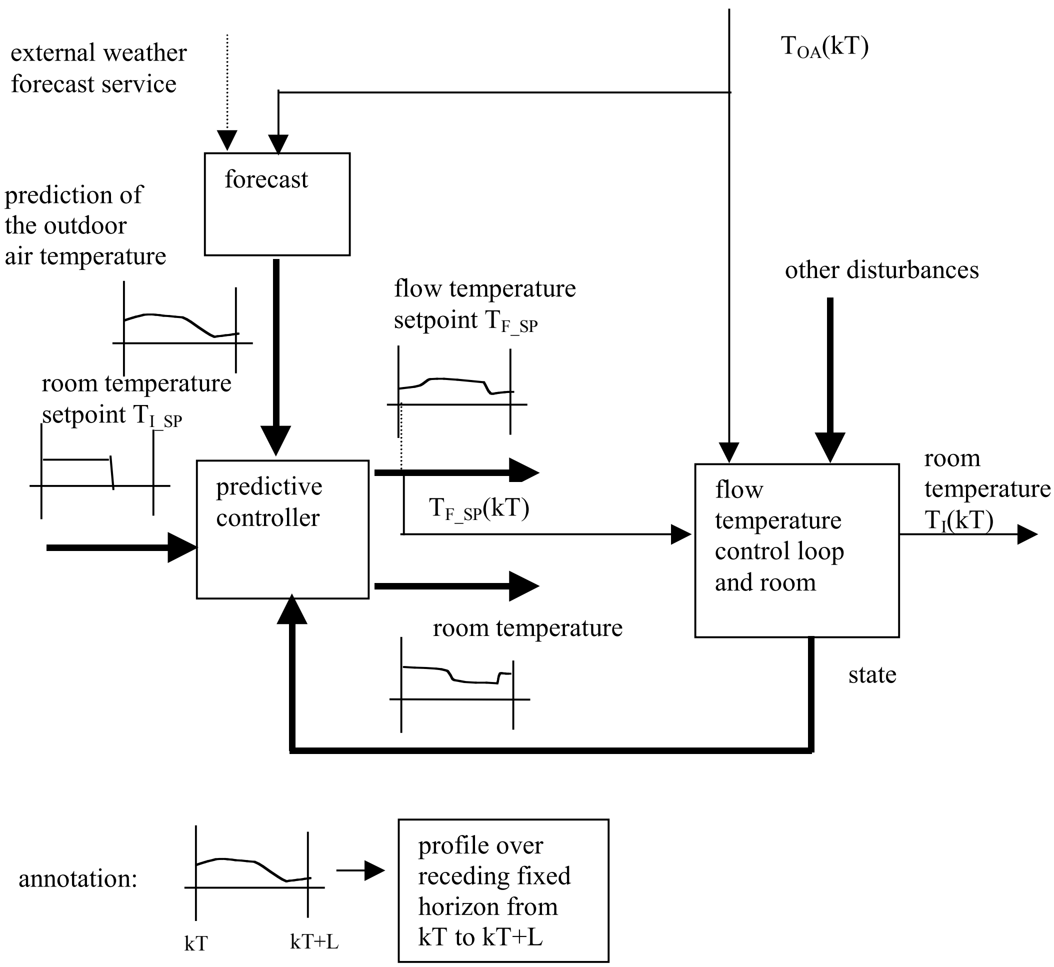

Figure 1: basic control concept

5) The predictive controller computes the future flow temperature set point profile such that the predicted room temperature profile fulfills the desired conditions with minimum energy. In order to do that the objective function is minimized. Additional inequality constraints on the flow temperature set point due to practical limitations have to be met too. An additional output of the control algorithm is a profile of the state over the horizon.
6) The control profile that is computed in step 5) is an open loop control profile under the assumption that everything that influences the system in the time interval [kT, kT

+ L] is known at time t=kT. As there are uncertainties in the disturbances and the modeling, the computed profile is not perfect and therefore is corrected periodically. This leads to a closed loop control structure, where the actual state is fed back periodically, the current value of the proposed future control signal is applied and the rest is discarded.

7) All the above steps are carried out at every sample instant, which is known as the receding horizon strategy.

The chosen control algorithm has the following additional features:

- The room model chosen is a linear second order model capturing the most important features of the room needed for fulfilling the given task. A linear model allows the use of fast optimization methods. It is also assumed that the flow temperature is controlled by a PI controller such that the set point is perfectly met.
- Linear programming technique has been chosen as optimization technique. With this technique all kind of equality and inequality constraints can be easily incorporated. Additionally, the objective function to be minimized is linear in the variables to be optimized.
- The receding optimization horizon can be extended to up to three days that allows to anticipate weekend room temperature setbacks and the ¨Monday morning¨ effect.
- The prediction can be evaluated for two (or three) different intervals in series, one with a short sampling time and one with a longer sampling time. This feature takes into account that for temperature control applications events in the distant future have less influence on the immediate behavior than events in the near future.
- An adaptive algorithm has been implemented which can adapt the linear process model continuously. The identification can be done by a linear least square method because the discrete model is linear in the discrete parameters.
- The measured room temperature can be filtered with the observer used for the estimation of the non-measured elements of the state in order to smooth oscillatory behavior due to differences between the real room and the used model in the controller.
- Major nonlinearities are reduced by underlying control loops, justifying the use of a linear model

The algorithm is described in greater detail in [Gruber et al. 1999]

3. WEATHER FORECAST

The weather forecast is only done for the outdoor temperature. It can be extended to solar gains depending on the applications. In the literature several sophisticated methods like ARX models or neural networks have been used [NEUROBAT 1998].

We used here a variation of the simple persistency method: from the temperature profile of the last 24 hours the next 24 hours are calculated by just copying the profile and make a linear correction over the next 6 hours by taking the measured actual outdoor air temperature into account. This is repeated at every new sampling time (e.g. 20 minutes).

The persistency method has been evaluated on long time series of historical data and showed a performance in terms of standard deviation from the correct values from 2.5 up to 4 degrees Celsius for a one day up to a three-day prediction. The method was also compared with forecast methods where the forecasted values of the minimum and maximum daily temperature are supplied from an external weather forecast service. For these methods different kind of interpolation functions [ASHRAE 1993] were used for the profile generation. With this approach a standard deviation of 1.7 up to 2.2 were achieved [in ‘t Groen 2000]. The influence of inaccurate temperature predictions on the control performance is considerably smaller than the standard deviations obtained above. Solar gain prediction would be more difficult to predict [NEUROBAT 1998]. Extensions of the presented method will investigate how the solar influence can be built in usefully.

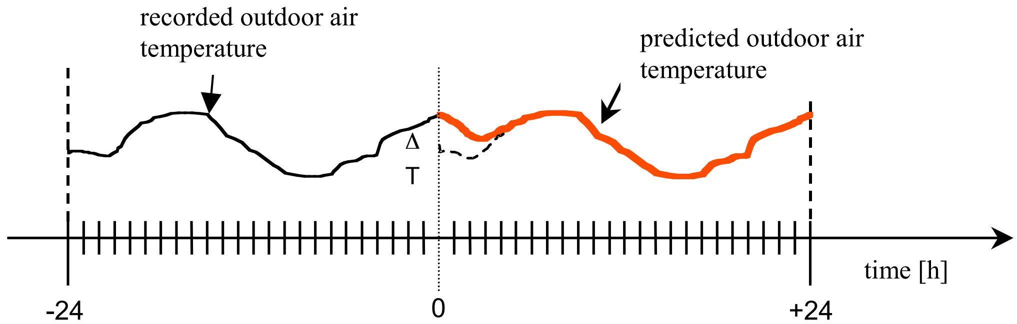

Figure 2: weather prediction

4. ROOM MODEL

4.1 Continuous model

The controller uses a linear room model of second order for the optimization. The physical representation is shown in Fig 3. The two heat storages with its heat capacities are 1) the room air and inner light construction and 2) the outside wall. On the first node act the heating power and the heat gains directly. Across the two overall thermal conductances G_{ID} of the outside wall an indirect heat exchange between inside and outside is possible via the outside wall node. Across the thermal conductance G_D, representing the thermal conductance of the windows and the air exchange rate, a direct heat exchange between inside and outside is possible. A continuous state space model can then be derived with the following equations:

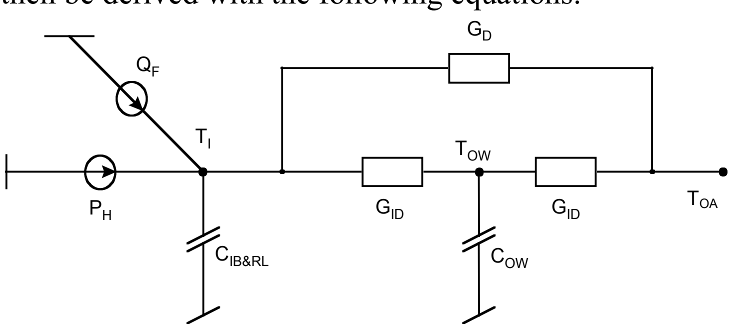

Figure 3: room model

$$\dot{\underline{x}} = A\underline{x} + B\underline{u}$$

$$\begin{bmatrix} \dot{T}_{IB\&RL} \\ \dot{T}_{AW} \end{bmatrix} = \begin{bmatrix} -\dfrac{G_D + G_{ID} + kF\,f(v)}{C_{IB\&RL}} & \dfrac{G_{ID}}{C_{IB\&RL}} \\ \dfrac{G_{ID}}{C_{AW}} & -\dfrac{2G_{ID}}{C_{AW}} \end{bmatrix} \begin{bmatrix} T_{IB\&RL} \\ T_{AW} \end{bmatrix} + \begin{bmatrix} \dfrac{kF\,f(v)}{C_{IB\&RL}} & \dfrac{G_D}{C_{IB\&RL}} & \dfrac{1}{C_{IB\&RL}} \\ 0 & \dfrac{G_{ID}}{C_{AW}} & 0 \end{bmatrix} \begin{bmatrix} T_{VL} \\ T_A \\ Q_F \end{bmatrix}$$

$$\underline{u} = \begin{bmatrix} T_F \\ T_{OA} \\ Q_F \end{bmatrix} \quad \underline{x} = \begin{bmatrix} T_I \\ T_{OW} \end{bmatrix} , \quad \begin{aligned} &P_H = kFf(v)(T_F - T_I) \\ &f(v) = v(1 - e^{-\frac{1}{v}}), \qquad v = \frac{c_w \dot{m}_w}{kF} \end{aligned} \qquad \text{[Tödtli 1984]} \qquad (1)$$

Q_F: heat gains
P_H: heating power
T_I: temperature of room air and inner light construction
T_{OW}: temperature of the outside wall
G_D: overall direct thermal conductance between T_I and T_{OW}
G_{ID}: half of the thermal conductance of outside wall
$C_{IB\&RL}$: heat capacity of room air and inner light construction
C_{OW}: heat capacity of outside wall
kFf(v): modified thermal conductance of radiator
T_F: flow temperature, equal to T_{F_SP} (ideally PI controlled)

4.2 Discrete model

From the set of equation (1) the following discrete time model can be derived:

$$\begin{aligned} \underline{x}_{k+1} &= F\underline{x}_k + G\underline{u}_k \\ y_k &= \begin{bmatrix} 1 & 0 \end{bmatrix} \underline{x}_k \end{aligned} \qquad (2)$$

The parameters of the matrices F and G are complicated functions of the parameters of the continuous matrices A and B and the sampling time T. The difference equation for the output variable y_k corresponding to $T_{I,k}$ is:

$$\begin{aligned} y_k = (f_{11} + f_{22})y_{k-1} + (f_{12}f_{21} - f_{22}f_{11})y_{k-2} + g_{11}u_{k-1} + (f_{12}g_{21} - f_{22}g_{11})u_{k-2} \\ + g_{12}w_{k-1} + (f_{12}g_{22} - f_{22}g_{12})w_{k-2} \\ + g_{13}q_{k-1} + (f_{12}g_{23} - f_{22}g_3)q_{k-2} \end{aligned}$$

$$y = T_{IB\&RL} \qquad u = T_{VL} \qquad w = T_A \qquad q = Q_F$$

As no predictions are available for the gain q, the terms with q_{k-1} and q_{k-2} are treated as one unknown coefficient p_7. The difference equation can therefore be written as:

$$y_k = p_1 y_{k-1} + p_2 y_{k-2} + p_3 u_{k-1} + p_4 u_{k-2} + p_5 w_{k-1} + p_6 w_{k-2} + p_7 \qquad (3)$$

$$\begin{aligned} &p_1 = f_{11} + f_{22} && p_2 = f_{12}f_{21} - f_{22}f_{11} && p_3 = g_{11} && p_4 = f_{12}g_{21} - f_{22}g_{11} \\ &p_5 = g_{12} && p_6 = f_{12}g_{22} - f_{22}g_{12} && p_7 = g_{13}q_{k-1} + (f_{12}g_{23} - f_{22}g_{13})q_{k-2} \end{aligned}$$

4.3 Adaptation of the model parameters

Generally the parameters of the discrete model have to be identified and eventually adapted. Consecutive measurements of the outdoor air, flow and room temperature are used in the adaptation method. If one looks at the seven parameters p_1,.., p_7 in equation (3), one can distinguish for different kind of parameters:

p_1 and p_2 represent the dynamic of the room

p_3 and p_4 represent the coupling of the flow temperature to the room

p_5 and p_6 represent the coupling of the outdoor air temperature to the room

and p_7 represents the internal and external gains.

The parameter update is done by a recursive estimation scheme with a bounded gain forgetting factor [Ljung, 1987].

$$\underline{\hat{p}}_k = \underline{\hat{p}}_{k-1} + \frac{P_{k-1}\varphi_k(y_k - \varphi_k^T \underline{\hat{p}}_{k-1})}{\lambda_{k-1} + \varphi_k^T P_{k-1}\varphi_k} \qquad \underline{\hat{p}}_k \text{ is the estimate of } \left[p_1\ p_2\ .....p_7\right]^T \text{ at time kT}$$

$$P_k = \frac{1}{\lambda_{k-1}}\left[P_{k-1} - \frac{P_{k-1}\varphi_k\varphi_k^T P_{k-1}}{\lambda_{k-1} + \varphi_k^T P_{k-1}\varphi_k}\right]$$

$$\lambda_k = \lambda_{\min} + (1 - \lambda_{\min})\frac{\left\|P_{k-1}\right\|_{Frobenius}}{p_{\max}} \qquad (4)$$

The measurement vector is $\varphi_k = [y_{k-1}\ y_{k-2}\ u_{k-1}\ u_{k-2}\ w_{k-1}\ w_{k-2}\ 1]^T$ and the norm of the covariance matrix P_k of the estimation error of $\hat{p}_k$ is the Frobenius norm:

$$\|A\|_{Frobenius} = \sqrt{\sum_{i,j}\left(a_{ij}^2\right)}$$

λ_{min} and p_{max} are chosen as 0.99 and 0.2. Initialization of P is a diagonal matrix with elements of value 0.001 and the initialization of the parameter vector is done by a crude approximation. The experiences that were made during the field tests showed that the initialization is not critical. The controlling of the forgetting factor is done by the equation (4) given above. Arguments for this equation can be found in [Kraus 1986].

4.4 Observer

The predictive controller needs an estimate of the complete state of the system. In the difference equation form (equation (3)), the state corresponds to two consecutive measurements y_k and y_{k-1} of the indoor temperature. Because the model does not correspond fully to the reality, differences cause unwanted oscillatory behavior. This could be observed in simulations where the simulated room was not identical to the room model used in the controller and also in the field tests. The second order linear observer that was implemented reduced this effect: it acts as a smoothing filter of the system state. The advantage to a simple low pass filtering of the output is, that the filtering function of the observer could be realized with shorter delays.

5. OPTIMIZATION

5.1 Equality constraints

The previous paragraph derived the model that is used in the predictive controller for computing future outputs. In the optimization scheme the model equation leads to an equality constraint for each future point in time which is computed. Let us denote the number of predicted values by n. To complete the formulation of the optimization problem, the objective function and the inequality constraints must be formulated.

5.2 Inequality constraints

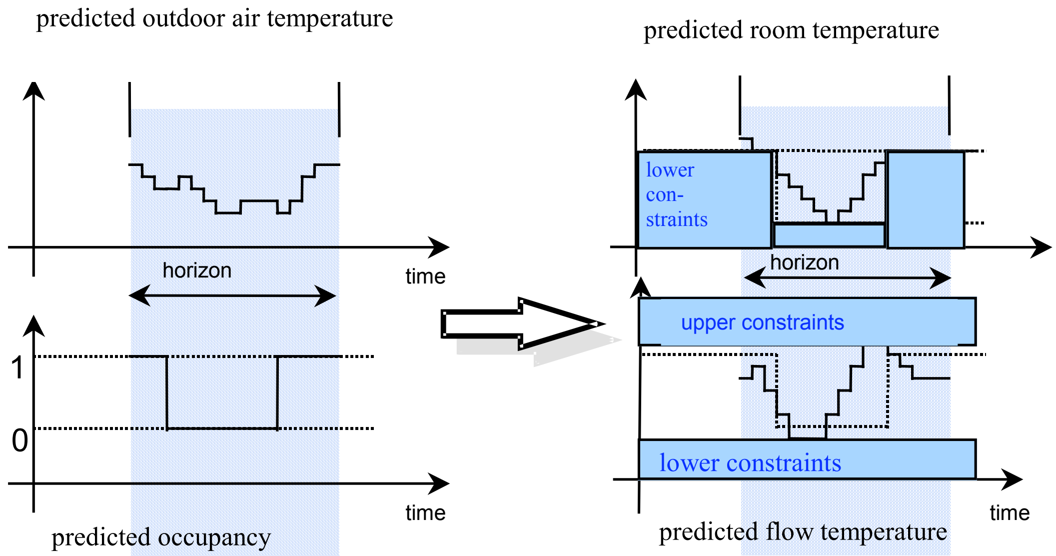

Figure 4: constraints for the predicted profiles

Figure 4 illustrates the main constraints that have to be taken into account. Four profiles are displayed: on upper left side the predicted outdoor air temperature and on the lower left side the occupancy profile. From that profile the room temperature set point profile is deduced, that is visible on the upper right side picture. In the occupied mode the set point is set to $T_{comfort}$ and in the non-occupied mode to the set back temperature T_{min}. This room temperature set point profile acts as a lower bound for the room temperature; that means at each calculated point in time of the horizon the following inequality constraints is formulated:

$$T_{I,k+j} \geq T_{\min} \text{(non occupied mode) or } T_{comfort} \text{(occupied mode)} \qquad j = 1,..n \qquad (5)$$

A typical profile of the room temperature is also shown in the upper right side picture. In the lower right side picture a profile of the predicted flow temperature is shown. This profile is squeezed in between the upper and lower bound for the flow temperature. The upper bound is here assumed to be constant. A generalization with a time dependent bound is possible. The lower bound is either also constant or can be made dependent on the room temperature. These constraints lead then to the following inequalities

$$T_{I,k+j} \leq T_{F,k+j} \leq T_{F\max} \qquad j = 1,..,n \qquad (6)$$

Additional to these constraints, the upward and downward change in the flow temperature from one sampling time to the next one is also formulated constraints:

$$-\Delta T_{F\_down} \leq T_{F,k+j} - T_{F,k+j-1} \leq \Delta T_{F\_up} \qquad j = 1,..,n \qquad (7)$$

The total number of equality constraints is n and of inequality constraints is 4n. By a transformation of the variables, the number of inequality constraints can be halved:

$\widetilde{T}_F = T_{F\max} - T_F \qquad \widetilde{T}_I = T_I - T_{I\_\min}$

where T_{I_min} is either T_{min} or $T_{comfort}$. With this transformation new inequality constraints of the form

$\widetilde{T}_F \geq 0 \qquad$ and $\qquad \widetilde{T}_I \geq 0$

are introduced. These inequalities are easier treated by the linear programming methods than the former ones.

5.3 Objective function

In order to formulate the objective function it is useful to look closer at the division of the optimization horizon into the different time steps. As was mentioned before, the horizon of lenght L is split into two intervals L_1 and L_2 such that $L = L_1 + L_2$. The first interval is divided into n_1 small intervalls of length T, and the second interval into n_2 intervalls of length 4T. The restriction to n_1 and n_2 is:

$(n_1 + 4n_2)T = L$

Figure 5 illustrates this partitioning of the optimization horizon. With two different sampling times T and 4T the difference equation (3) must be formulated twice leading to two sets of p parameters. A specific difficulty arises when the sampling switches from T to 4T. For this step a special set of p parameters has to be derived.

The partitioning of the horizon is not limited to two intervals and the relation between fast and slow sampling can be also another integer ratio. The reason for this partitioning (apart from the reason given in section 2 of this paper) lies also in the fact that the dimension of the optimization poblem is quadratically dependent on the number of points in the optimization horizon.

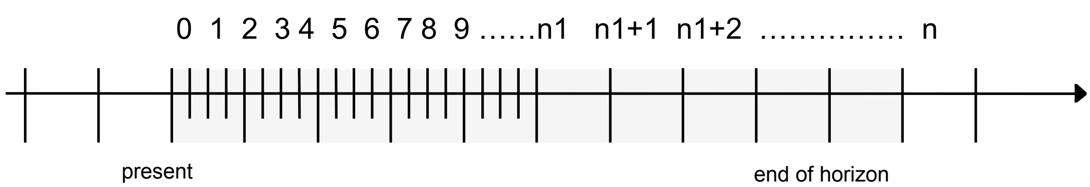

Figure 5: partitioning of the horizon

The objective function in the case of linear programming can now be formulated in this way:

$$J(\underline{y},\underline{u}) = \sum_{i=1}^{n} f_i y_i + \sum_{i=n+1}^{2n} f_i u_{i-(n+1)} \tag{8}$$

The elements of $\underline{u}$ and $\underline{y}$ are the flow temperatures and room temperatures (or the transformed variables) at t=kT+iT, i=1,..n1, and t=kT+i4T, i=n_1+1,..n. The vector $\underline{f}$ is a weighting vector for the variables. The objective function, as already mentioned in section 1) and 2), is used to minimize the energy consumption. This is achieved by minimizing the integral of the profile of the flow temperature set point. Therefore the elements of the vector $\underline{f}$ are now chosen as follows. The first n weights are set to zero. The second n weights of $\underline{f}$ for the flow temperature that are related to the energy consumption, have to be divided into two separate values. Due to the different lengths of the time intervals in the time horizon the flow temperatures have to be weighted with the corresponding weights in order that the energy is weighted equally. For the factor 4 between fast and slow sampling time the following weighting vector results:

$$\underline{f} = \begin{bmatrix} 0 & 0 & 0 \ldots\ldots\ldots\ldots 0 & 1 & 1 & 1 \ldots . 1 & 4 & 4 & 4 \ldots . 4 \end{bmatrix}^T$$

It must be emphasized that in the optimization procedure the constraints are more important than the objective function. First the constraints must be satisfied and then the objective function is minimized.

The optimization is not restricted to the linear programming case, but can also be formulated for a quadratic objective function. In that case the weighting terms for the indoor temperatures cannot be set to zero and the lower limit of the indoor temperatures must be redefined.

5.4 Optimization algorithm

Two algorithms were used for solving the above problem. Both solve the standard linear programming problem [Gill & al. 1991]. The first algorithm is a projection method or active set method as it is included in the optimization toolbox of MATLAB [Branch 1996]. The second algorithm is a C-coded version of the simplex algorithm [Press 1992] that was used in the prototype implementation.

6. SIMULATIONS

The algorithm has been developed and tested in the MATLAB/SIMULINK environment. Extensive simulations with yearly data have also been done with this tool. The influence of several parameters of the algorithm has been investigated by simulations in order to find good default values. The main parameters of the algorithm are:

- fast sampling time T (10min,...,30min)
- number n_1 of fast sampling times (16,....48).
- horizon length L (24-72h)
- forgetting factor parameters p_{max} and λ_{max}.
- observer design parameters

The testing of the algorithm was carried out in four steps. These steps were:

1) Assuming a perfect forecast of the disturbances and using the same second order model for the simulated room as is used in the predictive controller, an ideal situation is generated which cannot be realized. It serves as performance bound for realizable controllers and as test of the software. That means that the set point profile for the room temperature in the occupied mode can be fulfilled perfectly with minimum energy. After setback the room temperature reaches the comfort temperature at exactly the right time and remains perfectly on it. Fig. 6 displays three set of a pair of curves, room temperature and flow temperature set point. The first two curves on Fig. 6 show the room temperature and the corresponding flow temperature set point. The flow temperature set point exhibits a nearly periodic behavior with an early morning boost and then an exponentially decreasing function during the occupied period.

2) In a second step the second order model for the simulated room is replaced by a complicated sixth order model that no longer can be matched by the identified second order model in the controller. The result is shown in the third and fourth picture of Fig.6. Clearly the comfort temperature cannot be maintained all the time. The tendency to be

noted is that the control acts always a little too late. This indicates that the parameter of the second order model may not yet have been fully adjusted or that the model cannot be better adjusted to the simulated room. Also the flow set point shows a less smooth behavior.

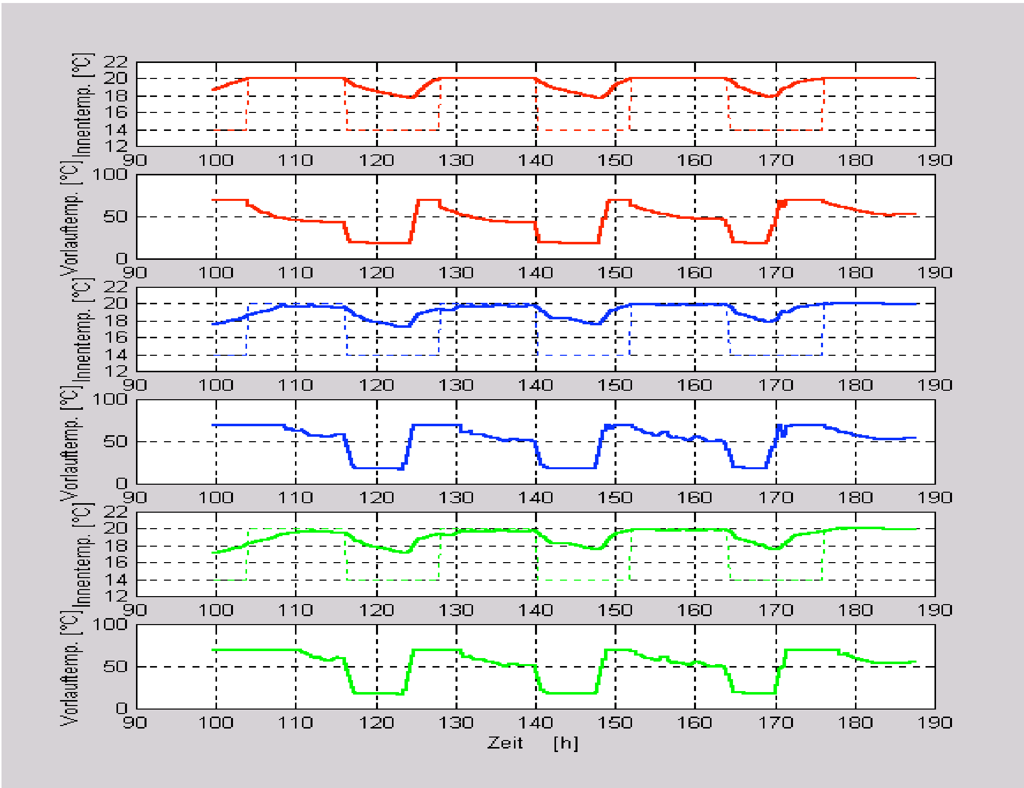

Figure 6: Three simulation results (pair of two curves each) with different kind of simulated room model and forecast information

3) In the next step the predicted outdoor air temperature is used instead of the perfect weather information. The result is shown in the two lower pictures of Fig.6. The difference to the two previous curves is rather small. This suggests that the way how the predicted weather is computed does not decrease the performance significantly.

4) In a final step the algorithm is tested on real buildings. Experiences with the prototype installations are given in part 7.

7. PROTOTYPE INSTALLATIONS AND RESULTS OF FIELD TESTS

For the on-line version only MATLAB code was used with no special functions from various toolboxes (control and optimization toolboxes). The algorithm has been tested on two office buildings in Zug, Switzerland. Both buildings were office buildings where one heating circuit serves several rooms. In both situations the algorithm was implemented with the same default values and installed on a separate PC that was hooked up to the building energy management station (BEMS). The algorithm ran with and without forecast information from an external weather forecast service. A special communication software transmitted data from the BEMS to the PC and vice versa. As the sampling time T was chosen as 20 minutes, the transmission and the control calculation in MATLAB had to be done only at this low rate. The task was started periodically by an auto-task program. On one site the algorithm runs for one and a half years, on the other side roughly one year. In the Fig. 7 and 8 only the reference room is shown, recorded were also other room temperatures. The flow temperature could only vary between room temperature and maximal 60°. The upward rate of change of the flow temperature was set to 10° per sampling time T, the downward to 7.5°. The pump was switched on and off over a hysteresis that compares the flow temperature set point and room temperature.

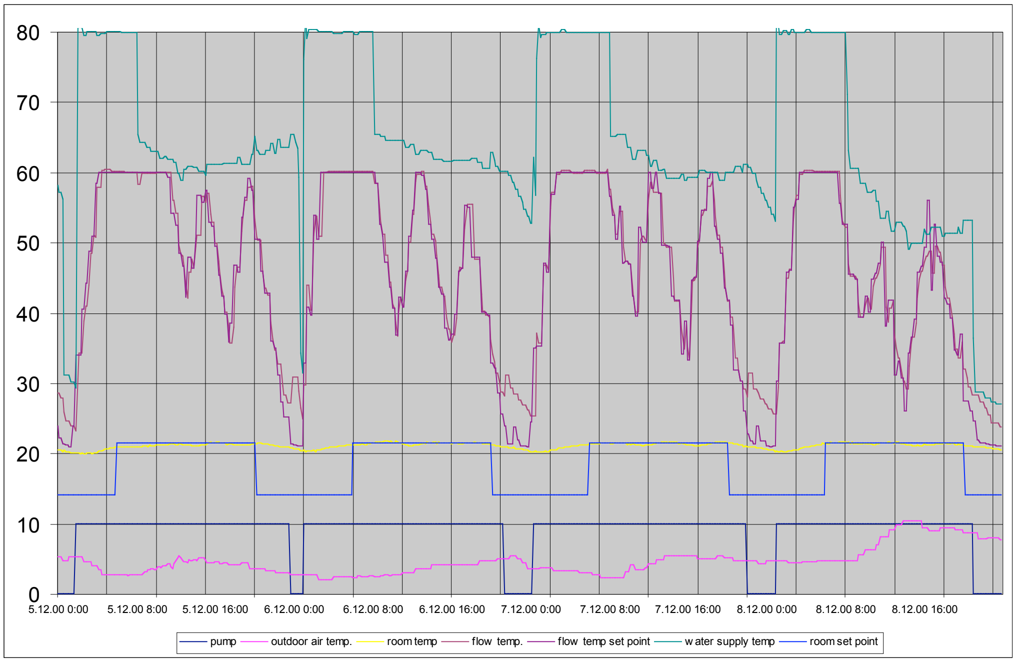

Figure 7 Real measurements during weekdays Dec.5-Dec.8 2000

The results obtained have been very promising. We look at two recorded time periods for one building, one is a period of working days (Fig.7) and one a weekend period with longer setback (Fig.8). On the two graphs the following curves are shown:

- pump signal, that is either off (0) or on (10)
- outdoor air temperature varying between 0° and 10°
- room temperature set point, that is either 14° or 21.5°
- room temperature (white line)
- water supply temperature (going up to 80°)
- flow temperature set point (between room temperature and 60°)
- flow temperature that is tracking the set point

A speciality of that site is that the water supply temperature is following a fixed time pattern during the day.

The first measurements (Fig.7) show the weekday situation. As the outdoor air temperature was relatively warm, the room temperature during the night drops very little. During the occupied period the set point is met very well. The set point of the flow temperature that is computed by the predictive control algorithm shows some interesting features, if one compares it to the simulations of Fig.6. The early morning boost is clearly visible with a rather smooth shape. During the day the controller acts more oscillatory (two bumps per day), that might be explained by the modeling error and especially by the disturbances. Also visible is that during the setback periods, the flow temperature cannot

follow its set point because the model in the controller takes not into account that the flow temperature is cooled down only slowly.
The second measurements (Fig.8) show the weekend situation. Similar explanations can be given as before. It is clearly visible that on Sunday the heating switches on rather early (around 16:00) resulting in a long boost with maximal flow temperature set point. Still the room set point cannot be met exactly on Monday morning. The reason for this is that in the beginning of the heating phase, the flow temperature set point (60°) is higher than the water supply temperature (55°). For the optimization it is assumed that the set point can reach 60°. If one knows the water supply restrictions beforehand, this can be included in the optimization as well. If this function is not known one can avoid the above situation by setting the upper bound of the flow temperature more conservatively. The oscillatory behavior of the set point is less dominant in these measurements.
Overall it can be said, that the algorithm fulfills all its expectations. For the operator the way how the predictive controller works is very appealing because the practical limitations are taken into account. No specific complaints came also from the office people working in the building.

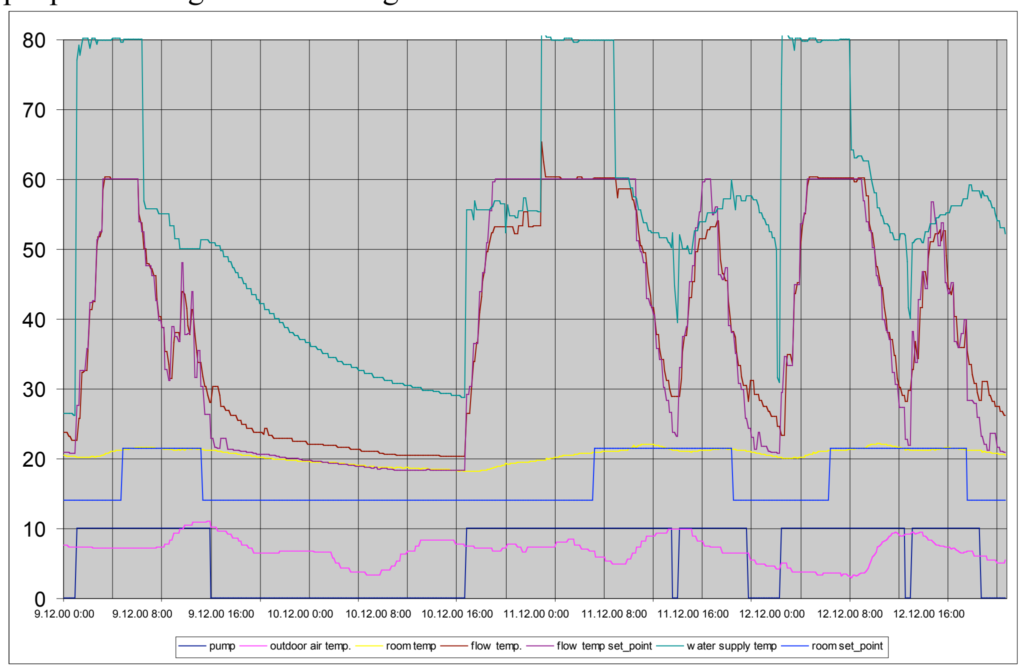

Figure 8: real measurements during weekend setback period Dec.9. until Dec.12, 2000

8. CONCLUSIONS

The algorithm proved to be very successful. It met the goals that were given in the beginning. The comfort could be maintained, the tuning was very simple and the acceptance was good. For the operators it was especially pleasing that the method could be understood with little effort and that the practical limitations are included in the optimization in a natural way. How much energy can be saved with such an algorithm needs still to be determined. A comparison with existing algorithm must be performed very carefully, otherwise unrealistic numbers are generated. It can certainly be said that the proposed controller behaves at least as good as a very well tuned conventional controller. The implementation issue is now tackled in two directions. For an implementation in a standard controller some modifications have to be done, that will be reported later. The modifications were concerned with memory and speed of the algorithm. An implementation on the building management level is under way.

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