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# Optimal Indoor Temperature Control Using a Predictor

Peter Lute and Dolf van Paassen

This article deals with optimal control of the indoor temperature in a building. The control system attempts to find an economic optimum to supply heat to the building with the use of a predictor for the indoor temperature, while maintaining a comfortable temperature in the building. A general control structure is described that uses a linear objective function, which is minimized by linear programming. This general control structure is applied to a specific test facility, called passive climate system, whose main feature is that it uses natural ventilation by means of adjustable windows for cooling purposes. This article also describes some field tests with the optimal predictive control system applied to the passive climate system.

## Introduction

Researchers in the area of thermal comfort [1] have learned that the required indoor temperature of a building is not a fixed value. In fact a certain range of temperatures is sufficient to create a comfortable situation. From an economic point of view this means that it is preferable to operate the heating, ventilation, and air-conditioning (HVAC) installation in that temperature region, representing the lowest operating costs of the HVAC installation. Often it is not possible to maintain the indoor temperature within a required temperature range instantaneously, because the capacity of the HVAC installation is not sufficient to accomplish this. This happens, for instance, in the morning when the building must be heated from the temperature that has established after cooling down at night, to the required temperature during the day, when people occupy the building. Another possibility might occur in summer, when outdoor temperatures are high and solar radiation heats up the building too much, while the capacity of the cooling installation is not adequate to maintain the indoor temperature within the required temperature range. To be able to deal with these types of problems a control system is required that can assess the effects of the HVAC installation on the indoor temperature correctly.

The control of the heating or cooling process allows the temperature to be kept between two predefined limits, instead of a strict set-point. These limits may, however, be selected or altered by the user. It is also required that the process operate between these limits at an economic optimum. Besides these two main requirements, many additional conditions may exist, such as input and output constraints, stability requirements, and rate constraints. To deal with the control of a process under such conditions a concept is developed called linear predictive control (LPC).

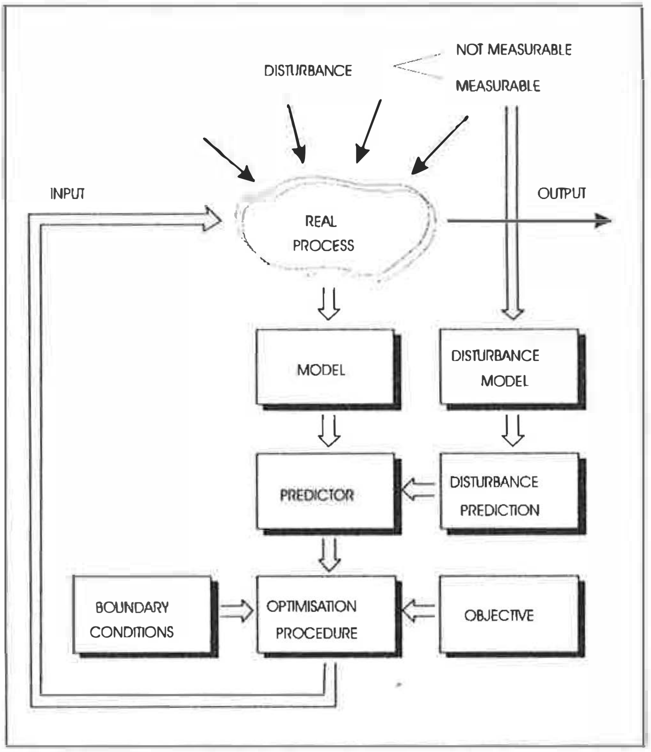


*Fig. 1. Optimal predictive control system.*

The approach of LPC control consists of the following steps. The indoor temperature process is described by an ARMAX model, from which an optimal multi-step predictor is derived by the solution of the Diophantine identity for the required time steps in the future. The problem of exceeding the required limits for a certain period in the future is minimized with the use of the multi-step predictor by an objective function based on the $L_1$ norm. The $L_1$ norm is chosen to obtain a fuel-economic optimum and to deal with exceeding the temperature limit and other problems. The objective function incorporating additional conditions is then minimized on-line by linear programming, which is with some provision perfectly suited to handle this kind of problem. The required ARMAX model is estimated by a recursive estimation algorithm to make the LPC control system self-adaptive. The structure of the control system is shown in Fig. 1.

The motivation to use the LPC algorithm approach discussed herein has been to use the exterior climate as much as possible to heat and cool a building in order to achieve the lowest possible

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energy consumption of the building. On the other hand, the LPC approach was chosen to deal with the large influence of the exterior climate on the process, which is very often larger then the control inputs themselves. Meanwhile, it would also be an advantageous approach to be used with other processes, where large disturbances can influence the process output and where a fuel (cost) economic optimum is required.

Cost aspects are described in [10], in which a comparison is made with more conventionally controlled systems. An overview of other predictive techniques in indoor temperature control can be found in [2]. Most of these predictive techniques focus on the use of solar radiation predictions. Related approaches for industrial purposes are described in [3]. The LPC approach, however, uses an optimal predictor and uses output limits rather then an output set-point.

This article will explain the LPC procedure, which is described in detail in [2], for the multiple-input/single-output system with two control inputs (heating and cooling) and two uncontrolled but measurable and predictable disturbances (exterior temperature and solar radiation). A survey is made of the tuning parameters of the LPC algorithm. And finally the performance of the LPC algorithm is reviewed. Some practical results of the algorithm are applied to a test facility, called passive climate system, and an electric radiator and natural ventilation by means of windows for cooling purposes will be presented.

## Overview of the HVAC Process

A passive climate system is a building that tries to utilize the outdoor climate as much as possible to reduce the energy consumption of the building [4]. The outdoor climate is used, besides the heating and cooling device, for indoor temperature control. It is also used for fresh air supply and lighting. To be able to regulate the contribution of the outdoor climate, the facade of the building is equipped with ventilation windows and shading devices. It is obvious that the outdoor climate is not always capable of providing the energy to maintain a required level of comfort in a building. However, it might be possible to use the outdoor climate in an advantageous way by storage of energy in the walls. This would require a control system, which is able to predict the future thermal behavior of the building and use this prediction to maximize the outdoor climate contribution to the indoor comfort, simultaneously minimizing the energy consumption.

The proposed control system must be able to determine control actions in advance (such as ventilation with cold outdoor air or heating just before the occupied period of the building starts) by using prediction of the indoor temperature. This prediction of the indoor temperature will also include prediction of the outdoor climate, especially solar radiation and temperature.

Research reported in [5] has shown that energy can be saved by intermittent conditioning of the building. It is also possible to save energy by allowing a certain deviation from the temperature set-point. The control system can try to maintain the indoor temperature between an upper and a lower temperature boundary, which leads to a minimum energy consumption. Acceptable temperature boundaries can be deduced from the theory of thermal comfort [1].

During the unoccupied night period of an office building, the temperature may float freely between certain safe temperature boundaries (e.g., 12° C and 30° C). Thus the average heat loss is as low as possible, and the required energy is minimal. During the occupied period of a building it is possible to save energy to allow a certain deviation from a desired temperature as long as a comfortable situation is achieved. According to [1], the predicted mean vote (PMV) value, which is a measure for a comfortable situation in a building, depends on the air speed, vapor pressure, air temperature $\theta_a$, and mean radiant temperature $\theta_r$. If it is assumed that both temperatures are almost equal and air speed and vapor pressure are constant, it is possible to translate the required values of the PMV boundaries of ±0.5 to a temperature range.

The following comfortable temperature ranges are obtained:

- Summer: $\theta_i = 24 \pm 2$ °C
- Winter: $\theta_i = 22 \pm 2$ °C

The indoor temperature should be maintained within these ranges during the occupied period of the building.

## Linear Predictive Control (LPC) System

The required control actions, which the control system must calculate to keep the indoor temperature within the required range, may have to be taken in advance because of the limited capacity of the heating and cooling systems. This requires that the control system know how the indoor temperature behaves in the future. An optimal indoor temperature predictor is used for this purpose and is derived from an ARMAX model of the indoor temperature behavior. The passive climate system has three control inputs (assumed to be in the range of 0-1), which are:

- $u_h$: Heater input signal
- $u_a$: Awning position input signal
- $u_w$: Window position input signal

The model of the indoor temperature behavior is based on the heat balance of the room and includes both controlled inputs (radiator, ventilation window, and awning positions) and uncontrolled disturbances (internal heat and outdoor climate). This type of model always leads to bilinear terms involving air flows times temperature differences. Moreover, the control input corresponding to the awning position leads to a highly nonlinear term in the model involving trigonometric functions of the solar radiation, caused by the rotation of the earth, multiplied with the effect of the awning.

The linearized model of the indoor temperature of the passive climate system is therefore chosen as:

$$A(q^{-1})\theta_i(k) = B_1(q^{-1})u_h(k) + B_2(q^{-1})q_s(k, u_a(k))$$

$$+ B_3(q^{-1})u_w(k)(\theta_o(k)-\theta_i(k)) \qquad (1)$$

$$+ B_4(q^{-1})\theta_o(k) + B_5(q^{-1})e_{24}(k) + C(q^{-1})e(k)$$

where $\theta_i$ is the indoor temperature [°C]; $q_s$ is the solar radiation that reaches the vertical window surface, which is a function of the awning position [W/m$^2$]; $\theta_o$ is the outdoor temperature [°C]; $e_{24}$ is the integrated 24-hour model error $e$ (assumed to be a measure for the internal heat load) [°C]; and $e$ is the model error $\theta_i$ - $\hat{\theta}_i$ [°C].

The polynomials A, B, and C in Equation (1) are polynomials of the time shift operator $q^{-1}$. The integrated 24-hour error $e_{24}$ is calculated as

$$e_{24}(k) = e_{24}\left(k - \frac{24}{\Delta t}\right) + e(k) \qquad (2)$$

The predictor for $k+i^{th}$ time step in the future is derived by splitting the model into past and future parts with the future model error $e(k+i) = 0$ (best guess, see [7]). The resulting predictor is written for a certain future point of time $k+i$ as a regression function of the control inputs and the free response of the indoor temperature $\theta_f(k+i)$, which is completely determined by the past inputs and outputs, according to

$$\begin{aligned}\theta_i(k+i|k) = {} & G^*_{1i}(q^{-1})u_h(k+i-1)\\ & +G^*_{2i}(q^{-1})q_s(k+i-1, u_a(k+i-1))\\ & +G^*_{3i}(q^{-1})(\theta_o(k+i-1)-\theta_i(k+i-1))u_w(k+i-1)\\ & +\theta_f(k+i)\end{aligned} \qquad (3)$$

for $i = 1, \ldots, N$, where $N$ is the prediction horizon. The term $\theta_f(k+i)$ is the free response of the system and is given by

$$\begin{aligned}\theta_f(k+i) = {} & \Gamma_{1i}(q^{-1})u_h(k-1) + \Gamma_{2i}(q^{-1})q_s(k-1, u_a(k-1))\\ & + \Gamma_{3i}(q^{-1})u_w(k-1)(\theta_o(k-1)-\theta_i(k-1)) \qquad (4)\\ & + G_{4i}(q^{-1})\theta_o(k-1) + G_{5i}(q^{-1})e_{24}(k)\\ & + F_i(q^{-1}\theta)_i(k-1)\end{aligned}$$

The polynomials $G(q^{-1})$, $G^*(q^{-1})$, $\Gamma(q^{-1})$, and $F(q^{-1})$ with the regression coefficients of the predictor of Equation (3) follow from the Diophantine identities [7]

$$C(q^{-1}) = A(q^{-1})E_i(q^{-1}) + q^{-1}F_i(q^{-1})$$

$$G_{ji}(q^{-1}) = B_j(q^{-1})E_i(q^{-1}) \qquad (5)$$

$$G_{ji}(q^{-1}) = G^*_{ji} + q^{-i}\Gamma_{ji}(q^{-1})$$

To be able to calculate $\theta_i(k+i|k)$ the predictor requires values for $q_s(k+i-1)$, $\theta_o(k+i-1)$, and $\theta_i(k+i-1)$. The outdoor climate term is replaced by that for the predicted outdoor climate, $q_s(k+i-1|k)$ and $\theta_o(k+i-1|k)$. The yet unknown indoor temperature is taken to be the predicted indoor temperature of the previous time step $\theta_i(k+i-1|k-1)$, which is the best possible prediction of $\theta_i(k+i-1)$ at time $k$.

The heater input variable $u_h$ is the only control variable that involves energy consumption, which must be minimized. The objective function to be minimized incorporates a comfort part, an energy consumption part, and a stabilizing part. The comfort part consists of two terms: the exceeding of the output $\theta_i$ of the upper output limit and the exceeding of the output $\theta_i$ of the lower output limit (see previous paragraph and Equation (7)). The amount of energy that is involved that must be minimized is reflected in the second part of the objective function. The heater energy is taken linear with the heater input $u_h$. The solar radiation that can be influenced by means of the awning (input $u_a$) must be maximized because it is free energy. The last part of the objective function weights the rate of change of the inputs against the previous parts to be able to influence the stability of the control system. The weighting factors $\beta_h$, $\beta_a$, $\rho_h$, $\rho_a$, and $\rho_w$ determine the influence of the different parts on the value of the objective function. The choice of the weighting factors $\beta$ and $\rho$ of the objective function (6) depends on the indoor temperature process. In [2] it has been pointed out that the value of $\beta$ must at least be smaller then the value of the first coefficient $g_I$ of the corresponding polynomial $G_{ji}(q^{-1})$ of the predictor of Equation (3). The value of $\rho$ depends besides the characteristics of the process on the behavior of the disturbances (outdoor climate) and the required behavior of the control inputs. A value of $\rho$ between 0 and $\beta$ has turned out to be a reasonable initial value (see [2]).

The object function $J$ thus becomes:

$$\begin{aligned}J = {} & \sum_{i=1}^{N}\max(0, e_l(k+i)) + \sum_{i=1}^{N}\max(0, e_h(k+i)) && \text{(comfort)}\\ & \sum_{i=1}^{N}\beta_h u_h(k+i-1) - \sum_{i=1}^{N}\beta_a q_s(k+i-1) && \text{(energy)}\\ & \sum_{i=1}^{N}\rho_h \Delta u_h(k+i-1) + \sum_{i=1}^{N}\rho_a \Delta q_s(k+i-1) && \text{(stability)}\\ & \sum_{i=1}^{N}\rho_w \Delta u_w(k+i-1)\end{aligned} \qquad (6)$$

which must be minimized for $i$=1 to $N$ with the following conditions, which are the predicted temperature offsets from the upper and lower temperature boundaries $\theta_{i,min}$ and $\theta_{i,max}$:

$$e_l(k+i) = \theta_i(k+i|k) - \theta_{i,min}(k+i)$$

$$e_h(k+i) = \theta_{i,max}(k+i) - \theta_i(k+i|k) \qquad (7)$$

The inputs $u_h$, $u_w$, and $u_a$ are scaled to range from 0-1 and must meet the following inequality conditions:

$$u_h(k+i-1) \le 1 \qquad q_s(k+i-1) \le q_s(k+i-1, u_a = 0)$$

$$u_h(k+i-1) \ge 0 \qquad q_s(k+i-1) \ge q_s(k+i-1, u_a = 1)$$

$$u_w(k+i-1) \le 1 \qquad (8)$$

$$u_w(k+i-1) \ge u_{w,min}(k+i-1) \qquad \text{occupied}$$

$$u_w(k+i-1) \ge 0 \qquad \text{occupied}$$

(8)

where $u_{w,min}$ is the minimum window opening for fresh air supply.

The position $u_a$, to which the awning is moved in order to shade the sun, is calculated in two steps. By minimizing the objective function $J$ the required solar radiation is calculated concerning its possible range and then the corresponding awning position $u_a$ is calculated by a fixed relation $q_s = f(u_a)$ (see [2]).

Outdoor climate prediction is done by a combination of a model determined a priori and estimated ARMAX models. Solar radiation is calculated from the course of the sun toward a determined point on earth. Outdoor temperature is predicted by an ARMAX model with solar radiation as input. The minimization of the above problem is a typical linear programming problem, which is solved by the "revised simplex" algorithm as for instance described in [6].

For large prediction horizons the complete linear programming problem can become rather extensive. It would therefore be better to split the problem into smaller subproblems depending on the situation. A large prediction horizon is basically only necessary when large changes in temperature are required in the future. This is only the case during the unoccupied period when either preheating or pre-cooling is required to keep the temperature between the boundaries during the occupied period. During the occupied period the temperature will be close to the boundaries and large changes will not be required. Therefore, a small prediction horizon will be sufficient during this period. It is also possible by observing the free response $\theta_f(k+i)$ of the indoor temperature process to split the problem into a heating ($\theta_f(k+i) < \theta_{i,min}(k+i)$) or cooling $\theta_f(k+i) > \theta_{i,max}(k+i)$) problem and solve them separately.

## Experiments

A test cell has been built to investigate the phenomena that influence the indoor climate of this passive solar building. These phenomena are natural ventilation through the windows, cooling possibilities with outdoor air, shading of the window, heat loss reduction with a shutter, and lighting. A detailed description of the design is given in [2], which is available from the authors upon request. The test cell is equipped with the passive components, a rolling shutter, ventilation windows, and Venetian blinds. This test facility has been used to test the proposed LPC system.

### TU Delft Test Facility

The test cell is of light construction with small thermal capacity; therefore some thermal inertia is added by means of a wall filled with approximately 1 $m^3$ water. The orientation of the facade is almost south faced (30° E) and located in Delft at the site of the Technical University.

The upper and lower windows can open independently from each other by means of an electric motor. The position of the windows is measured by a potentiometer that is connected with the motor actuator.

The auxiliary heating is supplied by electric radiators. In this way the supplied heat to the room can be measured exactly. The power supply of one or two electric heaters of 1750 [W] is regulated with a thyristor controller.

### Control System Experiments

The first condition for successful application and performance of a predictive control system is the availability of an accurate dynamic model of the TU Delft test passive climate system. To be able to estimate a stable and physically correct model of the real system, it is necessary to take into account some differences between the actual system and the ideal system of Equation (1). There are three main differences that can cause problems with the parameter estimation, when no corrective provisions are made in the model structure. The first difference is that time delays are not considered, because they are not essential for the predictive control system structure. They simply cause a shift in time of the control system output, while the procedure stays unchanged. However, in a real situation there are time delays, which are unlikely to be a multiple of the sample time, and cannot be neglected in both parameter estimation and the control system. Another difference is that the input signals (both controlled and uncontrolled) of the simulated discrete system are assumed to be constant between two sample periods (zero-order hold). For the real situation this is certainly true for the controlled inputs, which are generated by a digital control system, but for the uncontrolled disturbances, which are also fed into the parameter estimation procedure and the control system, this is certainly not true. A third difference to be considered is a possible offset introduced by the fact that the simplified model structure cannot be fitted exactly on the more complex real process.

The following provisions are taken to be able to deal with the delay times, non-constant input signals, and offset.

1. Time delays. Time delays are caused by the transport of heat from the heat source to the location of the temperature sensor. This is especially the case with the heat supplied by a radiator. When the radiator heats up an air flow slowly develops, which transports the heat from the radiator into the room. The time delay is approximately seven minutes. The usual suggestion to overcome problems with the parameter estimation is to extend the order of the $B(q^{-1})$ polynomial to at least cover the time delay (see [8]).

2. Input signal variations between two samples. This is the case for the outdoor climate input signals $q_s$ and $\theta_o$. Also, the controlled input signal of the cooling by ventilation will not be constant, because it depends on the difference between the indoor and outdoor temperature. The effect on the indoor temperature is opposite to that of time delays. It means that the indoor temperature is also dependent on the value of the input signals at a point in time, that the indoor temperature is measured (no delay time at all). This effect can only be considered with the uncontrolled outdoor climate. The controlled input signals have to be calculated by the control system at the actual point of time on the basis of the measured indoor temperature (not the other way around). This means that the model always has to have one time step delay for the controlled input signals. Therefore the outdoor climate inputs of the model are not delayed.

3. Offset. Basically the parameter estimation procedure deals with variations of the input and output signals around their mean values. A constant k is added to the model and the parameter estimation to be able to estimate the offset.

All polynomials of Equation (1) are chosen to be second order, except for the C polynomial, which is chosen to have order zero. With these considerations the parameters are estimated by a recursive least-squares estimator with UD factorization (see [9]). The time step is chosen as 15 minutes, and the internal heat load is 0 [W], (therefore the $B_5$ polynomial of Equation (1) is omitted).

With the experiments of the LPC system it is assumed that the air speed $\bar{s}$ in the window opening is constant to simplify the control system. The amount of ventilation is then approximated by

$$\phi_v \approx \bar{s} A_w \sin(\alpha_{max}) u_w \tag{9}$$

The solar radiation that enters the room by the vertical window surface (input $q_s$) is considered to be proportional to the measured solar radiation on a horizontal plane.

The final estimated model, considering the seven-minute time delay, is:

$$\begin{aligned}(1 - 1.2015q^{-1} + 0.2590q^{-2})\theta_i(k) \\ = (2.4500q^{-1} + 0.2259q^{-2} - 1.0024q^{-3})u_h(k) \\ + (0.3469q^{-1} - 0.2225q^{-2})u_w(k)(\theta_i(k) - \theta_o(k)) \\ + (0.0025 + 0.0001q^{-1})q_s(k) \\ + (0.2119 - 0.1865q^{-1})\theta_o(k) \\ + 0.6387 + e(k)\end{aligned} \tag{10}$$

with roots of

$A(q^{-1})$: 9.2000e-001, 2.8150e-001

$B_1(q^{-1})$: 3.4672e-001

$B_2(q^{-1})$: 4.133e-001

These parameter values are physically meaningful in the sense that all roots are real and the zeros are located between the two poles, as would be the case with a theoretical model of a room [2].

The crucial question is, how well suited is the estimated model for usage with the predictive control system? There are the several operating situations where the control system uses the estimated model. The first situation is to control the indoor temperature with the heater or by cooling with natural ventilation by the windows. The second situation occurs when the heater has to start in advance to reach the required indoor temperature. The estimated model is required to determine the point of time to start. The third and fourth situations that require the usage of the estimated model occur when cooling with natural ventilation by the windows is not adequate to keep the indoor temperature below the required limit. The estimated model is used to determine whether night ventilation is necessary, or pre-cooling is necessary during the day. The occurrence of these situations depends largely on the weather conditions and the thermal behavior of the test cell. By observing the indoor temperature responses of the test cell, it can be seen that night ventilation is rarely possible because even without ventilation at night the indoor temperature drops low enough to start the heater in the morning. Despite the addition of some thermal mass to the test cell, it is still a light construction. Therefore application of pre-cooling is doubtful, because the thermal storage effect of the test cell is rather limited. Moreover, pre-cooling is only necessary when the outdoor temperature is rather high (close to the indoor temperature); however, its effect is rather small because of the high outdoor temperatures. In other situations the air flow through the window openings is large enough to supply the necessary cold air.

The situations that remain to test the merits of the estimated model are thus reduced to indoor temperature control by either heating or cooling and startup of the heater in the morning. Fig. 3 and 4 show a part of series of measurements with model-based controlled indoor temperature. The control algorithm is based on

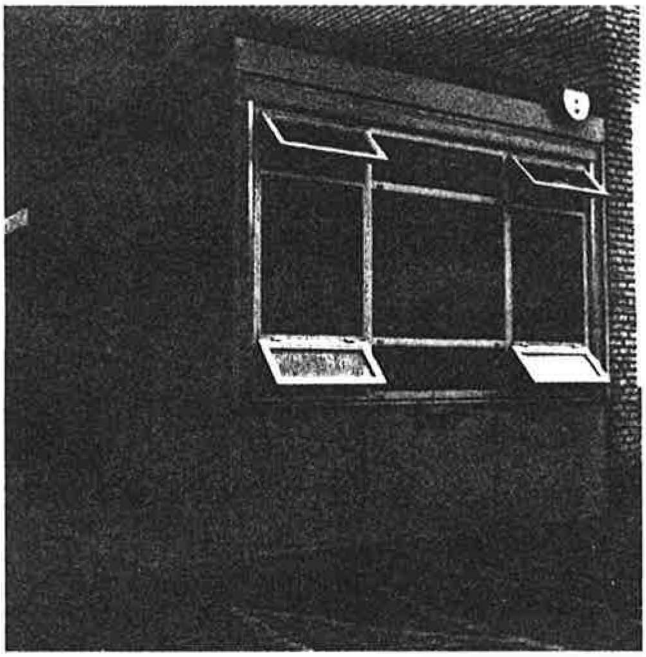

*Fig. 2. TU Delft test cell.*

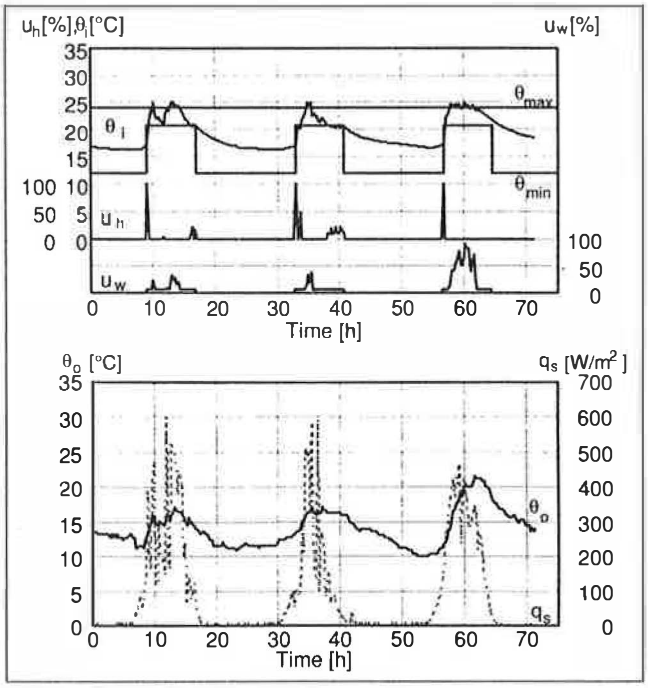


*Fig. 3. Indoor temperature control. Cooling situation (low set-point = 21° C).*

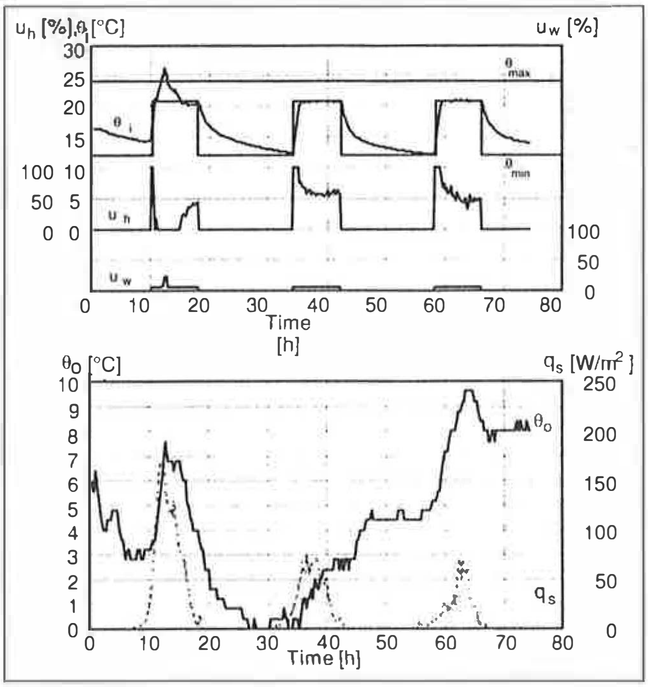


*Fig. 4. Indoor temperature control. Heating situation.*

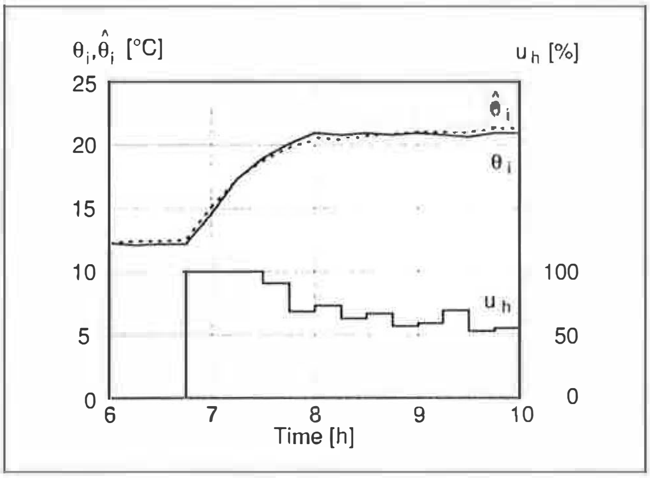


*Fig. 5. Example of prediction for start of the heater in the morning. Solid line: original. Dotted line: predicted.*

the LPC algorithm explained previously with a single step prediction of the indoor temperature and the model structure of Equation (10). The disturbance by the outdoor climate is predicted to be constant for the prediction period and the same as the previous time step.

Fig. 3 shows a situation with alternating heating and cooling during the day. At night the indoor temperature drops significantly because of the low outdoor temperature. Except for situations with excessive changes of the window opening(s) caused by excessive fluctuation of the solar radiation, the indoor temperature predictions seem reasonable accurate and stable. It can be seen that the largest disturbance factor is the solar radiation. Large amounts of solar radiation (second plot of Fig. 3) quickly increase the indoor temperature (first plot of Fig. 3). It can also be seen that the LPC system almost immediately reacts on these disturbances and nicely keeps the interior temperature on the required temperature limits. Fig. 4 shows another (colder) situation with much more heating and cooling by ventilation. The interior temperature is controlled extremely well at the required temperature limits (no overshoot or oscillations). It can be observed (first day in first plot) that the output error increases with larger window openings, which is also indicated by correlation analysis (see [2]). The estimation procedure obviously tends to fit the model on small (minimum) window openings, which occur much more than large openings. The nonlinear ventilation effect on the indoor temperature is not accurately described in the model. The average-occurring situation is described well by the model, but the error increases with deviant situations. However, there is not much alternative when a linear parametric model structure is used.

Fig. 5 shows that the model is well-suited to predict the point of time to start the heater. In this case it takes about one hour to reach the required indoor temperature at eight o'clock, when the heater starts with full power. This time is reasonably predicted by the model.

## Conclusion

The experiments concerning parts of the predictive control system show that with some thoughtfulness concerning the model estimation, the proposed control structure is capable of controlling the indoor temperature of the test cell within the required limits most of the time. For the test cell situation the time step of 15 minutes is sufficient to control the indoor temperature with the heater. However, the suppression of disturbances caused by large fluctuations of the solar radiation by means of cooling by natural ventilation might need a smaller time step. The problem is that this will lead to more window movements per hour, which might not be acceptable. Suppressing the movement rate by weighting or limiting it in the objective function in combination with the time step of 15 minutes might provide an acceptable solution, but needs further attention.

The research described in [2] mentions comparisons of the proposed LPC system with conventional on/off and PI control systems with the same type of temperature limits. It shows the LPC system saves about 10% in terms of energy consumption annually, which is basically caused by the effect that stricter control at the required limits is possible and no overshoot and oscillations occur. It also leads to a better indoor climate, because fewer hours of excessive temperature exceedings of the required temperature limits occur.

A problem that has not yet been mentioned might be computing time and computer memory requirements. In this article relative short prediction periods are used which do not cause any problems, but it is obvious that with larger prediction periods more computing time is necessary and the linear programming problem requires more computer memory.

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# Sampled Data

## Back in the Future?

The recent methodology of integrator backstepping has introduced important new concepts and terminology to the field of control. Here is some additional terminology which we hope will not become standard:

| **Backstepping in...** | **...might be called:** |
|---|---|
| time varying systems | — backtracking |
| variable structure systems | — backsliding |
| discrete systems | — backbeat |
| dynamic programming | — backstage |
| game theory | — playback |
| time optimal control | — fastback |
| delay systems | — throwback |

| **Other terminology...** | **...might be called:** |
|---|---|
| location of state vector | — backspace |
| equilibrium point | — backrest |
| invariant subspace | — backplane |
| location of poles | — backfield |
| root locus | — backfield in motion |
| cost functional | — back pay |
| exponent | — backlog |
| inadmissible input | — wetback |

*Contributed by Mark Spong, over the Editor's email.*

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## SPECIAL ISSUE ON CONTROL APPLICATIONS



## COLUMNS



## DEPARTMENTS