

Application of a Model Based Predictive Control Algorithm for Building Temperature Control

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Abstract: - The paper presents a model-based predictive control algorithm that uses a limited number of control sequences for on-line simulation of future behaviour of the process. Each control sequence used in simulation generates a predicted sequence of the output signal. The predicted output sequences are analysed and evaluated and then, using a set of rules, the 'optimal' control signal is computed. To simulate the future behaviour of the process it is used a process model and also the previous sequences of the input and output signals from the process. The algorithm permits directly use of the nonlinear model of the process. The algorithm is used for simulation of the temperature control in a house.

Key-Words: - building, modelling, identification, temperature control, model based predictive control algorithm.

1 Introduction

Reducing and optimization of the energy consumption in the residential sector is an important issue in the context of the global warming effect. An essential step in this direction is the implementation of a measuring system and monitoring of the electrical energy consumption.

This thing can lead to a better usage of the different electrical consumers. In the same time are necessary strategies that take into account the changing (optimization from the point of view of electrical consume) of the user behaviour. In this context, it's necessary the realization of a simulator that will permit the study of different strategies for reducing the electrical energy consume [1]. As it's known, the main part of the energy consume of a house is represented by heating. From this reason, a first step is realization of the thermal model of a house. In literature are presented many examples of modelling and simulation of energy consumption in a household [2], [3] [4]. Thermal model can be used also for the study of some systems HVAC (Heating, Ventilation and Air Conditioning) with electrical heating. Also, the simulator is needed to give solutions in the implementation phase of the project (living houses) and can be used also by the final users. A simulator can be use throughout the whole development phase. It can be used as well for the studies of control strategies (classical, fuzzy, genetic, neural network, model based predictive etc.) as well as for finding the solutions for reducing the electrical energy consumption and for maintaining acceptable indoor air conditions related to thermal comfort. Also, the reduction of the electrical consumption as well as the aspects that belong

to the thermal comfort may be included in the control laws, the main objective being maintaining thermal comfort within an acceptable range.

Testing of the system by usage of a simulator can introduce a series of problems:

- what are the measurable variables and which are the controlled variables (temperature, humidity, air quality, natural light / artificial, etc.);
- the controller is considered as being an independent component or such a combination that includes the sensor, actuator or other elements;
- where and how has the control loop to be divided;
- where is the controller's sensor placed;

The house model can have different levels of complexity: from simple "well mixed" models with one air node representing the whole air volume to complex computational fluid dynamic (CFD) models that take into account the conservation equations of mass and energy.

In the control field there are typical simplified models using supplementary identification or correlation. The necessary phenomena can be modelled by identification with measurements. The system can then be represented as a state space model with the parameters obtained by off- line or on-line identification.

Other type of model is lumped parameter model which have the advantage of a low number of parameters. A set of a few parameters describes the system. A lumped parameter model can integrate all layers of one envelope element (wall, floor, roof, etc.), all elements of the envelope of a room or the whole room model (convection, conduction and radiation in a room). The latter is currently used to simulate rooms in controller

studies. In the same way, one or more envelope elements can be modelled as a lumped parameter model. This modelling permits fast simulations since the system is reduced to a first order system. The model can be described as by thermal-electrical analogy.

2 The Thermal Model of a House

The biggest part of energy consumed in a house is used for heating. From this reason is important realization of a thermal model as detailed and precise can be, thus the simulator can offer solutions for reduction of energy consumption. Sometimes, a simple model can offer also good results.

In this paper it is used a simplified zone thermal model which was originally introduced in [5]. The model has two dynamic temperature nodes roughly representing the air and a lumped structure node. Two dynamic heat balance equations are used [6]:

$$C_a \frac{dT_a}{dt} = Q - K_i(T_a - T_w) - K_f(T_a - T_o) \quad (1)$$

$$C_w \frac{dT_w}{dt} = K_i(T_a - T_w) - K_o(T_w - T_o) \quad (2)$$

where,

- T_a Air temperature (°C)
- T_w Mean wall temperature (°C)
- T_o Outside air temperature (°C)
- Q Heat input to the air node (kW).

The model uses five parameters: C_a (kJ/K) is the thermal capacity of the air in the zone, together with other fast-response elements, C_w (kJ/K) represents the lumped thermal capacitance of the structure, K_f (kW/K) is the fast conductance ascribed to ventilation and elements with little thermal capacitance e.g. windows, K_i (kW/K) is the conductance between the air and structure nodes, K_o (kW/K) is the conductance between the structure node and the outside air.

These parameters can be estimated from physical data for the building, but also it is possible to obtain the values of parameters using a parameter identification technique.

3 The Control Algorithm

Use of the control system is that if you provide better information to people then they will make better decisions. The goal is to enable and encourage users to make better judgements with regard to energy consumption and emissions. The output data from the household sensors needs to be standardised to allow the

control system to handle a variety of household types. The control system needs to be generic in its design. A simulation model using Matlab/Simulink would enable various models to be evaluated and tested. Research needs to be carried out to identify other examples of energy management control systems.

Today, many industrial systems are still controlled by simple PID (proportional-integrative-derivative) algorithms, despite the better performances usually provided by systems developed following the modern control theory. PID controllers can be used to control a wide range of different processes, need only rough process models to be easily tuned and give pretty good set-point tracking performances. On the other hand it is clear that PID performances, although satisfactory, could be improved when dealing with highly nonlinear processes, or processes featuring unmodelled dynamics and external disturbances.

A Model Based Predictive Control (MBPC) algorithm is described by using a model to compute the predicted process outputs. The parameters of the model are obtained through an identification algorithm. Also, a cost function related to the closed loop performance of the system is defined, and the control signal is obtained by means of minimization the cost function. Finally, the first of these signals is applied to the process [7].

The extension of linear MBPC to nonlinear processes is straightforward at least conceptually. But there exists some difficulties [8]: the availability of nonlinear models due to the lack of identification techniques for nonlinear processes, the computational complexities, the lack of stability and robustness results.

The purpose of the controller is typically to force the output to follow the reference signal. If reference is a constant, the problem is commonly referred to as set-point regulation. When the reference is time varying (but is known in advance), defining a control law to force the output to follow the reference signal is called the positioning control.

The basic idea of the algorithm is the on-line simulation of the future behaviour of the control system, by using a few candidate control sequences [9]. Then, using rule based control, these simulations are used to obtain the 'optimal' control signal.

In [10] it was proposed an algorithm (MBPC-A1) designed for setpoint regulation problem (but setpoint can be arbitrary changed). The main idea of the algorithm is to compute for every sample period:

- the predictions of output over a finite horizon (N);
- the cost of the objective function,

for all (hypothetic situation) control sequences:

$$u(\cdot) = \{u(t), u(t+1), \dots, u(t+N)\}$$

and then to choose the first element of the optimal control sequence.

For a first look, the advantages of the proposed algorithm include the following:

- the minimum of objective function is global;
- this algorithm can be easily applied to nonlinear processes;
- the constraints can easily be implemented.

The drawback of this scheme is an unrealistic computational time. Therefore, the number of sequences must be reduced. Of course, this will lead to some difficulties in finding the global minimum of objective function. Choosing the sequences has to be made with attention, thus through simulation to be obtained information more helpful for computing the control signal.

For a first stage, we used the next four control sequences:

$$\begin{aligned} u_1(t) &= \{u_{\min}, u_{\min}, \dots, u_{\min}\} \\ u_2(t) &= \{u_{\max}, u_{\min}, \dots, u_{\min}\} \\ u_3(t) &= \{u_{\min}, u_{\max}, \dots, u_{\max}\} \\ u_4(t) &= \{u_{\max}, u_{\max}, \dots, u_{\max}\} \end{aligned} \quad (3)$$

where u_{\min} and u_{\max} are the accepted limits of the control signal, limits imposed by the practical constraints. These values can depend on context and can be functions of time.

Using these sequences results four output sequences $y_1(t)$, $y_2(t)$, $y_3(t)$, $y_4(t)$. The control signal is computed using a set of rules based on the extreme values $y_{\max 0}$, $y_{\max 1}$, $y_{\min 0}$, $y_{\min 1}$ (fig. 1- d is dead time, $t_1=N$, y_r is setpoint) of the output predictions.

In the followings, considering processes with positive sign, it can be put in evidence four usual cases:

Case 1: If $y_{\max 0} < y_r$ (corresponding to $u_1(t)$ sequence) and $y_{\max 1} > y_r$ (corresponding to $u_2(t)$ sequence) Then (using a linear interpolation):

$$u(t) = \frac{u_{\max} - u_{\min}}{y_{\max 1} - y_{\max 0}} y_r + \frac{u_{\min} y_{\max 1} - u_{\max} y_{\max 0}}{y_{\max 1} - y_{\max 0}} \quad (4)$$

Case 2: If $y_{\min 0} < y_r$ (corresponding to $u_3(t)$ sequence) and $y_{\min 1} > y_r$ (corresponding to $u_4(t)$ sequence) Then (using a linear interpolation):

$$u(t) = \frac{u_{\max} - u_{\min}}{y_{\min 1} - y_{\min 0}} y_r + \frac{u_{\min} y_{\min 1} - u_{\max} y_{\min 0}}{y_{\min 1} - y_{\min 0}} \quad (5)$$

Case 3: If $y_{\max 0} > y_r$ Then $u(t) = u_{\min}$ (6)

Case 4: If $y_{\max 1} < y_r$ Then $u(t) = u_{\max}$ (7)

In fig. 4, every output prediction curve is marked with a number which correspond to the number of control sequence from relations (3). Similar to case 3 and case 4, there are two similarly cases if $dy/dt < 0$ for $t < t_0$.

If the algorithm uses only these 6 rules, the variance of $u(t)$ will be large [10]. So, in the second stage, to limit this variance, depended by behaviour of the control system, are used next methods:

-an algorithm that modifies the limits of control signal:

$$\begin{aligned} u_{\min} \leq u_{\min st}(t) \leq u(t) \leq u_{\max st}(t) \leq u_{\max} ; \\ \Delta u_{\min} \leq \Delta u \leq \Delta u_{\max} \end{aligned} \quad (8)$$

For example:

$$u_{\min st}(t) = f_1(u_{\min st}(t-1), u_{\max st}(t-1), y(t), y_r(t)) \quad (9)$$

$$u_{\max st}(t) = f_2(u_{\min st}(t-1), u_{\max st}(t-1), y(t), y_r(t)) \quad (10)$$

where f_1 , f_2 are functions which decrease or increase (depended by behaviour of the control system) the difference between $u_{\max st}(t)$ and $u_{\min st}(t)$. In relations (3).. (7), the values of u_{\max} , u_{\min} are replaced with $u_{\min st}(t)$, $u_{\max st}(t)$. In the following, if is necessary, the next relations are used:

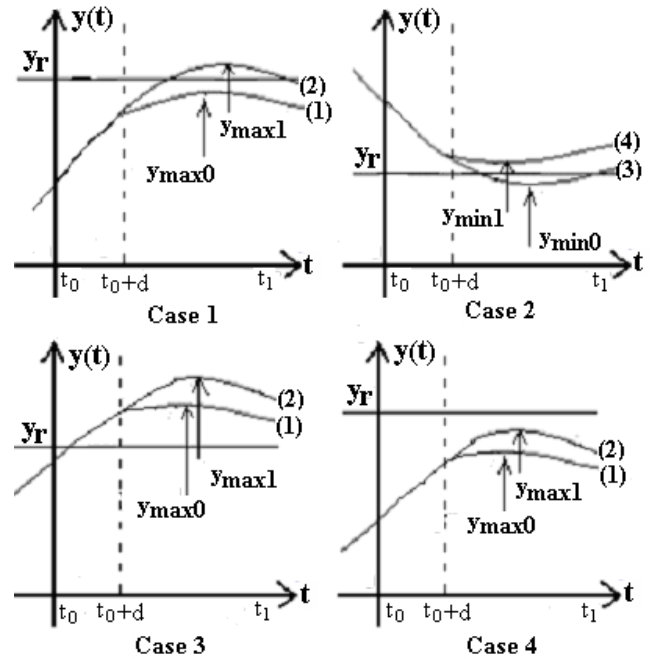


Fig. 1. Examples of output predictions

$$u_{\min st}(t) = u_{\min st}(t-1) + k_{st}(u_{st} - u_{\min st}(t-1)) \quad (11)$$

$$u_{\max st}(t) = u_{\max st}(t-1) - k_{st}(u_{\max st}(t-1) - u_{st}) \quad (12)$$

where k_{st} is a weight parameter and u_{st} is the estimated value of control signal in steady state. But in some circumstances (perturbations, inaccurate model) the limits of control signal must increase. Also, it is necessary to limit the minimum value of $u_{\max st}(t) - u_{\min st}(t) > d_{ust} > 0$, where d_{ust} is a parameter of the control algorithm.

-using the “variable setpoint”[9]:

$$y_r1(t) = y_r(t) + k_{ref}[y(t) - y_r(t)] \quad (13)$$

where k_{ref} is a weight factor;

- using a filter to compute control signal (especially in steady state regime).

4 Application of the Algorithm in Thermal Building Control

Usually, based on building characteristics (dimensions of wall, windows, floor, ceiling, construction material parameters, etc.) are realized the thermal model of the building. This model can be used for realization of on-line simulations needed, thus based on the presented algorithm to be computed the control signal considered optimal.

Although, the methodology in which it is used the detailed thermal model of the building is difficult to be applied. On one hand, in the case of already built building, the needed data can be hard to be found. On the other hand there are situations in which the thermal characteristics are modified in time or due to the disturbing factors of which integration in the thermal model can be difficult or insufficient precisely (for example the solar radiation effect).

As a consequence, it was developed also solutions that take into account a lumped formulation of the model [4, 11-13].

A solution which from the practical viewpoint would be simpler to be used (by avoiding the introduction of the model building parameters), as well as by implementation, is approximation of the building model with a linear parametric model and usage of on-line identification for renewal of the parameters. This solution was used in simulations presented in fig. 2..5.

The process is simulated using the equations (1), (2). In the first part of simulation (steps 0..200) (fig. 2,3), are identified the parameters of the linear parametric model (this is the reason of the large variation of control signal $u(t)$). Then the setpoint is changed periodically with one degree.

In [6] the parameters of the model described by equations (1),(2) were determined experimentally using a constrained evolutionary strategy. These parameters are: C_a , C_w , K_f , K_i , K_o .

Some relations between these parameters can be found in some circumstances. In fig. 3, before steps 600 (label 1) and 800 (label 2), because the variation of air and wall temperatures are very small, we can write:

$$0 = Q - K_i(T_a - T_w) - K_f(T_a - T_o) \quad (14)$$

$$0 = K_i(T_a - T_w) - K_o(T_w - T_o) \quad (15)$$

where heat input Q is proportional with control signal $u(t)$. As a result, we can find useful relations between parameters K_i and K_o and also between K_i and K_f .

In fig.4, 5 the setpoint has a trapeze shape. It was choosed a situation in which $T_a = T_w$ (fig. 5), so we can write:

$$C_a \frac{dT_a}{dt} = Q - K_f(T_a - T_o) \quad (16)$$

$$C_w \frac{dT_w}{dt} = K_o(T_w - T_o) \quad (17)$$

As a result, we can find useful relations between parameters C_a and K_f and also between C_w and K_o .

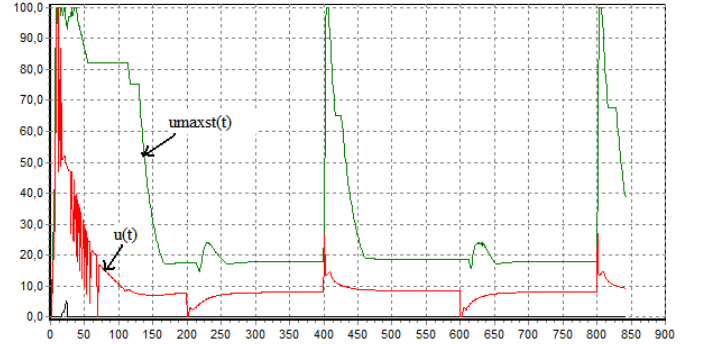


Fig. 2. The control signal

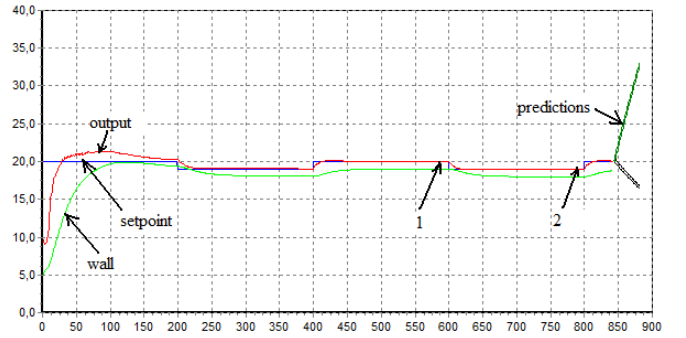


Fig. 3. The setpoint, indoor and wall temperatures

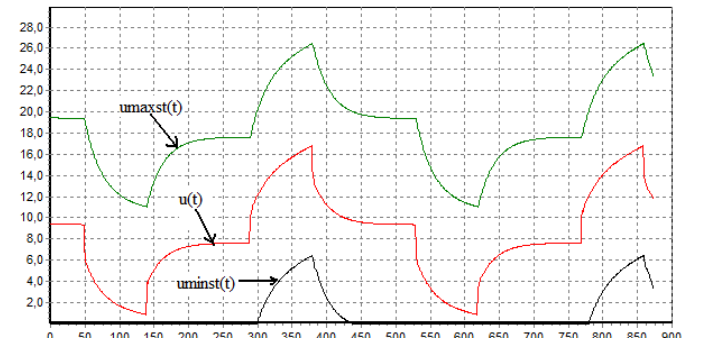


Fig. 4. The control signal

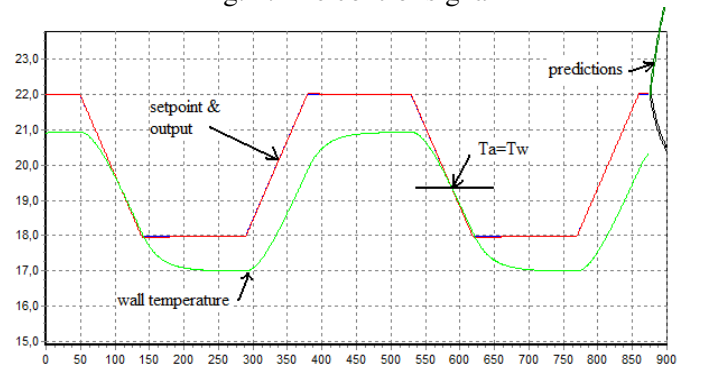


Fig. 5. The setpoint, indoor and wall temperatures

5 Conclusion

In the paper a model based control algorithm that can be applied to nonlinear systems was presented. The algorithm is applied for control of the temperature in a building and can use for predictions the discrete model of the building. By the way it works the algorithm permits implementation of the optimization solutions of the energy consumption in conditions of maintaining a proper thermal comfort. The algorithm can be easy to realize in the case of the HVAC systems that is more difficult to control by means of classical PID control algorithms.

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