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Short communication

Parameter identification and model based predictive control of temperature inside a house

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ABSTRACT

HVAC (Heating, Ventilation and Air Conditioning) systems used for heating or cooling buildings, consume a considerable amount of energy. To optimize the energy consumption, the behavior of occupants must be changed. This can be achieved by providing information and suggestions to occupants. A first step is developing of a less expensive and non-invasive measurement system and metering of the electricity and heat consumed. Based on collected experimental data, it can identify the parameters of a thermal model of the house. The model obtained will be used to simulate different aspects that can help to reduce the energy consumption. This paper presents a simple solution for thermal modeling of a house which includes experimental identification of the model's parameters. Such data are used to simulate the thermal behavior of the house and to obtain solutions to reduce energy consumption. In simulation, the control of the thermal system is performed using a model based predictive control algorithm.

1. Introduction

Reducing and optimizing 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 and monitoring system for the electrical and thermal energy consumption.

This system 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 behavior. In this context, it is necessary to create a simulator that will permit the study of different strategies for reducing the thermal and electrical energy consumption [1]. As it is known, the main part of the energy consumption of a house is represented by heating. For this reason, a first step is to generate the thermal model of the house. In the literature there are presented many examples of modeling and simulation of energy consumption in a household [2–4]. The thermal model can be used also for the study of some HVAC (Heating, Ventilation and Air Conditioning) systems with electrical heating [5]. Also, the simulator is needed to provide solutions in the implementation phase of the project (living houses) and can be used also by the final users. A simulator can be used 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 energy 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 [6].

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.

Another type of model is the lumped parameter model which has 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 modeled as a lumped parameter model. This modeling permits fast simulations since the system is reduced to a first order system. The model can be described as by thermal–electrical analogy.

Black box linear parametric models are used in Refs. [5–7]. This approach involves the identification of parameters of the model

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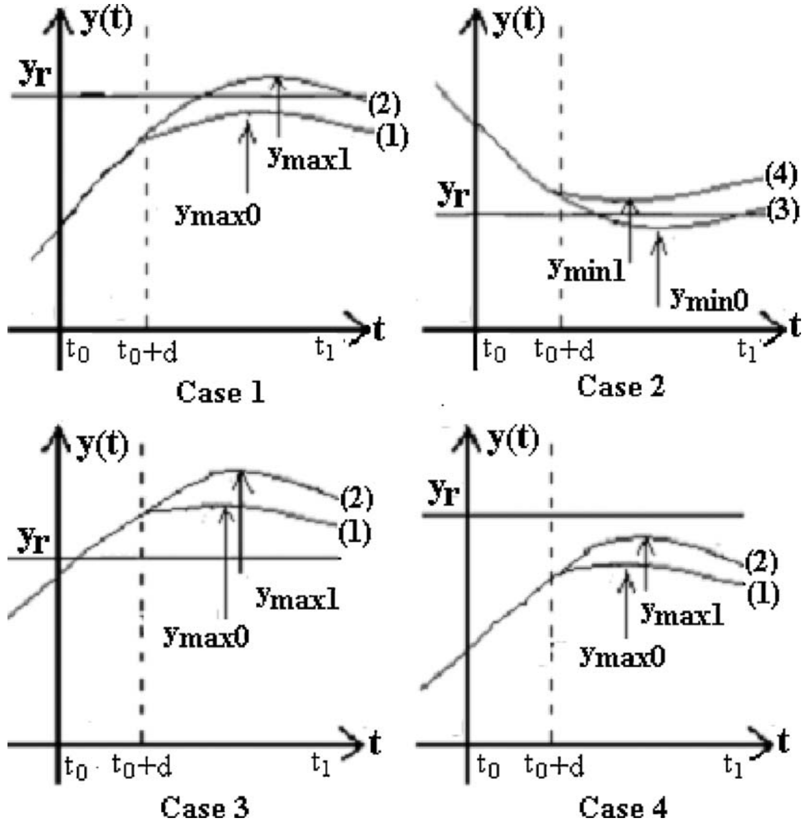

Fig. 1. Examples of output predictions.

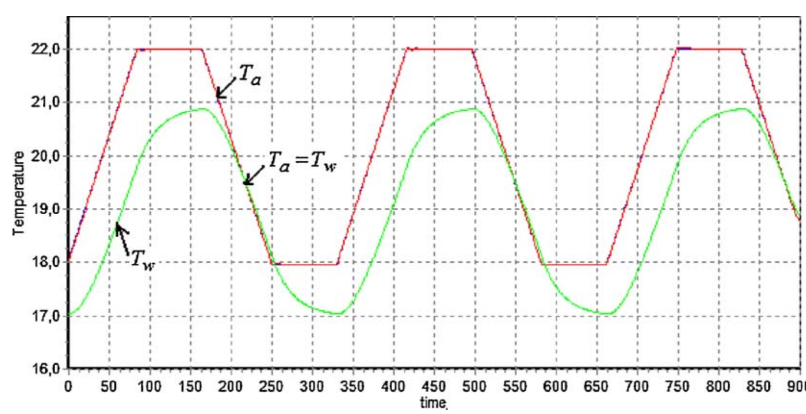

Fig. 2. Parameter identification.

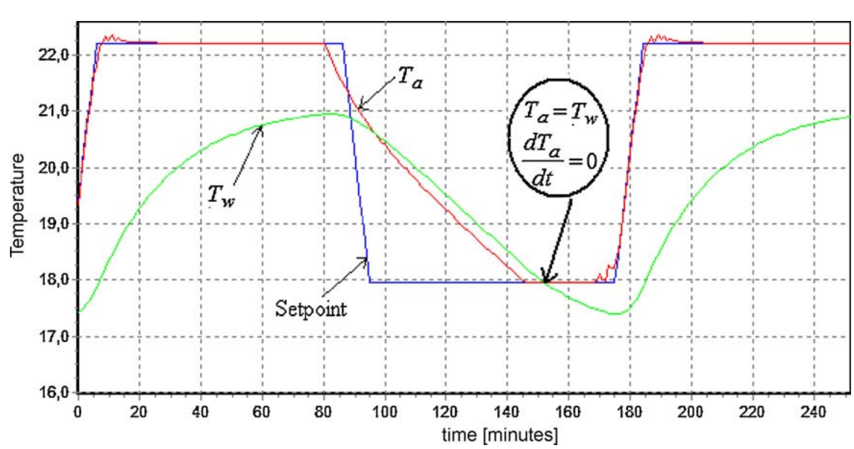

Fig. 3. Identification of the parameter K_f.

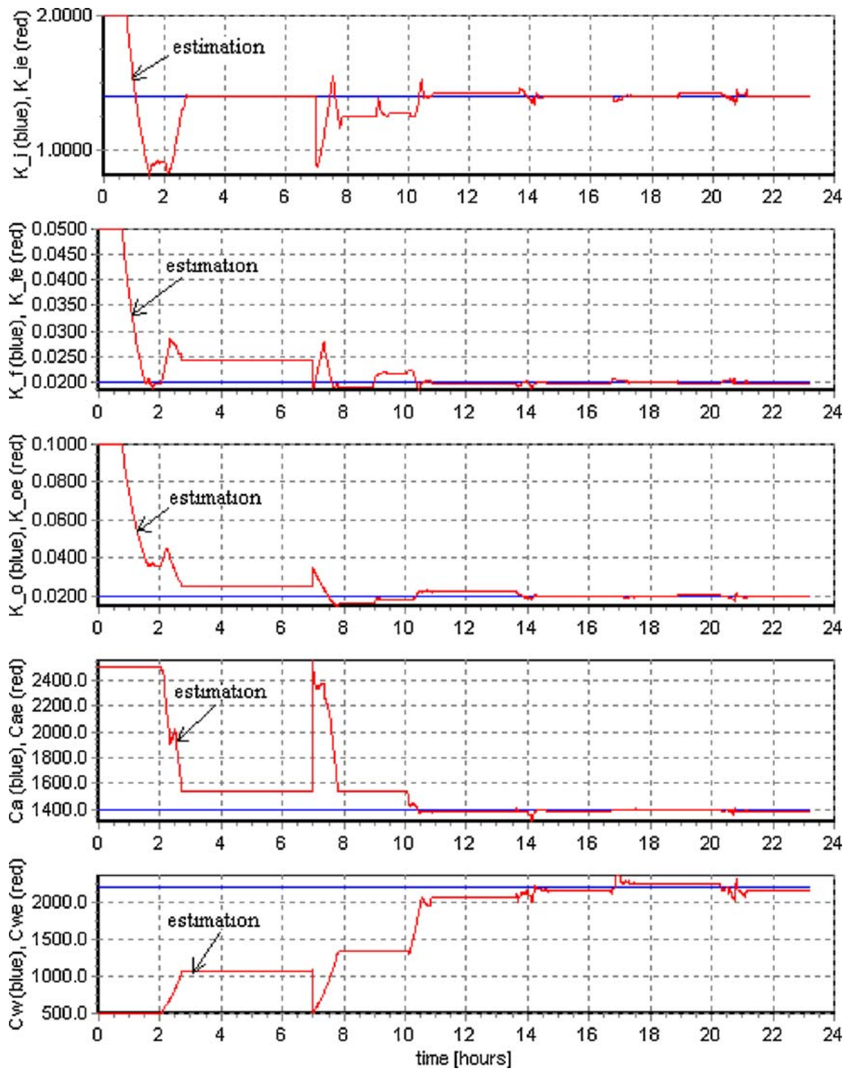

Fig. 4. Parameter identification.

based on input and output data. The method is less expensive and does not require knowledge of detailed system.

In the control field there are used simplified models using supplementary identifications or correlations. The necessary phenomena can be modeled 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.

In Ref. [8] control strategies with both feedback and feed-forward are investigated and discussed. In order to compare different strategies for temperature control, one small experimental building, with one room of 11 m^2 is studied. The mathematical model of the room was obtained by a combination of theoretical modeling and experimental identification.

In Refs. [9–11] are presented aspects regarding the use of control systems in residential buildings and also solutions for optimization of the thermal energy consumption.

Other researchers present algorithms for calculating the reference temperature in the rooms of a building [12]. This aspect is important if we have in mind that a home may be not continuously occupied.

2. The thermal model of a house

The highest percentage of the energy consumed in a house is used for heating. For this reason it is important to create a thermal model as detailed and precise as it can be, thus the simulator can offer solutions for reducing the energy consumption. Sometimes, a simple model can also offer good results.

In this paper it is used a simplified zone thermal model which was originally introduced in Ref. [13]. The model has two dynamic temperature nodes roughly representing the air and a lumped structure node. Two dynamic heat balance equations are used [14]:

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

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

where T_a is the air temperature (°C); T_w is the mean wall temperature (°C); T_o is the outside air temperature (°C); Q is the 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 the physical data of the building, but also it is possible to obtain the values of parameters using a parameter identification technique.

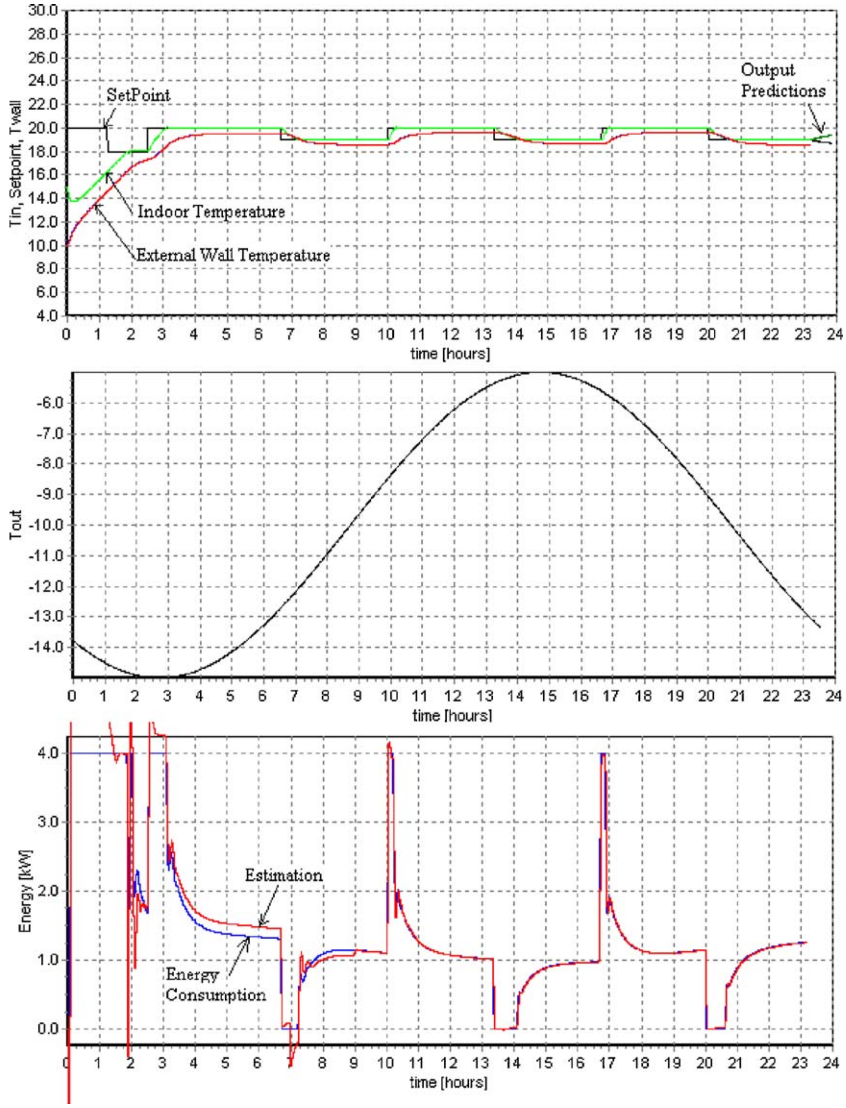

Fig. 5. Measured, control and estimate signals.

To use the model represented by Eqs. (1) and (2) these equations must be rewritten in a numerical form. We use a simple approximation for the derivate:

$$\dot{x} = \frac{x(t+T) - x(t)}{T} \tag{3}$$

where t is the time and T is the sampling period. In the following, for simplicity, instead of $(t - i \cdot T)$, we will write $(t - i)$.

It is obvious that Eq. (3) is an acceptable approximation only under certain conditions. As a result we can write:

$$T_a(t) = T_a(t-1) + \frac{T \cdot (Q(t-1) - K_i \cdot (T_a(t-1) - T_w(t-1)) - K_f \cdot (T_a(t-1) - T_o(t-1)))}{C_a} \tag{4}$$

$$T_w(t) = T_w(t-1) + \frac{T \cdot (K_i \cdot (T_a(t-1) - T_w(t-1)) - K_o \cdot (T_w(t-1) - T_o(t-1)))}{C_w} \tag{5}$$

The model represented by Eqs. (4) and (5) can be used to characterize the house from thermal point of view. It is possible to provide some useful comparative data for the user:

- comparisons with other similar users;
- comparisons with past consumptions;
- how the thermal consumption is changed if the temperature setpoint is changed with one degree;
- how the thermal consumption is changed using different scenarios of temperature setpoint evolution;
- other data.

Such information may lead to changing the user behavior.

The proposed system is dedicated only for the measurement of the heat consumption (it is preferable to not change the existing control system; the system is designed to be non-invasive). For this reason, to test through simulation an algorithm for parameters identification of the model (1...5), it is possible to proceed as follows:

- it is considered that the process is in the form (4) and (5) with parameters (C_a, C_w, K_f, K_i, K_o) known and constant;
- the existing control system will be simulated;
- the estimations of the parameters (C_{ae}, C_{we}, K_{fe}, K_{ie}, K_{oe}) will be obtained using experimental input–output data.

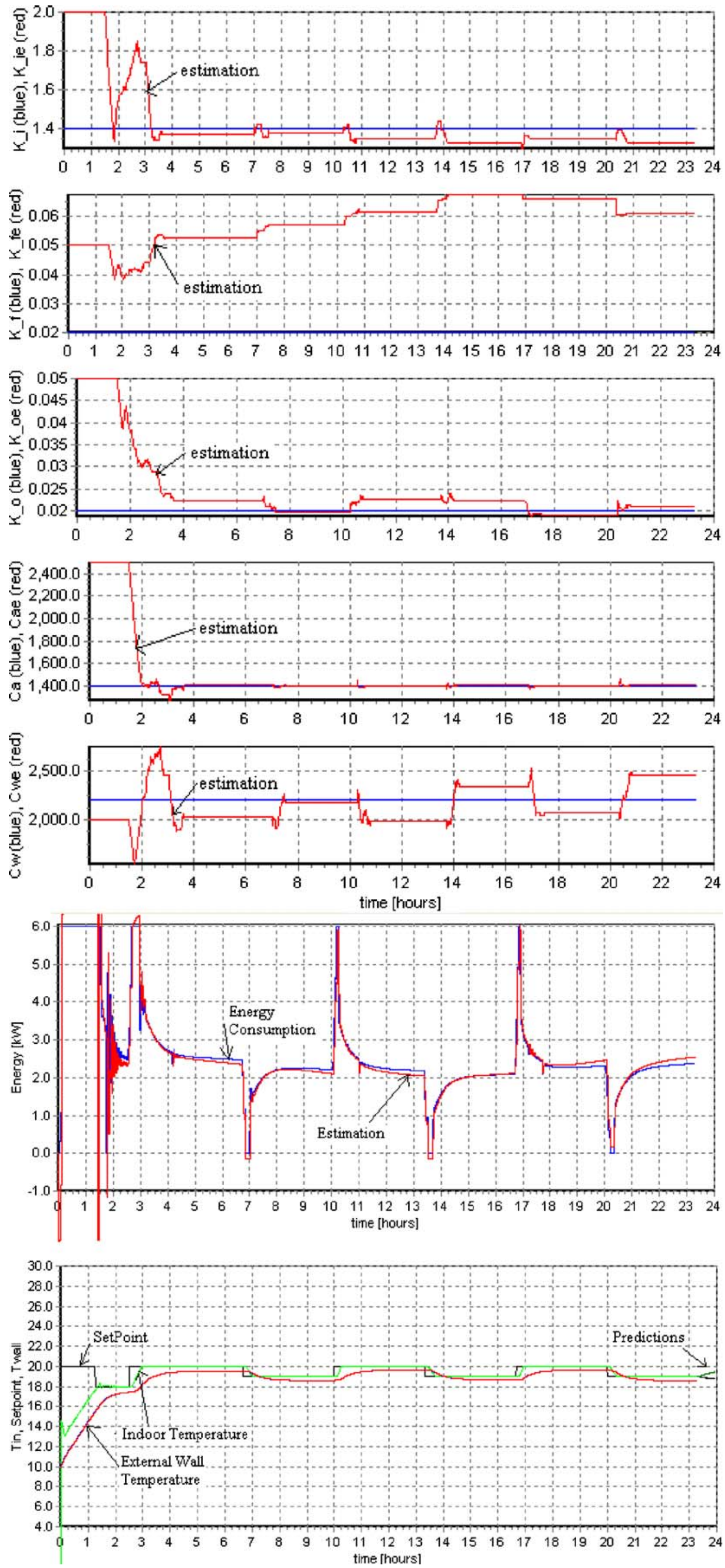

Fig. 6. The process and the model have different structures.

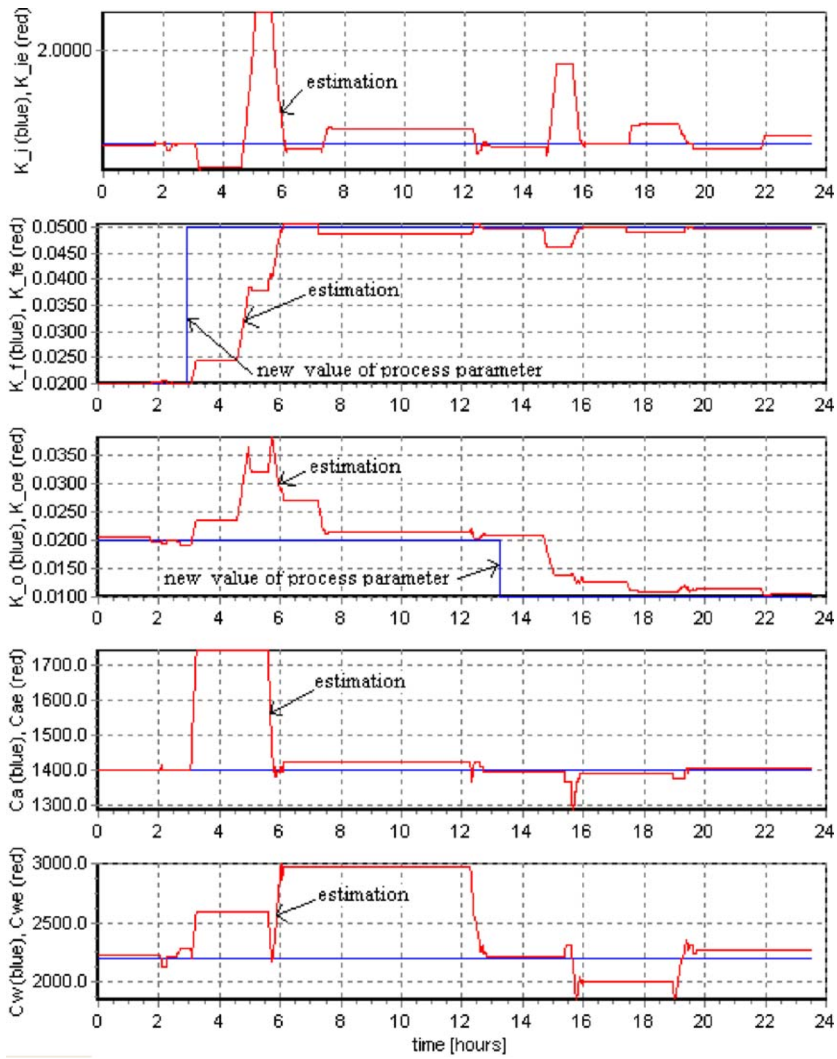

Fig. 7. Parameter identification. Adaptive case.

3. The control algorithm

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 of the cost function. Finally, the first of these signals is applied to the process [15].

The extension of linear MBPC to nonlinear processes is straightforward at least conceptually. But there are some difficulties [16]: 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 the reference is a constant, the problem is commonly referred to as setpoint 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.

In this paper a type of model based predictive control algorithm is used. The basic idea of the algorithm is the on-line simulation of the future behavior of the control system by using a few candidate control sequences [17]. Then, using rule based control these simulations are used to obtain the 'optimal' control signal. In Ref. [18] it was proposed an algorithm designed for setpoint regulation problems (but setpoint can be arbitrary changed). The main idea of the algorithm is to compute for every sample period:

- the predictions of the output over a finite horizon (N);
- the cost of the objective function, for all (hypothetic situation) control sequences:

$$u(.) = \left\{u(t), u(t+1), \ldots, u(t+N)\right\} \tag{6}$$

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

At 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 be easily 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, so that through simulation the information obtained is more helpful for computing the control signal.

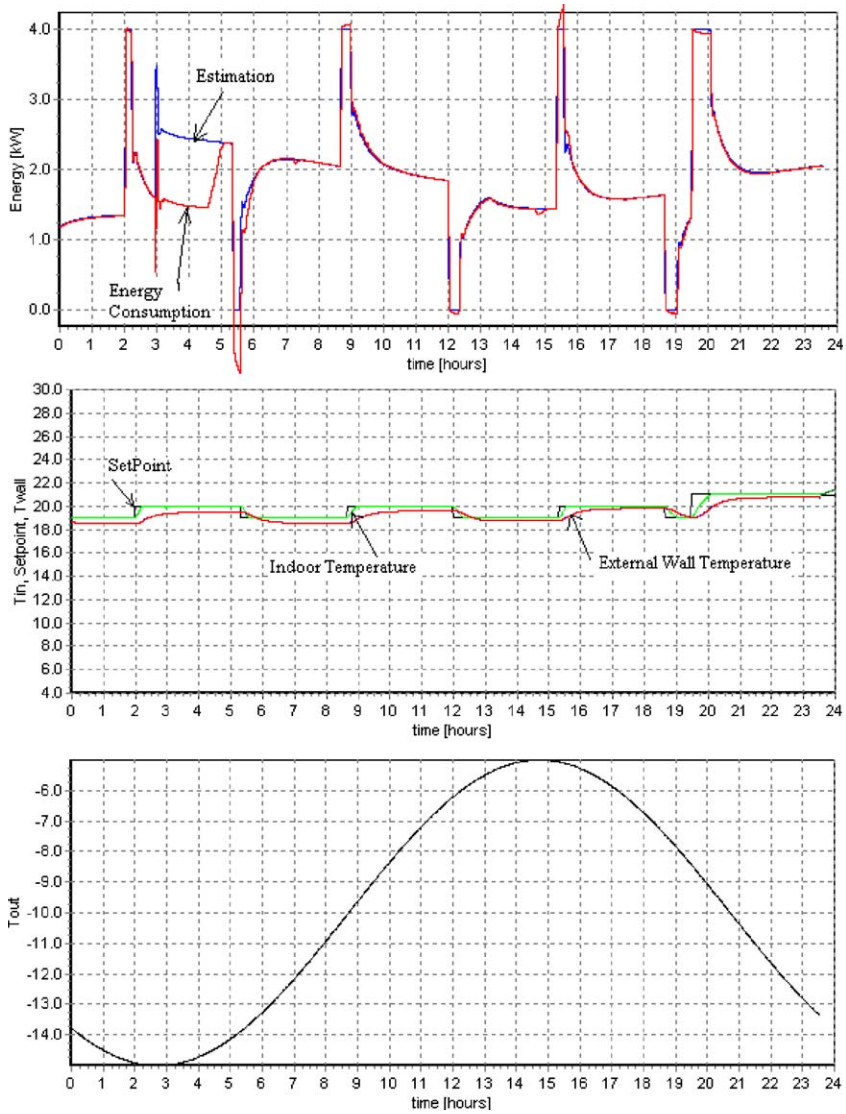

Fig. 8. Evolution of signals. Adaptive case.

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

$$\begin{aligned} u_1(t) &= \{u_{\min}, u_{\min}, \ldots, u_{\min}\} \\ u_2(t) &= \{u_{\max}, u_{\min}, \ldots, u_{\min}\} \\ u_3(t) &= \{u_{\min}, u_{\max}, \ldots, u_{\max}\} \\ u_4(t) &= \{u_{\max}, u_{\max}, \ldots, u_{\max}\} \end{aligned} \tag{7}$$

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 $y_{\max0}$, $y_{\max1}$, $y_{\min0}$, $y_{\min1}$ (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 underlined four usual cases:

Case 1: If $y_{\max0} < y_r$ (corresponding to $u_1(t)$ sequence) and $y_{\max1} > y_r$ (corresponding to $u_2(t)$ sequence).

Then (using a linear interpolation):

$$u(t) = \frac{u_{\max} - u_{\min}}{y_{\max 1} - y_{\max 0}} y_r + \frac{u_{\min} y_{\max 1} - u_{\max} y_{\max 0}}{y_{\max 1} - y_{\max 0}} \tag{8}$$

Case 2: If $y_{\min0} < y_r$ (corresponding to $u_3(t)$ sequence) and $y_{\min1} > y_r$ (corresponding to $u_4(t)$ sequence).

Then (using a linear interpolation):

$$u(t) = \frac{u_{\max} - u_{\min}}{y_{\min 1} - y_{\min 0}} y_r + \frac{u_{\min} y_{\min 1} - u_{\max} y_{\min 0}}{y_{\min 1} - y_{\min 0}} \tag{9}$$

$$\text{Case 3 : If } y_{\max 0} > y_r \quad \text{Then } u(t) = u_{\min} \tag{10}$$

$$\text{Case 4 : If } y_{\max 1} > y_r \quad \text{Then } u(t) = u_{\min} \tag{11}$$

In Fig. 1, every output prediction curve is marked with a number which corresponds to the number of control sequence from relations (7). 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 [18]. So, in the second stage, to limit this variance, depending on the behavior of the control system, are used next methods:

- an algorithm that modifies the limits of control signal:

$$u_{\min} \le u_{\min\,\mathrm{st}}(t) \le u(t) \le u_{\max\,\mathrm{st}}(t) \le u_{\max}\ \Delta u_{\min} \le \Delta u \le \Delta u_{\max} \tag{12}$$

For example:

$$u_{\min\,\mathrm{st}}(t) = f_1(u_{\min\,\mathrm{st}}(t-1), u_{\max\,\mathrm{st}}(t-1), y(t), y_r(t)) \tag{13}$$

$$u_{\max\,\mathrm{st}}(t) = f_2(u_{\min\,\mathrm{st}}(t-1), u_{\max\,\mathrm{st}}(t-1), y(t), y_r(t)) \tag{14}$$

where f_1, f_2 are functions which decrease or increase (depending on the behavior of the control system) the difference between $u_{maxst}(t)$ and $u_{minst}(t)$. In relations (7) and (11), the values of u_{max}, u_{min} are replaced with $u_{minst}(t)$, $u_{maxst}(t)$. In the following, when necessary, the next relations are used:

$$u_{min\ st}(t) = u_{min\ st}(t-1) + k_{st}(u_{st} - u_{min\,st}(t-1)) \tag{15}$$

$$u_{max\ st}(t) = u_{max\ st}(t-1) - k_{st}(u_{max\ st}(t-1) - u_{st}) \tag{16}$$

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 $u_{maxst}(t) - u_{minst}(t) > d_{ust} > 0$, where d_{ust} is a parameter of the control algorithm.

- using the "variable setpoint"[17]:

$$y_{r1}(t) = y_r(t) + k_{ref}(y(t) - y_r(t)) \tag{17}$$

where k_{ref} is a weight factor;

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

4. Parameters identification

Usually, based on the characteristics of the building (dimensions of the walls, windows, floor, ceiling, the parameters of the building materials, etc.) the thermal model of the building is created [2]. This model can be used for on-line simulations and therefore using the presented algorithm it can be computed the control signal considered to be optimal.

Sometimes, the methodology used for the detailed thermal modeling of the building is difficult to be applied. On one hand, in the case of already built building, it can be hard to collect the data needed. On the other hand there are situations in which the thermal characteristics have changed in time or, due to the disturbing factors, the integration in the thermal model can be difficult or not precise enough (for example the solar radiation effect).

As a consequence, there are solutions that take into account a lumped formulation of the model [4,6,19,20].

A solution which from the practical viewpoint would be easier to use (by avoiding the introduction of the model building parameters) and implement, is the approximation of the building model with a linear parametric model and usage of on-line identification for renewal of the parameters.

The model may be as follows:

$$a_1 y(t) + \ldots + a_n y(t-n) = b_1 u(t-1-d) + \ldots + b_m u(t-m-d) \tag{18}$$

where $y(t)$ is the output signal (indoor temperature), $u(t)$ is the control signal (energy consumption), m and n are the dimensions of the model, d is dead time, $a_{1.n}$, $b_{1.m}$ are the parameters of the model and usually $a_1 = 1$. Parameters (n, m, d) define the model structure. This black-box type model is easy to use but has the following disadvantages:

- the model does not use the physical parameters of the process; as a result it is not possible to obtain further information using these parameters;
- this form of the model does not include the outside temperature (it is considered disturbance); as a result the identification process will be slowly.

If a model which is described by Eqs. (1)–(5) is used, the identification of the 5 parameters allows us to obtain a direct physical interpretation which leads to a strong advantage. Using the model obtained the user can simulate different thermal scenarios. Also it can be obtain information regarding solutions for reducing the energy consumption.

In this paper, for simulating the existing control system, it's used the predictive control algorithm presented previously and a model of a black-box type (18).

The parameters of the gray-box type model described by Eqs. (1)–(5) will be identified based on the analysis of input–output data (indoor and outdoor temperature, consumption). A hurdle might be the fact that control signal is generated by the existing control system. For the identification algorithms to be efficient it is mandatory that the prescribed temperature varies sufficiently.

We will present two solutions that allows the identification of parameters of gray-box type model represented by Eqs. (4) and (5), respectively (C_{ae}, C_{we}, K_{fe}, K_{ie}, K_{oe}).

4.1. Obtaining the dependence relationship between parameters (A1)

In the first variant, the aim is to seek relationships between parameters of the model by choosing an appropriate reference signal. If the air temperature T_a remains constant for a sufficiently long period and if it is possible to consider the wall temperature constant, then we can write:

$$0 = Q - K_i(T_a - T_w) - K_f(T_a - T_o) \tag{19}$$

$$0 = K_i(T_a - T_w) - K_o(T_w - T_o) \tag{20}$$

Therefore, if are known the values of air temperature (T_a), mean wall temperature (T_w), outdoor temperature (T_o) and consumption Q then it is possible to obtain next intermediate parameters:

$$x_1 = \frac{K_o}{K_i} = \frac{T_a - T_w}{T_w - T_o} \tag{21}$$

$$x_2 = \frac{Q}{T_a - T_o} \tag{22}$$

$$x_3 = \frac{T_a - T_w}{T_a - T_o} \tag{23}$$

Of course, in reality, the values of these intermediate parameters x_1, x_2, x_3 will be used with caution and it is necessary to use filtering algorithms.

In a different scenario, using a trapeze reference signal, the air temperature differs slightly from mean wall temperature for a sufficiently long time (Fig. 2). In this case, Eqs. (1) and (2) can be written:

$$C_a \frac{dT_a}{dt} = Q - K_f(T_a - T_o) \tag{24}$$

$$C_w \frac{dT_w}{dt} = -K_o(T_w - T_o) \tag{25}$$

To reach this situation, a trapezoidal reference temperature was chosen, with the observation that the negative slope value should be chosen accordingly. Following intermediate variables can be estimated as follows:

$$x_4 = \frac{C_w}{K_o} = -\frac{T_w - T_o}{dT_w/dt} \tag{26}$$

$$x_5 = \frac{Q}{dT_a/dt} \tag{27}$$

Therefore, we can write the following relationships:

$$\begin{aligned} K_o &= x_1 \cdot K_i \\ K_f &= x_2 - x_3 \cdot K_i \\ C_w &= x_4 \cdot K_o = x_1 \cdot x_4 \cdot K_i \\ C_a &= x_5 - x_6 \cdot K_f = x_5 - x_6 \cdot x_2 + x_6 \cdot x_3 \cdot K_i \end{aligned} \tag{28}$$

To obtain the estimations of the parameters it should be found a specific situation to allow estimation of a parameter. One solution is to control the thermal system to obtain the conditions from Fig. 3:

- the air temperature is constant;
- the initial wall temperature is higher than the air temperature and then it drops below the air temperature.

In this case Eqs. (1) and (2) becomes:

$$0 = Q - K_f(T_a - T_o) \tag{29}$$

$$C_w \frac{dT_w}{dt} = -K_o(T_w - T_o) \tag{30}$$

The first equation allows to determine the value of K_f parameter and then, using relations (28), to obtain the other parameters. This variant of calculation is very sensitive to noise and, from practical point of view, if a filtering solution is not used, is not feasible. In particular, the method of determining the parameter (29) is difficult to apply.

4.2. Search based on simulation and optimization (A2)

The second option involves knowing every step of sampling the following values:

$$T_a(t),\ T_w(t),\ T_o(t) \text{ and } Q(t) \tag{31}$$

These data are memorized for a number of n_{sim} previous steps of sampling. Therefore at each sampling step will be possible to simulate the evolution of the process, using as initial data the information of $(t - n_{sim} \cdot T)$ sampling. The simulation will use the current values of estimated parameters ($\hat{C}_{ae}$, $\hat{C}_{we}$, $\hat{K}_{fe}$, $\hat{K}_{ie}$, $\hat{K}_{oe}$). A performance index is defined to compare the evolution of the measured internal temperature $T_a(t)$ and measured energy consumption $Q(t)$ by the evolution obtained by simulation based on estimated parameters ($\hat{C}_{ae}$, $\hat{C}_{we}$, $\hat{K}_{fe}$, $\hat{K}_{ie}$, $\hat{K}_{oe}$).

If temperatures $T_a(t)$, $T_w(t)$, $T_o(t)$ and the estimations of the parameters of the model are known, then the model of the process can be used to obtain estimation of the energy consumption. This estimate is important when the heat consumption is not measured or, even if it is measured, this consumption is read from time to time, usually one month, and instant readings are not available. Unlike the measurement of electrical consumption (which involves using a hardware interface components which is cheap enough), instantaneous measurement of gas consumption can be more expensive and usually involves invasive solutions.

Performance index can be chosen as:

$$J_{sim} = \sum_{i=0}^{i=nsim} (abs(T_a(t-i) - T_{ae}(t-i)) + \rho(t) \cdot abs(Q(t-i) - Q_e(t-i))) \tag{32}$$

where $\rho(t)$ is a weight factor.

Another issue which is considered is the quantification of the type of regime at a certain time. Some parameters of the model (C_{ae}, C_{we}) cannot be estimated in steady state. One possibility to quantify the type of the regime is:

$$trans = \frac{\sum_{i=2}^{i=nsim} abs(Q(t-i) - Q(t-i-1))}{a_t + \sum_{i=1}^{i=nsim} Q(t-i)} \tag{33}$$

where a_t is a positive number (it is possible to choose: $a_t = Q_{\max}/nsim$).

Algorithm for simulation and calculation of performance index (ACost)

Step 1: Initialization:

- parameters of the model: $\hat{C}_{ae}$, $\hat{C}_{we}$, $\hat{K}_{fe}$, $\hat{K}_{ie}$, $\hat{K}_{oe}$
- temperatures:

$$T_{we}(t - n_{sim} - 1) = T_w(t - n_{sim} - 1)$$
$$T_{ae}(t - n_{sim} - 1) = T_a(t - n_{sim} - 1)$$
$$T_o(t - i)|_{i=1..nsim+1}$$

- energy consumption $Q(t-i)|_{i=1\ldots nsim}$
- performance index $J_{sim} = 0$.

Step 2: Simulation of the evolution of the process for n_{sim} steps and compute the performance index:

For $i = n_{sim}.0$ do:

$$T_{ae}(t-i) = T_{ae}(t-i-1) + \frac{T}{\hat{C}_{ae}} \cdot (Q(t-i) - \hat{K}_{ie} \cdot (T_{ae}(t-1) - T_{we}(t-1)) - \hat{K}_{fe} \cdot (T_{ae}(t-1) - T_{oe}(t-1))) \tag{34}$$

$$T_{we}(t-i) = T_{we}(t-i-1) + \frac{T}{\hat{C}_{we}} \cdot (\hat{K}_{ie} \cdot (T_{ae}(t-i-1) - T_{we}(t-i-1)) - \hat{K}_{oe} \cdot (T_{we}(t-i-1) - T_{oe}(t-i-1))) \tag{35}$$

$$Q_e(t-i) = (T_a(t-i) - T_a(t-i-1)) \cdot \frac{C_{ae}}{T} + K_{ie} \cdot (T_a(t-i-1) - T_{we}(t-i-1)) + K_{fe}(T_a(t-i-1) - T_o(t-i-1)) \tag{36}$$

$$J_{sim} = J_{sim} + (abs(T_a(t-i) - T_{ae}(t-i)) + \rho(t) \cdot abs(Q(t-i) - Q_e(t-i))) \tag{37}$$

4.3. Identification algorithm

A bank of models will be used (i.e. sets of parameters (C_{ae}, C_{we}, K_{fe}, K_{ie}, K_{oe})); the models are numbered $0\ldots n_{\rm b}$. The models will be introduced/removed from the bank using specific performance criteria.

Step 1: execute *ACost* algorithm for the current values of parameters ($\hat{C}_{ae}$, $\hat{C}_{we}$, $\hat{K}_{fe}$, $\hat{K}_{ie}$, $\hat{K}_{oe}$); results the performance index J_{sim}.

Step 2: execute the algorithm *ACost* for all models of the bank; results the performance index $J_{sim,0..nb}$

Step 3: Choose the best model in term of performance index:

$$J_{sim} = \min\{J_{sim}, J_{sim,\,0\ldots nb}\} \tag{38}$$

and up-date the parameters of the model:

$$(\hat{C}_{ae},\ \hat{C}_{we},\ \hat{K}_{fe},\ \hat{K}_{ie},\ \hat{K}_{oe}) \leftarrow (C_{ae},\ C_{we},\ K_{fe}\, K_{ie},\ K_{oe}) \tag{39}$$

Step 4: Calculate the value of the index *trans* (relationship 33);

Step 5: If $trans > trans_1$ (transitory regime), then it will be generated new models as:

$$(C_{ae} + \Delta C_{ae}, C_{we} + \Delta C_{we}, K_{fe} + \Delta K_{fe}, K_{ie} + \Delta K_{ie}, K_{oe} + \Delta K_{oe}) \tag{40}$$

Otherwise if $trans < trans_2$ (stationary regime) then it will be generated new models as:

$$(C_{ae}, C_{we}, K_{fe} + \Delta K_{fe}, K_{ie} + \Delta K_{ie}, K_{oe} + \Delta K_{oe}) \tag{41}$$

The values of $trans_1$, $trans_2$ parameters will be determinate experimentally (may be chosen in wide limits).

Step 6: For each generated model, using the algorithm *ACost* it will be computed the performance index; if the value of the performance index is lower than the present value of cost function (step 3) then the current parameters of the model will be updated:

$$(\hat{C}_{ae}, \hat{C}_{we}, \hat{K}_{fe}, \hat{K}_{ie}, \hat{K}_{oe}) \leftarrow (C_{ae}, C_{we}, K_{fe}, K_{ie}, K_{oe}) \tag{42}$$

and update the value of the cost function.

Step 7: If the parameters of the model were updated according to (42) then it will be tested if the new model will be introduced or not in the model bank. It must be sufficiently different from those models which already exist in the bank and will replace the least efficient model of the bank.

Comments:

1. The role of the bank of models. The use of a bank of models and of the presented algorithm generates some obvious advantages:
   - significantly improves the speed of the identification of the parameters of the model;
   - most important aspect: the risk for a divergent identification process decreases very much;
   - the risk of a local minima decreases also very much;
   - in the case of nonlinear systems, the method permits to obtain piecewise models;

   Difficulties:
   - the computing time increases;
   - to find optimal solutions for introduction/removed of a model in the bank; if the model which is inserted is too much closer to one existing model from the bank then the method effectiveness decreases.
2. The values of parameters $trans_1$ and $trans_2$ are obtained experimentally. The minimum value of the parameter $trans_1$ is chosen so that the control signal $Q(t)$ can vary sufficiently (obviously transitory regime); the maximum value of the parameter $trans_2$ is chosen so that the control signal $Q(t)$ is sufficiently constant (obviously steady state regime).
3. The generation of the new models (step 5) can be done by different methods. In this paper it is adopted a simple search around the actual parameters $\hat{C}_{ae}$, $\hat{C}_{we}$, $\hat{K}_{fe}$, $\hat{K}_{ie}$, $\hat{K}_{oe}$.

For example, the variation of the parameter $\hat{C}_{ae}$ can be chosen as follows:

$$\Delta C_{ae} = n_s \cdot \frac{C_{ae}}{k_s} \tag{43}$$

where n_s gets all the integer values $\{-s, -s+1, \ldots, 0, 1, \ldots, s-1, s\}$ and k_s can be chosen in the interval (10...1000). An acceptable value at the beginning of the identification process is $k_s = 100$; this value can be increased further to obtain more accurate values of parameters. As a result, using the algorithm *ACost*, at every sampling step, will be done $(2 \cdot s + 1)^5$ simulation calculations. Tests show that the search algorithm works well even for $s = 1$. In conditions (41) the number of calculations is $(2 \cdot s + 1)^3$. Of course there are solutions to reduce the number of calculations. At the same time, it will be considered the case of local minimum. To avoid reaching of a local minimum, one practical solution is that every step of sampling to test a limited number of random variations of the parameters ($\hat{C}_{ae}$, $\hat{C}_{we}$, $\hat{K}_{fe}$, $\hat{K}_{ie}$, $\hat{K}_{oe}$). Obviously, based on physical considerations, it will be accepted a range for the values of the parameters $\hat{C}_{ae}$, $\hat{C}_{we}$, $\hat{K}_{fe}$, $\hat{K}_{ie}$, $\hat{K}_{oe}$, respectively maximum and minimum values.

5. Simulations

We will consider the next values of the process parameters:

$$C_a = 1400, C_w = 2200, K_f = 0.02, K_i = 1.4, K_o = 0.02$$

and the initial estimate:

$$C_{ae} = 2500, C_{we} = 500, K_f = 0.05, K_i = 2, K_o = 0.1$$

These values correspond to a type of small studio apartment. It is considered that the maximum power is 4 kW. Chosen sampling period is $T = 60$ s. The results are presented in Fig. 4 (parameter identification) and Fig. 5 (the evolution of temperatures $T_a(t)$, $T_w(t)$, $T_o(t)$, control signal $Q(t)$ and control signal estimation $Q_e(t)$).

Comments:

- it is used a model based control algorithm, the algorithm presented in Section 4. The model used by the algorithm is black-box;
- reference of the indoor temperature is adjusted from time to time in order to produce a change in control signal which contributes to improve the identification process;
- after initialization, a number of sampling periods (in Fig. 4 after midnight for 40 min), the parameter identification algorithm is not used; the reason is to avoid obtaining of incorrect results because of the possible differences in the initialization of the process parameters, for example $T_w(t)$;
- it may be observed that up-dating of estimated parameters values is made only if the control signal has a certain type of variation;
- to simulate the evolution of the outdoor temperature it is used a sine variation;
- in a real case it is possible to appear difficulties due to variation of the contribution of the secondary heat input (due to solar radiation energy, electrical equipment, the presence of occupants, etc.). An acceptable solution would be to find the parameters of the model by one or more experiments in different conditions: at night, in the day with or without any input of solar energy, and other cases where secondary heat input exists. In this way, it is possible to obtain a set of models which characterize the house.
- this set of models will be used later to find the best model at a certain time;
- based on identified parameters it is estimated the energy consumed (Fig. 5) by using Eq. (36). Initially, the estimation is imprecise; however, with increasing accuracy of estimating the parameters of the model, the estimation of the energy consumption becomes more precise;
- in the present paper the process and the model have the same structure thus leading to simplifying of the algorithms testing. For the case in which the process and the model have different structures, there have been realized multiple tests that show a good behavior of A2 algorithm, the identified parameters of the model being used both by the predictive control algorithm as well as for estimation of the energy consumption. For example, if the process has Eq. (1) in the form:

$$C_a \frac{dT_a}{dt} = Q - K_i(T_a - 0.95 \cdot T_w) - K_f(0.5 \cdot T_a - T_o) \tag{44}$$

and the model is described by Eqs. (1) and (2), then choosing $u_{\max} = 6$ the control system has the behavior from Fig. 6.

Figs. 7 and 8 present the results obtained as a result of the change of process parameters. First, it is changed the value of parameter $K_f = 0.02$ to $K_f = 0.05$ (at 3 a.m.) and then it is changed the value of parameter $K_o = 0.02$ to $K_o = 0.01$ (at 13:15 p.m.).

6. Conclusions and future work

For reducing of the thermal energy consumed in a house by changing the behavior of the occupants, it is necessary to create a simulator which includes different scenarios of using of the thermal energy and also to provide users with solutions to reduce the energy usage. This paper presents solutions for the modeling and for the experimental identification of the parameters of the model and also solutions for the estimation of energy consumption. As a result, the model can be used to provide information and suggestions on questions such as:

- how to reduce energy consumption if the average temperature in the home falls with a given number of Celsius degrees;
- how big is the decrease of the energy consumption if the thermal profile associated to a day (e.g. stop heating when nobody is home) is changed;
- what is the effect of changing the parameters of the model associated with the house (five parameters characterizing the house).

The developed simulator also includes a control algorithm based on the model. Control signal is derived from a set of rules.

The solutions presented to identify the parameters of the model require the measurement of the external mean wall temperature. Given the need for non-invasive measurement systems, it is necessary to find solutions that do not require measuring of this temperature. This is a future work. Some tests show that, without measuring the external mean wall temperature, it is possible to estimate energy consumption and some parameters of the model.

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