

Human behavior changing based on the simulation of the temperature control of a house

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Abstract. To optimize the energy consumption in a house, the behavior of the occupants must be changed. This can be achieved by providing information and suggestions to the occupants. Based on a web application, some suggestions can be offered only if it is available a thermal model of the house. This paper presents a simple solution for thermal modeling of a house which includes experimental identification of the parameters of the model, using a less expensive and noninvasive measurement system (indoor and outdoor temperatures and thermal energy consumption). Such data are used to simulate the thermal behavior of the house, to estimate the energy consumption and to obtain solutions to reduce energy consumption. In simulation, the control of the thermal system is performed using a model predictive control algorithm.

Key words

Building management systems, modeling, grey-box model, parameter estimation, model predictive control.

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 and thermal energy consumption. If these data are collected, analyzed, processed, systemized and memorized for a large number of households and if these data become available to the occupants of the households (based on a web application), then it's expected that based on the information, tips, comparison with the consumptions of the other similar households, comparison with its own previous energy consumption, and also other available data, occupants to be able to change the behavior in the sense of more efficient use of electrical and thermal energy.

DEHEMS project [1] aims realization of this objective based on a strategy that involves:

- measuring the energy consumption for each consumer;
- minimal installation costs of the additional equipments;
- non-invasive feature (e.g. it's avoided the significant modification of the measuring existent equipments or introduction of other new equipments or some invasive actions such as introduction of temperature sensors inside of a wall);

Some comments about restrictions referred to the costs and non-invasive features of the adopted solutions:

- for realization of the thermal model of the household and for experimental validation it was created a solution that involves the usage of two temperature sensors (indoor and outdoor temperature) as well as measuring the thermal energy consumption (at least in the identification of the thermal model parameters);

- the control system is of type 'man in the loop'; For example, in the case of a household with its own heating system, the temperature control of the household is realized by the existing control system. Based on the measured and/or estimated information, and based on the information received by the web application, it's expected that the occupant to actuate on the control system of the heating system so that the energy consumption to decrease in conditions of maintaining in acceptable limits the thermal comfort.

Of course, exists a large variety of software [2] that permits the obtaining of the thermal model of the household. In the most cases however, the user has to know more data regarding the household features (construction materials, different parameters etc.), data that can be difficult to obtain. Taken into account the specific of the DEHEMS project, it's obvious that it's not expected the obtaining of a very accurate model; the model will be used in the first place for obtaining useful information in the process of changing the occupant's

behavior. On the other hand, an accurate thermal model will facilitate implementation of some estimation procedures of energy consumption (without being direct measured) that constitutes a great advantage.

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 of 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 [2]. The model has two dynamic temperature nodes roughly representing the air and a lumped structure node. Two dynamic heat balance equations are used [3]:

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

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

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 the physical data of the building, but also it is possible to obtain the values of parameters using a parameter identification technique.

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

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

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

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

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

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

The model represented by equations (4), (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;
- others 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), (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 data.

3. The control algorithm

In this paper a type of model based predictive control algorithm it 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 [4]. Then, using rule based control these simulations are used to obtain the 'optimal' control signal. The algorithm computed 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:

$$u(.) = \{u(t), u(t+1), \dots, u(t+N)\} \quad (6)$$

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;
- the algorithm can be 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. We used the next four control sequences:

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

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 $y_{\max 0}$, $y_{\max 1}$, $y_{\min 0}$, $y_{\min 1}$ (fig. 1- d is dead time, $t_1=N$, y_r is setpoint) of the output predictions.

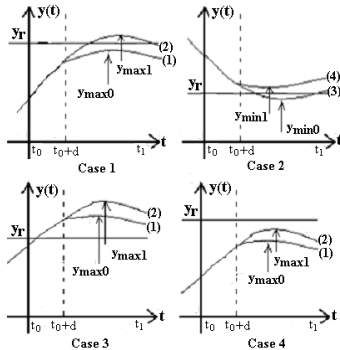


Fig. 1. Examples of output predictions

It can be underlined four usual cases:

Case 1: If $y_{\max 0} < y_r$ and $y_{\max 1} > y_r$

Then (using a linear interpolation):

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

Case 2: If $y_{\min 0} < y_r$ and $y_{\min 1} > y_r$

Then (using a linear interpolation):

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

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

Case 4: If $y_{\max 1} < y_r$ Then $u(t) = u_{\max}$ (11)

4. Parameters identification

Usually, the thermal model is created based on the characteristics of the building [2]. This model can be used for on-line simulations. 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.

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; 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 the equations (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.

The parameters of the gray-box type model described by the equations (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's mandatory that the prescribed temperature varies sufficiently.

Two methods were tested. In the first variant, the aim is to seek relationships between parameters of the model by choosing an appropriate reference signal. 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. The second option involves knowing every step of sampling the values of $T_a(t)$, $T_w(t)$, $T_o(t)$ and $Q(t)$.

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 $(\hat{C}_{ae}, \hat{C}_{we}, \hat{K}_{fe}, \hat{K}_{ie}, \hat{K}_{oe})$. Also, a search strategy is used to find the optimal estimated parameters.

5. Applications- Information for occupants

The proposed model can be used both for estimation of the thermal energy consumption as well as for offering the user different information. An example is presented in figure 2. The user can choose the desired profile of evolution of the prescribed temperature (tables Time_of_the_day and T_Setpoint), it may choose the displaying of other two profiles of temperature offset with $-5...5$ Celsius degrees, it can choose the modification of the model parameters and can choose the shape of the variation of the outdoor temperature.

It will display data like: average energy consumption for chosen profiles of temperature, evolution of the energy during a day, graphic of the average energy consumption function of the initial temperature (TOD=0).

In figure 2 is presented data obtained for the case in which prescribed temperature is constant over the day. It's noticed that, for the chosen model, the reducing with one

degree of the prescribed temperature leads to a reduction of the consumption with more than 3%. Choosing of an adequate profile of temperature evolution may lead to a significant reduction of the energy consumption. If outdoor temperature is bigger than, in percentage, the saved energy may increase. The user can test different strategies of choosing the prescribed temperature and may obtain other information regarding the thermal energy. The user may obtain information regarding the possibilities of reduction of the energy consumption by taking some measures of reducing the losses. As we presented previously, in equations (1) and (2) the parameters have a physical interpretation and their modification can be realized by taking some measures of isolation of the building, optimization of the time intervals in which is realized the ventilation etc. The optimization solutions may take into account also using the renewable energy or contribution of the energy due to solar radiations. In figures 3 and 4 are presented the effect of the changing of the parameter K_f (the fast conductance ascribed to ventilation and elements with little thermal capacitance e.g. windows).

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. 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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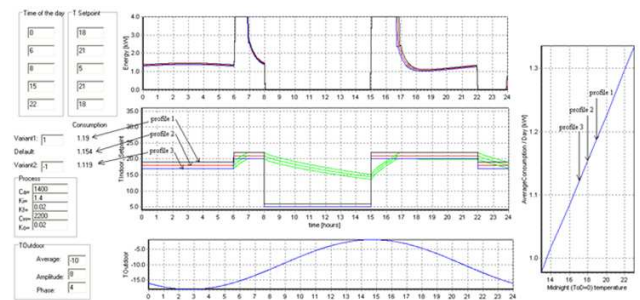


Fig. 2 The effect of the changing of temperature setpoint – case 1

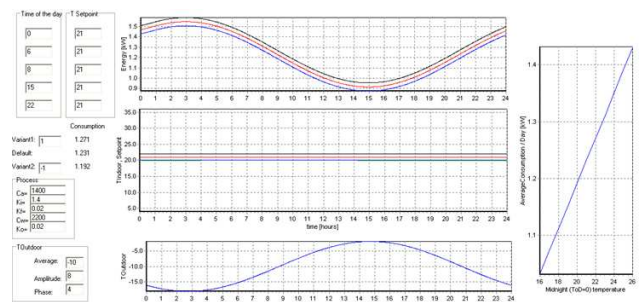


Fig. 3 The effect of the changing of temperature setpoint– case 2

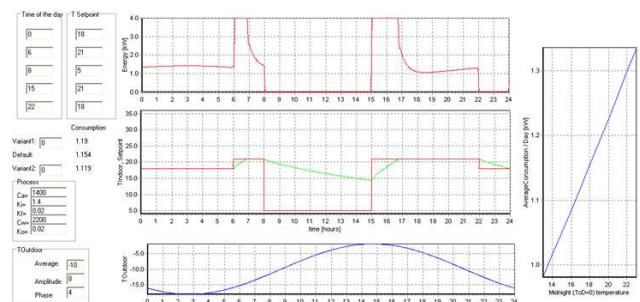


Fig. 4 The effect of the parameter $K_f=0.02$

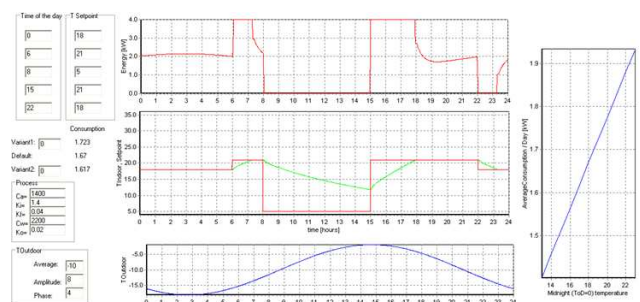


Fig. 5 The effect of the parameter $K_f=0.04$