Session IX No. 5

Dynamic Modeling for Microprocessor Thermal Control of Buildings Using Identification Techniques

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ABSTRACT

Knowledge of the dynamic thermal response of buildings is needed in HVAC control applications. The input and output physical quantities involved in the energy budget of a building can be related either using a physical model or using the black-box approach. Following the latter approach, the building is identified as a system with a given number of outputs (e.g., the energy demand for heating, the internal temperature, etc.) and inputs (e.g., the meteorological data, the occupancy pattern, etc.) related by simple linear equations. The calculation of the black-box parameters from sampled experimental input-output data is called identification of the system. This type of approach is particularly well suited for on-line control of the HVAC system, where a physical description would be heavy in terms of number of equations and unreliable due to uncertainties in the physical parameters of the building. Data measured in a highly-instrumented room, part of an existing office building, have been used to test identification methods that can be implemented on a microcomputer. Results of the analysis are presented and discussed.

INTRODUCTION

One of the aims of building physics is to investigate the thermal phenomena in buildings and HVAC systems in order to determine mathematical models of such phenomena. In the modeling procedure, the standard methodology has been so far usually a deductive one, based on a detailed analysis of the phenomena which take place within the system (e.g., heat and mass transfer, energy storage, etc.) in terms of physically defined quantities (e.g., air temperatures, solar radiation flux, wind velocity, thermal properties of building materials, etc.).[1] Such analyses are usually developed by making use of classical mathematical tools (e.g., differential equations).

In this research a different approach has been used: following the system theory point of view, attention has been focused on the determination of cause-effect (input-output) relationships between defined sets of variables on the basis of measured data. In this case, a detailed physical description of the phenomena is not needed. This approach to system modeling is called black-box identification. It must be stressed, however, that models obtained by inductive black-box procedures are not as general and physically meaningful as those given by the deductive method.

Identification techniques can be used in a wide range of applications in which no information about system internal behavior is required. Typical applications are the determination of system transfer functions, the comparison among different system dynamic responses and the definition of their "figures of merit", data and signal processing, and the synthesis of controllers.

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The aim of this study is to apply black-box identification techniques to the analysis of the dynamic thermal response of buildings and building subsystems (zones, rooms, walls, etc.). In particular, the system under study is a single instrumented room, part of an existing office building. The room air temperature has been assumed as the output of the system, whereas outdoor air temperature, solar radiation flux, and temperature of the adjacent rooms are the inputs.

Identification is defined as the determination, on the basis of input-output (I/O) measured data, of a model within a specified class of models to which the process under study is equivalent.

Parameter estimation is the numerical determination of the parameters of a predetermined model structure capable of fitting the dynamic behavior of the process.

A simple representation of this problem is shown in Fig. 1. $u(t)$ and $y(t)$ are, respectively, the process input and output. $n(t)$ represents the uncertainties, and $\hat{y}(t)$ the model output. The identification process generates the model parameters by making use of sampled sequences of I/O data.

Comparison of the model output $\hat{y}(t)$ with the real process output $y(t)$ may be utilized in a recursive algorithm either in order to optimize the model parameter estimate, or to adapt at each sampling time the model parameters to the real process behavior. While in the former case a constant parameter model is obtained, in the latter case the model adapts itself to changes in the process structure. It is evident that this last method is very powerful in the case of non-linear and/or time-variant systems and of unknown uncertainties.

With no changes in the basic methodology described in this paper, identification techniques can be applied to HVAC systems, particularly for control purposes. Moreover, identification is needed by a particular class of controllers, called adaptive controllers. Adaptive controllers (see Fig. 2) are those in which the transfer function is modified on-line in order to satisfy optimal criteria while allowing for process structure variations and uncertainties.

The use of these sophisticated techniques appears particularly well suited for HVAC system control and may lead to substantial energy savings.[2,3] The actual implementation of adaptive digital control philosophies is now possible at relatively low cost thanks to the availability of powerful but cheap microcomputers. For such an application, efficient identification algorithms portable on low-mass storage microcomputers are needed. The algorithms presented in this paper have been successfully implemented on an 8-bit, 32-kbyte memory microcomputer.

EXPERIMENTAL SETUP

The test room used in this study is part of a multistory office building with masonry walls and single-glazed windows. The room is located at the second floor on the south east - south west corner of the building (see Fig. 3).

Sixty-four analog sensors are currently used in order to measure the physical quantities that identify the room's thermal response, i.e.:

1. indoor and outdoor air temperature,
2. inside and outside wall surface temperature,
3. conduction heat fluxes through the walls,
4. wind velocity, and
5. solar radiation flux.

All temperatures are measured by means of Pt-100 Resistance Thermometers (RTD) with a 4-wire connection for more accurate measurements. Air temperature RTDs are properly shielded against radiation and ventilated. Three RTDs at different heights are used indoors to evaluate the vertical thermal gradient. One RTD is used to measure the outdoor air temperature. An accuracy of 0.1°C is likely to be reached.

Surface temperature RTDs are slightly embedded in the wall plaster and covered with a thin aluminum ribbon insuring the equalization of temperature over the wall surface. The aluminum ribbon has been covered with the same paint used for the wall surface in order to make the sensor's radiative properties closer to those of the wall. About 40 RTDs are used to measure all the surface temperatures. The high number of sensors installed on each wall was justified by the fact that deviations on the order of ±1.5°C around the mean wall temperature were found.

Conduction heat fluxes are measured by heat flow meters (HFM). These devices are based on the principle that heat flow can be determined by measuring the surface temperatures of a layer of known thermal conductance. HFM must present low capacity and high thermal resistance in order to detect a significant temperature difference. HFM have been embedded in the wall plaster in order to reduce random disturbances caused by air turbulence.

Wind velocity is measured by means of a mechanical cup anemometer. Solar radiation is measured by two horizontal and vertical South-facing pyranometers.

The results presented in this study were obtained using only some of the sensors of the experimental room. In particular, the following quantities were used:

1. indoor temperature (system output),
2. outdoor temperature (1st input),
3. mean adjacent rooms temperature (2nd input), and
4. vertical South-facing solar radiation (3rd input).

An automatic data acquisition unit (DAU) was employed to collect, record, and process the experimental data. The DAU (see Fig. 4) consists of a 6502 microprocessor computer, which controls a 150-channel scanner through an IEEE-488 bus. The A/D conversion and readout of the sampled data is performed by a DVM. Data are stored on disk or, alternatively, on tape, and printed on a line printer. A second tape unit is employed mainly for program storage. Data are sampled continuously, but only the values averaged over a given time step (e.g., 10 minutes) are recorded. This is convenient because noise is filtered out by the averaging process and because, given the high system time constants (principal time constant on the order of 10 hours), the identification may be performed using I/O data sampled at relatively long time steps.[4]

IDENTIFICATION METHODS

In an earlier stage of this research, identification experiments were performed using SIMIDE, a FORTRAN package of identification and simulation algorithms developed at the Istituto di Elettrotecnica Generale of the Politecnico di Torino.[5,6] The identified model structure in SIMIDE is represented in the classical discrete state variables form:

$$\begin{aligned} x(i+1) &= A\,x(i) + B\,u(i) \\ y(i) &= C\,x(i) + D\,u(i) \end{aligned} \qquad (1)$$

where

x = state-vector of dimension n (n = model order)
u = input-vector of dimension m
y = output-vector of dimension p
A,B,C,D = identified constant matrices of proper dimensions.

The identification algorithm belongs to the least squares family (using instrumental variable method) and applies fast and efficient numerical techniques drawn from linear algebra (essentially orthogonal factorizations).[7] Compiling, linking, and execution of SIMIDE requires about 200 kbytes. This package is therefore not suitable for on-line identification and control.

The results presented in this paper have been obtained by using a different class of identification algorithms, which can be conveniently implemented on adaptive controllers.[8,9]

The following I/O ARMA (Auto Regressive Moving Average) model has been selected to represent the physical process:

$$
\begin{aligned}
y(t) = {} & a_1 y(t-1) + a_2 y(t-2) + \ldots\ldots\ldots\ldots\ldots\ldots + a_n y(t-n) + \\
& + b_{0,1} u_1(t) + b_{1,1} u_1(t-1) + \ldots\ldots\ldots\ldots + b_{n,1} u_1(t-n) + \\
& \vdots \\
& + b_{0,m} u_m(t) + b_{1,m} u_m(t-1) + \ldots\ldots\ldots\ldots + b_{n,m} u_m(t-n) + \\
& + e(t) + c_1 e(t-1) + \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots + c_n e(t-n) = \\
& = \left[y(t-1) \ldots y(t-n) \; u_1(t) \ldots u_m(t-n) \; e(t-1) \ldots e(t-n) \right] \theta + e(t) \qquad (2)
\end{aligned}
$$

where

n = system order
m = number of inputs
y = system output
$u_1 \ldots u_m$ = system inputs
$\theta = \left[a_1 \ldots a_n \; b_{0,1} \ldots b_{n,m} \; c_1 \ldots c_n \right]^T$ = s-vector of parameters
$s = 2n + m(n+1)$

In Eq 2, $\{e(t)\}$ represents a sequence of non measurable random variables. If $\{e(t)\}$ represents white noise, Standard Least Squares (SLS) techniques give estimates of the parameters which converge to the true values. On the other hand, the presence of generally colored noise corrupting the data leads to adoption of the Extended Least Squares (ELS) technique to avoid biasing of the estimated parameters.[10] The following prediction model is introduced

$$\hat{y}(t) = \left[y(t-1) \ldots y(t-n) \; u_1(t) \ldots u_m(t-n) \; \hat{e}(t-1) \ldots \hat{e}(t-n) \right] \hat{\theta}_{t-1} \qquad (3)$$

where $\hat{y}(t)$ is the predicted value of $y(t)$, given the data $(y(t-1) .. u_m(t-n))$ and the estimated parameters $\hat{\theta}$ up to time $t-1$; $\hat{e}(t) = y(t) - \hat{y}(t)$ is the prediction error. Let $A_N(t)$ and $Y_N(t)$, where $N = (n+1)(m+1) + n$, be defined as:

$$
A_N(t) = \begin{bmatrix}
y(t-N) .. y(t-N-n+1) & u_1(t-N+1) .. u_m(t-N-n+1) & \hat{e}(t-N) .. \hat{e}(t-N-n+1) \\
\vdots & \vdots & \vdots \\
y(t-1) .. y(t-n) & u_1(t) \ldots\ldots u_m(t-n) & \hat{e}(t-1) .. \hat{e}(t-n)
\end{bmatrix}
$$

$$Y_N(t) = \left[y(t-N+1) \ldots\ldots y(t) \right]^T$$

Then, the cost functional

$$J = \left\| Y_N(t) - A_N(t) \; \theta \right\|^2 \qquad (4)$$

is minimized with respect to θ to obtain the estimate $\hat{\theta}_N$ of the parameters.

It is well known that the estimate $\hat{\theta}$ minimizing J is the solution of the normal equation

$$A_N^T A_N \theta = A_N^T Y_N \qquad (5)$$

It is also known that the solution of Eq 5 may be ill-conditioned. A more accurate method is to solve the following system of algebraic equations

$$R_N \hat{\theta}_N = \hat{Y}_N \qquad (6)$$

where R_N is an upper triangular $s \times s$ matrix (s = number of parameters to be estimated, defined above) obtained by the transformation

$$P_N \left[\begin{array}{c|c} A_N & Y_N \end{array} \right] = \left[\begin{array}{c|c} R_N & \hat{Y}_N \\ \hline 0 & \varepsilon_N \end{array} \right] \tag{7}$$

where P_N is an orthogonal N x N matrix such that

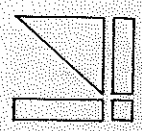
$$P_N A_N = \left[\begin{array}{c} R_N \\ \hline 0 \end{array} \right] \tag{8}$$

The error index is

$$J_{min} = \left\| \varepsilon_N \right\|^2 \tag{9}$$

Recursive ELS solution is performed based on orthogonal factorization of A_N. The first step, as above, is to obtain R_N. At the sampling time t+1, $\hat{e}(t) = y(t) - \hat{y}(t)$ is computed and R_N and Y_N are updated as follows

$$\left[\begin{array}{c|c} R_N & \hat{Y}_N \\ \hline \gamma(t) & y(t+1) \end{array} \right] \tag{10}$$



where

$$\gamma(t) = y(t) \ldots y(t-n+1)\ u_1(t+1) \ldots u_m(t-n+1)\ \hat{e}(t) \ldots \hat{e}(t-n+1)$$

A new orthogonal factorization leads to solve the triangular system of algebraic equations

$$R_{N+1}\, \hat{\theta}_{N+1} = \hat{Y}_{N+1} \tag{11}$$

using the following transformation

$$R_{N+1} = G_s \cdot G_{s-1} \cdots G_1 \left[\begin{array}{c} R_N \\ \hline \gamma(t) \end{array} \right] \tag{12}$$

where

$$G_i = \begin{array}{c} \left[\begin{array}{cccccccc} 1 & & & & & & & \\ & \cdot & & & & & 0 & \\ & & 1 & & & & & \\ & & & c & & & & s \\ & & & & 1 & & & \\ & 0 & & & & \cdot & & \\ & & & & & & 1 & \\ & & & -s & & & & c \end{array} \right] \leftarrow \text{i-th row} \\ \uparrow \text{i-th column} \end{array} \tag{13}$$

$c = R_{N_{i,i}} / \rho$

$s = \gamma_i / \rho$

$\rho = \text{sign}\,(R_{N_{i,i}}) \sqrt{R^2_{N_{i,i}} + \gamma_i^2}$; (sign(0) = 1)

For the aims of the present study, this identification method shows several advantages in comparison with the method used earlier. Firstly, fewer parameters are needed, so that less computer memory is required. Secondly, the algorithm is well suited for recursive estimates, which are typical of on-line processes.

RESULTS

The identification methods have been tested using experimental data recorded in four measurement campaigns during the spring and summer 1982 under the following experimental conditions:

1. no HVAC system on duty,
2. no people present in the room, and
3. no change in window shielding.

Each campaign lasted about one week.

Typical statistical characteristics of the data are presented in Fig. 5, which shows the relative magnitude of outdoor temperature and solar radiation flux harmonic components.

The system model considers three inputs, namely:

1. solar radiation,
2. outdoor dry-bulb temperature,
3. adjacent rooms dry-bulb temperature, and

a single output, namely indoor dry-bulb temperature.

Standard Least Squares (SLS) and Extended Least Squares (ELS) identification methods have been adopted. Comparison of identification/simulation (I/S) results* (Fig. 6 a, b) shows no relevant differences between the two methods. This fact is due to the high accuracy of the measurement techniques adopted, which reduces the noise to very low levels. Consequently, all the I/S results presented in the following graphs and tables have been obtained using the SLS method only. (In presence of greater noise, however, ELS methods have proved capable of efficient filtering and are therefore more reliable than SLS.)

A series of analyses have been performed in order to test the sensitivity of the identification method to model order and sampling interval. The plot of model output and system output provides a meaningful representation of the identification "goodness."

Two types of identification/simulation are presented: one type (type-A I/S) uses a constant set of estimated parameters; the other (type-B I/S) makes use, at each time step, of the model parameters identified at the previous step.

Typical plots of the parameters a_1, a_2, and a_3 of Eq 2 vs. time step of the identification are shown in Fig. 7 a,b,c. For the first few steps a certain "wiggling" of the parameters occurs; thereafter, due to natural convergence properties of the algorithm, the parameters reach stable values. Some slight variations, however, can be still detected due to system nonlinearities.

In addition to model parameters, the poles of the system transfer function have been computed. Typical values of the principal time constant, calculated from the coefficient a_1, are in the range 8 to 12 hours, in good agreement with analytical predictions.

In type-A I/S, it is obviously necessary to avoid using parameters values that have not yet stabilized, as demonstrated by the results in Tab. 1; the STD in fact drops drastically when stability is reached (from time step 100 on). As a general rule, it is advisable to use the final identified set of parameters. Type-A I/S, which is a typical off-line procedure, has been performed using data sets obtained by subtracting the mean value from the original I/O data. The STD as a function of model order (1 through 7) and for two sampling intervals (30 and 60 minutes) is shown in Fig. 8 a. Similarly, Fig. 8 b shows how the STD of the I/S results varies as a function

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*) The following apply to all I/S results presented in this paper:

1. solid line indicates measured data (system output),
2. dashed line indicates simulated data (model output), and
3. the box at the upper right corner of each graph shows model order (ORD), standard deviation (STD,°C) between system and model outputs, and sampling interval (DT), in minutes.

of sampling interval for a third order model.

For type-B I/S, a typical on-line procedure, the original data sets have been used instead. In this case the STD is not a very significant indicator of the goodness of the result, and it is better to compare directly the time trends of the model and system outputs. Type-B I/S results for different model orders and for a sampling interval of 30 minutes are presented in Fig. 9. Similarly, Fig. 10 shows results for various sampling intervals (third order model). It is important to observe that the identification requires an adjustment time until the parameters converge to stable values.

From the results of Fig. 8 b (type-A I/S) and Fig. 10 (type-B I/S), it can be seen that the optimal sampling interval falls in the 30-to-60 minutes range. Identification performed with lower sampling intervals produces ill-conditioned calculations.

A further validation of these I/S methods has been obtained by simulating the system output using data sets different from those used in the identification. Results are shown in Fig. 11. The downward shift of the model output with respect to the system output in Fig. 11 a is due to the different system and model steady-state gains. The two data sets, in fact, correspond to two different working conditions: the data used for identification were measured in the summer (T_{out} = 30°C), and data used for simulation were measured in the early spring (T_{out} = 16°C). The shift, obviously, disappears when the mean value is subtracted from both I/O data sequences (Fig. 11 b).

CONCLUSIONS

The results obtained confirm that reduced order models (up to the fourth one) are capable of accurately representing the dynamic thermal behavior of the test room. The estimate of the optimal sampling interval in the range of 30-to-60 minutes is fully in agreement with the 60 minutes sampling interval adopted in most heuristic models. At this stage of the study it can be stated that the adopted identification algorithm has proved effective from the modeling point of view and reliable with regard to portability characteristics and computational speed.

Future developments of this research will be in the direction of integer computation and actual implementation of these methods in adaptive control systems for building HVAC.

ACKNOWLEDGMENTS

This work was partially funded by CNR (National Research Council of Italy) under research grant 80.00880.92. The authors wish to thank Prof. V. Ferro for the encouragement and guidance provided throughout this effort, and Mr. G. Vannelli for his valuable contribution to the experimental and computational phases of the research.

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TABLE 1

Standard Deviation (STD) Between Model and System Outputs as a Function of Number of Steps (N) Used to Identify the Parameters

N	50	100	150	200	250	294
STD (°C)	1.69	0.42	0.37	0.40	0.44	0.46

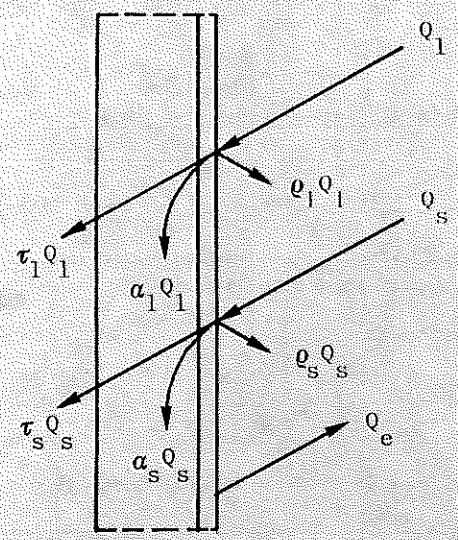

Figure 1. Radiation balance over a surface

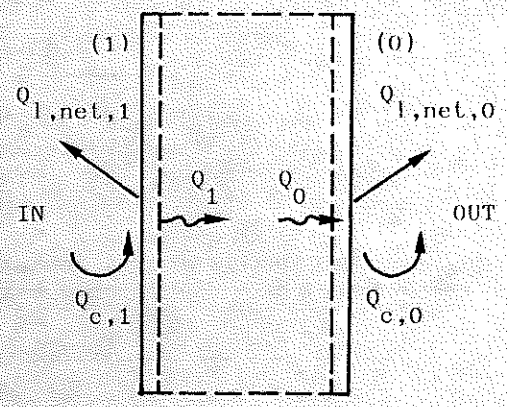

Figure 2. Global energy balance of the wall

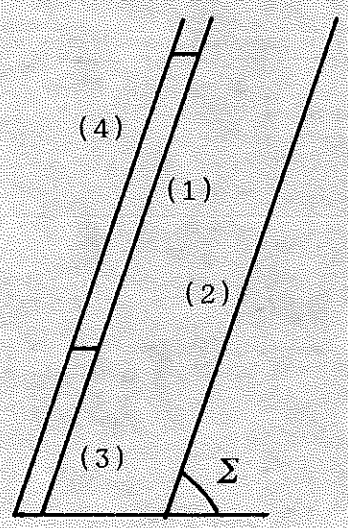

Figure 3. The ideal room

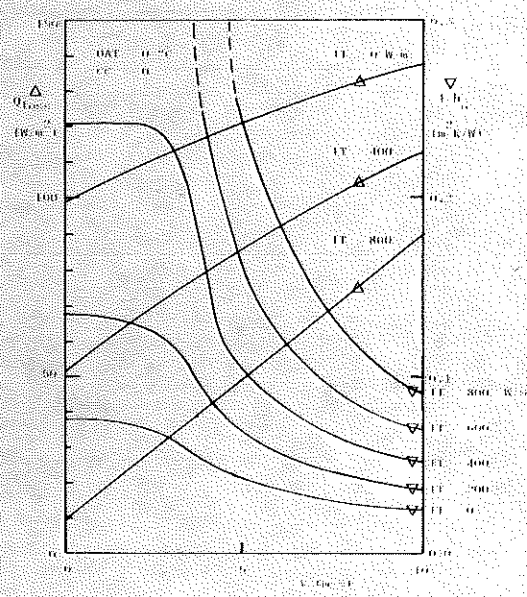

Figure 4. Outgoing heat flux Q_{loss} and outside surface heat transfer resistance $1/h_i$ vs. wind velocity and solar radiation with coud cover and outdoor air temperature as constant parameters