ON SITE IDENTIFICATION OF BUILDING ENERGY PERFORMANCES

V. Richalet
LASH
Ecole Nationale des Travaux Publics de l'Etat
Rue M. Audin
69120 Vaulx en Velin

F. Neirac
Centre d'Energétique
Ecole des Mines de Paris
Rue C. Daunesse
06565 Sophia Antipolis Cedex

SUMMARY

Several attempts have been made these past few years to obtain a simplified dynamic model of thermal behaviour of buildings from recorded data. System identification techniques are well known in other fields, such as aeronautics. They have been applied with success to analyse various aspects of building analysis.

We applied system identification to the problem of the static and dynamic characterization of building energy performances, in order to write an user friendly software.

An important feature of system identification is the choice of the appropriate mathematical model, whose parameters are obtained by a numerical estimation technique. For instance, we can select a lumped parameter model, or an ARMA model, or a state space model. We compared the results and ease of use of these various mathematical models, to select the most appropriate one for building characterization. Artificial sets of data (i.e simulated data) have been produced to focus on problems like correlations between input data, biased air temperature, wind effects, and their weight on the validity of calculated parameters.

A second order state space model (2 time constants), based on modal analysis, has been chosen to be set up in a software, which we called LADY. Inputs are sampled recorded inside and outside air temperatures, global solar radiation, and power HVAC. We give a help to initialize the algorithm with "physically" meaning parameters. Main outputs are global U-value of the building, equivalent solar aperture, and time constants, with calculated standard errors. Furthermore, the model issued from the analysis can be used for comfort evaluation or heating consumption calculation under different climatic conditions.

We hope a large use of this software to better analyse and understand successes and failures of' system identification techniques in the field of thermal building.

I - INTRODUCTION : WHY IS BUILDING THERMAL CHARACTERIZATION A DIFFICULT PROBLEM ?

I - 1 Main thermal characteristics of a building

The problem we are dealing with in this article is a very simple one : consider a building (tipically an individual house) in its natural environment, and without any occupant. We are trying to write its thermal balance in the following way :

$$UA(\bar{T}_i - \bar{T}_0) = \bar{Q} + A_s \bar{I} \qquad (1)$$

where :

- T_i = internal air temperature (°C)
- T_0 = external ambient temperature (°C)
- Q = heating load (W)
- I = solar south irradiance (W/m^2)
- $\bar{.}$ denotes the averaging over a long period

The two parameters UA (WK^{-1}) and A_s (m^2) leading to a correct heat balance are expected to be respectively the *global heat loss coefficient* and the *solar apperture* of the building, and we call them *main thermal characteristics (MTC).*

To derive these values from experimental measurements is a well known problem : equation (1) means that internal temperature (T_i) depends mainly on three variables (T_0, I, and Q_h), but since the effects of the three "inputs" are mixed in the "output" T_i value, it becomes very difficult to separate their respective contributions Two main class of methods are curently used to solve it.

I - 2 Static methods

Since equation (1) is a static equation (i.e. where the dynamic behaviour of the system has been neglected due to averaging over a long period), the first natural incoming idea is to try to find the MTC by using a static method : setting a constant setpoint for T_i, and measuring average values of T_0, Q and I with a large timestep (day, week, or month) leads to UA and A_s values by a simple linear regression.

A large number of methods derived from this principle are today available ([1]). Their main advantage is simplicity. But they also have some unavoidable defaults. First of them is the necessarily high duration for the measurements : one month is a minimum, and best results are obtained with a complete heating season. They also present a large sensitivity to the climatic conditions : if very good results can be obtained for cold and sunny climates (as in Northern Europa), it is more difficult to have the same accuracy when the internal-external temperature difference becomes lower.

I - 3 Dynamic methods

Dynamic methods use a different approach of the problem : since a building is never in static equilibrium, but always in transient conditions, we can try to obtain a dynamic modelling of the building, instead of a static one as (1). Static modelling can be derived from the dynamic model, leading in particular to the MTC values. Moreover, the dynamic model can be used for specific needs, such as consumption prediction.

Such a dynamic model can be obtained from on site measurements by using sytem identification techniques. They request hourly or half-hourly measurements instead of the daily or weekly average values requested by static methods.

The expected advantages of these methods are short duration for the measurements and best accuracy. But they are also much more complex than static methods, and numerous difficulties are to be solved before to obtain confident results. The methodology we present in this paper refer to several years of researh in the field of building characterization with system identification techniques.

II - SYSTEM IDENTIFICATION

II.1 Principle

In a first time, building is seen as a conceptually dynamic system described as in figure 1. The system is controlled by input variables u(t), and its response is observed throughout an output variable y(t). It might be also affected by a disturbance v(t). u(t) and y(t) are recorded measured variables whose model of the system is to be fitted. This task is called system identification and building is only a particular application case of this large field of automatics.

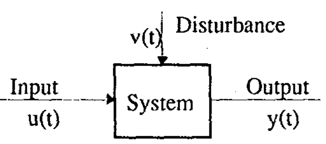
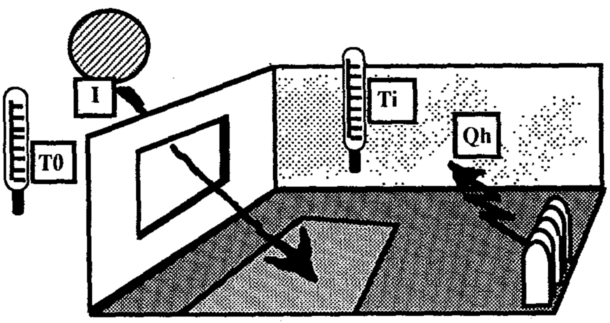


figure 1

In our particular case the system is the building in its surrounding environment :



Its inputs and output are respectively :

• $u(t) = \begin{bmatrix} T_0(t) \\ I(t) \\ Q_h(t) \end{bmatrix}$

• $y(t) = T_i(t)$

The sytem identification procedure includes two major choices :

• choice of the mathematical modelling : many kinds of parametric dynamic models exist for the transient behaviour simulation of the system. They are described in section II-2.

• choice of the statistically based method to use to estimate the unknown parameters of the model : depending on the shape and the complexity of the model choosen in the preceding step, a certain number of identification algorithms are available. The classical Marquardt-Levenberg algorithm is convenient for a large class of problems. Its basic principles are given in section II-3.

The global system identification procedure has to be done in an iterative way : beginning by the choice of a parametric model, continuing by the design of experiment and the collect of data, it ends by the parameter fitting itself. Depending on the quality of the results obtained, some changes have to be done on the initial choice of the model or on the experimental protocol.

We give in section II-4 and II-5 some elements on the comparison of different models and the main reasons leading to the choice of a modal model as a good working tool for identification.

Finally, we give in chapter III our conclusions on the best experimental conditions, by the use of the software LADY elaborated around a modal modelling of the building.

II - 2 Possible parametric models

For use in identification, we can only consider models including a very little number of parameters. Such models can be obtained by two diferent approaches :

• The first one is based on physical considerations and leads to lumped parameter models.

• The second approach uses results issued from model reduction techniques and leads to what we call "mathematical" models.

II.2.1 - Physical models

Building behaviour is represented by an analogic circuit whose resistances are thermal resistances between nodes, and capacities are thermal capacities of part of the building. It is possible to give a specific meaning to the elements according to their localization so they are called "physical" models. We chose to present here two of the numerous models ([2], [3]) used by different authors (figure 2).

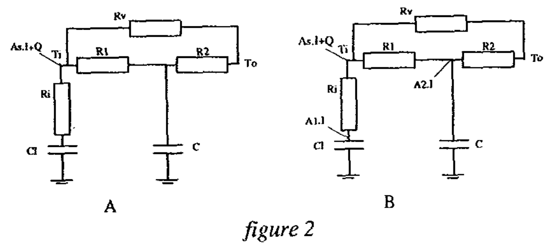


figure 2

In model A, solar radiation is only affecting internal node of air temperature. In model B two more parameters are taken for solar influence. Both have two capacities to represent thermal inertia, and one resistance R_v for direct effect of outside temperature on inside temperature.

I.2 - "Mathematical" models

An other way to obtain reduced behaviour models is to use more mathematical considerations. The detailed thermal behaviour of a building can be described by large linear systems. Model reduction techniques can be applied to such models, which give as result that, if we are interested in one particular output of the model (in our case the internal temperature T_i), its dynamic behaviour can be approximated by a very low order model, instead of the large initial physical model.

Such models contain a few parameters. Because they result not directly from physical considerations, but also from some mathematical transformations, we call them mathematical models. Practically, two major forms are used :

• (1) modal state space models ([4]):

$$\begin{cases} y(t) = x_1(t) + x_2(t) + k\, u(t) \\ \dot{x}_1(t) = f_1\, x(t) + g_1\, u(t) \\ \dot{x}_2(t) = f_2\, x(t) + g_2\, u(t) \end{cases}$$

in which the two eigen values f_1 and f_2 can be related to the two main time constant of the building by :

$$f_1 = -\frac{1}{\tau_1} \text{ and } f_2 = -\frac{1}{\tau_2}$$

and where the quick phenomena are taken into account by the direct input output coupling denoted by k u(t).

• (2) recurrent or ARMA models [3]:

$$y(t) + a_1 y(t-1) + a_2 y(t-2) = b_0 u(t) + b_1 u(t-1) + b_2 u(t-2)$$

which can be seen as a translation in the time space of the state space models.

Note : we didn't mention a third approach, wich can be seen as intermediate between physical and mathematical models, and wich consists to build RC models with R and C values deriving not only from physiscs, but including some mathematical considerations to lead to accurate modelling ([5]). Such models are more than simplified physical models for a modelling purpose, but when used for our identification problem, they can be considered as belonging to the lumped parameter model class.

II.2.3 What model to choose ?

In fact, all three above models, being lumped parameter, state space or recurrent model, give a representation of a 2 order system. Differences are to be seen in the number of the parameters.

Choice of an adequate parametric model must take into account other considerations, such as physical interpretation of the parameters and numerical conduct of the identification. Let us wait for more datails concerning identification algorithm.

II.2 - The Marquardt algorithm

The mathematical system whose parameters are to be identified is linear relative to the describing variables. It is not linear relative to the parameters. The problem is then, in the nonlinear case, to minimize the distance between the recorded measured output $\hat{y}(t)$ and the output issued from the model y(t). A mathematical sense must be given to "distance"; generally is retained the least square sense, so that the function to minimize is:

$$J(t) = \sum_t (\hat{y}(t) - y(t))^2$$

J is a function of the vector of parameters to be fitted, θ.

Marquardt's method is a compromise between the gradient method and the linearization (or least square method) and appear to combine the best features of both, while avoiding their most serious limitations. It can be explained briefly as follows. Suppose we start from a certain point θ_0 in the parameter space. If the gradient method is applied, a vector in the steepest descent direction is obtained for movement away from the initial point. This is the best local direction to attain smaller values of J, but as θ is approaching to the minimum, the method is likely to "zigzagg" with very little steps and the least square method tends to work better. Marquardt's algorithm provide a method for interpolating between both directions and for obtaining a suitable step size as well.

We shall not go into the detail of the method here. Just mention the necessity to give first starting values for parameters and to calculate the first and second derivatives of the function J(θ) which can be a complex task if the model is not in a convenient form. Some mathematical library routines turn out the difficulty approximating these derivatives by ordinary differentiation of functions.

II.3 - Comparison of selected models

A calculation using a Marquardt's algorithm from the SLATEC library is done for the three previous parametric models.

For practical reasons (giving initial values to parameters is not an easy task), the vector of parameters has been transformed so that it makes appear physical characteristics such as UA, As and time constants. Other parameters depend on the chosen model.

Two examples are given : one using simulated datas, and one using real measured data.

III.3.1 Simulated data (TEST1)

The first comparison is issued from the simulation of an ordinary house using the ESP code ([6]). In this case we know a priori the UA value and the main time constant to be identified :

$$UA = 205.2\ W/°C \qquad \tau 1 = 51.7\ h$$

Results obtained are as follow :

TEST1	cri * (°C)	UA (W/°C)	As (m2)	τ1 (h)	τ2 (h)
ARMA	0.098	204.24	8.90	52.28	3.23
State space	0.098	204.07	8.88	52.32	3.34
RC-A	0.345	207.75	8.81	48.07	0.23
RC-B	0.121	207.36	9.32	51.47	1.43

Table 1: Identification of building TEST1 characteristics

* cri = square discrepancy criterion = $\sqrt{\frac{J}{N}}$, N = nubcr of measurements

We observe that :

• Arma and State space models gives the same results with the same acuracy.
• RC-A model is less accurate than RC-B model.

III.3.2 - Real data (TEST2)

The second test is issued from the experiment of an individual house located near Bordeaux in the West of France. Measurements were stored with an half-hourly time step. It leads to the following comparison :

TEST2	cri (°C)	UA (W/°C)	As (m2)	τ1 (h)	τ2 (h)
ARMA	0.111	214.81	2.71	46.05	1.47
State space	0.111	214.82	2.71	46.05	1.47
RC-A	0.196	208.20	2.02	36.22	1.09
RC-B	0.179	215.10	2.59	34.77	1.02

Table 2 : Identification of building TEST2 characteristics

We have this time no reference value for UA, but we observe the same results as with the simulated data :

• Identical results for ARMA and State space models
• Better accuracy (in terms of littler criterion) for RC-B than for RC-A

III.4- Analysis of results

We have only given two examples of differences between the results of four models, but our conclusions are based on a great number of experiments on simulated and real data. They can be summarised as follow :

• Choosing a lumped parameter or a mathematical model makes no difference for the identification algorithm. All models are only input-output parametric models, the only difference beeing the number of free parameters (10 for ARMA and State space, less for lumped parameter).

• As expected, there are no differences between results from an ARMA model and a modal state space one. Both lead to a satisfactory description of the building with a mean discrepancy between modelled and measured output equal 0.1 °C.

• Concerning lumped parameters models, differences between RC-A and RC-B are important. Result depends on what parameters are considered necessary to give a "physical" description of the building. Adding two more parameters, here solar apertures, increases accuracy (the criteria is lowered from A to B), but the identified parameters might be non physic: here solar aperture A1 of RC-B is negative for TEST2. Moreover, never mentioned in litterature is the difficulty to find valuable starting values of R and C. Although these parameters are "physic", we are not able to give them an estimated value.

Remarks : It is possible to define a lumped parameter model with 10 free parameters, adding one more resistance to model B between outside node and inside capacity node. This model should give same results as ARMA or modal state space models. But it leads to unnecessary complexity (it is easier to deal with diagonalised systems of equations as modal state space model), and does not solve the problem of starting values.

Previous remarks lead us to prefer mathematical models to lumped parameters models. In fact, it is easier to find back a valuable physical description of the building with mathematical parameters, than to a priori define a physical description of it in terms of resistances and capacities.

III.4 - Conclusions on the choice of a model

Now, we already mentioned that both ARMA and modal state space models are equivalent. We chose to use a modal state space model for the following reason: modal reduction leads to the exact form of the used model, with a specific meaning of every parameters. To better understand, let us represent the model (2) as a little scheme of figure 3.

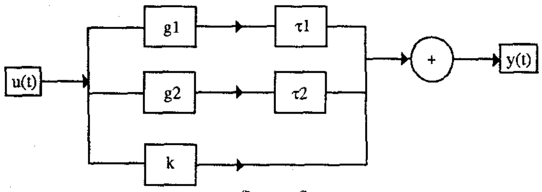


figure 3

where $\tau i = -1/fi$

The ouput of the building is a sum of
- a direct effect of the input with a contribution of k,
- a filtered effect of u with a contribution of g1 and a time constant of τ1 (slow dynamic)
- a filtered effect of u with a contribution of g2 and a time constant of τ2 (fast dynamic)

The total static gain of y relative to u is $\Gamma=(k+g1+g2)$. That means that g1 and g2 are contributions of modes 1 and 2 to the static gain of the input. They can be expressed as poucentages of Γ. A negative value of g2 means that the input has a lagged effect on the output (note that it is often the case with well insulated buildings).

Static gains for the input are known expressions of the usual static parameters of the building.

$\Gamma = 1/UA$ for heating flux

$\Gamma = As/UA$ for solar radiation

Finally, the modal state space model lead to a description of the building in terms of MTC parameters (UA, As), time constants (τ1, τ2), and contributions of modes (k,g1,g2).

We developp the previous state space model in a software called LADY (Logiciel d'Analyse DYnamique du bâtiment), whose features are described in the next chapter.

III - THE SOFTWARE: LADY

This software has been developped by the authors with financial help from the French Energy Agency (A.F.M.E).

III.1 - Overall description

Two major constraints of developpment were: ability of use by people other than specialists in thermics, and working on PC micro-computer.

The used model and method are those previously described. A second order state space model is to be identifed by a Marquardt algorithm. Because of the first constraint, additional features were developped to help potential users: a method to find valuable starting values of parameters, and a calculation of confidence intervalls.

III.1.1 Good starting values

The used iterative procedure requires starting values of the parameters to be identified. All available information should be used to make these initial values as reliable as possible. This leads to a faster solution and limits probability to find a local minimum instead of the absolute one. Importance of physical meaning of the parameters is double : it is more easy to choose intial values, and it is more easy to detect unwanted estimates.

This task was easy when we found that LADY was very robust to rude starting values in a large number of cases where experiment is "good" enough. (We'll see what is a good experiment in the second section). We just help the user to find an estimation of UA and major time constant from an overview of the building.

III.1.2 Adding confidence intervalls

An other important point to be discussed is the evaluation of confidence contours around the final estimates of the parameters : θ, with an error function $J(\theta) = J$. Making assumption that the linearized form of the model is valid around θ, an ellipsoidal confidence region can be obtained using the formula:

$$\Delta\theta^T A \, \Delta\theta \leq \frac{p\hat{J}}{n-p} F(p, n-p, 1-\alpha)$$

A denotes the variance-covariance matrix, whose coefficients write:

$$a_{ij} = \sum_t \left(\frac{\partial y(t)}{\partial \theta_i}\right)\left(\frac{\partial y(t)}{\partial \theta_j}\right)$$

The ellipsoid above will not be a true confidence region as the model is nonlinear . An exact confidence contour is defined by taking J = constant, but since we do not know the correct distribution property in the general nonlinear case we are not able to obtain a specified probability level. But the proposed contour is an approximate 100(1-α)% confidence contour valid if the linearized form provides a good approximation to the true model. We can then determine the end points on the major axes of this ellipsoid by canonical reduction to obtain confidence intervalls on the estimates.

We can give such intervalls (in parenthesis) for the the two previous examples (tables 3 and 4).

TEST1	To	I	Q
τ1=52.32 h (0.88)	0.990 (0.006)	0.953 (0.007)	0.848 (0.012)
τ2=3.34 h (0.06)	0.018 (0.021)	0.049 (0.007)	0.061 (0.010)
cri=0.098 °C	UA=204.07 (2.37)		
s = 6.5	As=8.88 (0.36)		

Table 3 : Identified model for TEST1 with confidence intervalls

TEST2	To	I	Q
τ1=46.05 h (5.55)	0.940 (0.022)	0.986 (0.024)	0.856 (0.006)
τ2=1.47 h (0.16)	0.059 (0.086)	0.061 (0.037)	0.165 (0.011)
cri=0.111 °C	UA=214.82 (5.71)		
s = 8.4	As=2.71 (0.47)		

Table 4 : Identified model for TEST2 with confidence intervalls

Accuracy of identified parameters is very good for TEST1 (simulated data). Confidence intervals are larger for experimental data of TEST2, especially contribution parameters associated with fast dynamic.

This method is a powerful way to detect wrong experiment conditions, as confidence intervalls will increase in such cases. This is a consequence of the stretching of the ellipsoid contour along one or more axes of the parameters. A measure of excentricity of ellipsoid is then a helpful tool. We used as a measure the logarithm of the ratio major/minor axis : s.

Now we see how to design experiment so that information from the data is sufficient to obtain accurate estimations.

Standard Cases	UA W/°C (s.e)	As m^2 (s.e)	τ1 hours (s.e)	Sens. s criterion
Case 0 Reference	162.57 (0.49)	2.20 (0.13)	39.20 (0.30)	3.9 0.110
Case 1 Ti=20°C	166.50 (*)	2.42 (*)	282.74 (*)	(*)
Case 2 To=5°C	161.75 (0.99)	1.97 (0.10)	36.59 (0.81)	18.0 0.064
Case 3 To=17±1°C	160.32 (2.35)	1.90 (0.05)	35.56 (0.60)	8.2 0.017
Case 4 10 clouded days	163.37 (3.00)	2.76 (0.15)	36.30 (1.39)	8.4 0.065
Case 5 To=I/20	161.12 (0.53)	1.80 (0.15)	39.59 (0.27)	16.9 0.119
Case 6 Q=20 .I	125.19 (292.29)	-2.75 (40.27)	39.77 (0.34)	16.8 0.085
Duration (**) 3 days	163.03 (1.88)	1.97 (0.15)	38.26 (1.79)	0.045
2 days	169.76 (6.06)	2.34 (0.35)	39.50 (2.82)	0.042
1 day	147.02 (15.58)	2.82 (2.80)	33.77 (3.16)	0.030

(*) In this case, algorithm was not able to stop alone, so we give values of parameters after 100 steps.
(**) To study necessary duration, we built a artificial set of data for which input data are the same every day.

Table 5

During experiment, it is absolutely necessary to prevent from these specific conditions. From our experience we can give other recommendations. For example, if only a one degree setback of inside temperature appears sufficient for simulated data, in real buildings it is desirable to have a larger one (2 °C seems reasonable). When sun is always shining during experiment, accuracy is damaged by daily similar information about solar radiation, so that it is better if experiment includes both clouded and sunny days. It is also preferable if outdoor temperature is cold. At last, a duration of 3 days is valid if all necessary information is included in the experiment. Very often, this duration will be lengthened to 5 or 7 days to validate previous recommendations.

The more severe constraint to conduct experiment is then indoor temperature variance which obliges to control the heating system. As a final example, we give results issued from experiment of the same house than TEST2, using a constant heating setpoint, so that variations of indoor temperature are very low in TEST3. The identified time constants are very big, and poorly accurate.

TEST3	To	I	Q
τ1=126.29 h (35.78)	0.796 (0.030)	1.141 (0.028)	0.740 (0.043)
τ2=7.26 h (0.99)	0.224 (0.031)	-0.143 (0.023)	0.262 (0.043)
σri=0.088 °C	UA=199.00 (4.49) As=1.46 (0.46)		

Table 5 : Identified model for TEST3 without night setback

III.2 - Optimization of experimental conditions

Identification of building thermal characteristics is confronted with particular experiment conditions. We mean that climatic conditions and occupancy influence are uncontrolled variables that we cannot prevent from.

Several well known problems are studied, with standard conditions:

- there is a perfect control of the inside temperature by the heating system : *Case 1*
- outside temperature is constant : *Case 2*
- outside temperature is very high : *Case 3*
- weather is always clouded : *Case 4*
- outdoor temperature and solar radiation inputs are intercorrelated : *Case 5*
- heating flux and solar radiation inputs are intercorrelated : *Case 6*
- duration of the experiment is short

We looked at these conditions and study influence of them on the estimated parameters and their confidence intervalls. The investigation might be quite large as influencing factors are very numerous for building. We began this task with an ordinary detached house. The study includes tests of simulated data with an intermittent heating control and artificial climatic sets. Results from the identification in such cases are compared to a reference model for a simulated cell (*Case 0*) with a Pseudo Random Binary Signal of heating power.

We found out that the method was robust and give satisfactory results except in the following cases:
- when indoor temperature is constant: it leads to biased, preciseless estimates of biggest time constant
- if weather is always clouded during experiment: this leads to unvaluable estimate of As
- when solar radiation and heating power are intercorrelated: it leads to unsatisfactory estimates of UA and As, that may vary with other starting values of parameters.
- if length of experiment is less than 3 days, accuracy on parameters is low

IV - GENERAL CONCLUSIONS

The main point we wanted to illustrate in this paper is that thermal characterization of a building is possible by using identification techniques. We have to insist on the fact that this result has been obtained after more than eight years of research in this field. From the initial idea to the actual methodology, we encountered a lot of problems that we tried to solve step by step.

The first important progress was obtained when we decided to work with modal state space models instead of RC models : this allowed us to solve problems such as lack of accuracy, non repetability, and initialization of the identification algorithm.

By setting the problem in such a form that the physical characteristics (UA and A_S particularly) were directly parameters to be fitted by the algorithm, and by introducing the calculation of confidence intervalls on these values, we then had the possibility to solve the problem of the optimization of the experimental protocol.

In such a way that the simple problem exposed at the beginnig of this paper (wich appears to be much more complicated than it seems) has today a satisfactory solution with only one week of measurements.

Numerous problems remain to solve now, especially the one wich consists to work with occupied houses. This is our main research topic for the incoming years...

REFERENCES

[1] **Richalet, V.**, 1990, "Le point sur les méthodes de signature énergétique", Rapport Final, CETE de Lyon.

[2] **Hammarsten, S.**, 1989, "Lumped parameter models", Ispra courses.

[3] **Rabl, A.**, 1989,"Application of identification of energy balances in buildings, an overview", Ispra courses.

[4] **Neirac, F.**, 1989, "Approche théorique et expérimentale des modèles réduits du comportement thermique des bâtiments", Thèse de doctorat de l'Ecole des Mines de Paris.

[5] **Laret, L.**, 1980, Contribution au développement de modèles mathématiques du comportement hthermique transitoire des structures d'habitation, Thèse de doctorat de l'université de Liège.

[6] **Clarke, J.**, 1985, "Energy simulation in building design", Adam Hilger Ltd.