

CAN GENERAL SIMULATION MODELS IDENTIFY EXISTING BUILDING CHARACTERISTICS?

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ABSTRACT

The experimental evaluation of the energy performance of existing buildings and components is implemented usually via stochastic modelling from experimental data (Rabl 1988, Jiménez 2008, Enriquez 2008). The most popular methods, stochastic black and grey box modelling, produce predictive models and in some cases identify successfully the principal thermal parameters of the building. However, the models obtained are hard to generalize to other situations. On the other hand, simulation techniques are becoming popular tools used commonly in the design stage of a building to optimize its energetic behaviour. However, it is uncommon to check experimentally the validity of simulations or employ them to design, tune or optimize the buildings control systems and their operation.

In this work a different approach to the identification problem is explored. It is studied the possibility of creating a general purpose simulation model for an office room and fit it to experimental data of different occupied and oriented rooms in order to identify their main thermal parameters.

INTRODUCTION

The Spanish Ministry of Science and Innovation is promoting a Singular Strategic Project of Research and Development, PSE-ARFRISOL (Bioclimatic Architecture and Solar Cooling, in Spanish). This project plans to demonstrate that is possible to save up to 60% office building energy demand by means of solar passive techniques and reduce the conventional energy consumption with active solar devices: solar thermal collectors for heating and cooling and photovoltaic panels for electricity. For this purpose, five office buildings have been built or restored in different climatic zones of Spain.

These buildings are being used as research prototypes to implement and analyze different bioclimatic strategies as well as the integration of renewable energies. With this aim, many theoretical and experimental evaluations of the buildings are being performed. One experimental procedure is to employ a version of the average method (ISO 9869:1994, Bloem 1994, Norlén 1994) applied to the building itself. This method requires long periods of monitoring and gives no information about dynamic processes.

Previous simulation studies have been performed to analyze its dynamic thermal behaviour. Since the buildings have been under supervision since the very early stages of its construction, it opens the possibility of fitting and validating simulation studies. One step further, it opens the possibility of developing identification methods suitable for constructions already built for which less constructive information is available.

The question that arises in this context is if, starting only from the available data, the information about the buildings envelope can be recovered by fitting a simulation model. That is, if we can solve the thermal dynamics in an inverse way to evaluate the thermal characteristics of the envelope of a building.

This paper focuses on the possibility of fitting general purpose simulation models to experimental data to identify the thermal characteristics of the envelope of a building in conditions of real use.

EXPERIMENTAL SETUP

This study is related to the building located at Madrid, called Ed70. It is a building of near 2000 m² of total surface distributed in three storeis plus a basement. It has a ventilated façade and double insulation glass. It implements a field of 180 m² of TIM solar thermal flat

plate collectors for Domestic Hot Water Production, heating and cooling (coupled to four absorption pumps). It also implements semitransparent PV modules integrated as shadowings in the south façade. The indoors climatization consists of an four pipe installation for air-air climatization with Air Treatment Units (ATUs) and inductors as final units. Finally, it implements an intelligent illumination system which regulates artificial lights in function of the existent luminosity. A view of the south façade of the building is presented in figure 1 and the locations of the offices for this study inside the building is presented in figure 2.



Figure 1. South façade of the building.

They are located at the ground floor, one facing south (p0.13) and one facing north (p0.20). Their only indoors constructive difference is orientation. Geometry and materials are the same, but occupancy rates and internal gains are different. Internal divisions among offices are made of furniture and divisions between any office and the corridor are made from glass. Each office studied is prepared for six people occupancy and has a surface of about 22 m². In figure 3 it is shown a view of one of those offices in real use conditions.



Figure 2. Location of the rooms under study.

The monitoring installation must take into account the thermal response of the building to the internal and the external perturbations. The thermal response of the building is taken into account by measuring indoors

temperature. The energy introduced in the room is measured in the heating and cooling circuits of the inductor and a redundancy is added by measuring the temperature and speed of its outlet air. Internal gains for illumination and equipments are measured by wattmeters installed at the correspondent circuit of each office of this study. Internal gains from occupancy are estimated from indoors CO₂ concentration sensors.



Figure 3. View of the p0.20 room.

In order to be able to evaluate the heat exchange with the adjacent rooms and the corridor indoors temperature sensors have also been installed. Temperature sensors have also been installed in the upstairs and downstairs adjacent rooms in order to evaluate the heat exchange through the ceiling and the floor of each office of this study. Other sensors complete the installation such as relative humidity, glass temperature, wall surfaces temperature and openings of doors and windows. Table 1 summarises the indoors monitoring details of each sensor used in the indoors monitorization.

To be able to analyze the response of the building to the external perturbations, meteorological variables must be included in the monitoring system. These are installed on a weather station located on the top of the building. The most representative variables for this study are the external air temperature and humidity, the global solar radiation on the horizontal, the wind direction and speed and the external CO₂ concentration. Table 2 summarises the outdoors monitoring system employed in this study.

Data are measured and recorded every minute in an automated system with a 16-bit A/D conversion to reduce uncertainties and postprocessing tools have been developed to produce data at other time basis from the minatural frequency. This system has been designed and implemented to reduce the total global uncertainty.

SENSOR	PRECISION	RANGE
Temperature, PT100	0.03 K	-20 ... 100 °C
Hygrometer	2 %	0 ... 95 %
CO ₂ concentration	3 %	0 ... 2000 ppm
Wattmeter	0.5 %	0 ... 3000 W
Opening doors	N/A	{0,1}
Hot wire anemometer	3%	0.05 ... 2.5 m/s
Flowmeter	2.5 %	0.5 ... 100 l/min

Table 1. Sensors used in the indoors monitoring.

EXPERIMENTAL DATA

Data is provided on an hourly basis for the building in full operation since the 1st of January to the 30th of september of 2009. In figure 4 is presented the indoors and outdoors temperature of office p0.20. It can be seen that indoors temperature is quite constant near to 25 °C, due to the action of the climatization system. The peaks in the first half of the data series correspond to experiments to identify dynamics of the system performed during weekends with no occupancy.

SENSOR	ACCURACY	RANGE
Temperature, PT100	0.2 °C	-39 ... 60 °C
Higrometer	1 %	0.8 ... 100 %
CO ₂ concentration	3 %	0 ... 2000 ppm
Sonic anemometer (speed)	0.01 m/s	0 ... 60 m/s
Sonic anemometer (direction)	3 °	0 ... 359 °
Piranometer	10 W/m ²	0 ... 4000 W/m ²

Table 2. Sensors used in the outdoors monitoring

In figure 5 is presented the indoors and outdoors CO₂ concentration together with the electrical consumption of illumination and equipments of the same office. It can be seen that the indoors CO₂ concentration is almost always higher than the outdoors one. When the indoors

concentration rises up over the outdoors one, the electrical consumption also grows. That correlation between electrical consumption and CO₂ concentration suggest that the difference between indoors and outdoors CO₂ concentration could be a good indicator of occupancy in the room. Between the hours 5200 and 5500 the room is unoccupied and the difference between indoors and outdoors concentration keeps very small, which encourages the suspicion that CO₂ concentration is a good variable to measure occupancy in an indirect way. Data series for the south-facing office present a similar pattern and is not displayed in this document.

Other variables involved in this study and also of interest (such as energy consumption for heating and/or cooling) are available but not plotted in order to summarize the work.

IDENTIFICATION BY GENERAL SIMULATION FITTING METHODOLOGY

The main idea of this methodology is to get a general and fully parametrized simulation model for a room that could be fitted to experimental data from any office, in order to identify the thermal characteristics of the room under study. The fitting is performed for some interval of the time series and the validity of the fitted model is judged by comparing the predictions of the model in the rest of the data series.

This can be done by running multiparametric simulations covering all the search space. Then, looking for the one that minimizes the sum of the squares of the differences between the experimental and the simulated indoors temperatures in the interval of fitting.

With this method, each parameter added increases exponentially the number of simulations to be performed. In order to reduce the computational effort an evolutionary algorithm to search for the global minimum is employed: Particle Swarm Optimization.

General model assumptions

The general model has been implemented in the software TRNSYS 16.1 coupled to GenOpt 2.0 to perform the evolutionary search for the best model fitting.

It consists of a general purpose model for an office implemented in Type 56, fully parametrized in order to be able to fit it at the experimental data coming both from north and south offices, respectively.

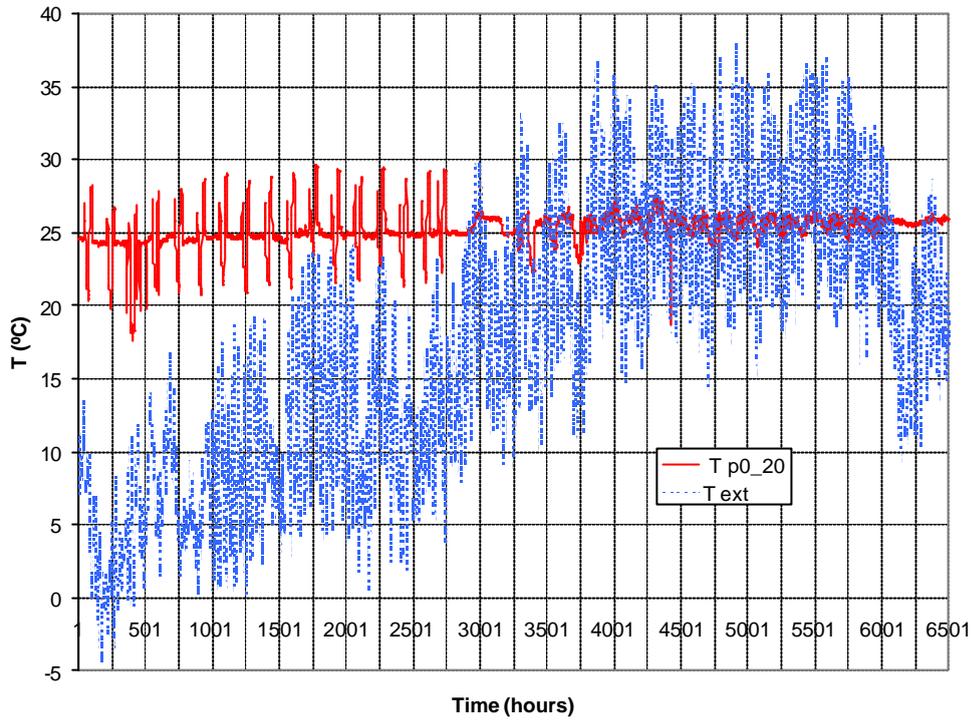


Figure 4. Inside and outside temperatures for p0.20 office.

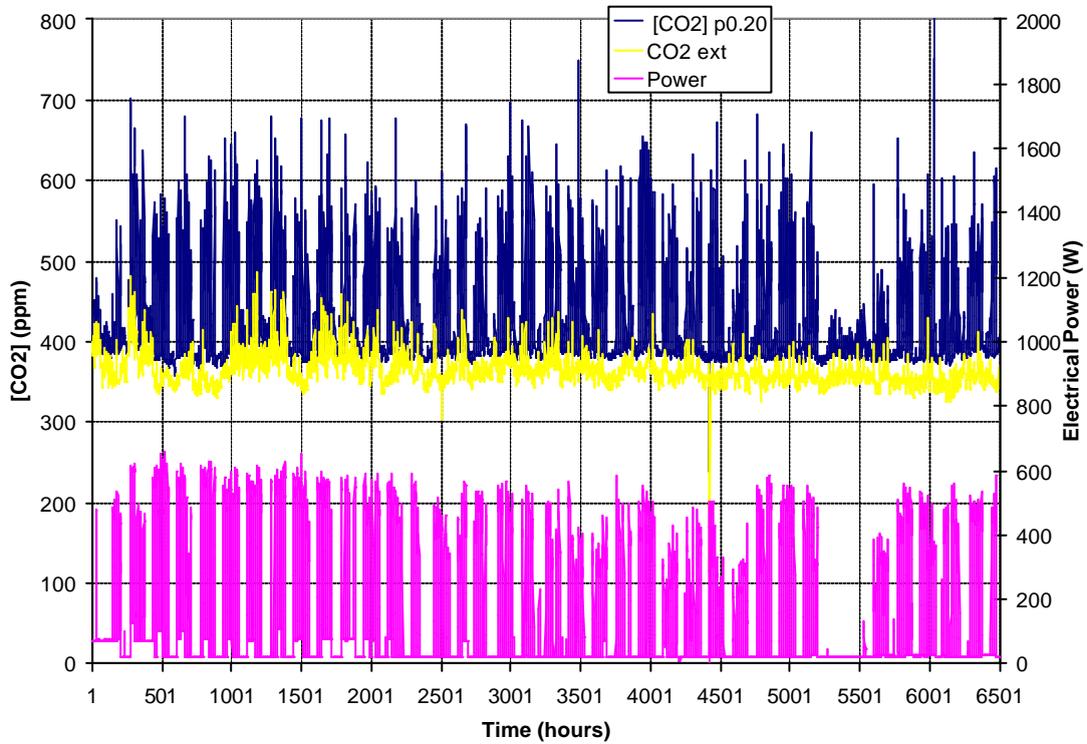


Figure 5. Inside and outside CO2 concentration and electrical consumption for p0.20 office.

The general characteristics of the simulation are:

- Temperature from adjacent rooms is included as a boundary condition for the internal divisions
- One ventilation system is included to modelize the climatization system. The temperature of the air is measured and the air introduction rate is an input to be identified a posteriori by fitting.
- Other ventilation system is included to take into account air exchanges with the corridor. It only works when the door is open (coupled with the opening measurement) and the air exchange rate is an input to be identified a posteriori by fitting.
- There are two coefficients coupled to the dissipation of heat from illumination (a_1) and equipment (a_2), also to be identified a posteriori by fitting.
- Each person considered in the model is modeled as a 75 W sensible heat and 75 W latent heat dissipation.
- The occupancy rate is derived as a function of the difference between the indoors and outdoors CO₂ concentration. The function chosen is an additive step-like one for every 50 ppm of difference of concentrations. That function is multiplied by a constant to be identified a posteriori by fitting.
- An internal wall has been added to take into account the mass inside the room, affecting thermal inertia. The amount of mass is to be determined a posteriori by fitting.
- For the exterior wall, insulation thickness, inside and outside convection coefficient, inside and outside absorptance are parameters to be determined a posteriori by fitting.

In this work, the parameters to be identified by the algorithm are presented at table 4.

Particle Swarm Optimization

PSO algorithms exploit a set of potential solutions to the optimization problem. Each potential solution is called a particle, and the set of potential solutions in each iteration step is called a population. PSO algorithms are global optimization algorithms and do not require nor approximate gradients of the cost function. The first

population is typically initialized using a random number generator to spread the particles uniformly in a user-defined hypercube. A particle update equation, which is modeled on the social behavior of members of bird flocks or fish schools, determines the location of each particle in the next generation.

The update equation can be described in a general way as follows. Let $k \in \mathbb{N}^+$ denote the generation number, let $n_p \in \mathbb{N}^+$ denote the number of particles in each generation, let $x_i(k) \in \mathbb{R}^{n_c} \in \{1, \dots, n_p\}$ denote the i -th particle of the k -th generation, let $v_i(k) \in \mathbb{R}^{n_c}$ denote its velocity, let $c_1, c_2 \in \mathbb{N}^+$ and let $r_1(k), r_2(k) \sim U(0,1)$ be uniformly distributed random numbers between 0 and 1. Then, the update equation is, for all $i \in \{1, \dots, n_p\}$ and all $k \in \mathbb{N}^+$,

$$v_i(k+1) = v_i(k) + c_1 r_1(k)(p_{l,i}(k) - x_i(k)) + c_2 r_2(k)(p_{g,i}(k) - x_i(k)),$$

$$x_i(k+1) = x_i(k) + v_i(k+1),$$

Where $v_i(0) = 0$ and

$$p_{l,i}(x) = \arg \min_{x \in \{x_i(j)\}_{j=0}^k} f(x)$$

$$p_{g,i}(x) = \arg \min_{x \in \{x_i(j)\}_{j=0}^k, j=1}^{n_p} f(x)$$

Thus, $p_{l,i}(k)$ is the location that for the i -th particle yields the lowest cost over all generations, and $p_{g,i}(k)$ is the location of the best particle over all generations. The term $c_1 r_1(k)(p_{l,i}(k) - x_i(k))$ is associated with cognition since it takes into account the particle's own experience, and the term $c_2 r_2(k)(p_{g,i}(k) - x_i(k))$ is associated with social interaction between the particles. In view of this similarity, c_1 is called *cognitive acceleration constant* and c_2 is called *social acceleration constant*. Table 3 shows the data used in this study.

Neighborhood topology	Von Neumann
Size of the neighborhood	25
Number of generations	120
Seed	1
Cognitive acceleration	2.8
Social acceleration	1.3

Table 3. Parameters introduced for the PSO algorithm

The set of points over which the minimum is taken is defined by the neighbourhood topology. In this case,

von Neumann topology of range 1 has been employed. The particles are enumerated in a 2-dimensional lattice and the topology is defined, for $i, j \in \hat{U}$ as the set of points whose indices belong to the set:

$$N_{(i,j)}^v \equiv \{(k, L) \mid |k - i| + |l - j| \leq 1 \forall k, l \in Z\}$$

RESULTS

The interval for fitting simulation has been chosen from the hour 3500 to 3800 to avoid the part of the data series where the experiments were run. The results for the best model fitted for each room is presented in figures 6 and 7. Despite the simulations have been run for all the data series, only the results from hour 3500 and on is presented. The data presented at the left of the vertical thick line is the identification interval and the data at the right are the prediction of the model fitted.

In both cases the fitting periods give residuals lesser than 0.5 °C, being more accurate for the facing-north room. It must be noticed that with only 300 hours of data the models fitted follow the dynamics in the rest of the data series.

In the case of the facing-north office the residual in the prediction is below 1° C and from hour 600 to 1600 the residual is almost negligible, which is a good feature of the algorithm. In the facing-south room residuals are higher, about 1° C. This could be due to the treatment of the solar radiation, that must be improved in the model selected for this study.

The estimated insulation thickness for the envelope in the p0.20 case is close to the real situation while in the p0.13 case are far from reality (see table 4). Other parameters such as the coupling coefficient of the people, the electrical power or the air exchange with the corridor give quite similar estimations in both models.

It should also be noticed that in both cases, the group of the best fitted models have very similar parameters estimated (not facilitated in order to summarize the work), which is a good indication that the algorithm is robust in identification.

However, it can also be seen that different set of parameters produce simulations not very far in the temperature prediction. This is a problem if the monitoring system is not so accurate as the employed in this study (which is the most usual practice).

Parameter	Minimum value	Maximum value	P0.20 Estimation	P0.13 Estimation
Insulation thickness (m)	0.01	0.25	0.18 (0.14 real)	0.03 (0.14 real)
Inside convection coefficient of envelope (kJ/h m ² K)	1	64	56.6	77.5
Outside convection coefficient of envelope (kJ/h m ² K)	1	64	54.7	80
Inside absorptance of envelope	0.1	0.9	0.62	0.3
Outside absorptance of envelope	0.1	0.9	0.29	0.44
a ₁	0.01	1	0.98	0.79
a ₂	0.01	1	0.99	0.97
Air exchange due to ventilation (ren/h)	1	10	5.2	1.79
Air exchange due to door opening (ren/h)	0.05	1	0.96	0.98
Occupancy coefficient	1	10	9.64	9.95
Internal mass	100	1000	142	108

Table 4. Range of variation of the parameters of the model to be identified.

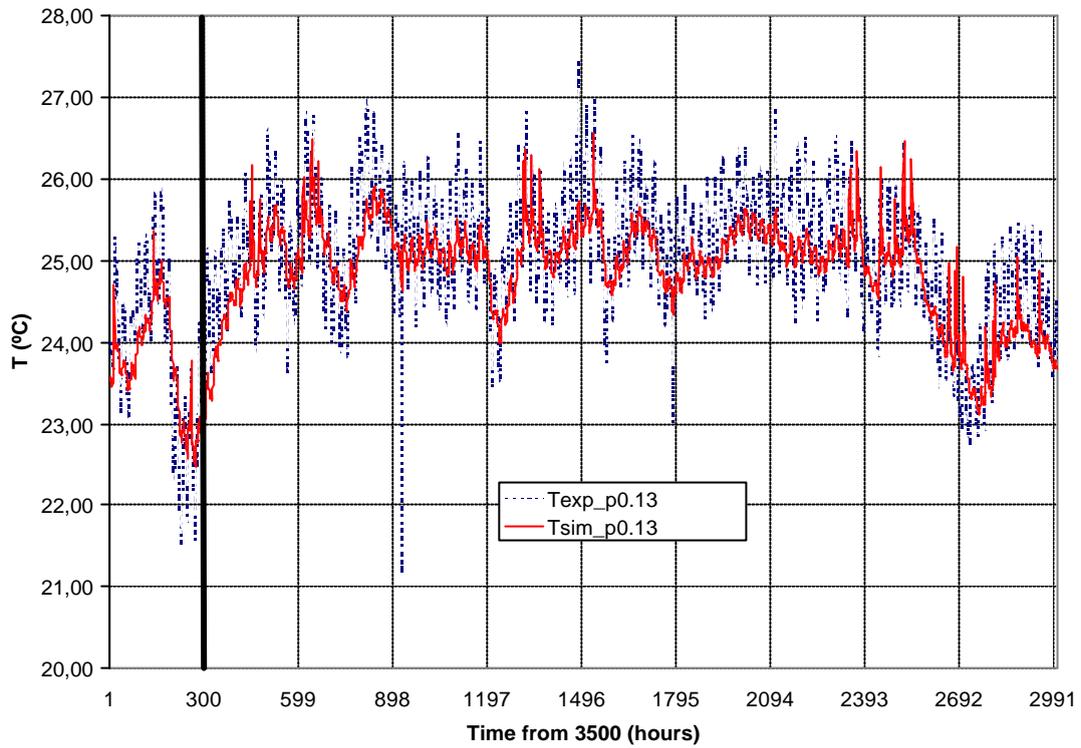


Figure 6. Measured and simulated temperatures for the best fit in room p0.13.

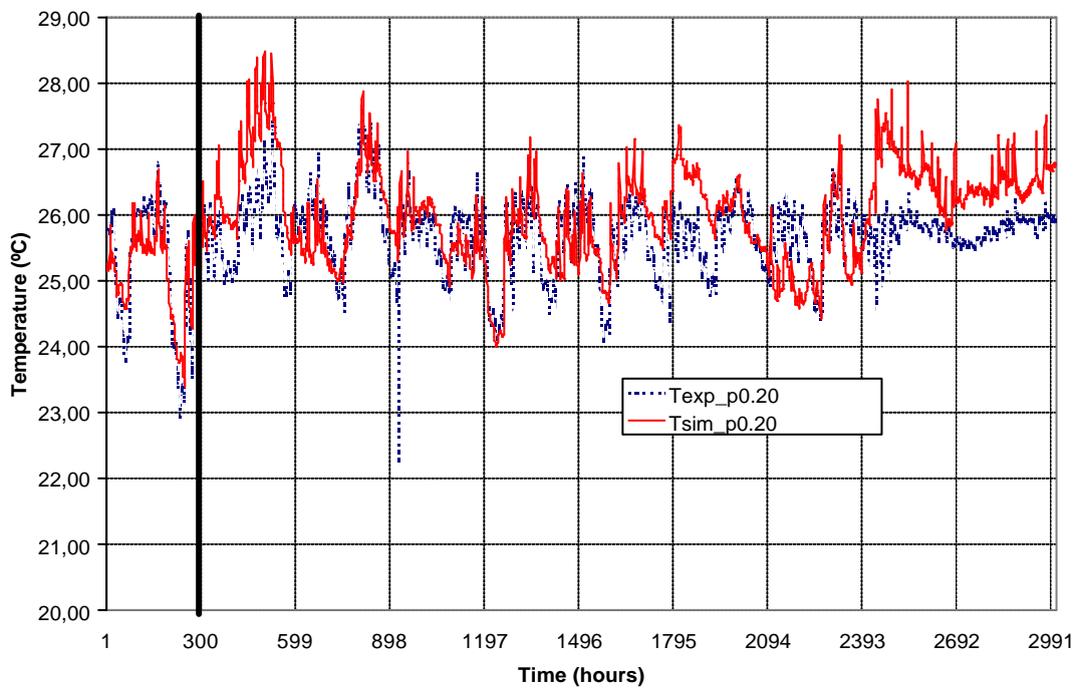


Figure 7. Measured and simulated temperatures for the best fit in room p0.20.

To distinguish the more close to reality of these situations more variables should be included as constraints. For example, it could be possible to minimize not only the difference in the indoors temperature, also the temperature of the inside surface of the envelop or use other predictions such as energy consumption of the air conditioning system.

In fact, the selection of the output for a model is a key issue in the accuracy of the predicted parameters. This phenomenon appears, for example, in the energetic evaluation of walls (Jiménez, 2008). In that case the selection of the heat flux as an output produces more accurate models than the selection of the indoors temperature as an output. Probably the selection of the air conditioning energy as a target for the optimization could help to discriminate among different models.

Those research lines will be part of future work.

CONCLUSIONS AND FURTHER WORK

With few variables measured and registered and in a short period of time general models can be fitted accurately. This can be done even in buildings occupied and in real use.

CO₂ concentration measurements show a good potential to estimate the occupancy of a room. However, further studies must be done in order to find a more accurate relationship.

The introduction of new variables as constraints to the optimization could help to distinguish between different sets of parameters that produce temperature patterns inside the error of the experimental devices.

This technique shows a good potential for application in building thermal parameter identification, but further work is required to solve the problems encountered.

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REFERENCES

PSE-ARFRISOL www.arfrisol.es

Bloem, J. J. 1994. Application of the average method to all cases. In: *System Identification Competition* (Edited by Bloem, J.J.), 67-76. Published by the Commission of The European Communities DG XIII, Luxembourg, 1994.

Enríquez R., Jiménez M.J., Heras M.R. 2008. Identification of a change in the thermal dynamics of a Wall. *Proceedings of the 27th AIVC*, Kyoto, Japan.

Generic Optimization Program (GenOpt), <http://gundog.lbl.gov/GO>

ISO 9869:1994. 1994. In-situ measurement of thermal resistance and thermal transmittance.

Jiménez M. J., Madsen H. 2008. Models for Describing the Thermal Characteristics of Building Components. *Building and Environment. Special issue on Outdoor testing, analysis and modelling of building components*. 43, pp. 152-162.

Jiménez M. J., Porcar B., Heras M. R. 2008. Estimation of UA and gA values of building components from outdoor tests in warm and moderate weather conditions. *Solar Energy*. 82(7), pp. 573-587.

Jiménez M. J., Madsen H., Andersen K. K. 2008. Identification of the Main Thermal Characteristics of Building Components using MATLAB. *Building and Environment. Special issue on Outdoor testing, analysis and modelling of building components*. 43, pp. 170-180.

Norlén, U. 1994. Determining the Thermal Resistance from In-Situ Measurements. In: *Workshop on Application of System Identification in Energy Savings in Buildings* (Edited by Bloem, J.J.), 402-429. Published by the Commission of The European Communities DG XIII, Luxembourg.

Rabl A. 1988. Parameter estimation in buildings: methods for dynamic analysis of measured energy use. *J. Solar Energy Eng*, 110, pp. 52-66.

Transient Systems Simulation program (TRNSYS). <http://sel.me.wisc.edu/trnsys>