Conference Proceedings

EuroSun 2014
Aix-les-Bains (France), 16 – 19 September 2014

A COMPARATIVE ANALYSIS OF ROOM AIR TEMPERATURE MODELLING FOR CONTROL PURPOSES

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Abstract

The use of accurate models is a relevant point for simulation, optimization and control purposes. More specifically, they represent a cornerstone for the development of different based on model control strategies, as Model-based Predictive Control (MPC) or Internal Model Control (IMC). These control strategies help to obtain high thermal comfort levels inside buildings in an efficient way by an optimal combination with passive strategies. For control purposes, the selection of an appropriate kind of model will depend on its complexity, aim and available resources. In this work, a comparison between the complexity and accuracy of several models is performed. To do that, three different room-level indoor air temperature models have been developed: i) a Linear Time-Invariant (LTI) model estimated by means of a Pseudo-Random Binary Sequence (PRBS) signal; ii) a nonlinear model based on Artificial Neural Networks (ANNs); and iii) a nonlinear first principles model. These models have been calibrated and validated using real data from a characteristic office room of a bioclimatic building. The obtained results show as the three approaches provide good results with an NMAE error less than 14% in the worst case (LTI model) and approximately equal to 5% in the best one (first principles model), and thus, they could be used to develop appropriate control strategies.

Keywords: Room dynamic modelling; System identification; Thermal comfort control; Indoor temperature

1. Introduction

In last decades, it has been an increasingly concern about climate change which is mainly originated by human activities. It has occasioned the apparition of different regulations and strategies all around the world. Within the European Union the framework the strategy Europe 2020 (Europe2020, 2014) whose main objectives from both climate change and energy points of view are: i) to reduce greenhouse emissions by 20% in comparison to 1990; ii) to increase the market share of renewable energy sources in final energy consumption to 20%; and iii) to improve energy efficiency by 20%; appeared. On the one hand, several studies establish that energy consumption in buildings represents approximately 40% of total world energy consumption, mainly attributed to Heating, Ventilation and Air Conditioning (HVAC) systems (Pérez-Lombard et al, 2008). On the other hand, since people usually perform their quotidian activities inside buildings, it is necessary to obtain a commitment between users'thermal comfort and energy efficiency. To do that, different approaches can be considered, as the construction of bioclimatic buildings which include control strategies able to optimize the energy consumption derived from users'thermal comfort.

One of the most used techniques that allow us to maintain users' thermal comfort is Model-based Predictive Control (MPC) (Castilla et al, 2014a; Donaisky et al, 2007; Ma et al, 2011; Privara et al, 2011a) since it uses dynamic models of the controlled system, noise and disturbances to obtain predictions of behaviour of the system as a function of the estimated control signals. Besides, models can provide very useful information about the design and reaction of different control systems avoiding the associated costs and risks derived from testing these systems in a real plant. Moreover, there are in literature different kinds of models which can be classified as a function of their nature, complexity and available resources (Brosilow and Joseph,

doi:10.18086/eurosun.2014.04.01 Available at http://proceedings.ises.org

2002). Within the context of process control area, it is very usual to develop nonlinear models based on first principles of the controlled system. However, and mainly due to the complexity and necessities of it, it is possible to obtain linear and nonlinear models by means of classical identification techniques (Rivera, 2007).

In general, the most part of the models available in literature are devoted to evaluate energy performance in buildings (Olofsson and Mahlia, 2012; Saelens et al., 2011), to design energy efficient buildings (Jiang and Rahimi-Eichi, 2009), or even to develop adequate control strategies at building level (Hazyuk et al. 2012; Kummer et al., 1996; Sagerschnig et al., 2011). Moreover, it is possible to found in literature several techniques that allow obtaining black-box models such as Artificial Neural Networks (ANNs) (Mustfaraj et al., 2011) and identification techniques (Privara et al., 2011b). Therefore, there are different kinds of models which are developed with different perspectives and with several final objectives.

This work presents an analysis, from both performance and efficiency points of view, between the complexity and accuracy provided by three different room-level indoor air temperature models, specifically a Linear Time-Invariant (LTI) model, an ANN model and a nonlinear one based on first principles. The calibration and validation results showed in this work have been obtained in a real bioclimatic building, the CDdI-CIESOL-AFRISOL building (http://www.ciesol.es/en). In addition, and as a conclusion of this work, some advices about the main factors that should be taken into account to select an appropriate model for control purposes are provided.

The paper is organized as follows: Section 2 provides a brief description of the building and the selected room which is used to validate the indoor air temperature models which are shown in Section 3. More specifically, Section 3.1 is devoted to an LTI model. Section 3.2 shows an ANN room-level indoor air temperature model. The main formulation of the first principles model and a brief description of the methodology followed to calibrate and validate this model are presented in Section 3.3. The obtained results are shown and widely commented in Section 4. Finally, in Section 5 the main conclusions and future works are described.

2. Scope of the research

The bioclimatic building used in this work to calibrate and validate the proposed models is a research centre on solar energy, the CDdI-CIESOL-ARFRISOL building, see Fig. 1 (a). It was built following several bioclimatic architecture criteria. Hence, it includes several passive strategies which take advantage of the environmental characteristics of the place where the building is located, and active ones which make use of renewable energies, such as a HVAC system based on solar cooling composed by a solar collector field, a hot water storage system, a boiler and an absorption machine with its refrigeration tower. Furthermore, this building has its more representative rooms monitored through a wide network of sensors whose data are stored in a database by means of an acquisition system. The historical data saved during the daily use of these rooms have been used for calibration and validation model purposes. A detailed description of this building can be found in Castilla et al. (2014b).

Furthermore, the selected room with a total surface of 76.8 m^3 and north orientation, see Fig. 1 (b), counts with a huge variety of sensors, see Tab. 1 and also a set of actuators, such as a window opening/closing system and a shading system, that provides more degrees of freedom to control users' comfort.

Tab. 1: Sensors network into the selected room (Castilla et al. 2014b)

Type of sensor	Unit	Number of sensors
Air temperature	ºC	6
Air velocity	m/s	3
Air CO_2 concentration	ppm	2
Fan coil water flow	l/m	1
Fan coil water temperature	ºC	2
Globe temperature	ºC	1
Plane radiant temperature	ºC	6
Air relative humidity	%	3

(a) Outside of the building **(b) Representative room of the building**

Fig.1: The CDdI-CIESOL-ARFRISOL building

3. Indoor air temperature models

Generally, the obtaining of an appropriate model which precisely represents the dynamic behaviour of the indoor air temperature requires both effort and time. A room can be defined as a complex system where interferes several kind of elements and the surrounding environmental conditions about it. At the same time, these elements are characterized by their thermal and optical properties. However, although there is a priori knowledge of the modelled system it is difficult to obtain a first principles model mainly due to their complexity. In these cases, it is very common to use identification techniques which will allow us to obtain black-box models.

In this section, different approaches for the modelling of indoor air temperature are shown. Therefore, in all the cases, the system output will be the indoor air temperature. Besides, as the main aim of the proposed models is the development of future controllers, a distinction in input signals between control inputs (variables which can be manipulated) and disturbances (variables which cannot be manipulated) has been performed. On the one hand, the control inputs are the natural ventilation by means of the window opening, the forced ventilation through the HVAC system and the blind. On the other hand, the disturbance inputs are the outdoor environmental conditions, such as the outside air temperature, wind speed and its direction, direct, diffuse and reflected irradiance, and the indoor conditions, i.e. the plane radiant temperatures of all the surfaces and the number of people inside the room.

3.1. Linear Time-Invariant model

First of all, and with the main objective of obtaining a simplified model for control purposes an LTI model for indoor air temperature has been obtained following the methodology for system identification proposed by Ljung, (1999). To do that, the following assumptions have been taken into account:

- It has been considered that there was only one available actuator, the HVAC system, which allows the users to control indoor air temperature through its fan velocity (on/off).
- As disturbances inputs it has been taken into account the outdoor air temperature and the number of persons inside the room.
- It is supposed that the indoor air temperature is homogeneously distributed around the whole room.

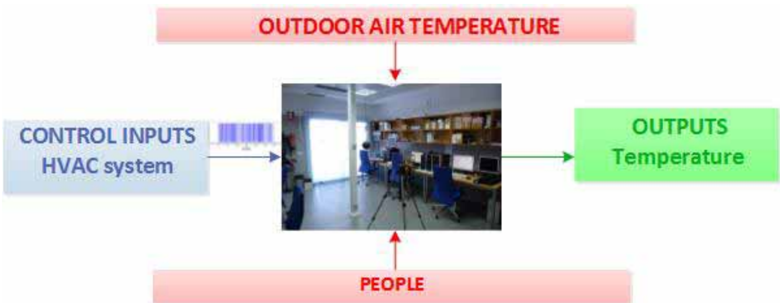


Fig.2: Inputs/output scheme of the LTI model

Therefore, from the previous assumptions, a Multiple Input Single Output (MISO) model, see Fig. 2, has been used where the chosen structure has been Auto-Regressive with eXogeneus inputs (ARX) since it considers disturbances as white noise. To do that, appropriate Pseudo-Random Binary Sequence (PRBS) signals were designed using the tuning methodology proposed by Rivera (2007) to obtain a signal with enough power over the frequency range of interest for the indoor air temperature model. Afterwards, the identification process has been carried out using the *System Identification Toolbox* of Matlab® (Ljung, 1999, 2007). This tool allows obtaining a linear model based on certain established premises and a selected model structure. In this case, an ARX model whose general structure which can be expressed as a simple linear difference equation can be observed in eq.1. This difference equation relates the current output of the system,$y(k)$, with a finite number of past outputs, $y(k-j)$, and inputs, $u(k-j)$ and a white noise, $v(k)$.

$$y(k) + a_1 y(k-1) + \cdots + a_{na} y(k-na) =$$
$$= b_1 u(k-nk) + \cdots + b_{nb} u(k-nk-nb+1) + v(k) \quad \text{(eq. 1)}$$

where na is the number of poles of the model, $nb+1$ is the number of zeros, and nk is the delay of the system, if it exists.

The model was estimated by means of PRBS signal with a total duration of 4 days, that is, 96 hours. This test was performed during working days with specific requirements to smooth the disturbance effects, that is, the door was closed with several disturbances due to the people going in/out, the window was closed, and the room had its typical occupation along work hours during the whole test. The lineal different equation which represents the identified ARX model can be observed in eq.2.

$$y(k) - 0.47y(k-1) - 0.328y(k-2) - 0.233y(k-3) - 0.145y(k-4) - 0.065y(k-5) +$$
$$-0.006y(k-6) + 0.04y(k-7) + 0.454y(k-8) + 0.083y(k-9) + 0.078y(k-10) =$$
$$= 0.0001u_1(k) - 0.001u_2(k) - 0.0002u_2(k-1) - 0.0003u_2(k-2) - 0.0004u_2(k-3) +$$
$$-0.00007u_2(k-4) + 0.00003u_2(k-5) + 0.0004u_2(k-6) + 0.0003u_2(k-7) +$$
$$+0.0002u_2(k-8) + 0.00005u_2(k-9) + 0.0007u_2(k-10) + 0.0036u_3(k) + v(k) \quad \text{(eq. 2)}$$

In the previous equation, u_1 represents the outdoor air temperature, u_2 is the fan velocity of the HVAC system, and finally u_3 is the number of persons inside the room.

3.2. Nonlinear model based on Artificial Neural Networks

The indoor air temperature inside a certain environment usually presents a nonlinear nature. For that reason, in this section, an ANN nonlinear model estimated through input – output data is presented. ANNs are universal approximators (Cybenko, 1989) and they can be considered as a black-box model where its inputs represent the number of neurons in the input layer, the model parameters are symbolized by the number of neurons and their interconnection weights in the hidden layers, and finally, the outputs are represented by the number on neurons in the output layer. The main difference with the LTI model developed in the previous section is that ANN can model nonlinear behaviours.

As there is a previous knowledge of the processes involve in the dynamic behaviour of the air temperature inside a room, the selection of inputs for the ANN has been performed as a function of this knowledge. More specifically, the selected variables have been the following ones:

- The surface temperature of the walls, ceil and floor since they are involved within the convection process $\left(T_{s_{east}}, T_{s_{south}}, T_{s_{west}}, T_{s_{north}}, T_{s_{ceil}}, T_{s_{floor}}\right)$.
- The ones related with forced ventilation that is with the HVAC system: the impulse and return temperatures $\left(T_{a_{imp}}, T_{a_{ret}}\right)$ and velocities $\left(V_{Fan_{imp}}, V_{Fan_{ret}}\right)$, and the water flow through the HVAC system (q_W).
- Variables which make reference to both natural ventilation and infiltration processes, that is, the aperture of the window (Ap_w), the wind velocity (v_{wind}) and direction (d_{wind}).
- The number of persons inside the room$\left(N_p\right)$.

- The outside climatic conditions are taken into account by means of the outdoor air temperature $(T_{a_{out}})$ and the diffuse irradiance (I_{df}).
- Finally, the modelled variable, the indoor air temperature $(T_{a_{in}})$ is also considered since the output of it is feedback as an input.

Furthermore, the ANN estimated for the indoor air temperature model presented in this section is a multilayer perceptron with a Feed-Forward (FF) configuration composed of a hidden layer with 11 neurons with sigmoidal activation function, 19 neurons in the input layer and one neuron in the output layer, the indoor air temperature, see Fig. 3. Besides, the obtained ANN has been also combined with Tapped Delay Lines (TLD) blocks which have been used to provide an appropriate number of past values for the inputs (Arahal et al., 1998). The methodology used to determine the optimal number of past values was the False Neighbours Method (kennel et al., 1992).

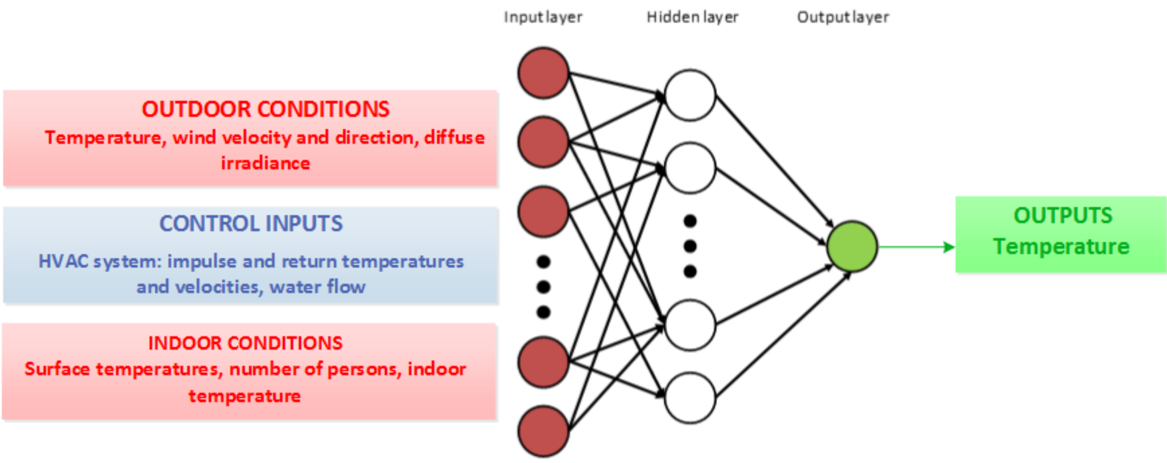


Fig.3: Inputs/output scheme of the ANN model

The proposed ANN has been trained using appropriate data sets. In this case, real data sets acquired during the normal operation of the CDdI-CIESOL-ARFRISOL building have been used. The selected data sets cover the most characteristic profiles of the warmer periods of the year, that is, spring and summer. More specifically, they comprise three different intervals: from 15th April 2013 to 5th May 2013, from 22nd May 2013 to 16th June 2013 and from 7th July 2013 to 31st July 2013 with a sample time of 1 minute. In addition, the training process has been performed using the MATLAB's implementation of the Levenberg-Marquardt algorithm (More 1978) and the goodness of fit has been calculated by means of the Root-Mean-Square (RMS) error, see eq.3.

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(x(i) - \hat{x}(i)\right)^2} \quad \text{(eq. 3)}$$

where $x(i)$ symbolizes the real value of the modelled variable and $\hat{x}(i)$ is the approximation estimated by means of the ANN model.

The selection of the optimal ANN has been performed taken into account that an ANN with an insufficient number of neurons may be unable to capture the dynamic behaviour of the indoor air temperature, and that an ANN with too many neurons can occasion overtraining, and thus, degrade the generalization capabilities.

3.3. Nonlinear first principles model

In this approach, the existing relationships among the different components of the room and between them and the environment are determined by means of mass and heat transfer laws, see Fig. 4. More specifically, this model has been obtained using the "*Heat Balance Method*" described in Ashrae (2009) and subjected to the following assumptions:

- It has been considered that the room is composed of seven elements: indoor air, walls, windows, shading system, HVAC system, people and electrical appliances.

- The physical characteristics of the different elements except from indoor air, such as specific heat, have been supposed constant. Besides, the physical characteristics associated with the indoor air are calculated as a function of indoor air temperature.
- The air inside the room has been considered as a perfect mix, i.e. the indoor air temperature is uniform in the whole room (Fisher and Pedersen, 1997).
- The surfaces of the room are supposed to have a uniform surface temperature, similar wave irradiance and one-dimensional heat conduction process.

Therefore, the indoor air temperature has been modelled by means of a dynamic equation based on heat and mass transfer principles as it is shown in eqs. 4-10.

$$m_a C_{p_a} \frac{dT_{a_{in}}}{dt} = Q_{conv} + Q_{fv} + Q_{inf} + Q_{iGain} + Q_{nvnt} + Q_{glass} \quad \text{(eq. 4)}$$

$$Q_{conv} = f\left(T_{a_{in}}, T_{s_{east}}, T_{s_{south}}, T_{s_{west}}, T_{s_{north}}, T_{s_{ceil}}, T_{s_{floor}}\right) \quad \text{(eq. 5)}$$

$$Q_{fv} = f\left(T_{a_{imp}}\right) \quad \text{(eq. 6)}$$

$$Q_{inf} = f\left(T_{a_{in}}, T_{a_{out}}\right) \quad \text{(eq. 7)}$$

$$Q_{iGain} = f\left(T_{a_{in}}, T_{mr}, H_r, N_p\right) \quad \text{(eq. 8)}$$

$$Q_{nvnt} = f\left(T_{a_{in}}, T_{a_{out}}\right) \quad \text{(eq. 9)}$$

$$Q_{glass} = f\left(T_{a_{in}}, T_{a_{out}}, I_{dr}, I_{df}, I_{rf}\right) \quad \text{(eq. 10)}$$

In the previous equation m_a and C_{pa} are, respectively, the mass in (kg) and the specific heat in $(Jkg^{-1}K^{-1})$ at constant pressure of the indoor air. $T_{a_{in}}$ is the indoor air temperature in(K). Furthermore, the terms located on the right hand of the equation, that is $Q_{conv}, Q_{fv}, Q_{inf}, Q_{iGain}, Q_{nvnt}, Q_{glass}$ represent respectively, the heat gain due to natural convection through walls, floor and ceil, the heat gain through forced ventilation, the heat gain by means of infiltrations, the heat gain caused by internal gains related to people, electrical appliances and lighting, the heat gain occasioned by natural ventilation, and the heat gain owed to the glass of the window, all of them in (W). A more detailed description of the methodology followed to estimate each one of the terms can be found in Castilla et al. (2014b).

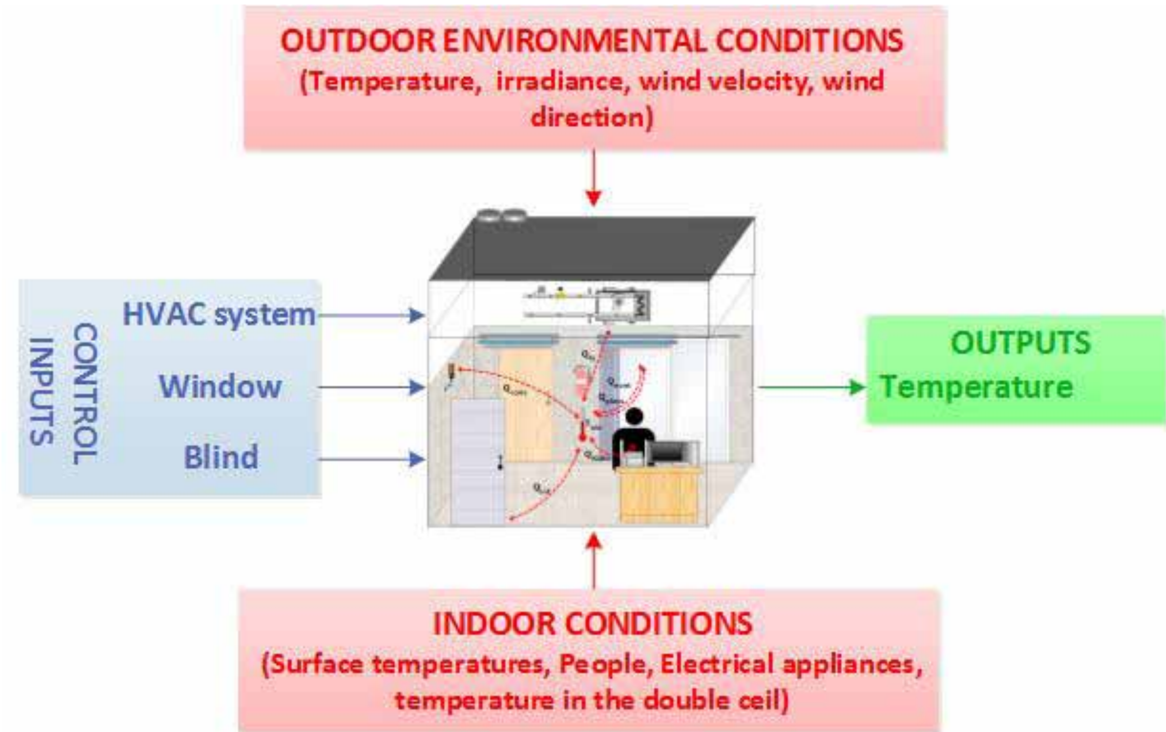


Fig.4: Inputs/output scheme of the first principles model

The indoor air temperature model presented in eqs.4-10 has a set of 9 unknown parameters which have been calculated by a specific calibration methodology. Furthermore, it consists in a cascade calibration process consisting of, first, a brute force sequential search to determine an initial approximation for the unknown parameters, and afterwards the use of evolutive algorithms to obtain the final value. A complete explanation of this calibration technique can be found Castilla et al. (2014b).

4. Results and discussion

As it was mentioned previously, the models presented in Section 3 have been calibrated and validated for the particular conditions of a typical office room inside the CDdI-CIESOL-ARFRISOL building. In this section, the validation results obtained for summer conditions are shown and widely commented. More specifically, the selected validation set with a total size of 4320 data points comprises from 10th to 12th May 2013 with a sample time equal to 1 min and it includes different conditions. The main objective of this validation data set was to obtain the most common situations inside this room along a warmer half-time period. Therefore, this test contains some periods where the room was empty, and others with the presence of its usual occupants, see Fig. 5 (a). In addition, while the room was occupied some controlled experiments were performed using the window and the HVAC system, see Fig. 5 (b) and (c) respectively. Finally, these controlled experiments provide a validation set with an absolute variation equal to 2.49ºC from 24.71ºC to 27.21ºC. The results obtained under the conditions described previously, see Fig. 5, can be observed in Fig. 6. Specifically, in this figure, it is shown the real indoor air temperature measured inside the characteristic room of the CDdI-CIESOL-ARFRISOL building (in blue) and the results provided by each model (LTI model in yellow, ANN model in green and first principles model in red).

Furthermore, in order to analyze the goodness of the proposed models and be able to establish a comparison among them, a statistical analysis is also included, see Tab. 2. Concretely, this statistical analysis includes the number of samples (N), the absolute variation (Rng) of the measured indoor air temperature, its Mean Absolute Error (MAE) and Mean Relative Error (MRE), the maximum absolute error ($MaxAE$), the standard deviation (S_N) and the variation Normalized Mean Absolute Error ($NMAE$), see eqs. 11-16.

$$Rng = |\max(x) - min(x)| \qquad \text{(eq. 11)}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|x(i) - \hat{x}(i)| \qquad \text{(eq. 12)}$$

$$MRE = \frac{1}{N}\sum_{i=1}^{N}\frac{|x(i)-\hat{x}(i)|}{x(i)} \qquad \text{(eq. 13)}$$

$$MaxAE = max\big(AE(x,\hat{x})\big) \qquad \text{(eq. 14)}$$

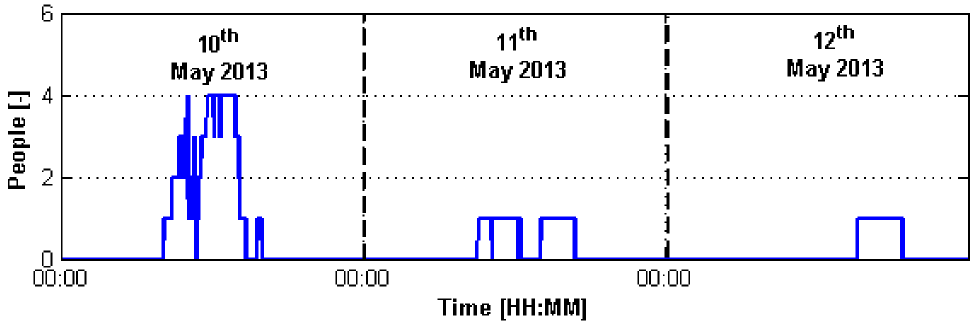
$$S_N = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{x}(i) - \bar{x})^2} \qquad \text{(eq. 15)}$$

$$NMAE = \frac{MAE\ x\ 100}{Rng} = \frac{\left(\frac{1}{N}\sum_{i=1}^{N}|x(i)-\hat{x}(i)|\right)x100}{|\max(x)-min(x)|} \qquad \text{(eq. 16)}$$

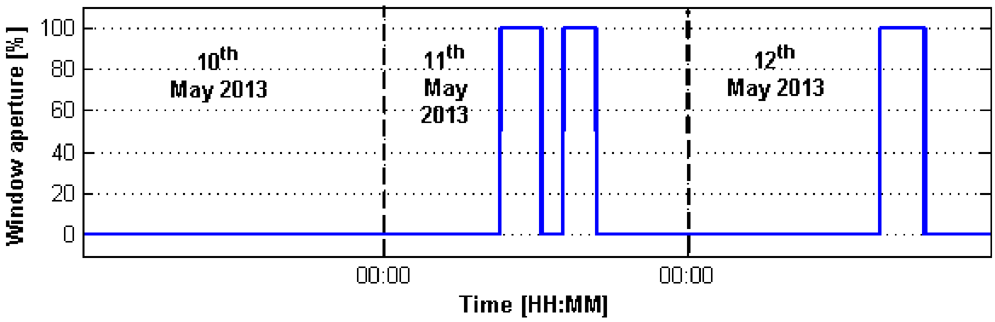
In the previous equations, eqs. 11-16, x are the real values measured inside the modelled room, $\hat{x}$ and $\bar{x}$ represents the results obtained from the model and the mean value of these results respectively, and finally, AE is the absolute error.

As can be observed in Fig. 6. the developed models are able to capture the dynamics of the indoor air temperature under different conditions. On the one hand, the worst model is the LTI with an NMAE index close to 14% and an MAE equal to 0.34ºC. However, these results are the expected ones, since the LTI model considers as inputs less variables than the others approaches. Hence, after a detailed analysis of the conditions along the periods where it provides worst results it has been concluded that it is not able to react properly to the disturbances occasioned by the window. On the other hand, the other two models provide similar results with an NMAE index between 5% and 6%. Therefore, it can be concluded that the three approaches are valid to develop control strategies for users' thermal comfort.

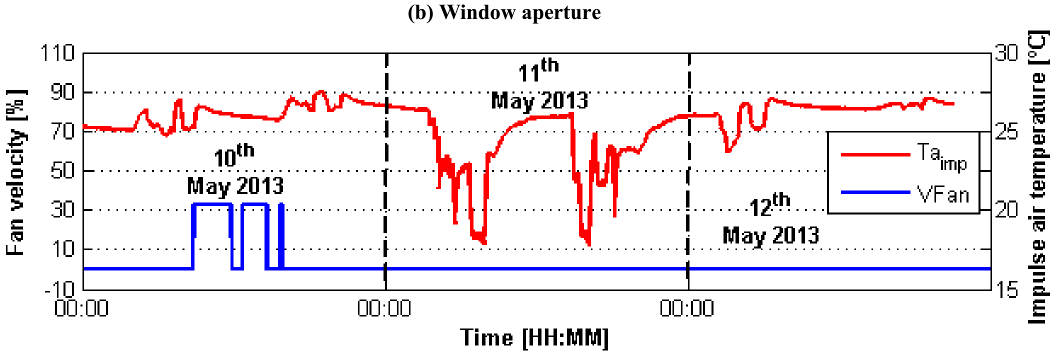
However, one of the most important factors in order to develop appropriate control techniques is the available resources that allow us to obtain both more or less accurate models of the indoor air temperature. More specifically, the accuracy of these models depends on the size of the sensors network available, the number of actuators and their characteristics, and the previous knowledge of the modelled system. Concretely, if there is not any limitation due to the network of sensors it should be recommendable to develop first principles models since they take into account different disturbances and their influence on the modelled system, and thus, they will allow to the controller react more precisely than with other kind of models. However, to develop first principles models it is necessary to have a priori knowledge of the system. Hence, if there is not any knowledge of it, the best option will be to develop black-box models (LTI or ANN).



(a) Room occupation



(b) Window aperture



(c) HVAC system

Fig.5: Conditions of the validation set

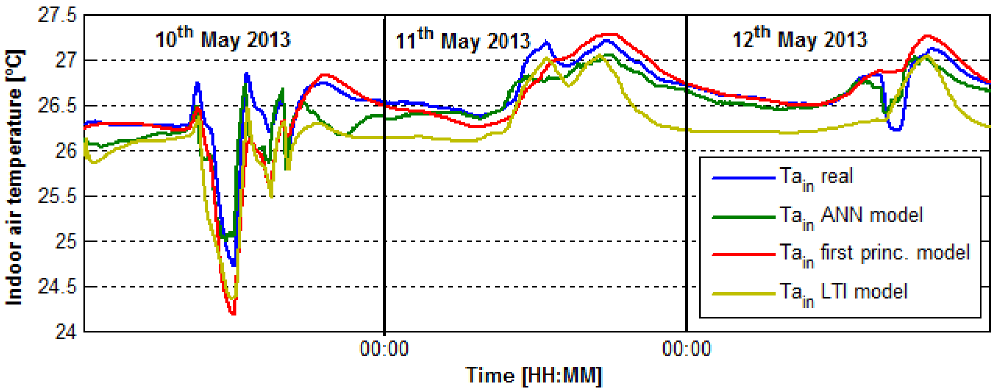


Fig.6: Results of validation set for the indoor air temperature models

Tab. 2: Results from the validation of the indoor air temperature models

Parameter	LTI model	ANN model	First principles model
MAE	0.34 ºC	0.15 ºC	0.13 ºC
MaxAE	0.85 ºC	0.73 ºC	0.88 ºC
MRE	0.01 ºC	0.005 ºC	0.004 ºC
S_N	0.37 ºC	0.35 ºC	0.48 ºC
NMAE	13.81%	6.07%	5.04%

5. Conclusions and future works

Models are necessary to develop appropriate control strategies for users' thermal comfort since they can precisely represent the dynamic behaviour of the temperature where the people is. In this work, three different modelling approaches have been presented. Concretely, in a first approach, an LTI model obtained through identification techniques was developed. Afterwards, a nonlinear model based on ANN has been presented. Finally, an indoor air temperature model based on first principles was done. In addition, a comparison among them has been performed based on statistical analyses and the necessary goodness from control techniques point of view. The obtained results show as the three approaches provides good results with an NMAE error less than 14% in the worst case and approximately equal to 5% in the best one, and thus, they could be used to develop appropriate control strategies. Hence, the selection of one approach will depend on the available resources as it was discussed in Section 4.

As future works, the obtained models will be integrated within an MPC controller which allows the users to maintain thermal comfort in an efficient way. The main objective will be to demonstrate the hypothesis established in this work. Moreover, the results will be analyzed from both performance and necessaries resources points of view.

Acknowledgments

The authors are very grateful to Andalusia Regional Government (Consejería de Economía, Innovación y Ciencia), Spain, for financing this work through the Program "Formación de personal docente e investigador predoctoral en las Universidades Andaluzas, en áreas de conocimiento deficitarias por necesidades docentes (FPDU 2009)". This is a programme co-financed by the European Union through the European Regional Development Fund (ERDF). José Domingo Álvarez is a fellow of the Spanish 'Juan de la Cierva' contract program. This work has been partially funded by the following projects: PSE-ARFRISOL PS-120000-2005-1 and DPI2010-21589-C05-04 (financed by the Spanish Ministry of Science and Innovation and EU-ERDF funds); PHB2009-0008 (financed by the Spanish Ministry of Education; CNPq-BRASIL; CAPES-DGU 220/2010). The authors would like to thank all companies and institutions included in the PSE-ARFRISOL project.

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