ENERGY PERFORMANCE CHARACTIRISATION OF THE TEST CASE "TWIN HOUSE" IN HOLZKIRCHEN, BASED ON TRNSYS SIMULATION AND GREY BOX MODEL

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ABSTRACT

In the frame of the IEA Annex 58 project, this paper presents an exercise of building energy performance characterization based on full scale dynamic measurements. First focus of the exercise is the verification and validation of the numerical TRNSYS BES-model of the case study test house in Holzkirchen. Second focus is on the modelling of the house through a second order inverse "grey box" model in order to determine reliable performance indicators which include UA-value, total heat capacity, and solar aperture. Final issue is the comparison of predicted indoor temperatures of free floating period, results of TRNSYS and "grey box" models simulation.

INTRODUCTION

Different models and known methodologies for energy performance characterization can be summarised in three categories of models: white-box, grey-box and black-box models (Bohlin, 1995) (Madsen et al., 1995) (Kristensen et al., 2004).

TRNSYS model is typically a white box model based on a complete description of the physical properties of the building. Grey-box model is used when the knowledge of these properties is not comprehensive enough. It is based on a partial dataset and partially on empiricism (Kramer and al., 2012). Black box model is used when parameters have no direct physical meaning. No physical properties knowledge is required for this model (De Coninck et al., 2014).

This paper presents an exercise of verification and validation of a test case house using white box and grey-box models. First section describes the test case house, experimental set up and data sets. Second section concerns TRNSYS modelling, according to the "modelling specification report" provided in the exercise. Inputs of the model are the measured outdoor climate data. Part of outputs, are indoor temperatures which will be compared to real measured temperatures of each zone of the house.

Third section deals with the modelling of the house as a second order inverse grey box model. Data from a 32-day-long experiment is analyzed and used to fit lumped parameter models formulated as coupled stochastic differential equations. Outputs of the model are the indoor air temperatures. The model is fitted using PEM (prediction error method) techniques with MATLAB. The estimated physical parameters which include UA-value, total heat capacity, and solar aperture for the building are discussed. Last part of the paper presents a simulation of the white and grey box models to predict indoor temperatures of a free floating period. Results of both simulations are compared and discussed.

EXPERIMENT SET UP

Description of the test case house

The experiment was undertaken on a test case house named "House O5" situated at Holzkirchen, Germany (near Munich). The latitude and longitude are respectively 47.874 N, 11.728 E. The elevation above mean sea level (MSL) is 680m. Figure 1 shows an East view the house. Figure 2 shows a vertical section and the internal layout. For the experiment, the layout was divided into north and south areas. South side includes: the living room, the children's bedroom, the corridor and the bathroom. North side includes: the parent's bedroom, the lobby and the kitchen.

A full specification of the house, including: constructions, windows and roller blinds description, systems of ventilation, heating and cooling, air leakage, ground reflectivity and weather data, was provided in the "modelling specification report" of the exercise.(Strachan et al., 2014).

Figure 1 East view of the test case "house 05"

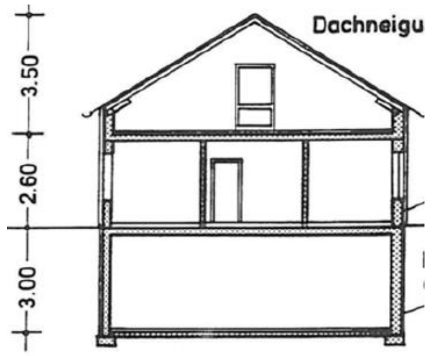

Figure 2 Vertical section of the house O5

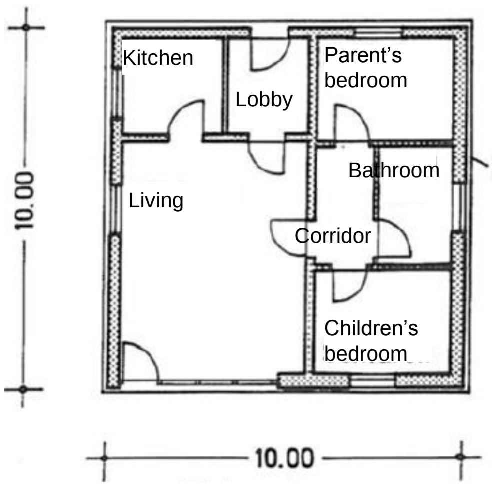

Figure 3 Layout of the house O5

Data and experiment device

Measurements were undertaken on the house in cooler conditions on April and May 2014. The Schematic of proposed test schedule is shown in figure 4. The schedule used is shown in Table 1.

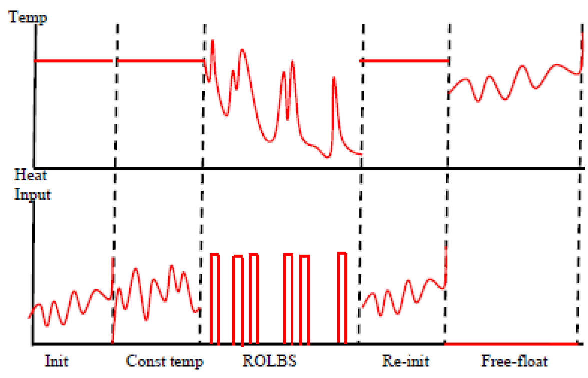

Figure 4 Schematic of proposed test schedule

A Randomly Ordered Logarithmic Binary Sequence (ROLBS) for heat inputs into the living room was applied. This was designed to ensure that the solar and heat inputs are uncorrelated (Strachan et al., 2014).

The experiment includes the cellar and attic temperatures as boundary conditions. Ventilation supply flow rate and ventilation air temperature are also included.

Indoor temperatures and heat inputs of each room of the house are measured and provided except during the free floating period.

Table 1
Planned experimental schedule

PERIOD OF MEAUSREMENTS	CONFIGURATION OF THE EXPERIMENT
From 09.04.14, 00:00 To 29.04.14, 01:00	Initialisation/constant temperature-30°C in living room, corridor, children's room and bathroom, and 22°C in attic, cellar and north rooms.
From 29.04.14, 01:00 To 14.05.14, 01:00	ROLBS sequence in living room with 1800W heater; same ROLBS sequence in bathroom (500W heater) and south (children's) bedroom(500W heater). 22°C in attic, cellar and north rooms.
From 14.05.14, 01:00 To 20.05.14, 01:00	Re-initialisation-30°C in living room, corridor, children's room and bathroom, and 22°C in attic, cellar and north rooms.
From 20.05.14, 01:00 To 03.06.14, 00:00	Free-float in living room, corridor, children's room and bathroom, and 22°C in attic, cellar and north rooms.

TRNSYS SIMULATION MODELLING

TRNSYS model

TRNSYS is a package for energy simulation of solar processes, building analysis, thermal energy, and more (Klein, 2000). The reported work was done with TRNSYS version 17.

Figure 5 shows the developed TRNSYS simulation model. "Type 56" represents the multizone model of the building. It includes descriptions of: zones, walls, windows, infiltration, internal gains and schedule, ventilation, heating and cooling systems as described in the "modelling specification report".

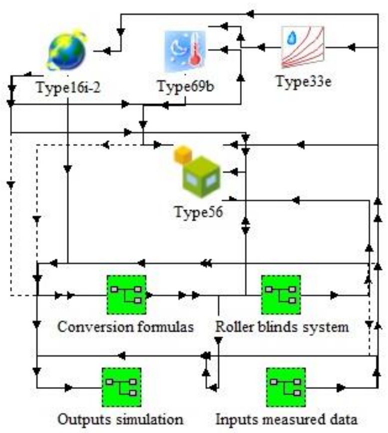

Figure 5 Trnsys simulation model

Simulation results and comparison with in situ measurements

Simulation results are presented in figures 6, 7, 8 and 9. Each zone's result is presented with the corresponding indoor measured temperatures. The gap between simulated and measured values is directly readable and allows to measure the reliability of the achieved TRNSYS model.

However, results of measured temperatures of: parent's bedroom, lobby and kitchen, include data logging failure period as shown in corresponding curves.

Temperatures of: living, children's bedroom, bathroom and corridor, are not measured during the free floating period as shown also in corresponding curves.

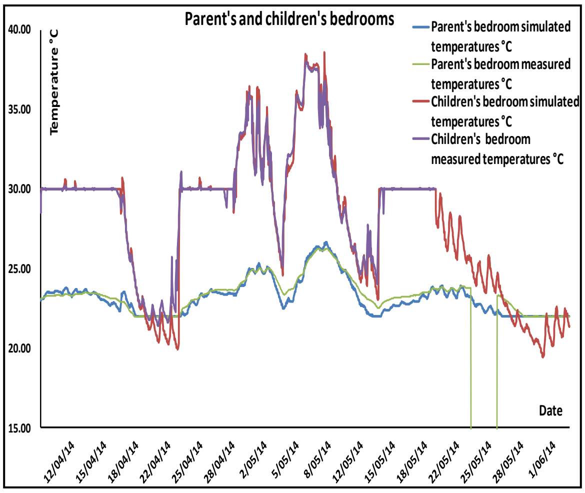

Figure 6 Simulated and measured indoor temperatures for parent's and children's bed rooms

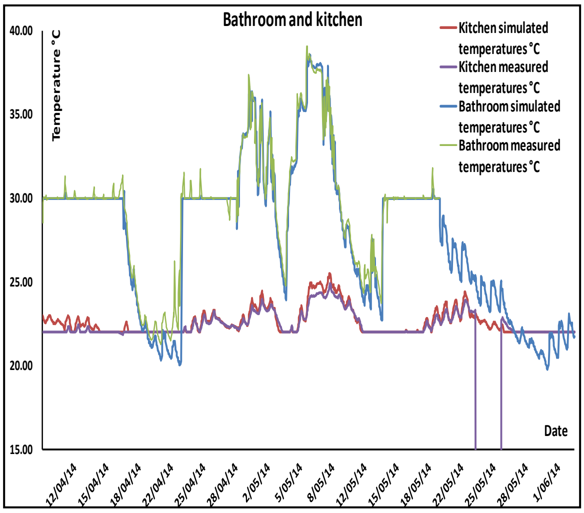

Figure 7 Simulated and measured indoor temperatures for bathroom and kitchen

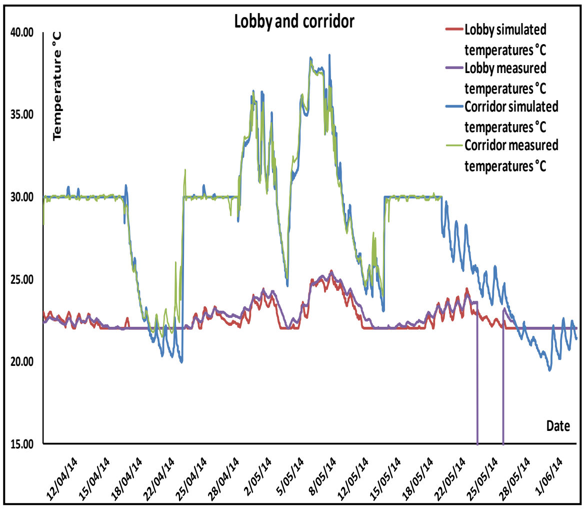

Figure 8 Simulated and measured indoor temperatures for lobby and corridor

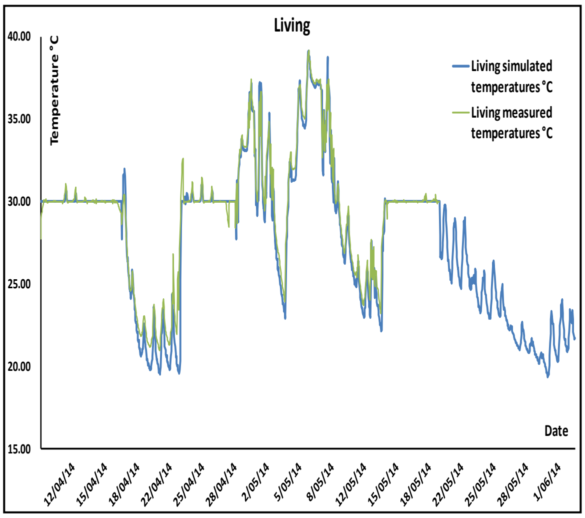

Figure 9 Simulated and measured indoor temperatures for living

Results show that simulated and measured values are close. This level of reliability was possible following a large number of simulations performed and improved each time by adjusting the various parameters of the TRNSYS model.

THERMAL MODEL DEVELOPMENT AND PARAMETERS ESTIMATION

Grey box model

Grey box model consist of a set of continuous stochastic differential equations formulated in a state space form that are derived from the physical laws which define the dynamics of the building (Madsen, 2008). The model structure is formulated by equations 1 and 2.

$$\dot{X}(t) = A(\theta)X(t) + B(\theta)U(t) \qquad (1)$$

$$Y(t) = C(\theta)X(t) + D(\theta)U(t) \qquad (2)$$

Equations (1) and (2) are respectively: the state equation and the output equation, where : X(t) is the state vector, Xdot(t) is the change of the state vector, U(t) is a vector containing the measured inputs of the system, A is the state matrix, B the input matrix, C the output matrix and D the direct transition matrix.

These inputs can be controllable, such as the heat delivered by the heating system or the airflow rate of the ventilation system, or not controllable, such as the outdoor temperature, solar and internal gains.

The model structures can be described as resistance-capacitance (RC) networks analogue to electric circuits to describe the dynamics of the systems. Thereby the distributed thermal mass of the dwelling is lumped to a discrete number of capacitances, depending on the model order.

The unknown parameters θ in these equations are calculated using estimation techniques. For current case study, the used technique was the Prediction Error Method (PEM). The goal is to find the parameter set that minimizes the error between the simulation result and the measurements. PEM estimaton criteria is given according to equation 3.

$$\hat{\theta} = \arg\min_{\theta}\{S(\theta) = \sum_{t=1}^{N} \varepsilon_t^2(\theta)\} \qquad (3)$$

$\hat{\theta}$ are the estimated parameters based on the data set called "estimation data". $\varepsilon_t(\theta)$ is the simulation error depending on the time and parameter value.

Following estimation of parameters θ, validation process will ensure that the model is useful not only for the estimation data, but also for other data sets of interest. Data sets for this purpose are called validation data.

To quantify the model's accuracy, the goodness of fit (fit) performance criteria were used as per equation 4.

$$fit = 100.(1 - \frac{norm(y' - y)}{norm(y' - \bar{y}')}) \qquad (4)$$

Where y' is the measured signal, $\bar{y}'$ is the average measured signal; y is the simulated signal norm(y) is the Euclidean length of the vector y, also known as the magnitude.

Accordingly, equation 4 calculates in the numerator, the magnitude of the simulation error, and in the denominator, how much the measured signal fluctuates around its mean. Consequently, the goodness of fit criterion is robust with respect to the fluctuation level of the signal.

Data set measurements of the test case house

Data set used for the model completion and validation were measured in situ, except the heat supplied by ventilation system Pv[W] estimated according to equation 5 (Delff, 2013).

$$c_v P_v = c_v c_{air} . \rho_{air} .(\dot{V}_{v,in} . T_{v,in} - \dot{V}_{v,out} . T_{v,out}) \qquad (5)$$

The period of measurements was from 09.04.2014 to 20.05.2014 as detailed in Table 1. Measurements from 09.04 to 14.05.2014 were used for the "estimation of thermal model parameters" stage. Remind measurements from 14.05 to 20.05.2014 were used for the "validation of the model".

Figure 10 and figure 11 represent respectively: data measurements of the "estimation" and "validation" stages. In both figures data are represented as following : indoor temperatures (the output) noted Tint[°C]; Outdoor temperatures Te[°C], attic temperatures Ta[°C], weighted temperatures of north zone (kitchen, lobby and parent's bedroom) Tn[°C], heat power P[W], solar radiation on horizontal [W/m2] and heat supplied by ventilation system Pv[W].

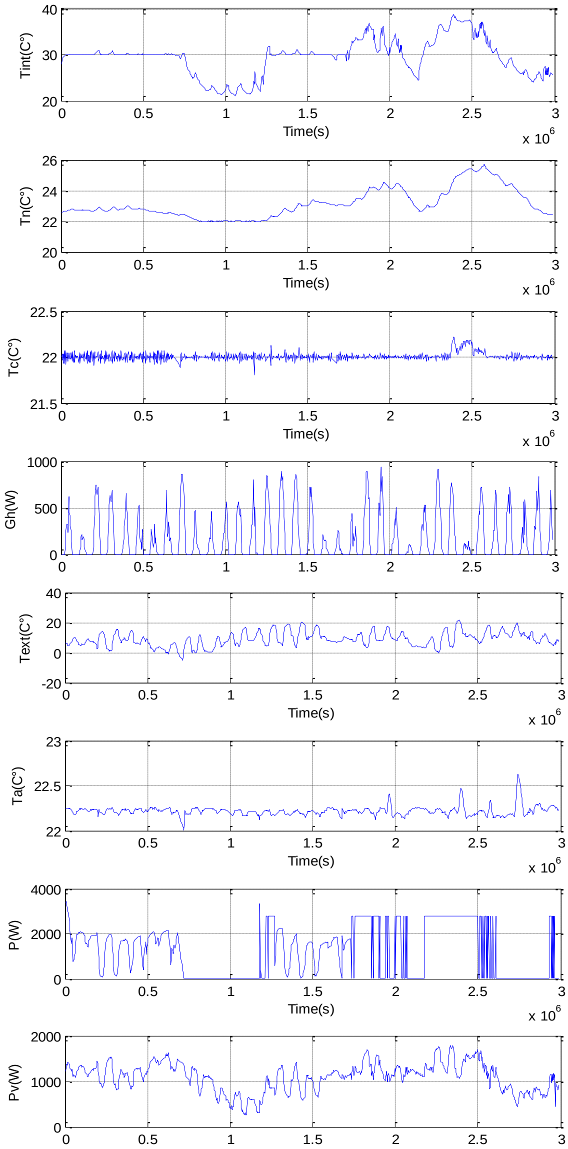

Figure 10 Estimation data

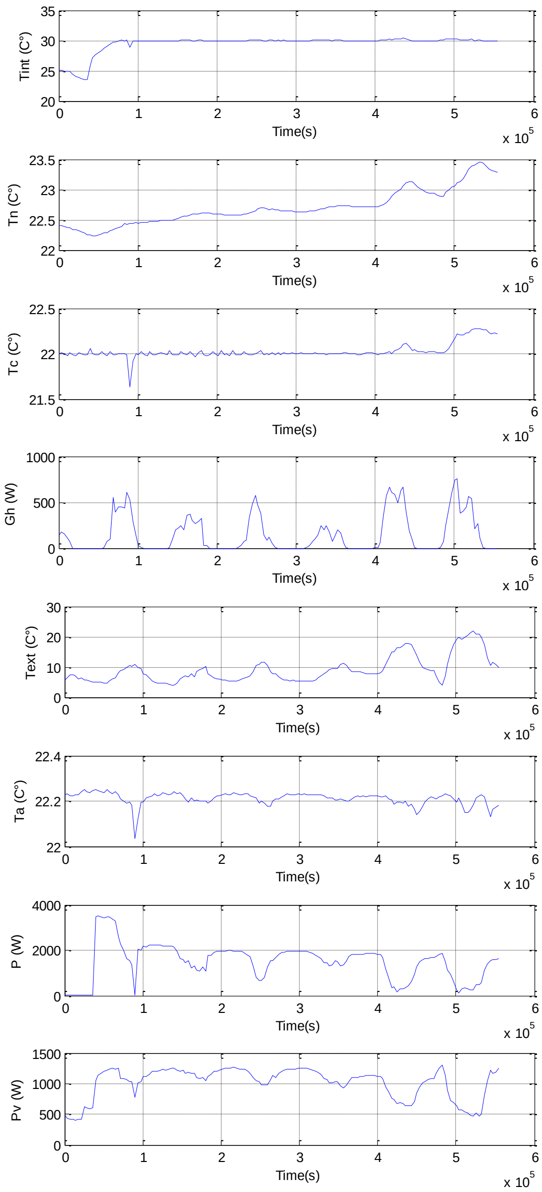

Figure 11 Validation data

RC model of the test case house

Thermal model concerns solely the south side of the house (living, corridor, bathroom, children's bedroom). It aims estimating the heat loss coefficients to the outside, to the adjacent north spaces (kitchen, lobby and parent's bedroom), to the attic and basement, the effective heat capacity and the solar aperture. Figure 12.

Identified models will be used to predict the output based on input data recorded in the free float period.

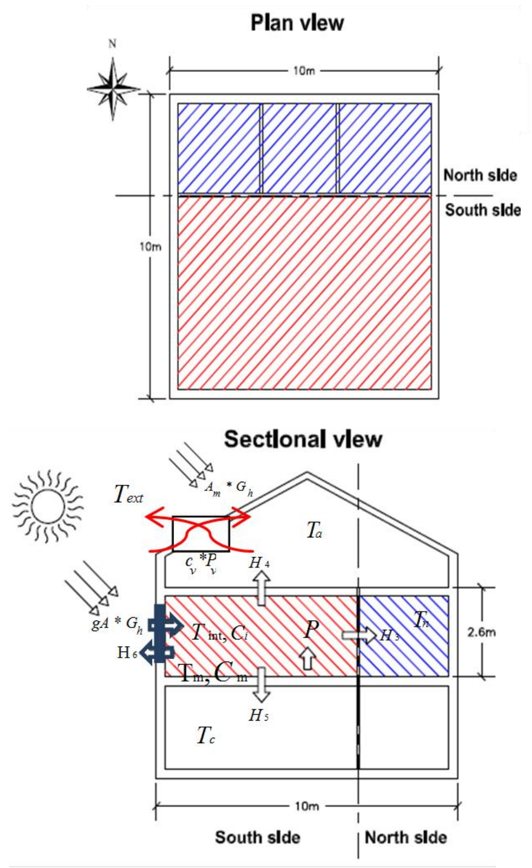

Figure 12 Illustration of the heat flows of the south side of the test case house

The model is made of 6 resistances and 2 capacities (R6C2 following the electrical analogy) where: C_i and C_m represent the structure and the interior air capacities. R_i, (i=1:6) are the thermal resistances between states or inputs. The model has been built to have a small number of parameters, simple enough to be identifiable but complex enough to represent all physical phenomena. Hazyuk in (Hazyuk et al., 2011) has demonstrated that a two order model is enough accurate for building energy parameters estimation. The representation of solar gains can be improved by separating the solar flux arriving on the external wall from the solar flux entering trough windows. The model can handle changes in mechanical ventilation thanks to the c_v parameter that represent the scaling of ventilation heating signal.

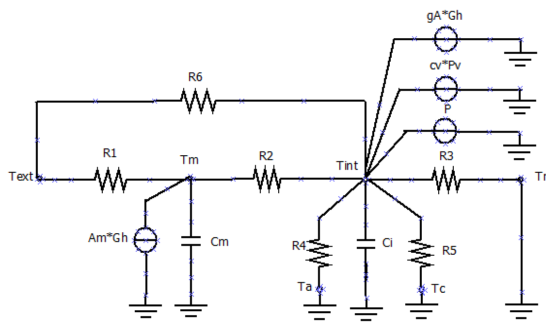

Figure 13 RC model of the test case house

The state space matrices of the RC model are:

$$A=\begin{bmatrix} -\left(\frac{1}{R_6*C_i}+\frac{1}{R_2*C_i}+\frac{1}{R_4*C_i}+\frac{1}{R_3*C_i}+\frac{1}{R_5*C_i}\right) & \frac{1}{R_2*C_i} \\ \frac{1}{R_2*C_m} & -\left(\frac{1}{R_1*C_m}+\frac{1}{R_2*C_m}\right) \end{bmatrix}$$

$$B=\begin{bmatrix} \frac{1}{R_6*C_i} & \frac{1}{R_4*C_i} & \frac{1}{R_3*C_i} & \frac{1}{R_5*C_i} & \frac{1}{Ci} & \frac{g}{Ci} & \frac{c_v}{Ci} \\ \frac{1}{R_1*C_m} & 0 & 0 & 0 & 0 & \frac{A_m}{C_m} & 0 \end{bmatrix}$$

$$C=\begin{bmatrix}1 & 0\end{bmatrix} \quad D=\begin{bmatrix}0 & 0 & 0 & 0 & 0 & 0 & 0\end{bmatrix}$$

With: input matrix: $\vec{U}=[T_{ext} \quad T_a \quad T_n \quad T_c \quad P \quad G_h \quad P_v]^T$

State matrix: $\vec{X}=[T_{int} \quad T_m]^T$

And output Y: $Y=T_{int}$

Results and discussion

The grey-box model Identification was done using MATLAB. It consists on founding the parameter set that maximize the fit between the simulation and measurement results. The parameters set, was identified under a fit of 85.46% as per figure 14.

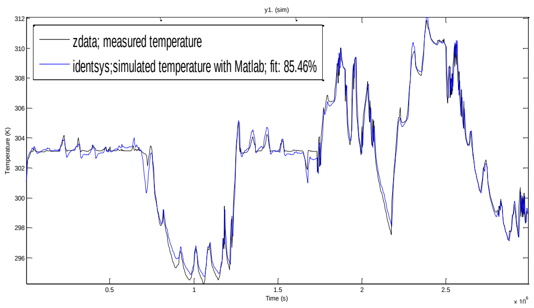

Figure 14 Identification: Comparison of simulated and measured indoor temperatures (fit of 85.46 %)

Validation stage consists on using the identified parameters set to simulate the indoor temperature and compare it to the measurements of the "validation period". The resulted fit given by MATLAB was equal to 70.60%..

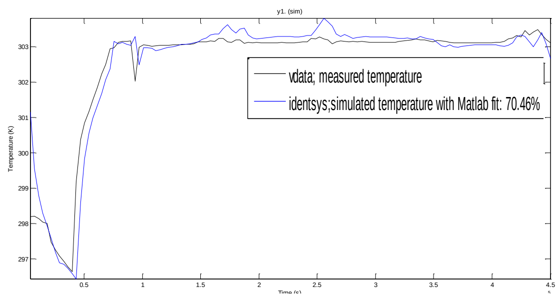

Figure 15 Validation: Comparison of simulated and measured indoor temperatures (fit of 70.60 %)

Inspite of good values of fit criteria, it is important to make an analysis of residuals to ensure an adequate model.

The part of the measured signal that is unexplained by the model, results in simulation errors, called residuals. Hence, ε = y'- y where ε is the residuals, y' is the measured signal and y the simulated signal. There are many possible reasons for the remaining residuals: measurement errors, missing inputs, over simplified model, incorrect model structure and computational errors (Kramer et al., 2013).

The residual analysis consists of two tests: The whiteness test and the independence test. The whiteness test was used to analyze the autocorrelation between the residuals. Ideally, the residuals only consist of measurement errors as white noise and the autocorrelation is within acceptable limits. If the model fails on the whiteness test, there is a strong indication that inputs are missing and the model is over simplified (Kramer et al., 2013).

The independence test was used to analyze the cross correlation between residuals and inputs. A significant cross correlation indicates that the influence of input x on output y is not correctly described by the model. This denotes an incorrect model structure.

Figure 16 shows the autocorrelation and cross correlation for the thermal model. The yellow area represents the tolerated bandwidth. The model's autocorrelation exceed the tolerated bandwidth in some points. This is an indication of missing inputs. However, Ljung in (Ljung, 1999) states that less attention should be paid to the autocorrelation function if no error model is included. The cross correlation of all inputs is within the tolerated bandwidth: this shows that the models' structure is correct and that it describes the influence from inputs to outputs correctly. Accordingly, table 2 summarizes the parameters values with the related uncertainty, where H_i,(i=1:6) is the inverses of R_i, (i=1:6).

Table 2
Estimated parameters values

PARAMETERS	ESTIMATED VALUE	UNCERTAINTY (+/-)
H6 (W/K)	37,46	0.0059
C_i (Kj/K)	170,3	0.0142
H2 (W/K)	4,5	0.0154
H4 (W/K)	11,75	0.0137
H3 (W/K)	28,86	0.0158
H5 (W/K)	15,29	0.0152
H1 (W/K)	5	0.0008
C_m (KJ/K)	6303,6	0.0005
GA (m^2)	2,9	0.0176
c_v (-)	0,8	0.0047
Am (m^2)	20	0.0032

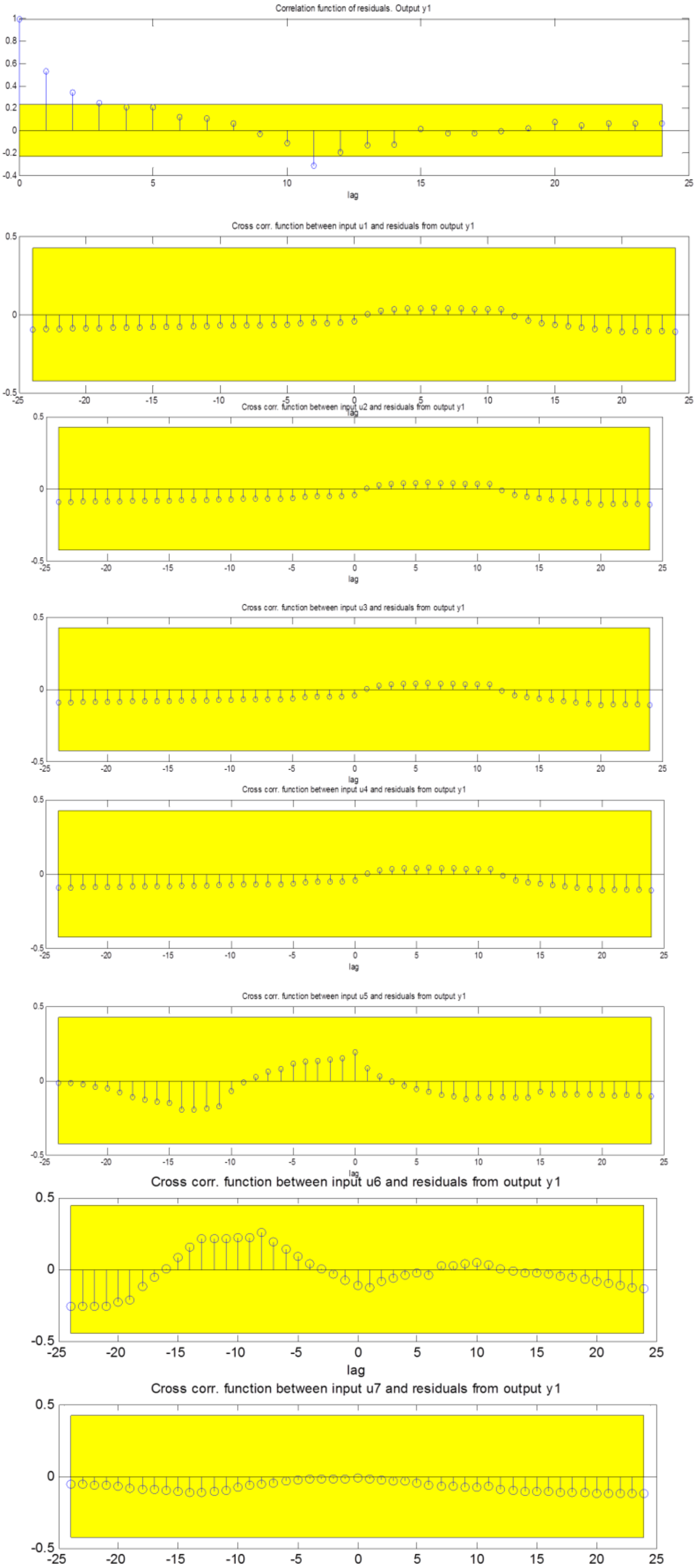

Figure 16 The autocorrelation and cross correlation functions of the thermal model fitted to in situ measurements. The yellow area represents the tolerated bandwidth

INDOOR TEMPERATURES PREDICTION FOR THE FREE FLOATING PERIOD

The grey-box model was simulated using MATLAB software during the period of free floating. This is to permit the prediction of indoor temperature. In addition, the TRNSYS model was simulated during the same free float period.

In order to allow the comparison between results the two models, the TRNSYS resulted temperatures of south side of TRNSYS were weighted to a single indoor temperature (∑ [room temperature X volume/ ∑ volume). Figure 17 shows the results of simulation in free float period, both for TRNSYS and grey-box models. Blue curve is representative of the prediction results of MATLAB and black curve is representative of the prediction results of TRNSYS.

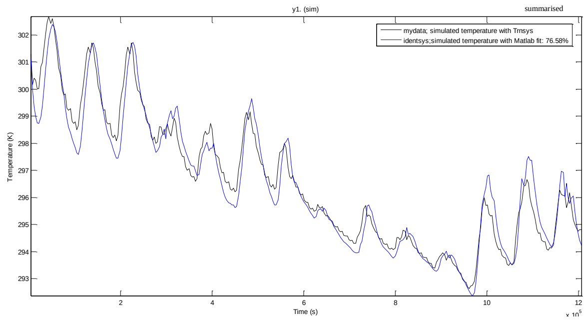

Figure 17 Prediction indoor temperature for free floating period

Comparison shows that both models gave fairly the same results. This could be explained by the fact that TRNSYS model was performed following several simulations and the grey-box model was validated by fit criteria and residual analysis. It reminds nevertheless a small difference of behaviour between the two curves due to the different mode of construction of the models.

CONCLUSION

A double verification and validation of the energy performance of a test case house was presented based on two types of energy building models: white-box and grey-box models.

Both experiments are based on full-scale in situ measurements. The protocol of measurement and configuration of experiment were well documented and introduced. The quality and quantity of measurements have a direct impact on the reliability of obtained models.

First verification and validation with white-box model was performed with TRNSYS 17 software. The experiment demonstrates that it is possible, with a good knowledge of physical proprieties, to realise a reliable TRNSYS model. Results of simulation show that the TRNSYS model is capable of reproducing indoor climate temperature accurately.

Second verification and validation with grey-box model was performed with MATLAB. The building model in state space form was presented with an inverse modelling approach to identify parameters. Identification and validation were analysed according to fit criteria. Additionally, validation took into account an analysis of residuals. Obtained model shows that it is capable to simulate as good as the TRNSYS model indoor temperature accurately (weighted temperature). This could allow to draw the conclusion that the obtained models can be considered enough reliable to perform other identification of parameters of similar construction to the test case house.

NOMENCLATURE

- A_m : area with which the global horizontal solar radiation is scaled (m^2)
- C_i : Heat capacity of the indoor air (J/K)
- C_m : Heat capacity of heavy walls of the envelope of the chamber (J/K)
- c_v : scaling of ventilation heating signal
- gA: solar aperture (m^2)
- Hi: inverse Ri represent the thermal conductances i=1:6
- P : Heating power injected into the chamber (W)
- P_v : estimated ventilation heating (W)
- R_1 : External convection resistance + ½ of the wall conduction resistance (K/W)
- R_2 : Internal convection resistance + ½ of the wall conduction resistance (K/W)
- R_3 :Equivalent resistance of adjacent walls in north side (K/W)
- R_4 : Equivalent resistance of ceiling (K/W)
- R_5: Equivalent resistance of floor. (K/W)
- R_6 : Equivalent strength light walls and infiltration (K/W)
- Ta: attic indoor air temperature (°C)
- Tc: cellar indoor air temperature (°C)
- T_{ext} : Outside temperature (°C)
- T_{int} : Indoor temperature (°C)
- T_m : Node temperature corresponds to the walls of the south side (°C)
- T_n : North side indoor air temperature (°C)
- UA : common UA-value for the building envelope (W/K)

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