VERIFICATION OF THE ENERGY PERFORMANCE OF THE "JACQUES GEELEN" CLIMATE CHAMBER OF CAMPUS D'ARLON, BY CO-HEATING AND GREY BOX MODEL

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ABSTRACT

Building energy performance characterization at design stage is theoretical and could be subject to errors. In operation, it is difficult to verify the reliability of these calculated parameters. The aim of this paper is to set in, a method of verification based upon full-scale dynamic measurements. It presents a complete experimentation of identification/validation of energy performance parameters, upon the "Jacques Geelen" climate chamber of Arlon campus in Belgium.

The experiment uses a co-heating method for identification under stationary regime and grey box model under the dynamic regime. Additionally, a Kalman filter is used to estimate the different disturbances of internal gains in the grey box model. A reliable mathematical model is finally provided for identification of building energy performance parameters.

INTRODUCTION

Estimation of the buildings energy performance is part of the design phase by calculating the theoretical energy use. Actual performance after realisation may deviate significantly from this theoretically design-based performance. Building performance characterization based on full-scale dynamic measurements could help to bridge the gap between theoretically predicted and real life performance of buildings (Roels, 2011).

The purpose of the following experimentation is to build a robust mathematical model for the identification of building energy performance parameters. The structure of the paper follows up the approach leading to this goal.

It presents in thefirst section the "Jacques Geelen" climate chamber and the theoretical calculation, as per the design data, of the U value (heat transfer coefficient) characterizing its energy performance.

Second section concerns the verification of the calculated energy performance under stationary regime by means of co-heating method.

Third section is about the verification under dynamic regime by means of mathematical identification. In a first step, verification considers a dynamic regime without disturbance. In the second step, it considers through a Kalman filter, the disturbances of internal gains. The results of each step of identification are compared to co-heating results in order to validate (or not) the obtained mathematical models.

Figure 1 describes in "blue" the methodology of verification and in "red" the construction of the mathematical models, which will give finally, an algorithm of verification usable in other similar case of verification/validation.

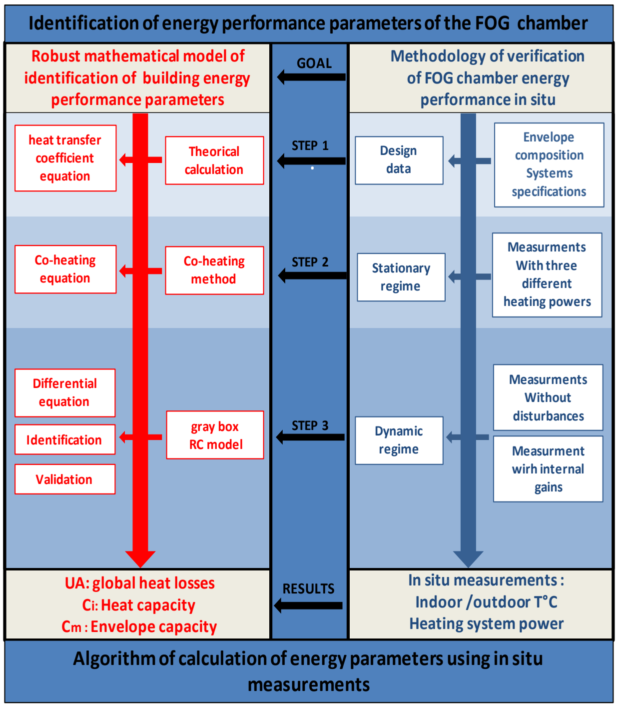

Figure 1 Methodology of identification of energy parameters of the climate chamber

"JACQUES GEELEN" CLIMATE CHAMBER PRESENTATION

Presentation

Jacques Geelen" climate chamber is a testing platform for building energy systems combining building demand, heating and cooling emitters, water-based and air-based distribution systems, storage systems and heat and cool production systems.

It was built between 2000 and 2002 and includes a climate chamber in which a well defined climate can be controlled in terms of temperature and humidity. (André, 2003).

It includes 4 zones as shown in figure 2: the climate chamber which is surrounded by a buffer space (1 m wide) where a given temperature profile can be imposed (internal view in figure 3); the offices zone where the measurement interfaces are located and the technical area where all the production, storage and distribution equipment is located. (André, 2003).

The dimensions of the climate chamber are 5m x 4m x 2.5m. The buffer space is 1m wide. The climate chamber can be the object of the testing (by submitting the energy system to controllable and reproducible heating and cooling loads) or can host the tested device (floor heating, air diffusion system, new concept of wall, etc).

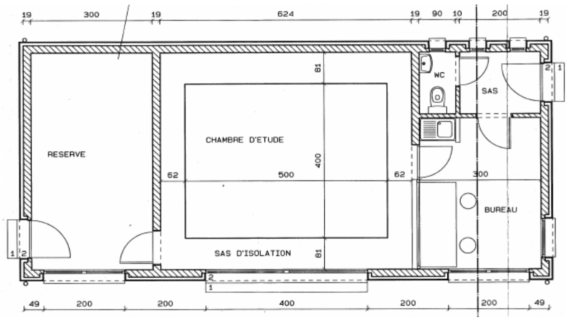

Figure 2 Floor plan of the fog chamber building

Figure 3 Internal view of the climate chamber

Walls composition is as follows: Wooden panel, thickness 12 mm; Wooden structure including rock wool panels, thickness 140 mm (wooden pieces, 89 mm thick, placed each 40 cm and separated by rock wool panels) ; Wooden panel, thickness 12 mm.

Floor composition is: Stone 200 mm; Sand 50 mm; Water bareer; Reinforced concrete 140 mm; Extruded polystyrene 80 mm; Mortar slab (including heating / cooling pipes) 100 mm; Floor covering; Rock wool 60mm; Underfloor heating.

Windows properties are: U = 1.1 W/m^{2}K.

Doors properties are: U = 1.1 W/m^{2}K.

Theorical calculation of the U value

Global heat loss of the chamber is the sum of heat losses due to transmission, infiltration and thermal bridges, as given by equation 1.

$$UA_{global} = UA_{transmission} + UA_{infiltration} + UA_{th\ bridge} \quad (1)$$

Calculation of the heat transfer coefficient for "walls in series" (regular multilayer construction) Us and “parallel walls” (construction with different sections) Up, are given by equations 2 and 3. Equation 4 gives the calculation of the $UA_{infiltration.}$

$$Us = 1/(Rsi + \sum e/\lambda + Rse) \quad (2)$$

Us : Heat transfer coefficient of the wall, W/m².K

e : material thickness m (meter)

λ: Lambda coefficient of thermal conductivity of materials, W/m.K)

Rsi : Inside surface resistance m².K/W.

Rse : Outside surface resistance m².K/W.

$$Up = (f1 * Up1) + (f2 * Up2) + \cdots (fn * Upn) \quad (3)$$

Up : Total heat transfer coefficient of the wall, W/m².K

Up1 : Heat transfer coefficient of the wall 1, W/m².K
Up2 : Heat transfer coefficient of the wall 2, W/m².K
f1, f2 : represents f1% and f2% of the total area (may vary depending on the walls)

$$UA_{infiltration} = 1/3 * n * V \quad (4)$$

Where V: Volume of the chamber (m3) and n: air change rate (h^{-1}).

$UA_{th\ bridge}$ is calculated using THERM software (Mirchell et al., 2013).

According to these equations, Global U value calculation gives following results:

$UA_{transmission}$ =37.26 W/K

$UA_{infiltration}$= 3.06 W/K

$UA_{thermal\ bridge}$ = 0.2744 W/K

Then,

UA= 40.598 W/K , Total area= 94 m²,

U-value= 0.4318 W/m²K

CALCULATION OF THE U VALUE BY CO-HEATING

Co-heating test

The co-heating method has been developed and further improved resulting in the current experimental guidelines available in the UK (Wingfield et al. 2011).

It is a quasi-stationary method based on the linear regression analysis of dynamic measurement data. It can be used to measure the whole building heat loss attributable to an unoccupied construction.

The test consists on heating the inside of an unoccupied construction electrically, using electric resistance point heaters, to a mean internal temperature (typically 25 °C) over a number of days. The period of test typically ranges from 1 to 3 weeks once the construction has been heat saturated (Steskens, 2015).

Whilst heating the construction, a number of parameters are measured, namely total electrical energy input, internal temperatures and relative humidity, and various external climate conditions. By measuring the total amount of electrical energy that is required to maintain the mean elevated, internal temperature each day in response to the external conditions, the daily heat input (in Watts) to the construction can be determined. The heat loss coefficient can then be calculated by plotting the daily heat input against the daily difference in temperature between the inside and outside of the construction (ΔT). The resulting slope of the plot gives the raw uncorrected heat loss coefficient in W/K. (Johnston et al., 2012). The co-heating test essentially assumes the following heat balance on the investigated building:

$$Q + R.S = (\sum A.U + C\,v).\Delta T \qquad (5)$$

Where Q is the heat input from electric heaters [W]; R is the solar aperture [m²]; S the solar radiation [W/m²]; ΔT the temperature difference inside outside [K]; ∑A.U is the sum of Uvalues [W/m²] and respective areas of the thermal envelop [m²], given in [W/K]; and Cv is the infiltration heat loss [W/K].

In our case : R.S=0 (the chamber is inside the buffer zone and the blinds of the window are closed). So we can write the equation 6 as follows:

$$Q = (\sum A.U).\Delta T \qquad (6)$$

The experimental conditions

The experimentation consists on using three values of power heating. In the three cases, the temperature of the buffer is fixed at 18°C. The U value is determined when the steady state is reached.

The main items of equipment deployed within the tested climate chamber are: temperature sensors, fan heaters with three powers (400W ,900W, 1600W), circulation fans, thermostats, kWh meters, data logger able to record all data needs to be obtained from the climate chamber and buffer zone. These data are temperature from the sensors and kWh meters of the fan heaters.

The experiments were performed over period of 25 days, starting the 05/09/2013 and ending the 1/10/2013 as shown in table 1.

Table 1
Planned experimental schedule

POWER	START TIME	STOP TIME	TOTAL TIME (HOURE)
400 W	5/09/2013 12:05	13/09/2013 16:12	196 h
900 W	13/09/2013 16:20	20/09/2014 14:00	100 h
involuntary power failure	20/09/2014 14:10	23/09/2013 15:00	72 h
1600 W	23/09/2013 15:00	1/10/2013 11:00	188 h

Experimentation results

The results are obtained by plotting the heat input of each experience against the difference in temperature between the inside and outside (ΔT).

The resulting slope of the plot gives the heat loss coefficient in W/K as in table 2 and figure 4.

Table 2
UA heat loss coefficient calculated by co-heating

SLOPE OF THE GRAPH = UA (W/K)	U (W/m^2K) FOR A=94 m^2
40.95	0.435

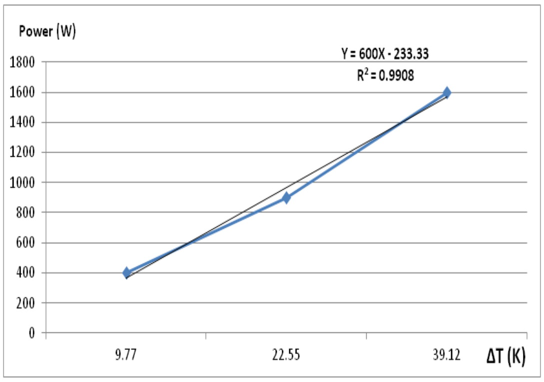

Figure 4 Heating power (Q [W]) as a function of temperature difference (ΔT [K]) between the indoor and outdoor air temperature

It results from this work that the U value calculated by the theoretical method is equal to the U value measured by experimentation. The value obtained is 0.43 W/m²K. As the U value is now verified by experimentation, the identification under a dynamic regime can be undertaken.

IDENTIFICATION WITH GREY BOX MODEL

Identification consists of searching mathematical models of systems from experimental data and data available as initial conditions. These models should provide a close approximation of the behaviour of the underlying physical system in order to estimate the physical parameters or design simulation algorithms, forecasting, monitoring or control (Garnier, 2006).

The conventional approach is to formalize the available data, collect experimental data and estimate the structure, parameters and uncertainty of a model, finally validate (or invalidate) the model. (Mejri, 2010).

The principle of a "grey box" is to use a simplified physical representation of a system and to identify the parameters of this model to minimize the prediction errors. Buildings can be modelled by simple dynamic differential equations representing conduction, convection and capacitive phenomena (Madsen, 2008).

These equations have been widely studied in the literature. It consists of a set of continuous stochastic differential equations formulated in a state space form that is derived from the physical laws which define the dynamics of the building (Madsen, 2008). The model space state is formulated by equations 7 and 8.

$$\dot{X}(t) = A(\theta)X(t) + B(\theta)U(t) \qquad (7)$$

$$Y(t) = C(\theta)X(t) + D(\theta)U(t) \qquad (8)$$

Equation 7 is the state equation, where X(t) is the state vector, Xdot(t) is the change of the state vector and U(t) is a vector containing the measured inputs of the system. Equation 8 is the output equation, where A is the state matrix, B the input matrix, C the output matrix and D the direct transition matrix. The model structures are derived from resistance-capacitance (RC) networks analogue to electric circuits to describe the dynamics of the systems. Thereby the distributed thermal mass of the chamber is lumped to a discrete number of capacitances, depending on the model order.

The unknown parameters θ in these equations are derived 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 method is given according to equation 9.

$$\hat{\theta} = \arg\min_{\theta}\{S(\theta) = \sum_{t=1}^{N} \varepsilon_t^2(\theta)\} \qquad (9)$$

$\hat{\theta}$ 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 10.

$$fit = 100.(1 - \frac{norm(y' - y)}{norm(y' - \bar{y}')}) \qquad (10)$$

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.

DYNAMIC TESTING AND PARAMETERS IDENTIFICATION

Test control strategy

The period of experimentation was 2 weeks. The temperature of the buffer was variable according to the sequence of the real external temperatures of September 2013 in Arlon, Belgium. The indoor temperature was measured. The heating system worked according to the following schedule of power along with the experimentation:

- 1.5 days initialization with constant low power 100W into test room;
- 1.5 days constant low power 100W;
- 1.5 days constant high power 1000 W;
- 3.5 days pseudo-random on/off power 1000W;
- 2 days medium power 500W; This sequence may be followed by a validation sequence:
- 4 days low power 100W.

Data set measurements

The thermal model's output and inputs data used for estimation parameters are presented in figure 5, respectively to the following description: Indoor temperatures (the output) noted Tint[°C] Outdoor temperatures (of the buffer) noted Text[°C] and the heat powers P[W].

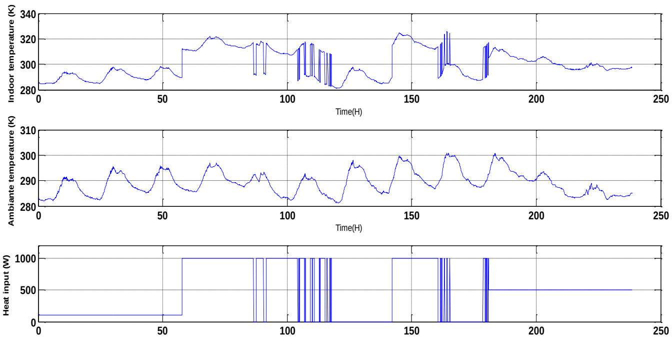

Figure 5 Estimation data

The thermal model's output and inputs data used for validation parameters are presented in figure 6 in the same order of estimation data in figure 5.

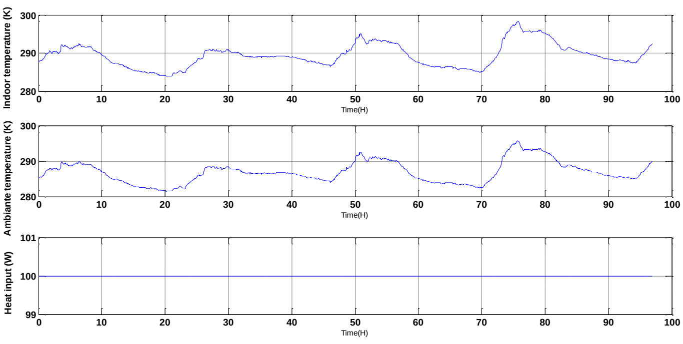

Figure 6 Validation data

RC model of the climate chamber

The model has been built to have a little number of parameters, simple enough to be identifiable but complex enough to represent all physical phenomena. Hazyuk (Hazyuk et al., 2011) proposes to use a two order model. The chamber is modelled by a linear second order differential equation RC.

Obtained model is made of three resistances and two capacities (R3C2 using the electrical analogy), as in figure 7, where:

- Cm and Ci represent the structure and the interior air capacities,
- The inverses of Rf, Rint, Re represent the thermal conductance.

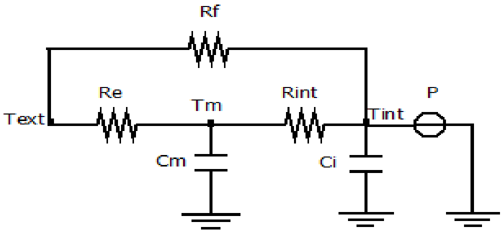

Figure 7 RC model of the climate chamber

It uses two inputs $\vec{U} = [T_{ext} \quad P]^T$: the outdoor temperature Text and the heating power P. It has the indoor air temperature $Y = T_{\text{int}}$ as output.

The state space matrices of the RC model are:

$$A = \begin{bmatrix} -(\frac{1}{R_{\text{int}} * C_i} + \frac{1}{R_f * C_i}) & \frac{1}{R_{\text{int}} * C_i} \\ \frac{1}{R_{\text{int}} * C_m} & -(\frac{1}{R_{\text{int}} * C_m} + \frac{1}{R_e * C_m}) \end{bmatrix}$$

$$B = \begin{bmatrix} \frac{1}{R_f * C_i} & \frac{1}{C_i} \\ \frac{1}{R_e * C_m} & 0 \end{bmatrix} \quad C = [1 \quad 0] \; D = [0 \quad 0]$$

$\vec{X} = [T_{\text{int}} \quad T_m]^T$ the state vector including the indoor temerature T_{int}, the structure temperature T_m.

Results of parameters estimation

The grey-box model was simulated using MATLAB software. The result of identification under MATLAB is shown in figure 8. The performance of the model expressed by the fit (see equation 10) is given by MATLAB and is equal to 75.82 %. The result of validation under MATLAB is shown in figure 9. The fit is given by MATLAB and is equal to 93.82%.

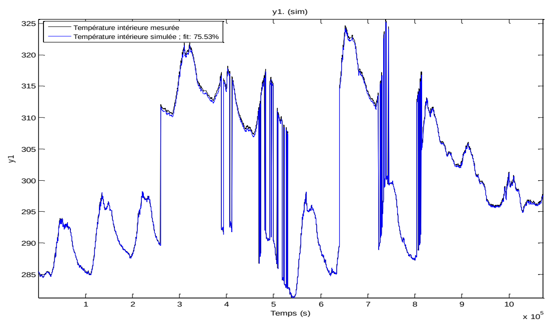

Figure 8 Identification: Comparison of simulated and measured indoor temperatures (fit of 75.82 %)

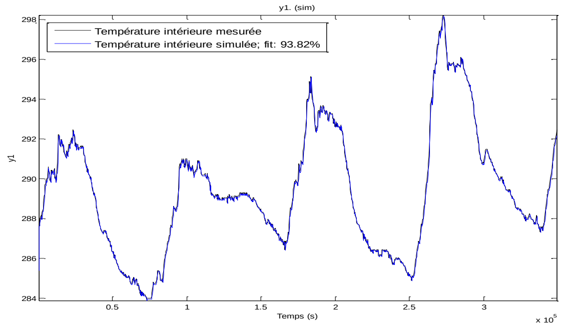

Figure 9 Validation: Comparison of simulated and measured indoor temperatures (fit of 93.82 %)

Analysis of residuals

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

The residuals from a fitted model are defined as the differences between the response data and the fit to the response data at each predictor value (r = y – ŷ). (Ljung, 2000).

. Thus, residuals represent the portion of the validation data not explained by the model.

Analysis of residuals consists of two tests: the whiteness test and the independence test.

According to the whiteness test criteria, a good model has the residual autocorrelation function inside the confidence interval of the corresponding estimates, indicating that the residuals are uncorrelated. If the fit for the signal is good, the residuals should be white noise.

According to the independence test criteria, a good model has residuals uncorrelated with past inputs.

Evidence of correlation indicates that the model does not describe how part of the output relates to the corresponding input. For example, a peak outside the confidence interval for lag k means that the output y(t) that originates from the input u(t-k) is not properly described by the model.

Figure 10 shows the autocorrelation and cross correlation for the thermal model. The yellow area represents the confidence interval. The model's autocorrelation exceed the confidence interval in some points. 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 confidence interval: this shows that the models' structure is correct and that it describes the influence from inputs to outputs correctly. Accordingly, table 3 summarizes the parameters values with the related uncertainty.

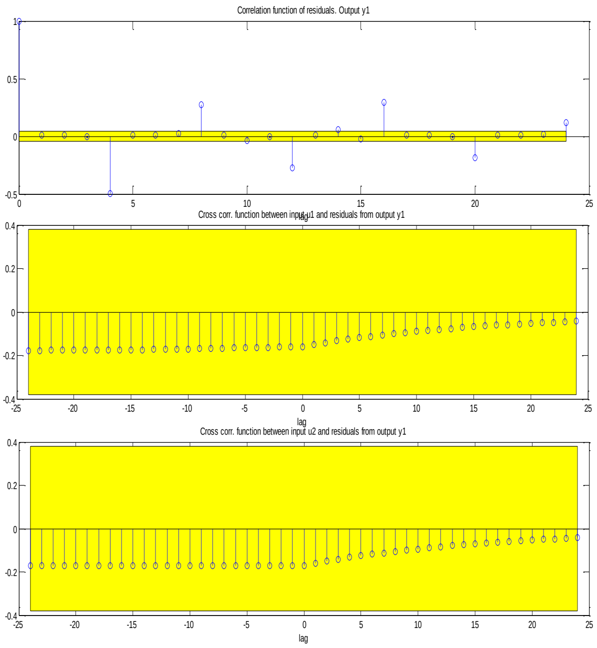

Figure 10 The autocorrelation and cross correlation functions of the thermal model fitted to in situ measurements. The yellow area represents the confidence interval

Table 3
Estimated parameters values

PARAMETERS	ESTIMATED VALUE	UNCERTAINTY (+/-)
Rf (K/W)	0.0372	0.2939*1.0e-008
Re (K/W)	0.0243	0.0125*1.0e-008
Rint (K/W)	0.0502	0.3232*1.0e-008
Ci (J/K)	250	0.2161*1.0e-008
Cm (J/K)	430.35	0.1505*1.0e-008

Where Rf, Re and Rint are respectively: Equivalent strength light walls and infiltration, External convection resistance +½ of the wall conduction, Internal convection resistance +½ of the wall conduction resistance.

It results that the overall heat losses coefficient of the chamber is :

- UA = 40.65 W/K => U = 0.429 W/m²K.

This result of verification under dynamic regime gave a similar result to the calculation by co-heating method under stationary regime.

The obtained grey box model is then enough accurate to estimate performance parameters when there is no disturbance in the construction.

Next step of the experimentation is to adapt the identification model to a dynamic condition with disturbance of internal gains. This adaptation is performed using a Kalman filter.

DYNAMIC TESTING AND PARAMETERS IDENTIFICATION WITH INTERNAL GAINS DISTURBANCES

Kalman filtering

Kalman filtering is a rigorous estimation technique, to estimate time varying unknown parameters. The Kalman filter can effectively estimate unmeasured states (which evolve in time) with the use of knowledge of the system, dynamics of measuring devices and statistical descriptions of the system noise, measurement errors, and uncertainty in the dynamic models (Kim et al., 2012).

This last step of experimentation addresses the estimation performance of a Kalman filter for internal gains disturbance. The internal gains consists on heat gains of: people, lightings, equipments, etc.

Test control strategy

The period of experimentation was for a week, during November 2014. Climate room was considered as an "office of two persons" with the following scenario:

- The temperature of the buffer was variable according to the sequence of the real external temperatures of September 2014 in Arlon, Belgium.
- A mechanical ventilation with constant double flow of 100m³/h and heat exchanger of 65%.
- Internal temperatures were fixed at 20°C during work hours and at 16°C the rest of the time.
- Internal gains were considered for: two persons (100W/person); two PCs, a printer and a lamp (88W for the total of equipments).
- Heating power was measured.

The internal gains were generated in the experimentation by an emulator of human presence.

RC model of the climate chamber

The model has been built on the same manner as for the experimentation "without disturbance". Figure 11 represents the obtained RC model where Pv is heating supplied by the ventilation system and P_{add} is the sum of internal gains.

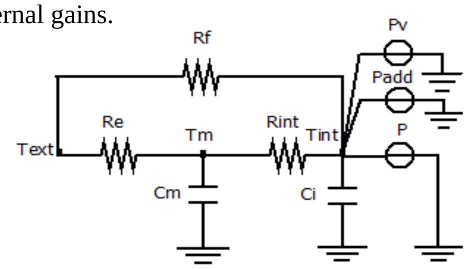

Figure 11 RC model of the climate chamber under dynamic with disturbance

For state descriptions, it is common to split disturbances into contributions from measurement noise $\omega(t)$ and process noise $\upsilon(t)$, acting on the states, so that the equations 7 and 8 are rewritten:

$$\dot{X}(t) = AX(t) + BU(t) + \upsilon(t) \quad (11)$$
$$Y(t) = CX(t) + DU(t) + \omega(t) \quad (12)$$

The state space equations of the RC model are:

$$C_i*\frac{dT_{int}}{dt}=\frac{1}{R_{int}}*(T_m-T_{int})+\frac{1}{R_f}*(T_{ext}-T_{int})+P+P_v+P_{add}+\upsilon_1(t) \quad (13)$$

$$C_m*\frac{dT_m}{dt}=\frac{1}{R_{int}}*T_{int}+\frac{1}{R_e}*T_{ext}-(\frac{1}{R_{int}}+\frac{1}{R_e})*T_m+\upsilon_2(t) \quad (14)$$

Where P_{add} is considered as a state described by a first order equation as (Pedersen et al., 2013):

$$\frac{dP_{add}(t)}{dt}=-\frac{1}{\tau_{add}}*P_{add}(t)+\upsilon_3(t) \quad (15)$$

$Y(t)=T_{int}(t)+\omega(t)$ are measured data.

Where C_m, C_i, R_f, R_i, R_e, $\upsilon_1, \upsilon_2, \upsilon_3, \omega, \tau_{add}$, are unknown, with : $\upsilon_1, \upsilon_2, \upsilon_3$ represent the noise of the three equations state 10,11, 12 and ω represents the noise of sensors.

To minimize the number of parameters to be estimated the variance of the four noise elements $\upsilon_1, \upsilon_2, \upsilon_3, \omega$ as well as τ_{add} have been kept constant in the estimation and have been chosen using physical insight.

Accordingly the prediction model based on the equations 10, 11, 12 using a Kalman filter is :

$$C_i*\frac{dT_{int}}{dt}=\frac{1}{R_{int}}*(T_m-T_{int})+\frac{1}{R_f}*(T_{ext}-T_{int})+P+Pv+Padd+K_1*(Y-T_{int})$$
$$C_m*\frac{dT_m}{dt}=\frac{1}{R_{int}}*T_{int}+\frac{1}{R_e}*T_{ext}-(\frac{1}{R_{int}}+\frac{1}{R_e})*T_m+K_2*(Y-T_{int})$$
$$\frac{dP_{add}(t)}{dt}=-\frac{1}{\tau_{add}}*P_{add}(t)+K_3*(Y-T_{int}) \quad (16)$$

The Kalman gain $[K_1\ K_2\ K_3]^T$ is determined using rough estimates of the noise properties. This includes the variance $\upsilon_1, \upsilon_2, \upsilon_3$ as equal to 0.3 and the variance of ω as equal to 0.4.

Results of parameters estimation

The result of identification under MATLAB is shown in figure 12. The performance of the fit of the model is equal to 93.82%. The result of validation is shown in figure 13. The fit is given by MATLAB and is equal to 85.7%.

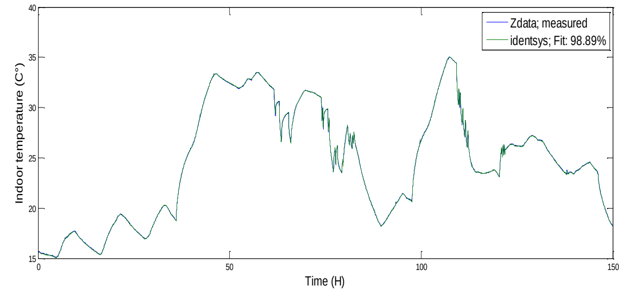

Figure 12 Identification: Comparison of simulated and measured indoor temperatures (fit of 93.82 %)

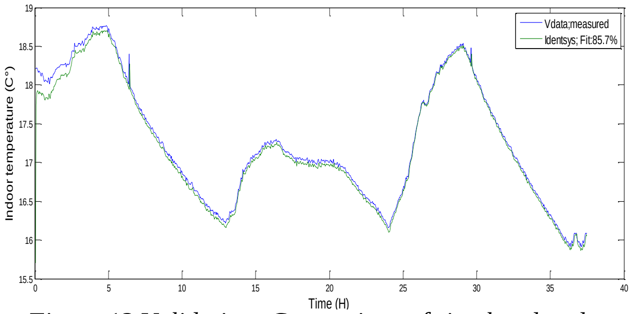

Figure 13 Validation: Comparison of simulated and measured indoor temperatures (fit of 85.7 %)

Analysis of residuals

Figure 14 shows the evolution of the residuals

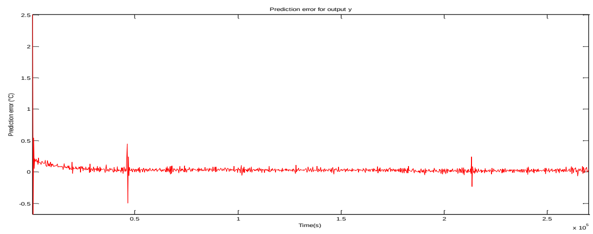

Figure 14 Prediction error for the identified model

The residuals appear to behave randomly and wth zero mean. It suggests that the model fits correctly the data.

Figure 15 shows the obtained residual autocorrelation for the model inside the confidence interval delimited by the blue lines (from tag 2). The residuals of the model can be considered as white noise.

Figure 16, represents the cross-correlation between each input and the residuals. In the three graphs, the cross-correlation functions are inside the confidence interval delimited by the blue lines. This shows clearly that there is no correlation between the inputs of the model and the residuals.

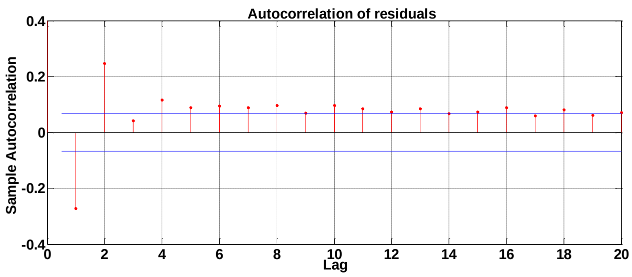

Figure 15Autocorrelation of residuals

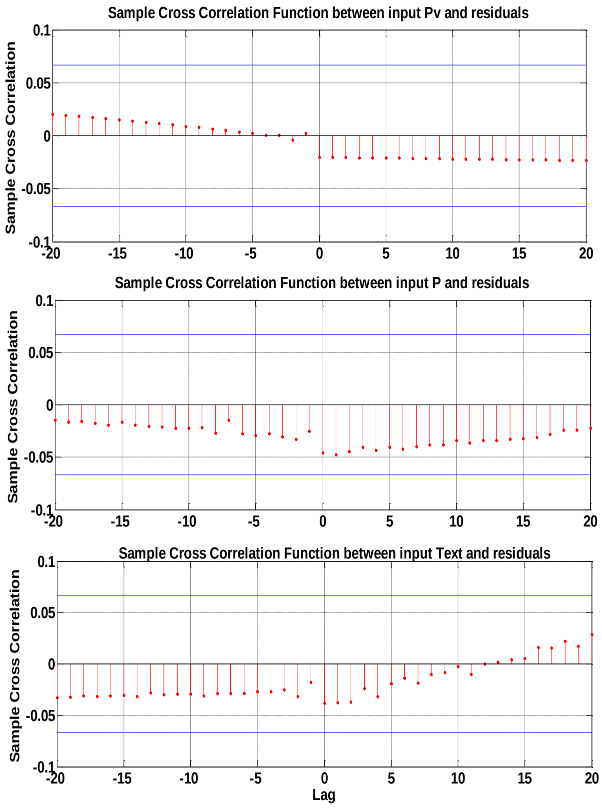

Figure 16 The cross correlation functions between inputs and residuals

Table 4
Estimated parameters values

PARAMETERS	ESTIMATED VALUE	UNCERTAINTY (+/-)
Rf (K/W)	0.0485	0.7382*1.0e-003
Re (K/W)	0.027	0.03458*1.0e-003
Rint (K/W)	0.0307	0.0587*1.0e-003
Ci (KJ/K)	268	0.1472*1.0e-003
Cm (KJ/K)	630	0.3625*1.0e-003
K_1	$0.9079*10^{-5}$	
K_2	$0.6361*10^{-5}$	
K3	0	

Table 4 summarizes the parameters values. It results that the overall heat losses coefficient of the chamber :

- UA = 38 W/K => U = 0.404 W/m²K.

CONCLUSION

A verification and validation of the energy performance of the "Jacques Geelen" climate chamber was presented based on co-heating and grey-box models. The first verification was by co-heating in order to obtain a value of reference which could validate or not the results of mathematical identification. Second verification and validation was with grey-box model. The building model in state space form was presented with an inverse modelling approach to identify parameters. Results were analysed according to fit criteria. Additionally, validation took into account an analysis of residuals. Obtained model shows that it is capable to simulate most indoor temperature and internal gains disturbance accurately. Results of calculation were also similar to results of co-heating experimentation. This could allow to draw the conclusion that the obtained model can be considered enough reliable to perform other identification of parameters constructions in same test conditions.

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