A LOW ORDER ENVELOPE MODEL FOR OPTIMISED PREDICTIVE CONTROL OF INDOOR TEMPERATURE: DEVELOPMENT METHODOLOGY AND CALIBRATION WITH A NUMERICAL MODEL

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ABSTRACT

This study adresses two slightly different macroscopic low order thermal envelope models (thermal-electric models) of a residential building room in Corsica, France. These models aim to be integrated to the in-site BMS controller to perform optimal predictive control of free cooling, thanks to opening windows. This paper will first present the building, the case study and the methodology used. A comparison of the calibration capabilities (with EnergyPlus simulations) of these models, with and without inside air capacity, will then be done. The more appropriate model will be deeply studied, by using optimisation technics, in order to make parameters identifications starting from the dynamic simulation results.

INTRODUCTION

In France, 67% of the whole production of electricity is used for heating, cooling and equipment for residential and non residential buildings. Cooling loads in France (and Mediterranean countries) has become a new problem causing some consumption peaks during summer periods. Facing the growth of population and development of active cooling equipments, passive design and systems will be enhanced for buildings in the future. Natural cross ventilation is claimed to be an effective solution, but has to be controlled correctly. To optimize the use of night cooling coupled with the high building thermal mass, onsite weather forecasts are planned to be used for optimal anticipated controls of opening windows. For this purpose, an envelope model, as well as an airflow model (giving the airflow rate passing through the opening windows depending on exterior conditions), are needed to predict the indoor environment behaviour. The airflow model won't be discussed in this paper. For the past decade, numerous studies related to building modelling and predictive controls have been done. A lot of different typologies of models have been experienced and discussed. Detailed models, reduced order models (from detailed models) and electrical equivalent models (usually low order models) have their own qualities and shortcomings. Whereas detailed building models are inappropriate for identification of parameters on measured data, electrical equivalent low order models suit well for this purpose. Based on Madsen (Madsen, 2012) and Zayane (Zayane, 2011), this study focuses on an electrical equivalent macroscopic model for the building envelope. It addresses on model parameters identification (or calibration) using a Sequential Quadratic Programming (SQP) algorithm (Powell, 1985), with EnergyPlus simulation results.

CASE STUDY BUILDING PRESENTATION

Building presentation

The case study building is "Le Charpak", which is part of Cargèse Institute of Scientific Studies (IESC), Corsica, France.

Figure 1: East facade of "Le Charpak" building

This institute is a CNRS (French National Center of Research) entity. "Le Charpak" is a two storeys residential building composed of 20 similar rooms and was put into service in 2011. It is a Net Zero Energy Building thanks to the renewable energy systems: vacuum tubes solar thermal pannels and a roof mounted 245m2 amorpheus PV membranes field. Scientists from all around the world who come at the institute sleep in these 25 m^2 rooms (bedroom and bathroom). The site is about 40km north of Ajaccio, a hundred meters from the sea, and the climate is a hot Mediterranean one. This building was mostly designed and oriented in sea breezes direction to deal with summer overheating and comfort problems: huge shadings to avoid most solar gains and passive cooling using natural cross ventilation.

Cooling and heating strategies

An innovative system controlled by a Building Management System (BMS) allow automized opening windows control for night cooling, enhanced by high thermal mass interior concrete walls, floors and roofs.

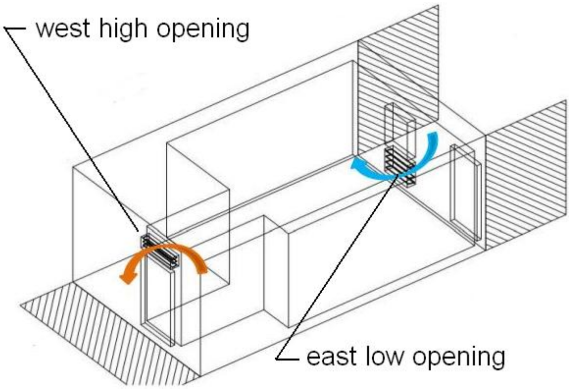

Figure 2: room natural ventilation principle

These opening windows permit cross natural ventilation, as shown in Figure 2. In case of severe overheating or incomfort, a ceiling fan is installed to improve the comfort (lower the incomfort), creating an air flow on the occupant skin's surface, giving him a colder air temperature sensation. Concerning heating equipments, a 56m^2 vacuum tubes solar thermal panels field provide 67% of heating (through radiant floors) and domestic hot water needs. A 20kW backup gas boiler is also installed. A simple Controlled Mechanical Ventilation (CMV) of about 30 m^3/h guarantees sufficient air renewal during winter and shoulder seasons.

Building Management System description

The BMS also centralizes and stores all sensor data available. Each room is equiped by two inside temperature sensors and one humidity sensor. Two specific rooms have two energy meters in addition (plug loads and lighting) and an air speed sensor. A roof mounted meteorologic station indicates environement air temperature and humidity, wind speed and direction, and global horizontal solar radiation. The BMS also knows at any time the position of opening windows. All these measurements can be accesed through a web application (Figure 3), which acts directly on the BMS modbus layer.

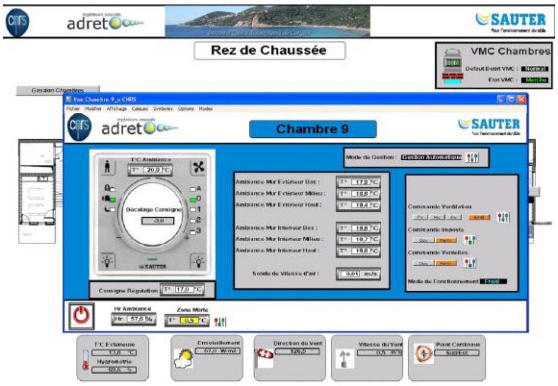

Figure 3: BMS web application, specific room n°9

Thanks to this interface, windows for natural ventilation can be opened / closed, and the ceiling fan can be turned on at three different speeds, or stopped.

Composition of the building

This building has a high thermal mass and exterior insulated envelope in order to play with night flushing, enabled by night natural cross ventilation. The envelope composition is given in Figure 4.

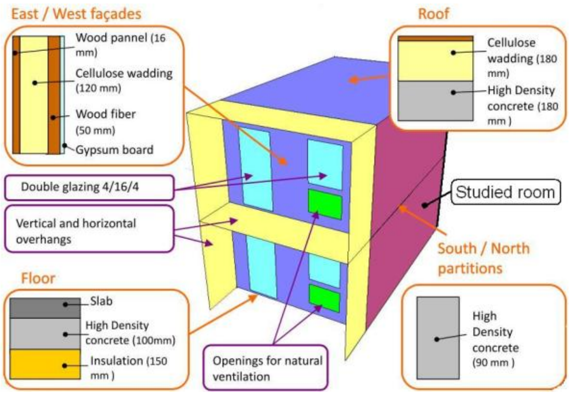

Figure 4: composition of the building

U-values:

- east and west facades: 0,21 W.m^{-2}.K^{-1}

- floor: 0.23 W.m^{-2}.K^{-1}

- double glazing with argon: 1,7 W.m^{-2}.K^{-1}

g-value:

- double glazing with argon: 0.53

Methodology

EnergyPlus models were created with the help of GoogleSketchup and OpenStudio plugin, and then simulated with EnergyPlus. A whole building model (Figure 5) was compared to a simpler two rooms model (Figure 6).

Figure 5: whole building GoogleSketchup view

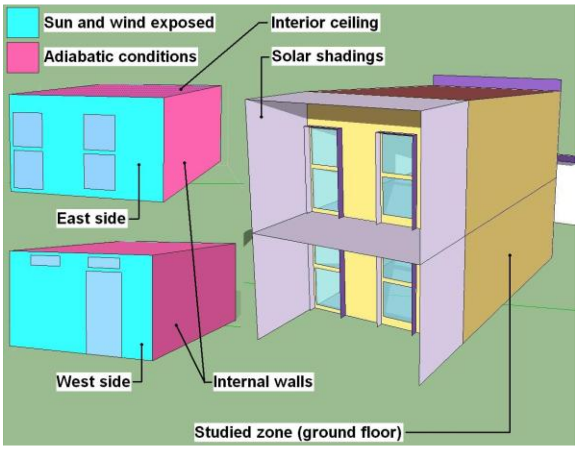

Figure 6: two rooms model description

The maximum indoor air temperature difference between these two configurations was around 0.2°C for the ground floor zone, which is assumed to be little enough to use the two rooms model instead.

MODELS DESCRIPTION

We consequently focused, for the purpose of this study, on a unique ground floor room surrounded by three similar rooms.

Assumptions on EnergyPlus simulations

This results on applying adiabatic conditions on internal walls and ceiling, as shown in Figure 6. Envelope surfaces conditions: wood façades are exposed to exterior conditions, and the floor is exposed to conduction transfer with the ground. A weather file of Ajaccio city (from TRNSYS) is used. A constant 30 m^3/h ventilation rate is applied. The exterior wind is not taken into account.

Internal gains: one person, monday till friday, as described below:

- 0AM to 7AM: 50W
- 7AM to 8AM: 80W
- 8AM to 1PM: 0W (nobody inside)
- 1PM to 2PM: 30W
- 2PM to 6PM: 0W (nobody inside)
- 6PM to 12PM: 50W

Output variables: Zone Mean Air Temperature, Outdoor Dry Bulb, Zone Transmitted Solar, People Total Heat Gain and Ground Temperature.

Results from EnergyPlus simulations are used as inputs to calibrate and test the macroscopic models presented below.

Description of the macroscopic envelope models

Thermal-Electrical analogy was used to create schemes and write corresponding equations. Temperature, heat gains, thermal resistances and capacities are assimilated to voltage, current source, electrical resistances and capacities respectively. Many envelope model configurations were tried, but only two of them (the best ones) are presented. As shown in Figure 7, the 5R2C model has got 5 resistances and 2 capacities.

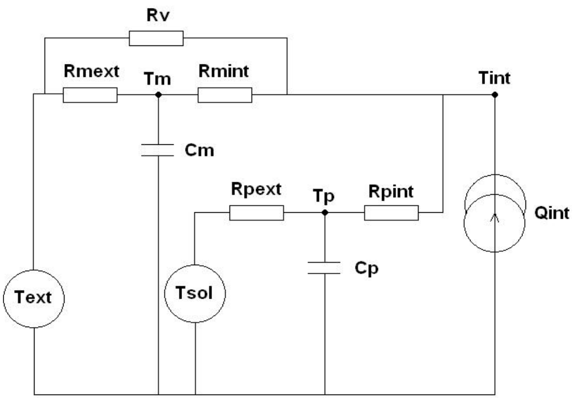

Figure 7: 5R2C model scheme

Text and *Tsol* represent the Outdoor Dry Bulb and Ground Temperature respectively. *Qint* is the sum of Zone Transmitted Solar and People Total Heat Gain. It represent the zone total internal heat gain. *Rmext* and *Rmint* are the exterior and interior lumped resistances of east and west wood façades respectively. Lumped means there that *Rmint,* for example, is the equivalent resistance that lumps conduction resistance through wall and surface convection with interior air. *Rpext* and *Rpint* are exterior and interior resistances of the floor respectively. *Rv* is the equivalent resistance representing ventilation. *Cm* and *Csol* are east and west wood façades capacity and floor capacity respectively. *Tint*, *Tm* and *Tp* represent Zone Mean Air Temperature, wood facades equivalent inside temperature, and floor inside temperature nodes respectively.

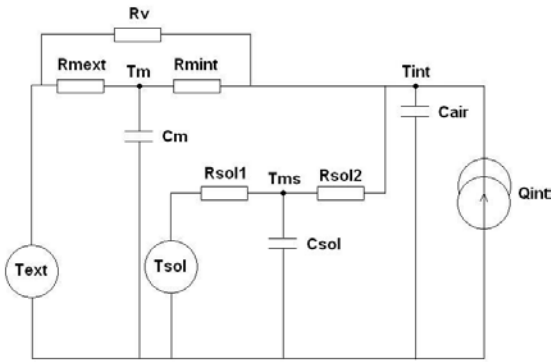

Figure 8: 5R3C model scheme

The 5R3C model shown in *Figure 8* is the same base as 5R2C model but has got an indoor air capacity, *Cair*, in more. *Rpext*, *Rpint*, *Tp* and *Cp* are renamed by *Rsol1*, *Rsol2*, *Tms* and *Csol* respectively. The unknown state variables are *Tm*, *Tms* and *Tint*. *Tint* is also the output variable of these models. Floor and walls were modelled separately because of two main reasons: the much higher thermal capacity of the floor compared to wood facades, and the huge difference in terms of exterior thermal loads. The floor is in contact with a very low frequency variation entity, the ground (in fact, its temperature is considered constant for a whole month). While wood façades are exposed to much higher frequency loads, as solar radiations and exterior temperature. This choice, for this case study, gives better results than a unique capacity for both floor and wood facades.

Initial models parameters calculations

Basic thermal properties calculations were done to determine *Rv, Cm, Csol and Cair* parameters based on walls and windows composition as shown in *Figure 4*. *Rmext*, *Rmint, Rsol1* and *Rsol2* were determined in two steps. First, basic calculations of the thermal equivalent resistances of wood façades walls and floor respectively. Then, as an estimation, an arbitrary split of these equivalent resistances regarding to materials and insulation placement.

Resistances and capacities units are [$K.W^{-1}$] and
[$J.K^{-1}$] and their values are listed below:

Rmext=0.085, *Rmint*=0.035, *Rsol1*=0.135 *Rsol2*=0.005, *Rv*=0.1, *Cm*=1,5E+6, *Csol*=2E+7, *Cair*=76080

Models equations

UsingThermal-Electrical analogy, Ohm's law and Kirchhoff's laws can be applied to establish the equations related to these models. As an exemple, 5R3C model equations are shown below:

$$Cm \cdot \frac{dTm}{dt} = \frac{Text - Tm}{Rmext} + \frac{T\text{int} - Tm}{R\min t} \quad (1)$$

$$Csol \cdot \frac{dTms}{dt} = \frac{Tsol - Tms}{Rsol1} + \frac{T\text{int} - Tms}{Rsol2} \quad (2)$$

$$Cair \cdot \frac{dT\text{int}}{dt} = \frac{Tm - T\text{int}}{R\min t} + \frac{Text - T\text{int}}{Rv} + \frac{Tms - T\text{int}}{Rsol2} + Q\text{int} \quad (3)$$

Equations 1, *equation 2* and *equation 3* are linked and form a dynamic equation system. It can be expressed with a state space model formalized as below:

$$\begin{aligned} \dot{\mathbf{x}}(t) &= A\mathbf{x}(t) + B\mathbf{u}(t) \\ \mathbf{y}(t) &= C\mathbf{x}(t) + D\mathbf{u}(t) \end{aligned} \quad (4)$$

where *x* is the state vector and contains respectively state parameters *Tm, Tms* and *Tint*; *u* is the input vector and contains respectively *Text*, *Qint* and *Tsol*, which come from *EnergyPlus* simulation. *y* is the output vector and only contain *Tint*, the output of this system. A, B, C and D are the building physical properties matrices, and are time-invariant.

Implementation in MATLAB environement

To calculate *Tint*, the model output, "c2d" and "lsim" *MATLAB* functions are used. The *MATLAB* script was already developped for a similar application. It was just adapted to this 5R2C and 5R3C models. *equation 5* is the universal script for "c2d" function, and *equation 6* is the "lsim" function used for 5R3C model:

sysd=c2d(ss(A,B,C,D),Te)	(5)

Tint=lsim(sysd,[Text,Qint,Tsol],Timed,[T_m(0) T_ms(0) T_int(0)])	(6)

"c2d" function discretizes the continuous-time dynamic system model "*sys*" using zero-order hold on the inputs and a sample time of *Te* seconds. "lsim" function simulates the (time) response of "*sys*" discrete systems to the input time history *[Text, Qint, Tsol],Timed.* The *Timed* vector specifies the time samples for the simulation and consists of regularly spaced time samples. *[T_m(0) T_ms(0) T_int(0)]* specifies initial state parameters for *Tm, Tms* and *Tint* respectively. The "lsim" output is a vector which contains *Tint* calculation value at each sample time.

Identification of parameters using an optimisation algorithm

In our case, a Sequential Quadratic Programming (SQP) algorithm (Powell, 1985), adapted to this medium-scale problem, is used. The aim is to find an optimal 5R2C and 5R3C parameters set that provide to these low order macroscopic models the same behaviour as EnergyPlus model. In other words, we try to minimize the difference between the inside air temperature *Tint* (output of 5R2C and 5R3C models) and Zone Mean Air Temperature from EnergyPlus simulations, so-called *T_int_Energyplus*. The MATLAB fmincon optimisation function finds the minimum of a constrained nonlinear multivariable function and is used for the purpose. The objective function "*ecart"* is expressed by means of least squares method and expressed as shown in *equation 7:*

ecart=sum((T_int_Energyplus-Tint)^2)	(7)

pmin and *pmax fmincon* constraints, expressed as vectors, contain minimum and maximum values for 5R2C and 5R3C parameters respectively, as described in *equations 8 and 9* (5R3C model). "*" means "multiplied by" in *equation 9*.

pmin = [Rmint/e3, Rmext/e4, Cm/e2, Rv/e, Rsol1/e4, Rsol2/e3, Csol/e5, Cair/e1]	(8)

pmax = [Rmint*e3, Rmext*e4, Cm*e2, Rv*e,Rsol1*e4,Rsol2*e3,Csol*e5,Cair*e1]	(9)

Different factors were assigned to give more or less liberty to the optimisation function, depending on parameters, as listed below:

e = Rv factor *e1 = Cair* factor *e2 = Cm* factor

e3 = Rmint and *Rsol2* (interior resistances) factor

e4 = Rmext and *Rsol1* (exterior resistances) factor

e5 = Csol factor

DISCUSSION AND RESULT ANALYSIS

Evaluation criteria of models calibration and prediction accuracy

In order to compare models or/and optimisation options (as *pmin* and *pmax*), "calibration" and "prediction" indicators have been set up. Their aim is to evaluate the ability of 5R2C and 5R3C models to fit with EnergyPlus simulation results. For each model, parameters are first optimised (calibrated or identified) on a given period of time, using SQP algorithms. This is the so-called calibration step. Then the model is run with optimised parameters on the following days, weeks or more. This is the so-called prediction step. For both calibration and prediction steps, the error beetween *Tint* and *T_int_Energyplus* (*Tint - T_int_Energyplus*), as their respective evolutions, are plotted. Average and maximum absolute errors indicators are computed and give a global vision of calibration and prediction accuracy.

Global simulation Hypotheses

For the purpose of this paper, only 3 prediction periods will be analyzed:

- 3/10_to_3/16: a typical shoulder season week, with variable exterior weather conditions (*Text* and solar irradiations)
- 7/18_to_7/24: a hot and sunny summer week, with similar weather conditions through the week
- 12/22_to_12/28: a quite cold winter week with variable weather conditions

For 5R2C model:

- *e*=1.0001, *e2*=10, *e3*=100, *e4*=10, *e5*=10

For 5R3C model:

- *e*=1.0001, *e1*=1.0001, *e2*=10, *e3*=100, *e4*=10, *e5*=5

e and *e1* are set to 0.0001 to fix *Rv* and *Cair* values, as *fmincon* function can't modify them. They are well known and time-invariant values, because the geometry of the zone, as its ventilation rate, are also time-invariant. For both models, all initial state parameters are set to *T_int_EnergyPlus* value at first sample time. *Te*, the simulation sample time can be 600s or 3600s.

Comparison of 5R2C and 5R3C models

These two models were simulated for each prediction periods described earlier in this essay. Many calibration periods were tried and only the ones which gave the better results were taken into account and presented below. Fixed *Te* sample time: *Te*=600s.

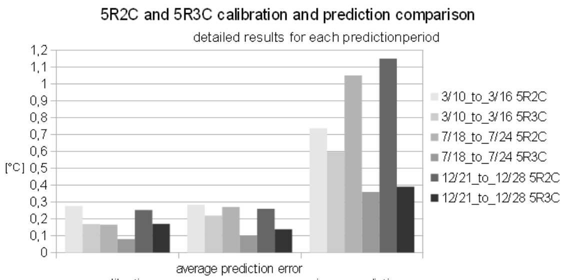

Figure 9: 5R2C and 5R3C detailed comparison

Figure 9 gives a global vision of models calibration and prediction skills. To compare 5R2C with 5R3C on the same period, let's read this graph by pairs of columns, left to right, for each average calibration error (ACE), average prediction error (APE) and maximum prediction error (MPE) indicators. 5R3C calibration and prediction errors are always lower than 5R2C ones.

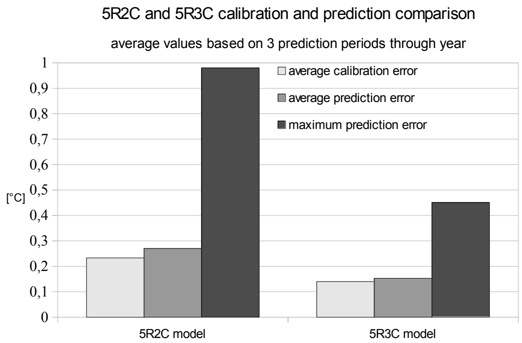

Figure 10: 5R2C and 5R3C comparison through year

Figure 10 represent the mean values of ACE, APE and MPE for these 3 prediction periods. This graph clearly confirms that 5R3C model has better prediction skills as 5R2C model. Same results and conclusions for *Te*=3600s. The additional parameter *Cair* adds a high frequency dynamic to 5R3C model. It combines very low frequencies dynamics (*Csol*), mid frequencies dynamics (*Cm*) and high frequencies dynamics (*Cair*). This last is essential for the main goal of this model. It must be able to predict inside air temperature in order to ensure optimal control of natural ventilation. Natural ventilation rates can reach numerous air changes per hour, which can results to important and quick inside air temperature changes. Consequently, the corresponding model must take into account such dynamics.

Influence of simulation sample time

Two different 5R3C models are compared on the 3 prediction periods, using the same period for calibration step. The same 5R3C model are used except the simulation sample time *Te* , which varies between 600s and 3600s. Results are presented below:

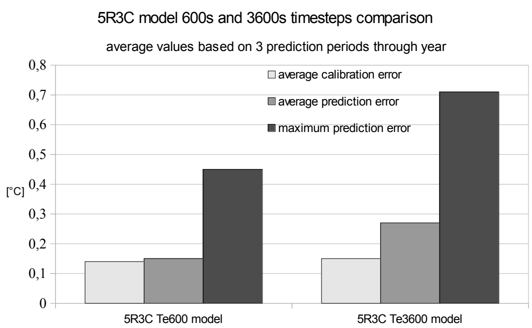

Figure 11: Te influence on 5R3C model

Figure 11 shows mean values of ACE, APE and MPE for these 3 prediction periods (and their respective calibration periods). For each period, the same trend appears: a 600s sample time gives better results in terms of prediction skills, at least for these considered periods.

Influence of calibration period length

For this part, we only consider the 5R3C model, with a 600s *Te* sample time (so called 5R3C_Te600) which is the best option for now. For each of the three prediction periods, five calibration periods were applied: 1, 2, 3, 4 and 5 weeks. Results are given, for each prediction period, in Figure 12, Figure 13 and Figure 14.

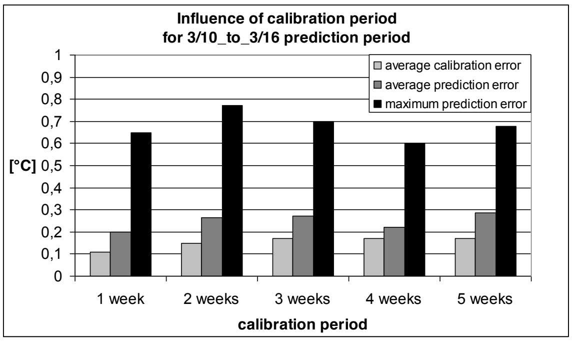

Figure 12: 3/10_to_3/16 calibration influence

For this shoulder season week, the calibration periods which give the best results in terms of prediction skills are: 1 week and 4 weeks. 3 and 5 weeks calibration periods give equivalent results.

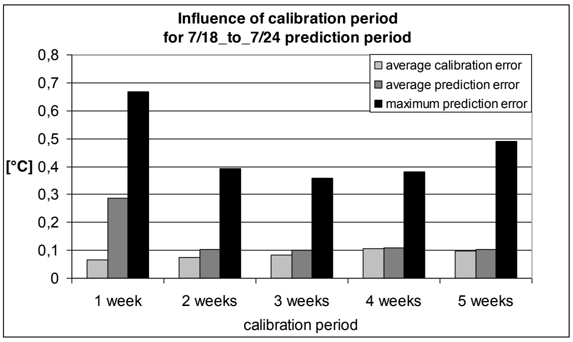

Figure 13: 7/18_to_7/24 calibration influence

Concerning this hot and sunny summer week, a 3 weeks calibration period is the optimal period, combining both lowest average and maximum prediction error. 4 and 5 weeks calibration periods give equivalent results.

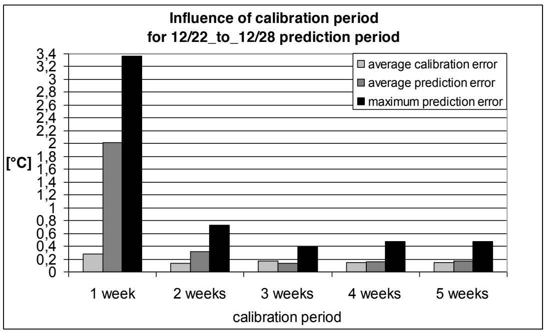

Figure 14: 12/22_to_12/28 calibration influence

For this winter week, a 3 weeks calibration period is also the optimal period, for same reasons explained earlier in the text. 4 and 5 weeks calibration periods give equivalent results.

For these 3 prediction weeks, the overall optimal calibration period seems to vary between 3 and 4 weeks. We can note that there is no link between average calibration and prediction errors skills. Typically, short calibration periods will tend to a small average calibration error but higher average and maximum prediction errors than for longer calibration periods.

5R3C_Te600 optimised parameters variability

In this section, the variability of 5R3C_Te600 optimised parameters will be addressed. A so-called optimised parameter is an initial model parameter that has been optimised by SQP algorithm during the calibration step. Results are shown for the 3 optimal calibration periods but also for a whole year calibration period. Initial parameter values are also reported to appreciate how the calibration step (in fact the so-called SQP optimisation) affects them.

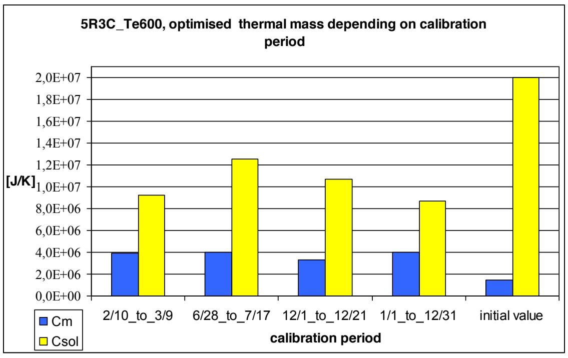

Figure 15: optimised Cm and Csol variability

Figure 15 compares initial and optimized *Cm* and *Csol* parameters (walls and floor capacities respectively). We can notice that *Cm* and *Csol* optimized parameters keep a physical meaning, and have the same order of magnitude respectively.

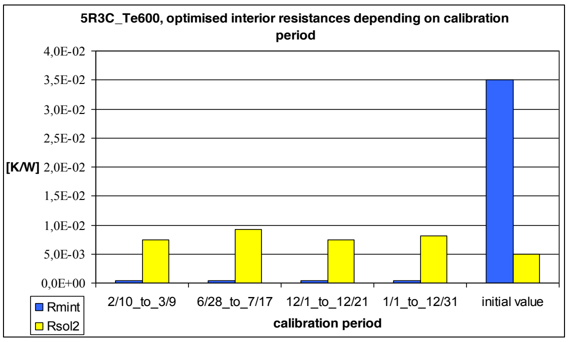

Figure 16: optimised Rmint and Rsol2 variability

Figure 16 shows initial and optimized *Rmint and Rsol2* parameters (interior walls and floor resistances respectively). Optimized *Rmint and Rsol,* for all calibration period considered, have the same order of magnitude. We notice that *Rmint* optimized and initial values are completely different.

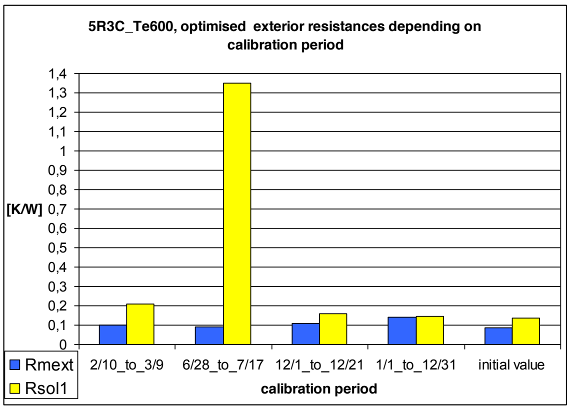

Figure 17: optimised Rmext and Rsol1 variability

Figure 17 shows initial and optimized *Rmext and Rsol1* parameters (exterior walls and floor resistances respectively). Except *Rsol1* for 6/28_to_7/17 calibration period, optimized parameters are of the same order regardless to calibration period. They are also close to their respective initial values. As a conclusion of this part, in all, optimised parameters seem to keep a physical meaning and globally are of the same order of magnitude as their respective initial values. Even if the 5R3C is a low order macroscopic model, its equations (Figure 1, Figure 2 and Figure 3) are based on physical laws. This property may ease the understanding of both model and optimisation algorithm behaviours.

CONCLUSION

“Le Charpak” is a real case study building, monitored and equipped with a Building Management System, which allows smart control of opening windows. This system is used for passive cooling, creating a natural cross ventilation of each room. This paper proposes a comparison between two low order macroscopic envelope models and a parameter identification approach based on SQP optimisation algorithm. It also shows the influences of different calibration periods and simulation sample times on prediction skills, for the 5R3C model proposed here. Prediction skills reflect the ability that the model (coupled with SQP optimisation process) has to fit with EnergyPlus model behaviour. It indicates if this model is suitable and ready to be use as a base envelope model for optimal predictive control of this case study. Related studies presented in this paper give indications on which order of model, sample time or calibration period suits best for this predictive model. Perspectives of this work are numerous and challenging:

- calibration with on site measured data
- development (and calibration) of a thermal airflow model for natural cross ventilation (in parallel to *Rv* on the scheme, Figure 8)
- implement an optimal predictive controller to the on site BMS, taking into account weather forecasts and optimising opening windows controls
- comparison of indoor air temperature, during summer season, between a room with basic controls of opening windows (temperature setpoints) and a room with optimal predictive controls.

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