Application of model predictive control for the optimization of thermo-hygrometric comfort and energy consumption of buildings

Ludovico Danza[1,*], Lorenzo Belussi[1], Fabio Floreani[2], Italo Meroni[1], Andrea Piccinini[3], Francesco Salamone[1]

1. *Construction Technologies Institute of National Research Council of Italy, Via Lombardia 49, San Giuliano Milanese, Milano 20098, Italy*

2. *Consorzio Intellimech, Parco Scientifico Tecnologico Kilometro Rosso, via Stezzano, 87, Bergamo (BG), Italy*

3. *University of Bergamo, Department of Engineering and Applied Sciences, via Marconi, 5, 24044 Dalmine (BG), Italy*

danza@itc.cnr.it

ABSTRACT. The use of tools of simulation in every field of engineering is in the last years widely spreading. Lot of them can be used and a large amount of simulators can be found on the market in order to perform every kind of analysis and prediction. In the field of building/plant system, tools based on white, grey and black box approaches are often used as a function of accuracy and reliability.

Several tools were developed according to mathematical models and transient analysis in order to perform Building Energy Simulations. The lumped capacitance models have a potential in terms of both data reliability and low computational cost.

The Resistance-Capacitance models can be realized with different orders to improve the dynamic thermal behavior of building and coupled with model-based design tools. Dymola with Modelica language can provide a useful tool for engineers to design a thermo-hygrometric comfort model optimizing the energy consumptions. The paper describes a calculation method developed with the aid of an outdoor test cell, based on a second order Lumped parameters model coupled with a hygrometric model and a Model Predictive Control thanks to a library for real time control and management of energy consumptions and thermal comfort.

RÉSUMÉ. L'utilisation d'outils de simulation dans tous les domaines de l'ingénierie s'est largement répandue ces dernières années. Beaucoup d'entre eux peuvent être utilisés et une grande quantité de simulateurs peuvent être trouvés sur le marché afin d'effectuer tout type d'analyse et de prévision. Dans le domaine des systèmes de bâtiments / installations, les outils basés sur les approches de boîte blanche, grise et noire sont souvent utilisés en fonction de la précision et de la fiabilité.

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Plusieurs outils ont été développés selon des modèles mathématiques et des analyses transitoires afin de réaliser des simulations d'énergie du bâtiment. Les modèles de capacité concentrée ont un potentiel en termes de fiabilité des données et de faible coût de calcul.

Les modèles Résistance-Capacité peuvent être réalisés avec différents ordres pour améliorer le comportement thermique dynamique du bâtiment et associés à des outils de conception basés sur des modèles. Dymola avec le langage Modelica peut fournir aux ingénieurs un outil utile pour concevoir un modèle de confort thermo-hygrométrique optimisant les consommations d'énergie. L'article décrit une méthode de calcul développée à l'aide d'une cellule de test extérieure, basée sur un modèle à paramètres concentrées de second ordre associé à un modèle hygrométrique et à une commande prédictive, grâce à une bibliothèque pour le contrôle en temps réel et la gestion des consommations d'énergie et du confort thermique.

KEYWORDS: *building energy simulations, model predictive control, lumped parameters model, dymola.*

MOTS-CLÉS: *simulations d'énergie du bâtiment, commande prédictive, modèle à paramètre concentrée, dymola.*

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1. Introduction

Buildings are responsible for 40% of energy consumption and 36% of CO_2 emissions in the EU (EU Commission, 2010). While new buildings generally need less than three liters of heating oil per square meter per year, older buildings require about 25 liters on average, up to 60 liters. Currently, in EU a variable percentage between 35% and 42% of the building stock is considered “old buildings”, i.e. built up to 1960, and between 38% and 49% is built up 1990 (Economidou *et al.*, 2011). These statistics highlight how an important refurbishment campaign of this sector is a promising action to reduce the energy consumption of each State. To overcome this issue very consistent investment and many ambitious initiatives were launched (Kaderják, 2012), based on the reduction of energy consumption, the improvement of the energy performance and the use of renewable energy sources in compliance with the Community Strategy (EU Commission & EU Commission, 2010; Danza *et al.*, 2018) and (EU Commission, 2014). Among the several available technologies, those related to control and management of the energy flows within buildings provide good results in terms of diagnosis and optimization of building performance (Zong *et al.*, 2016). This aim is achieved combining building simulation techniques, semantic data models (Terkaj *et al*., 2014; Gagliardo *et al.*, 2015) and automation processes also through the use of open source hardware for control (Salamone *et al.*, 2016; Salamone *et al.*, 2016; Salamone *et al.*, 2015; Salamone *et al.*, 2017) or monitoring purposes (Salamone *et al.*, 2015). In general, a traditional Energy Management Control System (EMCS) can save between 5% and 15% of energy consumption of buildings (Dong & Lam, 2014).

Thanks to Building Energy Simulation (BES) through numerical models (Coakley *et al.*, 2014) significant effort has been spent to predict the energy demand of buildings and to evaluate their energy performance. The BES models are especially built to simulate existing or designed buildings and are applied in different ways so as to improve the efficiency of the building sector (Belussi *et al*., 2013; Belussi *et al*., 2015; Belussi *et al*., 2015; Guazzi *et al*., 2017; Magrini *et al*., 2017). The BES models are mainly classified into three categories, “white”, “black” and “grey” box according to the method applied for the resolution of the transient heat equations and the parameters used (physical, statistical or a combination of them, respectively) (Amara *et al*., 2015). White box models require the analytical solution of the heat transient equation thorough different techniques: Conduction Transfer Function (CTF) method, Thermal response factor method, Radiant Time Series (RTS) method. Black box models are based on statistical and regression methods such as Multiple Linear Regression (MLP), Artificial Neural Network (ANN), etc. Finally, grey box models combine the characteristics of both approaches in terms of reliability, simplicity and reproducibility of results (Wang & Zhai, 2016). Expressions of this method are the so called lumped parameter models of Resistance-Capacitance models (RC). RC approach uses deterministic differential equations (Andersen *et al*., 2000) and continuous time modelling to calibrate the parameters of the model on data (Bacher & Madsen, 2011). RC models are often embedded in control system, thanks to the good prediction of building thermal behavior and ease of implementation (Berthou *et a*., 2014), with the aim of predicting the building energy demand and optimizing the operating plants (Harish & Kumar, 2016) coupled with model-based design tools, as Matlab/Simulink (Li & Wen, 2014), or equation-based methods, such as Modelica (Bünning *et al.*, 2017).

Local control, such as ON/OFF and PID, improves the thermal comfort of occupants (Moore & Fisher, 2003; Nassif *et al*., 2005; Zhang & Hanby, 2006). In the last decades, in order to describe phenomena that change continuously, Ordinary Differential Equations (ODEs), Artificial Neural Network (ANN) and MPC were implemented in dynamic software to enhance both energy consumption and thermal comfort. Nowadays, MPC is recognized as one of the best promised solution in building control, although constraints make it difficult to spread (Killian & Kozek, 2016). MPC uses a system model to determine the future state and to generate a control vector that minimizes a cost function on a finite horizon in the presence of interference and constraints. A crucial feature of the MPC is the building modeling (Privara *et al*., 2013). In this context the RC network is used for the building modeling phase.

The present article describes the development of a 3R2C model coupled with a hygrothermal model implemented in Dymola exploiting the solution of differential equations according to the electric analogy. Specific library are developed aimed at predicting the thermal behaviour of a case study. The reliability of the model is assessed using the co-heating test applied to a real test cell, and the results are evaluated through the Bland-Altmann test (Danza *et al.*, 2016). Furthermore, three types of energy control system are designed and applied to the test case in order to evaluate the achievable reduction in energy consumption and optimization of indoor thermal comfort.

2. Building model

2.1. Material and methods

In the world of automation, researchers and engineers rely on software which helps them in complex time and frequency domain system equations in a very short time. Modelica$^{(TM)}$ is an open standard of an object-oriented modeling language for heterogeneous, multi-domain dynamic systems (Fritzson, 2010). Modelica combines the power of equation based modeling with advanced object-oriented structuring features. A unique feature of Modelica is class parameters which allow a high-level parameterization of physical phenomena (Tummescheit, 2002). By the way, Dymola is a complete tool for modeling and simulating integrated and complex systems. Dymola is an object-oriented modeling language of large dynamical systems (Dempsey, 2006). Models are hierarchically decomposed into sub-models which are connected in accordance with the physical coupling of the components. The features of Dymola allow the development of domain specific class-libraries for e.g. electronic circuits, control systems, hydraulic systems, thermodynamics systems, bond graphs and others, which can all be used in conjunction for generating a specific multi-domain application model (Otter *et al.*, 1996).

Matlab/Simulink allows simulating and optimizing controller design, detecting and correcting errors in the design cycle and finally testing and validating controller design in real time (Riederer, 2005). The source code can be easily exported in many different program languages and directly uploaded on the hardware device, ready to actuate the best correction to the environment.

2.2. Hygro-thermal model

The equivalent RC scheme derives from the lumped capacitance solution of the transient heat transfer equations, a well-known consequence of the thermal-electric analogy. A lumped model is based upon the assumption that the temperature of an element (or a part of it) is spatially uniform during a transient heat transfer. Although this approach can not represent a fine temperature distribution, it is a good candidate to represent the overall thermal behaviour of a building (Dimitriou *et al.*, 2014; Nespoli *et al.*, 2015; Danza *et al.*, 2016). According to the lumped capacitance solution the heat balance equation acquires a second order differential layout and is capable to describe the evolving temperature of a thermal node T(t) [K] due to the storing Φ_{in} [W] and extraction Φ_{out} [W] of the heat power from the thermal mass of the system, as described by Eq (1). In (Danza *et al.*, 2016) a detailed analysis of the algebraic solution is provided.

$$\frac{CdT(t)}{dt} = \Phi_{in} - \Phi_{out} \tag{1}$$

As a consequence, the balance is described by a first order differential equation, where T_i and Φ represent the actuating variables, as Eq (2).

$$C_{t,i}\frac{dT_{s,i}}{dt} = H_{tr}\left(T_{s,e} - T_{s,i}\right) + H_{o,i}\left(T_i - T_{s,i}\right) + \Phi \tag{2}$$

The model, described by an implicit system of Differential/Algebraic Equations (DAE), has been solved by means of Differential/Algebraic System Solver (DASSL) (Linda *et al*., 1983), a variable step solver. DASSL solver uses backward differentiation formulas to integrate DAE. Dymola works implementing the Backwards Differentiation Formulas (BDF) from order one to five. BDF are linear multistep methods which approximate the derivative of a function taking data from previous time iterations reducing uncertainty introduced by the last approximation.

Moisture also has an impact on the hygrothermal comfort and satisfaction of building's occupants (Ferroukhi *et al.*, 2016). The air temperature, relative humidity and air pressure were chosen as the driving potentials (Liu *et al.*, 2016). The current state of art of the hygrothermal interactions modeling between the envelope and the indoor environment calls upon to Heat, Air and Moisture (HAM) transfer model coupled with dynamic simulation tools aimed at improving the way BES tools consider moisture exchange between the air zone and building envelope (Ferroukhi *et al.*, 2015). The humidity condition in the room is a consequence of the moisture fluxes over the interior surfaces, the user dependent moisture production rate (ω person), the gains or losses due to ventilation (ω external) and sources or sinks due to HVAC systems (ω HVAC) (Künzel *et al.*, 2005). In terms of absolute humidity, ω (t), the quantity of water in the air at time (t + 1) is described by Eq (3). In the present work the moisture transfer through building envelope is neglected.

$$\omega_{t+1} = \omega_t + \omega_{person} + \omega_{external} + \omega_{HVAC} \tag{3}$$

All the equation described above have as final result the calculation of the internal room temperature (T_i) and absolute humidity (ω) which need to perform the calculation of the Predicted Mean Vote (PMV), according to the Standard EN ISO 7730:2005, as following:

$$PMV_l = T_i 0.1997 + \omega 0.0299 \tag{4}$$

Where PMV_l is a linearization of the PMV because in the perspective of a real time control the performance of the controller is strongly correlated to the velocity of computation instead of the precision of calculation. The formula above is extracted substituting the internal air speed with a mean of the allowed value (as specified by labor lows) and approximating the radiance temperature with the air temperature. The nonlinear equation obtained is furthermore linearized in the range of 15-35 °C. The described mathematical process is a usual practice in automation engineering which must guarantee hard real-time in time cycle processing.

2.3. Dymola and MATLAB libraries

The theory explained in section 2.2 has been translated into a software library developed in Modelica language usable in Dymola environment. The library is composed by 15 elements: 11 buildings blocks and 4 sub-blocks which compose the 11 main blocks (Figure 1).

The wide set of blocks above is needed in order to let the composition of every kind of building possible, composing rooms, floors and the whole building step by step. The result is a hierarchic model where every room can be controlled with a different kind of thermostat or use a shared setting calculated on a sampled room.

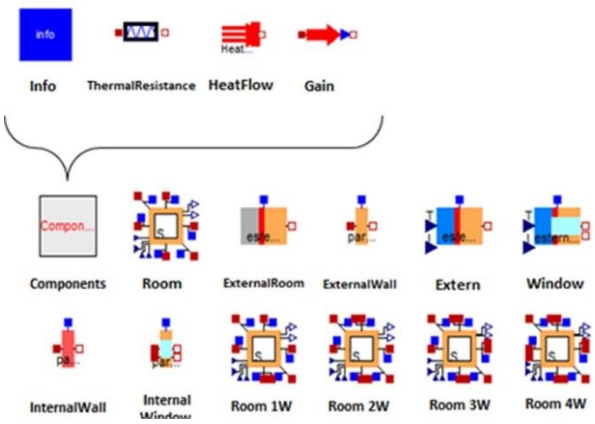

Figure 1. Block list

The Figure 2 shows a general example of the division of the model 3R2C into 3 blocks, where the first one (from left) represent the external part of the building, external weather conditions and surface wall state; the second block represents the internal structure of the wall approximated by a resistance and finally the third block represents the internal wall surface and a common condition state of the room linked to other wall.

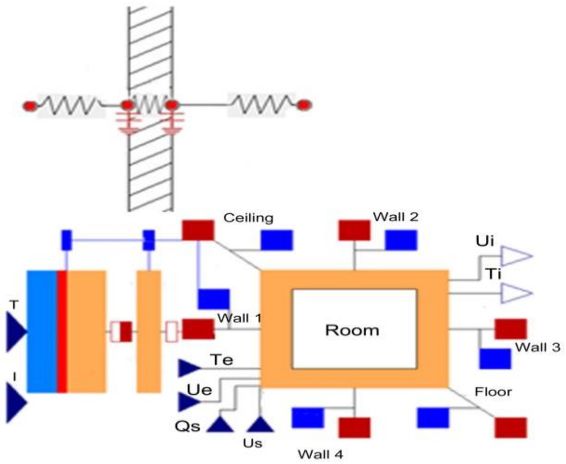

Figure 2. Translation from theoretical model to software library

Although Dymola is powerful software for modeling and simulation, the design and development of thermo-hygrometric controller is performed in MATLAB IDE where specific toolboxes for MPC and PID controller are available. Running a simulation with MATLAB/Simulink, the energy consumption profile of the controller can be saved and imported in Dymola environment; nevertheless PID controllers can be designed in MATLAB and replicated in Dymola replacing the PID parameters found. For the MPC controllers the first way mentioned is the easier way to obtain the expected results.

The developed model is depicted in Figure 3, the North wall confines for half with a building and for the other half with the external environment, because the model presents 7 walls instead of 6.

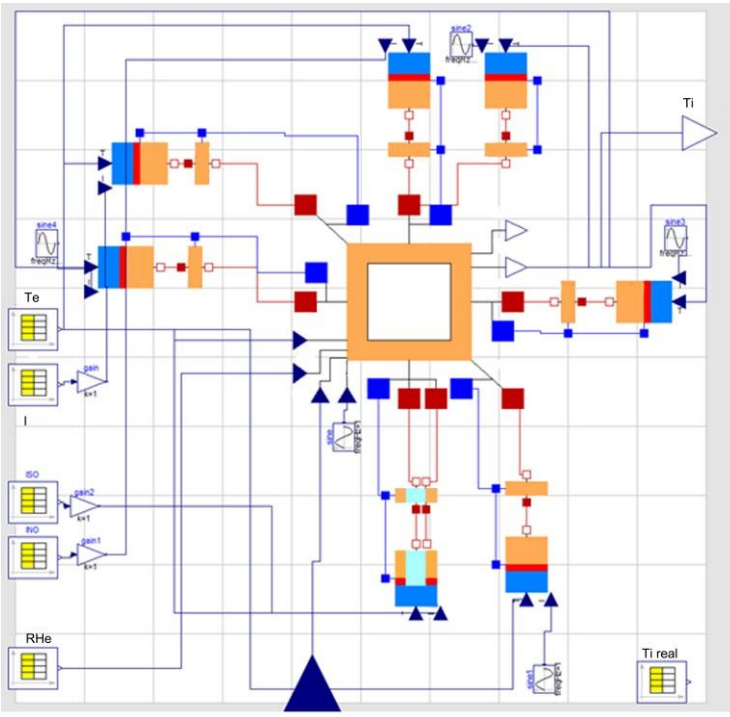

Figure 3. Dymola model of a room

The model needs solar radiance and temperature signal sensor input, as indeed the real system needs the real time data from sensors. In the example proposed the input Q is the control variable of the hygrothermal model in the same way the real system is controlled by actuators. In this way a complete simulation of controller can be performed and the efficiency can be estimated.

3. Model predictive control

From the appearance of computers in factories, various techniques of control have been developed. Engineering requires mathematical models to solve analysis problems. Model Identification and Data Analysis is that branch of automation which deals with mathematical representation of the behavior of a physical system. Model Predictive Control (MPC) is a technique based on data analysis of models; it has evolved from a basic multivariable process control technology into a technology that allows operation of processes inside a series of defined constraints (van den Boom & Backx, 2010). In particular the MPC is a collection of algorithms that manipulate a set of variables to optimize the future behavior of a process (Qin & Badgwell, 1997). MPC can be used in Multiple-Input Multiple-Output (MIMO) plants subject for closed-loop system controls (Figure 4).

For this methodology is necessary to know:

the whole process model (disturbances, parameters);

r(t), set point of the controller;

u(t), input variables constraints;

y(t), the output constraints;

horizon time of prediction.

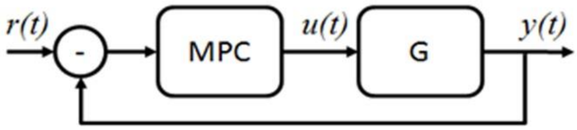

Figure 4. System schema: r(t) is the reference; u(t) is the input; y(t) is the output; MPC is the predictive controller; G is the model

In detail G represents the model in state equation as following:

$$x_{(t+1)} = Ax_{(t)} + Bu_{(t)} \tag{5}$$

$$y_{(t)} = Cx_{(t)} \tag{6}$$

The model in Figure 5 is the Laplace transformation of Eq (5) and Eq (6) plus the MPC controller with a negative feedback, or rather it is the representation in the frequency domain instead time domain and where the state x(t) is implicitly described in the feedback loop.

Furthermore the MPC solves an optimal control problem over a finite future horizon of N steps minimizing the equation J.

$$J = \sum_{k=0}^{N-1} (y_{(t+k)} - r_{(t)})^2 + (u_{(t+k)} - u_{r(t)})^2 \tag{7}$$

Minimizing the Eq (7), the controller MPC must respect the following constraints:

$$u_{min} \leq u_{(t+k)} \leq u_{max} \tag{8}$$

$$y_{min} \leq y_{(t+k)} \leq y_{max} \tag{9}$$

Each new measurement obtained, the optimization is repeated and the algorithm solved minimizing the J function.

Obviously the complexity of the algorithm needs a calculator to be performed such as Matlab.

Once defined the system schema as shown in section 2.2 (model G), the Matlab toolbox for MPC allows to specify the sample time of the discrete model, the horizon control time, hard and soft constraint for manipulated and output variables and, eventually, the model used to characterize noises and disturbances.

Briefly, after defined the matrix A, B, C and D, the instructions to set to Matlab are the following:

```
sys=ss(A, Bx ,C, D);

iMV=[1 2];

iDV=[3 4 5 6 7 8 9];

Plant = setmpcsignals(sys, 'MV', iMV, 'MD', iDV, 'MO', 1);

Plant=c2d(Plant, Ts, 'Tustin');

fh=12*3600/Ts;

ch=2*3600/Ts;

controller=mpc (Plant, Ts, fh, ch);
```

Where iMV and iDV specify the matrix A column which describes manipulated variables (the actuation) and disturbances (solar radiation and external temperature and humidity), respectively; while fh and ch describe the prediction and control time horizon, respectively.

Figure 5 shows the MPC implemented in closed-loop with the building model. The temperature and humidity are estimated and set into the model on the base of the actual value of PMV (Predicted Mean Vote) and the future prediction of this. Other MPC input like solar irradiation are not in closed-loop but hypothetically read from sensors and forced in the simulation model.

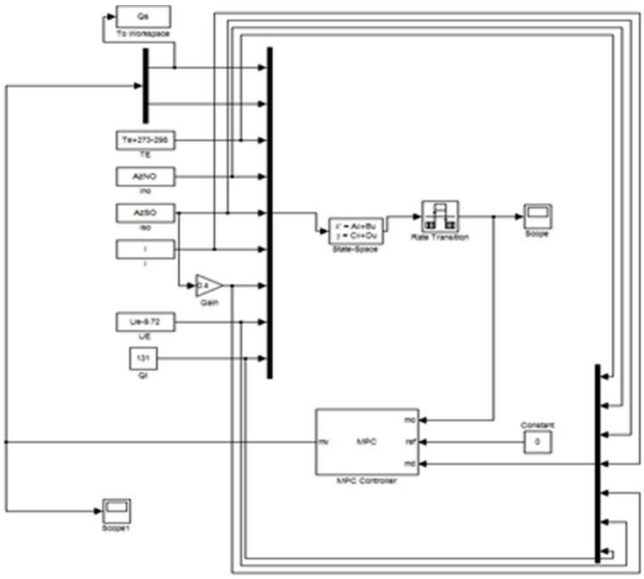

Figure 5. MPC Simulink model

4. Predictive control results

The experimental campaign processed has provided good results thank to the amount of data acquired in the year, the available dataset is the most critical aspect in every simulation test which requires a big initial effort in the first phases of project.

The validation phase consists into calculate the deviation of the real values respect the simulation ones.

The minimum standard deviation acceptable in a simulation model depends on the field of application. According to the Standard EN ISO 7730, for HVAC models is acceptable a standard deviation of 0.5°C for temperature.

At first, once have built the model, is important to understand the boundary conditions: initial state, real controller type and the value of the disturbances.

The controller installed in the building is an ON/OFF controller for both heating and cooling, the data gathered are from August in summer when the cooling system was working in order to keep the temperature around 301 K (Figure 6).

Replacing the same parameter of the real controller and inserting the external inputs detected with sensors installed in the building, into the simulation model a good approximation of the environment behavior is obtained. This is the start point where working for designing a controller for thermo-hygrometric condition.

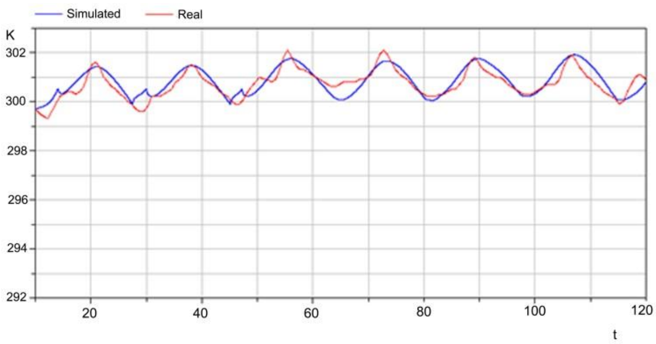

Figure 6. Temperature with controller ON/OFF

The model has been carefully modified with some iteration for reaching the best level of approximation needed for this work; indeed one of the main problems in this phase is linked to the translation of the physical structure of the walls into mathematical parameters.

In the next sections will be presented the implementation phase where the MPC controller is designed and built, further the result obtained will be shown in terms of comfort and energy saved.

After simulating the environment with the same conditions, three different type of controller have been tested: ON/OFF, PID and MPC.

As expected the MPC controller is the best choice in both aspects, comfort and energy consumption.

The comfort is estimated by the PMV index which convey on a 7-point based scale from -3 to +3, where -3 means very cold, 0 means neutral condition and +3 means very hot. An acceptable range of value of PMV is from -0.5 to +0.5.

Figure 7 represents the level of comfort with the three considered controllers: ON/OFF, PID and MPC. On the time axis, each sample is the mean value of 5 minutes of simulation.

In Figure 7a the PMV index with the use of an ON/OFF controller has a range from -0.2 to +0.2 with a linear variation. This happens because the ON/OFF controller works with boundaries and the closer the range of variation of the PMV the higher will be the consumption. Different is the behavior of PID (Figure 7b) and MPC (Figure 7c): the PMV index values are comparable and they are in the range from -0.1 to +0.1, the big difference is awarded in terms of energy.

Figure 8 shows the energy consumption express in Watt of ON/OFF, PID and MPC controllers, respectively. On the time axis, each sample is the cumulated value of 5 minutes of simulation.

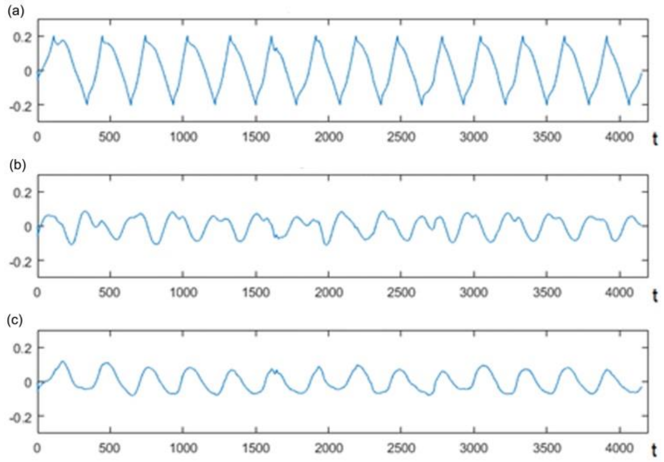

Figure 7. PMV index with three different controller types: (a) ON/OFF; (b) PID; (c) MPC

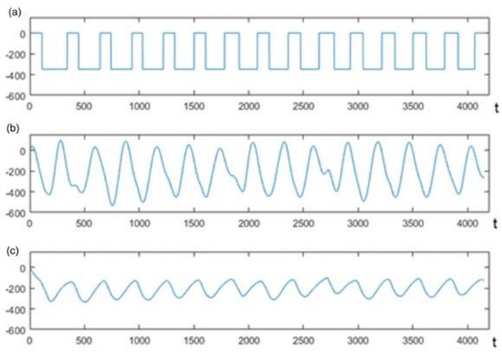

Figure 8. Electrical consumptions with three different controller types: (a) ON/OFF; (b) PID; (c) MPC

The negative consumption is due to the action of heating as positive contribute and the action of cooling as negative contribute. Once again the consumption of the ON/OFF provides only two values in output: 0 or the maximum, while the two other modules record an energy consumption that is in line with the needs of the environment.

Table 1. Consistency verifications of model values and experimental results

Type	Consumption (kWh)	Difference with the MPC (kWh)
ON/OFF controller	71'404	4'028
PID controller	78'768	11'392
MPC controller	67'376	-

Table 1 shows the cumulative consumption and the difference in terms of energy consumption with reference to the lower value calculated with the MPC controller.

5. Conclusions

The present work focuses on the idea of using the lumped solution to build a 3R2C module suitable for the representation of heat gains, losses and dynamic response of a single element of the building envelope. The idea is to make a state space representation of the building envelope using Dymola software. A whole system RC scheme is then assembled, connecting these modules according to the structure of the building envelope, through the internal air temperature node. Results obtained for the investigated test cell are compared with the hourly profiles of the measured data. The comparison shows a remarkable consistency between results and measured data. Both internal surface and air temperature exhibit a dynamic evolution, determined from internal space use conditions and weather variables. Each module shows its specific inertial behaviour, according to its thermo-physical features.

The library developed is a powerful tool for buildings simulation in order to test the performance of new type of controllers and offers the opportunity to demonstrate an estimation of savings with a small effort. Of course the flexibility is the strength of this library which allows developing the model of any buildings.

The work proposed wants to show how the type of the controller can impact with the consumption of energy, more over the performance in terms of comfort can be uncorrelated with the energy consumption. In this way the 40% of energy consumption attributable to buildings can be reduced up to 25% respect a standard ON/OFF controller which is the most diffused controller for heating and cooling systems after all.

Finally the savings are related only to the algorithm used to control the actuation without consider improvements in the actuation system.

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