Practical issues in modelling the temperature for the control of smart buildings

Domenico Gorni, Antonio Visioli

Dipartimento di Ingegneria dell’Informazione, Brescia University, Via Branze 38 2513 Italy,
Dipartimento di Ingegneria Meccanica Industriale, Brescia University, Via Branze 38 2513 Italy
E-mail: d.gorni001@unibs.it, antonio.visioli@unibs.it

Abstract. In this paper we propose a technique for modelling the temperature of the rooms of a smart building for control purposes. The approach consists in determining an (black-box) ARMAX model based on the first-principle thermodynamics equations of the system. Then, the model parameters are estimated by initially employing an ad hoc procedure and then by using a self-calibration method when the performance deteriorates. The selection of the user defined parameters in the overall procedure is thoroughly discussed by means of simulation results in order to highlight the practical effectiveness of the methodology.

1. Introduction
According to The World Business Council for Sustainable Development (WBCSD) the building sector consumes more than 40% of the world energy use with the resulting carbon emission more than the transportation sector [1]. A new study on energy efficiency in buildings indicates that the global building sector needs to reduce of 60% its energy consumption before the 2050 to help fulfilment of the global climate change targets. Furthermore, the current energy prices are at an historically high level; thus, a reduction of energy waste in Heating, Ventilation and Air-Conditioning (HVAC) systems needs to be provided. Engineers and architects have influenced the energy use of the new buildings through the design of the envelope, the HVAC systems selection and the operation sequences specification. However, when the building has been finished, the consumption of energy is decided mainly by its control, maintenance and by its occupants. Accurate, simple models of the building thermodynamics provide bases for intelligent and optimal control [6, 18], which have potential to reduce energy consumption of HVAC systems [9, 13]. The most important fact, from a control engineering point of view, which decreases the efficiency of the HVAC systems, is that they are set to operate at designed thermal loads. However, these loads are time-varying and a lot of different parameters affect their variation. Furthermore, another important goal of the intelligent buildings is to maintain, or even improve, the users’ comfort [4, 5]. Modelling the temperature of a building has been an active research field for decades, many software packages have been developed such as EnergyPlus, Modelica, TRNSYS, etc. [11, 17]. They use validated thermodynamic models to describe as accurately as possible the thermal processes in buildings. However, these models are too complex to be used for the purpose of designing model based controllers. Hence, simplified models have been proposed in order to provide a good approximation of the thermal behaviour of smart buildings. In particular, physical based models, for instance RC-networks, describe the
thermal system as a network of resistors and capacitors connected in series and in parallel form [10, 11, 12, 15]. In order to simplify the model, different kinds of grey-box, semi-physical models that are partially based on physical equation and partially on empirical knowledge, have been developed [14]. To further decrease the complexity of the modelling task, black-box models, such as ARMAX or neural-networks models [8, 7, 16], have been used to build a relations between inputs and outputs of the system by using measurements only.

In this paper we propose a methodology for the determination of a (simple) model of the temperature in the rooms of a smart building with the purpose of using it for the implementation of model-based control algorithm (for example, model predictive control strategies). First, the appropriate structure of an ARMAX model is determined by considering the first principle thermodynamics equations that describe the thermal behaviour of each single room in a house. Then, the procedure for the estimation of the parameters consists of a performing an ad hoc experiment in the first day and then by applying a self-calibration technique when the modelling error increases above a given threshold. Practical issues related to the implementation of the overall procedure, and in particular related to the choice of user-defined parameters, are discussed in order to provide useful guidelines for an effective use of the method.

2. Model description

The thermodynamic fundamental equation that describes the variation of the temperature of a single mass is:

\[ Q = c_s m \frac{dT}{dt} \]  

where \( Q \) [W] is the total amount of heat exchanged, \( c_s \) \[ J/kgK \] is the specific heat, \( m \) [kg] is the mass, \( T \) [K] is the temperature and \( t \) [s] is the time. By applying this equation to a room it is possible to describe the variation of its temperature by taking into account simplifying assumptions, such as: (i) the air inside the room is supposed to be at the same temperature; (ii) the room is considered a closed system with no mass exchange with the external environment.

The thermal flow can be transmitted from a room to another one passing through a wall as shown in Figure 1. This phenomenon occurs when the heat is exchanged from a fluid, such as air, to another one passing through a solid body, such as a window, a door or a wall. The wall is characterized by an own thermal capacity and a temperature that changes according to the quantity of heat that flows through it. Thus, by using (1), we obtain:

\[ q_1 - q_2 = \Delta Q = C_w \frac{dT_w}{dt} \]  

where \( q_1 \) [J] is the heat coming from the warmer room, \( q_2 \) [J] is the heat lost toward the colder room, \( T_i \) [K] and \( T_o \) [K] are the temperatures of the two rooms, \( T_{s1} \) [K] and \( T_{s2} \) [K] are the
temperatures of the two wall surfaces, $T_w$ [K] is the temperature and $C_w$ [J/K] is the thermal capacity of the wall. Considering the heat balance on the surface between the wall and the room 1 it is possible to determine $q_1$ and $q_2$ as:

$$q_1 = h_i A(T_i - T_{s1}) = \frac{KA}{d} (T_{s1} - T_w)$$

$$q_2 = h_o A(T_{s2} - T_o) = \frac{KA}{d} (T_w - T_{s2})$$

(3)

where $h_i$ [W/m$^2$K] and $h_o$ [W/m$^2$K] are the convective coefficient, $K$ [W/m$^2$K] is the thermal conductance of the wall, $A$ [m$^2$] is the area of the surface and $d$ [m] is the thickness of the wall. By combining these two equations and substituting them in (2), we obtain:

$$C_w \frac{dT_w}{dt} = \frac{1}{R_1} (T_i - T_w) - \frac{1}{R_2} (T_w - T_o)$$

(4)

where $R_1$ and $R_2$ are coefficients that represent the combination of convection and conduction resistances.

A single room is usually bordering with more different areas, for example with the ground through the floor, or with the external environment or with other rooms. Thus, it is important to take into account all the different heat flows to estimate the temperature evolution of a room. Moreover, heat sources like HVAC systems that can heat or cool the room are also usually present.

The whole system can now be written as follows:

$$C_i \dot{T}_i = \sum_{j=1}^{k} q_j + \sum_{j=k+1}^{n} q_j = \sum_{j=1}^{k} \frac{1}{R_{i1}} (T_i - T_{w1}) + \sum_{j=k+1}^{n} q_j$$

$$C_{w1} \dot{T}_{w1} = \frac{1}{R_{i1}} (T_i - T_{w1}) - \frac{1}{R_{o1}} (T_{w1} - T_o)$$

$$\ldots$$

$$C_{wk} \dot{T}_{wk} = \frac{1}{R_{wk}} (T_i - T_{wk}) - \frac{1}{R_{ok}} (T_{wk} - T_o)$$

(5)

where $T_{ok}$ are the temperatures of the $k$-th adjacent room, $q_1 \ldots q_k$ are the heat flows gained and lost to the external rooms and $q_{k+1} \ldots q_n$ are the exogenous heat sources like HVAC systems, the direct irradiation from the sun, electrical devices, etc.

The aim is to write a thermal model of the room based on:

- the temperature of the adjacent areas;
- the measured heat flow, or an estimation of it, of the exogenous inputs.

By applying the Laplace transform to (5) the system can be rewritten as:

$$sT_i(s) C_i = \sum_{j=1}^{k} \frac{1}{R_{ij}} (T_i(s) - T_{w1}(s)) + \sum_{j=k+1}^{n} q_j (s)$$

$$sT_{w1}(s) C_{w1} = \frac{1}{R_{i1}} (T_i(s) - T_{w1}(s)) - \frac{1}{R_{o1}} (T_{w1}(s) - T_o(s))$$

$$\ldots$$

$$sT_{wk}(s) C_{wk} = \frac{1}{R_{wk}} (T_i(s) - T_{wk}(s)) - \frac{1}{R_{ok}} (T_{wk}(s) - T_o(s))$$

(6)

As it is shown in (6), the temperature of the adjacent rooms appears only in the wall thermal balance equations, therefore the temperatures of the walls can be collected from all but the first equations and substituted into the first one. By assuming that the room has a parallelepiped shape ($k = 6$) and each wall border has a different area (four lateral walls, floor and ceiling), the transfer function between the temperature of a room and the temperature of the other
rooms becomes a seventh order transfer function. Note that \( T_i \) depends on several inputs, like temperatures of the border rooms and exogenous inputs in general, and unknown parameters:

\[
T_i(s) = f(T_{o1}(s), \ldots, T_{o6}(s), q_7(s), \ldots, q_8(s); R_1, \ldots, R_6, R_{o1}, \ldots, R_{o6}, C_i, C_{w1}, \ldots, C_{w6})
\]  

(7)

The second step is to transform this continuous transfer function in a discrete time transfer function by applying the Tustin bilinear transform [3] (for the sake of clarity we assume now that all the exogenous inputs are equal to zero):

\[
s = \frac{2(z - 1)}{T(z + 1)}
\]  

(8)

and therefore, by substituting the \( s \) value into (7), the discrete time transfer function of the room is obtained:

\[
T_i(z) = \frac{(a_{10}z^7 + \cdots + a_{16}z + a_{17})T_{o1}(z) + \cdots + (a_{60}z^7 + \cdots + a_{66}z + a_{67})T_{o6}(z)}{b_{10}z^7 + \cdots + b_{16}z + b_{17}}
\]  

(9)

By collecting the term \( z^7 \), we obtain:

\[
T_i(z) = \frac{(a_{10} + \cdots + a_{17}z^{-7})T_{o1}(z) + \cdots + (a_{60} + \cdots + a_{67}z^{-7})T_{o6}(z)}{b_{10} + \cdots + b_{17}z^{-7}}
\]  

(10)

and therefore,

\[
b_{10}T_i(z) = (a_{10} + \cdots + a_{17}z^{-7})T_{o1}(z) + \cdots + (a_{60} + \cdots + a_{67}z^{-7})T_{o6}(z) - (b_{11}z^{-1} + \cdots + b_{17}z^{-7})T_i(z)
\]  

(11)

which can be easily rewritten as follows:

\[
T_i(k) = g_1 \cdot T(k) + \cdots + g_8 \cdot T(k - 7)
\]  

(12)

where,

\[
\begin{bmatrix}
a_{10} \\
\vdots \\
a_{60} \\
0
\end{bmatrix}
\cdots
\begin{bmatrix}
a_{17} \\
\vdots \\
a_{67} \\
0
\end{bmatrix}
\]  

and

\[
T = \begin{bmatrix}
T_{o1} \\
\vdots \\
T_{o6} \\
T_i
\end{bmatrix}
\]  

(13)

Therefore by applying the same consideration to the exogenous inputs, the complete black-box model is defined as follow:

\[
T_i(k) = \sum_{j=1}^{8} \{g_j T(k - j + 1) + p_j q(k - j + 1)\}
\]  

(14)

where

\[
p_1 = \begin{bmatrix}
l_{11} \\
\vdots \\
l_{1m}
\end{bmatrix},
\quad p_8 = \begin{bmatrix}
l_{81} \\
\vdots \\
l_{8m}
\end{bmatrix},
\quad q = \begin{bmatrix}
q_1 \\
\vdots \\
q_m
\end{bmatrix}
\]  

(15)

Furthermore the system is also characterised from measurement noise, thus, the black-box model becomes an ARMAX model:

\[
T_i(k) = \sum_{j=1}^{8} \{g_j (T(k - j + 1) + \varepsilon(k - j + 1)) + p_j q(k - j + 1)\}
\]  

(16)
where $\varepsilon$ denotes the measurement noises.

The parameters estimation technique that is used to evaluate all the unknown parameters is the well-known least squares methodology [3]. This method is applied on (12) to determine all the $g_j$ and $p_j$ unknown parameters. Even though this equation is a direct consequence of the thermodynamical equations, during all the passages the parameters have lost their physical meaning, in fact such ARMAX models are defined black-box models.

3. Parameters identification methodology

In order for the parameters estimation methodology to be effective, it is essential to take into account that suitable exciting signals are necessary but, most of all, it has to be taken into account that all the nonlinearities (for example due to the solar irradiance effect) present in the true systems [4] have been neglected. For this reason, a self-calibrating methodology is proposed in order to automatically update the estimation when the operating conditions change.

The procedure consists therefore in performing an experiment during the first 24 hours (which can be any day of the year, when the fan-coil units are employed) and in estimating the ARMAX parameters based on the collected data. In this context, the choice of the set-point signals for the different rooms represents a crucial issue (see Section 5.1). Then, each $x_1$ hours, the estimation temperature error for the $i$th room, defined as

$$e_i = \frac{\sum |T_{oi}(k) - T_i(k)|}{N}$$

is evaluated, where $N$ is the number of samples in the considered interval which is determined by taking into account the preceding $x_2$ hours. If the estimation error (17) is greater than a given threshold $x_3$, then the least squares procedure is applied again by using the data collected in the preceding $x_4$ hours. In this context a maximum variation of $\pm 5\%$ for each parameter is allowed in order to account for typically slow weather changes from one season to another.

Note that $x_i$, $i = 1, \ldots, 4$ are design parameters that have to be selected properly in order for the overall procedure to be effective. The choice of these parameters, as well of the other factors which might influence the results is discussed in Section 5.

4. Model of the test building

In order to discuss the practical issues involved in the method described in the previous section, a large number of simulations have been performed by using TRNSYS (using a sampling period of 4 min). In this paper we consider tests performed on the two floor building shown in Figure 2, which has been implemented in SketchUp 2013 [2]. The ground floor is composed by two rooms while there is just one room in the first floor. The characteristics of the three rooms are given in Table 1.

Figure 2. Model of test building implemented in SketchUp 2013.
| Room                        | Dimensions | Windows |
|-----------------------------|------------|---------|
| East side ground floor      | 3x4x2.5    | 4       |
| West side ground floor      | 5x4x2.5    | 5       |
| First floor                 | 5x4x2.5    | 4       |

Table 1. Area and number of windows of each room in the test building.

| Element            | u-value | \(\frac{W}{m^2K}\) |
|--------------------|---------|---------------------|
| external walls     | 0.510   |                     |
| ground floor       | 0.039   |                     |
| external roof      | 0.316   |                     |
| internal walls     | 0.508   |                     |
| internal ceiling   | 4.153   |                     |
| external windows   | 2.890   |                     |

Table 2. Thermal conductivities of the test building.

The building is fictitiously placed in Milan Linate (Italy) and it is not surrounded by other houses. A file with the weather data of the whole year is available and therefore, by using the TRNSYS functionality to introduce it into the simulation algorithm, it is possible to take into account the real environmental conditions.

The most important parameters that characterize the building are the thermal conductivities (u-values) of the walls and of the windows. These parameters describe the thermal insulation coefficients of the main parts of the building and therefore they are responsible of the heat exchange rate between the rooms. They have been set as written in Table 2. The employed HVAC system consists of one fan-coil unit (Type 600 block in the TRNSYS HVAC library) and one temperature sensor for each room to keep the system as simple as possible. The temperature is controlled by means of PID low level controllers (see subsection 5.3).

5. Practical issues
As already mentioned in Section 3, for an effective implementation of the estimation methodology it is essential to appropriately choose the design parameters \(x_i\), \(i = 1, \ldots, 4\) as well as considering other relevant issues as the set-point signals to be employed during the first 24 hours and the tuning of the PID controllers for the regulation of the temperature of each room.

In order to simplify the analysis (and the design in practical cases), a reasonable selection can be done for the parameters \(x_1\), \(x_2\) and \(x_3\). In particular, the value \(x_1\) can be fixed equal to 8 hours in order to provide an accurate model without increasing too much the computational burden. By applying a similar reasoning, \(x_2\) is selected equal to 12 hours and \(x_3\) equal to 1 K. The other design choices are discussed in the following subsections (where simulation results are obtained with the previous values of \(x_1\), \(x_2\) and \(x_3\)).

5.1. Signals for the initial estimation
Since the first day estimation plays obviously a key role in the overall method, it is essential to accurately select the set-point signals to be employed in this context. From a practical point of view, it would be very nice to employ routine operating set-points, in order to avoid a possible uncomfortable situation for the user. However, the result provided in this case depend on the user’s choice and they are in general not accurate, that is, the self-calibrating procedure will be applied many times in the subsequent days, as it will be shown hereafter. In order to solve this issue we propose to use a pseudo-random signal, which is built by following some restrictions related to the comfort of the residents:
• the upper acceptable temperature is 22°C;
• the lower acceptable temperature is 17°C;
• the set-point of each room is changed each hour and it can increase or decrease only with a $\Delta T = 1$.

Obviously, the first two constraints are related to the case where the first 24 hours are in the cold season but the same rationale can be easily applied to other periods. Actually, a difference of five degrees is necessary to provide a good estimation and it has to be stressed that the values are in any case in a liveable temperature range.

The advantage of using a pseudo-random signal is illustrated in Figures 3 and 4 where the proposed method is compared with the use of routine set-points. They have been selected as shown in Tables 3 and 4. Two cases are considered where different pseudo-random signals and different routine set-point signals are chosen (obviously, if the set-point signals are selected by the user, it should be taken into account that the choice is entirely subjective and this also represents a drawback with respect to the pseudo-random signal approach. All the simulations have been performed by using well-tuned PID controllers (see subsection 5.3) and a value $x_4 = 48$ (see subsection 5.2). They are related to the first days of November (however, the considerations done hereafter can be done also for other periods of the year). From this illustrative examples it appears that a more accurate model is obtained by using the pseudo-random set-point signals than by using the routine set-point signals. Indeed, the model parameters need to be updated much less times during the following 19 days (in both cases a maximum of three times per room with the pseudo-random signals and seven times with the user-chosen signals).

| Room                        | Time intervals (hours of the day) |
|-----------------------------|-----------------------------------|
|                             | 0-6  | 6-8  | 8-12 | 12-16 | 16-22 | 22-24 |
| East side ground floor      | 17   | 17   | 21   | 21    | 21    | 18    |
| West side ground floor      | 17   | 18   | 20   | 20    | 20    | 17    |
| First floor                 | 21   | 21   | 21   | 17    | 20    | 20    |

Table 3. Case 1 of the user-chosen set-point signals (in Celsius degrees) for the first 24 hours.

| Room                        | Time intervals (hours of the day) |
|-----------------------------|-----------------------------------|
|                             | 0-16 | 16-24 |
| East side first floor       | 19   | 18    |
| West side first floor       | 20   | 21    |
| Second floor                | 18   | 17    |

Table 4. Case 2 of the user-chosen set-point signals (in Celsius degrees) for the first 24 hours.

5.2. Size of recalibration dataset array

Regarding the selection of the parameter $x_4$, namely, of the size of the array of data to be used for a new least-squares estimation of the model parameters when the error exceeds the given threshold, the following reasoning can be done. From one point of view, in order to reduce the computational burden and to consider the change of climate along the year it is sensible to use a small amount of data, for example 24 hours. However, this choice can introduce errors because the less samples are used the less filtered is an unusual behaviour of the system. For instance, in winter season the model is tuned to work with low environmental temperature and if a day hotter than usual occurs, the model error can exceed the 1°C threshold and the algorithm will estimate
Figure 3. Results related to the use of pseudo-random set-point signals. Top: case 1. Bottom: case 2. Blue line: measured temperature. Green line: model temperature. The application of the recalibration strategy is indicated by *.

Again the parameters. However, if only last 24 hours are taken into account, the parameters will be estimated based on an uncommon winter day and this may provoke another error the day after. On the other hand if 48 hours data are used, the model will be recalibrated based on two days data and the winter day will filter the contribution of the unusual one. For this reason, a suitable choice is to select $x_4 = 48$ hours. Illustrative examples with $x_4 = 24$ hours choice are shown in Figure 5 (two examples with a different pseudo-random initial set-point signals are considered) and it can be compared with the 48 hours choice employed in Figure 3. It appears that the longer time interval provides a more accurate modelling with less recalibration procedures applied in the subsequent days.
5.3. Tuning of the PID controllers

As a final design choice, the influence of the tuning of the PID controller on the estimation result is discussed. We consider two different kinds of PID tuning. The first one is performed in such a way the set-point step response (for each room) has a fast settling time but without overshoots (the related results are those previously shown in Figure 3). On the contrary, in the second case a more aggressive strategy is selected, that is, (small) overshoots are allowed in order to reduce the rise time. Results related to this latter case are shown in Figure 6. Once again, for the sake of completeness, two different pseudo-random set-point signals have been considered (note that also \( x_4 = 48 \) hours has been fixed). By comparing the results it appears that, overall, the less
aggressive tuning provides the best performance in terms of modelling errors, as witnessed by the reduced number of new estimations of the model parameters.

Table 5 shows the mean absolute temperature error in all the performed tests. The error is defined as in (17) where $N$ represents the number of instants of the whole test time interval.

6. Conclusions
In this paper we have proposed a methodology for the determination of an ARMAX model of the temperature of the rooms of a smart building. The technique is based on a first initial estimation of the model parameters (during the first 24 hours, by applying pseudo-random set-point signals)
Figure 6. Results related to the use of a more aggressive PID tuning and different pseudo-random set-point signals (top and bottom). Blue line: measured temperature. Green line: model temperature. The application of the recalibration strategy is indicated by ‘*’.

and then on the application of a self-calibration procedure. Practical issues related to the main design choices have been discussed and it has been shown that the proposed solution are capable to provide the required balancing between the need to follow the system changes along the year (mainly due to the weather change) and to avoid too many recalibration procedures.

Future work will include the comparison between the presented modelling approach with others proposed in the literature and the use of the obtained model for (optimal) control purposes.
Table 5. Mean absolute temperature error in all the performed tests.

| Test       | West side ground floor | East side ground floor | First Floor |
|------------|-------------------------|------------------------|-------------|
| Fig. 3 Top | 0.3419                  | 0.4265                 | 0.4111      |
| Fig. 3 Bottom | 0.4392                | 0.4661                 | 0.3755      |
| Fig. 4 Top | 0.5428                  | 0.4104                 | 0.3411      |
| Fig. 4 Bottom | 0.4431                | 0.4519                 | 0.5815      |
| Fig. 5 Top | 0.4281                  | 0.4060                 | 0.3622      |
| Fig. 5 Bottom | 0.5244                | 0.3776                 | 0.4848      |
| Fig. 6 Top | 0.4198                  | 0.4333                 | 0.3843      |
| Fig. 6 Bottom | 0.7697                | 0.4474                 | 0.3473      |

References

[1] http://www.environmentalleader.com/2009/04/27/building-sector-needs-to-reduce-energy-use-60-by-2050.
[2] http://www.sketchup.com/it/products/sketchup-pro.
[3] K. J. Aström and B. Wittenmark. Computer-Controlled Systems. Dover Publications, Englewood cliffs (NJ), 2011.
[4] M. Castilla. Advanced comfort control techniques for energy efficient buildings. PhD thesis, University de Almeria, Almeria, E, 2013.
[5] M. Castilla, J. Alvarez, M. Berenguel, M. Perez, J. Guzman, and F. Rodriguez. Comfort optimization in a solar energy research center. In Proceedings of IFAC Conference on Control Methodologies and Technology for Energy Efficiency, pages 36–41, Portugal, 2010.
[6] M. Castilla, J. Alvarez, M. Berenguel, F. Rodriguez, J. Guzman, and M. Perez. A comparison of thermal comfort predictive control strategies. Energy and Buildings, 43:2737–2746, 2011.
[7] M. Castilla, J. Alvarez, M. Ortega, and M. Arahal. Neural network and polynomial approximated thermal comfort models for HVAC systems. Building and Environment, 59:107–115, 2013.
[8] P. M. Ferreira, A. E. Ruano, S. Silva, and E. Z. E. Conceio. Neural networks based predictive control for thermal comfort and energy savings in public buildings. Energy and Buildings, 55:238–251, 2014.
[9] A. Kelman, Y. Ma, and F. Borrelli. Analysis of local optima in predictive control for energy efficient buildings. In Proceedings of 50th IEEE Conference on Decision and Control and European Control Conference (CDC-ECC), pages 5125–5130, Orlando, FL, USA, 2011.
[10] Z. O’Neill, S. Narayanan, and R. Brahme. Model based thermal load estimation in buildings. In Proceedings of Fourth National Conference of IBPSA-USA, pages 474–481, New York City (NY), 2010.
[11] S. Privara, Z. Vana, D. Gyalistras, J. Cigler, C. Sagerschnig, M. Morari, and L. Ferkl. Modeling and identification of a large multi-zone office building. In Proceedings of IEEE International Conference on Control Applications (CCA), pages 55–60, Denver (USA), 2011.
[12] P. Radecki and B. Henczey. Online thermal estimation, control, and self-excitation of buildings. In Proceedings of 52th IEEE Conference on Decision and Control, pages 4802–4807, Florence (I), December 2013.
[13] M. Trcka and J. Hensen. Overview of HVAC system simulation. Automation in Construction, 29:93–99, 2010.
[14] S. Wang and X. Xu. Simplified building model for transient thermal performance estimation using ga-based parameter identification. International Journal of Thermal Sciences, 45:419–432, 2006.
[15] X. Xu and S. Wang. A simplified dynamic model for existing buildings using ctf and thermal network models. International Journal of Thermal Sciences, 47:1249–1262, 2008.
[16] R. Yedra, F. Rodriguez, M. Castilla, and M. Arahal. A neural network model for energy consumption prediction of ciesol bioclimatic building. In Proceedings of the 8th International Conference on Soft Computing Models in Industrial and Environmental Applications, Salamanca (S), 2013.
[17] B. Yu and A. H. C. van Paassen. Simulink and bond graph modeling of an air-conditioned room. Simulation Modelling Practice and Theory, 12:61–76, 2004.
[18] X. Zhang, G. Schilbach, D. Sturzenegger, and M. Morari. Scenario-based MPC for energy efficient building climate control under weather and occupancy uncertainty. In Proceedings of the European Control Conference (ECC), pages 1029–1034, Zurich (SW), 2013.