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Low computational cost technique for predictive management of thermal comfort in non-residential buildings

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Abstract

In France, non-residential buildings account for a significant part of energy consumption. A large part of this consumption is due to HVAC (Heating, Ventilation and Air-Conditioning) systems, which are in most cases poorly handled. The present work deals with an efficient approach allowing energy consumption to be minimized while still ensuring thermal comfort. We propose a predictive control strategy for existing zoned HVAC systems and consider the PMV (Predicted Mean Vote) index as a thermal comfort indicator. In order to test this strategy, we modelled a non-residential building located in Perpignan (south of France) using the EnergyPlus software. The twofold aim is to limit the times during which the HVAC sub-systems are turned on and to ensure a satisfactory thermal comfort when people are working in the considered building. This predictive approach, computationally tractable, allows thermal comfort requirements to be met without wasting energy.

Keywords: non-residential building, energy consumption, zoned HVAC system, thermal comfort, artificial neural networks, model predictive control.

1. Introduction

Within non-residential buildings, almost half of the electricity consumption is due to Heating, Ventilation and Air-Conditioning (HVAC) systems [1]. As a

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consequence, new approaches are needed to make HVAC systems more efficient. First, energy efficiency can be improved in central heating systems by introducing zoned heating. This allows a more granular application of heat and HVAC sub-systems can be controlled independently. Another key point is indoor thermal comfort. Thermal comfort is subjective, hard to define and even harder to achieve in a non-residential building. It is mainly related to indoor conditions and impacted in a significant way by the effectiveness of the building envelope and the way the HVAC system is used.

Over the last few years, many studies have been conducted on thermal comfort management. These studies are based on the use of different tools [2], such as fuzzy logic [3][4] or genetic algorithms [5]. Bermejo et al. [6] proposed an adaptive system based on fuzzy logic, capable of learning the user thermal sensation to maintain an optimal comfort. Dounis and Manolakis [7] developed an algorithm to regulate the PMV index using a fuzzy system, capable of controlling both the temperature and humidity in a room. Fraisse et al. [8] used a self-learning fuzzy controller to find the optimal heating start time. With the exception of the last one, these approaches require to turn on the HVAC system at a fixed time and this can impact negatively thermal comfort if the system is started too late, or energy consumption if triggering happens too soon.

Predictive control [9][10][11] is a very good alternative to the above-mentioned approaches. Indeed, predictive algorithms can take advantage of the intermittent use of buildings, whose occupancy is regular and known. In particular, Artificial Neural Networks (ANN) have demonstrated on several occasions their efficiency in control and energy consumption optimization. Huang et al. [12] worked on a predictive model based on ANN to forecast temperature inside an area by taking into account the coupling effect between zones. Morel et al. [13] and Argiriou et al. [14][15] worked on similar predictive control strategies based on outdoor temperature and solar radiation forecasting. In [7] a water heating system is controlled in isolated rooms while in [8] an electrical heating system is controlled over individual solar houses. Control was done for only one area, without considering thermal exchanges. Moroşan et al. [16] developed a distributed predictive approach to control several areas simultaneously while taking into account thermal transfers. In this case, thermal comfort was defined on the basis of a reference temperature. The proposed algorithm is useful but on-line optimization is needed and computation time is extensive. As a result, such a solution cannot be implemented easily in an embedded system. Álvarez et al. [17] developed a predictive approach to control an HVAC system composed of solar collector fields. A key point was to ensure an acceptable thermal comfort in the different areas of the

considered building despite limited thermal resources. The PMV index was used as a thermal comfort indicator. Moreover, many solutions are based on controlling local heating systems in small areas [18]. This kind of approaches is not well adapted to changes in human activity but thermal comfort requirements can be met without wasting energy. Moreover, additional heating sub-systems are sometimes needed. Kolokotsa et al. [19] developed a predictive controller using a bilinear model. Comfort has been defined on the basis of both a fixed temperature and a humidity bandgap to satisfy.

Pyrescom Company has developed a monitoring system that carries out meteorological parameters and energy measurements to improve energy efficiency in non-residential buildings (Batnrj project). The collected data are used to find out possible ways to develop an efficient HVAC control strategy. Several buildings are currently instrumented using the Pyrescom monitoring system, including a non-residential building located in the city of Perpignan (south of France). This reference (pilot) building has been modeled using the EnergyPlus software and allowed the strategy about HVAC management we propose to be tested and evaluated. Energy consumption, thermal comfort and computation time are considered as performance indicators. Computation time is a key point to the project. For each instrumented building, an embedded system is used to collect data from various sensors (temperature, humidity, energy consumption, etc.) and these data are sent to a remote server. This server has a significant computational power but the embedded systems have limited capabilities. That is why the main objective of the work we present in this paper is to develop a computationally tractable approach for managing energy resources and satisfying thermal comfort requirements in non-residential buildings. The proposed strategy is based on predictive control and aims at managing thermal comfort in several areas of non-residential buildings equipped with HVAC sub-systems without on-line optimization. Thermal comfort is based on the PMV (Predicted Mean Vote [20]) index, which is a standardized indicator designed to estimate the thermal sensation of the occupants. This criterion allows temperature to be adjusted in a building according to the period of the year, occupant behaviour and activities. Moreover, air temperature set-point may be reduced when the wall temperature increases, while keeping an identical comfort. So, we used first feedforward Artificial Neural Networks (ANN) to model the non-linear behaviour of the PMV index, mainly from solar radiation, outdoor temperature and internal gains (ANN-based PMV models). Then, we considered the PMV index as a control set-point and thermal comfort can be maintained in a desired interval which can be adjusted by people working in a given building.

The present paper is organized as follows: first, the reference (pilot) building we modelled using the EnergyPlus software is described (section 2). Next, section 3 focuses on thermal comfort and the way the PMV index can be used as a relevant comfort indicator. The following section (section 4) is about the development and validation of the ANN-based PMV models (the interaction, i.e. heat transfer, between the three rooms we considered in the non-residential building is taken into account or not). The predictive control strategy we developed for HVAC subsystems is presented in section 5. Finally, the results we obtained are analyzed and compared with the results provided by standard (non-predictive) management strategies. The paper ends with a conclusion and an outlook to future work.

2. Non-residential (reference) building

To evaluate the proposed strategy, a reference building has been modelled using the EnergyPlus software, which is able to perform accurate building simulations. The considered building is a real two-storey building of 1000 m², built in 2008 and located in Perpignan (south of France). It is facing south and agrees with the French "Thermal Regulation 2005" [21]. This non-residential building is divided into three main areas of 340 m² each (figure 1), with different uses. About a dozen employees work in offices at the ground and first floors (green and yellow area). The red area in the first floor is a manufacturing zone where about 6 persons work seated or in a standing position. The last room of the ground floor is a warehouse (blue area) that is not heated.

For both the warehouse and the manufacturing area, ceiling is 3.90 m. In the offices, a suspended ceiling stands at 2.70 m. The materials used in the building

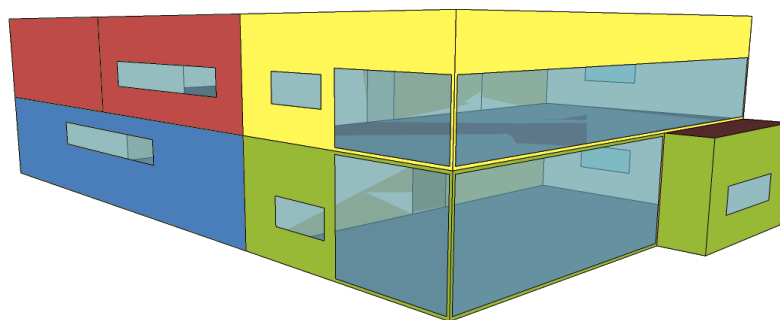


Figure 1: Topology of the considered non-residential (reference) building.

Table 1: Properties of the materials used in the exterior walls. l is the thickness, λ the conductivity, ρ the density and C the specific heat of a material.

Layer	l (cm)	λ ($\text{W}\cdot\text{m}^{-1}\cdot\text{K}^{-1}$)	ρ ($\text{kg}\cdot\text{m}^{-3}$)	C ($\text{J}\cdot\text{kg}^{-1}\cdot\text{K}^{-1}$)
Brick	10	0.89	1920	790
Heavy weight concrete	20	1.45	2000	1000
Insulation board	5	0.03	43	1210
Gypsum board	2	0.16	800	1090

Table 2: Characteristics of the three considered areas.

Characteristics	Ground floor offices	Manufacturing area	First floor offices
Surface (m^2)	165	230	155
Volume (m^3)	450	900	420
Heating power (W)	5000	10000	5000
Number of occupants	8	6	5
Metabolic activity ($\text{W}\cdot\text{m}^{-2}$)	70	116	70
Lighting power (W)	1000	1400	1000

are listed in table 1. The exterior walls consist of several layers of different materials. From the outside to the inside are juxtaposed a brick layer, heavy weight concrete, an insulation board, and finally a gypsum board. The interior walls are composed of two gypsum boards, for a total thermal resistivity of $2.2 \text{ m}^2\cdot\text{K}\cdot\text{W}^{-1}$. The south face and a part of the west face of the building are made from glass. Glass has been treated to filter infrared radiation and avoid overheating in summer. The other glasses in the building consist in 3 mm double glazed bays.

The present study focuses on the three following (occupied and equipped with sensors) areas: the offices on both floors and the manufacturing area, that is composed of an open space of 230 m^2 and three storage rooms of 110 m^2 (not heated). Heating is handled in the building by a zoned electrical HVAC system consisting in several sub-systems, one for each area, where only the temperature set-point can be adjusted. Each sub-system is managed by a local controller. The characteristics of the different HVAC sub-systems for each area are listed by table 2. All the units have a coefficient of performance (CoP) equal to 3.8. As previously stated, the proposed management approach is based on a model predictive controller that will supervise the HVAC sub-systems (figure 2).

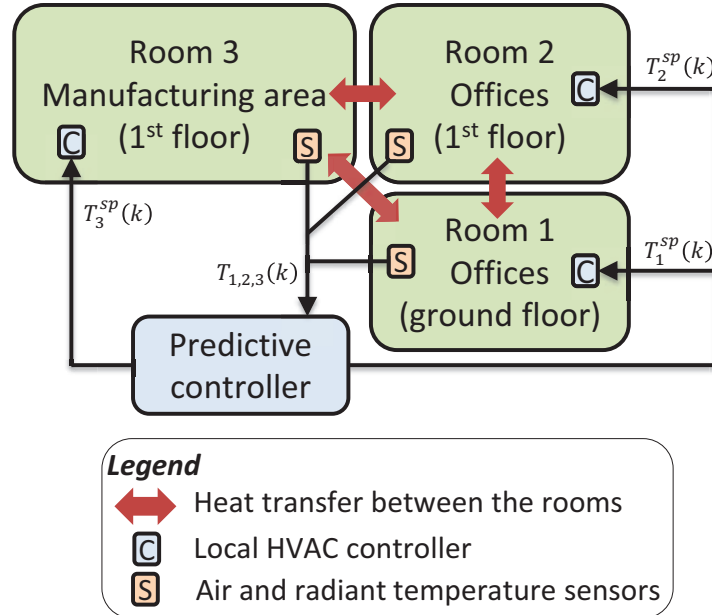


Figure 2: The three considered rooms equipped with sensors and HVAC sub-systems. Only the temperature set-points can be adjusted.

Weather data (outdoor temperature, solar radiation, wind speed) are required to perform the simulation process. We used real data from year 2011 provided by the Pyrescom monitoring system. Since atmospheric pressure measurements were missing, we used data from the Perpignan airport which is located 7 km away from the building. Measurements were carried out with a time step of 30 seconds while averaged values were saved every 15 minutes and stored in a database. As a consequence, the simulation time step is 15 minutes, what enables because of the characteristics of the building a reactive control approach to be developed. Let us note that Perpignan benefits from a relatively mild mediterranean climate. Figure 3 shows how outdoor temperature evolves at 6 a.m., from January to December 2011 (during the simulation period).

3. Thermal comfort

The Predicted Mean Vote (PMV) index is used as a thermal comfort indicator. This indicator was developed by Fanger [20], before to be standardized by inter-

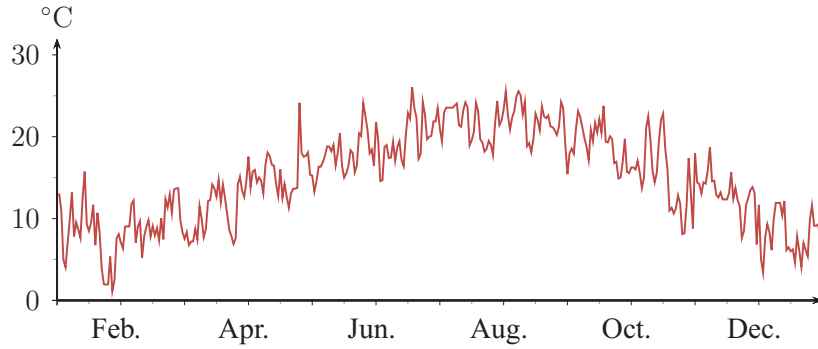


Figure 3: Evolution of outdoor temperature at 6 a.m., from January to December 2011.

Table 3: Thermal sensation scale.

PMV value	Thermal sensation
+3	hot
+2	warm
+1	slightly warm
0	neutral
-1	slightly cool
-2	cool
-3	cold

national organizations [22][23]. The PMV index quantifies the thermal sensation felt by some people in a room. This sensation is described by a scale ranging from -3 (cold) to +3 (hot) (table 3). The exchange of heat between the human body and its environment strongly governs thermal comfort. It is highly subjective and can be considered as perfect when the sum of exchanges is zero. Equation 1 depicts the way one can compute the PMV index:

$$PMV = [0.303exp^{-0.036M} + 0.028] \times L \quad (1)$$

with L the difference between the heat produced and the heat lost.

$$L = M - W - H_1 - H_2 - H_3 - H_4 - H_5 - H_6 \quad (2)$$

For the room j , $\forall j \in \llbracket 1; 3 \rrbracket$, M_j is the metabolism (described below). W_j is the external work and is considered to be null. H_1, \dots, H_6 are the heat losses coefficients ($W \cdot m^{-2}$). H_1 is the heat loss by diffusion through the skin and H_2 is

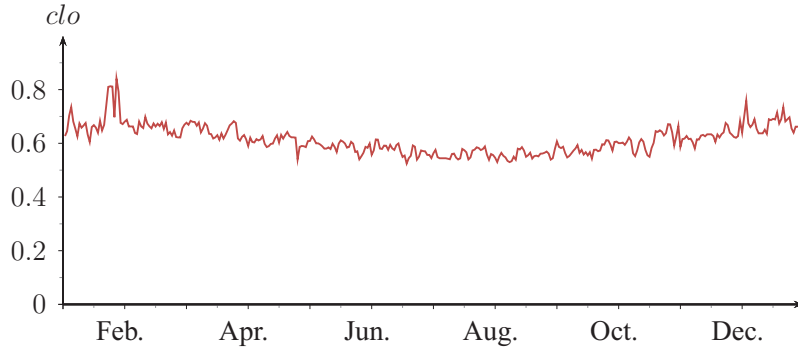


Figure 4: Evolution of clothing thermal insulation, from January to December 2011.

Table 4: Clothing thermal insulation.

Interval	ICL value (clo)
$t_6 < -5^{\circ}C$	1
$-5^{\circ}C \leq t_6 < 5^{\circ}C$	$0.818 - 0.0364t_6$
$5^{\circ}C \leq t_6 < 26^{\circ}C$	$10^{-0.1635-0.0066t_6}$
$t_6 \geq 26^{\circ}C$	0.46

the heat loss by sweating. H_3 and H_4 are the losses by latent and dry respiration, respectively. Finally, H_5 is the heat loss by radiance and H_6 is the heat loss by convection. To calculate these heat losses coefficients, several parameters about environment and occupants are taken into account: indoor air temperature (T_j), radiant temperature (T_j^{wall}), relative humidity (HR_j), air speed (v_j^{air}), metabolic activity, and clothing thermal insulation. Let us note that air speed is not calculated by the EnergyPlus software. However, this missing information is not critical because air speed has no influence on the PMV value as long as it remains below $0.1 \text{ m}\cdot\text{s}^{-1}$ [22]. This is mostly the case within the non residential building we considered as a reference building. Moreover, metabolic activity is supposed to be constant and only depends on the considered area. In offices, people work in a sitting position most of the time and, as a result, M is set to $70 \text{ W}\cdot\text{m}^{-2}$ (i.e. 1.2 met). Activity in the manufacturing area is more dynamic and M is set higher to $116 \text{ W}\cdot\text{m}^{-2}$ (i.e. 2 met).

Depending on outdoor temperature, people dress differently. As a result, clothing thermal insulation varies over time. Schiavon and Lee [24] developed a predictive model to estimate clothing thermal insulation (noted ICL). So, it is defined,

each day, from the outdoor temperature observed at 6 a.m. (t_6), as shown in table 4. According to these equations, clothing thermal insulation varies from 0.58 clo, during winter time, to 0.46 clo, during summer time. Figure 4 depicts the way such a parameter evolves between January and December 2011. Usual clothes for summer are a pant with a short-sleeved shirt, while during winter, usual clothes are a trouser with a long-sleeved shirt. Looking at figure 4, the result seems to be realistic. It can be highlighted that the 2011 winter was mild, so the clothing thermal insulation was moderate. At the end of January, outdoor temperature has strongly decreased and, as a result, the algorithm has automatically adjusted the clothing thermal insulation value.

4. ANN-based PMV models

4.1. Structure of the models

A model of the system to be controlled is required to evaluate the predictive control strategy and check if the PMV index can be maintained into the desired interval during occupancy periods $[-0.5; +0.5]$. In a first single-area approach, we used a linear state-space model. We obtained good results but the local controller used to regulate the air temperature in the building and whose behaviour is unknown induces nonlinearities. As a consequence, we decided for feedforward Artificial Neural Networks (ANN) [25] [26] to model the multi-area system. This kind of network consists of a series of layers. The first layer is connected to the network's input vector while each subsequent layer is connected to the previous layer. The final layer produces the network's output. Feedforward artificial neural networks can be used for any kind of input to output mapping. With only one hidden layer and enough neurons in this layer, such networks can approximate any nonlinear continuous function to any desired degree of accuracy [27]. A key point in using ANN to describe nonlinear dynamics is to define the right topology of the networks in order to avoid poorly fitted or overfitted models (generalization

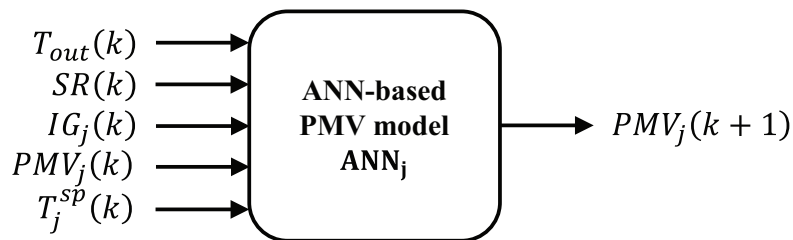


Figure 5: ANN-based PMV model for the room j , $\forall j \in \llbracket 1; 3 \rrbracket$ (no interaction between the rooms).

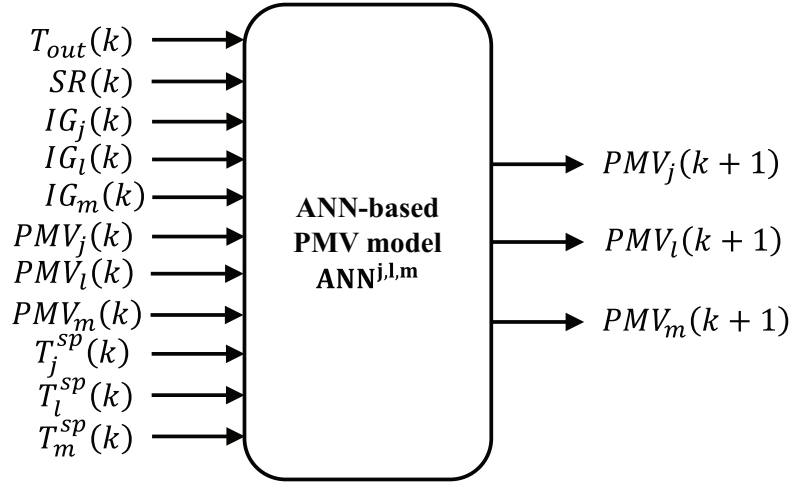


Figure 6: ANN-based PMV model for the rooms j, l and $m, \forall j, l, m \in \llbracket 1; 3 \rrbracket$ such as $j \neq l \neq m$ (with interaction between the rooms).

ability is affected in a significant way by overfitting). In addition, training has to be done using an efficient learning algorithm (for example, the well-known and efficient Levenberg-Marquardt (LM) algorithm [28] or, when using self-growing feedforward artificial neural networks, the Cascade-Correlation (CC) algorithm) and an adequate database of examples [29].

The proposed strategy is first designed to manage thermal comfort in the three considered areas (the offices in both floors and the manufacturing area) in a separate way. As a result, no interaction (i.e. heat transfer) is considered between these areas and three models, one per area, are needed. So, a model links the PMV index (at time $k + 1$) in the room $j, \forall j \in \llbracket 1; 3 \rrbracket$, with outdoor temperature (T_{out}), solar radiation (SR) and internal heat gain (IG_j) at time k . The most common sources of internal heat gain are metabolism, appliances, electronic devices, and lighting. In addition, the influence of the heating system of the room j is taken into account through the air temperature set-point (T_j^{sp}). Let us remember that a local controller operates in the three considered areas to regulate the air temperature. Finally, the PMV index in the room j at time k is also considered as a model input (figure 5). Equation 3 formulates the PMV index in the room j , without interaction with the two other considered rooms. So, $\forall j \in \llbracket 1; 3 \rrbracket$:

$$PMV_j(k+1) = ANN_j(PMV_j(k), T_{out}(k), SR(k), IG_j(k), T_j^{sp}(k)) \quad (3)$$

In a second time, thermal comfort is managed in the building taking into account the existing interaction (i.e. heat transfer) between the three areas. As a

result, the PMV indexes in the rooms j , l and m are simultaneously computed at time $k + 1$ with an overall model ($\text{ANN}_j^{j,l,m}$). This model (figure 6) uses as inputs all the air-temperature set-points (T_j^{sp} , T_l^{sp} and T_m^{sp}), internal heat gains (IG_j , IG_l and IG_m) and PMV indexes (PMV_j , PMV_l and PMV_m) at time k . In equation 4, $\text{ANN}_j^{j,l,m}$ denotes that $PMV_j(k+1)$ is the selected output among the three outputs of the model. So, $\forall j, l, m \in \llbracket 1; 3 \rrbracket$ such as $j \neq l \neq m$:

$$PMV_j(k+1) = \text{ANN}_j^{j,l,m} \left(\begin{array}{l} PMV_j(k), PMV_l(k), PMV_m(k), \dots \\ SR(k), IG_j(k), IG_l(k), IG_m(k), \dots \\ T_{out}(k), T_j^{sp}(k), T_l^{sp}(k), T_m^{sp}(k) \end{array} \right) \quad (4)$$

4.2. Training phase and generalization ability

A training phase is needed to identify the parameters of the ANN-based models (the synaptic weights and biases) from examples. So, we generated a database of examples using the EnergyPlus model of the considered non-residential building. Of course, training efficiency is highly related to data relevance. We simulated the behavior of the building during a whole year and turned on and off the HVAC sub-systems randomly every day (2 to 6 hours before people arrive at the building or after they left the building). In addition, we selected randomly temperature set-points in the interval $[19^\circ\text{C}; 26^\circ\text{C}]$. These set-points remained unchanged during all the day. Let us note that in a real building, the identification process will be carried out from measurements provided by the Pyrescom monitoring system. So, the thermal model of the considered building is not necessary. Using simulated (or measured) data, the training phase is achieved using Matlab[®] and its neural network toolbox. Because overfitting can be favoured by a badly-sized training subset, we decided to train the networks using different subsets of data randomly picked up among all the available examples. We used the Levenberg-Marquardt algorithm as learning algorithm [28]. It is accurate, fast and uses matrix decompositions to limit the amount of memory used. The validation phase has been carried out using new data sets dealing with realistic scenarios.

The parametric study we carried out to model the PMV index in the room j when interaction between the three considered areas is not taken into account (model ANN_j , $\forall j \in \llbracket 1; 3 \rrbracket$) has highlighted that generalization is very good when using feedforward neural networks with 30 hidden neurons while using about 15% of the available data during the training phase. As a consequence, we selected this configuration. In this case, the Mean Relative Error (MRE) over validation data is about 5%, whatever the room. Figure 7 depicts the impact on generalization of the number of hidden neurons and the quantity of training data used. This figure

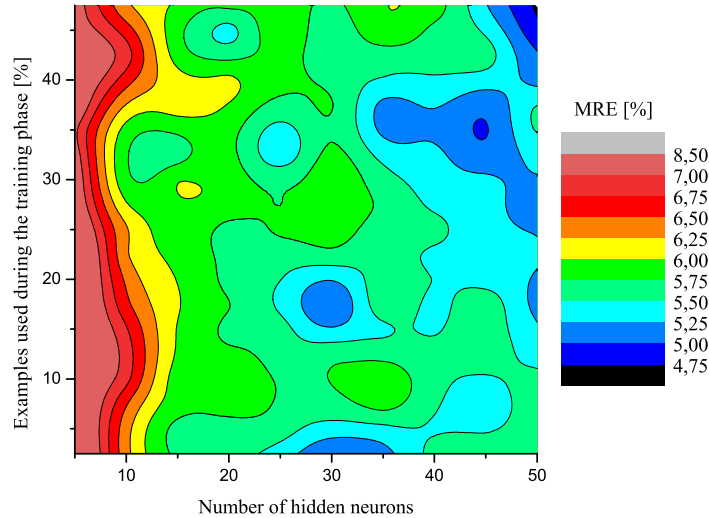


Figure 7: MRE [%] during validation, according to the number of hidden neurons and the percentage of data used to train the network (ANN_j , room of the building: manufacturing area).

is related to the manufacturing area. Learning is achieved in about 20 seconds, so it can be easily handled by a remote server without penalizing the other running applications. Taking a look at figure 7, one can also note that when using less than 15 hidden neurons (whatever the quantity of training data used) the PMV model is under-parameterized. In opposition, very good results can also be achieved with 40 to 50 hidden neurons and 25 to 50% of the available data used during the training phase. However, in this case, computation time is higher than it is with the selected configuration.

When taking into account the interaction (i.e. heat transfer) between the three considered areas (model $ANN^{j,l,m}$, $\forall j, l, m \in \llbracket 1; 3 \rrbracket$ such as $j \neq l \neq m$), generalization is also very good for a feedforward artificial neural network with 30 hidden neurons while using about 10% of the available data during the training phase. Again, the Mean Relative Error (MRE) over validation data is about 5%, whatever the room. Taking a look at figure 8 (manufacturing area), one can note that when using less than 10 hidden neurons (whatever the quantity of training data used) the PMV model is under-parameterized. In opposition, it is over-parameterized when considering about 40 hidden neurons. Finally, figure 9 shows values of the PMV index given by EnergyPlus and the ANN-based models (for a period of five

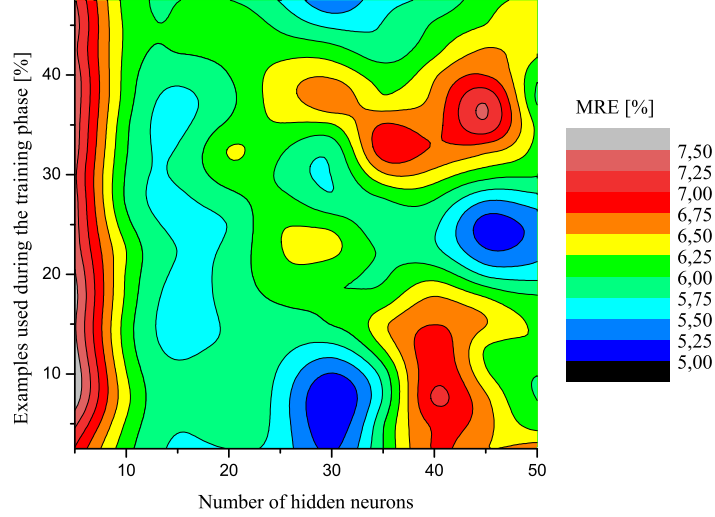
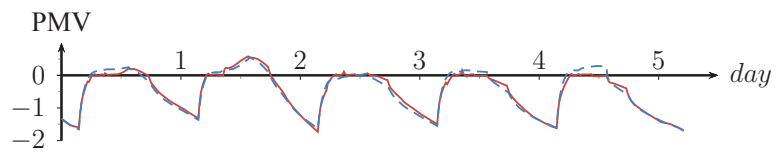


Figure 8: MRE [%] during validation, according to the number of hidden neurons and the percentage of data used to train the network ($\text{ANN}_j^{i,1,m}$, room of the building: manufacturing area).

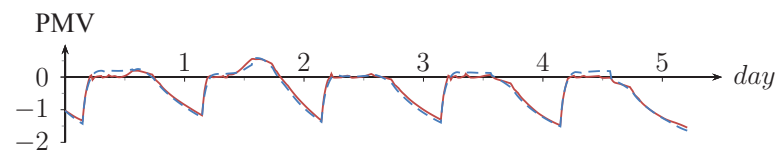
days), for each of the three considered rooms (interaction is taken into account). The HVAC sub-systems are turned on only during occupancy periods, with a temperature set-point set to 22°C . It clearly appears that the ANN-based models are able to estimate accurately the PMV index in the different areas when taking into account interaction.

4.3. Exogenous variables forecasting

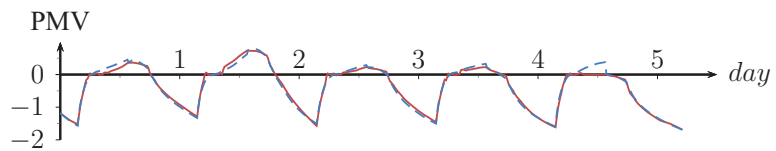
In order to estimate the PMV index, forecasting values of the model exogenous variables are needed. Because the internal heat gains are directly related to the building occupation, they can be easily estimated. As a consequence, only outdoor temperature and solar radiation have to be forecasted. Morel et al. [13] and Argiriou et al. [14] developed neural network models to forecast these variables but such a solution implies more calculation time. As a result, we considered first as a forecasted value, the value measured the previous day at the same time (SR and T_{out}). Next, with the aim of increasing the accuracy of the forecasted temperature, a correction term has been added by using the difference between the current value and the value of the previous day at the same time (equation 5). k is



(a) Ground floor offices. $R^2 = 0.9705$, MRE = 3.69%.



(b) Manufacturing area. $R^2 = 0.9726$, MRE = 3.53%.



(c) First floor offices. $R^2 = 0.9815$, MRE = 2.60%.

Figure 9: Estimation of the PMV index for each of the three considered areas. The red solid line is the PMV given by EnergyPlus and the blue dashed line is the estimation given by the ANN-based PMV models ($\text{ANN}^{j,l,m}$, $\forall j, l, m \in \llbracket 1; 3 \rrbracket$ such as $j \neq l \neq m$).

the present time, and i the forecasting horizon:

$$\begin{cases} SR(k+i) &= SR(k+i-24h) \\ T_{out}(k+i) &= T_{out}(k+i-24h) + T_{out}(k) - T_{out}(k-24h) \end{cases} \quad (5)$$

5. Control strategy

5.1. Control of thermal comfort

Since our objective is to satisfy thermal comfort requirements in the three considered rooms of the building, the HVAC air temperature set-point T_j^{sp} ($\forall j \in \llbracket 1; 3 \rrbracket$) has to be adjusted as necessary. As a key point, we need a set-point for the PMV index (PMV_j^{sp}) to be reached. From this set-point as well as T_j^{wall} , HR_j , v_j^{air} and M_j (figure 10), T_j^{sp} is estimated. Because of both the complexity and non-linearities of the PMV equation, one cannot solve it analytically to find the appropriate air temperature set-point. That is why a numerical method has been considered to solve equation 6. T_j^{sp} is then set according to this computed value:

$$PMV(T_j, \theta_j) = PMV^{sp} \quad (6)$$

with θ_j bringing together T_j^{wall} , HR_j , v_j^{air} and M_j and PMV_j^{sp} the PMV set-point value from which we computed the air temperature set-point T_j^{sp} . So, the final objective is to find the best value for $T_j^{sp}(k)$ such as if $T_j(k) = T_j^{sp}(k)$ then $PMV_j(k) = 0$.

In order to solve this problem, different iterative methods have been evaluated with the aim of finding the fastest and the most efficient one (the standard algorithms used are detailed in [30]). The stopping criterion is a tolerance of 0.05°C on T_j^{sp} . First, we used the binary search algorithm. The number of iterations is related to the desired accuracy, given that convergence is linear. The initial values of the minimal and maximal thresholds were set to 15 and 30°C , respectively. At

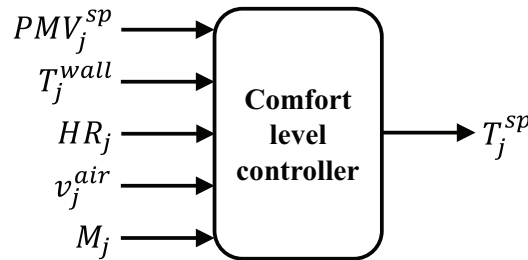


Figure 10: Control of thermal comfort.

Table 5: Evaluation of the tested algorithms.

Method	Number of iterations	Computation time (ms)
Binary search	9	4.6
Newton-Raphson	2-3	5
Secant	4-5	2.4

each iteration, the gap around the solution is reduced until it is lower than the desired accuracy. The second algorithm used is the Newton–Raphson method. The solution is computed on the basis of a correction term defined as the ratio between the function and its derivative. Since it is not possible to find the derivative analytically, it is approximated. The initial value was set to 20°C. The main advantage of the Newton–Raphson method lies in its quadratic convergence. The third algorithm we considered is the secant method. It is quite similar to the Newton–Raphson method, but uses a specific equation to approximate the derivative, based on the two previous values. The initial values were set to 20°C and 25°C.

Table 5 summarizes performance results for the three methods we tested. Although the Newton-Raphson method needs three times less iterations to reach the solution than the binary search algorithm, computation time is similar. Slowness is due to the PMV index being calculated three times per iteration instead of just one time with the binary search algorithm. With the secant method, convergence is slightly slower but the PMV index is computed only once per iteration. As a consequence, computation time is reduced by half and the secant method has been chosen among the three tested methods.

5.2. Predictive control strategy

The block diagram of the proposed control predictive strategy is presented by figure 11. EnergyPlus is used to simulate the behaviour of the real non-residential building, considered as the reference building. The controlled output is the PMV index. The proposed Model Predictive Controller (MPC) uses the identified ANN-based PMV models to perform some predictions and optimize the way the heating sub-systems will operate (we search for the optimal time to switch on or off the sub-systems), taking into account the constraints about thermal comfort during occupancy periods. The controller computes the HVAC air temperature set-point (the manipulated input) for the room j , $\forall j \in \llbracket 1; 3 \rrbracket$. Based on previous day values, the forecasting unit estimates the exogenous disturbances (T_{out} , SR and IG_j). As previously mentioned, thermodynamic simulations are carried out

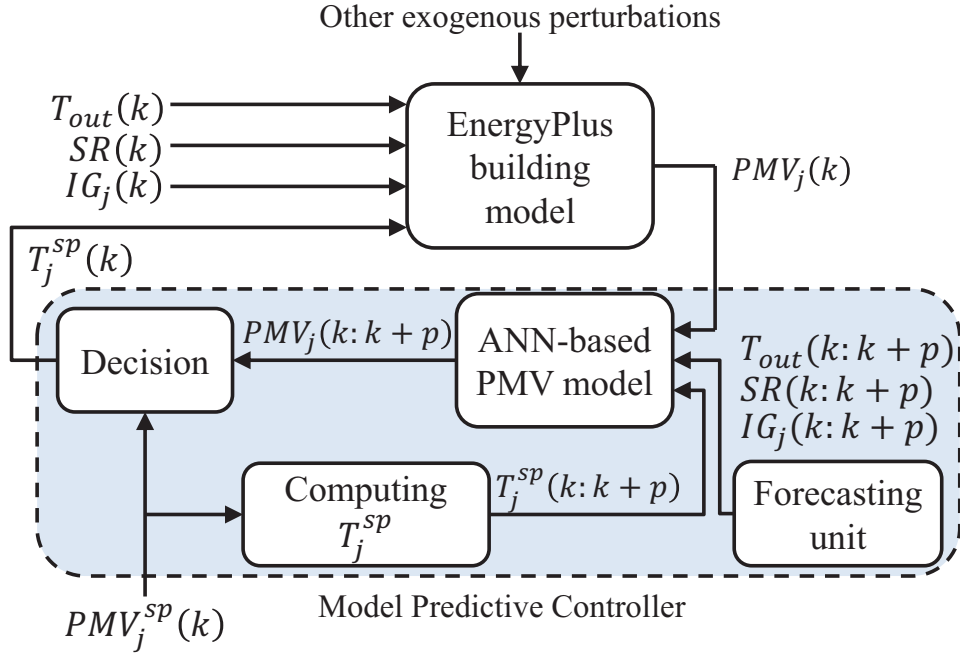


Figure 11: Block diagram of the predictive control strategy.

using EnergyPlus with MPC set-point values computed by Matlab[®]. These two softwares are interfaced using the MLE+ toolbox [31]. In real non-residential buildings equipped with HVAC sub-systems, EnergyPlus simulations are no more needed. To assess performance, energy consumption and thermal comfort during occupancy periods are considered. The main objective is to satisfy thermal comfort requirements when the different areas are occupied and avoid energy waste during the rest of the time. The thermal comfort interval is defined on the basis of a PMV value ranging between $PMV_j^{min} = -0.5$ and $PMV_j^{max} = 0.5$. The temperature set-point is computed to obtain a PMV index equal to zero in the room j , $\forall j \in \llbracket 1; 3 \rrbracket$. In real buildings, these parameters will be adjusted in real time, according to people's feelings. With the proposed strategy, one can optimize the way the HVAC sub-systems switch from one operation mode to another (on/off).

The optimization problem related to the search for the optimal time to switch the HVAC sub-systems on can be formalized in a standard way as a MPC problem. The aim is to minimize the time during which the HVAC sub-systems are on before the arrival of the first occupant (at time p). The criterion to be minimized is defined by equation 7, considering $k \in \mathbb{N}$ the actual time and $p \in \mathbb{N}$ the prediction

horizon. $u_j(k + i/k)$ is the vector of the manipulated variables for the room j . $HVAC_j(k + i/k) = 1$ if the HVAC sub-system is on and $HVAC_j(k + i/k) = 0$ if it is off. Let us note that $X(k + i/k)$ is the forecasted value of X at time $k + i$, based on the knowledge of X at time k :

$$\min_{\bar{u} \in \{0;1\}^p} \left(p - \sum_{i=1}^p (u_j(k + i/k)) \right) \quad (7)$$

Thus, $HVAC_j(k + i/k) = u_j(k + i/k)$ and if $HVAC_j(k + i/k) = 1$ then $T_j^{sp}(k + i/k) = T_j^{sp}(k)$, with $T_j^{sp}(k)$ the set-point temperature computed to ensure $PMV_j(k) = 0$ (see equation 6 and figure 11). Else, if $HVAC_j(k + i/k) = 0$ then $T_j^{sp}(k + i/k) = 0$. So, the vector $\bar{u} = [u_j(k + 1/k), \dots, u_j(k + p/k)] \in \{1;0\}^p$ and $u_j(k)$ is a binary variable. One can note that we consider an integer $n_j \in \llbracket 1; p \rrbracket$ which exists so that the constraints defined by equation 8 are satisfied. With such an assumption, the HVAC sub-system of the room j is switched on only once:

$$\begin{cases} [u_j(k + 1/k), \dots, u_j(k + n_j - 1/k)] = \{0\}^{n_j-1} \\ [u_j(k + n_j/k), \dots, u_j(k + p/k)] = \{1\}^{p-n_j+1} \end{cases} \quad (8)$$

The terminal constraints related to thermal comfort requirements are given by equation 9:

$$PMV_j^{min} \leq PMV_j(k + p/k) \leq PMV_j^{max} \quad (9)$$

The PMV index in the room j , $\forall j \in \llbracket 1; 3 \rrbracket$, is forecasted using the ANN-based model we presented in section 4 (equation 10). Equation 11 is about the forecasting of the exogenous variables, with SIG_j the function that defines the occupancy of the room j and computes the internal heat gain. Equation 12 deals with the computation of the air temperature set-point:

$$PMV_j(k + i + 1/k) = ANN_j \left(\begin{array}{l} PMV_j(k + i/k), T_{out}(k + i/k), \dots \\ SR(k + i/k), IG_j(k + i/k), \dots \\ T_j^{sp}(k + i/k) \end{array} \right) \quad (10)$$

$$\begin{cases} T_{out}(k + i/k) = T_{out}(k + i - 24h) + T_{out}(k) - T_{out}(k - 24h) \\ SR(k + i/k) = SR(k + i - 24h) \\ IG_j(k + i/k) = SIG_j(k + i) \end{cases} \quad (11)$$

$$T_j^{sp}(k + i/k) = T_j^{sp}(k) \text{ such as if } T_j(k) = T_j^{sp}(k) \text{ then } PMV_j(k) = 0 \quad (12)$$

As a key point, the criterion to be minimized can be reformulated to avoid searching the solution for each $u_j(k + i/k)$. With such a reformulation, we only need to find the best value of n_j as an integer parameter (equation 13), which is enough to find the vector of the manipulated variables, as shown in equation 8. The constraints remain unchanged:

$$\min_{n_j \in \llbracket 1; p \rrbracket} (p - n_j) \quad (13)$$

The optimization problem related to the search for the optimal time to switch the HVAC sub-systems off can be formalized in the same way. Our goal is to maximize the time during which the sub-systems are off before people leave the building (at time p). So, the criterion is defined as follows (equation 14):

$$\max_{n_j \in \llbracket 1; p \rrbracket} (p - n_j) \quad (14)$$

Except for thermal comfort requirements, the constraints remain the same as for the first optimization problem (the search for the optimal time to switch the HVAC sub-systems on). So, because thermal comfort has to be maintained until the end of the prediction horizon (p), equation 9 is replaced by equation 15. So $\forall i \in \llbracket 1; p \rrbracket$:

$$PMV_j^{min} \leq PMV_j(k + i/k) \leq PMV_j^{max} \quad (15)$$

Finally, with a centralized MPC controller, n_j is the same for all the considered areas and is so noted n . Moreover, the constraints related to thermal comfort when searching for the optimal time to switch on or off the HVAC sub-systems (equations 9 and 15) have to be respected in each of the considered rooms at the same time, i.e. $\forall i \in \llbracket 1; p \rrbracket$. In addition, PMV_j is computed for the room j using the model $ANN_j^{j,l,m}$, $\forall j, l, m \in \llbracket 1; 3 \rrbracket$ such as $j \neq l \neq m$, in order to take into account the existing interaction (i.e. heat transfer) between the different areas of interest (equation 16):

$$ANN_j^{j,l,m} \left(\begin{array}{l} PMV_j(k + i/k), PMV_l(k + i/k), PMV_m(k + i/k), \dots \\ IG_j(k + i/k), IG_l(k + i/k), IG_m(k + i/k), \dots \\ T_j^{sp}(k + i/k), T_l^{sp}(k + i/k), T_m^{sp}(k + i/k), \dots \\ SR(k + i/k), T_{out}(k + i/k) \end{array} \right) \quad (16)$$

In order to avoid on-line optimization that needs computing resources, we propose an algorithm allowing the optimal switching time (i.e. the optimal time to

turn on and off the HVAC sub-systems) to be found without optimization. Only one simulation of the prediction model (ANN_j or $\text{ANN}_j^{l,m}$) for each of the considered rooms is needed. Figure 12 depicts the predictive algorithm used. As mentioned above, the sampling time is 15 minutes. The occupancy schedule (people are present from 8:00 a.m. to 6:00 p.m.) is identical for the three considered areas. First, the air temperature set-points are computed to obtain $PMV_j^{sp} = 0$. Depending on the presence or not of people in the building, two different cases can be highlighted, $\forall j \in \llbracket 1; 3 \rrbracket$:

(i) When the building is occupied ($Z_j = 1$ for the room j), the objective is to turn off the HVAC sub-systems as soon as possible while ensuring that thermal comfort will meet requirements (equation 15) until all the people leave the different areas, taking into account their thermal inertias. All the HVAC sub-systems are considered to be turned off ($HVAC_j(k) = 0$) along the forecasting horizon p while outdoor temperature and solar radiation (both are exogenous disturbances) are estimated on the basis of the previous day values (equation 11). The PMV index is forecasted using the proposed ANN-based models (equation 10). As long as the building is occupied, the predictive algorithm checks if thermal comfort requirements are satisfied in each area of interest (the ground floor and first floor offices as well as the manufacturing area). If the constraints are not met, it means that the HVAC sub-systems must not be turned off at this time and, as a result, the air-temperature set-points are set to the values we computed initially (equation 12). When the building is no more occupied ($Z_j = 0$ for the room j), thermal comfort is necessarily satisfied and all the HVAC sub-systems are turned off ($HVAC_j(k) = 0$).

(ii) When the building is empty ($Z_j = 0$ for the room j), the predictive algorithm searches for the last moment to turn on the HVAC sub-systems. The optimal time to switch the sub-systems on is defined as the time allowing thermal comfort requirements to be met when the first worker arrives at the building. If thermal comfort is ensured at least two time steps before the first worker arrival, decision is delayed and the HVAC sub-systems stay off ($HVAC_j(k) = 0$). If thermal comfort is not ensured at least one time step before the first worker arrival (equation 9), the HVAC sub-systems are switched on ($HVAC_j(k) = 1$) and the air temperature set-points computed initially are used (equation 12).

6. Results

In order to evaluate performance regarding thermal comfort, we considered the percentage of time for which the PMV value remains between -0.5 and 0.5 ,

the building being occupied. This percentage is of course directly related to constraints satisfaction. In addition, calculation of energy consumption is based on an average consumption per day and square meter. With these criteria, one can compare the proposed predictive strategy with non-predictive ones. Finally, the time needed to compute the air temperature set-points is recorded. This allows computation requirements to be evaluated. The results are grouped in table 6.

Table 6: Performance of the strategies (simulation is from January to February 2011). (C) is for the Continuous strategy, (S) is for the Scheduler operating mode, and (P) is for the Predictive strategy.

	“Occupancy” set-point	“Vacancy” set-point	Consumption (Wh/day·m ²)	Comfort criterion (%)
S1 (C)	$T_j^{sp} = 22^\circ\text{C}$	$T_j^{sp} = 22^\circ\text{C}$	232	78.2
S2 (C)	$PMV_j^{sp} = 0$	$PMV_j^{sp} = 0$	253	74.1
S3 (S)	$T_j^{sp} = 22^\circ\text{C}$	Off	88	82.6
S4 (S)	$PMV_j^{sp} = 0$	Off	98	79.3
S5 (P)	$PMV_j^{sp} = 0$	Off	102	84.9
S6 (P)	$PMV_j^{sp} = 0$	Off	82.9	87.2
S7 (P)	$PMV_j^{sp} = 0$	Off	82	86.6
S8 (P)	$PMV_j^{sp} = 0$	Off	81.6	86.8

6.1. Standard (non-predictive) strategies

The situation described below is the reference scenario (S1). In the real non-residential building, the HVAC sub-systems are turned on and the air temperature set-points remain the same ($T_j^{sp} = 22^\circ\text{C}$ in the room j , $\forall j \in \llbracket 1; 3 \rrbracket$) during daytime, nighttime and week-end periods. With this scenario, thermal comfort is slightly lower than zero and exceeds this value when outdoor temperature and/or solar radiation are high. Figures 13a and 14a depict the way both the PMV index (top) and power consumption (bottom) evolves during two characteristic weeks (a cold one and a milder one). Scenario S2 allows the same strategy to be applied but using a PMV set-point, instead of an air-temperature set-point. This time, the average PMV index is very close to zero, but we observe the same problem as previously, that is to say overheating in case of high temperature and/or solar radiation. This explains why the comfort criterion is lower, even with a higher consumption of energy.

As an other option, we used a scheduler to stop the HVAC sub-systems during the night and the week-ends and to turn them on in the morning, two hours

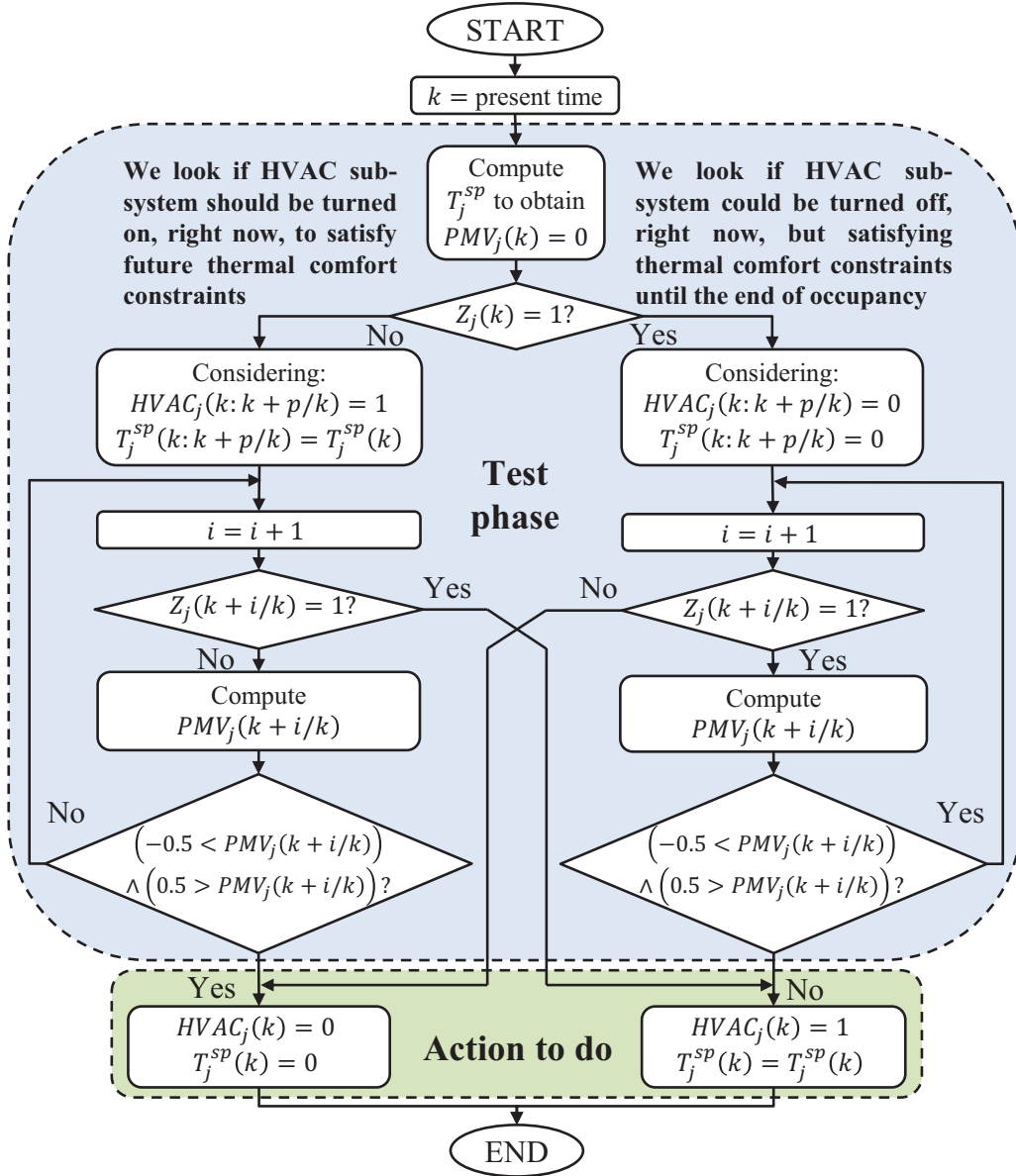


Figure 12: Predictive control algorithm for the room j , $\forall j = 1, 2$ or 3 (no interaction between the rooms), or for $j = 1, 2$ and 3 (with interaction between the rooms).

before people arrive in the manufacturing area. Two hours is a standard amount of time to heat a building during the cold period of the year concerned by heating. On this basis, we defined two scenarios: S3 ($T_j^{sp} = 22^\circ\text{C}$ in the room j , $\forall j \in \llbracket 1; 3 \rrbracket$) and S4 ($PMV_j^{sp} = 0$ in the room j , $\forall j \in \llbracket 1; 3 \rrbracket$). Quite logically, the results we obtained highlight a significant decrease in energy consumption: -62.1% ($-144 \text{ Wh/day}\cdot\text{m}^2$) with S3 and -57.8% ($-134 \text{ Wh/day}\cdot\text{m}^2$) with S4, taking as a reference the results we obtained with scenario S1. In addition, thermal comfort is improved : turning off the heating systems during periods of vacancy attenuates and delays overheating effects. Figures 13b and 14b show that scenario S3 suffers from a lack of flexibility. Indeed, thermal comfort is sometimes reached too early (for example during mild days), which leads to energy waste, while it is reached too late some other days. In this case, thermal comfort requirements are not satisfied.

6.2. Predictive control strategy

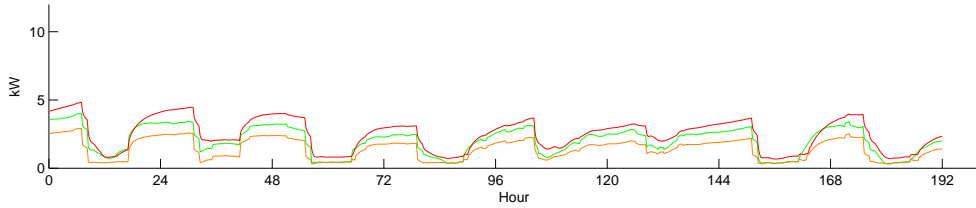
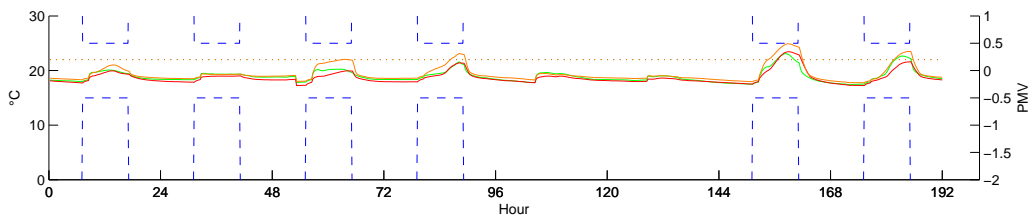
The next scenario (S5) introduces a predictive control with a single-area approach somewhat conservative because heat transfer between the three considered areas is not taken into account. As a result, the HVAC sub-systems are turned on too early and turned off too late. Otherwise, thermal comfort is good, even though electrical consumption is slightly higher than for both scenarios S3 and S4. As a key point, overheating is limited compared to what is observed when applying the non-predictive strategies. The three last scenarios (S6, S7 and S8) are based on the multi-area predictive algorithm. Due to the forecasting method used for outdoor temperature and solar radiation, they give different results. Scenario S6 is the ideal case because the real values of outdoor temperature and solar radiation are used. For scenario S7, uncorrected previous-day values are used. Finally, scenario S8 uses corrected previous-day values for outdoor temperature (see section 4.3) (figure 13c). These three scenarios allow the impact on the results of the forecasting procedure to be highlighted: with an ideal prediction of outdoor temperature and solar radiation (S6), the comfort criterion is the best. Of course, such a situation is not realistic because forecasting outdoor temperature and solar radiation without error is impossible. So, these results are only given to evaluate the performances of the other strategies in comparison with the ideal case. Using only the previous day values (S7) is efficient, but sometimes leads to sub-systems turned on too soon or too late. With the correction factor (S8), this problem is solved most of the time: the consumption of energy is slightly lower while thermal comfort is better. These results suggest the robustness of the proposed approach. So, an advanced forecasting approach, leading probably to an increase in computation time, seems

to be unnecessary. In addition, a study of the robustness of the proposed strategy has been carried out and is presented in section 6.4.

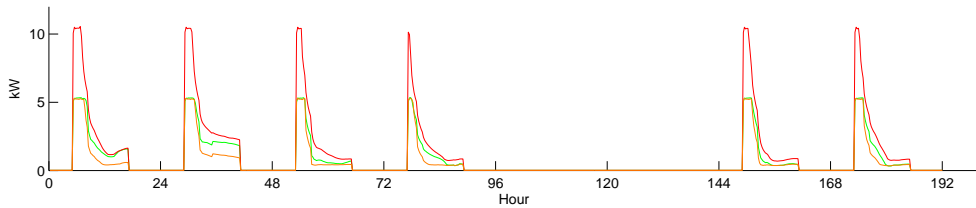
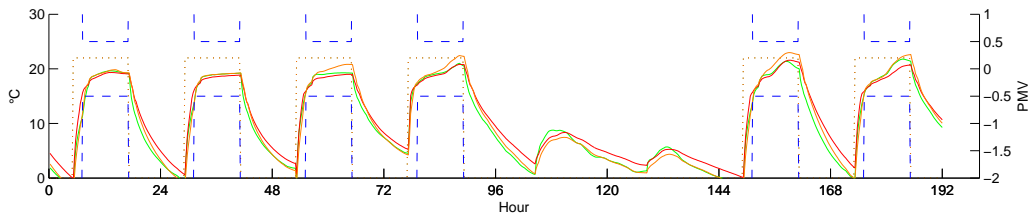
The multi-area predictive strategy allows the problems encountered by the standard strategies to be solved. During cold days or after week-ends, the anticipation time is longer than in case of warm days. The thermal comfort requirements are just met when the first worker arrives at the building in the morning. As a result, energy waste is low and thermal comfort is very good. In addition, the HVAC sub-systems are switched off before the end of the day, allowing energy savings without impacting thermal comfort in a negative way. This avoids the overheating problem encountered when applying the non-predictive strategies. During warm weeks, the predictive strategy has other advantages. The anticipation time is much shorter than when using the scheduler and the HVAC sub-systems are often turned off before the end of the morning, which allows big energy savings during the afternoon. Thermal comfort requirements are met until the last worker leaves the building. In comparison to the strategy currently being pursued in the building (scenario S1), the multi-area approach (scenario S8) allows energy consumption to be reduced of about 65%, while the duration of thermal discomfort is almost halved ($-150 \text{ Wh/day}\cdot\text{m}^2$). In comparison to scenario S3, which is an efficient scenario, energy saving is about 7.3% ($-6.4 \text{ Wh/day}\cdot\text{m}^2$) and thermal comfort is better. As a reminder, the building is occupied by people from 8:00 a.m. to 6:00 p.m. With the scheduler strategy, the HVAC sub-systems are always turned on 2 hours before the beginning of an occupation period and turned off when people leave the non-residential building. Tables 7 and 8 highlight the optimal on/off switching times for two simulation periods, when using scenario S8: from January 4 to 11 (figure 13c) and from November 2 to 9 (figure 14c), 2011. On/off switching times are related to outdoor temperature and solar radiation. As a key point, optimization strongly reduces the HVAC sub-systems operating time.

6.3. Computation time

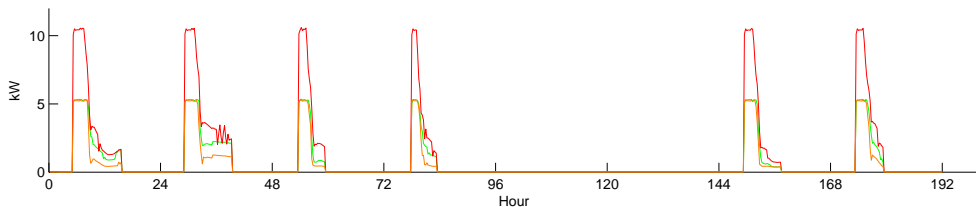
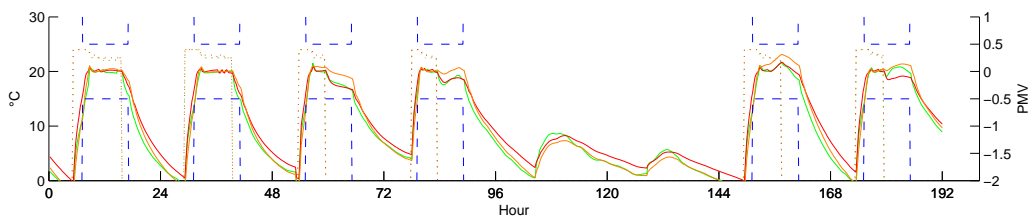
Strategies consisting in a direct control of temperature do not require any computation. In opposition, when the temperature set-points to be applied to the HVAC sub-systems are defined on the basis of the PMV indexes, computation is required. Duration is directly related to the resolution process, computation time is then 2.4 ms for each of the considered areas. Of course, predictive control is the slowest strategy. Duration is variable and strongly depends on the number of time steps needed to find the optimal solution of the problem (at each time step the ANN-based models are used to forecast the PMV index). If the stopping criterion is reached soon (i.e. thermal comfort is achieved before occupancy or not



(a) Scenario S1. consumption is 257 Wh/day·m².

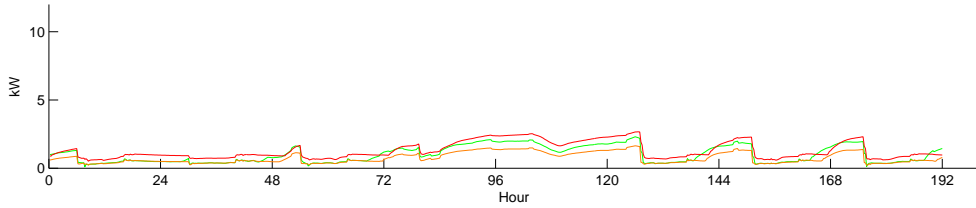
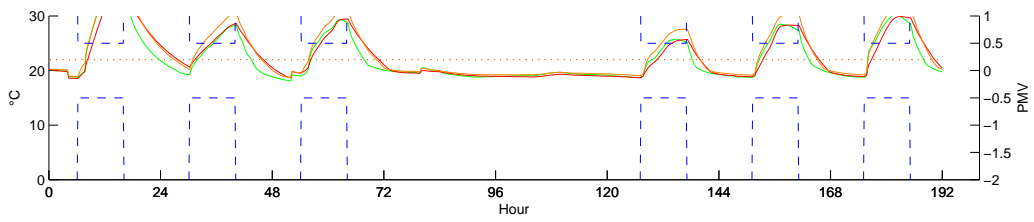


(b) Scenario S3. consumption is 111.5 Wh/day·m².

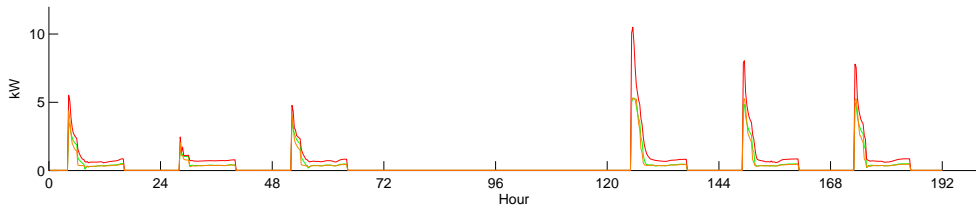
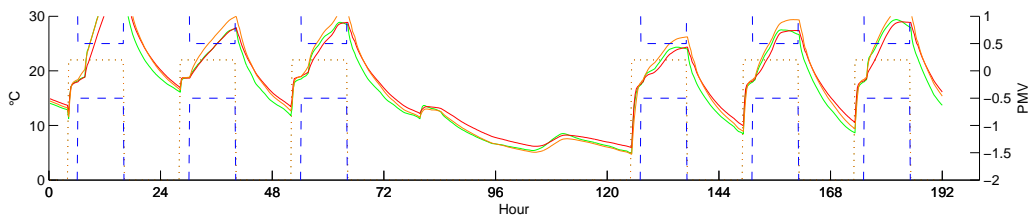


(c) Scenario S8. Consumption is 108.4 Wh/day·m².

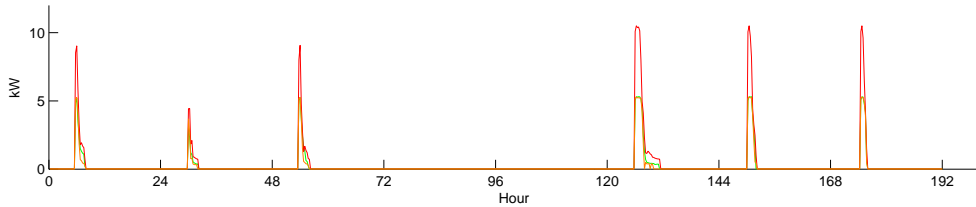
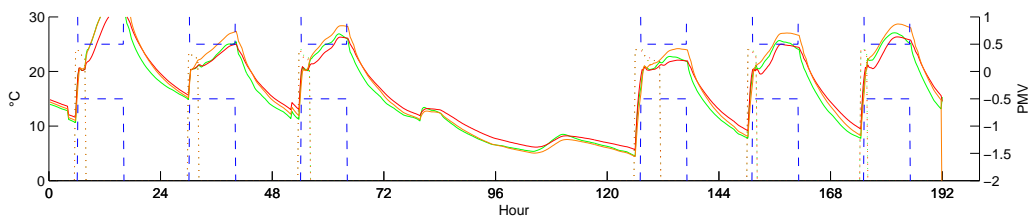
Figure 13: The simulation period is from January 4 to 11, 2011. At the top: temperature set-point (dotted line), PMV index (discontinuous line) and thermal comfort constraints (blue dashed line). At the bottom: power consumption. Green, orange and red lines are for the ground floor offices, the first floor offices and the manufacturing area, respectively.



(a) Scenario S1. Consumption is 131.8 Wh/day·m².



(b) Scenario S3. Consumption is 49.6 Wh/day·m².



(c) Scenario S8. Consumption is 31.1 Wh/day·m².

Figure 14: The simulation period is from November 2 to 9, 2011. At the top: temperature set-point (dotted line), PMV index (discontinuous line) and thermal comfort constraints (blue dashed line). At the bottom: power consumption. Green, orange and red lines are for the ground floor offices, the first floor offices and the manufacturing area, respectively.

Table 7: On/off switching times using scenario S8 (from January 4 to 11, 2011) and operating time saved in comparison to scenario S3. January 8 (Saturday) and 9 (Sunday), 2011, are weekend days.

Day	Jan. 4	Jan. 5	Jan. 6	Jan. 7
Starting time	6:00 a.m.	6:00 a.m.	6:30 a.m.	6:45 a.m.
Stopping time	4:30 p.m.	4:15 p.m.	12:15 p.m.	12:15 p.m.
Time saved (h)	1:30	1:45	6:15	6:30
Day	Jan. 8	Jan. 9	Jan. 10	Jan. 11
Starting time	n.a.	n.a.	6:15 a.m.	6:15 a.m.
Stopping time	n.a.	n.a.	2:15 p.m.	12:15 p.m.
Time saved (h)	n.a.	n.a.	4:00	6:00

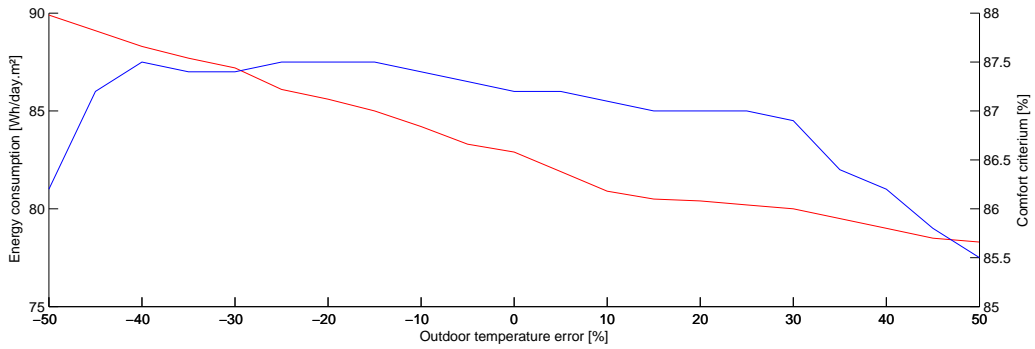
Table 8: On/off switching times using scenario S8 (from November 2 to 9, 2011) and operating time saved in comparison to scenario S3. November 5 (Saturday) and 6 (Sunday), 2011, are weekend days.

Day	Nov. 2	Nov. 3	Nov. 4	Nov. 5
Starting time	7:30 a.m.	7:45 a.m.	7:30 a.m.	n.a.
Stopping time	9:45 a.m.	10:00 a.m.	10:00 a.m.	n.a.
Time saved (h)	9:45	9:45	9:30	n.a.
Day	Nov. 6	Nov. 7	Nov. 8	Nov. 9
Starting time	n.a.	6:45 a.m.	7:00 a.m.	7:15 a.m.
Stopping time	n.a.	12:15 p.m.	9:00 a.m.	8:45 a.m.
Time saved (h)	n.a.	6:30	10:00	10:30

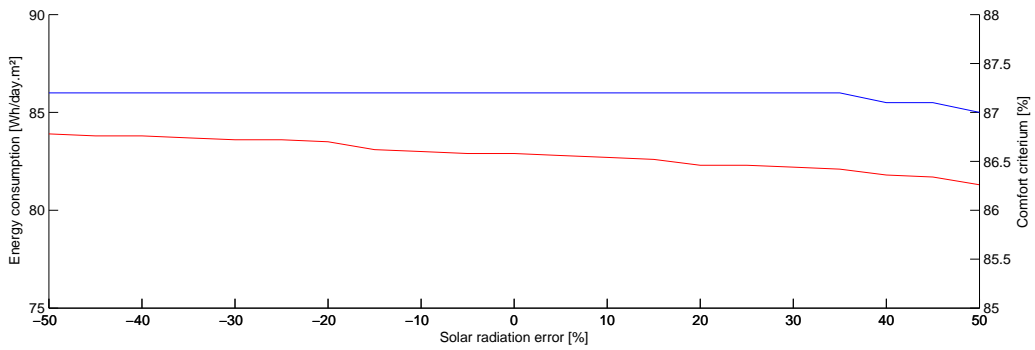
maintained while occupancy), computation is done in about 100 ms. Otherwise, computation lasts 400 ms at the maximum. As a consequence, the use of artificial neural networks has to be carefully considered in order for the proposed management solution to be implemented in an embedded system whose memory size and operation capability are limited.

6.4. Robustness of the predictive controller

The MPC strategy requires forecasting the exogenous variables. Consequently, evaluating how accuracy impacts on efficiency is necessary. So, we carried out a complementary study about the robustness of the proposed strategy. This study highlights the impact of underestimated or overestimated exogenous variables. We considered scenario S6 and we applied an error ranging between -50% and +50% to forecasted outdoor temperature (T_{out}) and solar radiation (SR) values.



(a) Impact of underestimated (negative percentage error) or overestimated (positive percentage error) values of outdoor temperature (T_{out}) on both energy consumption and thermal comfort



(b) Impact of underestimated (negative percentage error) or overestimated (positive percentage error) values of solar radiation (SR) on both energy consumption and thermal comfort

Figure 15: Robustness of the predictive control strategy (considering the manufacturing area as well as both the ground and first floor offices). The simulation is carried out from January to February, 2011. The blue line is for the average energy consumption and the red line is about the comfort criterion (the percentage of time for which the PMV value remains between -0.5 and 0.5).

Figure 15 depicts the results about robustness we obtained, considering the manufacturing area as well as both the ground and first floor offices. Figure 15a is about outdoor temperature. When T_{out} is underestimated (outdoor temperature is higher than estimated by the proposed model), energy consumption increases. In this case, the control algorithm decided for a PMV index and more time is needed to reach the desired comfort level at 08:00 a.m. As a result, the HVAC sub-systems are turned on earlier than when outdoor temperature is correctly estimated. In the same way, the predictive controller has estimated that once the HVAC sub-systems are shutted down, thermal comfort will decrease in the rooms faster than it really does. As a consequence, the action to turn the HVAC sub-systems off is delayed. Likewise, an overestimation of T_{out} (outdoor temperature is lower than estimated by the model used) generates an opposite behaviour: heating starts too late, what decreases energy consumption but affecting thermal comfort. However, one can note that a forecasting error ranging between -40% and +30% affects only slightly thermal comfort. As a result, the robustness of the model predictive controller with respect to the uncertainty in forecasting T_{out} is quite good. Beyond this interval, thermal comfort deteriorates in a more significant way.

Figure 15b is about solar radiation. Taking a look at this figure, one can clearly note that a forecasting error does not really affect control performance. Changes in both thermal comfort and energy consumption are very low. As a result, the proposed model predictive controller can be considered as consistent. As one can see in the figure, the HVAC sub-systems are turned on early in the morning (at dawn). From this time to the time people arrive at the non-residential building to work, solar radiation is very low. So, the prediction error impacts in a more significant way when the HVAC sub-systems must be turned off. Let us note that solar radiation and outdoor temperature are linked together: when solar radiation is low, because of clouds, outdoor temperature is also low.

Overall, accuracy in forecasting T_{out} and SR impacts on thermal comfort and energy consumption. The robustness of the proposed predictive control strategy is quite good, even if accuracy is not high. However, if T_{out} (and/or SR) is underestimated, the HVAC sub-systems are turned on too early. If underestimation is moderate, thermal comfort is improved but to the detriment of energy consumption. In opposition, if underestimation is significant, overheating can be highlighted and thermal comfort is deteriorated. An overestimation of T_{out} (and/or SR) reduces energy consumption and thermal comfort. If solar radiation is overestimated, the impact of overestimation can be considered as insignificant. This impact is slightly higher when outdoor temperature is overestimated. However, the predictive controller is still performing in a good way.

7. Conclusion

The aim of the work presented in this paper was to develop an efficient strategy based on predictive control to satisfy thermal comfort requirements in non-residential buildings equipped with zoned HVAC systems and local controllers, while minimizing energy consumption. We used the PMV (Predicted Mean Vote) index as a thermal comfort indicator. With such an indicator, one can estimate the thermal sensation of people in a building. The algorithm we developed allows the air temperature set-points of the HVAC sub-systems to be computed and the PMV set-points to be reached. Energy consumption can be minimized if operation time is reduced. Thus, we proposed a model predictive controller in order to supervise the local controllers and estimate the optimal time to turn on and off the HVAC sub-systems.

Low-order models based on Artificial Neural Networks (ANN) have been identified to forecast the PMV index in the considered rooms of a non-residential building. These ANN-based models are used as internal models of the predictive controller. We evaluated two different approaches: first, we developed one model per room. In this case, interaction (i.e. heat transfer) between the rooms is not taken into account. In a second time, we proposed a global model for all of the rooms we considered. With such a model, interaction is allowed for. In both cases, thermal comfort is improved and comfort constraints are met.

In order to evaluate the proposed strategy, a dedicated software for building simulation has been used to develop a complete model of a real non-residential building located in Perpignan (south of France). This high-order model allowed different strategies and scenarios to be evaluated and compared. As a key point, one can note that the predictive controller based on the global ANN-based model (interaction between the rooms is taken into account) offers a significant improvement in energy efficiency and thermal comfort assessment. This strategy allows saving up to 65% of energy when compared with the current strategy used in the real building. With this strategy, the HVAC sub-systems are turned on and off at the right time, that is turned on a few hours before the next occupation period to satisfy thermal comfort requirements (when people arrive at the building) and turned off to reduce energy consumption before people leave the building.

In comparison to a standard scheduler, the proposed predictive strategy is more flexible, the switching times being automatically adapted to the actual state of the building, occupancy (internal heat gain) and exogenous perturbations (the weather conditions). Moreover, the developed algorithm is computationally tractable (it does not need extensive on-line optimization like with standard MPC) and will

be implemented in an embedded system. So, one can note that the results we obtained meet the objectives that were defined at the start of the Batnrj project.

Future work will first focus on trying out the proposed predictive strategy in the real non-residential (reference) building. Then, the developed algorithm will be refined in order to compute an optimal and particular switching time for each of the HVAC sub-systems. Finally, the strategy should be improved to optimize the cooling process during summer time.

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