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Advanced fuzzy logic controllers design and evaluation for buildings' occupants thermal–visual comfort and indoor air quality satisfaction

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Abstract

The aim of this paper is to present and evaluate control strategies for adjustment and preservation of air quality, thermal and visual comfort for buildings' occupants while, simultaneously, energy consumption reduction is achieved. Fuzzy PID, fuzzy PD and adaptive fuzzy PD control methods are applied. The inputs to any controller are: the PMV index affecting thermal comfort, the CO_2 concentration affecting indoor air quality and the illuminance level affecting visual comfort. The adaptive fuzzy PD controller adapts the inputs and outputs scaling factors and is based on a second order reference model. More specifically, the scaling factors are modified according to a sigmoid type function, in such a way that the measured variable to be as closer as possible to the reference model. The adaptive fuzzy PD controller is compared to a non-adaptive fuzzy PD and to an ON–OFF one. The comparison criteria are the energy required and the controlled variables response. Both, energy consumption and variables responses are improved if the adaptive fuzzy PD type controller is used. The buildings' response to the control signals has been simulated using MATLAB/SIMULINK.

Keywords: Fuzzy logic; Adaptive control; Reference model; Energy consumption; Building users satisfaction

1. Introduction

Energy efficiency in buildings is becoming a crucial issue nowadays as it contributes simultaneously to conventional fuels consumption reduction, energy costs cut for building owners and decrease in global warming gas release to the atmosphere. In any case, energy efficiency must never compromise indoor comfort for building users. Lack or poor indoor comfort has a direct effect on users productivity [1] and an indirect effect to actual buildings' energy efficiency. As people spend 80% of their life indoors, indoor contaminants and poor indoor air quality may incur more harmful health effects than outdoor contaminants [2]. Unreasonable users reaction is proved to be disastrous for energy efficiency, i.e. heating greenhouse extensions to buildings, using internal blinds during the day to cut daylight and keeping electric lights on, etc. are some examples of "ineffective" efficient buildings. Moreover, tight control of the indoor environmental variables (temperature and humidity) and simultaneously installing mechanical ventilation systems for air circulation, which sometimes compete each other, is related with the buildings related illness or Sick Building Syndrome [3].

Furthermore, the conventional control strategies for indoor comfort proposed up to now are limited to ON–OFF and conventional PID methods. The difficulty to determine the exact mathematical model lays to the use of trial and error methods to develop the PID strategy for each building. As far as ON–OFF control in buildings is concerned, the controlled variable swings continuously and thermal comfort is regulated only by the indoor temperature. Moreover, classical PID control does not respond well with disturbances and modifications required for different buildings. On the other hand, recent research in building related artificial intelligence topics has shown that "smart control techniques" such as fuzzy systems and neural networks can contribute to reduction of energy consumption [4,5] while maintaining indoor comfort in acceptable margins. In any case, users preferences are not taken into account in all the above works.

The present paper aims to formulate the specifications of a fuzzy control system, which integrates users preferences and the user is encountered as dynamic part of the control strategy. The system is applicable in different buildings

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without modifications, as it does not take into consideration the building elements and characteristics. Moreover, it responds well under disturbances and it is easily programmed and executed. Finally, the control strategy achieves reduction of energy use, avoiding overshootings and oscillations.

2. The control strategy

The objectives of the proposed control strategy are:

- Satisfaction of the users preferences for (a) thermal comfort, (b) visual comfort and (c) indoor air quality, simultaneously.
- Optimum response of the controlled variables, avoiding overshootings and oscillations that can cause energy waste.
- Monitoring the energy consumption for heating/cooling and electric lighting.

For comparison purposes, a non-adaptive fuzzy PD, a non-adaptive fuzzy PID, an adaptive fuzzy PD controller and an ON–OFF controller are developed. The above controllers are compared to the conventional ON–OFF controller.

The comparison criteria are:

- The controlled variables response.
- The energy consumption and cost.

The indoor thermal comfort is controlled by modulation of the predicted mean vote (PMV) index, an idea introduced by Fanger [6]. The PMV index incorporates (apart from the indoor temperature, which is the most widely used indicator of thermal comfort), relative humidity, mean radiant temperature, indoor air movement and subjective parameters, such as occupants metabolism rate and clothing. When the PMV lies in the range between -0.5 and 0.5, the 90% of people is satisfied [7].

Generally, the indoor air quality depends upon CO_2, total volatile organic compounds (TVOC) and volatile organic compounds (VOC) concentration [8]. The CO_2 concentration ($[CO_2]$) is the controlled variable used for regulation of the indoor air quality and generally should be kept below 800 ppm [9].

The visual comfort is controlled by the illuminance levels measured in lux [10]. Glare is a significant issue related to visual comfort [11] but it is very difficult to be measured, because a lot of sensors especially positioned in the task plane is required. As long as users declare their preferences for lighting, the glare is not considered necessary to be measured. The system detects if the user experiences glare problems, because he or she changes his preferences for lighting continuously. The rule base gives priority to ambient sources of energy (solar energy) to satisfy the users, thus reducing the overall energy consumption.

Users preferences are recorded in a smart card, using a system especially designed for that purpose in the framework of the EU BUILTECH project (CT-97-0044). The preferences are read from the smart card to the controller and satisfied using the methods described below.

3. Satisfying the users preferences

Two non-adaptive fuzzy controllers and an adaptive one are developed and compared to each other on the basis of users preferences satisfaction and energy consumption reduction. The description of each controller follows.

3.1. The non-adaptive fuzzy PID controller

The fuzzy PID type controller consists of two parts: a PI- and a D-type part, as illustrated in Fig. 1.

The errors for each controlled variable (PMV, $[CO_2]$ and illuminance) are calculated as the difference between the desired users preferences and the current variables values. The present error value, $e(k)$, and the previous error value, $e(k-1)$, are fed as inputs to the PI-type part. Its output is the change to the actuators values. The actuators

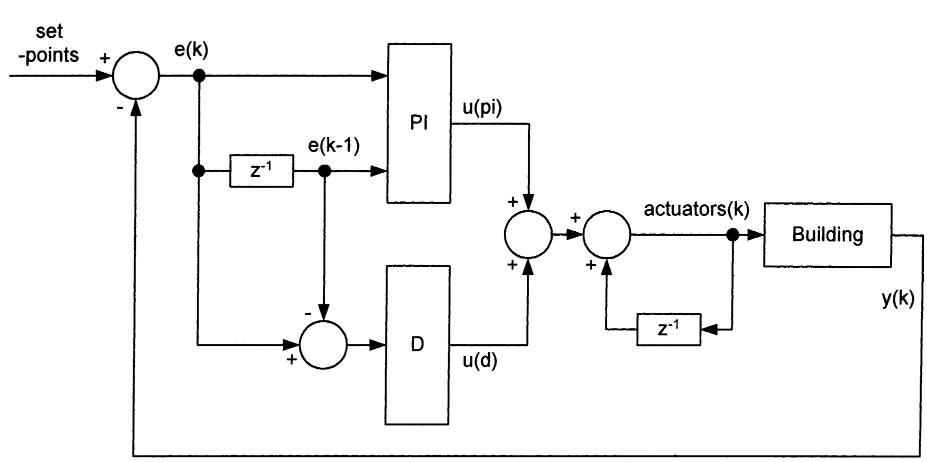

Fig. 1. The fuzzy PID controller block diagram.

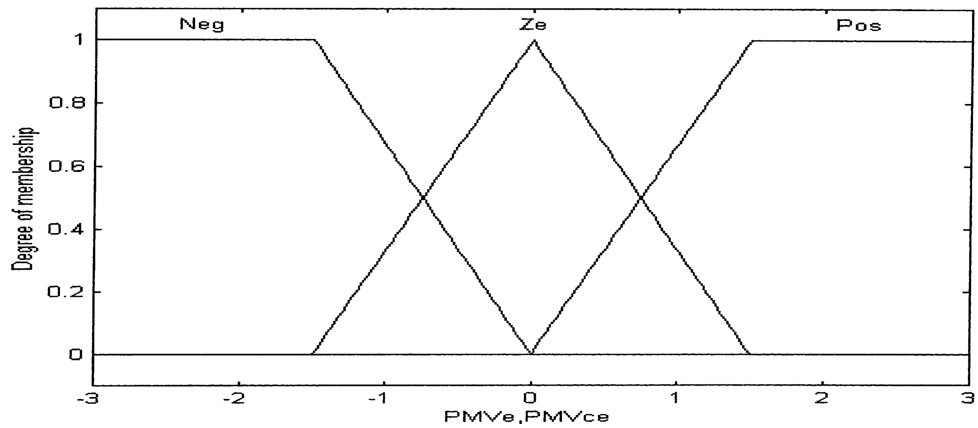

Fig. 2. Membership functions for the PD and PI controllers' PMV inputs.

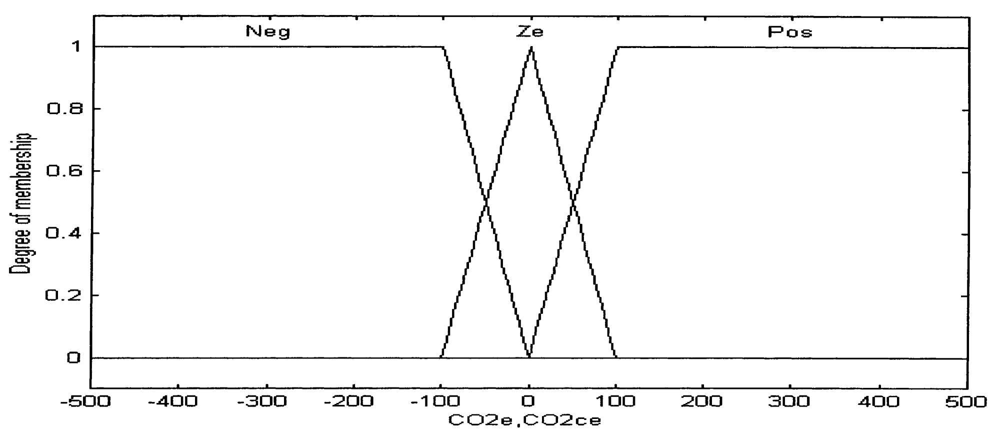

Fig. 3. Membership functions for the PD and PI controllers' CO_2 concentration inputs.

are the heating/cooling systems valves, the window opening mechanism, the shading devices and the electric lights. The difference between the previous and present errors, $ce(k) = e(k) - e(k-1)$ is the input to the D-type part, which has the same output as the PI part [12]. The input membership functions for the PI-type part are illustrated in Figs. 2, 3 and 4, respectively, while the output membership functions are depicted in Fig. 5. The D-type part input and output membership functions are illustrated in Figs. 6 and 7, respectively.

As shown in the above figures, three membership functions cover the input space, whereas five of them cover the output space of the PI Controller. The simulation results and relevant comparisons are described in Section 4.

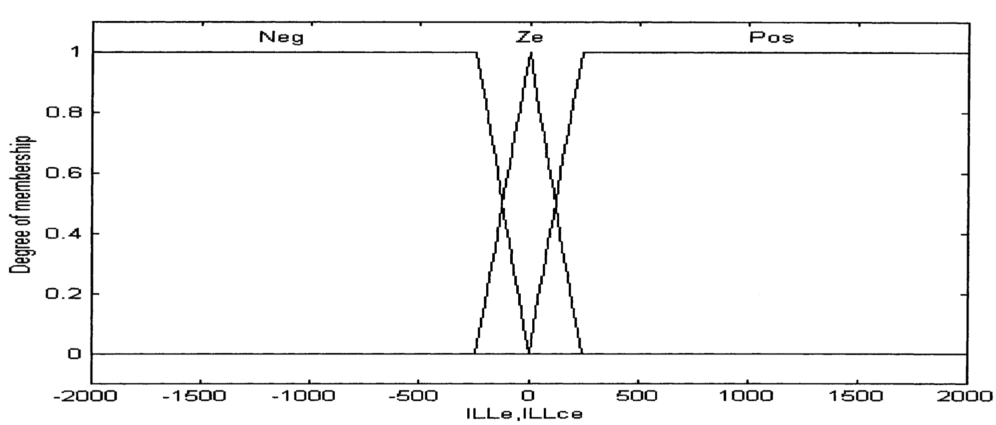

Fig. 4. Membership functions for the PD and PI controllers' illuminance inputs.

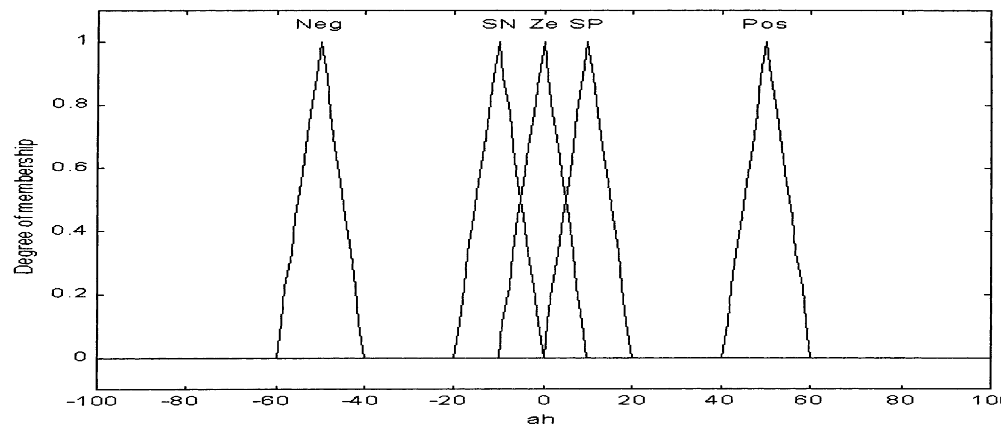

Fig. 5. Membership functions for the PD and PI controllers outputs.

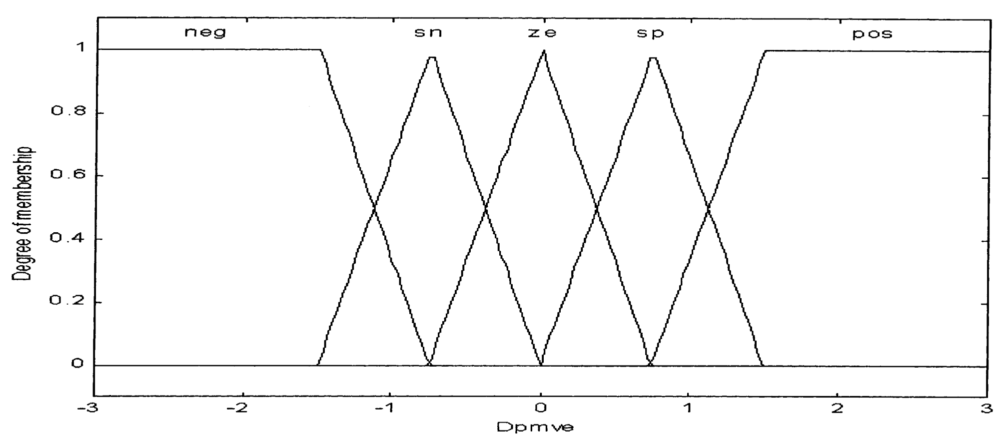

Fig. 6. The PMV input membership functions for the D-type controller.

3.2. The non-adaptive fuzzy PD controller

The non-adaptive fuzzy PD controller is introduced to simplify the architecture, reduce the number of rules and the computational time. The architecture of the fuzzy PD controller is depicted in Fig. 8.

The present error, $e(k)$, and the error change, $ce(k) = e(k) - e(k-1)$, are input to the fuzzy PD controller [13]. The output is exactly the same as for the fuzzy PID controller. The membership functions are the same to those of the fuzzy PID controller, illustrated in the above figures. The scaling factors $Ge(k)$ and $Gce(k)$ are constant and set equal to 1.

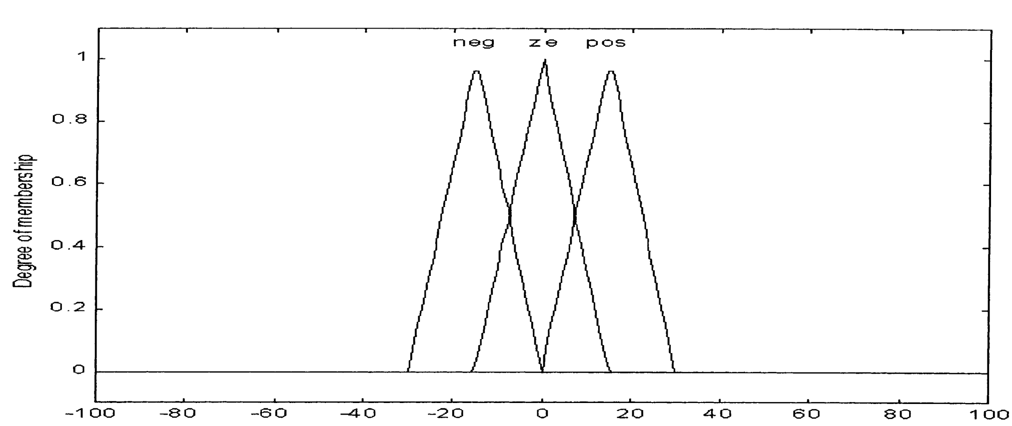

Fig. 7. The output membership functions for the D-type controller.

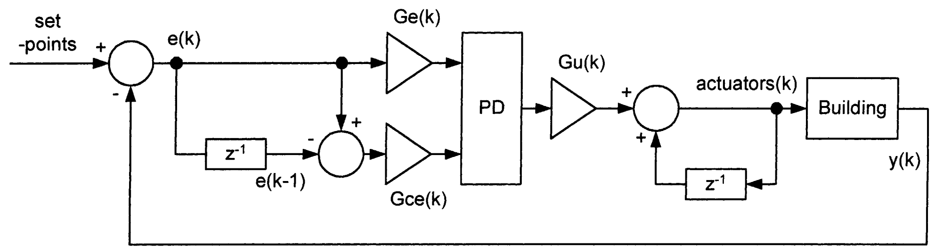

Fig. 8. The fuzzy PD controller block diagram.

A fuzzy PD controller with seven input–output membership functions (fuzzy-PD7) is also developed for comparison purposes [14]. The response of the fuzzy-PD7 controller is identical with that of the fuzzy PD controller with three membership functions (fuzzy-PD3), described above. This can be verified comparing the results given in Fig. 9. However, the computational time required for the fuzzy-PD7 operation is much higher than that of the fuzzy-PD3. Furthermore, Gaussian type membership functions are also tested, replacing the corresponding PMV index triangular and trapezoidal membership functions. The results are depicted in Fig. 10. No visible differences are observed in the response, apart from the fact that the energy consumption for heating is slightly higher. The above analysis led to the conclusion that triangular and trapezoidal type membership functions is the optimum option.

Considering the outputs membership functions, illustrated in Fig. 5, negative (NEG) and positive (POS) values are introduced to provide a strong control signal to the actuators when the input errors are high, whereas small negative (SN) and small positive (SP) values are used to regulate the controlled variables, introducing correction control signals when the input errors are small.

The rule base is depicted in Tables 1–3.

The rule base is structured in such a way to avoid overshootings. For example, if the input variable $e(k)$ lies in ZE and $ce(k)$ lies in POS then there is a tendency for positive overshoot, although the desired value has been reached. Therefore, a small negative control signal contributes to avoidance of overshooting. Moreover, if both input variables $e(k)$ and $ce(k)$ fall into negative (NEG), the error tends to be reduced, hence the control signal requires no correction. The max–min inference method and the center of gravity defuzzification methods are used throughout the above analysis.

3.3. The adaptive fuzzy PD controller

3.3.1. General theory

The concept for adaptive fuzzy PD controller [15] is the regulation of the scaling factors $Ge(k)$ and $Gce(k)$ in order to improve the system response. The block diagram of the controller is illustrated in Fig. 11.

As can be noticed in the figure, the inputs, the outputs and the structure of the adaptive fuzzy PD controller are the same as for the non-adaptive one. The difference is that a second order system is used as a reference model, for the

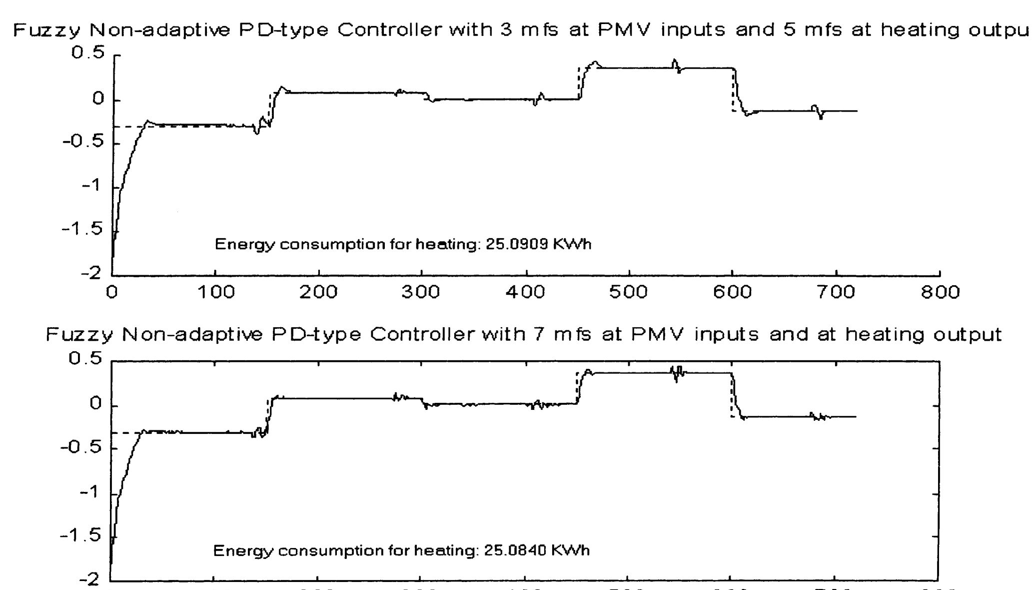

Fig. 9. Comparison of the PMV responses with fuzzy-PD3 and fuzzy-PD7.

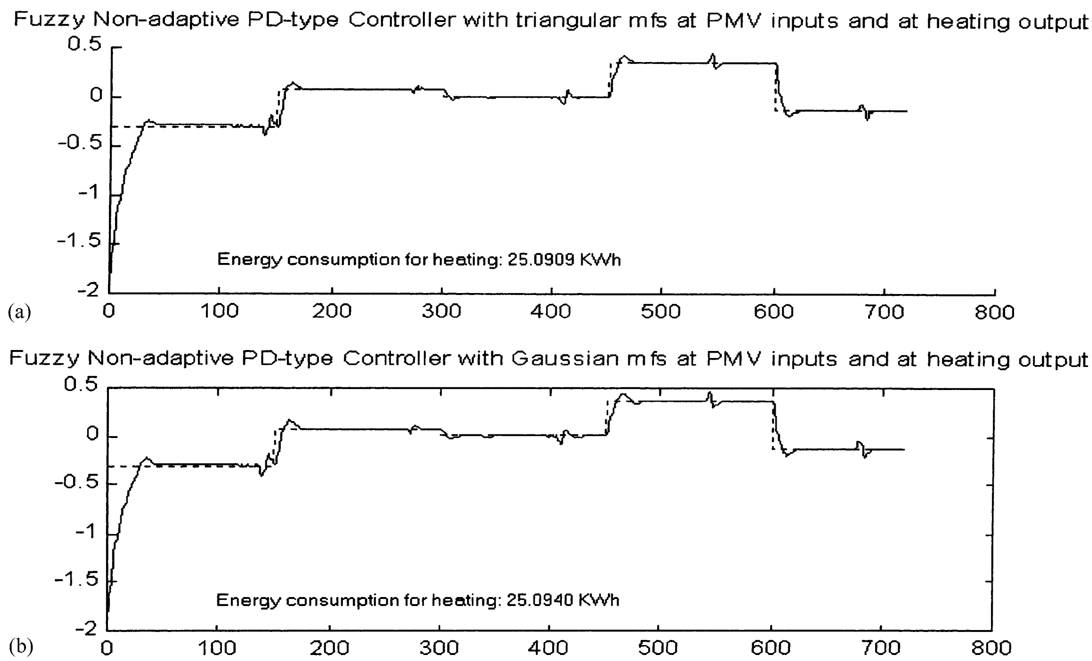

Fig. 10. Response of the PMV index using the fuzzy PD controller with (a) triangular and (b) Gaussian type membership functions.

Table 1
Rule base for heating control

PMV*e*	PMV*ce*		
	NEG	ZE	POS
NEG	ah → ZE	ah → SN	ah → NEG
ZE	ah → SP	ah → ZE	ah → SN
POS	ah → POS	ah → SP	ah → ZE

Table 3
Rule base for window opening control

CO_2e	CO_2ce		
	NEG	ZE	POS
NEG	w → ZE	w → SP	w → POS
ZE	w → SN	w → ZE	w → SP
POS	w → NEG	w → SN	w → ZE

determination of the scaling factors for the controller inputs and outputs.

The adaptation algorithm is based on the computation of the values z_1 and z_2, which are predicted values for the two inputs $e(k)$ and $ce(k)$, for the PMV, $[CO_2]$ and illuminance levels, according to the reference model. The values z_1 and z_2 are calculated by the following state equations:

$$\frac{z_1(k+1)-z_1(k)}{T} = \alpha z_1(k) + \beta z_2(k), \tag{1}$$

$$\frac{z_2(k+1)-z_2(k)}{T} = -\beta z_1(k) + \alpha z_2(k), \tag{2}$$

where α and β are coefficients related to the second order model.

The poles of the above described system are computed solving the equation:

$$\det(\boldsymbol{A} - \boldsymbol{I}s) = 0 \tag{3}$$

where $\boldsymbol{A}$ is the matrix.

$$\boldsymbol{A} = \begin{bmatrix} \alpha & \beta \\ -\beta & \alpha \end{bmatrix} \tag{4}$$

The poles computed by Eq. (3) are of the form:

$$s_{1,2} = -\alpha \pm j\beta \tag{5}$$

Table 2
Rule base for lighting control

ILL*e*	ILL*ce*		
	NEG	ZE	POS
NEG	al → ZE, sh → ZE	al → SN, sh → SP	al → NEG, sh → POS
ZE	al → SP, sh → SN	al → ZE, sh → ZE	al → SN, sh → SP
POS	al → POS, sh → NEG	al → SP, sh → SN	al → ZE, sh → ZE

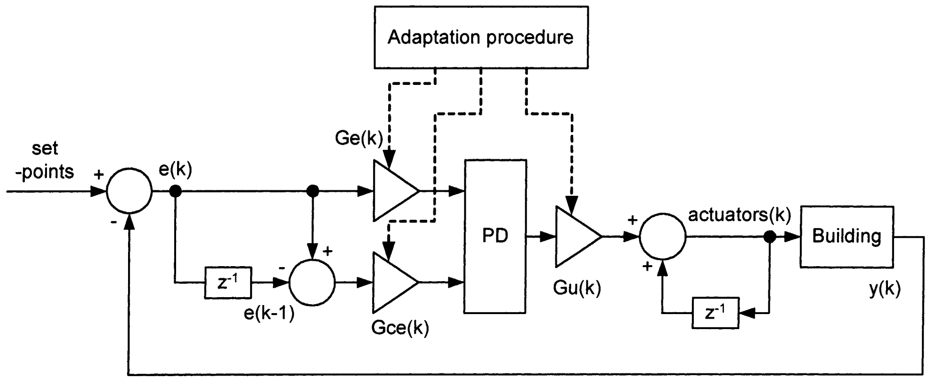

Fig. 11. The adaptive fuzzy PD controller block diagram.

The second order system that is used as a reference model is closed loop with unit feedback and has the following transfer function:

$$\frac{Y(s)}{R(s)} = \frac{\omega_n^2}{s^2 + 2\zeta\omega_n s + \omega_n^2}, \tag{6}$$

where ζ and ω_n are constants [16].

The poles of the above system are:

$$s_{1,2} = -\zeta\omega_n \pm j\omega_n\sqrt{1-\zeta^2}. \tag{7}$$

The coefficients α and β are calculated using Eqs. (5) and (7) as follows:

$$\alpha = -\zeta\omega_n, \tag{8}$$

$$\beta = \pm\omega_n\sqrt{1-\zeta^2}. \tag{9}$$

The quantity ω_n is computed by the following relation, which is valid for $0 < \zeta < 1$ for this second order system [16]:

$$\omega_n \cong \frac{1.1 + 0.125\zeta + 0.469\zeta^2}{t_\mathrm{d}} \tag{10}$$

where t_d is the delay time.

As ζ increases, the overshoot for the unit step response of the system, decreases. Thus, the value of ζ is set equal to 0.98, which is in the valid space and the overshoot is the smallest possible. In order to compute the time delay, t_d, the actuators are set to their maximum value and the simulation continues until the controlled variable is stabilized.

Taking into account that α and β are known, replacing z_1 with $e(k)$ and z_2 with $ce(k)$, the Eqs. (1) and (2) become:

$$z_1(k+1) = \{(1+\alpha T)e(k) + \beta T ce(k)\}\mathrm{scalar} \tag{11}$$

$$z_2(k+1) = \{(-\beta T e(k) + (1+\alpha T)ce(k)\}\mathrm{scalar} \tag{12}$$

The quantity 'scalar' is given by:

$$\mathrm{scalar} = \left|\frac{\max(y) - \mathrm{init\_exp}(y)}{\mathrm{sp} - y(k)_{\mathrm{init}}}\right| \tag{13}$$

where max(y): is the maximum value of the controlled variable extracted from the procedure for determining the ω_n; init_exp(y): the initial value of the procedure; sp: the set point that is determined by the user in the building and y_{init}: the value of the controlled variable measured when the user changes the set point.

The constant "scalar" is used for normalization of the reference model, since the system time response is approximately proportional to the initial error.

3.3.2. Tuning of the input scaling factors

The scaling factors are adapted so as the final values of the inputs to be as close as possible to the inputs that correspond to the reference model.

Therefore, if $Ge(k)e(k) < z_1(k)$ then $Ge(k)$ should be increased, whereas if $Ge(k)e(k) < z_1(k)$ then $Ge(k)$ should be decreased.

The following sigmoid functions are used to carry out the adaptation.

$$Ge(k+1) = \frac{2Ge(k)}{1 + \exp(-\mathrm{abs}\,(z_1(k)) + \mathrm{abs}\,(Ge(k)e(k)))} \tag{14}$$

$$Gce(k+1) = \frac{2Gce(k)}{1 + \exp(-\mathrm{abs}\,(z_2(k)) + \mathrm{abs}\,(Gce(k)ce(k)))} \tag{15}$$

3.3.3. Tuning of outputs scaling factors

The controller outputs tuning procedure presumes an indication of the influence of the control signal to the response. The $ce(k)$ input reflects more accurately the influence of the control signal to the response, compared to the $e(k)$, since it is purely a function of the controlled variable. Thus, $ce(k)$ and its relevant scaling factor are used for the adaptation of the scaling factor of the output.

The multiplier of the output $u(k)$ is given by:

$$Gu(k+1) = \frac{2Gu(k)}{1 + \exp(-\mathrm{abs}\,(z_2(k)) + \mathrm{abs}\,(Gce(k)ce(k)))} \tag{16}$$

if $e(k)(\mathrm{sp} - y(k)_{\mathrm{init}}) > 0$or

$$Gu(k+1) = \frac{2Gu(k)}{1 + \exp(-\mathrm{abs}\,(z_2(k)) - \mathrm{abs}(Gce(k)ce(k)))} \tag{17}$$

if $e(k)(\mathrm{sp} - y(k)_{\mathrm{init}}) < 0$

The first condition (Eq. (16)) is valid during the transient state before overshooting, while the second condition (Eq. (17)) is valid during overshooting.

Therefore, during the transient state and before overshooting, the reference model must be followed. For example if $Ge(k)ce(k) < z_2(k)$, the desired rate is higher than the current one, $Gu(k)$ should increase, so that a higher output signal to be produced by the controller. During overshooting, if $Gce(k)$ is increased, then $Gu(k)$ should be decreased and visa versa, in order to avoid oscillations.

3.4. The ON–OFF type controller

The optimized ON–OFF type controller is studied for comparison purposes. The ON–OFF control for thermal comfort is simulated using two radiators in the building. Therefore, the resulting three states of operation are the following: both radiators are in the OFF state, only one radiator is in the ON state or both radiators are in the ON state. Regarding the CO_2 concentration, it is supposed that the windows actuators operate in six discrete steps. The considered ON–OFF control takes the PMV as controlled variable instead of temperature. The response and energy consumption using the optimized ON–OFF control, are compared to the previous described fuzzy controllers and the results are presented in Section 4.

4. Simulation Results and discussion

The simulations are performed using the Sibil tool, which is a MATLAB/SIMULINK building model, developed by the Group Building Environmental Studies of the University of Athens [17]. Three buildings are simulated and the responses of the PMV, [CO_2] and illuminance levels are recorded for each of the above controllers. The simulation time step is set to 15 s while the simulation time lasts for 1 winter day. The outdoor conditions are kept constant for comparison feasibility.

The three buildings' characteristics are included in Table 4.

The users preferences are input using three random number generators. During the simulation, the users preferences change every 4 h, taking extreme values corresponding to the most demanding users. For example, while the average PMV index is -0.5 for winter with 90% of the users satisfied (corresponding to an indoor temperature of 21–22°C) the PMV preference reaches 0.5, which corresponds to extreme conditions for the winter period (approximately 27–28°C). The same applies for the rest controlled variables.

The simulation results prove that the adaptive fuzzy PD controller provides the optimum response for all three buildings for both [CO_2] and PMV (Figs. 12, 13 and 14) and the less energy consumption, compared to all other control methods described in this paper. More specifically, the response of the PMV index, using the adaptive controller, experiences lower overshoots, optimum performance against disturbances (opening or closing of the windows for regulating [CO_2]) and reduced energy consumption for heating. If the only criterion concerned is the energy consumption for heating, the differences between the fuzzy adaptive control and non-adaptive fuzzy control are not significant. The adaptive fuzzy controller saves less energy during a whole year period than the energy required per day for heating or cooling. Additionally, the indoor conditions regulated by the fuzzy adaptive controller are much more stable than by the other controllers.

The PMV index tolerance is set to 0.15 for the ON–OFF type controller, which is acceptable for indoor conditions regulation. Moreover, it is noticed that the energy consumption using the optimized ON–OFF control, with the PMV as controlled variable, does not cause significant increase to the energy consumption per day. The energy consumption improvement is evaluated relatively to the conventional ON–OFF control, where the controlled variable is the indoor temperature. The energy consumption using conventional ON–OFF control is 15.7 kWh/day, with temperature set

Table 4
Characteristics of all buildings used for simulation

Building no.	Area (m^2)	Wall	Roof	Floor	No of openings	Openings area (m^2)
	15	200 mm light concrete			1	1
1	15	25 mm polystyrene			1	1
	15	19 mm finishing			1	1
	15	200 mm concrete	200 mm concrete	200 mm concrete	1	1
2	15	25 mm polyurethane	25 mm polystyrene	25 mm polystyrene	1	1
	15	10 mm plaster	19 mm finishing	19 mm finishing	1	1
	18	200 mm concrete			2	2
3	18	25 mm polyurethane			2	2
	18	10 mm plaster			2	2

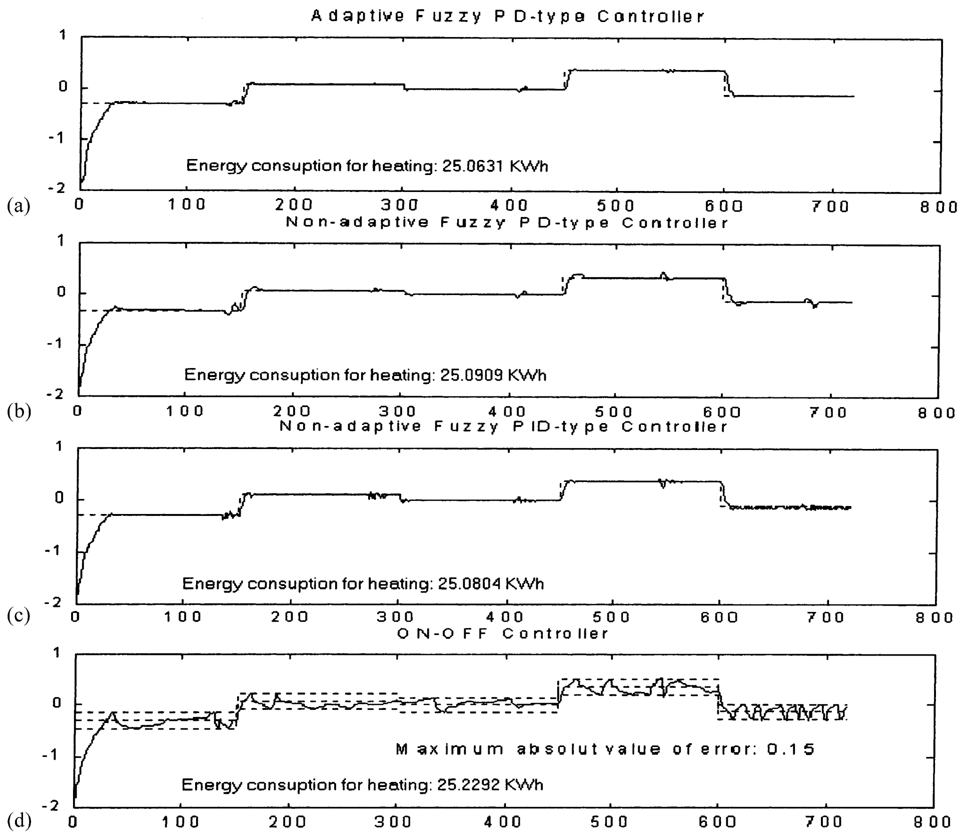

Fig. 12. PMV index responses for the first building, using (a) the adaptive fuzzy PD controller, (b) the non-adaptive fuzzy PD controller, (c) the non-adaptive fuzzy PID controller and (d) the ON–OFF type controller.

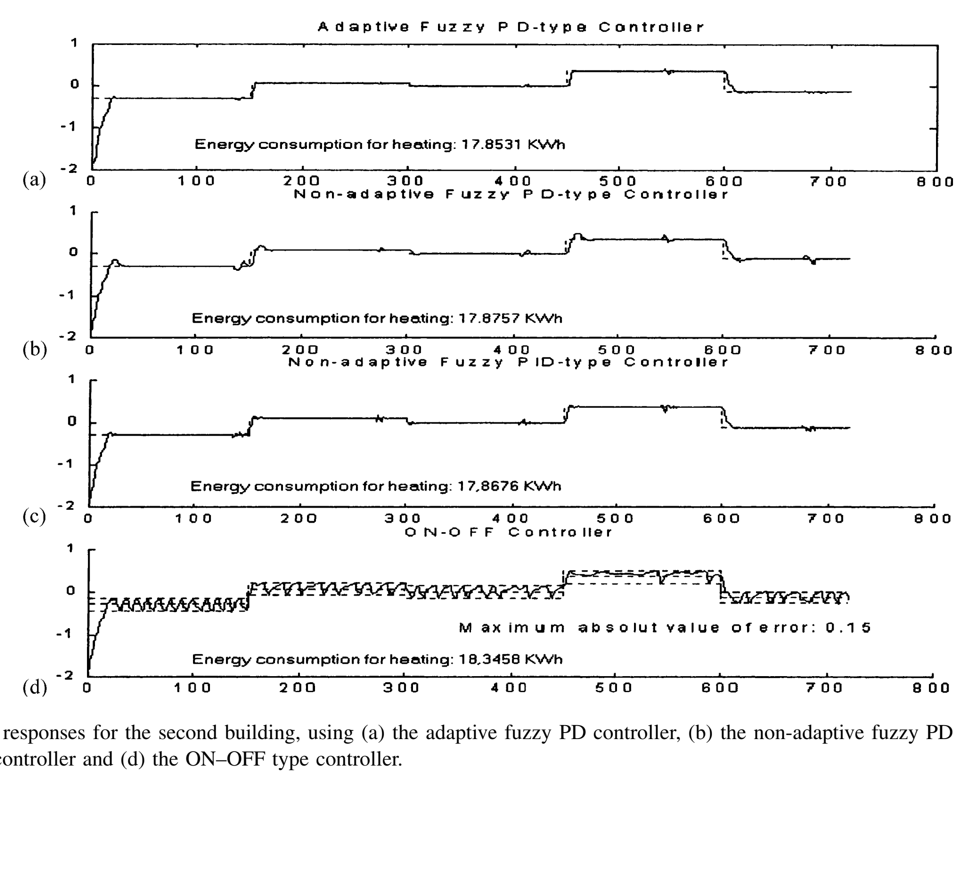

Fig. 13. PMV index responses for the second building, using (a) the adaptive fuzzy PD controller, (b) the non-adaptive fuzzy PD controller, (c) the non-adaptive fuzzy PID controller and (d) the ON–OFF type controller.

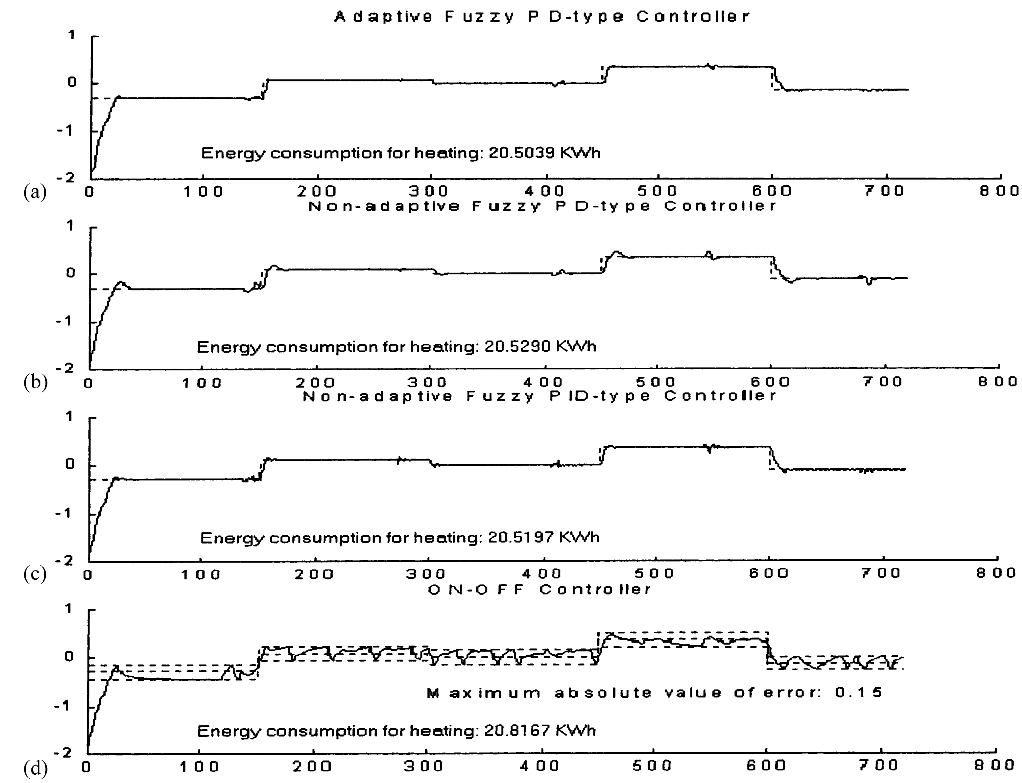

Fig. 14. PMV index responses for the third building, using (a) the adaptive fuzzy PD controller, (b) the non-adaptive fuzzy PD controller, (c) the non-adaptive fuzzy PID controller and (d) the ON–OFF type controller.

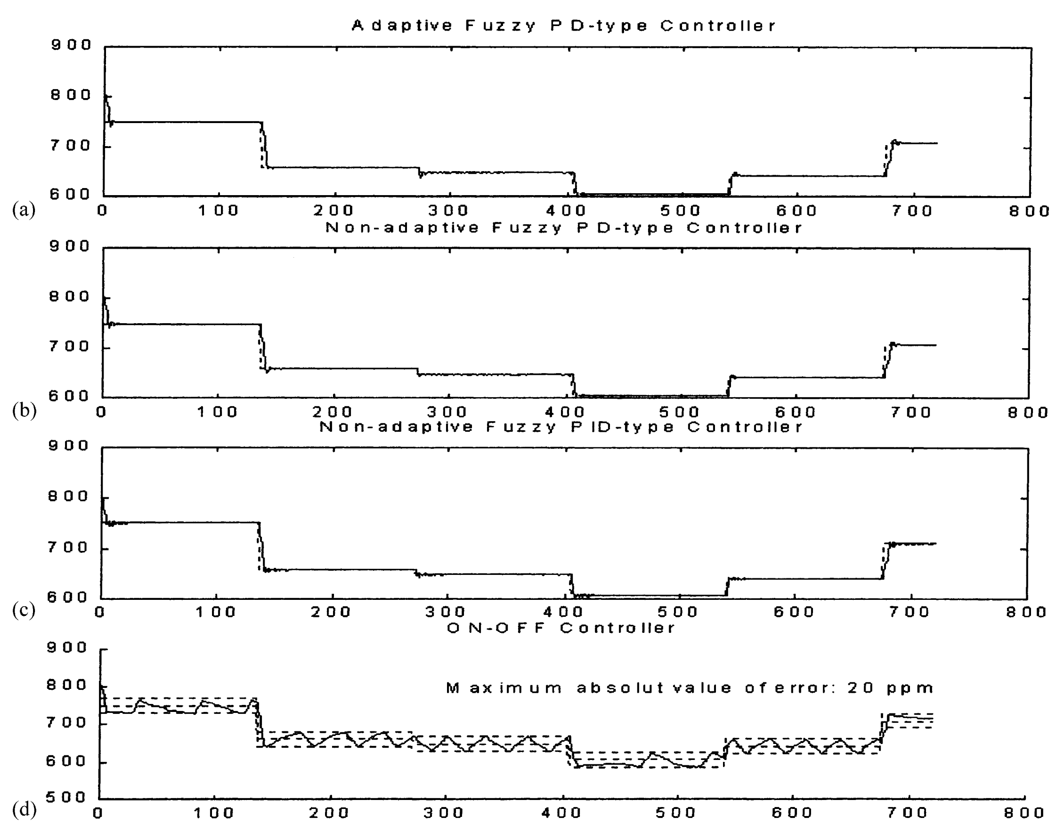

Fig. 15. The CO_2 concentration responses for the first building, using (a) the adaptive fuzzy PD controller, (b) the non-adaptive fuzzy PD controller, (c) the non-adaptive fuzzy PID controller and (d) the ON–OFF type controller.

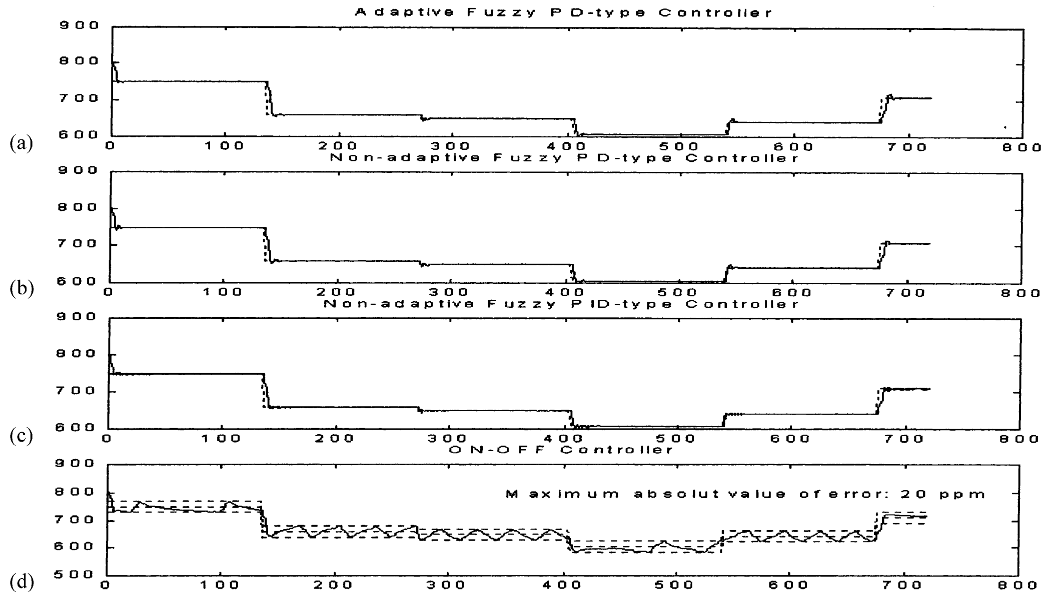

Fig. 16. The CO_2 concentration responses for the second building, using (a) the adaptive fuzzy PD controller, (b) the non-adaptive fuzzy PD controller, (c) the non-adaptive fuzzy PID controller and (d) the ON–OFF type controller.

point equal to 24°C corresponding to a PMV preference value of −0.5. The energy consumption, using the adaptive fuzzy PD controller, with the PMV equal to −0.5 is calculated to be 10.0 kWh/day. Therefore, a reduction to the energy consumption of upto 25–30% is achieved. The energy consumption of 15.7 kWh/day is less than the consumptions for the other types of controllers, depicted in Figs. 12–14. This cannot be considered as an advantage because it reflects the average users preferences, while extreme preferences are used for the other controllers.

The energy consumption per square meter is higher for the first building compared to the other two buildings. This is attributed to the building envelope characteristics and the insulation material used for the first building walls.

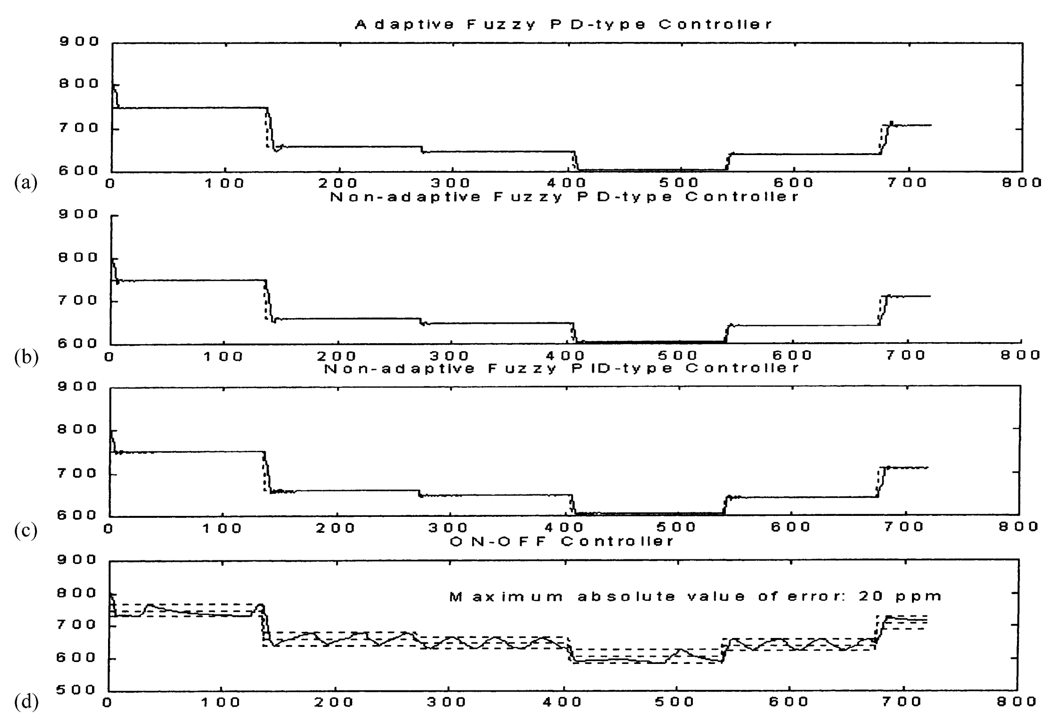

Fig. 17. The CO_2 concentration responses for the third building, using (a) the adaptive fuzzy PD controller, (b) the non-adaptive fuzzy PD controller, (c) the non-adaptive fuzzy PID controller and (d) the ON–OFF type controller.

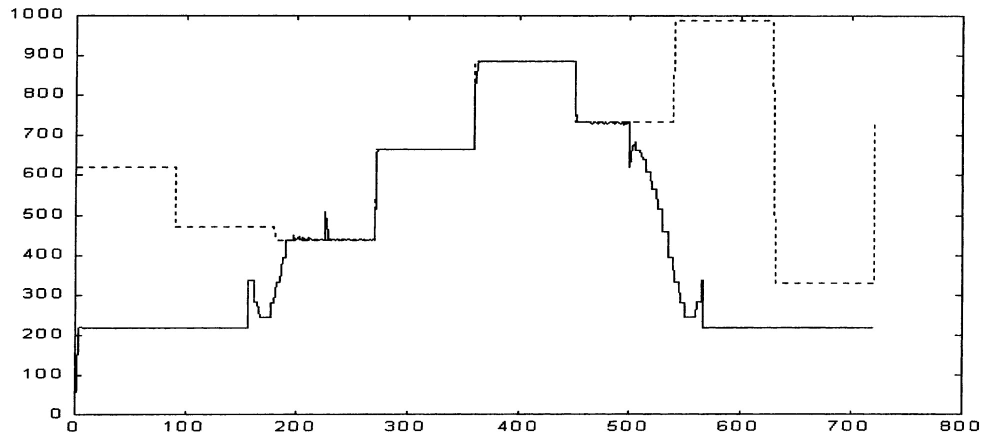

Fig. 18. The illuminance response using the non-adaptive fuzzy PD controller.

Considering double-glazing windows, the influence of one or two window openings as concerns the energy consumption is negligible.

The indoor air quality regulation is performed using natural ventilation. The window opening never goes higher than 10% of the total opening. There are no significant differences regarding the CO_2 concentration response with and without adaptation for the fuzzy controller (Figs. 15, 16 and 17) for all three buildings. An adequate number of simulations are performed for various indoor air quality demands. Improving the indoor air quality, using natural ventilation during winter, can increase the energy consumption of up to 5–10 kWh/day. Mechanical ventilation, which is widely used in northern European countries, can be less energy wasting (especially if it provides heat recovery) depending on the climatic conditions and the mechanical ventilation facility. Night ventilation though is far more energy efficient during summer. Mechanical ventilation has a well-predicted airflow, causing no severe disturbances compared to the unpredicted airflow of natural ventilation. Taking into account that the controller responds well using natural ventilation techniques, it is assumed that can also be applied for mechanical ventilation applications, where the opening of the window is replaced by the airflow damper opening. The ON–OFF regulation of the indoor air quality has a tolerance of 50 ppm of $[CO_2]$, which is completely acceptable.

The response of the illuminance levels using the fuzzy PD controller is depicted in Fig. 18. The fuzzy PD controller reaches optimum response for the illuminance levels, therefore the adaptive fuzzy PD controller is not required for visual comfort regulation. The illuminance preferences vary in the range from 500 to 1000 lux. The users requirements are fulfilled simply regulating the shading devices during the day. Thus, no energy consumption for electric lighting is required. The overall energy consumption for electric lighting overnight is 0.0139 kWh/day using two bulbs of 100 W each.

5. Conclusions

From all controllers proposed in this paper, the adaptive fuzzy PD controller ensures the lower energy consumption, even under extreme users preferences. The reduction of the energy consumption, compared to that of the conventional ON–OFF control, is achieved optimizing the response of the PMV index. This is done by elimination of overshootings and oscillations that contribute to significant increase of energy waste. The indoor air quality requirements are reached for all extreme conditions, but the energy consumption for heating is increased.

For the satisfaction of the indoor visual comfort requirements, the non-adaptive fuzzy PD controller is sufficient.

In cases where the artificial intelligence techniques proposed in this paper, couldn't be easily applied, the optimized ON–OFF control, using the PMV index as a controlled variable, is a good compromise.

Finally, all controllers are applicable in any building, without the necessity to take into account the specific building characteristics and without any modifications to the controller's structure.

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