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# Indoor-environment simulator for control design purposes

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ABSTRACT

Building-management systems (BMSs) are becoming increasingly important as they are an efficient means to having buildings that consume less energy as well as for improving the indoor working and living environments. On the other hand, implementing automated control and monitoring systems in buildings is still relatively new, and one of the obstacles for their wider implementation is the ease of setting up the appropriate parameters for the controllers. During our work on an experimental controller for an indoor environment that is installed in an occupied office in the building of the Faculty of Civil and Geodetic Engineering, University of Ljubljana, Slovenia, it has become evident that a computer simulator of the system would be a welcome aid for the optimization of its functioning. In this paper we present a simulator application developed in a combined Matlab/Simulink and Dymola/Modelica environment. The simulator mirrors the functioning of the control system and the dynamics of the indoor environment, where the thermal model of the simulator was developed in the Dymola/Modelica environment, while the illuminance model was developed and parameterized as a black-box model on the basis of measurements in the Matlab environment. The simulator can emulate the response of conventional ON/OFF controllers as well as fuzzy controllers. The paper presents the design of the simulator with all of the key elements described. The underlying models for the thermal and illuminance control are also separately described. Finally, the performance of the simulator is presented for a selected day.



## 1. Introduction

The use of automated control in buildings has been shown to have a great deal of potential for reducing the energy consumption of HVAC systems as well as for artificial illumination [1,2]. Building automation can also greatly enhance the quality of the indoor environment and in this way increase the performance and enhance the comfort of the occupants. Recent developments in building-management systems (BMSs) have been predominantly driven by the advances in computers and telecommunications technology. The possibilities of using wireless-communication technologies as well as a reduction in prices have enabled their wider application in the construction industry. Despite this it needs to be stressed that the primary focus in the development was not on new control concepts, but on the application of existing technologies [3], although advanced control methods have been used in numerous experimental systems. The use of fuzzy-logic in the field of indoor-environment control was presented by Kolokotsa et al. [4] and Kristl et al. [5] for the regulation of thermal and visual environments as well as for the control of ventilation, while Guillemin [6] supplemented fuzzy-logic controllers with genetic algorithms for the optimization of the decision matrix. Neural networks are also used. Argiriou et al. [7] employed them for the control of hydronic solar heating, while Castilla et al. [8] used them for thermal-comfort models of HVAC systems. Široky et al. [9], Castilla et al. [10] and Ma et al. [11] showed through their work that model predictive control (MPC) was well suited for the control of an indoor environment. An upgrade of the conventional MPC, the adaptive multiple model MPC, was implemented by Kim [12] for the optimization of thermal storage in buildings. Another point that is also very evident in the field of "smart buildings" is that in many building applications the primary goal is just a reduction of the energy being consumed. Other benefits that could be reached with a holistic control system for the indoor environment [13] (e.g., enhanced daylighting [14], user comfort [15], indoor-air quality [16]) are neglected or ignored [17]. Such an approach contradicts the basic philosophy of bioclimatic design, where the higher efficiency of buildings does not only mean the use of less energy for

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heating and cooling, but primarily better working and living conditions for the occupants [18]. With an integrated treatment of the buildings and installed systems, better results can be achieved simultaneously in terms of occupant comfort as well as energy use.

The Integral Control system of Indoor Environment (ICsIE) presented and described by Košir et al. [17] is based on the above-stated basic presumption of bioclimatic design. The system regulates the indoor workplace illuminance, heating, cooling and natural ventilation, linked to the indoor $CO_2$ concentration. The ICsIE is installed in an occupied office of the main building of the Faculty for Civil and Geodetic Engineering in Ljubljana, Slovenia. The indoor environmental conditions are regulated via available actuators that consist of external motorized venetian blinds, ceiling-suspended radiant heating and cooling panels, conventional office fluorescent lights and an automated window. The control and monitoring of the environmental conditions are achieved through an elaborate array of internal and external sensors. These sensors record the internal and external illuminance, the temperature, the relative humidity, the internal $CO_2$ concentration, the global and reflected solar radiation, the precipitation detection, the wind speed, the wind direction and the consumption of energy for heating and cooling. Further information regarding the control logic and the structure of the system is available in the above reference.

By using and experimenting with the ICsIE it has become evident that if appropriately tuned, the system performs satisfactorily [14,17]. Nonetheless, because at its core the ICsIE utilizes a black-box approach, the knowledge of the system operators has to be substantial in order to achieve a satisfactory control performance. Such an approach can also be tedious for the operators as they have to set-up the control parameters and wait for the experimental results. Even if the results are satisfactory, the operator cannot know if the system set-up that was used is the best possible for the given task [3] as the experiment cannot be repeated due to changes in the weather. What is missing is an underlying physical model or a simulator of the control system. Although the thermal (i.e., heating and cooling) control algorithm implemented in the ICsIE is partly based on an earlier thermal model of a building developed by Škrjanc et al. [19] and Sodja et al. [20], the illuminance control is completely based on experimentally acquired knowledge [5,21]. In order to overcome the above-described shortcomings associated with conducting real-life experiments with the ICsIE to set-up its control parameters, a simulator application has been developed. The simulator enables the testing of different set-ups of the ICsIE on a standard PC equipped with the Matlab and Simulink [22] applications. The simulations are conducted on the basis of real weather data recorded by the ICsIE for the duration of its operation since 2009. This paper presents the methodology of the simulator, the underlying models for the thermal and illuminance control as well as the user interface and functioning of the application.

### 1.1. The purpose of the simulator

The simulator was developed in order to obtain a virtual environment that would accurately imitate the real-world conditions and enable the rapid and process-safe testing of the impact of all the included parameters on the results of the simulation. Besides that, the aim was also to achieve the relatively simple use of the simulator, even for inexperienced users. For this purpose a user interface was added, through which the parameters can be adjusted and different actions can be performed with the user controls. The presented simulator has several advantages over real-system testing, for instance: the simulation runs are very fast in comparison to the real-time experiments; the simulations can be performed for any day of the year, independent of the actual day of the year; the simulation runs can be performed for several days in a row (up to ten) without having to wait for several days to get an overall insight into the results (e.g., for control design or testing purposes); a day with the desired weather conditions can be selected; and the simulation can be repeated multiple times with different control parameters. At this point, the simulator gives an immediate insight into the impact of various parameters, such as hysteresis, references, time constraints, fuzzy controllers' settings, etc., as well as the end results, which can be obtained relatively quickly and afterwards tested on a real system. Since the real-system testing, besides being slow, could also be disturbing to the occupants of the room, the use of the simulator for such purposes seems to be an optimal solution.

## 2. Simulator

The developed simulator is derived on the basis of an indoor environment installed in an occupied office in the building of the Faculty of Civil and Geodetic Engineering, University of Ljubljana, Slovenia. The indoor environment is on the 4th of 5 floors and consists of a room of approximately 40 m$^2$ area with one window of approximately 11 m$^2$ area and one outside wall. It is equipped with an automation system that consists of several control schemes, all the necessary sensors and actuators, automated venetian blinds with five possible positions, automated artificial illuminance (lights), automated window and heating/cooling panels.

### 2.1. Parts of the simulator

The simulator consists of three major parts, i.e., the controller, the model and the user interface, which are schematically shown in Fig. 1.

As can be seen in Fig. 1, the controller allows two different control algorithms to be executed, depending on the user's selection, i.e., ON/OFF control or fuzzy-logic control. The first algorithm consists of multiple ON/OFF controllers for illuminance, temperature, lights and $CO_2$ concentration, which are supported by several time and other restrictions. The fuzzy-logic algorithm consists of two separate fuzzy controllers for illuminance and temperature, and two ON/OFF controllers for the lights and for the ventilation connected to the $CO_2$ concentrations. Regardless of the control-algorithm selection, the controller is connected to the mathematical model of the temperature and illuminance processes in a feedback loop, which represents the second part of the simulator.

The model used in the simulator consists of two sub-models, which represent the necessary dynamic mechanisms describing the relations between the room temperature and the illuminance

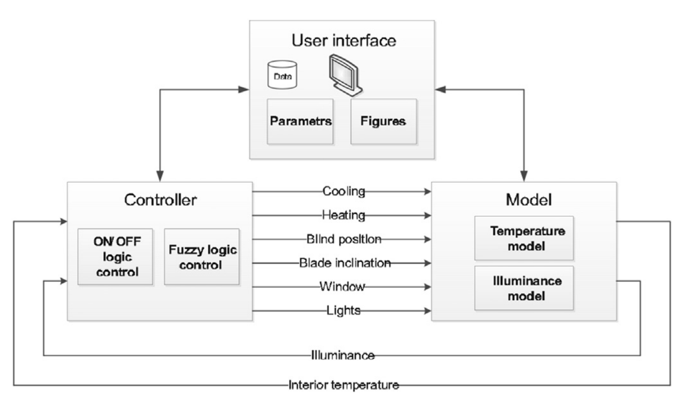


**Fig. 1.** Parts of the simulator.

levels, on the one hand, and the influential quantities, such as solar radiation, illuminance, outdoor temperature, blinds position, windows position, lights status, heating/cooling, etc., on the other. The first sub-model represents the thermal model of the building and considers all the relevant mechanisms of heat transfer to determine the indoor building temperature with regard to the constructional properties of the building and the influential quantities. The model used in this study was developed in our laboratory by Sodja and Zupančič [20] and was at that point validated using real-environment measurements in a smaller test chamber. The developed model was implemented in the Dymola/Modelica object-oriented environment. For the purpose of the simulator presented in this study, the existing model has been extended with some additional mechanisms and re-parameterized according to available measurements that correspond to the modelled room. The main differences between the model developed by Sodja and Zupančič and the model proposed in this work are as follows: the purpose of the old model was mainly to develop the Dymola/Modelica libraries, with its validation being of secondary importance; the old model incorporated the mechanisms describing roller blinds in order to obtain the amount of solar radiation that passes through the window, while the new model incorporates the mechanisms describing venetian blinds; the new model also incorporates mechanisms for the heating/cooling of the room using the heating/cooling panels and ventilation.

The second sub-model (realized in the Matlab and Simulink environments) represents the indoor illuminance model and considers the impact of the solar illuminance (external illuminance level), the position of the blinds and the status of the artificial lighting on the current illuminance levels in the room. The proposed illuminance model was developed especially for the purpose of the indoor-environment simulator and has not been used in any of the previous studies. The model was developed as a black-box model, using a fuzzy-inference system that was trained using real-time measurements as the inputs and outputs of the model. The black-box model uses the outdoor illuminance, the position of the blinds and the status of the artificial lighting as its inputs and, according to the set of parameterized fuzzy rules, computes the indoor illuminance level as its output.

The third part of the simulator, i.e., the user interface (Fig. 2, realized in the Matlab and Simulink environments), represents the connecting link between the processes running in the simulator background and the user performing simulation runs with different parameters and observing the corresponding results. The user interface is also an important part of the simulator; however, it does not represent the core of the simulator. For this reason, a large portion of this paper is dedicated to the presentation of the models and the controllers, as they represent the two basic parts of the simulator.

The presented simulator was developed, parameterized and validated using the Matlab, Simulink and Dymola environments, employing real-time measurements of the test room.

#### 2.1.1. ON/OFF control

The illuminance levels in the room can be changed either by the position of the blinds, the inclination of the blade or by the artificial lighting (the indoor illuminance can only be changed by one control variable at a time). The priority is always on the "passive" control variable, meaning that natural light is always the preferred solution for the indoor illuminance control. As described by Košir et al. [17], the correct position of the blinds in our simulator is determined by the ON/OFF inclination controller, whose I/O characteristic is shown in Fig. 3a.

As can be seen in Fig. 3a, the input to the controller is the error $e_L = ST_{IL} - M_{IL}$, where $ST_{IL}$ represents the indoor illuminance set-point and $M_{IL}$ represents the measured indoor illuminance,

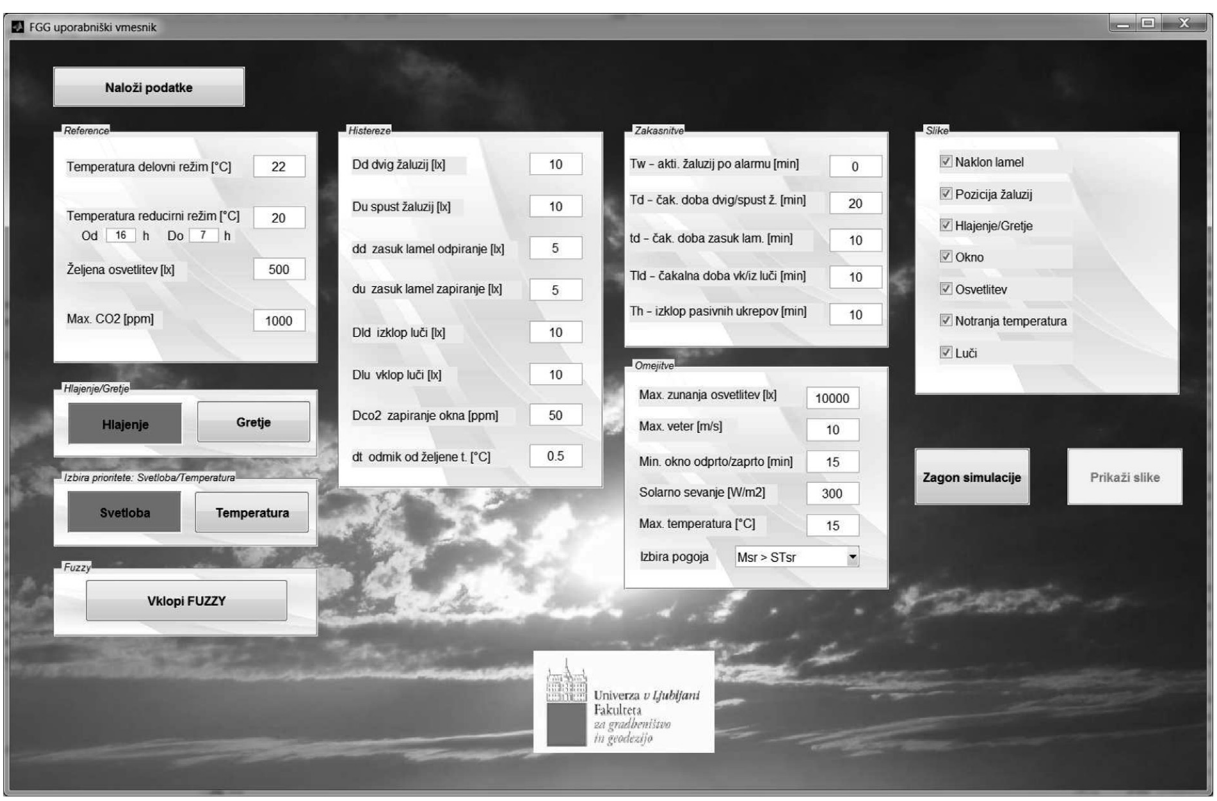


**Fig. 2.** User interface.

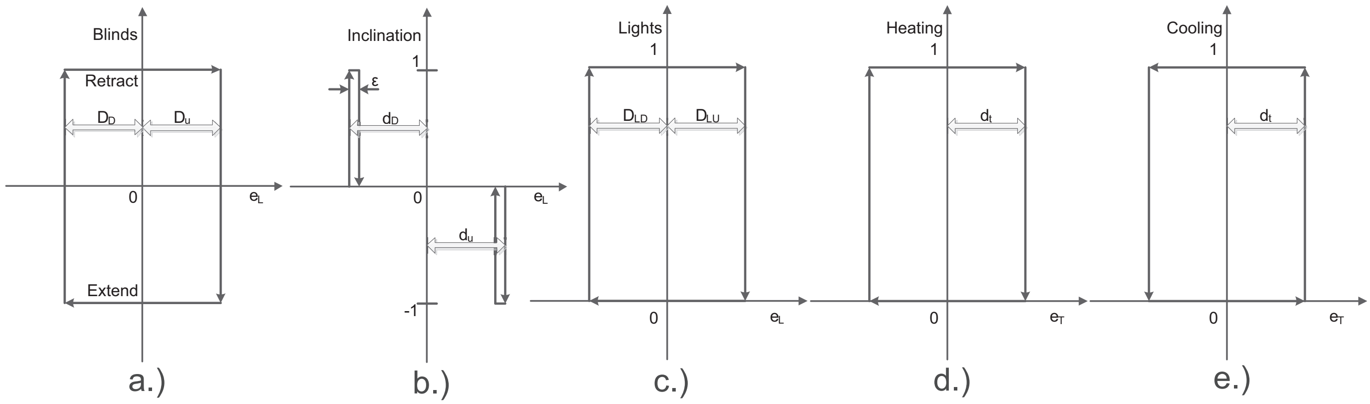


**Fig. 3.** I/O characteristics of the ON/OFF controllers.

obtained from the illuminance model. The hystereses $D_D$ and $D_U$ define the dead-zone between $-D_D$ and $D_U$, where the output of the controller does not change. If the error $e_L$ reaches the value $-D_D$, the controller detects a low illuminance in the room and checks to see whether the blades are completely open and retracts the blinds. If the error $e_L$ reaches the value $D_U$, the controller detects excessive illuminance and extends the blinds.

In the case that the blinds are extended, i.e., when the error $e_L$ is larger than $-D_D$, the indoor illuminance is controlled by changing the inclination of the blade. The blades can take four different angles, i.e., 0° (vertical position – completely closed), 30°, 60° and 90° (horizontal position – completely open). Fig. 4 shows a part of the flowchart from the paper of Košir et al. [17], which describes the blade-inclination control.

Labels $d_U$ and $d_D$ represent the hystereses that determine at which error value $e_L$ the blade inclination will be changed. Fig. 5 shows the control diagram that explains how the blade-inclination controller $R$ corrects the previous value of the slope and reduces the error value $e_L$.

Observing Fig. 5, label $w$ represents the indoor illuminance set-point, $e_L$ represents the indoor illuminance error, $R$ denotes the blade-inclination controller, $u$ represents the controller output, $u_1$ represents the input to the process, $P$ denotes the process (illuminance model) and $y$ represents the output of the process. Block $z^{-1}$ returns the previous value of the blade inclination. Thus, the current slope of the blades is defined as the prior slope changed for the value returned by the controller $R$.

Controller $R$, which is part of the control diagram shown in Fig. 5, is described by the I/O characteristic shown in Fig. 3b.

Fig. 3b shows that in the case of the error value $e_L = -d_D$ the controller outputs a value of 1; and −1 in the case of the error value $e_L = d_U$. Each time the controller outputs a value of 1, the blade slope is increased by one degree (if it is not equal to 90°). If the controller returns a value of −1, the blade slope is decreased by one degree (if it is not equal to 0°). $\epsilon$ represents an infinitesimal value as the output of the controller immediately drops to zero when the absolute error is reduced.

The indoor illuminance is also controlled by means of artificial lighting. The lights are controlled by the ON/OFF controller, whose I/O characteristic is shown in Fig. 3c.

Fig. 3c shows that the lights are turned on in the case of an error value $e_L$ being smaller than $-D_{LD}$, and are turned off in the case of an error value $e_L$ being larger than $D_{LU}$. The dead-zone defined by the hysteresis $D_{LD}$ in $D_{LU}$ denotes the area where the status of the lights does not change. The algorithm, which together with the lights controller determines the status of the lights, also includes restrictions due to energy efficiency. The lights can only be turned on when the blinds are completely retracted and the external illuminance is below the lowest limit, denoted by $ST_{EIL}$ (this restriction is valid if it is assumed that illuminance has priority over temperature – described below). Due to energy conservation, it is better to completely retract the blinds first and afterwards turn the lights on. The rules of the controller are set in such a way as to follow the principles of bioclimatic design. One such principle is that the building should use the available natural resources (i.e., natural daylight) to the maximum, and if the desired indoor conditions are not met with these, then the controller activates additional active measures (i.e., artificial illumination).

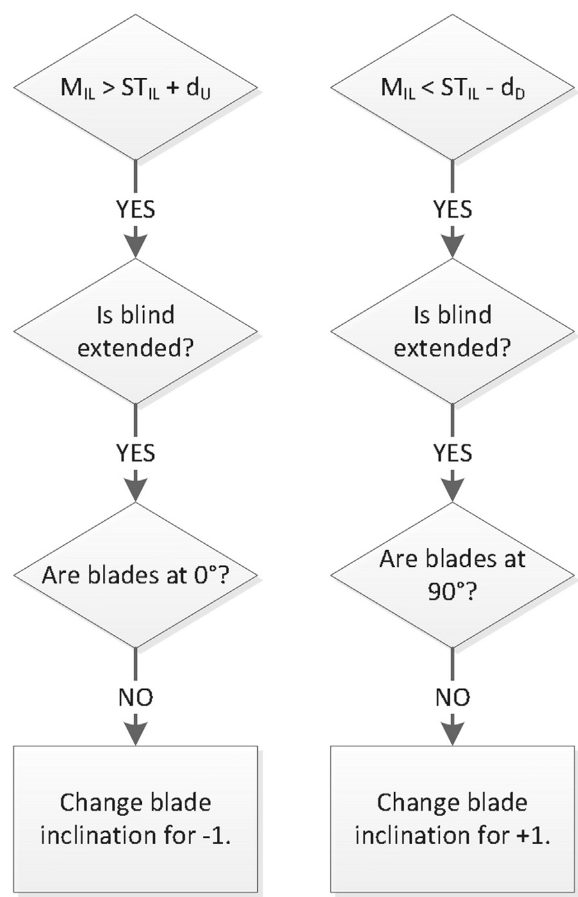


**Fig. 4.** Flowchart of the blade inclination control.

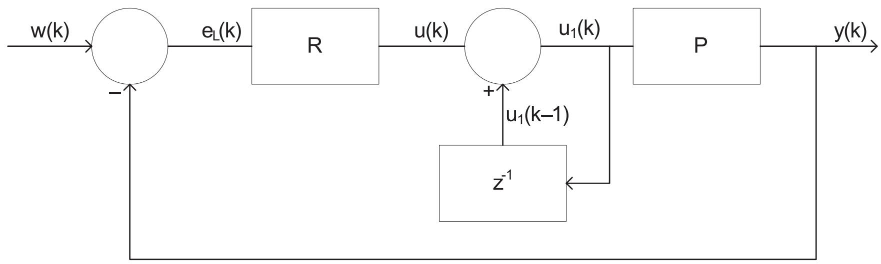


**Fig. 5.** Feedback control of the blade inclination.

The purpose of all the described hystereses is to ensure that the inclination of the blade, the position of the blinds and the status of the lights are not changed each time the illuminance level changes. However, in the case of the presented model, the limitations represented by the hystereses do not suffice, due to large deviations from the set-point values, which often occur in illuminance levels. Therefore, it is important that the illuminance control algorithm also utilizes additional time limitations, which determine the time intervals during which the position of the blinds, the inclination of the blade and the status of lights can be changed. When dealing with the control of external blinds in practice, another limitation, i.e., a strong wind, has to be taken into consideration. For this reason, the simulator also includes a mechanism to prevent the retraction of the blinds, which prevents the blinds from being damaged due to a strong wind.

The temperature in the studied room can be affected in multiple ways, i.e., switching on the heating/cooling panels, using solar radiation as a heating source or opening the window for passive cooling. The temperature-control algorithms allow two basic modes of operation, i.e., the heating mode and the cooling mode, where the temperature is controlled by an ON/OFF controller, regardless of the selected operating mode. Fig. 3d and e shows the I/O characteristics of the controller in the heating and cooling modes, respectively.

The input to the controller is the error value $e_T = ST_T - M_T$, where $ST_T$ represents the indoor-temperature set-point and $M_T$ represents the measured indoor temperature. The output of the controller can be 0 or 1, where 1 denotes that the cooling or heating is turned on and 0 denotes that the cooling or heating is turned off. In Fig. 3d and e the hysteresis is represented by $d_t$, which means that the width of the dead-zone is $2d_t$. Fig. 3d shows that the heating is turned on in the case of the error value $e_T = -d_t$ and is turned off in the case of the error value $e_T = d_t$. When the controller operates in the cooling mode (Fig. 3e), the process of activation is reversed, meaning that the cooling is turned on if the error value $e_T = d_t$ and is turned off if the error value $e_T = -d_t$.

When the controller is operating in the cooling mode, the passive cooling has priority over cooling with the cooling panels, which means that when the outdoor temperature is lower than the indoor reference temperature, the window opens. Due to measurement noise associated with the outdoor temperature, the algorithm incorporates a limitation that defines a minimum time for which the window must be opened or closed. In the case of rain or a higher outdoor temperature compared to the set-point temperature, the window remains closed and the cooling panels are turned on.

Since the intensity of the solar radiation significantly affects the indoor temperature, the algorithm has the possibility to select a priority quantity, i.e., the temperature or the illuminance [17]. If the illuminance has priority over the temperature, the blinds controller ensures that the illuminance levels are as equal as possible to the defined set-point. If the temperature has priority over the illuminance, the blinds position and the blade inclination are controlled in such a way as to prevent overheating in the summer and to make use of the solar radiation for passive heating in the winter. Therefore, in the summertime, when sufficient solar radiation and/or a sufficient external temperature are present, the blades are completely closed. On the other hand, in the wintertime, the blinds are retracted if the solar radiation exceeds the limit of $ST_{SR}$ and/or the outdoor temperature is higher than the set limitation $ST_{to}$.

The simulator also enables control of the carbon dioxide concentration, which represents one of the air-quality indicators in the room. The algorithm is based on the ON/OFF controller with hysteresis $D_{CO_2}$, which returns a value of 1 in the case of the error value $e_{CO_2} = -D_{CO_2}$, meaning that the window is opened; and a value of 0 in the case of the error value $e_{CO_2} = D_{CO_2}$, meaning that the window is closed. The error value is defined as $e_{CO_2} = ST_{CO_2} - M_{CO_2}$, where $ST_{CO_2}$ represents the $CO_2$ concentration set-point and $M_{CO_2}$ is the measured $CO_2$ concentration. In the case of rain, the window stays closed.

### 2.1.2. Fuzzy control

The complete ON/OFF control algorithms have some drawbacks (e.g., ON/OFF controllers can only have two different output values and they cannot follow the reference signals without errors. This causes the oscillations around the reference signals, when applied to the real test environments. Therefore, the control algorithm described above was improved with fuzzy-logic. The fuzzy controllers were chosen as they seem to be the best option, since the concept of fuzzy control is very close to human decision-making, so the inexperienced users can understand them. The controllers (ON/OFF) for the blinds position and the blade inclination were replaced

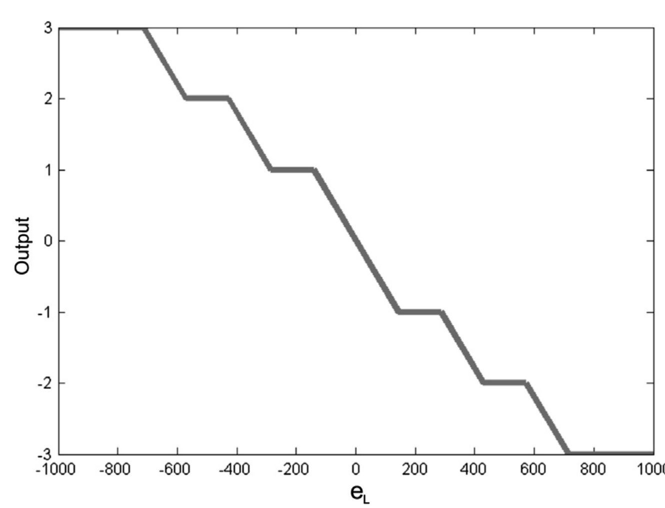


**Fig. 6.** Fuzzy illuminance control.

by the fuzzy-logic P controller, whose I/O characteristic is shown in Fig. 6. The controller was developed using the built-in Matlab FIS editor [23] and incorporates a fuzzy-inference system in a Takagi-Sugeno (TS) [24] form, which returns crisp values to its output.

The input to the illuminance fuzzy controller is the error value $e_L$, which varies in the range between −1000 and 1000, while the output from the controller can take values between −3 and 3. Fig. 7 shows the shape and the distribution of the membership functions of the input variable $e_L$, which are used by the illuminance fuzzy controller for the appropriate blinds position and blade inclination.

The output of the controller defines the change of the blinds or blade position, where a new position is defined when the current position changes to the value returned by the controller. Since in this case only one controller for the blinds position and the blade inclination is used, the position and the inclination were merged and labelled with values between 0 and 4. Values 0, 1, 2 and 3 represent the blade inclination from 0° (vertical position) to 90° (horizontal position) and at the same time indicate that the blinds are extended. Value 4 means that the blinds are completely retracted, which allows an unobstructed light flow into the room. The actual output from the illuminance fuzzy controller is determined depending on which fuzzy set the error $e_L$ belongs to and is shown in Table 1. The labels of the fuzzy sets have the following meaning: XLN – extra-large negative, LN – large negative, MN – medium negative, SN – small negative, ZE – zero, SP – small positive, MP – medium positive, LP – large positive and XLP – extra-large positive.

Since some processes, such as lights operation and room ventilation, do not need a more complex fuzzy control, simple ON/OFF controllers, as described previously, were retained in the extended control scheme. This means that the lights and room ventilation are still controlled by the ON/OFF controllers, whose I/O characteristics have already been shown. In order to avoid the movement of the blinds and switching on/off of the lights too often, time limitations were added in a similar manner as with the ON/OFF control.

Similar to the fuzzy illumination controller, a fuzzy temperature controller was also developed using Matlab's FIS editor. In the case of temperature control, a fuzzy PD controller was used, with two inputs, i.e., the error value $e_T = ST_T - M_T$ and the indoor-temperature derivative $dT$. Similarly, the fuzzy-inference system is of the TS form with triangular membership functions. When determining the if-then fuzzy rules, the logical operator AND (MIN) was used between the two fuzzy sets of linguistic variables and the weighted average was used for the de-fuzzification technique. The I/O characteristic of the default fuzzy temperature controller is shown in Fig. 8.

**Table 1**
Fuzzy control rules.

| | | | |
|---|---|---|---|
| if $e_L$ is | XLN | then output is | −3 |
| if $e_L$ is | LN | then output is | −3 |
| if $e_L$ is | MN | then output is | −2 |
| if $e_L$ is | SN | then output is | −1 |
| if $e_L$ is | ZE | then output is | 0 |
| if $e_L$ is | SP | then output is | 1 |
| if $e_L$ is | MP | then output is | 2 |
| if $e_L$ is | LP | then output is | 3 |
| if $e_L$ is | XLP | then output is | 3 |

As can be seen in Fig. 8, the calculated error can take values between −7 and 7, the temperature derivative can take values between −2 and 2, while the output from the controller can take values between −1 and 1; 1 meaning that the heating is on, −1 meaning that the cooling is on, and 0 meaning that both the heating and cooling are turned off. When the controller returns a value of −1, the algorithm checks whether it is possible to make use of the passive cooling, by opening the window. Meaning, if the outdoor temperature is lower than the desired indoor temperature, the window will be opened. If this is not the case or if it rains, the cooling panels are turned on. When the control algorithm determines that heating is required, the heating panels are switched on.

Similar to the ON/OFF control, the fuzzy controller also allows the selection of the priority quantity (illuminance or temperature).

### 2.1.3. Thermal and $CO_2$ models

The thermal and the $CO_2$ models used in the simulator are developed in the Dymola/Modelica object-oriented environment. This allows the use of objects such as walls, windows, heating/cooling panels, heat flows, etc., each described by its own dynamic characteristics. The objects have to be put together in order to obtain a model of the room with an arbitrary complexity. Such a model of a room, if treated as an object, can be used for simulating the thermal and $CO_2$ concentration processes of any desired room or building. However, the model, to achieve its purpose, has to be properly parameterized and validated using relevant measurements of a real room environment. The real-time measurements

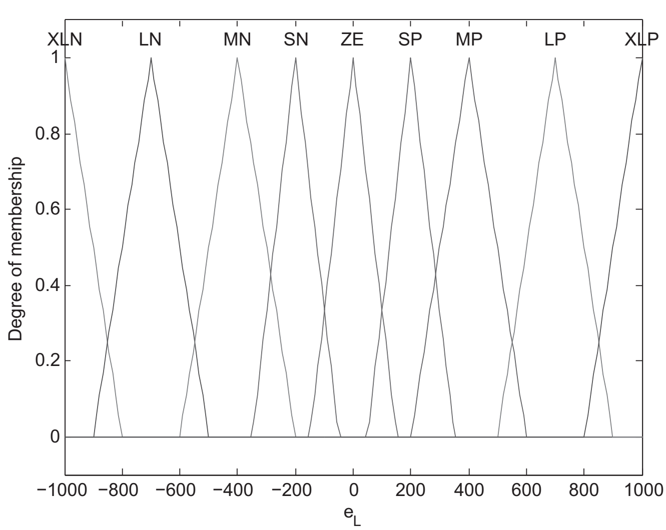


**Fig. 7.** Fuzzy set of input variable $e_L$ for the illuminance control.

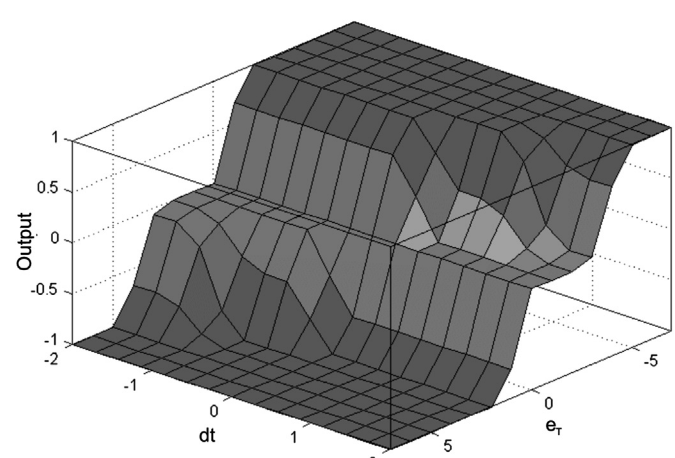


**Fig. 8.** Fuzzy temperature control.

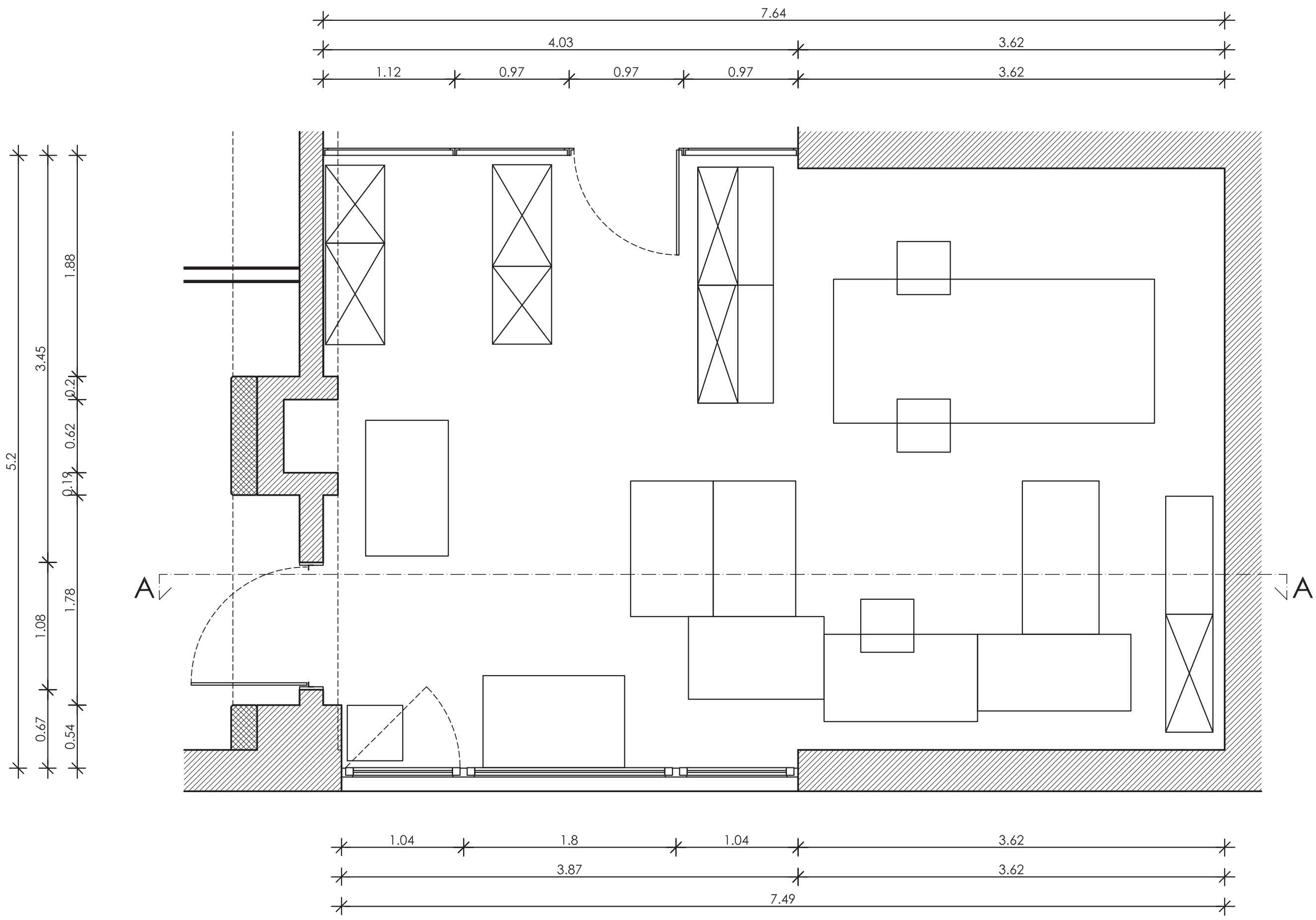


**Fig. 9.** Floorplan of the modelled room. The outdoor wall is on the bottom side of the figure, with the marked window area.

used in this study are obtained for a room that is located on the 4th out of a 5-floor building, with one outdoor wall having a window, facing south-west (rotated by approximately 30° counter-clockwise from the east-west direction). The dimensions of the room are 7.48 m × 4.95 m × 3.88 m (l × w × h), where the outdoor wall is the longest. The area of the window is 11.4 $m^2$. Fig. 9 shows the floorplan of the particular room.

The characteristics of the room used in the model are as follows. The thickness of the outdoor wall is 260 mm, with a $U$ value of 1.29 $W/m^2$ K; the thickness of the indoor walls is 220 mm, with a $U$ value of 1.17 $W/m^2$ K; the thickness of the floor and ceiling is 520 mm, with a $U$ value of 0.83 $W/m^2$ K; and the $U$ value of the window is 2.9 $W/m^2$ K.

The goal of the presented model is to accurately represent the indoor temperature based on the initial conditions and the influential quantities. The parameterization of the model was carried out using real-time measurements (15-s sample time) of the following: solar radiation (global and diffuse), outdoor temperature, indoor temperature, blinds position, window position and heating or cooling status. Fig. 10 shows the validation of the thermal model by comparing the measured and model simulated indoor temperatures for 10 consecutive days.

As can be seen in Fig. 10, the indoor temperature obtained using the model simulation accurately follows the measured indoor temperature for all 10 days. Therefore, the validation of the model is considered as successful and the model can be used as a satisfactory approximation of the real conditions in the building for further simulations using different control algorithms.

Finding the $CO_2$ concentration in the simulator can involve two different mechanisms. The first mechanism is to use the actual $CO_2$ levels from the measured data, while the second mechanism involves a simple nonlinear differential equation, which determines the amount of $CO_2$ according to the room volume, the window position and the number of persons inside the room:

$$\frac{dC_{in}}{dt} = \frac{1}{V_{room}}\left(\phi_{airflow}(C_{out} - C_{in}) + \phi_{person} n_{person} \cdot 1000\right), \qquad (1)$$

where $V_{room}$ represents the volume of the room (set to 160 $m^3$), $C_{in}$ represents the $CO_2$ concentration in the room in ppm, $\phi_{airflow}$ represents the amount of airflow that passes through the window (set to 0.025 $m^3/s$), $C_{out}$ represents the outdoor $CO_2$ concentration (set to 500 ppm), $\phi_{person}$ represents the $CO_2$ generation rate of one person (set to 0.005 $m^3/s$) and the $n_{person}$ represents the number of people in the room.

Fig. 11 shows the differences in $CO_2$ concentration and indoor temperature between an occupied and an empty room.

As can be seen in Fig. 11, the first-panel figure shows a comparison of the temperature of the empty room (black solid line) and the temperature of the occupied room (grey dashed line). The second-panel figure shows the comparison of the empty room (black solid line) and the occupied room (grey dashed line) $CO_2$ concentration using an ON/OFF control. For the occupied room, the simulation assumes there are three people present in the room (100 W each), each using a laptop computer (50 W each) during office hours (8.30–16.30), denoted in the third-panel figure. From

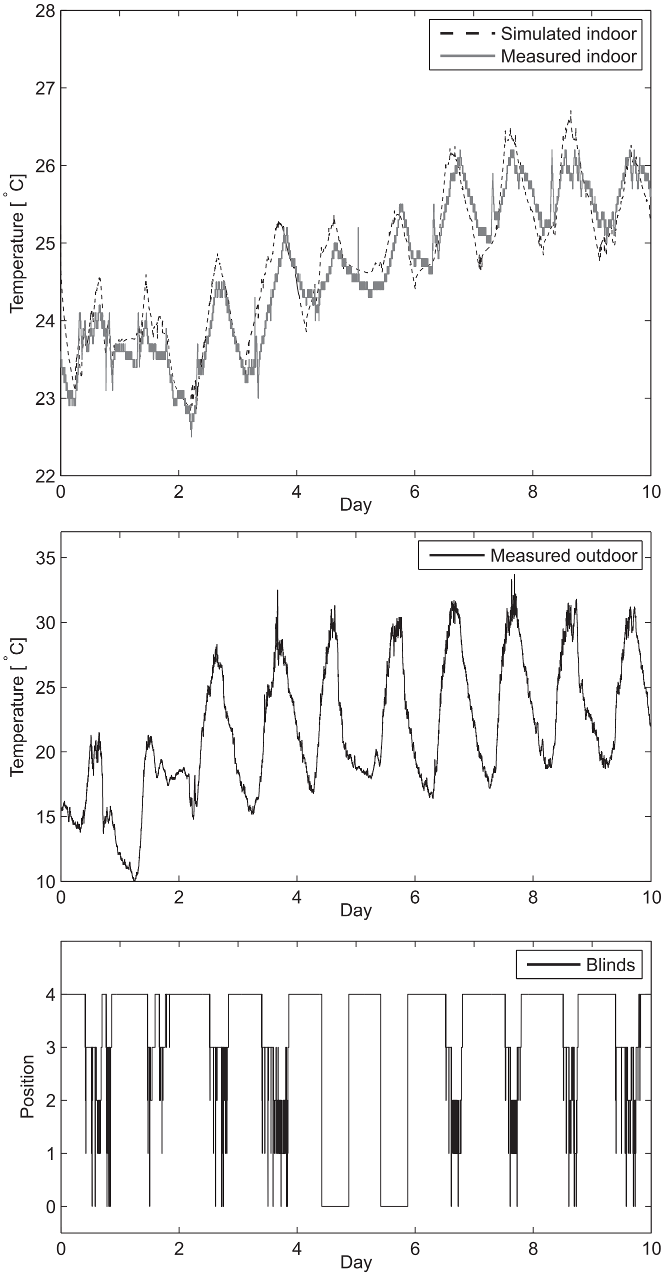


**Fig. 10.** Thermal model validation; comparison between the measured and model simulated indoor temperatures for 10 consecutive days.

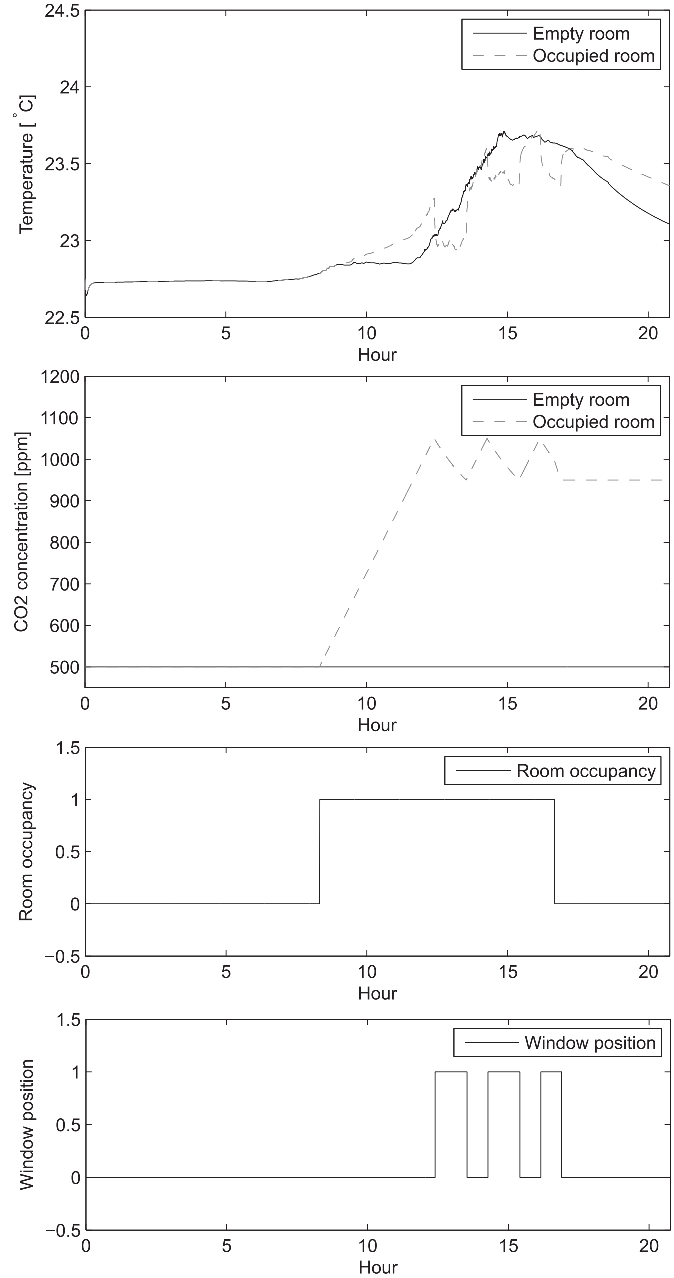


**Fig. 11.** First panel: comparison of the empty room (black solid line) and the occupied room (grey dashed line) temperature; second panel: comparison of the empty room (black solid line) and the occupied room (grey dashed line) $CO_2$ concentration; third panel: room occupancy (0 – empty, 1 – occupied); fourth panel: window position (0 – closed, 1 – opened).

the indoor temperature comparison it is clear that occupancy of the room quickly starts to increase the temperature of the room, which rises until approximately 12.00, when due to the high $CO_2$ concentration (1050 ppm) a window is opened, visible from the fourth-panel figure. When the $CO_2$ concentration drops below 950 ppm the window is shut and the temperature starts to rise. A similar pattern repeats two more times until the office hours are over.

### 2.1.4. Illuminance model

The illuminance model used in the simulator is developed and parameterized as a black-box model, based on the TS fuzzy-inference system. The model, in TS form, approximates a nonlinear system by smoothly interpolating affine local models [24]. Each local model contributes to the global model in a fuzzy subset of the space characterized by a membership function. The affine TS model can be used to approximate any arbitrary function with any desired degree of accuracy [25–27]. The generality can be proven with the Stone-Weierstrass theorem [28], which suggests that any continuous function can be approximated by a fuzzy basis-function expansion [29].

Nowadays, there are many software applications that are able to compute illuminance levels at an arbitrary position in a room, given its geometry, global orientation, sun position and surface characteristics [30,31]. However, most of these programs use complex and computationally demanding algorithms that calculate the illuminance of a given surface based on the input light flow, intensity and angle, surface reflections, interior, etc. For this reason and due to the available real-time measurements of the room illuminance, a black-box fuzzy model, describing the in-to-out relations was developed. Since the light dynamics can be (from the room-illuminance point of view) considered as infinitely fast or instantaneous (in contrast to the temperature dynamics) the black-box model is regarded as a static model from the modelling perspective. This means that the change of the outdoor illuminance, blinds position or lights status has an immediate effect on the change of the observed surface illuminance, with no transitional dynamics. Fig. 12 shows the schematic representation of the model.

The parameterization of the fuzzy model, also known as training, involved 1 year of consecutive measurements, which include many possible real-world situations, such as sunny, cloudy, foggy weather, different sun azimuths and elevations, rapid illuminance changes due to partial cloudiness or incoming thunderstorms, lights operation, etc. The measurements that were used for the model training were the following: outdoor illuminance, blinds position, lights status (model inputs) and indoor room illuminance (model output). The model was built in a TS form, with five data clusters and Gaussian membership functions. The Fuzzy C-Means (FCM) clustering algorithm was used for model training. Fig. 13 shows the validation of the model by comparing the measured and model-simulated indoor illuminance for 10 consecutive days.

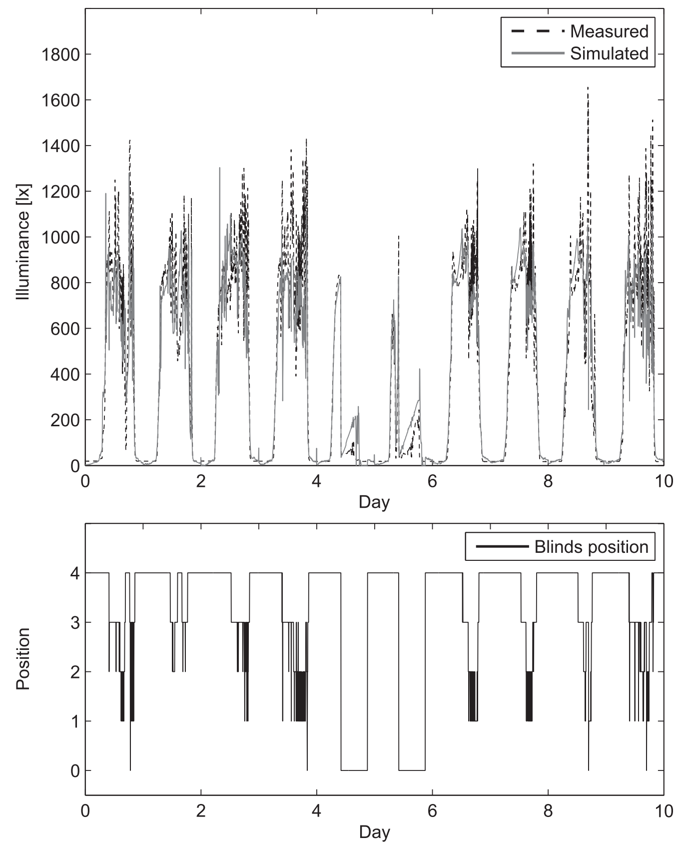


**Fig. 13.** Illumination model validation; upper-panel figure shows the comparison of the measured (black line) and model simulated (grey line) indoor illuminance for 10 consecutive days; the lower-panel figure shows the corresponding position of the blinds.

As can be seen in Fig. 13, the illuminance levels obtained by the model follow the measured illuminance levels satisfactorily, which indicates that the validation of the model can be considered as successful and the model can be used as a satisfactory approximation of the real conditions in the building for further simulations using different control algorithms.

The fuzzy black-box model has several advantages over conventional illuminance models. One of these advantages is that it does not use complex algorithms to obtain the illuminance intensity of a particular surface, but incorporates a simple set of fuzzy rules, which, by using several membership functions, outdoor illuminance levels and blinds positions, define a certain surface illuminance instead. Another advantage of the black-box model is that the fuzzy training algorithm is capable of determining the amount of light that passes through the blinds, where the position of the blinds can simply be provided as an integer number, i.e., 0 to 3 - blinds completely extracted, with the following angle: 0 – 0° angle (vertical), 1 – 30° angle, 2 – 60° angle, 3 – 90° angle (horizontal) or 4 – blinds completely retracted. According to the illuminance measurements and the position of the blinds (0–4) the fuzzy model is able to define the nonlinear relations between the blinds position, the outdoor illuminance and the corresponding decrease in the indoor illuminance, which would, in the case of a conventional illuminance model, have to be provided in some other way. Also, since the fuzzy model utilizes the in-to-out mapping of the measured data, the determination of the illuminance level should be more accurate than with conventional algorithms.

Although the black-box modelling approach has several advantages over conventional models, it also has some general drawbacks, where fuzzy is no exception. One of the disadvantages is that a substantial amount of data (measurements) in as many real situations as possible is needed in order to obtain a robust and versatile model. However, if the measurements are available, the black-box model represents one of the better options for determining the indoor illuminance, due to its simple structure and its parameterization. The other disadvantage is that the illuminance level in a building can only be obtained for the surface for which the measurements were obtained, in comparison to conventional models, which are usually able to determine the illuminance of an arbitrary surface in the building. Nonetheless, since inner-comfort studies mostly focus on particular workplace conditions in the building and not on complete rooms, illuminance information just from such a place seems sufficient. When the illuminance levels of different positions in a room are required, measurements can be

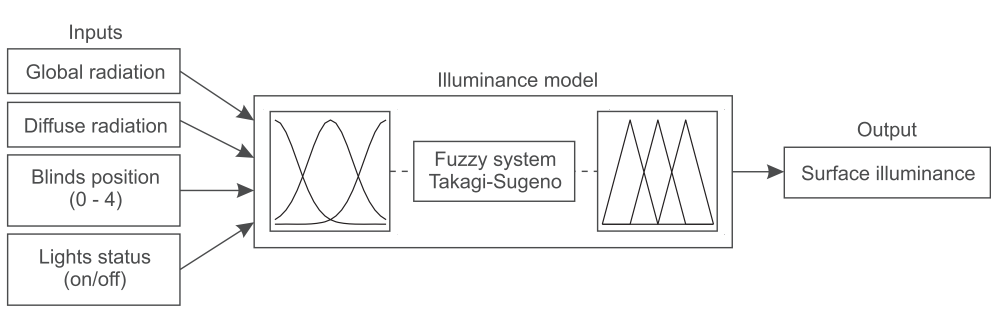


**Fig. 12.** Schematic representation of the fuzzy black-box illuminance model.

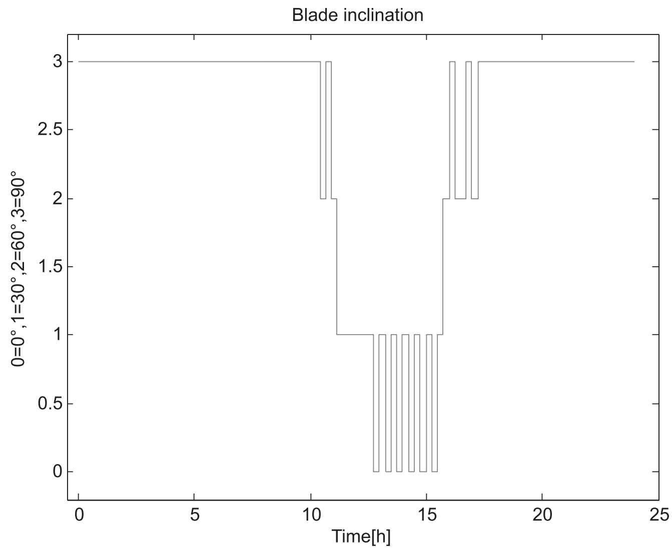


**Fig. 14.** Blade inclination (ON/OFF control).

obtained with multiple illuminance sensors, which are then used to train the multiple-output fuzzy model.

## 3. Using the simulator

In order to make the simulator user friendly, the user interface was designed in a manner that enables easy changing of the parameters and shows the results immediately. The interface parameters are logically divided into blocks belonging to references, hystereses, delays and restrictions. At the start of the simulation, all the parameters that are part of the controller or the model are set to the default values. However, before the start of the simulation, the parameters can be optionally configured. Also, real-time measurements of the relevant data, such as the outdoor temperature, the outdoor illuminance, the solar radiation, the wind speed, etc., are loaded for each simulation run, since the simulator is designed to use real-time measurements rather than artificially generated ones. The data can be loaded for up to 10 days. Depending on which time of the year the loaded data belong to, the heating or cooling mode can be selected. Moreover, a higher priority can be chosen for either the illuminance or the temperature.

As described previously, the simulator utilizes two control modes, i.e., the ON/OFF and the fuzzy control. The selection of the

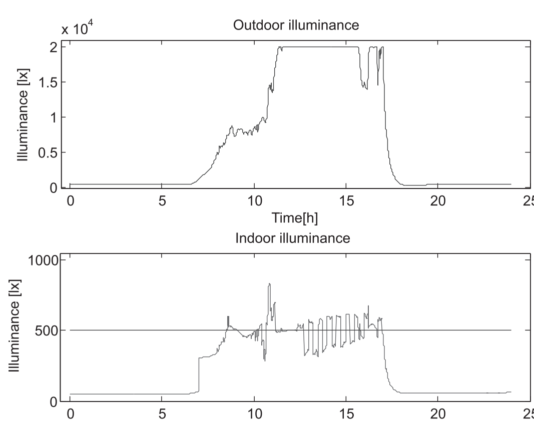


**Fig. 15.** Indoor and outdoor illuminance (ON/OFF control).

control mode is up to the user. When fuzzy control is selected, different pre-configured controllers for the illuminance and the temperature can be engaged. Moreover, using the built-in FIS editor, new controllers can be designed by either modifying the existing controllers or building them completely from scratch. All the generated controllers are saved and can be used for later simulation runs.

When the simulation is finished, user-selected figures are displayed from the set of pre-defined figures, such as: blade inclination, blinds position, heating/cooling, window position, indoor and outdoor illuminance, indoor and outdoor temperature and lights status.

## 4. Results

The following section presents the simulation results obtained with two different control modes, i.e., ON/OFF and fuzzy; the former for a winter and the latter for a summer day.

Since in practice it is undesirable for the blinds and the blade position to change too often, both control modes use a 30-min inactivity interval between two successive ascents/descents of the blinds and a 15-min inactivity interval between two successive inclination changes, meaning that the blinds can be retracted or extended only every 30 min and the blade inclination can be changed only every 15 min. The lights controller uses a 100 lx hystereses $D_{LU}$ and $D_{LD}$, while the inactivity interval is equal to 10 min. In both control modes, higher priority is assigned to the illuminance.

### 4.1. ON/OFF control

Fig. 14 shows the simulated blade inclination using the ON/OFF controller with 50 lx hysteresis. Values from 0 to 3 denote the blade position (0 − completely closed, 3 − fully opened).

As can be seen in Fig. 14, the blades close several times between noon and 3 pm, as the external illuminance is the highest at that time of the day. The blinds position (extended/retracted) is changed only twice, i.e., in the morning at 8.30 am, when the blinds extend, and in the evening at 5 pm, when they retract (not shown in the figure). The hysteresis of the controller of the blind position is equal to 100 lx.

Fig. 15 shows the indoor illuminance obtained from the model and the external illuminance obtained from the loaded data. The indoor illuminance set-point is 500 lx, chosen according to the recommended values stated in the ISO/CIE 8995-1 standard [32].

As shown in Fig. 15, the controller is able to roughly follow the desired reference value. However, due to the inactivity interval, the illuminance deviates from the reference value by more than 50 lx, as much as the controller hysteresis should allow, several times, which is a consequence of a rapid external illuminance change.

At the time of the working regime (between 7 am and 4 pm), especially in the morning, artificial illumination is needed, as the indoor illuminance, despite the fully-open blinds, does not reach the desired set-point. In our case, the lights are switched on from 7 am to 8.30 am, which can be seen in Fig. 15 as a rapid increase in the illuminance.

Since the ON/OFF control is simulated using the data for a winter day, the heating mode is selected within the user interface. The hysteresis of the temperature controller is equal to 0.5 °C.

Fig. 16 shows the indoor temperature ($T_{in}$) obtained from the model, the outdoor temperature ($T_{out}$) obtained from the loaded data and the indoor temperature set-point ($ST_T$) obtained from the user interface. The latter is equal to 25 °C at the time of the working regime (between 7 am and 4 pm) and 24 °C during the reduced regime. The set-point values for the indoor-air temperature were set according to the recommendations of the CR 1752 [33] document of the European Committee for Standardization. Also, the heating and window operation (0 – OFF, 1 – ON) are shown on the lower panel of the figure.

As shown in Fig. 16, the heating is turned on at the change of the set-point (7 am), and remains active until about noon, when the indoor temperature reaches 25.5 °C. The figure also shows that the indoor temperature starts to decrease at noon, which is the consequence of the open window. The ON/OFF controller, which controls the room's air quality, detects high carbon dioxide concentrations (>1050 ppm) and thus changes the window status to open. After one hour the window is closed and then the indoor temperature starts to rise.

### 4.2. Fuzzy control

The second example shows the simulation results obtained when using the fuzzy controller.

Fig. 17 shows the simulated blade inclination using the fuzzy controller. Values from 0 to 3 denote the blade position (0 – completely closed, 3 – fully opened).

As already mentioned, the blade inclination changes only if the blinds are extended, which in this case is at 8 am, when the outdoor illuminance is high enough, and then they retract at 8 pm, when the external illuminance decreases. The blade inclination increases and decreases depending on the size of the error $e_L$. All the changes of the blades inclination, except one, are one-step inclination changes. The interval of inactivity between two successive movements of the blinds is the same as in the first simulation.

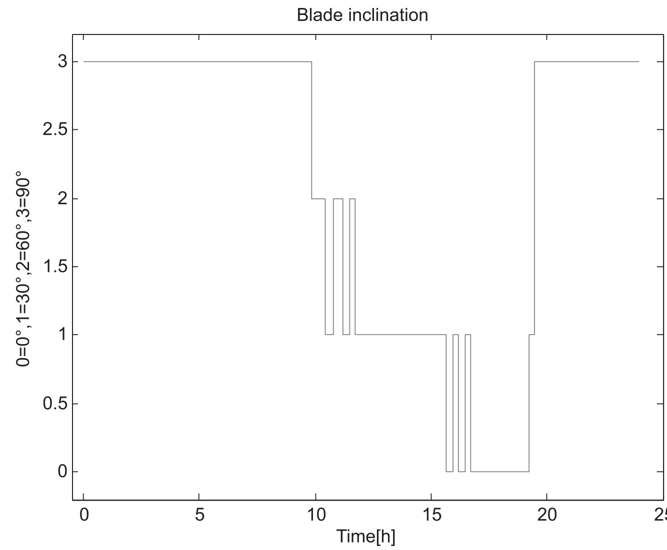


**Fig. 17.** Blade inclination (Fuzzy control).

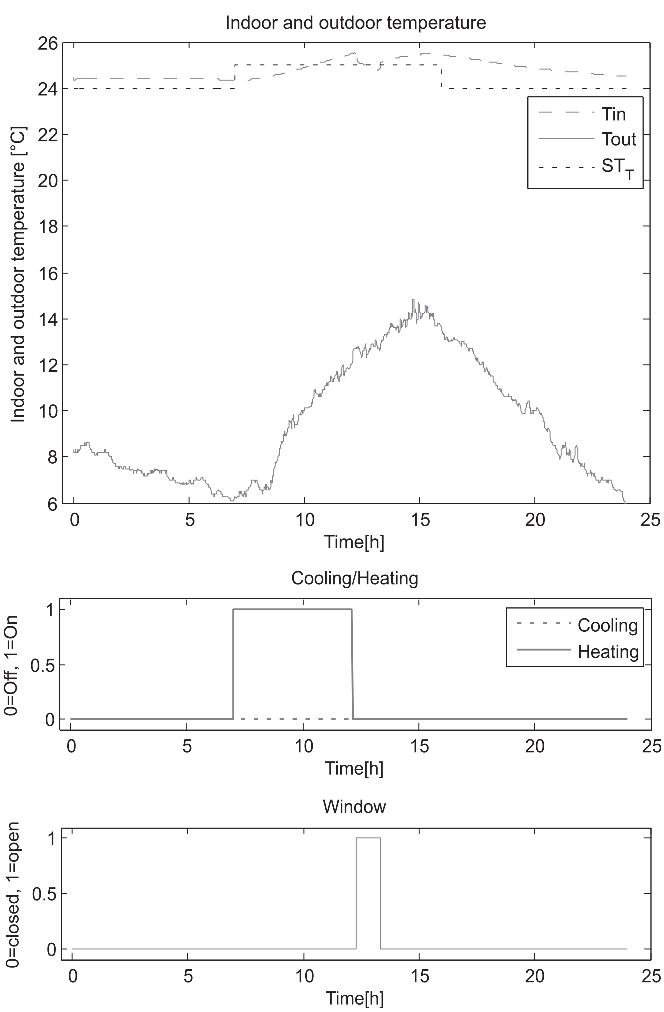


**Fig. 16.** ON/OFF temperature control; the upper panel figure shows indoor and outdoor temperature, the middle panel figure shows when the heating is turned on, and the lower panel figure shows the position of the window.

Fig. 18 shows the indoor illuminance obtained from the simulation and the measured outdoor illuminance. Therefore, the lights are turned on only between 7 am and 8 am.

As shown in Fig. 18, the indoor illuminance is close to the set-point in the working regime (between 7 am and 4 pm), which is provided by two controllers, i.e., the illuminance fuzzy controller and the ON/OFF lights controller. The hysteresis and the inactivity interval of the ON/OFF controller are the same as in the first simulation results.

Since the fuzzy control is simulated using the data for a summer day, the cooling mode is selected within the user interface. The hysteresis of the temperature controller is equal to 0.5 °C.

Fig. 19 shows the simulated indoor temperature, the measured outdoor temperatures and the user-defined indoor-temperature set-point.

As is clear from Fig. 19, the actual and the set-point temperatures between midnight and 7 am are close enough (small error $e_T$) so that cooling is not necessary. At 7 am, when the working regime is activated, the error $e_T$ increases because the

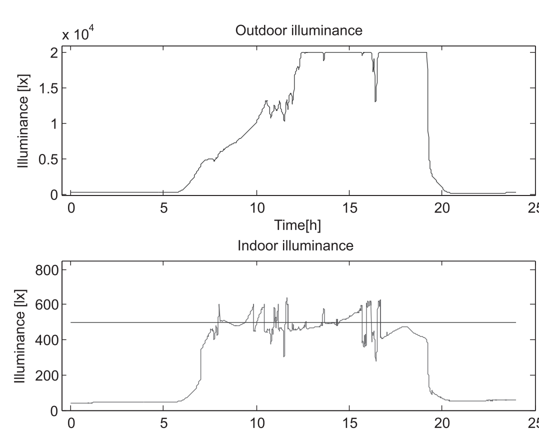


**Fig. 18.** Indoor and outdoor illuminance (Fuzzy control).

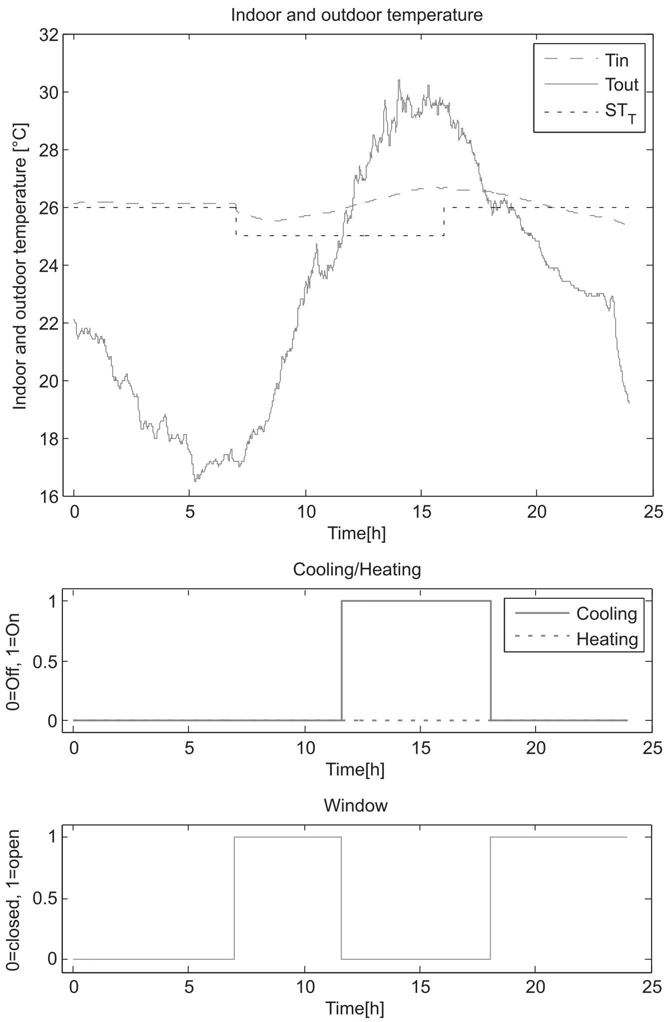


**Fig. 19.** Fuzzy temperature control; the upper panel figure shows indoor and outdoor temperature, the middle panel figure shows when the cooling is turned on, and the lower panel figure shows the position of the window.

temperature set-point is lower than in the reduced regime, meaning that the cooling must be engaged. When the outdoor temperature is lower than the desired indoor temperature, passive cooling is activated by opening the window. As the outdoor temperature reaches the desired indoor temperature, i.e., at about noon, the window is closed and the cooling panels are turned on. They stay activated until 6 pm, when the outdoor temperature decreases and passive cooling can be switched on again. As can be seen in Fig. 19, the indoor temperature continues to increase even though the cooling panels are turned on. The reason for this is that the panels are too small compared to the room volume, meaning that the full cooling power of the panels cannot counteract the higher outside temperatures.

## 5. Conclusion

This paper presents the development of a simulator and the underlying mathematical models of the experimental indoor environment. The models for the temperature and illuminance processes were built using the Dymola/Modelica object-oriented environment (temperature) and a fuzzy black-box (illuminance) approach. Both models were validated using the real-weather environment measurements of the ICsIE and proved to be accurate enough for further simulation studies in the framework of the presented simulator. The simulator, together with the user interface, enables users to perform a variety of different simulation experiments, from control-system design through energy conservation to studies of indoor comfort. As mentioned, the simulator has several advantages over real-system experimentation, such as fast and process-safe testing, unlimited repeatability and almost arbitrary weather conditions, to mention just a few of them. All the presented tools enable studies on the energy efficiency of buildings, building automation, better working and living conditions for the occupants, etc., to be initially performed on the PC simulation level and, after achieving satisfactory outcomes, applied to real living environments.

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