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An innovative lighting controller integrated in a self-adaptive building control system

A. Guillemin*, N. Morel

Laboratoire d'Energie Solaire et de Physique du Bâtiment (LESO-PB), Ecole Polytechnique Fédérale de Lausanne, CH-1015 Lausanne, Switzerland

Abstract

An innovative and self-adaptive integrated system for building energy and comfort management has been developed. Both artificial and natural lighting controllers have been designed in order to fit the integrated approach. The shading device controller is split into two parts depending on the user presence. When the user is present, priority is given to visual comfort, and when he is absent, priority is given to thermal aspects (heating/cooling energy saving). The artificial lighting controller is used to complete the illuminance in the room up to the level desired by the user, which is learned by the system through the user wishes. Many simulations have allowed comparing different variants of the lighting controllers. The models used in the control system are regularly adapted to the measurements. Therefore, the system continuously adapts itself to the environment and the room characteristics. Four months of experiments in the occupied LESO-PB office building have demonstrated that this integrated system leads to interesting energy saving (25% less of total energy consumption) compared to a conventional one. © 2001 Elsevier Science B.V. All rights reserved.

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1. Introduction

Only very few building control systems nowadays integrate the main innovations of these last years in the building energy management system (BEMS). In particular, the continuous adaptation of the system to the environment and building characteristics is a very promising feature that is rarely studied (only few studies have been done on adaptive controllers in buildings [1,2]) and nearly never implemented. In addition, a predictive approach in the control algorithms is quite necessary to obtain really efficient control systems. The heating control system NEUROBAT [3], developed in part at the LESO-PB, is one of the very few systems that takes into account both the adaptation and prediction aspects for the control. Nevertheless, the main drawback of current building control systems is that they deal separately with each kind of controller (heating, ventilation, lighting) and they are not able to optimise the overall multi-controller system.

However, such an integration could bring several benefits at both economic and social levels. A potential of large energy saving has been demonstrated when integrated control strategies are used instead of individual strategies: 10 to 30% less of total energy consumption when considering only the heating and lighting controllers [4]. Moreover, an improvement of the indoor comfort brings better working conditions, and therefore, well-being and higher productivity. This allows to reduce partly the huge economic and social burdens of work related health problems. In USA, for instance, total direct and indirect costs due to these problems have been estimated to be 26 billion dollars per year [5].

The EDIFICIO (Efficient Design Incorporating Fundamental Improvements for Control and Integrated Optimisation) research project, funded in part by the EU Commission in the framework of the JOULE III programme has precisely the goal to develop an innovative and integrated control system for heating, ventilation, shading and artificial lighting, which increases the overall performance of the BEMS and the indoor comfort.

The LESO-PB, as partner of this project, has mainly worked on the development of the control algorithms for the shading device and for the artificial lighting, on the overall optimisation of the controllers and on the experimental evaluation of the integrated system. This integrated controller is presented in Section 2 of the paper. Section 3 describes the self-adaptation of the models included in the various controllers. The overall optimisation process uses Genetic Algorithms (GA). Even if the learning of fuzzy control rules using GA has already been studied [6], a dedicated adaptation process has been defined for our case and it is explained in Section 4. The experimental validation

* Corresponding author. Tel.: +41-21-693-45-51; fax: +41-21-693-27-22.
E-mail address: antoine.guillemin@epfl.ch (A. Guillemin).

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is running at three different sites: at the LESO-PB (Switzerland), at CONPHOEBUS (Italy) and at the VTT (Finland). This way, the system will be validated for three different climates. The experimental results of the LESO-PB are presented and discussed in Section 5.

2. Integrated controller

Four different device categories are considered for the control: the heating/cooling system, the ventilation, the blinds (shading devices) and the artificial lighting. The integrated system is built on the principle of three nested control loop levels (see Fig. 1).

Level 1 performs the translation from physical values (heating power, blind position, etc.) into the appropriate commands of the corresponding device (changing the heating system valve position, raising or lowering the blind, etc.).

The level 2 control loop includes the domain knowledge. It is based on expert fuzzy rule and uses adaptive models for thermal, lighting and air quality in order to produce a smart global control strategy. The outputs of this level are the physical values that are the inputs of the level 1 control loop.

Finally, level 3 ensures the long-term adaptation of the level 2 algorithms. The adaptation is done in a continuous way to take into account all the long-term changes in the building and device characteristics. Moreover, an adaptation task using Genetic Algorithms is undertaken in order to improve the efficiency of the system. The GA allow minimising a global "cost function" in adjusting the algorithm parameters of the level 2 smart controller.

It should be noticed that level 1 is specific to each building but both levels 2 and 3 are very easily adjustable to any kind of controller device. The self-adaptation of the system will lead to a simplified commissioning, and a good performance of the system is ensured without complicated parameter adjustment.

This Section presents in detail the smart controllers of the level 2. The LESO-PB building has no ventilation system, so only the heating and lighting controllers are explained here.

2.1. Shading device controller

The shading device controller described here deals only with textile blinds. However, a similar controller has been developed and simulated for venetian blinds (with both vertical position and slat angle regulated) and its description can be found in [7]. The textile blind controller is split into two cases, depending on whether the user is present or not in the room. This partition is inspired by the DELTA blind controller [4]. When the user is present, the blind controller primarily provides optimal visual conditions in the room; otherwise, only thermal considerations are taken into account in order to minimise the heating energy consumption.

2.1.1. User present: visual optimisation

When the user enters the room, the controller switches to the visual optimisation mode. Several algorithms for blind control have been studied. First the algorithm called *Sun-Position*, which seems to be the most promising one, is explained in detail and then the other algorithms are quickly presented.

The *Sun-Position* algorithm consists of two parts. The first part determines a maximum blind aperture in order to avoid glare (using a fuzzy rule base) and the second part tries to find the blind position (below the maximum value) that leads to the inside illuminance, which corresponds to the illuminance setpoint chosen by the user.

2.1.1.1. Maximum blind aperture. There are 25 rules in the fuzzy inference system, four inputs (direct outside horizontal illuminance, season, height and azimuth of the sun) and one output (maximum blind position). The main principles used in the rules are:

- Priority is avoiding glare, but the system also tries to save some energy by differentiating the rules depending on the season. In winter, during the day the maximum of solar gains is accepted and during the night the blinds are closed in order to increase the insulation and reduce the heat losses through the window. In summer, the opposite behaviour is applied.

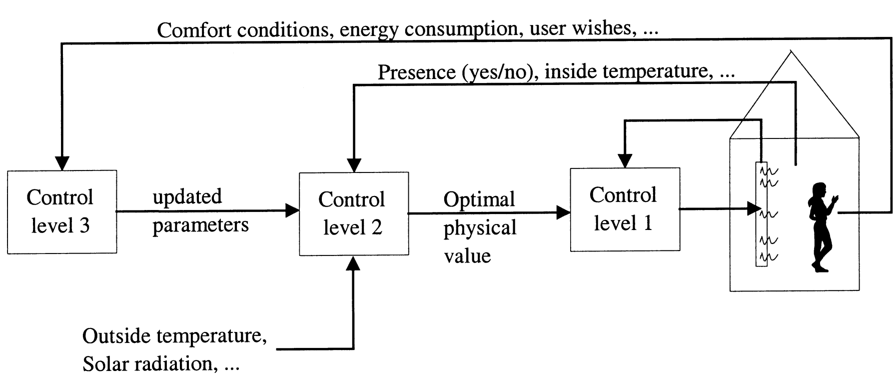

Fig. 1. Principle block diagram of the three nested control loop levels.

- A position of the sun near the horizon leads to closed blinds if the direct solar irradiance is high enough to disturb the user (typically higher than 100 W/m^2).
- If there is only diffuse radiation incident on the facade, there is no restriction on the maximum aperture of the blind.

The innovative idea of the algorithm is to take into account not only the incidence angle of the direct radiation on the facade (which was one limitation of the DELTA blind controller) but the exact position of the sun relatively to the facade, that means both the azimuth and the height of the sun. This allows different behaviours for different sunlight penetration scenarios. If the sun illuminates the wall in front of the user or illuminates the user directly, the algorithm may give different maximum blind apertures although the incidence angle is the same in both cases.

2.1.1.2. Blind position according to the inside illuminance measurement. The final position of the blind is determined through an ''Illuminance Ratio'' RI. This ratio links the inside horizontal illuminance (Eh_{in}) with the outside vertical illuminance (Ev_{out}). It depends on the blind position (α).

$$Eh_{in} = RI(\alpha) \cdot Ev_{out}$$

Setting the inside horizontal illuminance (Eh_{in}) equal to the illuminance setpoint and solving this equation for α, a final position of the blind can be calculated. The only constraint is that the blind position must be lower than the maximum blind aperture previously determined. If the inside illuminance level is still too low, artificial lighting is used to complete the inside illuminance up to the setpoint defined by the user.

The measurement of the inside illuminance is not used directly (it is used, however, for adapting continuously the RI expression in function of the blind position), the benefits are:

- Avoid the oscillations (which could come from a closed-loop control).
- Keep a smart control even if the sensor gives a temporary wrong value (in case of paper on the sensor, etc.).
- Blind position may be predicted (necessary for the heating controller).

The continuous adaptation of the RI model is explained in Section 3.1.

2.1.1.3. Algorithms comparison. Five other algorithms have been considered. Only the three most interesting are presented here.

The so-called Reference algorithm is the DELTA blind controller; it is a simple fuzzy logic open-loop controller that uses the vertical direct illuminance on the facade and the height of the sun.

The so-called Variation algorithm is different from the others in the fact that the output of the fuzzy logic is a step-variation of the blind position and not directly the blind position. Depending on a calculated glare risk, the blind move is applied or not.

The so-called I-Ratio algorithm uses three luxmeters for the control. One measures the horizontal illuminance and two measure illuminances on the walls. From these three measurements a value of ''contrast'' (ratio of illuminances) may be calculated, and the algorithm looks for a blind position that gives the right illuminance level in the room while keeping a reasonable value of this contrast. The benefit of this method using three luxmeters is that it is possible to take into account some glare aspects. But the drawback is that the right positioning of these luxmeters is a very difficult thing to do. It is important to notice that the simulations have not tested the algorithm behaviour (for the I-Ratio) with different values of the input variable contrast; it was chosen constant.

In order to compare all the algorithms, the toolbox Simulink of the MATLAB® program has been used to carry out the simulations. Each algorithm has been tested during one week with external weather conditions taken from synthetic values produced by the METEONORM program [8]. The simulations are done for the period that corresponds to the first seven days of July. Different weather conditions are represented (sunny and cloudy days). During the night (from 21.00 to 7.00 h), the user is considered as absent, so the tested algorithm is stopped (no blind movements, no artificial light).

The physical software model of the room (that plays the role of the real room for the simulations) used for the calculation of the inside illuminance is simply the illuminance on the facade multiplied by a kind of daylight factor (0.05 for our case) and a blind transmission factor. This illuminance blind transmission factor depends linearly on the blind position between a value of 1 (blind completely open) and 0.2 (blind completely closed).

The simulations give, as results, the extreme values of inside illuminance reached in the room, the difference between the setpoint value and the current value of illuminance integrated on the period of the presence of the user, the electrical power consumption of the artificial lighting system and the total number of blind movements during the simulation.

The results of the simulations are given in the Table 1.

All the algorithms work reasonably, without too many blind movements or too high an electrical energy consumption. Concerning the inside illuminance level, they all keep a value not too far (<300 lux of difference) from the setpoint value (600 lux), except the Reference algorithm, which is the only one with no closed-loop control. From a quantitative point of view, none of the tested algorithms is really bad. But, qualitatively, some interesting comments can be made:

- *Reference*: Except the fact that the level of illuminance is far from the setpoint, the algorithm does not take into account various window (and room) characteristics (e.g.

Table 1
Simulation results of the different visual optimisation algorithms[a]

Algorithm	Inside illuminance extrema (lux)	Integrated "error" (lux)	Electrical energy consumption (MJ)	Number of blind movements
Reference	400–1500	690	13.6	16
Variation	400–600	80	22.3	52
Sun-Position	380–800	230	13.5	42
I-Ratio	380–960	490	11.2	36

[a] The inside illuminance setpoint is 600 lux.

daylight factor), and therefore, it has to be adjusted for every new room configuration.

- *Variation*: This algorithm leads to nearly perfect visual conditions in the room. But this very small value of the integrated error of illuminance is due, in fact, to an extensive use of artificial light and a low position of the blind. Because of the low position of blind, the illuminance level is not much influenced by the outdoor conditions and can be kept very constant with the use of a big amount of artificial light. The possible blind positions are pre-defined and fixed, which avoids recurrent blind movements but leads to a lack of flexibility. Another drawback of this algorithm is the fact that it deals with blind variation instead of blind position and it is not really compatible with the nested loop control (levels 1 and 2 are no longer clearly separated).
- *I-Ratio*: This algorithm gives a continuous blind position and since it works in a dynamic way, the blind moves until a balance is found. Thus, the blind would move too often if no discretisation were applied to the output of the algorithm (note that for the simulations, a simple discretisation by step has been used). Unfortunately, this necessary discretisation is nearly impossible to do without spoiling the quality of the algorithm. Moreover, the algorithm is a bit too complicated and that may lead to have some troubles in the adaptation task.

To sum up, three algorithms (Sun-Position, Variation and I-Ratio) have been developed and tested for the visual optimisation task. The comparison of these algorithms with the Reference algorithm (coming from a project especially dedicated to blind control) has shown that all the new algorithms give the same kind of simulation results and even better ones than the Reference algorithm. The best one seems to be the Sun-Position algorithm. Its results are good and it combines well with the nested loop control. It takes into account both the azimuth and the height of the sun, which allows different behaviours for different penetrations of the sun in the room. This algorithm Sun-Position has been chosen to be implemented in the integrated controller.

2.1.2. User absent: energy optimisation

When the user has not been present for a certain amount of time (typically for 15 min at least) the controller switches from the visual optimisation to the energy optimisation algorithm.

2.1.2.1. Algorithms definition. The basic idea is taken from [4]. There are two main heat exchanges through a window: one is due to the transmitted solar irradiance (direct gain), the other to the heat transmission caused by the difference between inside and outside temperatures (gain or loss). Taking into account both contributions, which depend on the blind position, a window heat balance is calculated. The idea is that the fuzzy controller does not provide directly a blind position but a "desired window heat balance" (DWHB). A positive (respectively, negative) value of the DWHB (watts) corresponds to the desired heat gains (respectively, losses) for the room. The position of blind which gives a window heat balance as near as possible to this DWHB is calculated knowing physical parameters of the window and the blind (solar transmission coefficients, heat-loss coefficients).

Nine different blind controllers have been developed and tested. They are classified according to the inputs of the fuzzy inference system. Two controllers have only the variable heating power as input (controllers called *Only heating*). Three have only the variable season as input (controllers *Only season*). Finally, the last four have both the heating power and the season as inputs (controllers *Both*). The main ideas used to build the tables of rules were:

- The blind controller must always help the heating/cooling system.
- In winter, solar gains should be accepted as often as possible.
- In summer, solar gains should be rejected as often as possible.
- In mid-season, the situation is unclear, so several possibilities are studied.

Concerning this last point, two versions of fuzzy controllers of the same category are differentiated by the DWHB in mid-season. For instance, in the fuzzy rule base of the controller *Both* version 2 (*Both v2*, see Table 2), the DWHB value "positive-low" is replaced by the DWHB value "zero" in the controller *Both* version 1 (*Both v1*).

The fuzzy variable "season" is not determined from the period of the year but from the average outside temperature

Table 2
Fuzzy rules base for the lighting controller (*Both v2*)[a]

Season	Heating power		
	Negative	Zero	Positive
Winter	DWHB = negative	DWHB = positive	DWHB = positive
Mid-season	DWHB = negative	DWHB = positive-low	DWHB = positive
Summer	DWHB = negative	DWHB = negative	DWHB = positive

[a] DWHB is the desired window heat balance.

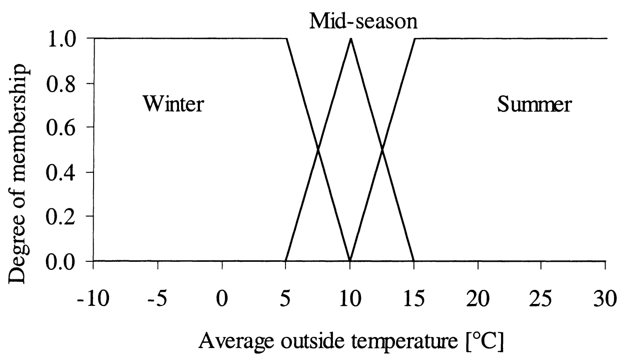

Fig. 2. Membership functions of the fuzzy variable "season".

during the last 24 h. Its membership functions are given in Fig. 2.

2.1.2.2. Algorithms comparison. The simulation tests have been done with Simulink (MATLAB® Toolbox), for a period of 1 week during three different periods of the year (winter (days 52–59), mid-season (days 100–107), summer (days 192–199)) with climate data of Lausanne (Switzerland). The external weather conditions are synthetic values produced by the METEONORM program. For each period, the controllers are tested with a heating/cooling system and with a heating only system. Both heating systems are predictive (inspired from the NEUROBAT project [3]).

The main conclusions of the simulations are:

- The variable "season" is essential in order to have an energetically efficient blind controller (see Fig. 3).
- The differences between controllers are particularly visible during the mid-season period.
- It is best to have a positive DWHB in mid-season when the heating power is zero.
- The best value to take for the DWHB in this case has not been defined. It depends strongly on the kind of heating/cooling system and on the window and room characteristics.
- Three controllers are clearly better than the others: *Both v2*, *Both v3* and *Only season v3* (the three controllers have a DWHB value "positive-low" in mid-season!). They lead to a quite comfortable inside temperature and their energy consumption values are the lowest (see Fig. 3).

The *Only season v3* controller has been chosen to be implemented in the integrated system as the controller for the user absent case. Although this controller is not exactly the best considering energy consumption, it does not use the heating power variable, and therefore, avoids a cross coupling heating-lighting, which could lead to instabilities. Indeed, the heating controller needs the blind position produced by the blind controller (in order to predict the future inside temperature), whereas the lighting controller needs the heating power variable produced by the heating controller.

2.2. Artificial lighting controller

The goal of the controller is to use the artificial light as a complement of illuminance when the natural inside illuminance level is too low. In order to permanently know the exact artificial part (and by the way also the natural part) of

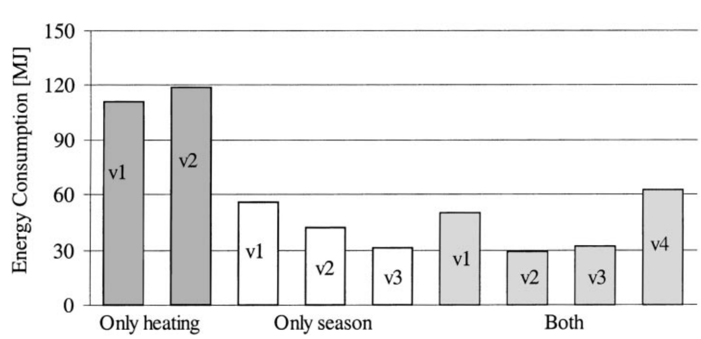

Fig. 3. Heating energy consumption of the nine controllers during the mid-season simulation ('v' is the version number of the considered algorithm).

the total illuminance, a relation between the current electric power applied to the artificial lighting system and the illuminance provided by the latter has to be known. This is given by the artificial lighting model (see Section 3.2).

From the vertical outside illuminance, the RI model (see Section 3.1) provides the natural horizontal inside illuminance. If this value is lower (at least 20% less) than the illuminance level wanted by the user (user setpoint), the artificial lighting system is switched on and it calculates (thanks to the artificial lighting model) the exact electrical power that should be applied in order to complete the illuminance up to the user level setpoint.

This user illuminance setpoint is continuously adapted in order to fulfil the user wishes. In fact, each time the user expresses a wish concerning the artificial lighting, the system learns (thanks again to the artificial lighting model and the RI model) which illuminance level suits at best the user.

The artificial lighting is switched off either when the user leaves the room or when the natural inside illuminance has become higher than the user setpoint.

2.3. Heating controller

The main idea of the heating controller is to take the power profile of the previous day, to change it depending on the current conditions (weather, user presence, inside and outside temperature) and to apply it to the current day. The correction applied to the power profile is done using a fuzzy logic inference system.

The fuzzy algorithm has two inputs, the current comfort level and the future comfort level (predicted comfort level in 6 h). They are defined as the difference between the inside temperature and the temperature setpoint, divided by the temperature setpoint. Several rule sets have been tested and it was found that nine rules were sufficient to correctly regulate the system. These rules are given in Table 3.

In this set, the current comfort level has a larger priority than the future one. In order to predict the future comfort level (that means the future inside temperature), a climate predictor and a thermal model of the room are used. Both models are realised using an Artificial Neural Network (ANN). A description of the two networks is done in Section 3.

Table 3
Fuzzy rule base for the heating controller[a]

Future comfort	Current comfort		
	Too cold	Normal	Too hot
Too cold	DP = +large	DP = +small	DP = −small
Normal	DP = +medium	DP = zero	DP = −medium
Too hot	DP = +small	DP = −small	DP = −large

[a] DP is the variation applied to the value of the power profile of the previous day.

The output of the fuzzy logic system is the variation that should be applied to the power profile in order to have a better comfort level. More precisely, the power profile is discretised in steps of 15 min. The power applied the previous day during the 15 min after the current time is changed depending on the output of the fuzzy inference system. Fig. 4 shows an example of the power profile use.

In fact, the heating controller uses two setpoints, the user setpoint (temperature desired by the occupant) and an energy-saving setpoint. The latter is applied when the user is not present, and it allows saving energy during nights and weekends. In order to provide the right comfort level in the morning and after the weekend, an occupancy schedule is used. In the future, the goal is to replace this fixed schedule by a presence predictor made with an ANN, which could learn the actual user presence schedule.

3. Self-adaptation of the models included in the controller

In order to adapt continuously the system to the parameters of the building and the environment, an adaptation of the different models used in the controller (namely the illuminance ratio model, the artificial lighting model, the climate predictor and the thermal room model) is done regularly.

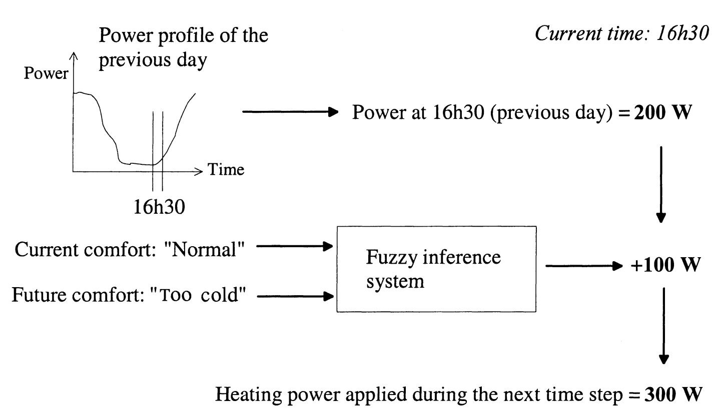

Fig. 4. Operation of the heating controller.

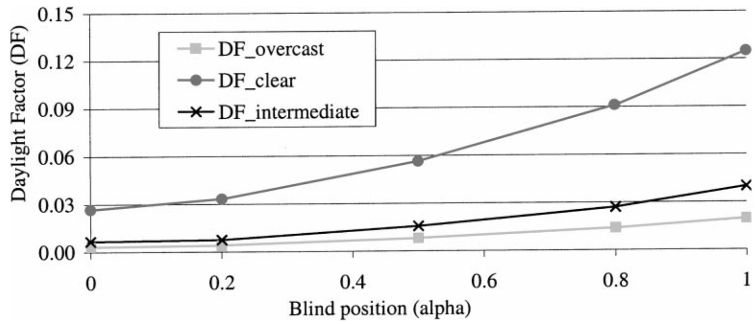

Fig. 5. Daylight factor (horizontal inside illuminance/horizontal outside illuminance) measured for three sky conditions (overcast, intermediate, clear).

3.1. RI model

The illuminance ratio model calculates the horizontal inside illuminance on the desk from the measurement of the vertical outside illuminance. Some experiments [9] have shown that the use of the vertical outside illuminance (RI model) gives better and more consistent results than the standard use of the horizontal outside illuminance (Daylight factor) when comparing with horizontal inside illuminance for different blind positions. The Figs. 5 and 6 show the results for both cases; the case with vertical outside illuminance (Fig. 6) clearly leads to less scattered results.

Every half an hour, the parameters of the RI model are changed in order to take into account the current measurements. If the new measured values of parameters are strongly different (five times higher or lower than the old ones), the values are rejected because it means that either a paper covers the inside illuminance desk sensor or direct radiation hits it. The strategy of the adaptation is then to adapt very slowly the RI parameters (small weights of the new values compared to the old one), which allows rejecting measurements only when they are very faulty. A slightly faulty measure will indeed not lead to a completely wrong illuminance model.

3.2. Artificial lighting model

The artificial lighting model is also regularly adapted in order to take into account the ageing of the lamp, the dust accumulation or the installation of a new artificial lighting system. This model has been developed for the situation with a dimming control of the artificial lighting. The hypothesis is that the relation between the internal illuminance provided by the artificial lighting system and the electrical power applied to this latter, is linear. So each night, when the user is not present, the artificial lighting is switched on with two different values of power. The illuminances in the two cases are measured and a simple calculation provides the lighting device characteristic. The new calculated values are then averaged with the old values in order to produce the new artificial lighting model.

3.3. Climate predictor

The climate predictor is in fact divided into two similar ANNs. One provides the outside temperature and the other provides the horizontal global solar irradiance. A simple feed-forward network structure has been chosen with one hidden layer (four-neurons layer). The Levenberg–Marquardt training algorithm is used because of its convergence faculty and the tangent hyperbolic activation function is chosen because of its non-linearity, continuity and derivability characteristics. The 4 inputs are the considered value (the outside temperature or the solar irradiance) at the current time, the value 1 h ago, the value 24 h ago and the computed maximum solar irradiance at the time of prediction. The training is done once a week on the data collected during the last whole year period.

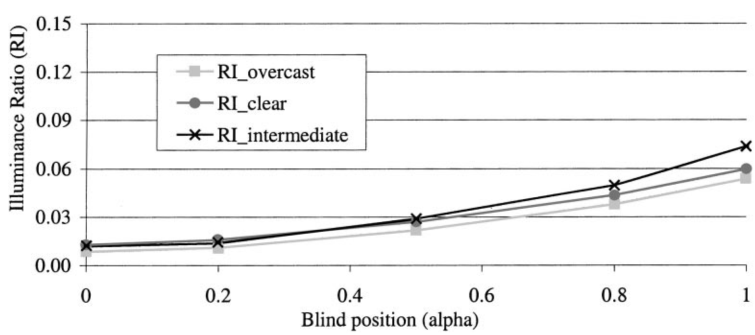

Fig. 6. Illuminance ratio (horizontal inside illuminance/vertical outside illuminance) measured for three sky conditions (overcast, intermediate, clear).

3.4. Thermal room model

The thermal room model [10] uses a special kind of ANN, called Radial Basis Function Networks [11]. There are six kinds of inputs: the inside and outside temperatures, the global solar irradiance on the facade, the heating power, the blind position and the ventilation rate (which may be replaced by a fixed value if there is no ventilation system). All these inputs, except the inside temperature, are composed of six values: the current value and the five values predicted on the next 5 h, by step of 1 h. It means that finally there are 31 inputs (five kinds $\times$ six predicted values + one current inside temperature) in the thermal room model. The output is the predicted inside temperature 6 h later.

A good accuracy of this model is very important for the efficiency of the heating controller. Therefore, the learning process is carried out as soon as the error of the predictive model has got larger than a certain threshold.

4. Global optimisation

Each night, a process of adaptation is undertaken. Using Genetic Algorithms (GA), the system looks for the most efficient set of parameters of the controllers.

The idea is to use the GA to apply small variations to the parameters of the current controller. Each gene is related to a certain parameter (for instance, the width of a membership function) but does not give the value of this parameter: instead, it gives the value of a small variation, which is applied to this coded parameter. The Fig. 7 shows an example of a small variation applied to the membership function "normal" of the fuzzy variable comfort. An individual is a set of small variations and each one corresponds to a slightly different controller. The main benefit of this approach is that the "experience" of the current controller is kept. In short, there is no risk of losing information that has previously been learned by the controller.

After randomly generating a population of individuals, the genetic operators (selection, crossover and mutation) are applied in order to obtain a new population. This is repeated until a sufficiently good solution is found. The individuals (controllers) are evaluated with a fitness function, which takes into account several factors: energy consumption, visual and thermal comfort provided. This fitness function is the opposite of a cost function like the one used in the NEUROBAT project [3].

More precisely, the algorithm works as follows:

1. Random initialisation of the population.
2. Each individual (set of small variations) is applied to the set of parameters of the current controller.
3. Each individual corresponds to a different controller. For each controller, outputs (blind position, heating power, etc.) are calculated.
4. From the outputs, a fitness for each individual is calculated, and then the genetic operators are applied. A new generation is obtained.
5. Back to step 2, until a sufficiently good solution has been found.

The best individual found by the GA is applied to the set of parameters of the current controller in order to produce the new and more efficient controller.

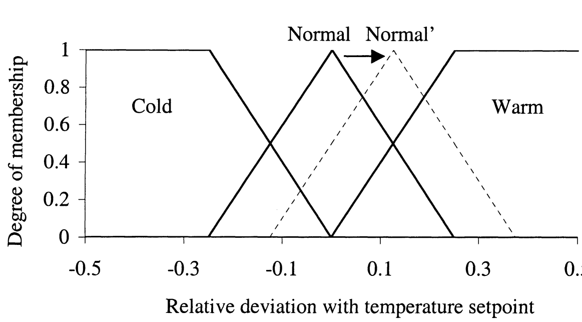

Fig. 7. Fuzzy parameters that are adapted using the Genetic Algorithms. Here the fuzzy membership function "normal" is changed.

5. Experimental results

The integrated system with heating, shading device and artificial lighting controllers, is currently tested on the occupied LESO-PB office building. Two rooms are used for the experiments. One room is equipped with the integrated system and one room with a conventional controller (no automatic blind control, no automatic artificial lighting control, proportional heating controller with saturation). The control system is hosted by a computer, which controls both rooms. The conversation between the computer, the actuators and the sensors is done via a Lonworks^{TM} bus with the standard protocol "Dynamic Data Exchange". The dimensions of the two rooms are $4.75\,m \times 3.6\,m \times 2.8\,m$. The windows are on the south wall, and the total area of window for a room is $5.75\,m^2$. They are rather large openings, but thanks to the low U-value ($1.4\,W/m^2K$) of these windows, the rooms are quite well thermally insulated.

In order to reduce the experimental bias, due to the possible slightly different room characteristics and the different user behaviour, the integrated controller is periodically (typically, every 2 weeks) replaced by the conventional controller while in the other room the conventional controller is replaced by the integrated controller. For the results analysis, the time each controller has worked in a room is taken into account.

5.1. Lighting controllers operation

Fig. 8 shows some qualitative results concerning the blind and artificial lighting operation. Two days of experiments are shown. The first day is a working day (Friday,

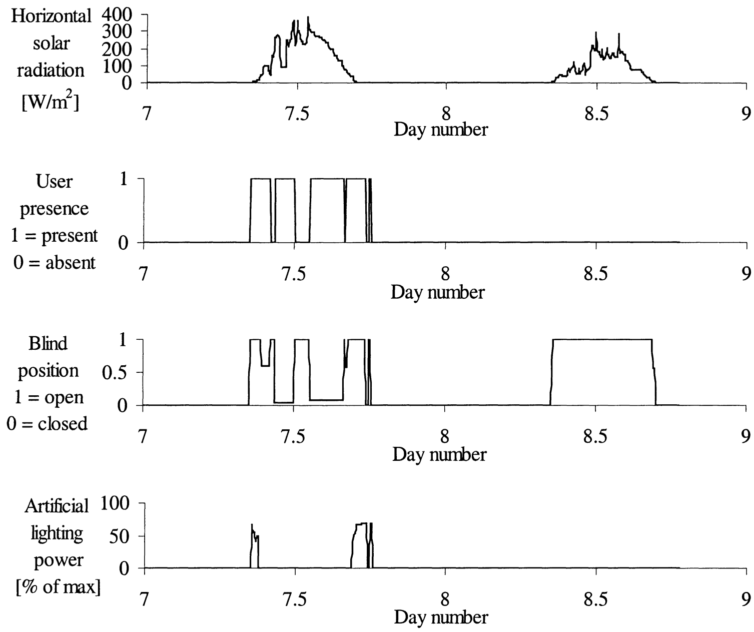

Fig. 8. Global solar irradiance, presence, blind position and artificial lighting power provided by the integrated controller. Day 8 corresponds to Saturday, 8 January 2000 at midnight.

7 January 2000) and the second one is a day-off (Saturday, 8 January).

During the working day (day 7), the user has left the room for a short time each in the morning and in the afternoon, and he had a longer lunch break at noon. The last peak in the presence graph corresponds to the coming of the cleaning staff. The corresponding blind position shows that when t he user is present, the blind has a very low position (<0.2) for glare considerations (winter + sunny day = high glare risk) and when the user is absent, the blind is completely open for thermal considerations. In the evening, the user is present while the solar irradiance is low, then the blinds are completely open in order to have a maximum of day lighting.

Since the measuring season was winter and the user was not present the day 8, the blind was open during this day in order to accept the maximum of solar gains and closed during the night in order to have a better thermal insulation of the window.

Concerning the artificial lighting controller, the day 7 (user present) shows that it operates correctly, bringing additional lighting only when it is necessary: early in the morning and late in the evening when the natural lighting was not sufficient and when somebody was in the room.

Moreover, it has to be said that the user has not interacted with the shading device controller during the whole working day (day 7), which means the visual comfort provided by the controller was probably sufficient. Questionnaires that are filled in by the user twice or three times a day have confirmed it. These questionnaires give information about the visual comfort, the thermal comfort and the user opinion about the automatic system.

5.2. Heating controller operation

Fig. 9 shows the results concerning the thermal controller. It corresponds to eight days of the year 2000 from Thursday, 10 February to Thursday, 17 February. The inside temperatures in the two rooms (one with the integrated controller and one with the conventional controller) are shown in parallel with the heating power profiles of the two controllers. Users in both rooms have chosen the temperature setpoint at 22°C.

The integrated controller shows a very interesting advantage compared to the conventional controller. It avoids

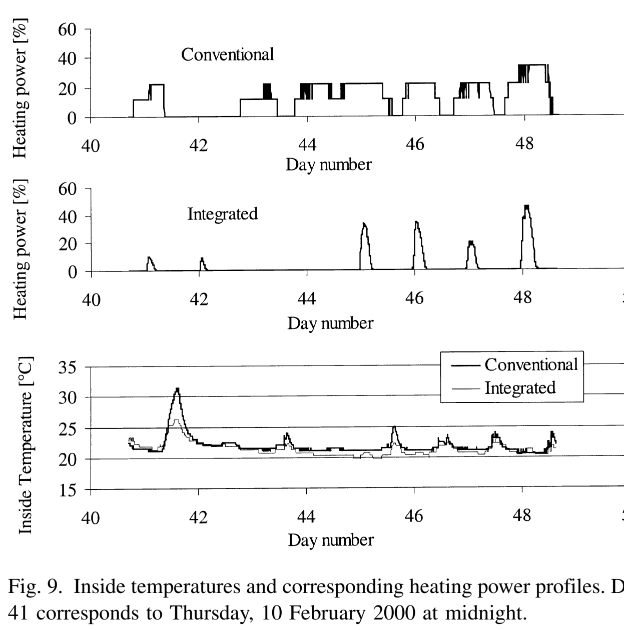

Fig. 9. Inside temperatures and corresponding heating power profiles. Day 41 corresponds to Thursday, 10 February 2000 at midnight.

Table 4
Total energy consumption (heating, artificial lighting, appliances) of the integrated and conventional controllers (in MJ)

System	Integrated system in room A (48 days)	Integrated system inroom B (46 days)	Total (94 days)
Integrated	319.5	261.1	580.6
Conventional	449.7	334.7	784.4

overheating (day 41 for instance) in the afternoon by taking into account the solar gains.

5.3. Energy consumption

The most significant quantitative result is the total energy consumption during the first 94 days of experiments (27 January to 1 May). The rooms were exchanged several times in order to reduce the experimental bias due to the slightly different room characteristics. The integrated system was running 48 days in the room A while the conventional system was in the room B. During the 46 other days, the situation was the opposite: the integrated system in room B and the conventional system in room A. The results are shown in Table 4.

The energy consumption in both rooms is clearly lower with the integrated system. During these 94 days of experiments, the integrated system has saved 25% of energy in comparison with the conventional controller.

Fig. 9 gives some explanations of this large energy saving. Thanks to the prediction capability of the integrated controller, it reduces the heating power during the night when it knows that solar gains will provide a large amount of solar energy in the afternoon. Moreover, the energy-saving setpoint applied during nights and weekends leads to additional energy savings. For instance, during the weekend, the integrated controller has completely stopped heating (see days 43 and 44 in Fig. 9). The different steps of the heating power of the conventional controller are due to a discretisation of the inside temperature measurement. Since the heating power is calculated using the inside temperature, a discretisation of this latter leads to a discretisation of the heating power.

5.4. Remarks and future prospects

The integrated system will allow saving, at least during the winter season, an interesting amount of energy while keeping a quite good thermal comfort level and even improving the visual comfort level. This may be explained by the energy efficiency control of blinds and also by the smart heating controller with the energy-saving setpoint applied during nights and weekends.

The experiments are going on and the performance of the system will be studied for a long period including mid-season and summer.

The questionnaires have shown that the user is quickly angry at the automatic system when it does not take into account his wishes. For example, if the user does not like the current blind position and moves it, the automatic blind control is held up during a certain amount of time (typically during 1 h) in order to avoid moving the blind again to the position disliked by the user. But since the user wish is not taken into account in the long-term by the system, the automatic control will keep giving an inadequate blind position. The conclusion is that the system should adapt itself on a long-term basis to the user wishes while keeping, from an energy point of view, the most efficient possible control of the blinds. This is a very complex problem and further studies are carried on in the project in order to find a good solution to that issue.

6. Conclusion

The multi-controller presented here has several advantages over the other known building controllers. First, the overall system is integrated in an optimised global controller. In particular, every part of the controller works in order to help the others. For instance, the shading device controller takes into account thermal aspects and is able to help strongly the heating/cooling system. Furthermore, there is an overall optimisation of the system realised through the use of GA. That leads to a system, which provides a high comfort level for both lighting and thermal aspects and gives at the same time very good results concerning the energy consumption.

Finally, it is self-adaptive, which means that the controller adapts itself to the building and its environment. The benefits are an easier commissioning and robustness towards the changes of the building characteristics and towards some possible dysfunction. Moreover, the study has shown that it is necessary for the control system to take into account the user wishes on a long-term basis. Otherwise, all the benefits of the automatic system would be lost since the user would reject it. Considerable efforts are currently made by the authors in this research area.

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