USING GENETIC ALGORITHMS TO TAKE INTO ACCOUNT USER WISHES IN AN ADVANCED BUILDING CONTROL SYSTEM

THÈSE N^{O} 2778 (2003)

PRÉSENTÉE À LA FACULTÉ ENVIRONNEMENT NATUREL, ARCHITECTURAL ET CONSTRUIT

Institut des infrastructures, des ressources de l'environnement

SECTION D'ARCHITECTURE

ÉCOLE POLYTECHNIQUE FÉDÉRALE DE LAUSANNE

POUR L'OBTENTION DU GRADE DE DOCTEUR ÈS SCIENCES

PAR

Antoine GUILLEMIN

ingénieur physicien diplômé EPF
de nationalité suisse et originaire de La Sagne et Les Ponts-de-Martel (NE)

acceptée sur proposition du jury:

Prof. J.-L. Scartezzini, directeur de thèse
Prof. D. Floreano, rapporteur
Dr N. Morel, rapporteur
Dr J. Pargfrieder, rapporteur
Prof. M. Tomassini, rapporteur

Lausanne, EPFL
2003

The reasonable man adapts himself to the world; the unreasonable one persists in trying to adapt the world to himself. Therefore all progress depends on the unreasonable man.

George Bernard Shaw (1856 - 1950)

Abstract

From a sustainable development perspective, the newly developed automatic controllers for building services are very promising in that they increase energy efficiency and reduce commissioning and maintenance costs. But a major problem has appeared as the automatic building control systems have been implemented: the user rejection of this kind of system is quite high. This is mainly due to a lack of user considerations in the controllers. An integrated blind, electric lighting and heating control system that adapts to user wishes on a long-term basis has been developed in this work to deal with this issue.

The adaptation of the control system to user wishes was achieved by means of Genetic Algorithms. They have been seen to be the most appropriate optimization method for this task. They ensure a 100% convergence whereas standard search methods such as Gauss-Newton and Nelder-Mead converge in less than 25% of the time and Simulated Annealing method converges in about 75% of the time. In addition, simulations with a consistent virtual user have shown that the user adaptive controller is capable of anticipation.

Nine months of experimental tests were carried out in 14 office rooms of the LESO building with a total of 23 users concerned. Three controllers were compared: a manual control system, an automatic controller without user adaptation and an automatic controller with user adaptation. Tests were conducted in a similar fashion as *clinical randomized trials* are carried out: control systems are randomly attributed to rooms and users do not know which system they have (single-blind study).

Results show that the automatic control rejection percentage is greatly reduced with the user adaptive system. Indeed, after four weeks with an automatic control, 25% of the users with the non-adaptive system reject the automatic control, whereas only 5% of the users with the user adaptive system reject it. These percentages depend neither on age or gender of the user, nor on the number of occupants in a room. Moreover, the energy savings due to automatic control (26% compared to a manual system) are not reduced by the user adaptation. These large energy savings are mainly due to the predictive feature of the heating controller and to the efficient control of electric lighting. In addition, indoor comfort is slightly improved by the automatic controllers for both thermal and visual aspects. The indoor comfort is even slightly more improved by the user adaptive control compared to the non-adaptive one.

The user adaptation has not converged properly in the mechanical workshop, a space used by several persons and also considered in the experiments. It has been concluded that user adaptive systems are probably not appropriate for places with irregular users, such as workshops, libraries, corridors and all public spaces.

Version Abrégée

Dans une perspective de développement durable, les récents progrès réalisés dans les systèmes de régulation des installations techniques du bâtiment permettent d'envisager, aujourd'hui, d'importantes réductions de consommation d'énergie ainsi que des coûts de mise en service et de maintenance. Malheureusement, le défaut des systèmes actuels est qu'ils ne tiennent pas compte, à long terme, des voeux des utilisateurs. Ainsi, les systèmes de contrôle sont souvent rejetés par ces derniers, les nombreux avantages de la régulation automatique étant ainsi perdus. Dans ce travail, un système de contrôle intégrant les stores, la lumière artificielle et le chauffage et s'adaptant aux voeux des usagers a été développé, en vue de remédier à ces difficultés.

L'adaptation a été réalisée en utilisant des Algorithmes Génétiques. Cette méthode d'optimisation s'est révélée être plus performante que les méthodes standards, comme les algorithmes de Gauss-Newton et Nelder-Mead et le recuit simulé. Alors que la convergence vers une solution satisfaisante est assurée pleinement par les Algorithmes Génétiques, les méthodes standards n'ont convergé que dans 25% des cas et le recuit simulé dans 75% des cas. De plus, une simulation avec un usager virtuel a mis en évidence une propriété d'anticipation du système adaptatif.

Une validation expérimentale a été menée dans 14 locaux de bureau du bâtiment LESO et a concerné 23 utilisateurs au total. Trois différents systèmes de régulation ont été comparés: un contrôle manuel et deux contrôles automatiques, l'un avec adaptation à l'utilisateur et l'autre sans. Une attribution aléatoire des systèmes par pièce ainsi qu'une procédure simple-aveugle ont garanti des résultats non biaisés.

Les résultats obtenus démontrent que l'adaptation à l'utilisateur permet de réduire fortement le rejet du système de contrôle automatique. Après quatre semaines, 25% des occupants munis d'un système non adaptatif le rejettent, alors que ce pourcentage n'est que de 5% pour les occupants bénéficiant d'un système adaptatif. Ces résultats ne dépendent ni de l'âge ou du sexe de l'utilisateur, ni du nombre d'occupants dans la pièce. De plus, les économies d'énergie obtenues grâce au contrôle automatique (26% par rapport au système manuel) ne sont pas réduites par l'adaptation à l'utilisateur. Ces économies d'énergie sont principalement dues à l'aspect prédictif du contrôleur de chauffage, ainsi qu'à la gestion plus efficace de la lumière artificielle. D'autre part, le confort thermique et visuel a été amélioré par les dispositifs de régulation automatique, en particulier par le système adaptatif, en comparaison avec le système manuel.

Enfin, il a été observé que l'adaptation à l'utilisateur a échoué dans l'atelier du LESO, un local particulier avec de nombreux usagers différents. Il apparaît donc que les systèmes adaptatifs à l'utilisateur ont vraisemblablement moins d'intérêt pour des espaces occupés de manière irrégulière, comme par exemple, des ateliers, bibliothèques, couloirs et en général tous les espaces publics.

Acknowledgements

I would like to thank the many people who have provided me with assistance, guidance and support during the whole time it took me to complete this PhD:

> Professor Jean-Louis Scartezzini for accepting me as PhD Student in the LESO-PB, for his valuable criticism and scientific rigour.
>
> Dr Nicolas Morel for his constant guidance and his great involvement in all parts of this thesis.
>
> René Altherr for his tremendous work in the EIB interface, that made the experiments possible.
>
> Simone Molteni for his very fruitful and efficient contribution to the Genetic Algorithms application.
>
> Dr Pierre-Edouard Sottas for giving me very useful hints concerning the Artificial Neural Networks and the Simulated Annealing.
>
> Laurent Deschamps for helping to prepare the monitoring of questionnaires.
>
> Dr Claude-Alain Roulet and Dr Jean-Bernard Gay for their multiple explanations concerning Building Physics and the LESO building thermal behaviour.
>
> Barbara Smith and especially Jessen Page for the English correction of this thesis.
>
> Marilyne Andersen for sharing the office room during all these years, for her magnificent support in all domains and for the numerous and helpful discussions we had.
>
> And all the members of the LESO-PB for the very friendly working environment and for having kindly answered the many questionnaires.

Finally, I wish to thank all my friends and my family, for their patience, encouragement and interest that hugely helped me to achieve this work.

Contents

Chapter 1

Introduction

> "*History is the version of past events that people have decided to agree upon.*" (Napoleon Bonaparte)

During the main part of the history of man, "housing conditions" have been one of his main concerns. From prehistory to now, man has discovered and invented a tremendous number of techniques related to his comfort in dwellings. This chapter gives some milestones of this evolution, first regarding the building services and then regarding the automatic controllers in buildings. The last section shows how the thesis contributes to this evolution.

1.1 Origins of Building Services

As man became a biped and started discovering tools (during the Old Stone Age, 2.5 millions years ago), he was already looking for some comfort and protection in caves and had even begun to build crude shelters. Substantial evidence of primitive dwellings coincide with the use of fire, discovered 400'000 years ago. Fire was used for cooking food and scaring animals away from shelters but also for keeping warm, as well as for lighting. It was the first heating and lighting system.

Historians have shown that fire was moved to different parts of a dwelling, and various schemes were tried to improve the draft of the fire by using stones. However, even the best open fire is 20% efficient, with most of the heat escaping with the smoke. Using larger stones heat was accumulated and re-emitted later, which was the premise of the radiant heating system. But, open fires still were only capable of warming very small spaces and required constant attention.

The discovery of the duct (probably in Mesopotamia 10'000 years ago for water manipulation, and in China during the 7^{th} century B.C. for air manipulation) brought the solution (see Figure 1.1). Distributed heating systems appeared around 220 A.D., when the Roman Emperor Heliogabalus is said to have a palace warmed by air. A stove was placed in a brick chamber under the rooms. Outdoor air was conducted into the chamber under the stove, the heated air then flowing through openings into the rooms above. The

Figure 1.1: *Clay heating ducts embedded in the wall of a house, Pompeii*

remaining drawback of such a system was the low specific heat value of the air that prevented proper heating of distant rooms.

The Industrial Revolution, which had brought new iron technologies, allowed to replace air by water with its larger specific heat value in ducts. At this point (towards the end of the 18$^{\text{th}}$ century) water distributed heating systems were realized using large pipes and a simple boiler. They operated by gravity, cold water being denser fell back to the boiler through pipes forcing the lighter warm water to rise to the radiators.

At the same time, cooling systems were rare because they were penalized by the problematic storage of ice. Nevertheless, some cooling systems were developed and a few of them are still in use after more than a century of service (for instance in the Hungarian Parliament building). Ice was simply placed in air ducts to cool and dehumidify warm air blown by fans.

During the 1920's in England and USA, use of water for heat transport gives impetus to the development of new heating systems. Heat distribution was not anymore limited to radiators but radiant ceiling and floor were used as well. Moreover, water solar collectors appeared and therefore supplied control opportunities in active solar homes, that was an interesting advantage over the older[1] but less flexible passive solar systems.

[1]The ancient Greeks, in the 5$^{\text{th}}$ century B.C., already planned whole cities in Greece and Asia Minor, such as Priene, to allow every homeowner access sunlight during winter to warm their homes.

In parallel, the long story of the artificial lighting system was going. Fire had been portable from the beginning (the first torch was a simple burning piece of wood) but it was not convenient and lighting autonomy was limited. During the Early Bronze Age (3'000-2'000 B.C.), the invention of the oil lamp in the Middle-East solved these problems and was widely spread. But despite the invention of the candle (around 100 B.C), the drawbacks of these lighting systems persisted: they only provided very low lighting levels and they produced ill-smelling smoke. Nearly two thousands years later, in 1784, use of coal gas as lighting fuel provided the solution for efficient lighting. Early in the 19th century, most cities in the United States and Europe had streets that were lit by gas. Nevertheless, the necessary gas pipes were quite inconvenient and the discovery of electricity provide an alternative system: the light bulb. Edison invented it in 1879 and it improved drastically artificial lighting capabilities. This also allowed the development of electric lighting control. Finally, first fluorescent lamps appeared in 1939, more than thirty years after the process had been demonstrated.

Concerning daylighting, the first system was the simple opening covered with animal skins of the Homo Habilis primitive dwellings. Real improvement come with the use of natural transparent stones that provided daylighting while preventing cold air to come in. The discovery of glass (around 3'000 B.C.) enabled the manufacturing of windows and thus rendered them thin and convenient. But the high cost of glass delayed the propagation of windows until the Middle Ages.

Since daylight entered rooms, solar protections became essential. First, fixed solar protections were used, like the Arabic Moucharrabieh (see Figure 1.2) that appeared during the 14th century. They let daylight enter the room but cut the direct solar radiation.
In countries where the external temperature varies over a large range depending on the season, fixed solar protections were inconvenient. Hence, in Italy, movable shading device such as roller blinds and venetian blinds appeared during the 18th century, providing control opportunities.

1.2 Ancestors of the Automatic Building Control Systems

The first known automatic regulators were developed in order to have an accurate measurement of time, which was a major concern in Antiquity. The Greek Ktesibios in about 270 B.C. was the first inventor of a float regulator to improve the accuracy of water clocks (clepsydras).

The field of automation really appeared much later, during the first part of the Industrial Revolution (1705-1830). All of Western Europe industrialized rapidly, but it was in England that the process was most highly accelerated. There, the realization of the first modern steam engine by Thomas Newcomen (in 1705) started the series of James Watts inventions. In particular, his first automatic regulator system for stabilizing the rotational speed of steam engines (patented in 1788) could be considered as the birth of the modern automation field.

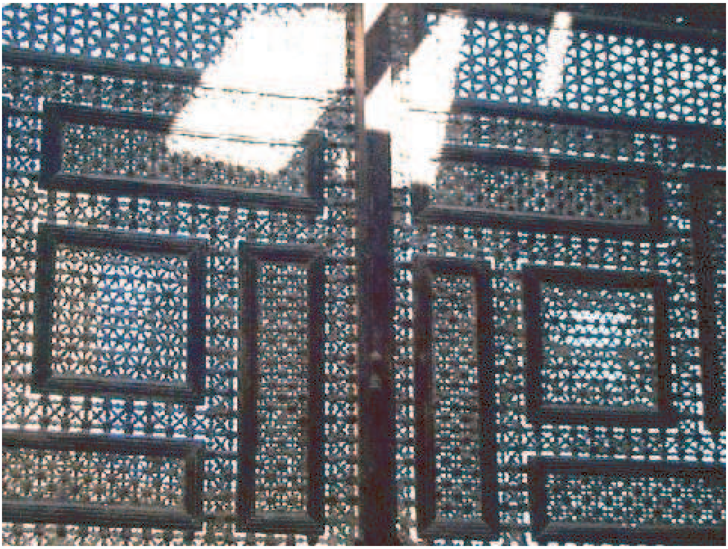


Figure 1.2: *Example of an Arabic Moucharrabieh*

Concerning automatic control applied in buildings, the first automatic heating control systems appeared in the middle of the 19th century with the invention of the bimetal thermostat (invented by Andrew Ure in 1830). With the coming of the Age of Electronics and especially the discovery of the "positive feedback amplifier" by Armstrong in 1912, major improvements in feedback control became possible. Thus, only ten years later, the famous Proportional-Integral-Derivative controller was introduced by Minorsky [Minorsky, 1922]. Then, the optimal control theory appeared with its numerous techniques: dynamic programming [Bellman, 1957], Kalman filters [Kalman, 1960] and Stochastic control [Aström, 1970]. Finally, alternative methods such as fuzzy logic control [Zadeh, 1965] and expert systems (many examples since 1970's) enlarged the building automation field.

1.3 Remaining Challenge

This evolution in building automation is clearly not ended: all around the world, numerous research laboratories are still involved in the field of Building Physics.

Because of the oil crisis in the 1970s, research in building control systems during these last decades was mainly centered on the energy point of view, neglecting to a certain extent the real user needs. The goal was to save energy while keeping a priori indoor comfort conditions. Nevertheless, some researchers began at the same period to provide innovative methods for comfort assessment (e.g. Fanger for thermal [Fanger, 1982] and

Guth [Guth, 1966] for visual aspects). But it is actually shown (see Chapter 2) that each user has specific needs and wishes towards his indoor environment.

The new challenge is then to develop innovative control strategies in buildings, that are still energy efficient and fulfill better at the same time the user specific requirements. To achieve this, these new automatic control systems should learn and integrate the behaviour and wishes of the user. In the context of this thesis, such a system has been developed. The main "soft computing techniques" namely Fuzzy Logic, Neural Networks and Genetic Algorithms were used to implement the necessary adaptive feature and to realize this system.

This thesis is formed of 5 main chapters. First, the statement of the problem and the actual available solutions are given in Chapter 2. Then, Chapter 3 gives a comprehensive description of the building control system. In Chapter 4, the method of adaptation to the user is shown. Finally, Chapters 5 and 6 deal with the experimental tests with real users and the validation of the proposed method .

Chapter 2

Problem Statement

"*I can't understand why people are frightened of new ideas. I'm frightened of the old ones.*" (John Cage)

Automatic controllers for building services are more and more used. But they do not take into account user wishes on a long-term basis. As a consequence, symptoms of the "sick building syndrome" (SBS) may appear together with their financial and social costs. The first section of this chapter states more precisely, through a literature review, the causes of the low user acceptance of automatic building controllers. The state of the art in advanced control systems is then described in the second section. Afterwards, outline of solutions are given and justified.

2.1 Limitations of Automatic Building Controllers

From a sustainable development perspective, automatic controllers for building services provide large improvements potential. The newly developed automatic controllers offer very promising possibilities to increase energy efficiency and to reduce commissioning and maintenance costs. But a major problem has appeared together with the automatic building control system spreading: the user acceptance of this kind of system is quite low as it has been shown in several studies [Elder and Tibbott, 1981, Vine et al., 1998, Guillemin and Morel, 2001]. In the Elder study, for instance, more than 400 employees were considered and the dissatisfaction assessed through questionnaires reached up to 80% regarding the heating control.

Explanations of the low user acceptance have to be found in the fact that current automatic controllers in energy efficient buildings are still not really user-oriented and only deal with comfort through norms (temperatures, illuminances, etc.) that come from statistical assessment (e.g. Fanger's theory for thermal comfort [Fanger, 1982]). Yet, a study [Begemann et al., 1997] in Netherlands with 170 subjects has shown a large range of individual preferences, and this rejects the idea of applying norms for comfort conditions. Moreover, the lack of user considerations in building control explains in part the appearance of the "sick building syndrome" (SBS) [LHC, 1990]. Indeed, McIntyre and Sterling denotes six building features strongly associated with SBS, two of them being directly linked to energy efficient control: application of energy conservation measures and lack of individual control opportunity over environmental conditions [McIntyre and Sterling, 1982].

The level of individual control is also mentioned as being strongly related to SBS symptoms in the book on workplace performances of Aronoff and Kaplan [Aronoff and Kaplan, 1997] and in the work of Willey, who says that “restrictions on occupant control of the environment in building is an ongoing cause of SBS” [Willey, 1997]. Substantial evidences of users suffering from the lack of individual thermal control in energy efficient building were shown by de Dear through his large database [de Dear, 1998] produced from the analysis of 12 offices in Australia. For automatic lighting systems, Vine et al. compared the user response with and without override facility of the same automatic lighting controllers (concerning both electric lighting and shading device). Through questionnaires, the study shows that more people (78% compared to 57%) felt lighting comfortable in the case with the override facility than in the other case [Vine et al., 1998]. And more recently, Moore et al. have found that people place a high level of importance on being able to control lighting. On a 5-point scale, 1 representing unimportant and 5 important, the mean response of the 410 subjects was 4.2 [Moore et al., 2002].

A very large study in England, PROBE (Post-Occupancy Review of Buildings and their Engineering), including a user survey in almost 50 buildings with more than 100 subjects in each building, brings very interesting clues related to the user rejection of automatic systems. The authors of the study conclude that “the environmental systems designs and controls often seem to have reduced the adaptive opportunity, which seems to be at the root of occupants’ higher tolerance” [Bordass and Leaman, 1997]. In particular, the study shows that frequently automatic control was used without manual override facilities, which irritates and in some case infuriates users. In the same study, Leaman and Bordass go one step further assuming that users get frustrated as soon as they are unable to achieve *speedy* and *effective* response from their own actions or from the control systems [Leaman and Bordass, 2001]. Vine et al. confirms this, saying that delays in feedback create an erroneous impression that the system is not working [Vine et al., 1998].

On a financial point of view, SBS related problems have huge consequences. Their costs may be divided into two contributions: a part of the work related health problems, estimated to be around 26 billion dollars per year in USA [Leigh et al., 1997] and a loss of the potential improved productivity estimated to be from 40 to 250 billion dollars per year [Fisk and Rosenfeld, 1997]. Independently, Wyon concludes following a review of the literature that “published experimental data indicate that conventionally acceptable indoor working environments may be affecting human performance by various mechanisms by as much as 5% to 15%” [Wyon, 1996].

It is interesting to notice the dates of these different publications: during the last five years, a deep consciousness of the lack of user consideration in automatic building control has been established. But only very few authors try to propose concrete solutions. Bordass and Leaman explain that “it is vital to make controls comprehensible, effective, responsive, and in the right place” [Bordass and Leaman, 1997]. Willey proposes a possible way for reintroducing a more human-oriented control system: a simulation of expert

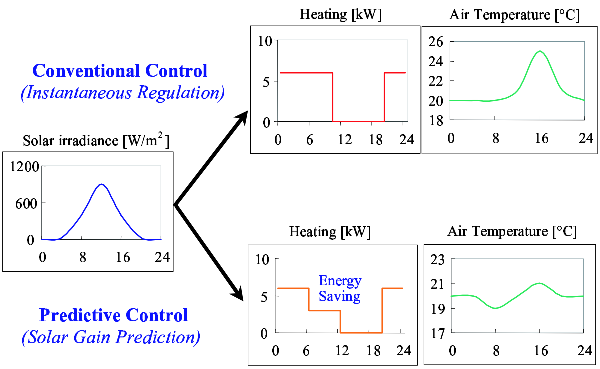


Figure 2.1: *The predictive control*

human control actions should be introduced as the strategy underlying automatic control [Willey, 1997]. But actually, no such systems have been developed.

2.2 State of the Art

The history of automatic control systems in buildings has shown that they were mainly concerned by the energy savings, while trying to keep standard indoor comfort conditions. The typical example of this kind of controllers is the optimal control [Burghes and Graham, 1980]. Given a certain function that expresses energy consumption and user discomfort (assessed through Fanger's theory, for instance) from a set of variables, these systems try to find the minimum of this function, applying different strategy of control (for instance, for Heating Ventilation Air-Conditioning (HVAC) systems). The optimization may be achieved in different ways, depending on the knowledge of the system: matrix inverse calculation, gradient descent or global minimization techniques such as Genetic Algorithms (GAs). The work of Lam is an example of the application of GAs in optimal control for air-conditioning system [Lam, 1993].

Even though optimal control was first using instantaneous cost function, predictive aspects became quickly a major concern: predictive control was born. Its principle (see Figure 2.1) is to anticipate future disturbances (as solar gains, user presence, etc.) and to control the heating plant accordingly. It has been shown that it may improve thermal comfort mainly by reducing overheating risk [Nygard, 1990]. And thanks to its great efficiency in energy savings, this kind of control is still widely used by researchers in building control [Chen, 2001, Kummert et al., 2000].

The adaptive control, an other important field of control, has become important because building control systems, which do not adapt to the building characteristics and to the climate conditions, have a severe drawback. They require to do the commissioning

of the building services in a very careful way; otherwise a large increase of energy consumption could result. Conversely, a self-adapting system would not need such a careful tuning, and would progressively adapt itself to the building and climate characteristics.
Since a dozen years, the adaptive control is well known and used successfully in plenty of domains: in robotics [Timofeyev and Yusupov, 1996], in medical engineering [Takahara and Wakamatsu, 1997], in energy production [Gelinas et al., 2001] and so on. But in the building domain, only rare authors have applied directly adaptive techniques to learn the building and environmental characteristics. Teeter and Chow, in USA, described a functional neural network approach to perform a HVAC thermal dynamic system identification [Teeter and Chow, 1998]. Chow et al. have improved this system by adding a genetic-based optimization [Chow et al., 2002]. Huang and Lam have shown a successful implementation of GAs in a simulation tool for automatically tune of PID controllers for HVAC systems [Huang and Lam, 1997].

The most promising way for adaptive control in buildings seems to be the adaptive fuzzy logic controller [Shoureshi et al., 1992, Fraisse et al., 1997, Kolokotsa et al., 2001]. Foundations of fuzzy logic were set by Lotfi Zadeh in 1965, and since then, comprehensive studies and applications have been undertaken [Zimmermann, 1991]. The main interest of fuzzy logic is the possibility to easily integrate expert knowledge into controllers. Moreover, it exists plenty of adaptation procedures for fuzzy logic controller using different techniques such as "standard" ones [Arabshahi et al., 1993], neural ones [Harris et al., 1993] and especially the GAs ones that are the most explored [Herrera et al., 1995b, Dadone and Vanlandingham, 1998, Abbod et al., 1998, Pham and Karaboga, 1998]. Nevertheless, fuzzy logic controllers in buildings adapted using GAs have almost never been developed. Only Pargfrieder in Austria [Pargfrieder, 2001] has realized such a controller.

In addition to this approach, an automatic building controller developed in a Swiss research project gathers the predictive and adaptive aspects. This system named NEUROBAT [Krauss et al., 1998, Morel et al., 2001] have been tested experimentally in two occupied office rooms during a complete heating season and the obtained energy savings are almost 13% compared to a conventional controller (open loop control depending on outdoor air temperature and with an adaptive start-stop algorithm) while thermal comfort, assessed through the Fanger's PMV model is slightly improved [Bauer, 1998].

At the Massachusetts Institute of Technology, Rodney Brooks, a famous specialist in Artificial Intelligence, works with his team since 1997 on the "intelligent room project", which focuses more on the user and domestic services interaction. That means to put cameras and microphones in order to provide voice control, person tracking and gestures recognition. The first applications proposed of such a system are in a command and control center for disaster relief and in an interactive space for virtual tours of the MIT Artificial Intelligence Laboratory [Brooks, 1997]. This new branch of research has brought an innovative way of dealing with building control systems: the controllers in the different rooms are considered as "distributed software agents" [Coen, 1997]. This artificial intelligence technique distributes the information on small entities, called agents, each one being very simple, and allows intelligence to emerge through the agents connections and interactions [Minsky, 1986]. Sharples et al. have developed a mock-building using a multi-agent architecture for intelligent building and sensing control [Sharples et al., 1999]. Yet, no results are apparently available until now.

Nearly none of the here mentioned controllers deal with blinds control because heating and daylighting are almost never considered together. Nevertheless, some studies address the blinds control issue. The first comprehensive work on shading devices control was done in Japan in 1988 [Inoue et al., 1988]. The authors studied four high rise office buildings in Tokyo and developed an optimal control from their investigations. In particular, they found that beyond a vertical solar radiation of 50 W/m^2 onto a facade, blinds closing was proportional to the depth of sunlight penetration into the room. More recently, Lee et al. have developed a prototype of a venetian blinds controller successfully, monitored workplane illuminance being above 90% of the design level for 98% of the year [Lee et al., 1999].
Bauer et al. propose to separate the blinds control issue into two parts: the thermal aspects and the visual aspects [Bauer et al., 1996]. In particular, their blinds controller named DELTA uses two different fuzzy rule bases, one for the user present case and the other for the user absent case. Meanwhile, in a survey involving 63 private offices in a university building in Wisconsin, USA, Pigg et al show the importance of the glare problems in the blinds control. Indeed, 37% of the users stated that they used blinds to reduce glare on their computer screen [Pigg et al., 1996]. This gave the idea to Guillemin and Morel not to only divide the blinds control in thermal and visual aspects but also to divide the visual part into two sections: one dealing with the illuminance and the other dealing with glare problems. It was implemented in an integrated control system [Guillemin and Morel, 1999], that has been proven to lead to large energy savings (20% compared to conventional systems) while improving visual comfort conditions [Guillemin and Morel, 2002b].

In the literature, only the work of Mozer mentioned a building control system that tries to adapt to the user [Mozer, 1998]. It is known as the “Neural Network House”. This house is located near Boulder in Colorado and is equipped with several sensors and actuators that allow observing the inhabitant behaviour and desires, and controlling electric lighting, ventilation and heating to fulfill these needs. But no blinds control is included in this study and no results are apparently available today.

2.3 Outline of Solutions

The aim of the present work is to realize a user-oriented and energy efficient building control system. This task should not have been difficult since users were shown as being quite tolerant with indoor comfort conditions [Fanger, 1982]. For instance, up to 2 °C of deviation on the air temperature may be easily tolerated [Nicol and Humphreys, 2002]. This rather large range of tolerance comes from the adaptation capability of the users. Indeed, thermal adaptation of the users can be attributed to four different processes (compiled from [Heerwagen and Diamond, 1992] and [Brager and de Dear, 1998]):

- Changes in behaviour (clothes adjustment, go outdoors, etc.)

- Environmental alterations (open a window, close blinds, etc.)
- Psychological processes (try to ignore the problem, etc.)
- Physiological acclimatization (changes in the settings of the physiological thermoregulation system)

So, why people become suddenly intolerant, despite these adaptation features?

Different authors [Leaman and Bordass, 2001, Nicol and Humphreys, 2002] recently reported that this adaptation process is absent when users have not the control on their environment. Thus, when there is an automatic control in the building, only two things may occur when users are not satisfied with their environmental conditions, depending on the override possibility:

Override possible Users switch off the automatic system and are satisfied, but all the energy savings may be lost (for instance, the electric lighting is not switched off by the user when leaving the room).

Override not possible Users become unsatisfied and frustrated, and symptoms of SBS may appear.

The capability of adaptation to the user preferences seems to be the necessary condition to lead to a wide acceptance of the automatic building control systems among the users and to keep an energy efficient control. An adaptation to users through the observation of their interactions and behaviours should be possible thanks to the fact that people are consistent in their way of reacting [Reinhart and Voss, 2002, Begemann et al., 1997]. Some researchers have tried to modelize user behaviour and interaction using stochastic models [Scartezzini et al., 1990, Nicol, 2001, Reinhart, 2001]. But the obtained results are not sufficiently precise to be implemented in a strategy of control that must be efficient and accepted by every user.

In the domain of computer and web-based applications, several methods for learning user preferences and profiles have been successfully implemented. Meyer et al. describe two intelligent agents that are able to learn human behaviour, to anticipate next actions and then act accordingly in a web-based application [Meyer et al., 1997]. Cuenca and Heudin have developed an agent system for learning profiles in broadcasting applications on the internet [Cuenca and Heudin, 1997]. Other studies in the same domain have shown more universal results applying the Theory of Reasoned Action (a person's attitude toward a behaviour is determined by that individual's beliefs about the behaviour's consequences). Their authors [Liker and Sindi, 1997, Morris and Dillon, 1997] have extracted many factors that influences user acceptance of expert systems, and Birnbaum et al. have summarized the three key principles for successful integration of intelligent control in expert systems [Birnbaum et al., 1997]. These principles may be translated into our building control vocabulary as follows:

- The user must keep the control on the whole control system (i.e. he/she must keep the priority over the values provided by the control system).
- The system must be responsive, providing always appropriate indoor comfort whatever the outdoor conditions and the changes in the user environment are.

- The system must take into account the user actions, which provide a “free” information to the system.

In conclusion, an automatic building control system that adapts itself to the user specific characteristics remains to be elaborated. It should not be based on a user model but should preferably adapt control parameters to fulfill the observed user needs while keeping the most possible energy efficient control strategy. Moreover, the development of the system should rely on the three key principles mentioned above, especially concerning the override facilities, which should always be provided.
Thanks to this user adaptation, the newly developed controller would increase the acceptance of automatic control systems. Therefore, it would bring better indoor environment conditions, and consequently, reduce the SBS symptoms and increase the productivity.

Chapter 3

Comprehensive Control System Description

“*Automatic simply means that you can’t repair it yourself.*” (Mary H. Waldrip)

This chapter gives a detailed description of the automatic controllers for the blind, electric lighting and heating systems used within this work. First, some preliminary studies related to the development of these controllers are described. Then, the governing basic principles and the data handling are explained. In the third and four sections, the final controllers and the needed adaptive models (concerning the environment, the building and the devices) are given.

3.1 Preliminary Studies for Blinds Control

The development of an efficient strategy for blinds control is very critical. The mix of direct (visual) and mid-term (thermal) consequences of the control variables is particular to this field. A way to address this problem was proposed by Bauer et al. in the DELTA project [Bauer et al., 1996]. The DELTA blind controller is divided into two cases, depending on whether the user is present or not in the room. When the user is present, the blind controller primarily provides optimal visual conditions in the room; otherwise, only thermal considerations are taken into account to minimize heating energy consumption.
This section presents the preliminary studies carried out for the development of an efficient blind controller. First, the thermal impact of blind control is assessed using a simple model of the window and blind, and then different blind controllers are tested by numerical simulations for both user present and absent cases.

3.1.1 Thermal Impact of Blinds Control

In order to quantify the thermal impact of solar protections, a simple model of a window and a blind has been defined. Assuming the independence of the energetic transmission coefficients of the blind and of the window, the steady-state heat balance of the model described on Figure 3.1 may be calculated as follows:

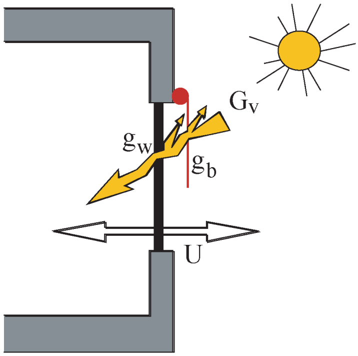


Figure 3.1: *Thermal static model for a window and a blind system*

$$P_w \;= G_v\, g_w\, \alpha + G_v\, g_w\, g_b\, (1-\alpha) - \Big(U\, \alpha + U\,(1-\alpha)/(1+R\,U)\Big)(T_{ind} - T_{out})$$

Where
- P_w: Specific power balance of the opening (W/m^2)
- G_v: Global vertical illuminance on facade (W/m^2)
- g_w: Window energetic transmission coefficient (-)
- g_b: Blind energetic transmission coefficient (-)
- α: Blind position, $0 \leq \alpha \leq 1$, $\alpha = 1$: blind fully open, $\alpha = 0$: blind fully closed
- U: Thermal transmittance of window (W/m^{2}K)
- R: Thermal resistance of blind (m^{2}K/W)
- T_{ind}: Indoor temperature (K)
- T_{out}: Outdoor temperature (K)

For the calculation, physical values for the window are assumed to correspond to a typical double-glazing with a thermal transmittance of 2.5 W/m^{2}K, and an energetic transmission coefficient of 0.7. Regarding blinds, physical values correspond to a tissue blind with a thermal resistance of 0.15 m^{2}K/W and an energetic transmission coefficient of 0.1.

This equation is applied to different cases: in summer and winter and for sunny and cloudy days. A global vertical irradiance G_v equal to 800 W/m^2 is assumed for a sunny day and a value of 100 W/m^2 for a cloudy day. A winter outdoor temperature is assumed at 5°C (corresponding more or less to Switzerland conditions), a summer outdoor temperature at 25°C and the indoor temperature is kept at 20°C.

For each case, the visual optimization and the thermal optimization are compared. The thermal optimization applied the most efficient strategy for blinds control (close completely the blind during a sunny day in summer, $\alpha = 0$) while visual optimization makes a compromise with visual aspects (blind only half closed during a sunny day in summer, α

= 0.5, in order to keep sufficient daylight in the room). In Table 3.1, the heat power balance for the window is given in the visual optimization case and the thermal optimization case. They are values per square meter of window. They take into account the solar gains through window and the heat losses due to the difference of temperature between indoor and outdoor.

	Summer		Winter	
	Sunny day	Cloudy day	Sunny day	Cloudy day
Visual Optimization	319 (0.5)	83 (1.0)	276 (0.5)	33 (1.0)
Thermal Optimization	65 (0.0)	16 (0.0)	523 (1.0)	33 (1.0)
Difference [W/m^2]	254	67	-247	0

Table 3.1: *Heat power balance of a window for different cases (in brackets the corresponding blind positions (α) are given)*

The results show the difference, in power per square meter of windows, that exists between the visual and the thermal optimization cases. As expected, there is potentially more thermal energy to save (or reject) during the sunny day.
In summer, during a sunny day, the thermal aspects lead to close the blind and the visual ones give a half-closed blind position. The difference between the two power balances is more than 250 W/m^2. It could be interesting to close the blind more than that the visual aspects ask for. For instance, if one would choose a position of the blind of 0.2 instead of 0.5, it has been calculated that 150 W/m^2 of solar heating (and its associated overheating) may be avoided.
During a sunny day in winter, the thermal aspects allow a gain 250 W/m^2 of heating power with a blind completely open instead of a half-closed blind position. But in this case, it is more questionable to consider a blind more open than that the visual aspects ask for, because of the high risk of glare that could occur.
During a cloudy day in winter, the same kind of strategies may be done so as to consider also thermal aspects, but the gain will be limited at about 50 W/m^2. In winter during a cloudy day, the visual aspects lead to the same blind position as the thermal aspects.

Thus, it is sometimes possible to save heating/cooling energy by considering some thermal aspects also during a visual optimization period (user present). To have an idea of the amount of energy saved during one year, let us consider the following calculation: 150 W/m^2 for a window of 4 m^2 during 5 hours/day for 50 sunny days in a year: $150 \cdot 4 \cdot 5 \cdot 3600 \cdot 50 = 540$ MJ. In comparison, the total thermal energy consumption of an office room of the LESO building is 2500 MJ. In conclusion, it may be very beneficial to also consider some thermal aspects during the visual optimization.

3.1.2 User Present

When the user enters the room, the controller switches to the visual optimization mode. Several algorithms for blind control have been studied in this preliminary study. First, the most promising algorithm (called *Sun-Position*) is explained. It consists of two parts, one determining a maximum blind opening in order to avoid glare (using a fuzzy rule base) and the second one trying to find the blind position (below the maximum value) that leads to appropriate indoor illuminance. Then, the other algorithms are briefly presented and compared through simulations.

3.1.2.1 *Sun-Position* Algorithm: Maximum Blind Opening

The first part of the *Sun-Position* algorithm is a fuzzy inference system[1] consisting of 25 rules, four inputs (direct outdoor horizontal illuminance, season, solar altitude and azimuth) and one output (maximum blind position). The main principles used to design the rules are:

- Priority is to avoid glare. The system tries however to reduce heating/cooling needs by differentiating the rules depending on the season. In winter, during the day solar gains are maximized (in accordance to visual aspects) and during the night blinds are closed so as to increase the thermal insulation and reduce the heat losses through the window. In summer, the opposite behaviour is applied.

- A position of the sun near the horizon leads to close blinds if the direct solar radiation is high enough to disturb the user (typically higher than 100 W/m^2).

- In absence of direct solar radiation on the facade, there is no restriction on the maximum opening of the blind.

The innovative idea of the algorithm is to take into account not only the solar incidence angle on the facade (which was one limitation of the DELTA blind controller) but both solar altitude and azimuth relative to the facade (see Appendix A.1). This allows different behaviours for different sunlight penetration scenarios (see Figure 3.2). In this example, if the sun is in the south-west direction and illuminates the east wall in front of the user 2 or is in the south-east direction and illuminates the user 2 directly, the algorithm may give different maximum blind openings although the incidence angle is similar in both cases. The two sun positions are equivalent for the user 1.

3.1.2.2 *Sun-Position* Algorithm: Blind Position According to Indoor Illuminance

The final position of the blind is calculated through a simplified illuminance model. This model links the indoor horizontal illuminance (Eh_{in}) to the outdoor vertical illuminance (Ev_{out}). It depends linearly[2] on the blind position (α) and it uses two coefficients c and d.

$$Eh_{in} = (c \cdot \alpha + d) \cdot Ev_{out}$$

Setting the indoor horizontal illuminance (Eh_{in}) equal to the required illuminance and solving this equation for α, a final position of the blind can be determined. The unique

[1] Detailed explanations about fuzzy logic can be found in the book of Zimmermann [Zimmermann, 1991]

[2] An improved model that varies exponentially with the blind position is used in the final version of the controller (see Section 3.4.2).

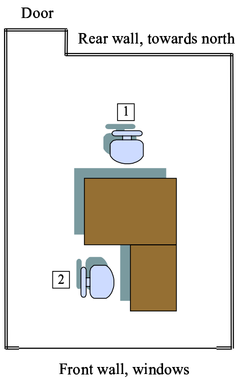


Figure 3.2: *Example of an office room layout*

constraint is that blind position must be lower than the maximum blind opening previously determined. If the indoor illuminance is too low, electric lighting is switched on to meet the setpoint defined by the user. The measurement of the indoor illuminance is not used directly (it should however be used for adapting continuously the c, d parameters of the model), the benefits being:

- Oscillations (that could appear with a closed-loop control) are avoided.
- An appropriate behaviour of the controller is kept even if the sensor gives a temporary wrong value (in cases of paper on the sensor, sensor failure, etc.).
- Blind position may be predicted as soon as a prediction of Ev_{out} is available (predicted blind position is used by the heating controller).

3.1.2.3 Algorithms Comparison

Three other algorithms were considered within this preliminary study.

The *Reference* algorithm is the one used by the DELTA blind controller [Bauer et al., 1996]; it is a simple fuzzy logic open-loop controller that uses the vertical direct illuminance on the facade and the solar incidence angle.

The *Variation* algorithm is different from the others in that the fuzzy logic rule base provides 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 *I-Ratio* algorithm uses three luxmeters for the control. One monitors the horizontal illuminance and two monitor 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 provides appropriate illuminance on workplane while keeping the contrast at a reasonable level. The benefit of this method using three luxmeters is that it is possible to take into account some glare aspects. The drawback is that the positioning of the luxmeters is very difficult to define. Simulations have not tested the algorithm behaviour with different values of the contrast input variable; it was chosen constant.

In order to compare the algorithms, the toolbox Simulink of the MATLAB® program was used to carry out the simulations. Each algorithm was tested during one week with synthetic values of external weather conditions produced by the METEONORM program [MeteoTest, 1996]). Simulations were made for the period that corresponds to the first seven days of July. Different weather conditions were represented (sunny and cloudy days). During the night (from 21h00 to 7h00), the user was considered as absent, so the tested algorithm was stopped (no blind movements, no electric lighting).
The physical model of the room (that plays the role of the real room for the simulations) used for the calculation of the indoor illuminance is simply the global illuminance on the facade multiplied by a fixed coefficient (0.05 in 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 outputs of simulations are the extreme values of indoor 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 electric lighting system and the total number of blind movements during the simulation (see Table 3.2).

Algorithm	Indoor illuminance extrema [lux]	Integrated difference [lux]	Electric lighting 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

Table 3.2: *Visual optimization algorithms comparison*

All algorithms have reasonable performances, without too many blind movements or too large electric lighting consumption. Concerning the indoor illuminance, they all keep a value not too far (difference < 300 lux) from the setpoint value (fixed at 600 lux), except the *Reference* algorithm. From a quantitative point of view, none of the tested algorithms gives really poor results. But, qualitatively, some interesting comments can be made.

- *Reference*: In addition to the large difference between the illuminances provided and aimed (due to its open-loop control strategy), a major drawback is the necessity of a precise adjustment of the algorithm parameters for each room configuration.

- *Variation*: This algorithm leads to nearly perfect visual conditions (concerning illuminance) in the room. But this very small value of integrated difference in illuminance is due, in fact, to a low position of the blind and an extensive use of electric lighting. Indeed, since the position of blind is quite low, the illuminance is not much influenced by the outdoor conditions and can be kept very constant using a large amount of electric light. Moreover, the possible blind positions are predefined and fixed, which avoids recurrent blind movements but leads to a lack of flexibility. An other 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 principle chosen for the final controller (levels 1 and 2 are not anymore clearly separated, see Section 3.2.1).

- *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 continuously if no discretization were applied to the output of the algorithm (a simple discretization by step was used for the simulations). Unfortunately, it was observed that the necessary discretization was nearly impossible to do without largely spoiling the quality of the algorithm.

To sum up, the comparison of the three newly developed algorithms with the *Reference* algorithm (coming from a project especially dedicated to blind control) shows that all the new algorithms give comparable or better simulation results than the *Reference* algorithm. The most promising controller is the *Sun-Position* algorithm. Its results are good and it combines well with the nested loop control. In addition, it considers both solar altitude and azimuth, which allows different behaviours for different penetration of the sun in the room.

3.1.3 User Absent

When the user is not present for a certain amount of time (typically for 15 minutes at least), the control system switches from the visual optimization to the thermal optimization algorithm. In this preliminary study, different controllers have been developed and compared to the DELTA controller (see [Bauer et al., 1996]).

3.1.3.1 Algorithms Definition

The basic idea is taken from the DELTA project. There are two main heat exchanges through a window: one is due to the transmitted solar radiation (direct gain), the other to the heat losses caused by the difference between indoor and outdoor temperatures. Considering both contributions, which depend on the blind position, a window heat balance is calculated (see the model presented in Section 3.1.1). The idea is that the fuzzy controller does not directly provide a blind position but a is aiming towards a "desired window heat balance" (DWHB). A positive (respectively negative) value of the DWHB corresponds to the desired heat gains (respectively losses) for the room. The position of blind that gives a window heat balance as near as possible to this DWHB is calculated knowing the physical parameters of the window and the blind (energetic transmission coefficients, heat-loss coefficients).

Nine different blind controllers were developed and tested. They are classified according to the inputs of the fuzzy inference system. Two controllers, called *Only heating*, have only the heating power as input and the fuzzy rule base is given in the Table 3.3. Three controllers, called *Only season*, have only the season as input (see Table 3.4). Finally, the last four controllers, called *Both*, have both heating power and season as inputs (see Table 3.5). The main ideas used to build these tables of rules were:

- The blind controller should always contribute to reduce the heating/cooling needs.
- In winter, solar gains should be maximized.
- In summer, solar gains should be rejected as often as possible.
- In mid-season, the situation being unclear, several possibilities are considered.

The blind controller *Only heating v2* provides a negative value of DWHB when the heating power is zero, since it is more expensive, on an energy point of view, to cool than to heat a room. Moreover, when there is no cooling system available, a negative value of DWHB prevents overheating due to solar gains.
The difference between the controllers *Only season v1* and *Only season v2* is the width of the fuzzy variable mid-season, which has been enlarged in the version 1. Indeed, The fuzzy variable "season" is not determined on the basis of the period of the year but on the average outdoor temperature during the last 24 hours. Its membership functions are given in Figure 3.3. The width of the mid-season fuzzy membership function in the controller *Only season v1* goes from 5°C to 15°C instead of the 8°C to 12°C applied in the other controllers. The mid-season fuzzy membership function is centered on 10°C[3]. At this temperature, heating loads are null for the LESO building. It is called the *non-heating* temperature.

The unique difference between versions 2 and 3 of the controllers *Both* is the value "positive low" in mid-season. In *Both v2*, 200 W/m^2 are aimed for DWHB whereas only 100 W/m^2 are aimed in *Both v3*.

3.1.3.2 Algorithms Comparison

The simulation tests were carried out with Simulink (MATLAB® Toolbox), for a period of one 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. The weather conditions are synthetic values produced by the METEONORM program [MeteoTest, 1996]. In these simulations, the thermal model of the room is a two-nodes model (a similar model is described in Section 3.4.4). One node corresponds to the indoor air (with also the furniture) and the other corresponds to the massive part of the rooms (walls, etc.). 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 [Krauss et al., 1998, Morel et al., 2001]).

In summer, energy consumption of all controllers is null and there are absolutely no differences in the results between the different controllers. The reason is that all blind controllers work in the same way during summer, they reject all solar gains: because of input "season = summer" for controllers *Both* and *Only season*, and because of the input

[3]For standard buildings, a value of 12°C for the non-heating temperature should be assumed.

Controller version	Current heating/cooling power		
	Negative	Zero	Positive
Only heating v1	DWHB = negative	DWHB = zero	DWHB = positive
Only heating v2	DWHB = negative	DWHB = negative	DWHB = positive

Table 3.3: *Fuzzy rule base for the lighting controllers "Only heating". DWHB is the desired window heat balance.*

Controller version	Season		
	Winter	Mid-season	Summer
Only season v1	DWHB = positive	DWHB = zero	DWHB = negative
Only season v2	DWHB = positive	DWHB = zero	DWHB = negative
Only season v3	DWHB = positive	DWHB = positive low	DWHB = negative

Table 3.4: *Fuzzy rule base for the lighting controllers "Only season". DWHB is the desired window heat balance.*

Season	Current heating power		
	Negative	Zero	Positive
Winter	DWHB = negative	DWHB = positive	DWHB = positive
Mid-season	DWHB = negative	DWHB = *	DWHB = positive
Summer	DWHB = negative	DWHB = negative	DWHB = positive

*depends on version : "zero" for v1, "positive-low" for v2,v3 and "negative" for v4.

Table 3.5: *Fuzzy rule base for the lighting controllers "Both". DWHB is the desired window heat balance.*

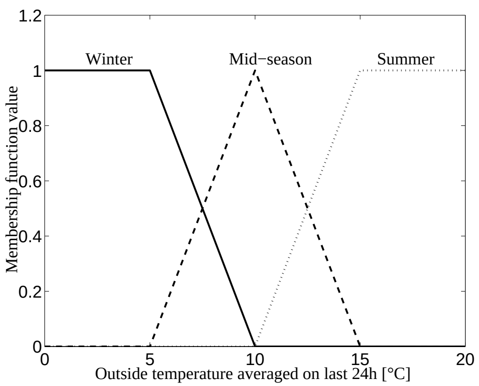


Figure 3.3: *Membership functions of the fuzzy variable "season"*

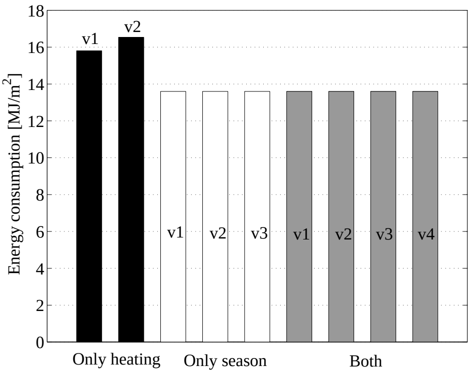


Figure 3.4: *Thermal optimization algorithms comparison during the winter period*

"heating power = zero" for the controllers *Only heating*. Moreover, the weather data used (typical from the Switzerland's climate) correspond to conditions not warm enough to have the usefulness of a cooling system.
In winter, all controllers with the season as input maximize the solar gains and yield very similar results. The two controllers *Only heating* reject solar gains as soon as the heating power is zero, and this lead to an increase of 15% to 25% of the heating energy consumption in winter. Results relatively to the controller *Only heating v1* are depicted in Figure 3.4 for the case with no cooling system (the other case is rather identical because of the uselessness of the cooling system for the Swiss climate).
In mid-season, there are more differences between controllers. The results are given in Figure 3.5. Excepting the two controllers *Only heating*, the worst controller is *Both v4*, which gives a negative DWHB in mid-season when the heating system is off. The similar poor results for the controller *Both v1* (that gives a zero DWHB in mid-season when heating is zero) confirm the importance of having a positive DWHB in mid-season when the heating system is off.

The *Only season v2* and *Only season v3* controllers are more efficient than the *Only season v1*. This comes from the fact that the fuzzy variable mid-season is narrower in these two cases and thus the variable winter has more effect during the simulation. Solar gains are larger and the power consumption is reduced. But opposite results could also have occurred: if the fuzzy mid-season membership function is not properly defined (e.g. does not correspond accurately to the non-heating average outdoor temperature and is slightly lower), the variable summer could be match more often and the solar gains would be too often rejected, that would lead to higher power consumption. So, it is hazardous to shrink the variable mid-season in order to have better results, without an accurate definition of the non-heating temperature. Moreover, the efficiency of a positive DWHB in mid-season is proven again by the better results of the *Only season v3* (with positive value of DWHB in mid-season) compared to the *Only season v2* (with a zero value of DWHB).

Three controllers are more efficient than others: *Only season v3*, *Both v2* and *Both v3*,

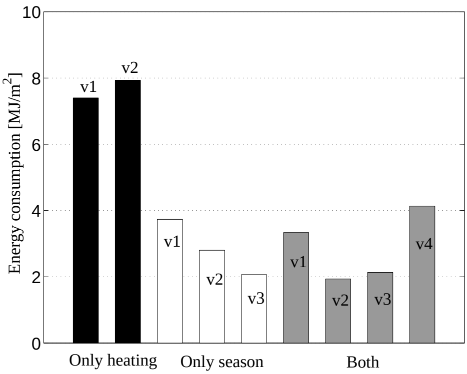


Figure 3.5: *Thermal optimization algorithms comparison during the mid-season period*

the latter two differentiated by their positive DWHB during mid-season when heating is zero. But there is no particular interest of finding the optimal value of DWHB, because heating energy consumption seems not to be very sensitive to the exact value. Moreover, it completely depends of the room and heating device characteristics.

Thus, the main conclusions of these simulations are:

- The differences between controllers are particularly visible during the mid-season period.
- The fuzzy variable season is essential to improve the efficiency blind controller.
- It is more advantageous to have a positive DWHB in mid-season when the heating power is zero.
- Shrinking the mid-season membership functions may only be interesting when the non-heating average outdoor temperature is accurately determined (which could be achieved through the adaptation process).
- Three controllers are clearly more energy efficient than others: *Both v2, Both v3* and *Only season v3* (the three controllers have a positive DWHB value in mid-season).

The *Only season v3* controller seems to be the most appropriate controller for the user absent case. Although it is not exactly the optimal one regarding the heating 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 would have needed the blind position produced by the blind controller (so as to predict the future indoor temperature), whereas the blind controller would have needed the heating power variable produced by the heating controller.

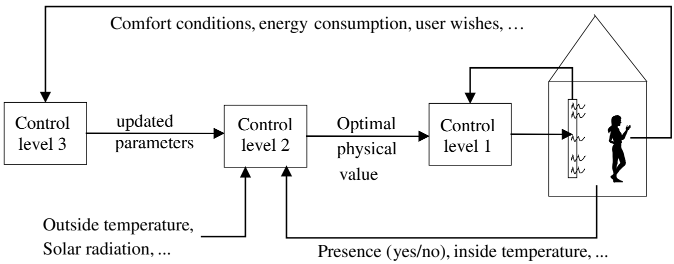


Figure 3.6: *Principle block diagram of the three nested control loop levels*

3.2 Basic Principles

Integrating all the different controllers in one unique system would have been very difficult and inefficient if there were no underlying principles. This section describes the basic principles used for the whole control system. It also explains how some additional physical data are prepared.

3.2.1 Integration Aspects

Three different device categories are considered for the control: the heating/cooling system, the blinds (shading devices) and the electric lighting. Ventilation was not taken into account since the LESO building (in which the experiments have been undertaken) has no mechanical ventilation system installed. Nevertheless, the chosen controller architecture allows implementing easily additional control devices[4]. The integrated system is built on the principle of three nested control loop levels (see Figure 3.6).

- Level 1 performs the translation from physical values (heating power, blind position, etc.) into electrical signals for field actuators (to modify the heating system valve position, to raise or lower the blind, etc.). The European Installation Bus (EIB) is used for this task (see Section 5.3.1).

- Level 2 control loop includes the domain knowledge. It is based on expert fuzzy inference systems and uses adaptive models for thermal and lighting aspects in order to produce an efficient global control strategy. The different fuzzy controllers are described later in this chapter. The outputs of this level are the physical values that are the inputs of the level 1 control loop.

- Level 3 ensures the long-term adaptation of the level 2 algorithms. The adaptation is performed in a continuous way to take into account all the long-term changes of the building and device characteristics (see Section 3.4). Moreover, an adaptation task using Genetic Algorithms is undertaken in order to optimize the system from both user and energy efficiency points of view (see Chapter 4).

[4]The possibility of an efficient ventilation integration in this architecture had been proven in a previous European project named EDIFICIO [Priolo et al., 2001].

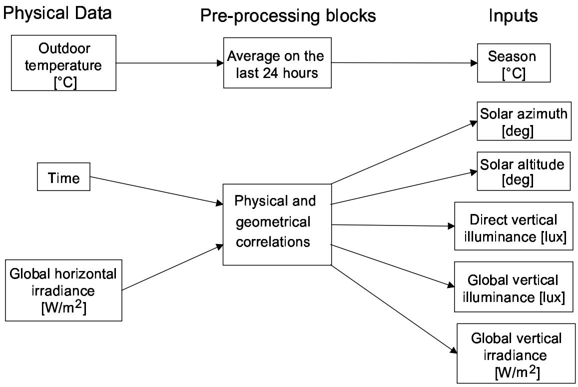


Figure 3.7: *Preprocessing phase*

The 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 leads to simplified commissioning and efficient working without complicated parameter adjustment.

The system provides also an interface that allows the user to change set-points or other operative conditions (see Section 4.1). This gives the maximum flexibility to the system, user actions always keeping the first priority over the automatic control.

3.2.2 Data Handling

The control system requires some variable that are not directly available through the sensors, but that have to be generated by preprocessing blocks described in the figure 3.7. The first block provides the average outdoor temperature during the last 24 hours, including the current outdoor temperature. It is used essentially to derive the current season as a fuzzy variable.

The second block provides all the needed illuminances for the controllers and provides also the solar altitude and solar azimuth relative to the facade. Its inputs are the time and the global horizontal radiation. Furthermore, four parameters are needed for the block calculations. The longitude λ, the latitude ϕ, the time zone T_z of the building location and the facade orientation a_0.

3.2.2.1 Solar Angles

First, the solar angles (namely the solar azimuth and altitude angles) are determined. Many references [Duffie and Beckman, 1974] provide the following expressions[5]:

$$\sin h = \sin \delta \cdot \sin \phi + \cos \delta \cdot \cos \phi \cdot \cos \omega \tag{3.1}$$

$$\sin a = \frac{\sin \omega \cdot \cos \delta}{\cos h} \tag{3.2}$$

Where
- h: Solar altitude, the angle between the sun direction and its projection on a horizontal plane (positive when the sun is above the horizontal plane)
- a: Azimuth angle of the sun, the angle between the south direction and the direction of the sun projected on a horizontal plane (positive towards the east direction)
- ϕ: Latitude (positive towards the north)
- ω: Hour angle, 0° at noon and $\pm$ 180° at midnight (positive in the morning and negative in the afternoon)
- δ: Declination, the angular position of the sun at solar noon with respect to the equator plane (positive towards the north)

The equations for δ and ω are:

$$\delta = 23.45 \cdot \sin\Big(\frac{360 \cdot (284 + n)}{365}\Big) \quad \text{[deg]} \tag{3.3}$$

$$\omega = 15 \cdot \Big(12 - \text{Solar time}\Big) \quad \text{[deg]} \tag{3.4}$$

$$\text{Solar time} = \text{Legal time} + \Delta H + (\lambda/15) - T_z \quad \text{[hours]}$$

Where
- n: Day number of the year (coming from the Time input)
- ΔH: "Time equation" [hour] that integrates both the ellipticity of the movement of the earth around the sun and the declination
- T_z: Time zone [hour] (0 for Greenwich Mean Time, positive towards East)
- λ: Longitude [deg] (0 at Greenwich, positive towards East)

So, the solar altitude h (used in the control algorithm) is simply given by:

$$h = \arcsin\Big(\sin \delta \cdot \sin \phi + \cos \delta \cdot \cos \phi \cdot \cos \omega\Big)$$

Since the solar azimuth a can be greater than 90° or smaller than -90°, an additional condition is needed depending on whether or not the sun is behind a south-facing vertical surface. That condition is given by the critical hour angle ω_s:

$$\cos \omega_s = \frac{\tan \delta}{\tan \phi} \qquad \forall\, \omega_s \quad \text{verifying} \quad 0 < \omega_s < 180$$

Thus, the azimuth a is depending on $\sin a$ and ω, which were given in Equations 3.2 and 3.4. The azimuth a is given in the table below:

[5]Warning: not all textbooks assume the same angle conventions. Depending on the author, some signs might differ, therefore it is not advisable to take an equation from one textbook and mix it with an equation from an other textbook.

ω	a	
$\lvert\omega\rvert < \omega_s$	$a = \arcsin(\sin a)$	morning: $a > 0$, afternoon: $a < 0$
$\omega = \omega_s$	$a = 90$	sun at east
$\omega = -\omega_s$	$a = -90$	sun at west
$\omega > \omega_s$	$a = 180 - \arcsin(\sin a)$	morning (sun between east and north)
$\omega < -\omega_s$	$a = -180 - \arcsin(\sin a)$	evening (sun between west and north)

Finally, the solar azimuth relative to the facade (a_r), which is used in the control algorithm, is given by:

$$a_r = a - a_0$$

Where a_0: Facade orientation (angle between the perpendicular to the facade and the south direction, positive towards the east)

3.2.2.2 Illuminances Determination

After the determination of the solar angles, the required illuminances and irradiances are calculated. Assuming an isotropic diffuse component, the Liu and Jordan correlation [Liu and Jordan, 1960] allows to calculate the direct and diffuse component from the global irradiance (Gh) on a horizontal surface. The direct (Gh_{dir}) and diffuse (Gh_{diff}) horizontal irradiances are given by:

$$Gh_{dir} = Gh \cdot (1 - f_{diff})$$

$$Gh_{diff} = Gh \cdot f_{diff}$$

With

$$f_{diff} = 1.0045 + 0.04349 \cdot f - 3.5227 \cdot f^2 + 2.6313 \cdot f^3$$

Where

$$f = \text{limit of } (Gh/Gh_{ext}, 0, 0.75)$$

And

$$Gh_{ext} = 1353 \cdot [1 + 0.034 \cdot \cos(\frac{2\pi \cdot n}{365}) + 0.001 \cdot \sin(\frac{2\pi \cdot n}{365})] \cdot \sin h$$

Gh_{ext} being the extraterrestrial solar radiation on an horizontal surface.

The first term corresponds to the average extraterrestrial solar radiation on the earth (1353 W/m^2). The second term takes into account the ellipticity of the earth's orbit around the sun and the third one deals with the orientation of the horizontal plane considered towards the sun direction.
Once the two components of the solar radiation are available on a horizontal surface, they can be calculated on a vertical surface of any orientation.

For the diffuse component:

$$Gv_{diff} = 0.5 \cdot Gh_{diff} + 0.5 \cdot Gh \cdot r$$

The albedo r is due to ground reflection is assumed to be equal to 0.3, which is a reasonable value for concrete surfaces and grass.

For the direct component, the following expression is applied depending on the sun position[6]:

If $\quad 5° < h \leq 90°$ and $-90° < a_r < 90°$

$$Gv_{dir} = Gh_{dir} \cdot \cos h \cdot \cos a_r / \sin h$$

Else

$$Gv_{dir} = 0$$

The last step is to translate the irradiance values into illuminances. Assuming a constant luminous efficacy for different irradiance, Winkelmann and Selkowitz [Winkelmann and Selkowitz, 1985] give the two following correlations:

$$E_{dir}[\text{lux}] = 93 \cdot G_{dir}[\text{W/m}^2]$$

$$E_{diff}[\text{lux}] = 111 \cdot G_{diff}[\text{W/m}^2]$$

Thus, the last three outputs of the preprocessing block (used in the control algorithm) are:

Global radiation on facade: $Gv_{glob} = Gv_{dir} + Gv_{diff}$

Direct vertical illuminance: $Ev_{dir} = 93 \cdot Gv_{dir}$

Global vertical illuminance: $Ev_{glob} = 93 \cdot Gv_{dir} + 111 \cdot Gv_{diff}$

3.3 Controllers

Three controllers are considered in this work: a shading device controller, an electric lighting controller and a heating controller. Each one is integrated in the whole system via the nested loops architecture (see Section 3.2.1). The present section deals only with the level 2 of the different controllers.

[6] When h (solar altitude) is below 5°, the building receives nearly no direct solar radiation. This assumption avoids numeric problems that could occur with very small value of $\sin h$.

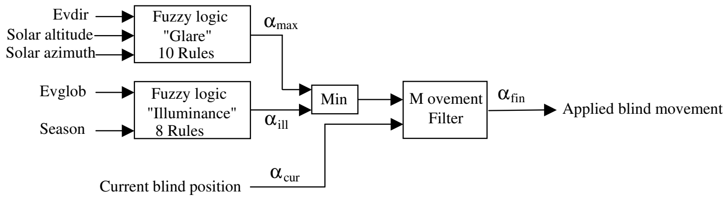


Figure 3.8: *Overall diagram of the blinds controller operation*

3.3.1 Shading Device

The shading device control system described here deals only with tissue blinds, since the available blinds in the LESO building are of this type. Nevertheless, a controller for venetian blinds was developed (with both vertical position of the blind and slats angle regulated). Its description can be found in Appendix B.

In this section, the tissue blind control system is presented: first the controller for the case where the user is present, and then the controller for the case where the user is absent.

3.3.1.1 User Present

From the preliminary study in Section 3.1.2, the main criteria of a blind controller in the visual case have been established:

- Priority is to avoid glare.
- Thermal aspects should also be considered.
- Both solar altitude and azimuth should be used to be able to provide different control strategy for different user positions in the room.
- There should not be a closed-loop control with indoor illuminance measurement.

The final controller presented here, is inspired by the *Sun-Position* algorithm described in Section 3.1.2. It keeps the distinction between glare and illuminance considerations. The main difference is that the thermal aspects have been shifted from the “Glare” fuzzy rule base to the “Illuminance” fuzzy rule base. This was done because eyes adapt easily to a wide range of illuminances whereas they have low tolerance towards contrast. Thus, compromises may done more readily between solar gains and illuminances than between solar gains and glare hazard.
Figure 3.8 shows the overall diagram of the blinds controller and the different included function blocks.

First, a maximum value α_{max} for the blind position is calculated through a fuzzy rule base in order to avoid glare. At the same time, a blind position depending on the illuminance setpoint α_{ill} is also determined. This last calculation is achieved using fuzzy logic inference systems, which is different from the *Sun-Position* algorithm that determined the illuminance through a simple illuminance model (see Section 3.1.2.2). Then, the final value for the blind position α_{fin} is determined: it corresponds to the minimum value of the two blind positions α_{max} and α_{ill}. A blind movement filter depending on the current position of blind α_{cur} prevents from moving the blinds too often, which could irritate the user.

The final controller architecture has been chosen for the following reasons:

- It is a simple and flexible system, containing only few rules, and therefore only few parameters have to be tuned by the adaptation process (see Chapter 4).
- The glare aspect is very important: a dedicated fuzzy inference system ("Glare") is used to deal with this problem.
- Providing a perfect illuminance is not aimed, because human eyes have a very low sensitivity towards the variation of illuminance. Moreover, the "Illuminance" fuzzy inference system allows finding a compromise between the illuminance and the thermal impact of solar gains. For instance, opening the blinds wider in winter in order to increase solar gains is quite acceptable for the user, as long as no glare occurs.
- The vertical direct illuminance Ev_{dir} on the facade is more relevant than the horizontal one to address glare problems.

In addition, the fuzzy membership function mid-season is removed in the final controller in order to optimize it on the thermal aspects. In fact, the preliminary study has shown the necessity of providing an accurate value for the non-heating temperature (see Section 3.1.3) in order to make the controller very energy efficient. Since this value is provided by the adaptive heating system (see Section 3.3.3), thermal optimization consists simply in deciding to maximize (in winter) or reject (in summer) solar gains. The fuzzy transition between winter and summer is probably sufficient to deal with mid-season. Thus, it has been decided to remove rules related to the mid-season, even it makes the control system less flexible for this period.
The fuzzy rule bases are given in the Appendices A.1 and A.2.

The "Movement filter" is made of two consecutive filters: a time dependent filter and a minimum step filter.
The time filter prevents too frequent blind movements by forbidding a blind movement when the precedent one has been applied less than 15 minutes ago. The time elapsed is reset to 0 even when the blinds do not move but would have moved towards down if the minimum step filter was not applied. This is done to prevent the blinds moving periodically (each time the 15 minutes pause is ended) during a day with an intermediate sky (sunny-cloudy). Moreover, the movements that lower the blinds are not concerned by the time filter, in order to avoid glare problems during these sunny-cloudy days. A blind position slightly too low is thus preferred to a position slightly too high.
When the blind movement is accepted by the time filter, it enters the minimum step filter: the movement is applied only if it is larger than a fixed minimum value $\Delta\alpha$ (in our case, $\Delta\alpha$ = 0.3, i.e. 30% of the movement between totally closed and totally open). This value is reduced by half when there is a risk of glare (i.e. when $\alpha_{max} < \alpha_{cur}$).

The control algorithm presented here deals only with one blind but in the LESO building there are two blinds to control per room (see Section 5.2). The idea is to control independently the two blinds with two similar algorithms. The unique difference[7] is in the fuzzy rule base "Illuminance" of the lower blind. A minimal opening of 0.4 is kept in order to allow visual contact with the outdoor environment, which has been clearly shown as an important criteria for user acceptance [Elder and Tibbott, 1981].

3.3.1.2 User Absent

The preliminary study in Section 3.1.3 has shown two interesting facts about the thermal blind controller.

- Energy efficiency of the blind controller largely depends on the use of the variable season.
- Providing a positive window heat balance in mid-season is the most efficient strategy.

The final controller for the user absent case is largely inspired by the controller named *Only season v3* described in Section 3.1.3. The distinctive characteristic of this controller is to only consider the current season (which is defined through the average of the outdoor temperature on the last 24 hours, see Figure 3.3, page 23) to determine the blind position. The basic idea is to use the window and blind system as a control of the incoming solar gains, which have to be minimized in summer and maximized in winter. The critical point is to have an accurate value of the temperature that delimits the heating season and the non-heating season. Thus, this value is adapted every month to the latest measurements (see Section 3.4.4).

The controller *Only season v3* has been slightly improved to avoid overheating or overcooling with an extreme blind position. Briefly, the blind controller tries to cool (reject solar gains, increase thermal losses through window) in summer and to heat (maximize solar gains, decrease thermal losses through window) in winter. But when the indoor temperature is really too low or too high compared to the temperature setpoint, the controller takes temporarily the opposite behaviour in order to attenuate the overheating or overcooling.
The fuzzy rule base is given in the Appendix A.4.

Two steps have been taken to minimize the number of movements (and prevents early mechanical wear). The first reduction of the number of blind movements is realized with a minimum step filter (similar to the one used in the user present controller) that allows moving blind only if the movement is large enough (larger than 40% of the movement between totally closed and totally open). The other reduction is done through the use of the two blinds (in the LESO building, see Section 5.2) in a sequential way, that means to consider the two blinds as only one larger blind. In the LESO building, one blind is above the other and a sequential control seems to be a natural solution.
The idea is to use a parameter called B_i that describes the importance of blinds regarding

[7] In fact, the two blind controllers will be more differentiated thanks to the adaptation to the user's preferences.

the illuminance provided.

$$0 < B_i < 1$$

Using B_i and the α value given by the controller, the blind position of the upper blind α_1 and the lower blind α_2 are calculated as follows:

If $\alpha \ \geq \ B_i$ then:

$$\alpha_1 = \frac{\alpha - B_i}{1 - B_i} \qquad \text{and} \qquad \alpha_2 = 1 \quad \text{(completely up)}$$

If $\alpha \ \leq \ B_i$ then:

$$\alpha_1 = 0 \quad \text{(completely down)} \qquad \text{and} \qquad \alpha_2 = \frac{\alpha}{B_i}$$

The B_i parameter is continuously adapted together with the RI model adaptation (described in Section 3.4.2).

3.3.2 Electric Lighting System

The electric lighting is used as a complement of the indoor illuminance E_{ind} (provided by the RI model, see Section 3.4.2) in order to reach the illuminance setpoint E_{set}. A hysteresis control is applied to avoid too frequent switches on or off:

If $\frac{E_{ind}}{E_{set}} < 0.75$ the electric lighting system is switched on.

If $\frac{E_{ind}}{E_{set}} > 1.0$ the electric lighting system is switched off.

But prior to switching on, the system tries to raise the blinds, as far as the user has not interacted with them. Thus, only in very special cases the electric lighting may be switched on with blinds being closed at the same time.
The calculation of the exact power fraction ($P_{al} \in [0,1]$) applied to the dimming control is performed using the electric lighting model described in Section 3.4.3 and the difference between the indoor illuminance and the illuminance setpoint:

$$aP_{al}^4 + bP_{al}^3 + cP_{al}^2 + dP_{al} + E_{set} - E_{ind} \ = \ 0$$

Where a, b, c and d are the parameters of the electric lighting model.

The electric lighting power is the root of this equation. It has to be noted that the solution P_{al} may be negative or higher than 1 but in the controller non-physical values are rejected and replaced by the nearest physical value.

In a post-occupancy evaluation of seven energy efficient buildings in USA, Heerwagen and Diamond had shown that users did not like the automatic daylight and electric light controls because they were distracting and disturbing [Heerwagen and Diamond,

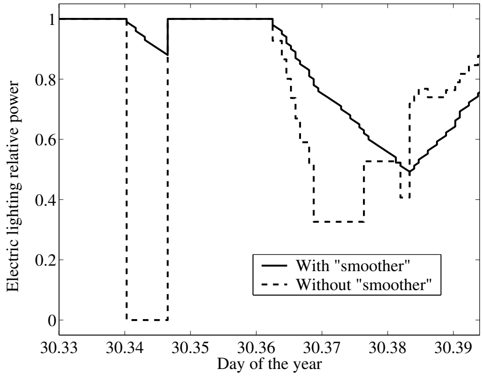


Figure 3.9: *Effect of the "smoother" feature on the electric lighting control*

1992]. Therefore, an electric lighting "smoother" have been developed and implemented. It varies the electric lighting power by maximum steps of 2% that are not noticed by occupants. Each time an event occurs and the main control module is called (see Section 5.4.2.3), a variation step of electric lighting is done, if needed, in the latest calculated direction (increasing or decreasing power).

Figure 3.9 shows the effect of the "smoother" compared to a lighting control strategy without the smoothing feature during a measurement day in January. The time range depicted corresponds to about one hour and a half. First, it prevents the frequent and very disturbing switching on or off as it occurred at time 30.34. Second, it avoids sudden large variations of electric lighting power as it occurred around times 30.37 and 30.38.

Larger steps of variation are permitted when users enters or leaves the room and if the current electric lighting power is really too low compared to the calculated power (difference larger than 50% of maximum power).

3.3.3 Heating System

An efficient heating controller should have predictive and adaptive features. Unfortunately, available controllers such as NEUROBAT [Krauss et al., 1998] consume too much computational time. Indeed, optimization of a cost function (grouping discomfort and energy consumption) is unsuited to our experiments with 15 office rooms and 15 heating controllers to run. Thus, a simpler empirical heating controller has been developed, that nevertheless has both predictive and adaptive features.

A simple proportional control that takes into account the predicted solar gains and the predicted presence is used. Its parameters are automatically adjusted to the room and heating device characteristics. The heating controller is defined as follows, with physical limitations:

$$P_h = \text{limit}\left(K_p \frac{T_{set} - T_{ind}}{\left(\xi \frac{P_{sun,pred}}{P_{sun,max}} + 1\right)} \text{ , } [0,1] \right) \tag{3.5}$$

Where
P_h: Heating power fraction [-]
T_{set}: Setpoint of indoor temperature [°C]
T_{ind}: indoor temperature [°C]
K_p: Gain parameter of the proportional control [°C^{-1}]
ξ: Solar effect coefficient [-]
$P_{sun,pred}$: Average solar irradiance predicted on the next 6 hours [W/m^2]
$P_{sun,max}$: Average maximum theoretical solar irradiance on the next 6 hours [W/m^2]

When large solar gains are predicted, the denominator of Equation 3.5 increases, leading to the reduction of heating power. This way of integrating solar gains ensures a reliable control even with inaccurate prediction of solar gains, because the controller still gives coherent command: it heats less, but it still heats to some extent.

The default value for the temperature setpoint (applied as long as the user does not interact) is set at 21°C. This value has been chosen because it was much easier (due to technical reasons) to implement it compared to a standard temperature setpoint of 20°C.

In addition, the heating power depends on the current presence, the presence predicted one hour later, and the presence predicted six hours later (see Section 3.4.5). The idea is to reduce the temperature setpoint T_{set} in Equation 3.5 of a value ΔT_{red} that depends on the different presence predictions. ΔT_{red} is determined through a fuzzy logic rule base, given in Table 3.6. Lower probability of presence leads to larger reduction of the temperature setpoint and conversely, higher probability leads to smaller reduction.

Current presence	Presence in 1 hour	Presence in 6 hours	Associated ΔT_{red}
0	0	0	-3
0	0	1	-2
0	1	0	-1
0	1	1	-0.5
1	0	0	-0.5
1	0	1	-0.5
1	1	0	0
1	1	1	0

Table 3.6: *Fuzzy rule base for reducing the temperature setpoint depending on current and predicted presence*

An exception to this behaviour of the heating system is that it is stopped if a window is open, in order not to needlessly heat.

K_p and ξ are two adjustable parameters of Equation 3.5. Their values at commissioning are set to 2 and 10 respectively. On the one hand, the gain parameter K_p of the proportional controller depends on the physical characteristics of the room and thus its adaptation procedure relies on the thermal room model adjustment (see Section 3.4.4). On the other hand, the solar effect coefficient ξ is directly adjusted from the real measurements and the procedure is described below.

Only the measurements during which ξ acts effectively are considered for the adaptation process. That means only when there were some solar gains and heat power applied to the room during the last six hours. Moreover, the temperature setpoint have to be constant on the last hour, in order not to consider transitional state cases.

A simplified model of the relative solar energy transmission g through the "window and blind" system has been used, which simply relates the energy transmitted to the blind position α_t at time t considering a blind solar transmission coefficient of 0.2:

$$g(t) = 0.2 + 0.8 \cdot \alpha_t$$

The empirical following rules are applied to adapt ξ from the current (t) and six hours ago (t_0) measurements:

$$\Delta T = T_{ind}(t_0) - T_{set}(t_0)$$

If $\Delta T > 0$°C then :

$$\Delta\xi = \frac{g\,(t_0) \cdot G_v(t_0) + g\,(t) \cdot G_v(t)}{2G_{vmax}} \Delta T$$

If -0.25°C $< \Delta T < 0$°C then :

$$\Delta\xi = 0$$

If $\Delta T < -0.25$°C then :

$$\Delta\xi = \frac{g\,(t_0) \cdot G_v(t_0) + g\,(t) \cdot G_v(t)}{2G_{vmax}} \Delta T$$

With G_v: Global vertical irradiance [W/m^2]
G_{vmax}: Average of maximum theoretical global vertical irradiance [W/m^2]

In the first case there is some overheating, therefore ξ is increased to lower the heating power in similar cases. Larger solar gains and thus stronger ξ parameter's effect cause adaptation of ξ to be more important.
In the second case, indoor temperature is very near from the setpoint and no adaptation of ξ is needed.
In the last case, the heating power was not sufficient and indoor temperature was too low. So, ξ is lowered to increase heating power in such cases. And once again, adaptation is more important if solar gains were important.

3.4 Adaptive Models

The different controllers being defined, the adaptive models used by them are described in the present section. All these models are adapting at a room level. Only the weather data prediction model is achieved at the building level.

3.4.1 Weather Data Prediction Model

The vector of solar irradiance predicted over the six next hours on the horizontal plane is needed by the control system. Such data could have been provided by public weather forecast service but in this case the information supplied is often averaged over several hours and is not directly usable for a six hours ahead prediction. Moreover, the necessary solar radiation sensor is already available in our system because it is required for the lighting and thermal controllers. Thus, a solar irradiance predictor is used within this work.

The approach used was developed and verified in the NEUROBAT project [Krauss et al., 1998, Morel et al., 2001]. It was there shown that artificial neural networks (see the book of Haykin [Haykin, 1999] for comprehensive explanations of ANNs) are the most effective method for the prediction of the horizontal global solar irradiance[8]. A new version of a similar feed-forward network has been re-developed. The same structure with one hidden layer of four neurons has been taken. Due to its convergence capabilities, the Levenberg-Marquart training algorithm was used. For the activation function of the neurons, the tangent hyperbolic was chosen due to its non-linearity, continuity and derivability. The training data were relative values because they were divided by the theoretical maximum solar irradiance, i.e. the solar irradiance with an atmospheric transmission factor of 1.0.

The Artificial Neural Network (ANN) used for the solar radiation predictor has four normalized inputs:

$G_{rel}(k)$:	Relative solar irradiance at current time k
$G_{rel}(k-1)$:	Relative solar irradiance at time $k-1$ (one hour ago)
$G_{rel}(k+6-24)$:	Relative solar irradiance 24 hours before the time of prediction
$G_{max}(k+6)$:	Computed maximum solar irradiance at the time of prediction

And one normalized output:

$G_{rel}(k+6)$:	Relative solar radiation at the time of prediction

The newly developed predictor (called "new ANN") is compared with the one used in the NEUROBAT project, with a reference model that uses the current measurement of the relative solar irradiance as the prediction value and with a more recent meteorological physical model (MRM) developed by Muneer et al. [Muneer et al., 1998]. Weather

[8]It was confirmed by Kemmoku et al. [Kemmoku et al., 1999] for the prediction of daily integrated solar irradiation

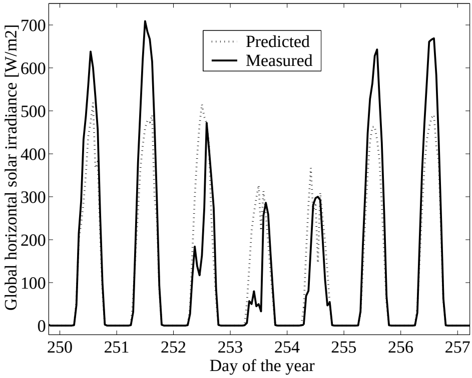


Figure 3.10: *Comparison of measured and predicted value of horizontal solar irradiance*

data used for the comparison are synthetic values generated by the METEONORM program [MeteoTest, 1996] (except the results of the Muneer model that have been obtained with real weather data). Training is performed on the six first months of the year, and evaluation is performed on the last six months. Results are given in Table 3.7. Both ANN models give better results than the reference one, which shows that it is worth using ANN for prediction. The accuracy of the new ANN model is confirmed by its results quite similar to the NEUROBAT ones. Moreover, results of ANN models are even better than the ones of MRM. But it should be mentioned that the latter come from real weather data, which is maybe detrimental.

Model	Mean error [W/m^2]	Standard deviation [W/m^2]
Reference[a]	72.8	160.6
ANN NEUROBAT[a]	-6.7	82.6
New ANN	-9.1	80.9
MRM[b]	12 - 54	39 - 112

[a] values coming from the NEUROBAT final report [Krauss et al., 1998]

[b] values from [Muneer et al., 1998] in lux translated in W/m^2 with the Winkelmann and Selkowitz correlations [Winkelmann and Selkowitz, 1985]

Table 3.7: *Mean values and standard deviations of the 6-hours prediction error of the horizontal global solar radiation for different models*

Even with ANN models, standard deviation is quite large, which attests to the difficulty of solar radiation prediction. Qualitative results of the prediction with the new ANN model are depicted on Figure 3.10. They are sufficiently accurate to provide valuable information to the heating system about future solar gains.

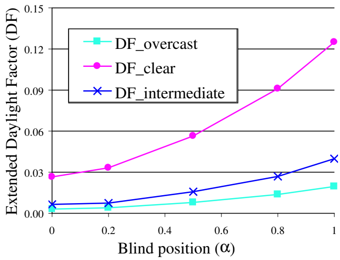


Figure 3.11: *"Extended daylight factor" (horizontal indoor / horizontal outdoor illuminances) measured for three sky conditions*

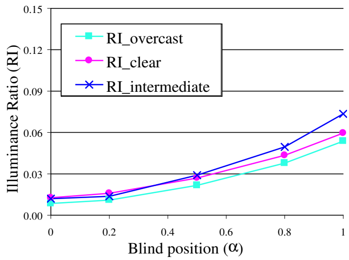


Figure 3.12: *Illuminance ratio (horizontal indoor / vertical outdoor illuminances) measured for three sky conditions*

3.4.2 Illuminance Ratio Model

The RI model calculates the horizontal indoor illuminance on the workplane from the measurement of the vertical outdoor illuminance. Some experiments have shown that the use of the vertical outdoor illuminance gives better and more consistent results than the standard use of the horizontal outdoor illuminance (equal to a *daylight factor* for overcast sky) when comparing with horizontal indoor illuminance for different blind positions (both upper and lower blinds are moved together). Figures 3.11 and 3.12 show the results for both cases. The case with vertical outdoor illuminance (RI model) clearly leads to less scattered results than the case with horizontal outdoor illuminance ("Extended daylight factor"). Hence, the RI model will give better results for different sky conditions. Note that sensors for indoor illuminance measurements were protected from direct solar radiation.

Three RI models have been compared. First, a simple exponential model (see Equation 3.6) that was shown to be better suited than a linear model[9], then an artificial neural network model and finally a model that mixes the exponential and the ANN models. The latter model first fits the data with an exponential model and then tries to fit the remaining error ΔE via an ANN model (see Equation 3.7).

$$Eh_{ind} = a \cdot \exp(b \cdot \alpha) \cdot Ev_{out} \tag{3.6}$$

$$Eh_{ind} = a \cdot \exp(b \cdot \alpha) \cdot Ev_{out} + \Delta E \tag{3.7}$$

Where Eh_{ind} is the indoor horizontal illuminance, Ev_{out} the outdoor vertical illuminance, α the blind position and a, b the model parameters.

[9]It probably comes from the fact that luminances of the sky are larger for higher altitudes, and their relative contributions to indoor illuminance are thus more important for larger blinds opening.

The fit of the exponential model is performed using the nonlinear least-squares Gauss-Newton method (MATLAB® toolbox). The ANN models are feed-forward networks with six neurons in the hidden layer and with the same two inputs: the blind position α and the outdoor vertical illuminance Ev_{out}.
The three models are fitted (trained on 100 epochs for the ANN) on experimental measurements of the whole month of August and evaluated on the measurements of the month of September, provided that there were no electric lighting and no saturation of the indoor illuminance sensor (values below 3500 lux). The results are given in table 3.8. The two models with the exponential characteristic are clearly giving more accurate results than the simple ANN model. The combination of the two models gives similar results to the simple exponential model in accuracy but it necessitates much more computational time. The corresponding ANN model does not improve the exponential model and requires too much computational time for a real implementation. Thus, the chosen RI model is the exponential model.

Model	Standard deviation	CPU time [s]
Exponential model	416	3
ANN model	494*	110*
Exponential + ANN model	417*	99*

*average value out of ten runs

Table 3.8: *RI models comparison*

The RI model is continuously adapted to the new monitored data of the day via the same procedure described above. It allows to take into account changes in the environment (trees in their winter dress, new building in the vicinity, etc.). So, every night the two parameters of the RI model and the B_i parameter (for the two blinds case, see Section 3.3.1.2) are fitted on the measurements of the indoor and outdoor illuminances during the last 15 days.

An additional feature related to the RI model is the shading mask detection. Indeed, shading from neighboring buildings and trees may largely affect the indoor illuminance. Thus, the system tries to detect shading cases in a room by calculating the indoor illuminance using the diffuse component of the vertical outdoor illuminance instead of the global one in the RI model. If the result is closer to the indoor illuminance measurement without the direct component, it is assumed that there is actually shading on the windows of the room and that it is better to only use the diffuse component. Figure 3.13 shows the RI model results during a sunny morning in January compared to the measurements. Thanks to the shading mask detection, the model provides good values even when direct solar radiation is cut by obstacles. At time about 7.42, there is no more shading and the RI model goes properly back to the no shading mask mode.

In addition, if a shading mask is detected, the calculated value of the vertical direct outdoor illuminance (see Section 3.2.2) is set to zero. This has repercussions on the blind and electric lighting controls, which need either RI model calculations or vertical illuminance data.

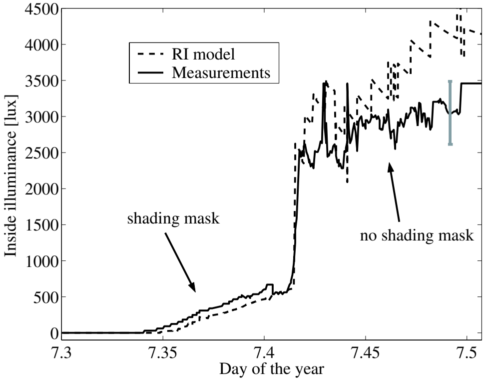


Figure 3.13: *Effect of the shading mask detection in the RI model - measurements have a relative error of 15%*

3.4.3 Electric Lighting Model

This model relates the illuminance provided by the electric lighting system to the electrical power applied. The variables to consider are the electrical power fraction (of the maximum power) applied to the electric lighting system ($P_{al} \in$ [0,1]), and the corresponding provided illuminance E_{al} ([lux]).

Every night during the user's absence, illuminances are measured for five different power fractions (0.2, 0.4, 0.6, 0.8 and 1). In order to reduce the impact of an adaptation with wrong measurements, they are averaged with the old ones. And if the values are clearly too low (monitored illuminance is lower than 50 lux with electric lighting power at full power), which could occur if a paper is on sensor or in case of sensor failure, the adaptation is postponed.

A fourth order polynomial is fitted to the five measurements, using the nonlinear least-squares Gauss-Newton method:

$$E_{al} \;=\; aP_{al}^4 + bP_{al}^3 + cP_{al}^2 + dP_{al}$$

Where E_{al} is the illuminance measured, P_{al} the fraction of power applied and a, b, c, d the parameters of the model. This model forces to give a zero value of illuminance when no electric lighting power is applied.

A fourth order model was chosen because it properly describes the typical characteristic of the electric lighting with only four parameters, as shown by the example depicted on Figure 3.14 (measurement values have a relative error of 15%).

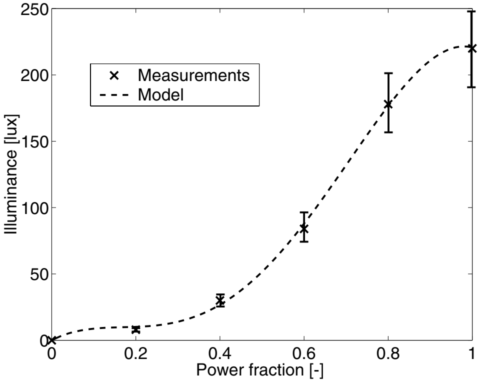


Figure 3.14: *Electric lighting model compared to measurements*

3.4.4 Room Thermal Model

A physical model (2-nodes) of the room has been developed. The Figure 3.15 described the model, with one floating node for the temperature of the indoor air and furniture (node 1), and an other floating node for the temperature of the thermal mass of the room such as walls, floor, ceiling (node 2). The outdoor temperature is considered as a fixed node.

The mathematical expression of this model comes from the following assumption on each floating node:

$$\sum_{\text{on node}} H_{g-l} = C \cdot \frac{dT}{dt}$$

Where	H_{g-l}:	Heat gains and losses (W)
	C:	Thermal capacity of node (J/K)
	T:	Temperature of node (K)
	t:	Time (s)

The free internal gains P_{int} (users, electrical appliances, etc.) and the heating power P_h are only delivered on the indoor air temperature node. The solar gains are separated into two fractions depending on a constant f_{sun}: $P_{sun} \cdot f_{sun}$ is applied to the first node and $(P_{sun} \cdot 1 - f_{sun})$ is applied to the second node. One obtains the two followings basic equations:

Node 1:

$$P_h - G_{out-1}(T_1 - T_{out}) - G_{1-2}(T_1 - T_2) + A_{equ} f_{sun} P_{sun} + P_{int} = C_1 \frac{dT_1}{dt} \qquad (3.8)$$

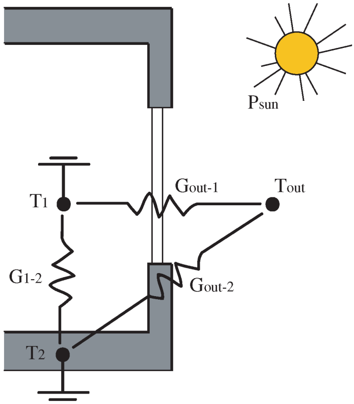


Figure 3.15: *Thermal 2-node model of the room*

Node 2:

$$-G_{out-2}(T_2 - T_{out}) - G_{1-2}(T_2 - T_1) + A_{equ}(1 - f_{sun})P_{sun} = C_2 \frac{dT_2}{dt} \tag{3.9}$$

Where
G_{out-1}: Thermal conductance between indoor and outdoor air (W/K)
G_{out-2}: Thermal conductance between outdoor air and thermal mass(W/K)
G_{1-2}: Thermal conductance between indoor air and thermal mass (W/K)
A_{equ}: Equivalent solar collection area (m^2)
C_1: Thermal capacity of the indoor air and furniture (J/K)
C_2: Thermal capacity of the thermal mass (J/K)
T_1: Indoor air and furniture temperature (K)
T_2: Thermal mass temperature (K)
T_{out}: Outdoor air temperature (K)

These expressions are integrated between t_1 and t_2 and divided by $\Delta t = t_2 - t_1$.

Node 1:

$$\overline{P}_h - G_{out-1}(\overline{T}_1 - \overline{T}_{out}) - G_{1-2}(\overline{T}_1 - \overline{T}_2) + A_{equ} f_{sun} \overline{P}_{sun} + \overline{P}_{int} = \frac{C_1}{\Delta t}\big(T_1(t_2) - T_1(t_1)\big)$$

Node 2:

$$-G_{out-2}(\overline{T}_2 - \overline{T}_{out}) - G_{1-2}(\overline{T}_2 - \overline{T}_1) + A_{equ}(1 - f_{sun})\overline{P}_{sun} = \frac{C_2}{\Delta t}\big(T_2(t_2) - T_2(t_1)\big)$$

With the following notation:

$$\overline{X} = \frac{\int_{t_1}^{t_2} X(t)dt}{\Delta t}$$

A supplementary hypothesis is assumed: T_1 and T_2 varies linearly on the interval $[t_1, t_2]$. Thus:

$$T_i(t) = at + b \quad \Rightarrow \quad \int_{t_1}^{t_2} T_i(t)dt \;=\; \frac{T_i(t_2) + T_i(t_1)}{2}\Delta t \quad \text{for} \quad i = 1, 2$$

The following index notation is defined:

$$T_{ij} = T_i(t_j)$$

Thus, for node 1:

$$\overline{P}_h + A_{equ} f_{sun} \overline{P}_{sun} + \overline{P}_{int} + G_{out-1}\overline{T}_{out} + T_{11}\Big(\frac{C_1}{\Delta t} - \frac{G_{out-1} + G_{1-2}}{2}\Big) + T_{21}\frac{G_{1-2}}{2} =$$

$$= T_{12}\Big(\frac{C_1}{\Delta t} + \frac{G_{out-1} + G_{1-2}}{2}\Big) - T_{22}\frac{G_{12}}{2}$$

And for node 2:

$$A_{equ}(1 - f_{sun})\overline{P}_{sun} + G_{out-2}\overline{T}_{out} + T_{11}\frac{G_{12}}{2} + T_{21}\Big(\frac{C_2}{\Delta t} - \frac{G_{out-2} + G_{1-2}}{2}\Big) =$$

$$= T_{12}(-G_{12}) + T_{22}\Big(\frac{C_2}{\Delta t} + \frac{G_{out-2} + G_{1-2}}{2}\Big)$$

These two equations may be expressed in a matrix form:

$$\begin{bmatrix} T_{12} \\ T_{22} \end{bmatrix} = \mathbf{A}^{-1} \cdot \mathbf{B} \cdot \begin{bmatrix} T_{11} \\ T_{21} \end{bmatrix} + \mathbf{A}^{-1} \cdot \begin{bmatrix} \overline{P}_h \\ 0 \end{bmatrix} + \mathbf{A}^{-1} \cdot \mathbf{C}$$

With:

$$\begin{aligned}
\mathbf{A} &= \begin{bmatrix} \frac{C_1}{\Delta t} + \frac{G_{out-1}+G_{1-2}}{2} & -\frac{G_{1-2}}{2} \\ -\frac{G_{1-2}}{2} & \frac{C_2}{\Delta t} + \frac{G_{out-2}+G_{1-2}}{2} \end{bmatrix} \\
\mathbf{B} &= \begin{bmatrix} \frac{C_1}{\Delta t} - \frac{G_{out-1}+\frac{G_{1-2}}{2}}{2} & \frac{G_{1-2}}{2} \\ \frac{G_{1-2}}{2} & \frac{C_2}{\Delta t} - \frac{G_{out-2}+G_{1-2}}{2} \end{bmatrix} \\
\mathbf{C} &= \begin{bmatrix} \overline{A}_{equ} f_{sun} \overline{P}_{sun} + \overline{P}_{int} + G_{out-1}\overline{T}_{out} \\ A_{equ}(1 - f_{sun})\overline{P}_{sun} + G_{out-2}\overline{T}_{out} \end{bmatrix}
\end{aligned}$$

Thus, the evolution of T_1 and T_2 may be calculated as soon as the parameters G_{out-1}, G_{out-2}, G_{1-2}, A_{equ}, C_1, C_2 and f_{sun} are known. Every month, the adjustment of these parameters is performed using the measurements of the longest available period. The necessary monitored data are the time t, the heating power P_h, the global solar irradiance P_{sun} and the temperatures of the two available nodes (T_1 and T_{out}). The optimal set of parameters is found through an optimization based on the Gauss-Newton method, with the quadratic error to minimize defined as follows:

$$E = \frac{1}{n}\sum_{j=1}^{n}\Big(T_{1,j} - T_{meas,j}\Big)^2$$

Where $T_{1,j}$: Indoor air temperature given by the model at time j
$T_{meas,j}$: Indoor air temperature measured at time j
n: Number of time step considered

Once these parameters are adjusted, an optimal value for the gain parameter of the proportional heating controller (see Section 3.3.3) may be found. In fact, proportional controllers lead always to a steady state error, which may be quite important. Higher gain parameter yields lower offset value, but too high a gain parameter leads to an unstable control. Thus, it has been chosen to tolerate an offset value ΔT_{max} of 0.5K, which is quite sufficient to avoid problems of stability, while keeping a suitable level of thermal comfort. Using the thermal model Equations 3.8 and 3.9 at steady state, one obtains using measurement values averaged on the last 24 hours:

$$\overline{T}_2 = \frac{G_{out-2}\overline{T}_{out} + G_{1-2}\overline{T}_1 + A_{equ}(1-f_{sun})\overline{P}_{sun}}{G_{out-2} + G_{1-2}}$$

$$P_{h,steady} = G_{out-1}(\overline{T}_1 - \overline{T}_{out}) + G_{1-2}(\overline{T}_1 - \overline{T}_2) - A_{equ}f_{sun}\overline{P}_{sun} - \overline{P}_{int}$$

Then, knowing the maximum heating power $P_{h,max}$ of the system, the proportional gain parameter K_p is given by:

$$K_p = \frac{P_{h,max} \cdot \Delta T_{max}}{P_{h,steady}}$$

Similarly, the non-heating average outdoor temperature (see Section 3.3.1.2) is calculated, assuming P_h = 0 and also using Equations 3.8 and 3.9 at steady state and for values averaged on the last 24 hours:

$$\overline{T}_{out} = \frac{(G_{out-1} + G_{1-2})\overline{T}_1 - \frac{G_{1-2}^2\overline{T}_1 + G_{1-2}A_{equ}(1-f_{sun})\overline{P}_{sun}}{G_{out-2}+G_{1-2}} - A_{equ}f_{sun}\overline{P}_{sun} - \overline{P}_{int}}{G_{out-1} + \frac{G_{1-2}G_{out-2}}{G_{out-2}+G_{1-2}}}$$

This temperature is then included in the fuzzy rule base of the blind controller for the user absent case.

3.4.5 User Presence Prediction Model

The heating controller needs the prediction of the user presence, in one hour and in six hours. At the beginning of the project, no set of presence data was available to develop and test a reliable predictor (using Artificial Network, for instance). Only fragmented data from two office rooms were recorded during the EDIFICIO European research project [Priolo et al., 2001].

Thus, a simple occupancy schedule has been used for the presence prediction: rooms are supposed to be occupied from 8 am to 18 pm during weekdays.

However, recent work [Scherz, 2003] shows that presence prediction using ANNs outperforms schedule prediction and may lead to large improvements for both comfort and heating energy consumption. Thus, a further improvement of the heating controller used in this work would be to develop and implement an advanced presence predictor.

3.5 Lighting Self-Commissioning

Each time a new automatic controller is applied in a room, a self-commissioning for lighting aspects is carried out. The goal of this procedure is to provide reasonable starting values for the parameters of the different adaptive models used by the controllers. It concerns the RI model, the electric lighting model and the blinds controller. This commissioning is only run when the global irradiance is higher than 50 W/m^2.

No commissioning is carried out regarding the heating, because a correct adjustment of parameters needs data on several days (to deal with inertial aspects of room characteristics) and these data are not always available.

3.5.1 RI Model

Two measurements are taken during the commissioning in order to provide reasonable values for the RI model parameters (see Section 3.4.2): illuminances (outdoor and indoor) with blinds completely open, and illuminances with blinds completely closed.
With the blinds closed (α = 0), the RI model gives:

$$Eh_{ind,closed} = a \cdot Eh_{out}$$

Then the commissioned value of a is calculated as:

$$a = \frac{Eh_{ind,closed}}{Eh_{out}}$$

And with the blinds completely open (α = 1):

$$Eh_{ind,open} = a \cdot \exp(b) \cdot Eh_{out}$$

Then

$$b = \log\left(\frac{Eh_{ind,open}}{a \cdot Eh_{out}}\right)$$

This commissioning allows to have directly decent values of indoor illuminance available through the RI model for the control, but a more accurate adaptation of the model is ensured by the daily adaptation procedure (see Section 3.4.2).

3.5.2 Electric Lighting Model

When blinds are completely closed, the electric lighting is switched on at full power and the indoor illuminance is measured. This value is then subtracted by the measurement of the indoor illuminance when the electric lighting was off (also with blinds completely closed). The additional illuminance provided by the electric lighting at full power is thus obtained and it replaces the initial default value. A fit of the fourth order model is undertaken with this new value and the four other default values (illuminances at 20%, 40%, 60% and 80% of maximum power, see Section 3.4.3). Measuring only the value at 100% is sufficient to obtain a reasonable electric lighting model used by the controller, and from the following night adaptation, the model will be more accurate.

In addition, the start value for the illuminance setpoint is fixed depending on the value of illuminance provided by the electric lighting system at full power (defined as E_{sys}). Assuming that the system was designed to provide sufficient light during night, a reasonable start value for the illuminance setpoint E_{set} is determined as follows:

$$E_{set} = \frac{E_{sys}}{2}$$

It has been observed that the average value of E_{sys} among the offices is equal to about 330 lux. That means the start value for illuminance setpoint in an office is, in average, equal to 165 lux. This value is probably too low, but it is surely more energy efficient to start with too low a value than too high a value for the setpoint. It forces the user to react and thanks to the biased adaptation (biased towards lower illuminances, see Section 4.2.1), the minimal value of setpoint (that satisfies the user) may be reached. Otherwise, user may not react with high illuminances, even if a lower value would also be satisfying.

3.5.3 Blinds Controller

The second fuzzy rule base ("Illuminance" rule base) of the blinds controller deals with indoor illuminance (see Section 3.3.1.1). Thanks to the commissioned RI model, it is possible to provide values of blinds position better suited to the reality.

For the rules in winter, the goal is to find blind positions that let enter the most possible solar gains, and thus a value of 2500 lux (considered as bearable by specialists in visual ergonomics) is aimed for indoor illuminance. For the rules in summer, a lower value of 400 lux is aimed in order to reject a maximum of solar gains.
For each season two rules are considered for this commissioning, that are the ones matching with *vertical outdoor illuminance is high* and *vertical outdoor illuminance is mid*. With the last rule, *vertical outdoor illuminance is low,* the corresponding blind positions are kept at 1.0 (completely open) (see Appendix A.2).
For the lower blind, a minimal opening of 0.4 is preserved to allow visual contact with the outdoor environment.

Chapter 4

Adaptation to User

"*They are in you and in me; they created us, body and mind; and their preservation is the ultimate rationale for our existence... they go by the name of genes, and we are their survival machines.*" (Richard Dawkins)

Several strategies are applied to make the automatic controllers adapted to user wishes. This chapter first explains how the system deals with the user interactions. Then, the adaptation to user concerning the electric lighting and heating systems is detailed. Afterwards, the functioning of Genetic Algorithms is described and its application to the shading device controller is provided. Finally, the adaptation process using GAs is tested on some set of synthetic wishes and its efficiency is compared to other optimization methods such as gradient descent and Simulated Annealing.

4.1 User Interactions

Chapter 2 has pointed out the necessity of overriding facilities to increase the acceptance of automatic controllers. In this work, standard interface modules were provided with the European Installation Bus that equipped the LESO building (see Chapter 5). Thus, there was no need to install additional interfaces for our purpose. A great benefit of this, is the fact that occupants were already used to this interface and introduction of automatic control was thus less disturbing. Moreover, using standard interfaces may, in some cases, avoid a kind of "Big Brother" fear that could appear when people feel being watched. The interface modules are described in Section 5.3.4.

User interactions have always a direct effect on the considered system in order to give the user the feeling that *he* controls his environment:

Electric lighting system Users may switch on or off the lights, or may precisely choose the electric lighting level.

Heating system Users may change the temperature setpoint, and an increase of the setpoint will immediately start the heating system as far as the indoor temperature is below this setpoint.

Blinds Users may choose any blind position they desire, blinds will always react to their interaction.

An additional interaction opportunity is the *temporary override selector*. It allows the user to stop the automatic control (regarding electric lighting and blind systems) as long as somebody stays in the room. This *sleep mode* gives the user the opportunity to have particular environmental conditions during exceptional situations (e.g. completely closing the blinds and switching off the lights during a slide show, completely opening the blinds for cleaning of windows, switching on the lights at full power for a temporary and special task, etc.). Interactions done when the automatic control is in the *sleep mode* are not considered for the user adaptation.

4.2 Electric Lighting and Heating Control Adaptation

The adaptation to user regarding electric lighting and heating is carried on immediately after a user interaction. These adaptation processes are described in this section.

4.2.1 Electric Lighting Control Adaptation

When the user interacts with the electric lighting system, the illuminance setpoint desired (E_{wish}) is determined by using the RI model and the electric lighting model (see Sections 3.4.2 and 3.4.3) with the current values of blind positions and electric lighting power. This desired setpoint is stored and the control is suspended during three minutes in order to let the user chooses exactly the illuminance. Three cases are eliminated and not taken into account for the adaptation:

- If the automatic control was in the *sleep mode*.
- If the user switches off the lights and the desired setpoint is higher than the current setpoint (because of a high daylight illuminance for instance).
- If the user switches off the lights and leaves the room.

If none of these cases appear, the adaptation takes place immediately after the three minutes timeout (this adaptation process takes less than one second of CPU time).

First, the desired illuminance E_{wish} is averaged with the current illuminance setpoint E_{set}, in order to smooth the adaptation and to reduce the impact of an erroneous wish:

$$E_{wish,av} = \frac{E_{wish} + E_{set}}{2}$$

At this point, two situations exist: either the new setpoint $E_{wish,av}$ is lower than the current one, or the new setpoint is higher than the current one. The goal is to integrate this new setpoint in the electric lighting control system, while trying to limit at maximum the electrical energy consumption. Thus, if the new setpoint is lower than the current one, the adaptation process simply replaces the old setpoint by the new one. But on the other hand, if the new setpoint is higher than the current one, the adaptation process tries to prevent reaching too high an illuminance setpoint, while still providing the possibility to reach any setpoint level if the user insists.

A method for limiting the adaptation towards high illuminance setpoint is to rely on the illuminance provided by the electric lighting system at full power (E_{sys}). If the current setpoint is already at this value, that means the illuminance has reached the upper limit of the electric lighting system, and one may assume that the system was designed to provide sufficient light during night. Thus:

- Additional increasing of the setpoint should be strongly held back and a maximum increase of 20% (fixed arbitrarily) of the current value is tolerated when $E_{set} = E_{sys}$.
- Higher current illuminance setpoint should lead to tolerate smaller change towards higher setpoint.
- Inversely, lower current setpoint should tolerate greater variation, up to a certain limit.

These three requirements are obtained with a function that has the behaviour depicted on Figure 4.1. A reasonable function, which included these requirements, is given by the following mathematical expressions:

$$\text{When} \quad E_{set} > \sqrt{0.2}\, E_{sys} \qquad \text{then} \qquad \Delta E_{max} = \frac{0.2\,(E_{sys})^2}{E_{set}}$$

$$\text{When} \quad E_{set} \leq \sqrt{0.2}\, E_{sys} \qquad \text{then} \qquad \Delta E_{max} = \sqrt{0.2}\, E_{sys}$$

The figure shows the ΔE_{max} in function of the current setpoint E_{set}, assuming an example value of 200 lux for E_{sys}. For lower values of current setpoint, the adaptation may be large (up to 90 lux), but with higher values of current setpoint the maximum adaptation decreases quickly. When $E_{set} = E_{sys}$, the aimed 20% of variation are reached (40 lux).

Finally, the new setpoint applied E_{newset} is equal to:

$$E_{newset} = \min(E_{wish,av}\ ,\ E_{set} + \Delta E_{max})$$

4.2.2 Heating Control Adaptation

When the user chooses a new temperature setpoint via the interface, a new calculation of heating power (see Section 3.3.3) is carried out. Thus, the heating controller is adapted directly to user wishes without using any override feature.

Providing such control opportunity seems in principle to be sufficient to satisfy the users regarding thermal comfort. In fact, assuming a metabolic activity of 1.2 met (typical for an office work activity), a clothing value of 1.1 clo (typical for winter inside clothing), an air velocity of 0.1 m/s and a relative humidity of 50% Fanger's equation [Fanger, 1982] allows to calculate a PPD (predicted percentage of dissatisfied people) lower than 10% for a difference of $\pm$ 2.5°C from the optimal indoor temperature (20°C in this case). That shows that the temperature range considered as comfortable is quite large. Thus, more accurate adaptation procedures are probably not necessary.

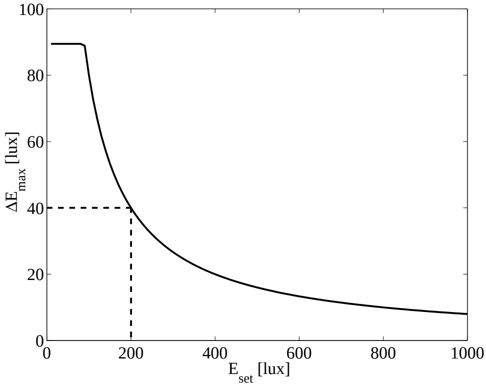


Figure 4.1: *Maximum increasing adaptation value in function of the current illuminance setpoint (E_{sys} = 200 lux)*

4.3 Genetic Algorithms

Among the numerous optimization techniques, Genetic Algorithms have become quite popular thanks to their robustness and their capabilities over a broad range of problems. This section presents a brief history of GAs and describes how they work through the different genetic operators. A mathematical justification of GAs is then provided.

4.3.1 History

In 1967, Bagley first used the phrase "Genetic Algorithm" in his dissertation [Bagley, 1967]. He studied adaptive systems and introduced Genetic Algorithms (GAs) to solve problems of game theory. But the history of GAs is most commonly traced to Holland's work. Holland conducted studies on cellular automata at the University of Michigan, and his text "Adaptation in Natural and Artificial Systems", published in 1975, is generally acknowledged as the beginning of the research in GAs.

At the beginning, during the 1970s, the main works was related to fixed length binary representation for function optimization such as Hollstien's work that provides detailed analysis of the effect that different selection methods and mating strategies have on the performance of a GA. Another famous author, De Jong, attempted to define the features of the adaptive mechanisms in the family of Genetic Algorithms that leads to a robust search procedure. But the research in GAs was still mainly theoretical, with very few real applications.

The situation changed in the early 1980s with the appearance of an abundance of applications in many domains. This brought a new perspective to the theory and several performance improvements were achieved by specializing the GA operators. Furthermore, new findings regarding the applicability, robustness and tuning of GA parameters became available [Goldberg, 1989].

Nowadays, many researchers still work on GAs development but many more are applying them in numerous domains. In engineering, in sciences and in the business world, GAs are applied for plenty of problems as data mining, routing, scheduling, time series prediction and of course optimization problems.

4.3.2 Basic Principles

Genetic algorithms are inspired from biological evolution (natural selection) and are an elegant way for finding optimal solutions (in GAs considered as the individuals) of a given problem space (the individuals' environment). Three basic principles:

- There is a population of individuals
- Each individual is represented by a finite string of symbols, known as the chromosome
- A chromosome encodes a possible solution in a given problem space (search space)

As in biology, the following definitions are used: *genotype*, which is the genetic composition of an individual, i.e. the information contained in the chromosome and *phenotype*, which is the expressed traits of an individual.

The genotype gives rise to the phenotype, which in turn is used to determine how well the individual is adapted to his environment, via a "fitness" function. This function allows to evaluate and classify the individuals on a performance point of view. It is specific to one problem, and its determination is one of the major challenges of the use of GAs.

The standard Genetic Algorithm works as follows:

1. Generate an initial population (at random, for example)
2. Each individual is then decoded and evaluated according to some predefined quality criteria, by using a fitness function
3. A new population is formed (corresponding to the next generation) using genetic operators:
   - Selection: individuals are selected in accordance to their fitness values
   - Crossover (recombination) : individuals are recombined
   - Mutation : small changes are randomly applied to individuals

The steps 2 and 3 are repeated until the "fitness" of an individual is good enough or over a certain number of generations.
In fact, natural selection ensures that chromosomes with the higher fitness will propagate themselves into next generations and genetic operators allow to explore the whole search space.

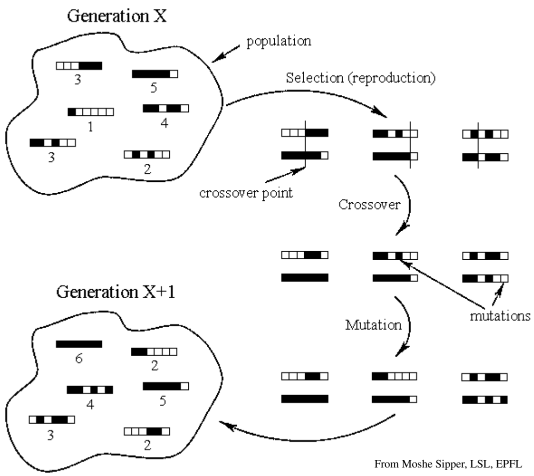


Figure 4.2: *Demonstration of a Genetic Algorithm over one generation*

A simple example is given in Figure 4.2 to illustrate the algorithm. It shows the transition from one generation to the next. The population consists of six individuals, each one represented by an artificial chromosome containing six genes. A gene can take on one of two values (marked by black and white boxes). In this simple example, the fitness of an individual equals the number of black boxes (genes) in its chromosome (fitness values are displayed below the chromosomes). Selection (reproduction) is here performed in a probabilistic way: the higher an individual's fitness is, the better is its chance of being selected. Thus, some parents are selected more than once while others are never selected. Each selected pair of parents is recombined to produce two offspring, an operation known as crossover. This is done by exchanging all genes to the right of a randomly selected crossover point. Mutation is then applied with low probability by simply flipping the gene's value.
The application of the genetic operators on the population of the generation X has yielded a perfect individual, with a fitness value of 6, at generation X+1. Furthermore, the average fitness of the population, computed over all individuals, has been increased (from 3.0 to 3.7 in this example).

In this example, the individuals (chromosomes) are very simple (containing only six binary genes), and there are no differences between the concepts of phenotype and genotype. There are complicated mappings of genotype/phenotype, but within this work, phenotype will simply refer to a genotype evaluated through the fitness function. Moreover this example does not show the difficulty of encoding the potential solutions of a specific problem in the chromosome, which is the main issue of the application of GAs.

4.3.3 Genetic Operators

GAs work thanks to the combination of three type of operators (selection, crossover and mutation), each of them being inspired by a biological process. They are individually described below. The mathematical description of all operators presented here can be found in the book of Mitchell [Mitchell, 1996].

4.3.3.1 Selection

A very important aspect is to decide which individuals should be chosen as parents for the reproduction process. A probabilistic selection is performed based upon the fitness of the individuals. It gives the better individuals a higher chance of being selected. An individual may be selected more than once while others will never be chosen to reproduce in the next generation. Several schemes of the selection process exist:

> **Roulette wheel** It chooses the offspring by using a roulette wheel with each individual's slot sized according to its fitness. The probability of choosing an individual is then proportional to the individual's fitness.
>
> **Elitism** The best individual (or a few best individuals) is copied to the new population. The rest are chosen in a classical way. Elitism prevents losing the best found solution to date.
>
> **Tournament** A set of n individuals is randomly selected and then the fittest is taken. n is often equal to 2. This method of selection applies an additional selective pressure over roulette wheel selection.
>
> **Ranking methods** When the different fitnesses differ greatly the roulette wheel selection will not work properly (certain slots would be extremely large compared to others). The idea is to rank the population and then replace the fitness of the individuals by their ranking.

Only few works have tried to compare the different selection methods, but during the last decade ranking methods have gained increasing popularity and are thought to be the best method, which seems to be confirmed by a recent study [Zhang and Kim, 2000].

Thus, the normalized geometric ranking method [Houck et al., 1995] was chosen. It assigns the following probability P_i to solution i when all solutions have been sorted:

$$P_i = \frac{q}{1-(1-q)^N} \cdot (1-q)^{r-1}$$

Where	P_i:	Probability of selecting the i^{th} individual
	q:	Probability of selecting the best individual
	r:	Rank of the individual, where 1 is the best
	N:	Population size

4.3.3.2 Crossover

The crossover operator is the prime distinguishing factor of a Genetic Algorithm from other optimization algorithms and its role is to spread the advantageous traits of individuals throughout the population.
Once two parents have been selected, the Genetic Algorithm combines them to create two new offspring. This recombination is performed by the crossover operator. Different crossover operators exist: the simple crossover, arithmetic crossover and heuristic crossover.
Let us denote the two parents as s-dimensional vectors $\mathbf{X}$ and $\mathbf{Y}$. The simple crossover generates a random number ζ uniformly distributed over the interval [1,s] and creates the two new offspring $\mathbf{X}'$ and $\mathbf{Y}'$ as follows:

$$x_i' = \begin{cases} x_i & \text{if } i < \zeta \\ y_i & \text{otherwise} \end{cases}$$

$$y_i' = \begin{cases} y_i & \text{if } i < \zeta \\ x_i & \text{otherwise} \end{cases}$$

The arithmetic crossover is similar but produces two complimentary linear combinations of the parents depending on a uniform random value $r = U(0,1)$:

$$\begin{aligned} \mathbf{X}' &= r\mathbf{X} + (1-r)\mathbf{Y} \\ \mathbf{Y}' &= (1-r)\mathbf{X} + r\mathbf{Y} \end{aligned}$$

The heuristic crossover is slightly different, because it produces a linear extrapolation of the two individuals. If the new individual is outside the solution boundaries, a new extrapolation is done until the individual is feasible. The extrapolation is performed as follows, assuming $\mathbf{X}$ is better than $\mathbf{Y}$ in terms of fitness:

$$\begin{aligned} \mathbf{X}' &= \mathbf{X} + r(\mathbf{X} - \mathbf{Y}) \\ \mathbf{Y}' &= \mathbf{X} \end{aligned}$$

In this work, the simple crossover was chosen for its simplicity.

4.3.3.3 Mutation

The last operator in the Genetic Algorithm is the mutation algorithm. The effect of mutation is to prevent the population from stagnating at any local optimum. With mutated genes, the GAs may be able to arrive at better individuals than was previously possible. Three main mutation operators are used:

Boundary mutation It replaces the value of a gene with either the upper or lower bound for that gene (chosen randomly).

Uniform mutation It replaces the value of a gene with a uniform random value selected between upper and lower bounds specified by the user.

Non-uniform mutation It replaces the value of a gene with a non-uniform random value selected between upper and lower bounds specified by the user. It increases the probability of having smaller mutation as the evolution gets to its later stages.

The non-uniform mutation operator is the more sophisticated one, and it has been seen to work well for our purpose. It randomly selects (using a uniform distribution) one gene located at the j position on the chromosome and sets it equal to a non-uniform random number:

$$x_i' = \begin{cases} x_i + (v_i - x_i)\left(r_2\left(1 - \frac{G}{G_{max}}\right)\right)^b & \text{if } i = j \text{ and } r_1 < 0.5 \\ x_i - (x_i + u_i)\left(r_2\left(1 - \frac{G}{G_{max}}\right)\right)^b & \text{if } i = j \text{ and } r_1 \geq 0.5 \\ x_i & \text{otherwise} \end{cases}$$

Where	u_i, v_i:	Lower and upper bounds for gene i
	r_1, r_2:	Uniform random number in the interval [0,1]
	G:	Current generation number
	G_{max}:	Maximum number of generations
	b:	Shape parameter

4.3.4 The Schema Theorem as a Mathematical Justification

Intuitively, it seems obvious that Genetic Algorithms work and may be considered as an optimization method. But it is quite hard to formally conceptualize GAs and thus only a few theories are available. A mathematical justification, first given by Holland [Holland, 1975], for the simple GA exists all the same.

This theory, detailed in the Goldberg's book [Goldberg, 1989], is based upon the definition of a *schema*. A schema is a template for a bit string of length l. Schema are made of ones and zeros (this demonstration only deals with a binary encoding GA) and asteriks ($*$) that act as wild cards within the string. So, the schema

$$H \ = \ 1 \ * \ 0\,1 *$$

represents the four followings bit strings: $1\,0\,0\,1\,0,\ 1\,0\,0\,1\,1,\ 1\,1\,0\,1\,0,\ 1\,1\,0\,1\,1$ which are called *instances* of the schema H.

Two important definitions:

The *order* of a schema is the number of defining positions it contains, that means the number of non $*$ bits. In the above example, the order $o(H)$ is 3.

The *defining length* of a schema is the distance between leftmost and rightmost defined bits in H. In the example, the outmost defined positions are the 1$^{\text{st}}$ and the 4$^{\text{th}}$. So, the defining length $\delta(H)$ is 3.

Let us suppose that there are m instances of the schema H at time t in a population of n individuals. This is denoted by $m(H, t)$. In addition, S_i defines a set of bit strings $(i = 1, 2, \ldots, n)$. Applying the first genetic operator (roulette wheel selection), a bit string S_j containing the schema H is selected according to the probability p_j:

$$p_j = \frac{f_j}{\sum_i f_i} \tag{4.1}$$

where f_i is the fitness of the individual i.

The number of instances of the schema H at time $t+1$ is given by the sum of all the selection probabilities of bit strings containing the schema H, multiplied by the number of selections applied (size of the population n):

$$m(H, t+1) = n \cdot \sum_j \frac{f_j}{\sum_i f_i} = n \cdot \frac{\sum_j f_j}{\sum_i f_i} \tag{4.2}$$

Defining $f(H)$ as the average fitness of instances of H, one obtains:

$$\sum_j f_j = m(H, t) \cdot f(H) \tag{4.3}$$

Thus, using 4.2 and 4.3:

$$m(H, t+1) = m(H, t) \cdot n \cdot \frac{f(H)}{\sum_i f_i} \tag{4.4}$$

Since the average fitness of the population is given by $f = \frac{\sum_i f_i}{n}$, Equation 4.4 becomes:

$$m(H, t+1) = m(H, t) \cdot n \cdot \frac{f(H)}{f} \tag{4.5}$$

Let us suppose that a schema H remains above the average of a quantity $c \cdot f$ with c being a strictly positive constant. Equation 4.5 is now:

$$m(H, t+1) = m(H, t) \cdot (f + c \cdot f) \cdot \frac{1}{f} = (1 + c) \cdot m(H, t) \tag{4.6}$$

Thus, beginning at $t = 0$ and after t generations, one obtains:

$$m(H, t+1) = m(H, 0) \cdot (1 + c)^t \tag{4.7}$$

This clearly shows that selection leads to an exponentially increasing of the number of individuals having a schema with above average fitness.
Now, let us calculate the probability p_s of our scheme H to survive a crossover operator. It depends on the defining length of the schema and of the total length l of the individual's chromosome:

$$p_s = 1 - \frac{\delta(H)}{l - 1} \tag{4.8}$$

If the crossover occurs with the probability p_c, the survival probability becomes:

$$p_s = 1 - p_c \cdot \frac{\delta(H)}{l - 1} \tag{4.9}$$

The selection operator and the crossover operator can be considered independent, so they can be gathered together and Equation 4.5 becomes[1]:

$$m(H, t+1) \geq m(H, t) \cdot n \cdot \frac{f(H)}{f} \cdot \left(1 - p_c \cdot \frac{\delta(H)}{l-1}\right) \tag{4.10}$$

The last step is to consider the mutation operator. The probability of a gene to survive to the mutation is $1 - p_m$, with p_m being the mutation probability. With the order $o(H)$ of the schema, the probability that H survives the mutation operator is $(1-p_m)^{o(H)}$. Finally, including this probability in Equation 4.10:

$$m(H, t+1) \geq m(H, t) \cdot n \cdot \frac{f(H)}{f} \cdot \left(1 - p_c \cdot \frac{\delta(H)}{l-1}\right) \cdot (1 - p_m)^{o(H)} \tag{4.11}$$

This result, known as the *Schema Theorem*, shows that short, low order and above average schema have a large survival probability and that they will grow exponentially with the number of generations. But there are several limitations of the Schema Theorem. In particular, it does not apply to schema with real numbers, and other operators such as the fitness ranking cannot be rigorously explained with the original interpretation of the theorem.

Moreover, the inexactitude of the inequality is such that if one were to try to use the Schema Theorem to predict the representation of a particular hyperplane over multiple generations, the resulting predictions would in many cases be useless or misleading.

However, an important information should be pointed out: during the encoding process (see Section 4.4.1), one has to take care to build a chromosome that enables robust and efficient schema to appear. This also deals with *epistasis*, the process in which a gene is expressed or suppressed due to the interaction between genes in the expression of the genotype [Rochet, 1997]. An example of this is when a certain gene can turn on or off the expression in the phenotype of other genes.

4.4 Shading Device Control Adaptation

The adaptation process for the blind controller occurs each night assuming that at least one wish has been expressed during the day. Expressing a wish means raising or lowering the blind. Since the system does not immediately learn user wishes (but only once a day), the automatic system is temporarily switched off (typically during one hour) when the user expresses a wish, in order not to interfere with the blind position decided by the user.

In addition, at the end of the week an adaptation process is carried out taking into account all wishes expressed during the week, starting from the original controller (default one). If the individual found via this method is better than the current controller, it replaces it. This additional adaptation process is performed in order to ensure that the

[1] The inequality is due to the possibility of generating a schema H from two schema not containing H.

optimal controller is currently running. For instance, considering several wishes of the user together may allow to determine if they were due to glare problems or illuminance preferences, and thus adapting and anticipating in the right way (see Section 4.5.8).

The adaptation has two aims with regard to the shading device controller: it has to learn the new user wishes concerning the blind position and it has to keep the accumulated experience concerning the previous learned wishes and the energy efficient control. Therefore, the GAs are applied on two bases, the so-called "wishbase", which contains the latest wishes expressed by the user, and the "contbase", which contains the outputs of the current controller. The "wishbase" allows to adapt the controller to the new user preferences and the "contbase" prevents forgetting the information already learned and contained in the current controller.

During the adaptation process, the system remains efficient from an energetic point of view for two reasons: the system is energy efficient before the first adaptation (the original rules lead to an energy efficient controller) and the wish filter prevents learning energetically bad wishes, as long as these wishes are not repeated by the user.

In the case where there are two (or more) blinds per room, two (or more) similar and independent controllers are used. The independence of the different controllers is the unique way to ensure a total adaptation to user wishes for both blinds. The same adaptation process is carried out independently for each blind.

4.4.1 Encoding

There are two main ways to adapt fuzzy system by using GAs [Herrera et al., 1995a]. The first consists in generating a set of fuzzy rules that covers the set of examples, and the second consists in tuning membership function parameters of a pre-existing fuzzy rule base. Since we already have an efficient and expert fuzzy rule base, the second solution is applied.

Generally, tuning fuzzy rule bases using GAs is achieved through the modification of the parameters of the different membership functions. And in order to reduce the number of parameters to be adjusted, not each membership function is described with a set of parameters but only few parameters are sufficient to describe the whole fuzzy variable, as depicted in Figure 4.3.
In this example, the mean temperature T_m of the mid-season (transition between winter and summer) and a width ΔT_m are sufficient to describe the whole variable.

But given the fact that there are only crisp values as outputs in our fuzzy system (see Appendix A), a simpler set of parameters is used in the adaptation process. The point is to only encode the crisp outputs of the fuzzy system for the user adaptation using GAs. For instance, in the rule

If "Season is winter" and "Ev_{glob} is high" then "α = 0.6"

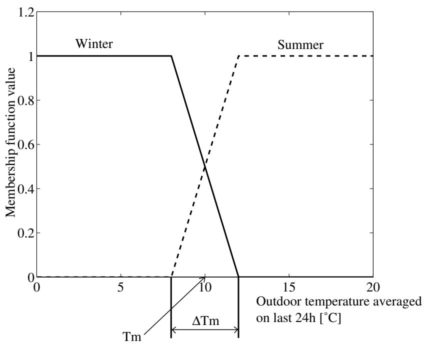


Figure 4.3: *Adaptation on membership function parameters*

the output blind position (here α = 0.6) is the parameter that will be adjusted by the adaptation process.

Thus, since there are 10 and 8 rules in the two fuzzy rule bases of the blinds controller (see Appendix A), there are 18 parameters to adjust. *Variations* of these parameters are represented as genes on a chromosome. Each individual (or chromosome) will consist of 18 genes encoding the 18 variations. The genes are *real numbers* that can take any value between -1 and 1. Thus, each gene characterizes a change in one fuzzy rule of the controllers and each chromosome corresponds to one controller for one blind. One advantage of such an encoding is that no additional constraint (the only constraint is to have values of blind position between 0 and 1) is needed because the logic of the rules is kept in any case.

The 18 genes are not randomly located on the chromosome. In order to enable robust and efficient *schema* to appear, some precautions have to be taken. Even if we do not know in advance which kind of schema may be interesting, some basic rules should however be applied.

First, genes related to the same fuzzy rule base should be gathered together. Thus, the first 10 genes of the chromosome concern the glare fuzzy rule base and the last 8 genes concern the illuminance fuzzy rule base.

Second, genes related to similar rules should be neighbors, since in fuzzy logic the output comes from the aggregation of matching (and therefore similar) rules. But, in fact, all rules are similar to some other rules, and it has to be decided which kind of variables should be linked together. For instance, in the fuzzy glare system, two main variables appear in the rules: the solar altitude and azimuth. Here, it has been chosen to group the rules in order to facilitate the tuning of the controller behaviour depending on the azimuth. Then, the genes related to different azimuth (and the same solar altitude) are grouped together, and schema containing efficient combinations of blind positions depending on azimuth will have a larger probability of survival.
The azimuth variable was chosen because it concerns the sun penetration direction and

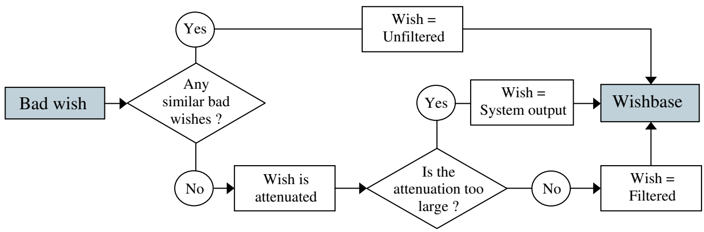


Figure 4.4: *Operation diagram of the "wish pre-processing filter"*

allows to tune the blind position precisely depending on how the sun illuminates the user (towards his face, his back or his profile), whereas the altitude is used to roughly determinate the blind position in order to control the sun penetration depth.

Regarding the fuzzy illuminance system, it was chosen to facilitate the tuning of the fuzzy rules depending on the global vertical illuminance instead of the season. This choice comes from the fact that it is more important to precisely control the blind position depending on the outdoor vertical illuminance rather than on the season, which is only used to detect if it is currently the heating period or not.
The encoding details are given in Appendix A.3.

4.4.2 Wishbase

Each time the user expresses a wish regarding the blind, the current conditions and the corresponding desired blind position are stored in the "wishbase" matrix (see Table 4.1). In addition, the last column provides the oldness of the wish, i.e. the number of adaptation steps encountered. The original value of oldness is set at 1, and at every adaptation step, this value is increased by 1. A wish older than 10 is removed from the "wishbase".

Conditions					Expressed user wishes	Oldness of wishes
Season [°C]	Ev_{dir} [lux]	Ev_{glob} [lux]	Solar altitude [deg]	azimuth [deg]	Blind position [-]	Steps [-]
17	1000	$13'000$	17	-85	0.5	1
21	$34'000$	$58'000$	64	-12	0.8	2

Table 4.1: *Example of a "wishbase" matrix*

Every night, all the new wishes expressed during the day are filtered before the adaptation is undertaken. If a wish can lead to very negative consequences from an energetic point of view, the wish is "attenuated" in order to become energetically better. The overall diagram of this pre-processing filter is given in Figure 4.4.

The new wishes are compared to the wishes of the last ten days, and the energetically "bad wishes" are only attenuated if no similar wishes have already been expressed. This method ensures that the "wrong" wishes (not firmly desired by the user, expressed only once) will be filtered, while the "special" wishes (particular taste of the user, expressed several times) will remain unfiltered and thus strongly taken into account.

There are two situations in which wishes could lead to very negative consequences from an energetic point of view. In summer, when the global vertical illuminance (Ev_{glob}) is high, a large opening of the blinds could lead to overheating in the room. In winter, also when the vertical illuminance is high, closing the blinds too much corresponds to a loss of free solar gains, which would have greatly reduced the heating load of the day. The "attenuation" ($\Delta\alpha$) is thus calculated through a simple fuzzy rule base summarized below:

If "Season is winter" and "Ev_{glob} is high" and "α is closed" then "$\Delta\alpha$ = +0.25"

If "Season is summer" and "Ev_{glob} is high" and "α is widely open" then "$\Delta\alpha$ = -0.25"

If "Other conditions" then "$\Delta\alpha$ = 0"

In some rare cases, the "attenuation" applied is too large and the filtered wish goes in the opposite direction of the unfiltered wish relatively to the position provided by the automatic system (see Section 4.5.4). In these cases, the wish value is set equal to the blind position value provided by the current control system, and this disables the wish. That means, it becomes useless for the adaptation process, but it is still stored as a wish. So, if a similar wish is expressed, it remains unfiltered.

When all the wishes have been filtered, the "wishbase" is ready to be used by the Genetic Algorithms.

4.4.3 Contbase

The second aim of the adaptation is to keep the accumulated experience from the previous learned wishes and the energy efficiency of the controller. The "contbase" is used for this task; it contains the blind positions given by the current controller in different conditions (season, outdoor illuminances, sun position).

The main difficulty is to choose the set of different conditions in order to fill at best the space of all the possible situations. Thanks to the fact that the GAs are just adapting the output values of the fuzzy rules (see Section 4.4.1) and are not changing the membership functions, it is possible to define a fixed set of values for each input of the fuzzy systems in order to have every fuzzy membership functions individually matching. For instance, the fuzzy variable "vertical global illuminance" has a fuzzy set of three membership functions (*low*, *medium* and *high*), so only 3 correctly chosen values are necessary to completely cover the space of this variable. Likewise, 2 values of season (summer and winter), 2 values of "direct vertical illuminance", 3 solar altitudes and 3 solar azimuths are needed. They are given in Table 4.2. The total number of combinations is $3 \cdot 2 \cdot 2 \cdot 3 \cdot 3 = 108$. Two supplementary conditions are added, one for a summer night and one for a winter night. Thus, the complete chosen set of values contains 110 different conditions.
The structure of "Contbase" is similar to that of "wishbase" (see Table 4.3).

Fuzzy variable	Corresponding set of values		
Season	0°C	20°C	
Ev_{dir}	1000 lux	30′000 lux	
Ev_{glob}	5000 lux	40′000 lux	80′000 lux
Solar altitude	10°	30°	70°
Solar azimuth	−60°	0°	60°

Table 4.2: *Values of fuzzy variables chosen for the contbase definition*

Conditions					Controller outputs
Season [°C]	Ev_{dir} [lux]	Ev_{glob} [lux]	Solar altitude [deg]	Solar azimuth [deg]	Blind position [-]
0	1000	5000	10	−60	1.0
0	1000	40′000	10	−60	0.4
⋮					
20	30′000	80′000	70	60	0.6

Table 4.3: *The "contbase" matrix*

Since the controller is adapted and therefore modified every night, this "contbase" should be re-filled daily with the latest controller before carrying out the GAs adaptation.

In addition to the use of the "contbase", a bias in the original population has been implemented to keep the experience accumulated in the current controller through the previous adaptations: at the beginning of the adaptation process 75% of the individuals of the initial population are randomly generated (using a uniform distribution) and the remaining 25% correspond to the current controller (individual with chromosome = [0 0 . . . 0]). This biased population generation has been defined in order to speed up the convergence and not to accidentally lose the genotype of the current controller.

4.4.4 Fitness Function

Once the two bases ("wishbase" and "contbase") have been prepared, the adaptation using GAs is carried out. In order to select the best individuals a measure of how efficient an individual is, has to be defined. This is done via the fitness function.
The fitness of an individual (i.e. a tested controller) is calculated using both bases. An efficient individual should give good results both on the "contbase" (difference between the values given by the old controller and the tested individual) and on the "wishbase" (difference between the blind position provided by the tested individual and the one desired by the user). The fitness of the controller c_i is thus defined as follows:

$$\text{fitness}(c_i) = 1 \Bigg/ \left[\sum_j \left(\alpha_j\left(c_i\right) - \alpha_j\left(\text{contbase}\right)\right)^2 + W \sum_k \frac{\left(\alpha_k\left(c_i\right) - \alpha_k\left(\text{wishbase}\right)\right)^2}{\sqrt{\text{oldness}(\alpha_k)}} \right]$$

Where $\alpha_j(c_i)$: Blind position given by controller c_i in contbase condition j

α_j(contbase):	Blind position given by old controller in contbase condition j
$\alpha_k(c_i)$:	Blind position given by controller c_i in wishbase condition k
α_k(wishbase):	Wish number k, expressed in wishbase condition k
oldness(α_k):	Number of adaptation steps encountered by the wish k
W:	Weight parameter

Importance of old wishes is slightly reduced in comparison to new wishes. This is achieved by using the square root of the oldness of a wish in the denominator of the second term of the fitness.

Moreover, since there are normally much less wishes expressed than the 110 different conditions contained in "contbase", a weight W larger than 1 is necessary to ensure a good adaptation to user wishes even if there are only few wishes expressed. The weight parameter has been chosen equal to 20, which is balancing to a ratio 5/1 the relative importance of "contbase" on "wishbase". That means, since 5 wishes are expressed during a day[2], the two bases have the same importance in the fitness function. The effect of the weight parameter is more precisely described in Section 4.5.6.

Later in this chapter, in Section 4.6, GAs will be compared with other optimization methods minimizing an "error" value $E_r = 1/\text{fitness}$. In order to assess and compare their performances, two different criteria (*moderate* and *severe*) are defined and related to a blind position error.

The *moderate* criterion is an error E_r of an individual equivalent to a controller that gives perfect blind positions for all "contbase" conditions and only one blind position wrong of 0.5 in the "wishbase" conditions. That means this individual completely fulfills the "contbase" conditions but does not fulfill only one wish, providing a blind position 0.5 higher or lower than the desired position (expressed in condition k' by the user).

The lower limit of this error E_r of the controller c_i may be determined as follows:

$$E_r(\textit{moderate}) = 1/\text{fitness} =$$

$$= \left[\sum_j \left(\alpha_j\left(c_i\right) - \alpha_j\left(\text{contbase}\right)\right)^2 + W \sum_k \frac{\left(\alpha_k\left(c_i\right) - \alpha_k\left(\text{wishbase}\right)\right)^2}{\sqrt{\text{oldness}(\alpha_k)}} \right]$$

But since

$$\sum_j \left(\alpha_j\left(c_i\right) - \alpha_j\left(\text{contbase}\right)\right)^2 \geq 0$$

One obtains

$$E_r(\textit{moderate}) \geq W \sum_k \frac{\left(\alpha_k\left(c_i\right) - \alpha_k\left(\text{wishbase}\right)\right)^2}{\sqrt{\text{oldness}(\alpha_k)}} \geq W \frac{\left(\alpha_{k'}\left(c_i\right) - \alpha_{k'}\left(\text{wishbase}\right)\right)^2}{\sqrt{\text{oldness}(\alpha_{k'})}}$$

With $\quad \alpha_{k'}\left(c_i\right) - \alpha_{k'}\left(\text{wishbase}\right) = 0.5 \quad$ and assuming $\quad \text{oldness}(\alpha_{k'}) = 1$

[2]The value of 5 wishes per day is about the maximum number of daily interactions with blinds observed during the experiments.

One finally has:

$$E_r(\textit{moderate}) \geq W \cdot \frac{0.5^2}{\sqrt{1}} = 5$$

The more demanding *severe* criterion corresponds to one wrong blind position of 0.1, and the error E_r is similarly obtained:

$$E_r(\textit{severe}) \geq W \cdot \frac{0.1^2}{\sqrt{1}} = 0.2$$

4.4.5 Genetic Algorithms Characterization

This subsection first deals with the setting of the different parameters of the Genetic Algorithms and then, the relative effect of the genetic operators is studied.

The whole adaptation module has been implemented on a MATLAB® platform, using the GA toolbox [Houck et al., 1995] developed by Houck et al. at the North Carolina State University (USA). Thanks to the convenience and flexibility of this toolbox, the code was easily modified to fulfill our needs.

4.4.5.1 Parameters Settings

Parameters settings is a major concern in GAs. The optimal set of parameters depends on each problem, and generally the setting is done by using some rules of thumb. In this work, a study of the most important parameters has been carried out extensively. The studied parameters are namely: the number of crossovers (10, 40 or 100) and mutations (10, 40 or 100) at each generation, the population size (40 or 80 individuals) and the shape parameter (2 or 3). All the possible combination of parameters have been tested, which corresponds to $3 \cdot 3 \cdot 2 \cdot 2 = 36$ different combinations. For each combination, *ten* simulations were run with a set of 32 real wishes observed during a mid-season period. These wishes are taken as they were expressed in only one day. This test is quite complex because all genes are involved and should be changed by GAs.

Some other parameters have been empirically chosen such as the maximum number of generations fixed at 50, to ensure a reasonable time for the optimization and the selection function parameter fixed at 0.08, which is the default value for the probability of selecting the best individual.

First, a matrix of correlations[3] has been calculated from the results of the simulations to check the influence of the different parameters on the GAs convergence characteristic. Table 4.4 shows the calculated correlations.

The time needed for the optimization depends quite obviously on the number of mutations and crossovers per generation (mutations are slightly more time consuming than crossovers). Higher number of operations leads to longer computational time. Moreover, as it could be expected, the shape parameter does not influence computing time (it requires no supplementary calculation). Surprisingly, a larger population does not lead to a higher time of computation (it even tends to be the opposite). This may come from the

[3] A reminder of basic statistics definitions is provided in Appendix C.

	Number of crossovers	Number of mutations	Shape parameter	Population size
Correl. with CPU time	0.59	0.75	0.02	−0.14
Correl. with E_r*	−0.34	−0.58	0.02	−0.28

$^*E_r = 1/\text{fitness}$

Table 4.4: *Correlations of Genetic Algorithm parameters with the computational time and the error E_r*

fact that the computational time is mainly due to the mutation and crossover processes (that do not depend on population size) and not from the selection process (that largely depends on population size).

The results quality (E_r) mainly depends on the mutation operator, a bit less on the crossover operator and again a bit less on the population size. The shape parameter does not seem to influence the results.
The relative importance of the mutation and crossover operators are studied more thoroughly in the next section.

Table 4.5 shows a summary of the results obtained. A very encouraging point is that GAs have converged for all set of parameters to sufficient results, the *moderate* criterion being always satisfied ($\Delta E_r < 5$) compared to the best result (lowest E_r) obtained.

	Number of crossovers	Number of mutations	Population size	E_r	Standard deviation	CPU time [sec]
Lower E_r	40	100	80	43.6	0.4	50.7
Longer CPU time	100	100	40	43.9	0.4	87.2
Shorter CPU time	10	10	80	45.2	1.0	5.4
Higher E_r	10	10	40	45.7	1.3	6.1

Table 4.5: *Summary of results*

Nevertheless, the set of parameters that gives the lowest E_r is quite time consuming and a compromise has to be found between quality of result and computational time. Since the considered computational times are not really excessive[4], the idea is to be rather tolerant with them by setting a “cost function” that gives an equivalent contribution to 10 seconds of calculation or an additional error corresponding to the *severe* criterion ($\Delta E_r = 0.2$). The “cost” for each set of parameters has been calculated and the results are given in Table 4.6. The best set found was chosen for the implementation of the adaptation process. It has, in addition, the fair advantage of balancing the number of mutations and crossovers.

To summarize, the chosen Genetic Algorithm engine has the following specifications:

- The size of the population is set to 80 individuals.

[4]The tests have been performed on a 800 Mhz computer with 512 MB RAM.

Rank	"cost" value	Nb of crossovers	Nb of mutations	Population size	E_r	Standard deviation	CPU time [sec]
1st	0.688	40	40	80	43.8	0.5	27.3
2nd	0.745	10	100	80	43.7	0.4	35.8
3rd	0.758	40	10	80	44.2	0.6	10.2
4th	0.770	100	40	80	43.7	0.4	39.8
5th	0.776	10	40	80	44.1	0.5	15.8
⋮							
36th	2.35	100	100	40	44.3	0.5	86.3

Table 4.6: *Parameters set classified depending on a "cost function" that groups together the error E_r and the CPU time*

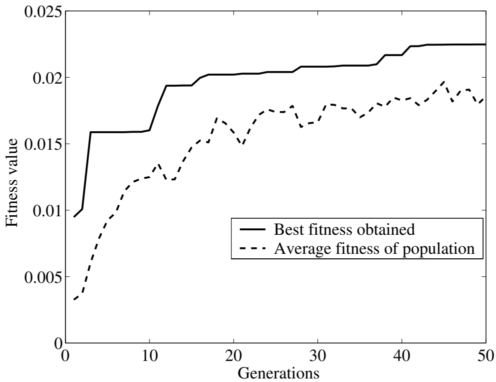


Figure 4.5: *Average and higher fitness evolution over the generations*

- The selection function used is the "normalized geometric ranking" method with a probability of selecting the best individual (parameter q) set to 0.08.

- At each generation, 40 simple crossovers and 40 non-uniform mutations (whose amplitudes are decreasing generation after generation) are performed.

- After a maximum number of 50 generations, the algorithm is stopped and the best individual found over the whole process is kept as the "best chromosome".

With these parameters and the same set of 32 real wishes, the fitness progresses over the generations as depicted in Figure 4.5. Both the average and higher fitness obtained at every generation are shown. The average fitness tends to apparently progress in a logarithmic way with a saturation at the end, whereas the best fitness progresses more by steps depending on the appearance of efficient *schema* in population. These behaviours are quite standard and confirm the correctness of the chosen set of parameters.

4.4.5.2 Genetic Operators Relative Effects

In order to quantify the effects of mutation and reproduction in the optimization performance, additional simulations have been carried out. In these simulations, the two operators have been alternatively inactivated by setting to zero their number of occurrences at each generation. When an operator is inactive, the computational time is reduced. Therefore, additional simulations were carried out with an extended number of remaining operator occurrences at each generation so as to keep, at best, a computational time equal to the one of the original algorithm. These results are denoted as "extended" (in opposition to the "normal" number of operator occurrence) in tables of results. If the crossover operator is inactivated, "extended" means that 85 mutations were performed at each generation instead of 40. If the mutation operator is inactivated, "extended" means that 220 crossovers were performed instead of 40. The values for extended calculations have been roughly estimated from the "normal" simulations results.

Simulations were carried out again on the same sets of real wishes previously used. Table 4.7 shows the results, that are average on *fifty* runs.
The results show that the mutation operator is more important than the crossover operator. Missing crossover leads to slightly worse results, ΔE_r exceeding by 5 times the *severe* criterion ($\Delta E_r < 0.2$) compared to original GAs, whereas missing mutation drastically reduces results quality, ΔE_r exceeding by 16 times the *severe* criterion.
The "extended" version manages partly to recover convergence percentage in the case of missing mutation, whereas it does not improve results in the case of missing crossover. This is due to the fact that mutation is more time consuming than crossover (missing mutation leads to 85% less computational time whereas missing crossover leads to only 50% less), and thus the extended version in missing mutation case has more substantial possibilities to make improvements.

Version	Percentage of convergence*	Mean (E_r)	Standard deviation	CPU time	Student t-test value
GA original	100	44.12	0.52	30.2	undefined
No crossover, "normal"	100	45.08	0.98	13.8	6.12
No crossover, "extended"	100	44.72	0.68	29.2	4.96
No mutation, "normal"	8	47.26	0.58	4.6	–
No mutation, "extended"	54	47.13	0.89	31.5	–

*Considering the *moderate* criterion

Table 4.7: *Comparison of mutation and crossover missing effects*

A Student test (see Appendix C) has been applied on the results concerning the case without crossover, in order to ensure that the differences in E_r with the original GAs are significant. As soon as the t-test value is higher than 3.5 (level of significance 0.001), the hypothesis: $E_r(no - crossover) > E_r(original)$ is verified and the difference is considered as "highly significant". Then, in both cases ("normal" and "extended"), the case without crossover is clearly leading to worse results. This shows *the necessity and usefulness of every operator and their combination* to get the most efficient optimization.

4.4.6 Sensitivity Filter

At the end of the GA process, a “best chromosome” corresponding to the best controller is obtained. A sensitivity filter is applied on this new chromosome in order to remove some inaccuracy in the GAs optimization method. Indeed, it was observed that sometimes after the adaptation process, certain genes gave variations very near to zero (less than 0.01) that were useless. These small errors could have introduced some biases in the results if they were piled up.

The filter tests each gene of the new chromosome separately by forcing the value of the gene to zero and re-evaluating the fitness. If the resulting fitness is higher (or equal) than the fitness with the new gene, the value of the gene is kept at zero. Once the sensitivity filter has been run on all the genes, the new chromosome is finally applied to the current controller to obtain the new and adapted controller.

4.5 Verification through Simulations

This section presents the adaptation process operation with different synthetic wishes. The complexity of the wishes is increasing through examples. These different examples will show that the concerned genes are found and changed correctly by the adaptation process, and that the others are protected from unwanted modifications. Finally, results of a simulation on a year time basis with a consistent user are presented. The content of this section has already been published in [Guillemin et al., 2001, Guillemin and Molteni, 2002, Guillemin and Morel, 2002a].

4.5.1 Simple Example

Winter night is a quite particular condition for the adaptation system, since one gene is dedicated to this situation. The example wish is described in the Table 4.8.

Conditions					Synthetic wish
Season [°C]	Ev_{dir} [lux]	Ev_{glob} [lux]	Solar altitude [deg]	Solar azimuth [deg]	Blind position [-]
0	0	0	-12	110	0.00

Table 4.8: *Wish expressed during a winter night*

The wish pre-processing filter has no effect on the wish because the corresponding conditions (in particular the absence of solar radiation on the facade) cannot lead to very negative consequences from an energetic point of view and the adaptation is applied directly using the original wish (see Table 4.9).

The second column of Table 4.10 shows the chromosome of the best individual obtained after this adaptation process. Only gene 11 (related to the rule “winter night” in the “Illuminance” fuzzy system) has to be changed, and the GA has easily managed to find the right gene to change. It is interesting to note that gene 10, which described the rule

	Blind position [-]
Controller output before adaptation	1.00
Wish before pre-processing filter	0.00
Wish after pre-processing filter	0.00
Controller output after adaptation	0.04

Table 4.9: *Controller output and wish in winter night conditions*

"Ev_{dir} is low" in the "Glare" fuzzy system could also have been changed: this would have fulfilled the wish, but it would have changed the outputs of the controller also in other situations (in summer nights for instance). This last solution would have been unsatisfactory and the GAs have found a better one.

Gene number	Simple example	Contradictory wishes	Ordinary wish	Sensitivity filter (before)	Sensitivity filter (after)	Weight effect (sol.1)	Weight effect (sol.2)	Multiple wishes
Genes concerning the "Glare" fuzzy system								
1	0	0	0	0	0	0	-0.6	0
2	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0
4	0	0	0.36	0	0	0	0	0.26
5	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	-0.47	0
7	0	0	0.07	0.16	0	0	-0.4	0.19
8	0	0	0	0.2	0	0	-0.4	0
9	0	0	0	0.02	0	0	0	0
10	0	0	0	0	0	0	0	0
Genes concerning the "Illuminance" fuzzy system								
11	-0.96	-0.73	0	0	0	0	0	-0.73
12	0	0	0	0	0	0	0	0
13	0	0	0.16	0	0	-0.16	0	0.06
14	0	0	0	-0.34	-0.34	-0.25	0	-0.42
15	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0
17	0	0	0	0	0	-0.13	0	-0.19
18	0	0	0	0	0	-0.24	0	-0.33

Table 4.10: *Values of the 18 genes of the best individual obtained after the GA adaptation process for each example*

4.5.2 Contradictory Wishes

In order to understand how the adaptation module proceeds with contradictory wishes, the previous simple example (winter night conditions) is taken and a similar wish is added with a different value of the blind position.

The controller, after the adaptation process (see the third column of Table 4.10 for the best chromosome obtained and Table 4.11 for the results), provides the average value of the contradictory wishes, thanks to the squaring of the differences in the fitness function. If there was no squaring (but only absolute values for instance), a large difference would not have been more penalized than a sum of two smaller differences, and the adaptation could have given any value in the range [0,0.5]. In the case where the wishes are not expressed the same day, the system will favor the latest wish.

	Blind position [-]
Controller output before adaptation	1.00
Wishes before pre-processing filter	0.00, 0.50
Wishes after pre-processing filter	0.00, 0.50
Controller output after adaptation	0.27

Table 4.11: *Controller output and “contradictory” wishes*

4.5.3 Ordinary Wish

This example (see Table 4.12) shows the adaptation process for a wish in ordinary conditions. Results are given in Table 4.13.

Conditions					Synthetic wish
Season [°C]	Ev_{dir} [lux]	Ev_{glob} [lux]	Solar altitude [deg]	Solar azimuth [deg]	Blind position [-]
0	30000	40000	35	60	0.00

Table 4.12: *Ordinary wish expressed during a winter day*

	Blind position [-]
Controller output before adaptation	0.60
Wishes before pre-processing filter	1.00
Wishes after pre-processing filter	1.00
Controller output after adaptation	0.96

Table 4.13: *Controller output and “ordinary” wish*

The chromosome corresponding to the best found individual is shown in the fourth column of Table 4.10 and its analysis allows us to understand the GAs operation. Gene 13 (that most corresponds to the wish conditions in the “Illuminance” fuzzy system) has been changed to fit to the user wish. But since the “Glare” fuzzy system prevents to raise the blinds high enough, the corresponding rules in “Glare” also need to be increased, which is done by adjusting the genes 4 and 7.

4.5.4 Wish Attenuation Effect

These two examples (see Table 4.14) show the wish pre-processing filter effect on energetically bad wishes in the case of an adequate “attenuation” and in the case of too large an “attenuation” (i.e. when the attenuated wish goes in the opposite direction of the original wish).

In the adequate case, the “attenuation” is applied by the wish filter and the system learns the wish. In the inadequate situation, the “attenuation” is not applied and the wish is disabled (the value of the wish is set equal to the value of the controller output).

	Blind position with a bad wish that leads to adequate "attenuation"	Blind position with a bad wish that leads to inadequate "attenuation"
Controller output before adaptation	0.57	0.57
Wish before pre-processing filter	0.90	0.70
Wish after pre-processing filter*	0.65 (0.65)	0.57 (0.49)
Controller output after adaptation	0.61	0.57

*wishes with the "attenuation" that would have been applied are given in brackets

Table 4.14: *Controller output and wishes for the "wish attenuation" effect*

4.5.5 Sensitivity Filter Effect

At first, the sensitivity filter was developed to deal with the inaccuracy of the GAs optimization method, but an other effect is also addressed with this filter: in some cases, certain genes (only the ones concerning the "Glare" fuzzy system) may become inactive when the blind positions provided by the "Illuminance" fuzzy system are always lower than the ones provided by "Glare". That means that if the blind positions asked by the user are always low enough, the risk of glare may completely disappear and some rules of the first part of the fuzzy controller may become useless.

This phenomenon (influence of certain genes on others) is called *epistasis*. The sensitivity genes filter, as previously designed, prevents randomly changing this kind of genes, and keeps them at their old values ensuring an adequate behaviour of the controller in case these genes are re-activated. This example (see Table 4.15) illustrates this feature, because it leads to three inactive genes (genes 7, 8 and 9).

	Blind position [-]
Controller output before adaptation	1.00
Wish before pre-processing filter	0.50
Wish after pre-processing filter	0.50
Controller output after adaptation	0.66

Table 4.15: *Controller output and wish for the "sensitivity filter" case*

In the fifth and sixth columns of Table 4.10, the chromosome of the best individual obtained by the GAs is shown before and after the sensitivity genes filter. Genes 7, 8 and 9 have become inactive, because gene 14 has been greatly reduced, and they may take any positive value without having any influence on the outputs of the shading device controller. The sensitivity genes filter has detected these inactive genes and has forced them to zero.

4.5.6 Weight Parameter Effect

Two different aims have to be balanced in the adaptation process: adapting the controller to user wishes and keeping the experience integrated in the controller. Depending on the weight W applied to the "wishbase" in the equation of the fitness function (see page 64) either the system can perfectly learn the wishes and lose the experience integrated in the controller (large weight) or the system can slightly adapt to user wishes and keep the experience (small weight). It is very critical to carefully adjust the weight. It is particularly risky to choose too large a value for the weight: in this case, GAs only look for a solution that satisfies the wishes and completely forget the "contbase" examples. Moreover, since the mutation width is necessarily decreasing during the GA search, GAs can never find the optimal solution if they take a wrong way at the beginning. The following example (see Table 4.16) illustrates this problem with a large weight (W=200), which is ten times larger than the weight normally used (W=20). This wish is particularly complex to fit, because it was chosen to match a large number of rules in the two fuzzy controllers ("Glare" and "Illuminance").

	Blind position [-]
Controller output before adaptation	0.59
Wish before pre-processing filter	0.00
Wish after pre-processing filter	0.00
Controller output after adaptation (solution 1)	0.13
Controller output after adaptation (solution 2)	0.16

Table 4.16: *Controller output and wish for the "weight effect" case*

The adaptation process has been run several times and on average, it leads in 60% of the situations to the solution 1 and in 40% to the solution 2 (see columns 7 and 8 of Table 4.10 for the corresponding chromosomes of these two solutions). Now, solution 2 should be avoided because it is a local minimum of the search space. The problem is that when solution 2 is first found by GAs, the system is no longer able to come back to solution 1, because of the too large weight (this local minimum is near the global minimum). In fact, solution 1 only changes the genes concerning the "Illuminance" fuzzy system and disturbs less the conditions that are not concerned by the wish. When the weight is 20, solution 1 is found every time. The weight finally chosen is equal to 20 and it has been seen to be a good compromise between the two aims of the adaptation.

4.5.7 Multiple Wishes

This example groups together the previous wishes described in "contradictory wish", "ordinary wishes", "sensitivity genes filter effect" and in "weight parameter effect" as if they were all expressed during the same day (see Table 4.17).

It shows that all wishes are taken into account, almost partly, even in case of a combination of them. The system still finds an adequate overall solution when several wishes are expressed together. The last column of Table 4.10 shows the chromosome of the best individual obtained.

	Blind position "contradictory"	Blind position "ordinary"	Blind position "filter"	Blind position "weight effect"
Output before adaptation	1.00	0.60	1.00	0.59
Wishes before filter	0.00 and 0.50	1.00	0.50	0.00
Wishes after filter	0.00 and 0.50	1.00	0.50	0.00
Output after adaptation	0.27	0.86	0.56	0.39

Table 4.17: *Controller outputs and wishes for the "multiple wishes" case*

4.5.8 Virtual User on an Extended Period

In the previous examples, the system was tested with several sets of synthetic wishes and has shown a powerful ability to find solutions, even with a complex combination of wishes. But in order to test the learning capability of the system on a yearly basis, a simulation was performed with a virtual user whose wishes are consistent and only season dependent.

The hypothetical user requests the blind to be almost completely closed (α = 0.2) in winter and almost completely open (α =0.8) in summer. During the simulation all the different possible conditions (defined by the membership functions of the fuzzy logic controller) are encountered. Figures 4.6 to 4.8 show that the conditions go from *winter with glare risk and low solar radiation* to *summer with no glare risk and high solar radiation*. Each area on the figure defined by the vertical lines includes nine different conditions that correspond to nine different sun positions relatively to the facade. The simulation is run sequentially on the different conditions by step of three conditions. That means it works as if there are three conditions encountered per day with three associated wishes expressed by the virtual user. The adaptation process occurs at each step (i.e. each day) considering these three wishes. Figures 4.6 to 4.8 describe the effect of the adaptation and the associated evolution of the controller at different times during the simulation. The bar at the top of the graphics spreads over the cases where an adaptation has already been carried out.

Figure 4.6 shows that thanks to the GA adaptation, the system has widely learned what the user wants in the encountered conditions (the controller after adaptation curve is very close to the simulated user wishes in comparison with the original controller dots) and has kept the original controller in the not encountered conditions. There is only one exception for the not encountered *winter with no glare risk and low solar radiation*, which has also been changed by the adaptation. This behaviour may be explained as follows: the system has "understood" that the user did not react towards a glare risk since his reactions were not related to the sun position (same value of blind position desired for every sun position). Thus, if the user is consistent, the system assumes that the user should react in the same way in similar conditions (at least when the solar radiation is low) without glare risk.

Figure 4.7 confirms the extrapolation capability of the system. After 27 encountered wishes, all the *glare risk* conditions in winter have been encountered and the system has extrapolated the user wishes to all the possible conditions in winter. Even for a few conditions in summer, the system begins to (wrongly) extrapolate. But it should be noticed that

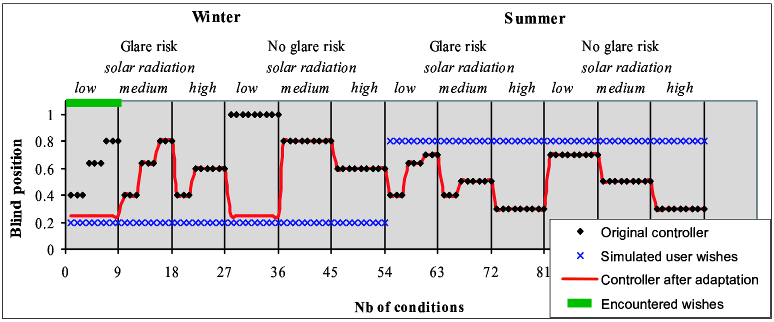


Figure 4.6: *Effect of the adaptation after 9 encountered wishes*

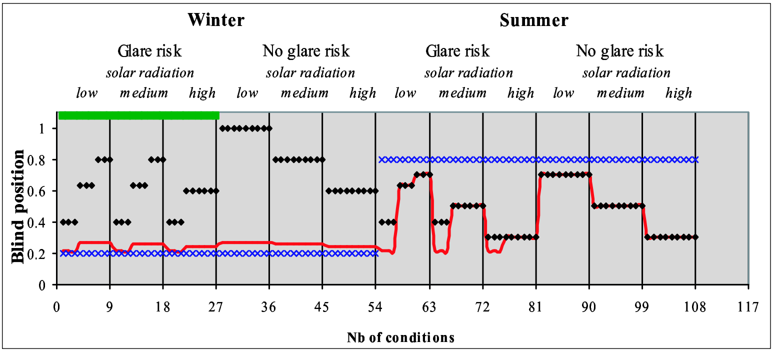


Figure 4.7: *Effect of the adaptation after 27 encountered wishes*

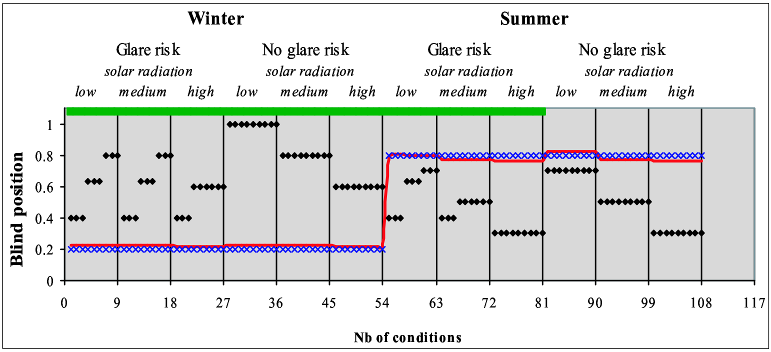


Figure 4.8: *Effect of the adaptation after 81 encountered wishes*

at this point, it was really plausible that the user wanted the same blind position during the whole year.

Figure 4.8 shows that, at this stage, the system has perfectly learned user wishes in winter, and has corrected the wrong extrapolation in summer. Moreover, the system has again adequately extrapolated to the unencountered *no glare risk* conditions. At the end of the simulation, the results are quite similar to the ones shown in Figure 4.8. The small discrepancy between the user wishes and the adapted controller comes from the wish preprocessing filter (described in Section 4.4.2). It tries to reduce overheating in summer (lower blind positions) and to maximize solar gains in winter (higher blind positions). The effect of this filter is strongly reduced in this simulation because the user has often repeated the wishes in similar conditions. Several other simulations were performed with more complex, but always consistent, user behaviours, and the system has always managed, at least in the end, to almost perfectly learn user wishes.

4.6 Adaptation Performances Comparison

The choice of Genetic Algorithms for the adaptation procedure regarding blinds has to be justified. The present section briefly introduces alternative methods for optimization task and compares their performances with GAs through simulations. These methods cover a wide range in the optimization domain, going from Simulated Annealing to direct search algorithm and gradient descent methods. For the performance assessment, both real and synthetic sets of wishes are used.

4.6.1 Standard Search Methods

The so-called “standard” search methods may be broadly categorized in terms of the derivative information that is, or not, used. The ones that do not use derivative information are called *direct search methods* and the others are called *derivative-based methods*.

4.6.1.1 Direct Search Methods

Direct search methods may be defined as minimization algorithms that only use function evaluations to look for the minimum. No gradient information is needed by this kind of algorithm. The Nelder-Mead algorithm, also known as the simplex method, is a typical example of a direct search algorithm [Lagarias et al., 1998]. The algorithm is based on an initial design of $k+1$ trials, where k is the number of variables. A $k+1$ geometric figure in a k-dimensional space is called a simplex. It works simply with two main rules:

- First rule is to reject the trial with the least favorable response value in the current simplex. A new trial is calculated, by reflection, opposite to the undesirable result.

- Second rule is never to return to a variable that has just been rejected, in order to avoid oscillations.

Even if this method is widely and happily used by practitioners since 1965, it was proved to be unreliable and inefficient in several cases, particularly when there are many independent variables [Wright, 1995]. Moreover, the lack of theoretical sounded background imply using it with care.

4.6.1.2 Derivative-Based Methods

The methods using gradient information find the way to travel down on search space surfaces, like a marble rolling freely through a surface of hills and valleys. Among the derivative-based methods, the most favored is the unconstrained Quasi-Newton method. This algorithm is used when the Hessian matrix (matrix of partial second derivatives) is difficult or time-consuming to evaluate. Instead of obtaining the Hessian matrix at every steps, this method gradually build up an approximation of this matrix by using gradient information from the previous iterations. The approximation procedure used in this work is the well known BFGS formula [Fletcher, 1980] provided by Broyden, Fletcher, Goldfarb and Shanno.

4.6.2 Simulated Annealing

Simulated Annealing (SA) was originally inspired by the annealing process in metallurgy: a piece of metal is heated (atoms are given thermal agitation), and then left to cool slowly. This slow and regular cooling allows the atoms to slide progressively in their most stable (corresponding to a minimal energy) positions. On the opposite, a rapid cooling would have frozen the atoms in whatever position they had at that time.
In 1983, Kirkpatrick et al. showed the analogy between this process and the optimization of parameters in combinatorial problems [S. Kirkpatrick and Vecchi, 1983].

4.6.2.1 Simulated Annealing Parameters Definition

The method is based on a random walk through the space at successively decreasing temperatures, looking for points with low energies. From the current solution x (or from a random initial x_0), the algorithm works as follows:

First a random walk is generated depending on the *step length* k_l:

$$x(t+1) = x(t) + k_l \cdot x_d$$

x_d being a uniform random deviation of the vector solution x. Larger value of k_l leads to larger deviation from the previous solution. The energy of a solution ($E(t)$) is evaluated through the function to minimize. In our case, the energy corresponds to the error E_r defined in Section 4.4.4.

The difference between the energy levels at times t and $t+1$ is denoted as $\Delta E = E(t+1) - E(t)$. The new solution is accepted according to a Boltzmann distribution probability p, where T describes a kind of "thermal agitation":

$$p = \begin{cases} 1 & \text{if } \Delta E < 0 \\ e^{-\frac{\Delta E}{T}} & \text{otherwise} \end{cases}$$

Accepting steps that lead to higher energy gives the algorithm the opportunity to get out from local minima. The higher the temperature T is, higher is the probability of getting out of a local minimum. This method is proven to find the global minimum of a function with very slow temperature cooling schedule [Geman and Geman, 1984]. Unfortunately, this cooling schedule is too slow to be of practical use. Nevertheless, a usual way is to use a fixed rate κ of temperature cooling, such as follows:

$$T(t+1) = \kappa \cdot T(t) \quad \text{with} \quad 0 < \kappa < 1$$

Simulated Annealing is widely used as a global optimization method, but its drawbacks are well-known and are comparable to the ones of GAs: risk of obtaining sub-optimal solutions, no explicit management of constraints, empirical parameters adjustment.

4.6.2.2 Simulated Annealing Parameters Optimization

Four parameters have to be carefully tuned: the initial temperature of the system T_0, the cooling rate κ, the maximum number of iterations N_{max} and the step length k_l.

All the simulations described below were performed on a set of 32 real wishes observed during a mid-season period. Each wish is taken independently, so that results presented here are averaged value on 32 different simulations. Dealing with the 32 wishes independently ensures to optimize parameters on a wide range of wishes conditions and not only on one particular case. But since every simulations lead to different values of E_r (varying from 1 to 100), the results are given relatively to GAs error E_r for every wishes in order to make results values comparable.

First, several simulations have been carried out to determine an optimal initial value for temperature (T_0). It should be not too high, in order to avoid useless large variation in the system state, and not too low in order to allow every initial conditions to converge[5]. The goal is to delimit a region where the energy (the error) of the system begins to frankly decrease in a simulation with too high a value of initial temperature.

Figure 4.9 shows an example of this determination: during a simulation with an initial temperature of 5 and a cooling rate of 0.998, around step 1000 a decreasing energy trend becomes clear. Thus, the optimal value of T_0 is calculated as follows:

$$T_0 = 0.998^{1000} \cdot 5 \approx 0.25$$

Then, an optimal value for the step length k_l is roughly assessed using a simulation with default values for the cooling rate (set to 0.998) and for the maximum number of iterations (set to 10'000). Simulations have been performed with eight different values of step length, from 0.001 to 1. Figure 4.10 depicts the results of these simulations. They show that standard deviation is particularly high, which is due to the fact that SA sometimes does not converge. Nevertheless, three step lengths are better than others: 0.01, 0.05 and 0.1. They are rather equivalent in term of mean, but standard deviation, which characterizes the non-convergence percentage, is lower (2.09 $\pm$ 2.00) when k_l = 0.1. Thus,

[5] Actually, the initial state is randomly defined.

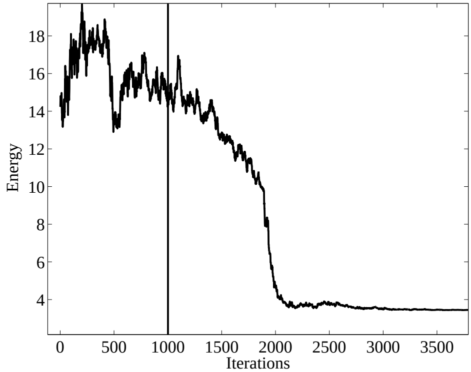


Figure 4.9: *Example of T_0 determination on a Simulated Annealing run*

the latter has been chosen for the following simulations.

The maximum number of iterations N_{max} and cooling rate κ are closely related. So, they have been optimized together through different combinations. Three values for N_{max} and nine for κ have been evaluated. Results are presented successively for the three values of N_{max} (in ascending order) in Figures 4.11 to 4.13.

The first figure presents results for the case with few iterations (N_{max} = 1000) and for all values of κ. Once again, standard deviation is high but it informs about non-convergence frequency. A clear trend is obtained for values of κ near 1.0: SA gives worse results (higher energy) and standard deviation is also getting larger, which denotes clearly that temperature decreased not sufficiently.
On the opposite, low values of κ also lead to slightly worse results, which means that temperature is decreasing probably too quickly in these cases and consequently, SA get more often stuck in local minima. An optimal value of κ for this case seems to be 0.975. Both mean and standard deviation are minimal. Thus, for the next and higher value of N_{max}, the optimal κ should be higher or equal to 0.975.

In Figure 4.12 results for κ values from 0.975 to 0.9999 are shown. Except a strange behaviour for κ = 0.998, similar conclusions may be found about the extreme values of κ. The optimal value seems to be 0.995 and thus, for the largest value of N_{max} (10'000), an optimal κ value higher or equal to 0.995 has been expected.
Results depicted on Figure 4.13, lead to conclude similarly to an optimal value of κ equal to 0.9995.

The three optimal results found for the three values of N_{max} are summarized in Table 4.18. First, results give some hints about the superiority of GAs on SA, since SA results are worse ($>$ 1) in any case. This will be more detailed in the next section. Considering mean and standard deviation, the optimal obtained set is, as expected, the one with largest N_{max}. Concerning computational time, astonishingly, the worst is the one

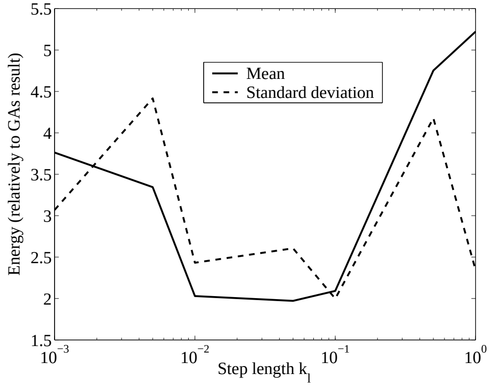


Figure 4.10: *Results for the step length rough determination*

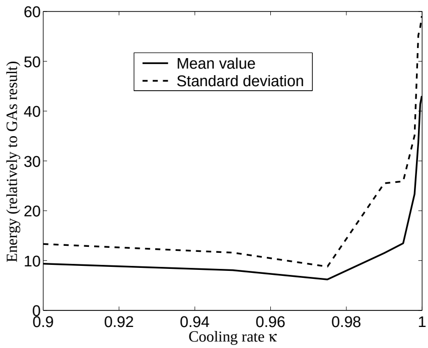


Figure 4.11: *Results for N_{max} and κ optimization, case with N_{max} = 1000*

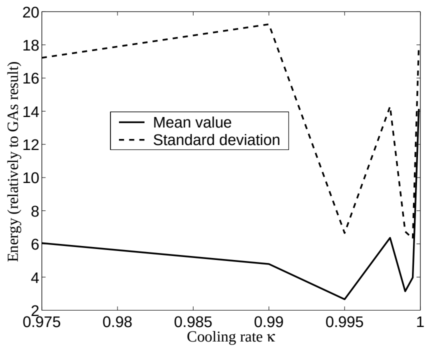


Figure 4.12: *Results for N_{max} and κ optimization, case with N_{max} = 5000*

with N_{max} = 5000. In fact, it has been observed that simulations with value of κ very close to 1.0 (i.e. κ = 0.999, 0.9995 or 0.9999) lead to shorter computational time. This is probably due to the combination of two facts:

- Low cooling rate involves many solution rejections.
- It is probably less time consuming to simply reject a solution than to accept it and replace the current system state.

N_{max}	κ	Mean of relative results	Standard deviation	Relative CPU time for one adaptation
1000	0.975	6.2	8.7	0.28
5000	0.995	2.7	6.7	1.36
10000	0.9995	2.0	3.4	1.31

Table 4.18: *Relative results (to GAs) for the three optimal cooling rate* κ

Since the major drawback of SA is the low quality of results and not the computational time, the set of parameters N_{max} = 10'000 and κ = 0.9995, which leads to results of highest quality without regarding the computational time, has been chosen. Besides, its corresponding time for one adaptation is not excessive in comparison with GAs.

Finally, with the new obtained set of parameters, additional simulations for optimizing one more time the step length value are carried out. They were performed once again with eight different values of step length, from 0.001 to 1. Figure 4.14 presents the results. A value of κ of 0.05 is clearly the optimal for both mean and standard deviation.

In order to assess the effect of the undertaken SA parameters optimization, ten runs of simulations were finally performed taking into account the 32 wishes all at once. Table 4.19 gives the results of these simulations.

	N_{max}	κ	k_l	Percentage of convergence*	Mean of E_r	Standard deviation	CPU time [sec]
Before opt.	10000	0.998	0.1	70	46.18	1.56	69
After opt.	10000	0.9995	0.05	90	43.84	0.47	67

*Considering the *moderate* criterion

Table 4.19: *Simulated Annealing parameters optimization effects*

The new obtained set of parameters is not very different from the initial values. Nevertheless, the improvements are quite noticeable. Convergence, mean value and standard deviation have all been improved without increasing computational time.

4.6.3 Comparison Results using a Synthetic Wish

Standard search methods and Simulated Annealing (with the optimized set of parameters) were compared with GAs in a case of a particular synthetic wish. This wish has been designed to force the adaptation process to act on two genes regarding two rules in the two

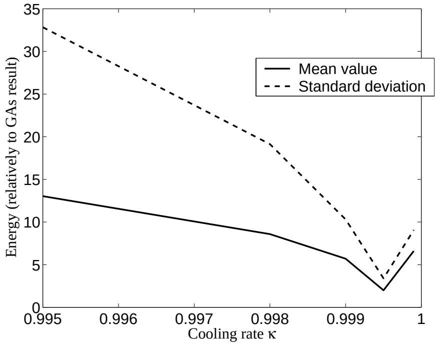


Figure 4.13: *Results for N_{max} and κ optimization, case with N_{max} = 10000*

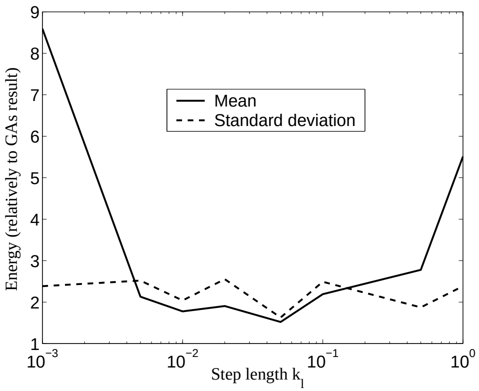


Figure 4.14: *Results for the step length final determination*

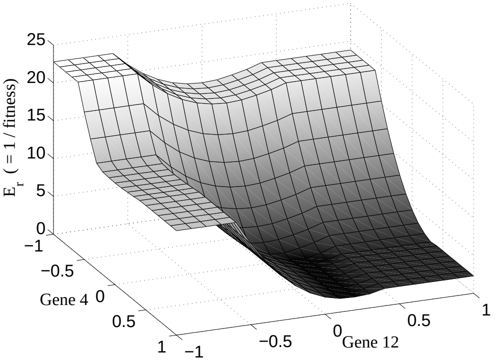


Figure 4.15: *Search space for the synthetic wish*

different fuzzy inference systems (one concerning glare and the other concerning illuminance). In fact, it concerns a sunny day in winter with sun localized at the medium-right position (see Appendix A), and the desired blind position is completely up. The adaptation should first change the gene (gene 12) related to the "Illuminance" fuzzy rule base up to a value of 1.0. Then, in order for this change to take effect, the maximum blind position provided by the glare fuzzy system in these conditions should also be modified to 1.0 (gene 4).

This wish is not particularly hard to be learned by the adaptation process but it illustrates well the limitations of standard search methods. In Figure 4.15, the space search is depicted. A large flat region and a wide valley near the optimum make the optimization hard for standard search methods.

Optimization procedures are carried out only on concerned genes. In this work, the MATLAB® implementations of the simplex and Quasi-Newton methods were used. The exit conditions of these two algorithms were set to stop when change in the solution is smaller than 10^{-6}. Supplementary simulations have shown that decreasing this value to 10^{-10} does not influence results by more than 10^{-4}, whereas it dramatically increases the computational time.

The search methods are very sensitive to the initial point, therefore optimizations have been performed from a grid of 441 ($21 \cdot 21$) initial points on the range [-1,1] for each gene. The grid step is 0.1 for both dimensions. Figures 4.16 and 4.17 represent the convergence results for the different initial points. An algorithm is said to have converged when the *severe* criterion is fulfilled, i.e. when the difference with the lowest error E_r (here 1.441) is less than 0.2 (see Section 4.4.4). In these figures, when algorithms have strongly diverged the corresponding results have been set to 2 for clarity.

Table 4.20 gives a summary of results. Convergence is always ensured with GAs, whereas it is the main drawback of the two standard search methods. Nelder-Mead is

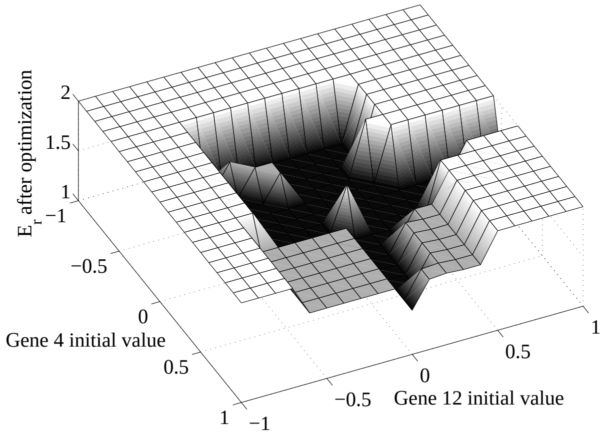


Figure 4.16: *Convergence results depending on initial conditions of the Nelder-Mead algorithm with the synthetic wish test*

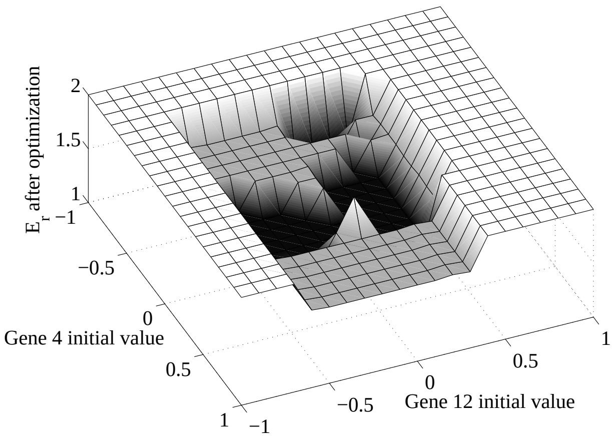


Figure 4.17: *Convergence results depending on initial conditions of the Quasi-Newton algorithm with the synthetic wish test*

better than Quasi-Newton both in convergence percentage (24% of the time compared to 16%) and in quality of results. However, it takes twice as much time, but still is very low (about 1 second, which is much lower than the 28 seconds needed by GAs).

Optimization method	Percentage of convergence*	Mean of E_r (when converged)	Standard deviation	CPU time for one adaptation [s]
Nelder-Mead	24	1.443	$< 10^{-4}$	1.16
Quasi-Newton	16	1.447	0.016	0.51
SA	72	1.448	0.004	63.8
GAs	100	1.445	0.002	28.1

*Considering the *severe* criterion

Table 4.20: *Comparison results for a synthetic wish*

The results for Nelder-Mead and Quasi-Newton methods were not improved with lower exit conditions and a larger optimization time. Thus, depending on the initial conditions, these algorithms often get stuck in local optima and do not succeed in getting out of them. This major observed drawback confirms the inadequacy of this kind of method for our task.

Regarding SA, the convergence percentage is 72%, with a computational time twice more than GAs. Thus, even if SA results (when SA converges) are equal to those of GAs, the overall SA performance is less. In the following section, a more detailed comparison of SA and GAs is made.

4.6.4 Comparison Results using a Complex Set of Wishes

For this comparison, the methods were tested on a set of 80 synthetic wishes and on the same set of 32 real wishes used for the SA parameters optimization (see Section 4.6.2.2).

All these 112 wishes are taken independently, which ensures a comparison on a wide range of wishes conditions. And unlike the comparison using one synthetic wish, the assessment of the two methods cannot be achieved through mean and standard deviation: they have no sense when each value come from a different distribution. Thus, convergence percentages are used for comparison and then, the difference between the two methods is calculated at each point and averaged.

The search space has 18 dimensions, each one with a range [-1,1]. Two examples of 2-D slices of search space are given. First, in Figure 4.18, a usual search space is depicted, with flat regions, discontinuity and suboptimal valley, all characteristics that would have made optimization really hard for gradient and direct search methods. In Figure 4.19, an interesting and unusual situation occurs with a basin with some steep walls around, which is not the global minimum. Probably due to an *epistasis* effect (see Section 4.5.5), the influence of gene 8 is suppressed by gene 16 for certain values and the global minimum of the 2-D search space is located at the whole bottom of the valley.

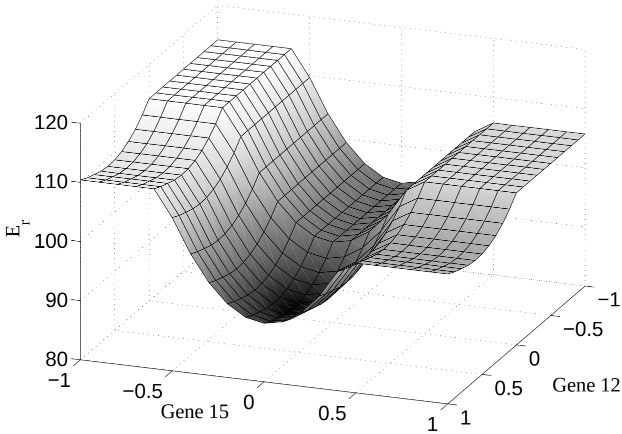


Figure 4.18: *2-D slice of search space for the real wishes test*

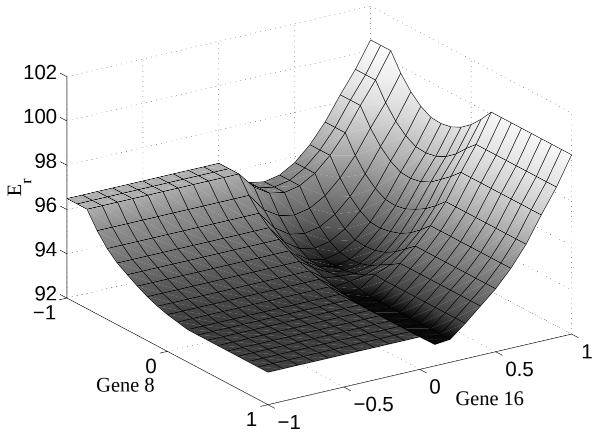


Figure 4.19: *2-D slice of search space for the real wishes test*

Table 4.21 presents the GAs and SA convergence percentage. Both *moderate* and *severe* criteria have been applied to determine the percentage of convergence of each method. Since the objective value is not known, the reference value for the criteria is the minimum of the two methods obtained at each point.

Method	Convergence percentage		CPU time for
	severe criterion	*moderate* criterion	one adaptation [s]
SA	75	99	79
GAs	99	100	34

Table 4.21: *Simulated Annealing results for the two different sets of wishes*

SA has greater difficulty in finding solutions. In 25% of the cases, SA did not manage to fulfill the *severe* criterion. That means GAs outperform SA considerably in 25% of the cases. Moreover, in one case, SA result is really poor (*moderate* criterion not fulfilled).

In comparison, GAs always provide satisfactory results (*moderate* criterion always reached) and manage almost always to fulfill the *severe* criterion.

Considering only the cases where both methods converged (*severe* criterion), a difference ΔE_r between GAs and SA errors is calculated at each remaining point. It gives:

$$\text{Mean}(\Delta E_r) = -0.0296 \quad \text{and} \quad \text{Standard deviation}(\Delta E_r) = 0.0656$$

It may so be concluded that if both methods converge they lead to very similar results. Even if the obtained mean value may show that SA gives very slightly better results, the difference is far less than the *moderate* criterion and may be considered as negligible.

Thus, even with a computational time 2.3 times greater than GAs, SA does not reach GAs overall performance. It is very probable that if one largely increases the maximum number of iterations N_{max} and changes accordingly the cooling rate κ, SA will be able to provide better results than the ones presented here. However, this will also surely requires much more computational time and will not allow SA to outperform GAs. In conclusion, GAs seem to be definitely more appropriate to our purpose than SA.

Chapter 5

Experimental Set-up

"An experiment is a question which science poses to Nature, and a measurement is the recording of Nature's answer." (Max Planck)

Field experiments such as the one carried out within this work require dealing with many different issues: experimental procedures definition, rooms and hardware set-up, software development and monitoring installation. This chapter describes the solutions applied for each one of these issues.

5.1 Experimental Procedure

The goal of the experiments is to study the effect of the user adaptation on the acceptance of automatic control systems and to quantify the cost in energy of such an adaptation. Therefore, three systems are compared: manual control, automatic control without user adaptation and automatic control with user adaptation.
This section details the difference between the compared systems and then describes the programme of experiments and some important experimental precautions that have been taken.

5.1.1 Systems Compared

The manual control system corresponds to the default control of the LESO experimental building running through the EIB network. This system has only two automatic features:

- If a room is unoccupied during more than 15 minutes, electric lighting is switched off.
- The heating system is driven by the default EIB control system, which is a proportional-integral controller without night setback.

The automatic control system with adaptation corresponds to the one described in Chapters 3 and 4.

It should be noticed that the default parameters of this system were defined to make the whole original system very energy efficient. Hence, the automatic control without user adaptation has some differences (in addition to the user adaptation missing feature) compared to the automatic control with user adaptation. They partly make the automatic control without user adaptation more user-friendly. The following points are thus changed:

Delay The time after a user interaction during which the automatic control for blinds is stopped, is increased from one hour to two hours.

Blinds (user present) There is no user adaptation, so values given at commissioning for blinds position depending on season should be less severe (see Section 3.5) to be accepted by a larger number of users. In winter, the blind position is determined so to provide an illuminance of 2000 lux instead of 2500 lux. In summer, the value aimed is 500 lux instead of 400 lux.

Blinds (user absent) The limitation of blinds thermal effect when indoor temperature is too low or too high (see Section 3.3.1.2) is inactivated. That means only energy aspects are taken into account and thermal comfort at the user's arrival is not considered (i.e. the temperature setpoint is absolutely not taken into account for controlling blinds when the user is absent).

Electric lighting There is no user adaptation, so illuminance setpoint is fixed at 400 lux. International norms concerning workplace illuminance for general tasks in offices are spread on a wide range: from 150 to 1000 lux depending on the country [Mills and Borg, 1999]. The value chosen is the average of the values recommended in Switzerland [ASE8912, 1977] for office general work (500 lux) and for visual display terminal task (300 lux). As for blinds, a user interaction stopped the automatic control for two hours.

5.1.2 Experimental Programme

The total duration of experiments is nine months, from 1st June 2002 to 1st March 2003. The goal is that every rooms have the three control systems during three different seasons. Thus, three periods have been defined as follows:

Summer period	corresponding to	"June, July, August"
Mid-season period	corresponding to	"September, October, November"
Winter period	corresponding to	"December, January, February"

The experiments were conducted in a similar way that *clinical randomized trials* are carried out [Jadad, 1998]: attribution of systems per room is randomly done with the constraint of having every system in every season in each room. Users do not know which system they have (single-blind study) in order to avoid any bias that could occur. A double-blinded study (experimenter does not know which system is applied in each room) was impossible to realize in this work, but interaction between users and experimenter was very limited (survey questionnaires appeared automatically on their computer, no intervention inside rooms was needed to start and stop control systems, etc.).

An additional constraint for the control systems attribution was to group together rooms with common energy consumption measurements i.e. rooms 101 and 102 and rooms 105 and 106 (see Section 5.2). Table 5.1 gives the attribution sequence of the different control systems in every room considered for the field study.

Room	June	July	Aug.	Sept.	Oct.	Nov.	Dec.	Jan.	Febr.
001	man	aut+ad	aut	man	aut+ad	aut	aut+ad	man	aut
002	aut	aut+ad	man	aut	aut+ad	man	aut+ad	aut	man
005	man	aut	aut+ad	man	aut	aut+ad	aut	man	aut+ad
101	aut+ad	man	aut	aut+ad	man	aut	man	aut+ad	aut
102	aut+ad	man	aut	aut+ad	man	aut	man	aut+ad	aut
103	man	aut+ad	aut	man	aut+ad	aut	aut+ad	man	aut
104	aut+ad	aut	man	aut+ad	aut	man	aut	aut+ad	man
105	man	aut	aut+ad	man	aut	aut+ad	aut	man	aut+ad
106	man	aut	aut+ad	man	aut	aut+ad	aut	man	aut+ad
201	aut	man	aut+ad	aut	man	aut+ad	man	aut	aut+ad
202	aut	man	aut+ad	aut	man	aut+ad	man	aut	aut+ad
203	aut	aut+ad	man	aut	aut+ad	man	aut+ad	aut	man
204	aut	aut+ad	man	aut	aut+ad	man	aut+ad	aut	man
205	man	aut+ad	aut	man	aut+ad	aut	aut+ad	man	aut

"man" = manual system (no automatic control)
"aut" = automatic system without user adaptation
"aut+ad" = automatic system with user adaptation

Table 5.1: *Attribution sequence of control systems per room*

5.2 Building Description

This section presents the LESO building considered for the experimental assessment of the automatic control systems. Important rooms characteristics such as sensors locations, temperature stratification and luminance distribution are provided.

5.2.1 The LESO Experimental Building

The LESO building is a small office building with about 20 office rooms, hosting the activities of the Laboratory of Solar Energy and Building Physics located on the EPFL (Swiss Federal Institute of Technology in Lausanne) campus. Its south facade was used for several years for experimenting various solar facade technologies. In 1999, it was retrofitted with a new facade conforming to the criteria of the sustainable development. The whole facade has been replaced by a new wooden facade sketched in Figure 5.1. The office rooms are all equipped with an anidolic (non-imaging) daylighting device [Courret et al., 1998] that is very effective for providing daylight to the user, but requires an additional blind and window area.

Figure 5.2 gives a view of the south facade from outside, showing the anidolic and conventional windows provided for each office room. Each facade element (for one typical office room) has two blinds: one for the lower (normal) window, and one for the upper (anidolic) fixed window. Both blinds are controlled independently.

The building is heavy, with a very well insulated envelope and large passive solar gains through the (dominant) south facade. A previous study [Altherr and Gay, 2002] pointed out interesting features of the LESO building:

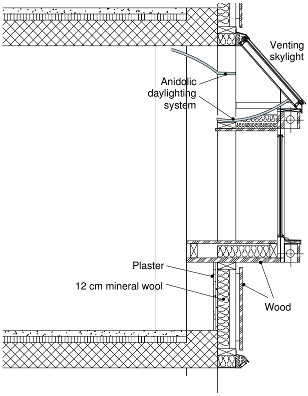


Figure 5.1: *Vertical section through the southern facade, showing the anidolic system*

Figure 5.2: *South facade view of the LESO experimental building*

- The total yearly energy intensity (heat and electricity) of the building is equal to 232 MJ/m^2, which is almost four times lower than the swiss average of comparable building.
- This total energy intensity corresponds to a consumption of 42 MJ/m^2 for lighting and 76 MJ/m^2 for heating. The remaining 114 MJ/m^2 correspond to computers and other electrical appliances.
- Solar gains cover 75% of the heat needs for the building.

The building is made of 9 thermally insulated "units" (3 units per floor), each unit including one or two rooms. Figures 5.3 to 5.5 shows the plan of the three floors. In these figures, North is towards the top.

5.2.2 The Rooms Considered

Fourteen rooms of the twenty available are considered for the experiments. Two of them are geometrically different from others in the way that they are equivalent to two office rooms grouped together. One of these rooms is the workshop (room 005) of the laboratory and the other is an office room with three users (room 205). Table 5.2 gives more information about every room and shows the chosen rooms. There are 21 users in the chosen rooms.

Electric convective heaters are used in all rooms, except for corridors and rooms 001, 200 and 206 that have water radiators. Energy consumption groups together the electrical heating energy, the electric lighting energy and all other electrical appliances.

5.2.2.1 Room dimensions and Sensors Locations

The following descriptions deal with the standard rooms.

Room size:

- Floor area of a room: 15.7 m^2
- Room height: 2.8 m

Walls and slabs[1]:

- Facade wall (to South): 5.4 m^2, light wall (1 cm plaster panel + 12 cm thermal insulation + 1 cm wood) + windows (see below)
- Rear wall (to North, circulation space): 7.0 m^2, heavy partition wall (12 cm concrete bricks + 8 cm thermal insulation + 12 cm concrete brick) + 3.0 m^2, door (2 cm wood)
- Wall to neighbor unit: 13.3 m^2, heavy partition wall (12 cm concrete bricks + 8 cm thermal insulation + 12 cm concrete bricks)

[1] All layers of the construction elements are given starting from inside the room; "thermal insulation" is either glasswool, polystyren or polyurethan, with a thermal conductivity equal to 0.04 W/mK.

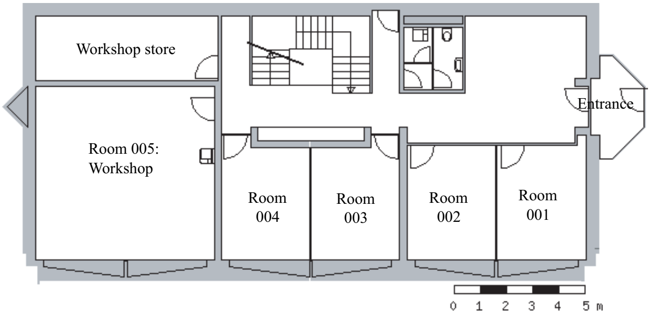


Figure 5.3: *Ground floor plan of the LESO building*

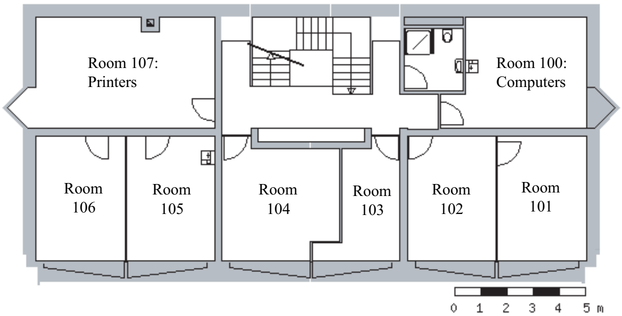


Figure 5.4: *First floor plan of the LESO building*

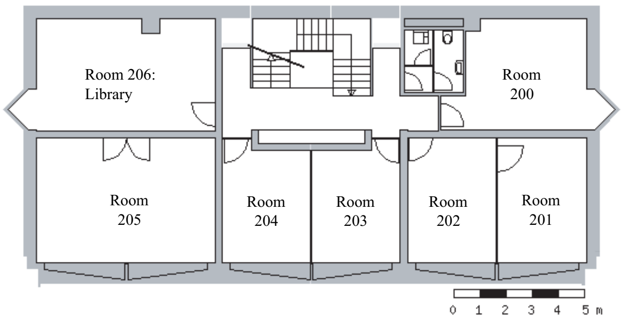


Figure 5.5: *Second floor plan of the LESO building*

Room	Nb of users	Energy consumption availability	Remarks	Standard room configuration	Chosen room
001	2	–		√	√
002	2	–		√	√
003	1	√	Used for an other project	√	–
004	1	√	Used for an other project	√	–
005	-	√	Workshop	–	√
100	-	–	Computers room	–	–
101	2	√*		√	√
102	2	√*		√	√
103	1	√		√	√
104	1	√		√	√
105	1	√*		√	√
106	2	√*		√	√
107	-	–	Printers room	–	
200	2	–		–	–
201	1	√		√	√
202	2	√		√	√
203	1	√		√	√
204	1	√		√	√
205	3	√		–	√
206	-	–	Library	–	–

*Energy consumption is grouped for two adjacent rooms

Table 5.2: *List of all office rooms of the LESO building and choice of the rooms considered for the present work*

- Wall to neighbor room of the same thermal unit: 13.3 m^2, light partition wall (1 cm plaster panel + 4 cm thermal insulation[2] + 1 cm plaster panel)

- Floor: 15.7 m^2 (1 cm rubber coating + 6 cm screed + 6 cm thermal insulation + 25 cm concrete slab)

- Ceiling (towards roof): 15.7 m^2 (25 cm concrete slab + 16 cm thermal insulation + 10 cm concrete and roof gravel)

Windows:

- Standard window: 2.1 m^2 net area (double glazing with IR coating, U-value 1.4 W/m2K)

- Anidolic window: 1.7 m^2 net area (double glazing with IR coating, U-value 1.4 W/m^2K)

- Frame area (total for the facade of one room): 0.9 m^2, U-value 2 W/m^2K

Figure 5.6 depicts a room configuration with the sensors and user interfaces locations. The presence and luminance sensors are placed on the ceiling as shown on Figure 5.7. Figures 5.8 and 5.9 shows the interfaces localization.

5.2.2.2 Daylight Factor Assessment

Assessment of Daylight Factor (DF) was performed in a standard room (room 004) in order to characterize the room behaviour according to daylighting concerns. DF is defined, with overcast sky conditions, as the ratio between indoor horizontal illuminance and outdoor horizontal illuminance. For this measurement blinds were completely open and outdoor horizontal illuminance was about 6'000 lux (overcast sky conditions). DF have been measured at 8 different distances from the window in a range of 0.8 m to 4.3 meters by steps of 0.5 meter, on three row (A, B, C) differently distanced from the east wall (1, 2 and 3 meters). Measurements were done 0.85 meter above ground. Figure 5.6 depicts precisely the locations of the different measuring points. The user interfaces, the VNR data acquisition system and the EIB communication bus are explained later in Section 5.3.

Results of this measurements are given in Figure 5.10. Missing points are due to obstacles preventing measurements at these positions. Results show that DF decreases as the distance from the windows increases. DF value varies from 5% to about 1.5%, which are quite usual values.

In addition, some luminance measurements (see Figure 5.11) provide information about the visual environment in the rooms. They were measured under clear sky conditions, with an external horizontal illuminance varying from 31'000 to 33'000 lux.

[2]In certain rooms the 4 cm thermal insulation is replaced by a simple air layer of also 4 cm.

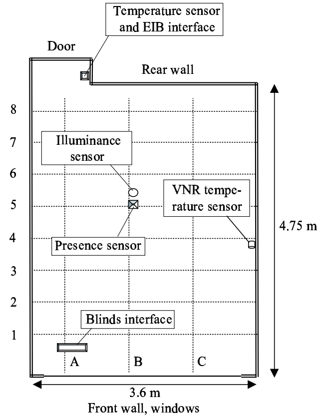


Figure 5.6: *Room configuration and location of sensors and user interfaces*

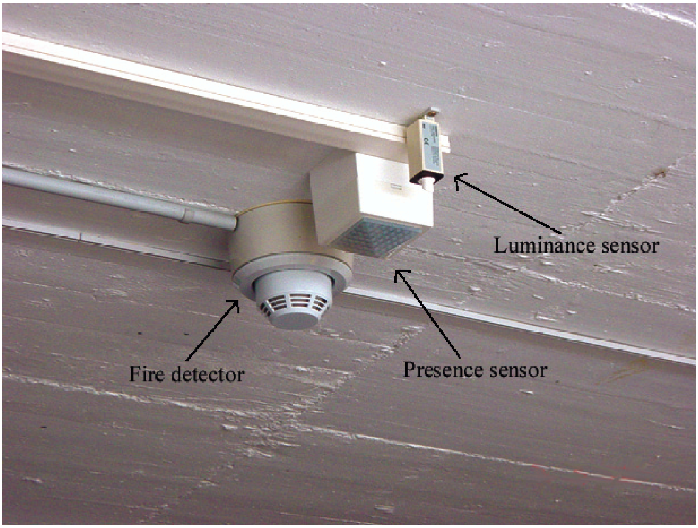


Figure 5.7: *Presence and luminance sensors on ceiling*

Figure 5.8: *EIB interface localization*

Figure 5.9: *Blinds interface localization*

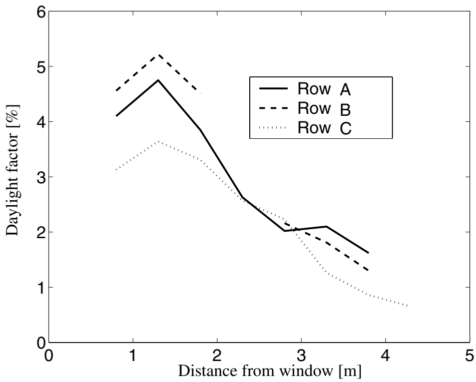


Figure 5.10: *Daylight factor assessment in a standard room*

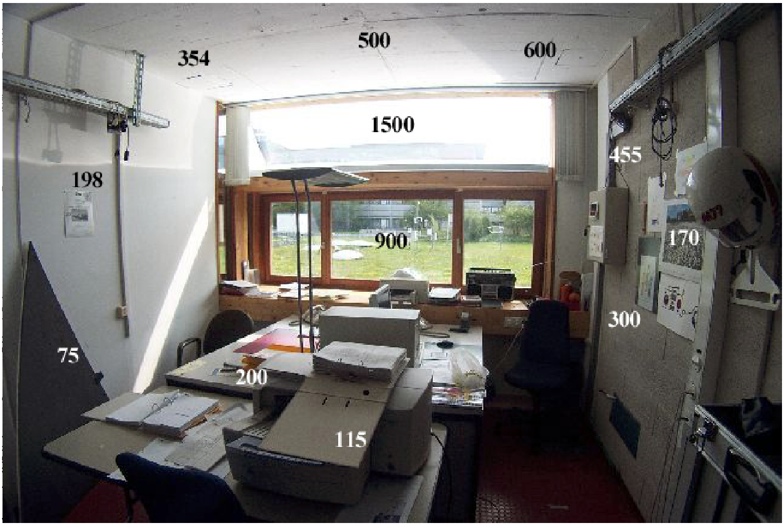


Figure 5.11: *Luminance measurements in a standard room, with external horizontal illuminance of 32’000 lux (values in [cd/m^2]) - Importance of daylight provided by the anidolic system is visible on the wall and the ceiling*

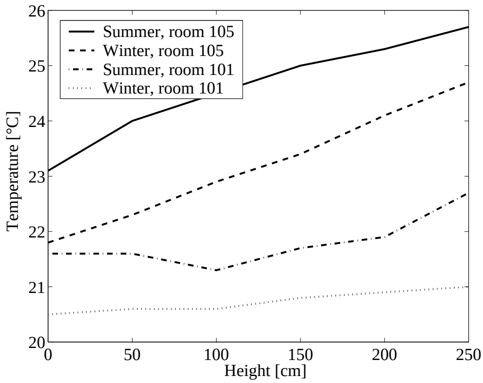


Figure 5.12: *Thermal stratification in two rooms during two different seasons*

5.2.2.3 Temperature Stratification Assessment

Measurements of temperature at different heights were taken to characterize the thermal stratification for two different rooms in winter and summer. Results, which are presented in Figure 5.12, show that stratification exists in all cases, but seems to be more room dependent than season dependent. In room 101, thermal stratification leads to less than 1°C of difference between upper and lower position in both seasons, while difference is up to 3°C in both seasons in room 105. Such different stratifications are due to different windows opening occurrence and depend on if the door is kept open or closed.

Difference between seasons is visible in the average of temperatures that are lower in winter than in summer in both rooms.

5.3 Hardware Set-up

Hardware issues are presented in this section. First the building communication bus used in the experiments is introduced and then some sensors calibration procedure and results are presented.

5.3.1 The European Installation Bus

The use of a building management bus allows an easy access to all sensors and actuators, and the sharing of the available information between all the partial control systems, making the integration of the different controllers easier (see Section 3.2.1). Several building buses types are available. Choosing a well-supported standard (for instance, European Installation Bus or LonWorks bus) provides wider choice of sensors and actuators from various manufacturers, which should be freely interoperable. The development work can be focused on the controller itself, instead of re-developing sensors and actuators that are already available on the market. A building management bus also makes easier the ca-

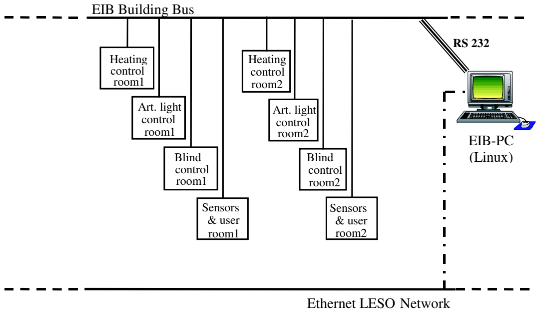


Figure 5.13: *EIB Overall diagram*

bling between sensors, actuators and controller, thanks to the standardization.

The whole building has been equipped with an EIB (European Building Bus) network, provided by Siemens. The heating system, the electric lighting and the blinds are connected on this bus.

Figure 5.13 gives the arrangement of the bus for two rooms. All rooms and the common circulation spaces are equipped in a similar way. For each room, sensors monitoring the presence, the air temperature, the window opening and the illuminance are available. A computer named EIB-PC is also depicted on the diagram: it allows other computers to communicate with EIB through the Ethernet network (see Section 5.4.2).

Every devices connected on the bus may theoretically exchange information with all other devices. Indeed, the work principle of the communication bus is to send and read *telegrams* containing a header that indicate to which device it is addressed, and the included message for the device. Thus, every devices are permanently “listening” to others, but take into account the included message only when they are concerned.

5.3.2 VNR Data Acquisition System

A monitoring system was already installed in the LESO building since 1981. It allowed to monitor several data (temperatures, heat flows, energy consumption) individually for each room. Due to its age, the VNR system is suffering today from a lack of reliability and stability. Nevertheless, the system still provides accurate measurements of weather data such as outdoor temperature and solar irradiance.

5.3.3 Sensors and Calibration

Many sensors are needed for monitoring for both outdoor and indoor conditions assessment. They are presented in Table 5.3. In addition, blind positions are not measured directly but calculated by the EIB-PC using the duration of blind movements.

Physical value	Type of sensors	EIB/VNR	Calibrated/verified in this work
Per room			
Air temperature for control	Pt100	EIB	$\surd$
Air temperature for monitoring	Pt100	VNR	$\surd$
Presence	infrared	EIB	$\surd$
Workplane illuminance	luminancemeter	EIB	$\surd$
Window opening 0/1	magnetic	EIB	–
Common for the whole building			
Outdoor air temperature	Pt100	VNR	–
Global horizontal irradiance	pyranometer	VNR	$\surd$
Wind speed	anemometer	VNR	$\surd$
Wind direction	weather vane	VNR	–

Table 5.3: *List of available sensors in the LESO building*

The table shows that many calibration and verification have been performed. Only the calibration regarding the most important values for comfort assessment (namely the indoor temperature and illuminance) are detailed in the following sections.

5.3.3.1 Temperature Sensors

All temperature sensors available (from EIB and VNR) have been preliminary calibrated using a mercury thermometer with precision of $\pm$ 0.1°C. It consisted in measuring the real temperature with the mercury thermometer and adjusting coefficients in VNR and EIB systems in order to obtain a similar value of temperature. This calibration was limited to a zero-order adjustment (constant correction value).

In order to assess the accuracy of the available calibrated temperature sensors, they have been compared with a measurement of the operative temperature on a period of ten days:

T-operative It measures the temperature really feels by user, which depends of the heat losses of human body due to convection and radiation. It thus combines the mean radiant temperature with the air temperature depending on air velocity. For instance, if air velocity is near zero, the operative temperature may be approximated by the average of the mean radiant and air temperatures. A specific calibrated device was used for this measurement. It was located at the centre of the room at the height of 1 meter.

T-EIB These temperature sensors (Pt100 type) are connected on EIB and embedded in the EIB interface (see Section 5.3.4), which is located near the door[3].

[3]Exact locations of EIB and VNR sensors are indicated in Figure 5.6 on page 97.

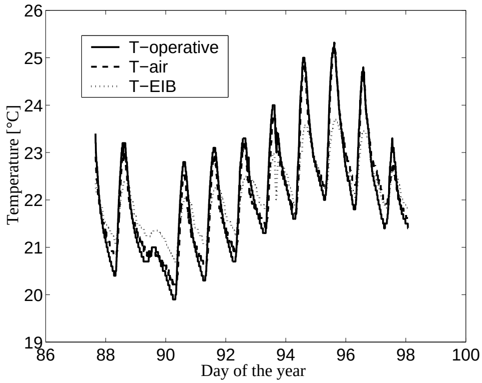


Figure 5.14: *EIB and VNR temperature measurements compared to the operative temperature*

T-air These sensors (Pt100 type) are connected to the VNR datalogger (see Section 5.3.2). There are sensors protected from radiation by a chrome cylinder, that let air passing vertically through it. Since radiation component is avoided, it should essentially measure the air temperature. They are located on walls (fixed 3 cm in front of the wall) and 1.5 meter above ground.

Figure 5.14 shows results of the ten days measurements. T-EIB measurement is clearly influenced by the fact it is embedded in the EIB interface box. The whole box should first be at the ambient temperature and then the sensor is getting to the air temperature. Inertial behaviour may also be explained by the fact this box is fixed directly on the wall, and is surely influenced by the wall surface temperature.

The T-air measurement is very near to the operative temperature, which indicates a low influence of the mean radiant temperature. However, some surprising inertial behaviour seems to appear for the T-air measurement compared to the operative temperature. A plausible explanation is that cylinders are influenced by wall proximity, and are measuring temperature of the *air layer* against the wall.

Hence, available sensors (from VNR and EIB) provide unbiased but less responsive measurements because of their contact with walls. This effect is particularly important for the EIB measurement, which are used for the thermal control of the room. It makes probably the system weakly responsive, which was indirectly confirmed by the fact that some users were complaining about the upper limitation and others about the lower limitation. To solve this problem, the default range provided by the temperature interface has been doubled from -2°C to +2°C, to -4°C to +4°C. It therefore corresponds to a range of 17°C to 25°C, assuming a basic temperature of 21°C.

5.3.3.2 Luminance Sensors

The EIB luminance devices installed in each room, translate the luminance measured by their sensor in a corresponding illuminance. Therefore, it is particularly important to properly calibrate these devices.

The sensor field of view is not circular but elliptic. The larger angle (38 degrees) has been set to correspond to the larger dimension of the room (from South to North) and the smaller angle (20 degrees) to correspond to the smaller dimension (East to West).

Calibrations are performed using a dedicated application program that has to be downloaded in the device. They have all been carried out during night with electric lighting, in order to have the most possible steady illuminance conditions. Moreover, since our system needs to know precisely the illuminance value mainly for electric lighting control, the calibration was achieved with values of illuminance between 200 and 400 lux. All EIB luminance sensors have been calibrated following the procedure described below:

1. The “calibration program” is downloaded in the luminance device.
2. The measured value of illuminance on the work plan is keyed in the parameters of the “calibration program”.
3. The *calibration parameter* is read from the device.
4. The original “illuminance program”, which measures the illuminance, is re-downloaded in the device.
5. The *calibration parameter* is keyed in the “illuminance program”

Figure 5.15 shows the results of the luminance calibration for room 001. The values given by the calibrated EIB luminance sensor are compared to the ones given by a LMT luxmeter ($\pm$ 1.9% accuracy) used as a reference. Estimated error bars of 15% are indicated for the EIB measurements. Accuracy of EIB sensor is sufficient under 500 lux (that corresponds to values considered for calibration process), but overestimate illuminance above 500 lux. This non-linear behaviour seems to be due to the sensor characteristic, each of them tending to overestimate above 500 lux. It has been decided to apply a linear correction at each sensor as follows:

$$E_{corrected} = \begin{cases} E & \text{if} \quad 0 \leq E \leq 500 \text{ lux} \\ 500 + 0.85 \cdot (E - 500) & \text{if} \quad E > 500 \text{ lux} \end{cases}$$

Figure 5.16 shows the results with the corrected EIB output. All results are thus close to the reference, that means being less than 15% wrong. Nevertheless, these results show that the applied correction is maybe a bit too low, but being conservative is safer.

Since every device has already gone through the calibration process, it was too huge a work to assess in each room, which correction coefficient should be applied. Thus, it has been chosen to apply the same coefficient to each sensor. Figure 5.17 depicts results of all sensors with the correction and calibration applied. Two measurements per room with different blind positions have been taken during a sunny day. Almost all discrepancies observed are below 15%. This accuracy is quite sufficient for our purpose, given the fact that human eye is not very sensitive towards illuminance variations.

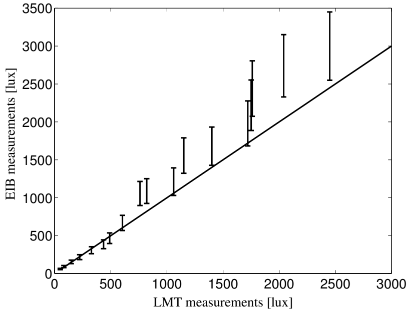


Figure 5.15: *Illuminance values given by the calibrated EIB sensor and a reference (LMT) in room 001 - The black line represents equivalence between the two measurements*

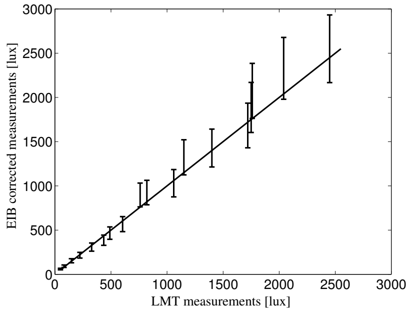


Figure 5.16: *Illuminance values given by the calibrated and corrected EIB sensor and a reference (LMT) in room 001 - The black line represents equivalence between the two measurements*

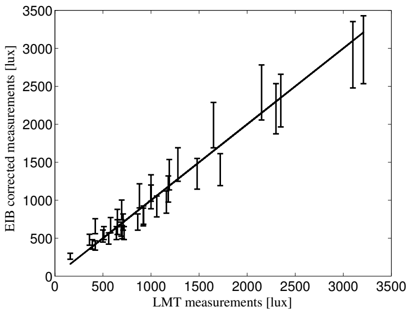


Figure 5.17: *Illuminance values given by the calibrated and corrected EIB sensors and a reference (LMT) in all rooms*

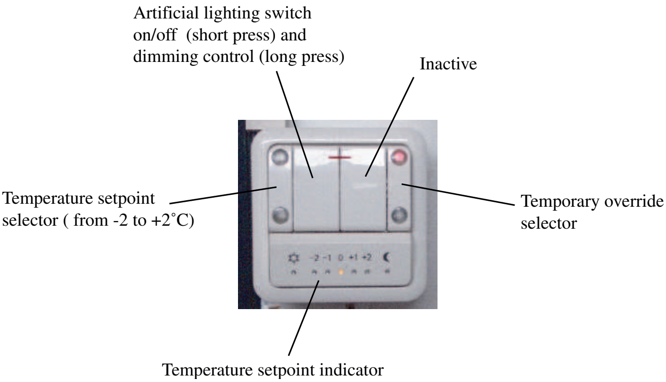


Figure 5.18: *Picture of the EIB interface for temperature and electric lighting controls*

5.3.4 User Interface Modules

Two standard interface modules were provided with the European Installation Bus. One is related to the electric lighting control and the temperature setpoint and the other is related to the blinds position control.

The main interface module is depicted on Figure 5.18. It mainly deals with the electric lighting control and is generally located near the door, in order to be able to switch on/off the lights at arrival/departure (see Figure 5.8 on page 98 to see the exact localization in the room). A short press on the upper part of the button switch on the lights at full power. A short press on the lower part of the button switch off the lights. Long pressures allow dimming (up or down) the electric lighting from 1% up to 100% of maximum power.

This interface provides also a control on the indoor temperature setpoint. The user can choose an offset value for the temperature setpoint from -4°C to +4°C by step of 2°C. The last control opportunity of this device is a temporary override selector and since it only concerns automatic control, it was not active before the experiments take place. It allows the user to stop the automatic control (for electric lighting and blind systems) as long as somebody stays in the room. There are two positions available, the activated one being indicated by a red LED. If the upper LED is switched on, that means the automatic control is running as usual. If the lower LED is switched on that means the concerned automatic controllers are temporarily stopped (*sleep mode*). It lets the user the opportunity to have particular environmental conditions during exceptional situations: completely closing the blinds and switching off the lights during a slide show, completely opening the blinds for windows cleaning or switching on the lights at full power for a temporary and special task.

The other interface module deals only with the blinds control. It is located near the window, on the wood shelf (see Figure 5.9 on page 98). It simply consists of buttons for raising or lowering the blinds. Since there are two blinds per room in the LESO building, there are two pairs of buttons for blinds control, as depicted on Figure 5.19.

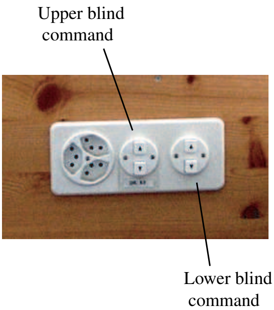


Figure 5.19: *Picture of the command buttons for blinds*

5.4 Overall System Description

Field experiments involve not only hardware setup but also numerous software developments and integrations in an overall structure. This section describes how the different software systems are interconnected and explains the role of each component.

5.4.1 Overall Architecture

The main purpose of the proposed architecture is to enable the Control-PC, which holds the automatic controllers presented in Chapter 4, to communicate with EIB for both acquisition of sensors measurements and sending commands to actuators.

The final chosen architecture is described in Figure 5.20. Three computers are needed, one being the Control-PC, an other that is able to communicate directly with EIB (EIB-PC) and one for the monitoring system (VNR-PC). They are all connected to the Ethernet LESO Network. Control-PC is the central node for the experiments; it contains different softwares that enables communication with the VNR data logger and with EIB.

5.4.2 Components Description

The components mentioned in Figure 5.20 are explained in this section. First, the roles of VNR-PC and EIB-PC are described and then a detailed description of Control-PC is given through its different software.

5.4.2.1 VNR-PC

This computer, running under Windows, is the pre-existing monitoring facility of the LESO building. Sensors connected to VNR and used in the experiment are listed in Table 5.3 on page 102. Every two seconds, new measurements of all these VNR sensors become available through a text file in the computer VNR-PC.

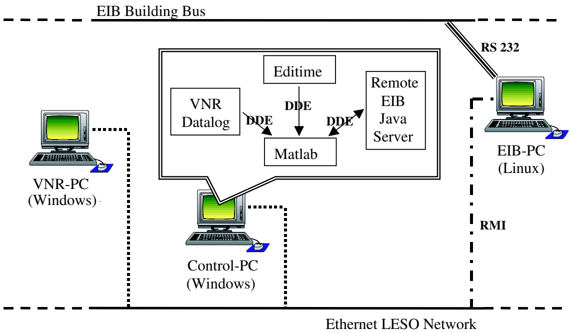


Figure 5.20: *Overall architecture of control system*

5.4.2.2 EIB-PC

A computer able to connect itself to EIB has been developed. It is a PC running under Linux[4], which is permanently connected to the communication bus through a RS-232 connection, and analyzes all telegrams passing through the bus (all telegrams are visible by all devices, see Section 5.3.1). EIB-PC contains a memory of all available variables in EIB and the values of these variables are continuously updates thanks to the fact that all telegrams are analyzed.
So, EIB-PC works as a server: when a client requests the value of a variable, the server provides this value without sending a telegram on the bus to ask the concerned device the current value of this variable. In addition, EIB-PC may also send telegrams to actuators, if it is requested by a client. It deals with all control algorithms concerning level 1 of the nested control loop structure (see Section 3.2.1).

5.4.2.3 Control-PC

This PC, running under Windows, contains four important softwares: the MATLAB® module, the remote EIB Java server, the VNR Datalog server and EDITIME.

The MATLAB® module is the central control part. It collects the all needed variables (from VNR and EIB), it calculates the controllers outputs and it deals with all adaptation aspects.
This implementation has been designed to make the system event-oriented, i.e. new calculations are only performed if an event occurs. This is done thanks to the *hot link* features provided by the remote EIB Java Server (see below). A *hot link* is established with every important variables for control, and thus each time one of these variables changes, the module receives an event from the remote EIB server. Table 5.4 summarizes the different possible events.

[4]At the beginning, the EIB-PC server was running under Windows, but approximately every week the computer crashes. Therefore, a more reliable solution had to be developed.

Variable modified	Corresponding event effect
Time	Scheduled tasks (heating, user adaptation, model optimization)
Global horizontal irradiance	New control calculation (for blinds and electric lighting)
Presence	New control calculation (for blinds and electric lighting)
External temperature	Update value
Indoor temperature	Idem
Indoor illuminance	Idem
Wind-alarm	Raise up blinds and deactivate blinds control
User interactions	
On electric lighting	Effect described in Section 4.1
On blinds position	Idem
On temperature setpoint	Idem
On *sleep mode*	Idem

Table 5.4: *Effects in the MATLAB® module of "hot linked" variables modification.*

The remote EIB Java server provides the same services as the ones provided by the EIB-PC server. It may gives values of variables, and receives command that should be send to EIB. It has been designed to only run under Windows (DDE protocol does not exist in Linux operating system) and to connect itself to an instance of the Linux EIB-PC server via a RMI connection through the Ethernet LESO network. Doing so, the hard job of serial port communication and telegram analysis is achieved by the EIB-PC server on a computer, which works under a more stable operating system. Thus, the Windows computer hosting the controller only needs to run this light remote EIB Java server and can choose to get events regarding only pre-selected rooms.
Two types of DDE link may be established by the client with the remote EIB Java server:

Cold link It allows communicating data in both ways: client to server, via a *poke* command and server to client, via a *request* command. Communication event only occurs on client demand.

Hot link It makes the server sending values whenever they change. Communication is only possible from server to client.

In our case, the unique client for this server, is the MATLAB® module.

The VNR Datalog server allows communicating through the Windows DDE (Dynamic Data Exchange) protocol, between a client (the MATLAB® module in our case) and the VNR data logger station. In fact, this server read every second the text file in the VNR-PC that contains latest sensors values and make them available through DDE connection for every clients on the Control-PC.

The last software is EDITIME, which is the time master for the whole system. It is a very simple DDE server that provides time through DDE communication. Either *cold* or *hot link* communication may be established. In this work, the MATLAB® module establishes a *hot link* connection with EDITIME, and the latter sends the current time every minute (the elapsed time between two time events may be changed via a DDE command).

5.5 Monitoring

Two main issues should be assessed in this experiment: energy efficiency of the automatic controllers and acceptance of them by the users. The first issue requires to record all values concerned by controllers and the second one requires an additional survey method, namely questionnaires. This section gives an exhaustive list of all variables recorded and describes the questionnaires used for assessing the users acceptance of the automatic system.

5.5.1 Recorded Variables

The MATLAB® module is the central node of the whole system. Thus, almost every interesting variables are directly available in this module. In fact, every time an event occurs (see Section 5.4.2.3), the system stores all relevant variables. Table 5.5 lists the whole set of recorded variables within the module. In average, there are two events per minute (and at least one since EDITIME sends an event every minute) that leads to about 90'000 sets of variables per room recorded in one month. In addition, models and controllers parameters are stored every night after the adaptation process, in order to assess their evolution over the time.

Nevertheless, two kinds of variables are not directly available in the MATLAB® module: the energy consumption and the additional indoor temperatures, both measured by the VNR data logger. So, every 5 minutes, these variables are get by a dedicated MATLAB® instance through the VNR datalog software and stored locally on the Control-PC. Energy consumption is available for almost each room (see Table 5.2); it groups together the heating energy and indoor temperatures are available for each room except room 005, which is a workshop. These temperatures coming from VNR are also recorded because they are more accurate than the ones provided by EIB (see Section 5.3.3.1) and because some redundancy may be useful (in case of sensor failure or to confirm measured values).

5.5.2 Questionnaires

In order to assess the user acceptance of the automatic controllers, a survey using questionnaires is carried out. These questionnaires are largely inspired by the ones developed by Hygge and Löfberg [Hygge and Löfberg, 1997] to address building's occupants appraisal towards daylighting system. They have been modified to mainly concern user response towards automatic control. They are divided into three type:

Personal Questionnaire Filled once at the beginning and once at the end of the experiments, these questionnaires allow to classify users depending on personal information (age, gender, wear glasses or not, etc.). They also allow to compare opinion of the users about automatic control before and after the experiments.

Recorded variables in the MATLAB® module	Units
Day of the year (fractional value)	[1 - 366]
Outdoor temperature	[°C]
Indoor temperature	[°C]
Indoor temperature setpoint	[°C]
Reduction of the temperature setpoint (for heating energy savings)	[°C]
Heat power fraction	[0 - 1]
Presence (for the controller, timeout of 10 minutes)	[0, 1]
Presence (given by the sensor)	[0, 1]
Ambiance	[1 normal, 2 fixed]
Global hor. irradiance measured	[W/m^2]
Vertical global illuminance on the facade calculated	[lux]
Vertical direct illuminance on the facade calculated	[lux]
Daylight indoor illuminance calculated (from RI model)	[lux]
Daylight indoor illuminance measured	[lux]
Illuminance setpoint	[lux]
Flag “mask detected on the window” (no more direct sunlight)	[0, 1]
Blind anidolic position	[0 - 1]
Blind normal position	[0 - 1]
Blind anidolic user flag	[0, 1]
Blind normal user flag	[0, 1]
Time of last blind move (fractional value)	[1 - 366]
Electric light user flag	[0, 1]
Electric light power fraction	[0 - 1]
Electric light power fraction (not updated with user interactions)	[0 - 1]
East window switch	[0 closed, 1 open]
West window switch	[0 closed, 1 open]
Flag wind danger	[0, 1]

Table 5.5: *List of recorded variables in the MATLAB® module*

Twice-Monthly User Satisfaction This questionnaire appears automatically twice a month on the computer screen of the users at startup. It has been found to be a less disturbing way for users compared to paper questionnaires, and it ensures a large proportion of filled questionnaires. These questionnaires concern the user satisfaction regarding automatic control installed in his office room.

Daily Comfort Twice a day, a very short questionnaire appears automatically on user computer screen. It asks three questions about current visual and thermal comfort in the room. It can be filled in less than 3 seconds, since user remembers the questions.

The three questionnaires are given in Appendix D.

Chapter 6

Experimental Results

"*I have had my results for a long time: but I do not yet know how I am to arrive at them.*" (Karl Friedrich Gauss)

The goal of the field experiments was to study the effect of the user adaptation on the acceptance of automatic control systems and to quantify the cost in energy of such an adaptation. Results are given and discussed in this chapter. First, energy consumptions of the three compared control systems are detailed per season. Then, thermal and visual comfort assessed through questionnaires is analyzed depending on the control system. Afterwards, evidences of effect of the adaptation to user are pointed out. The user acceptances of the two automatic controllers are then compared and the impact of the adaptation on acceptance is studied. Finally, some additional results related to the RI model performance are given.

Experiments should have covered nine months but at the end, only eight months of measurements are available. In fact, during November (considered as a mid-season month), the EIB-PC server (see Section 5.4.2) has crashed five times. A new version of the main software that should solve several remaining bugs (mainly regarding blinds control) had been installed in the beginning of November. Unfortunately, this new version was unstable and experiments were stopped several times until a more stable version was obtained. Hence, the adaptation processes (to user wishes and room characteristics) have not managed to converge properly during this month and, in addition, only fragmented data were available. It has been finally decided not to take into account the whole November month. Thus, results presented in this chapter cover all months but November.

6.1 Energy Consumptions

One major issue of the experiments was to assess the differences in energy consumptions between the three different systems (manual control, automatic control without user adaptation and automatic control with user adaptation).

6.1.1 Monitored Results

In order to compare the energy consumptions, some indicators were developed.

Let $C_{i_x j}$ denotes the energy consumption in room i with a controller of type x during month j. Four energy consumption indicators are thus defined:

$$C^x_{tot} = \sum_j \sum_{i_x} C_{i_x j} \qquad [\text{MJ/(m}^2\cdot\text{month)}]$$

$$C^x_{rel} = \frac{\sum_j \sum_{i_x} C_{i_x j}}{\sum_x \sum_j \sum_{i_x} C_{i_x j}} \qquad [-]$$

$$C^x_{rel/room} = \sum_{i_x} \left(\frac{C_{i_x j}}{\sum_x \sum_j C_{i_x j}} \right) \Big/ I \qquad [-]$$

$$C^x_{rel/month} = \sum_{j} \left(\frac{C_{i_x j}}{\sum_x \sum_{i_x} C_{i_x j}} \right) \Big/ J \qquad [-]$$

with I and J the total number of rooms and months, respectively.

C^x_{tot} is the total energy consumed during the experimental period by the controller of type x, expressed in [MJ/(m^2·month]. C^x_{rel} is the fraction of the total energy consumed during the experimental period by the controller of type x. $C^x_{rel/room}$ is the average fraction of total energy consumed per room by the controller of type x. $C^x_{rel/month}$ is the average fraction of total energy consumed per month by the controller of type x. The error margins mentioned are the standard deviation calculated on all rooms/months.

Table 6.1 shows the values of the different indicators of energy consumption for the whole experimental period. The three relative indicators give precisely the same relative values, which shows that there is no bias due to the room allocation or to differences in month: 40.4% of the total energy consumption is due to the manual control system, 29.7% is due to the automatic control system without adaptation and 29.9% is due to the automatic control system with adaptation. In other words, automatic controllers reduce the total energy consumption by about 26% compared to manual control. This confirms the result obtained in a similar study carried out only in two office rooms of the LESO building [Guillemin and Morel, 2001], which had shown that an integrated automatic controller allows 25% of energy savings on the total energy consumption compared to a conventional system (identical to the manual control system used in the present study).

Controller type	C^x_{tot} [MJ/(m^2·month)]	C^x_{rel} [-]	$C^x_{rel/room}$ [-]	$C^x_{rel/month}$ [-]
Manual	11.6	0.404	0.402 ± 0.069	0.405 ± 0.249
Automatic without user adapt.	8.5	0.297	0.290 ± 0.058	0.293 ± 0.115
Automatic with user adapt.	8.6	0.299	0.308 ± 0.058	0.302 ± 0.163

Table 6.1: *Energy consumptions on the whole experimental period*

The other very important result shown in this table, is the fact that the adaptation to user does not significantly increase energy consumption. Two Student t-tests have been applied to the values of $C^x_{rel/room}$ that have lower standard deviation than values of $C^x_{rel/month}$ (there are less energy consumption differences between rooms than between seasons). The first test confirms that the energy consumption of the manual system is higher than the energy consumption of the automatic controllers (difference is *highly significant*):

$$t\text{-value} > qt_{26}(99.5\%) \quad \text{i.e.} \quad 3.72 > 2.78$$

The second test shows that the difference in energy consumption between the user adaptive and non-adaptive controllers is not *significant*:

$$t\text{-value} < qt_{26}(95\%) \quad \text{i.e.} \quad 0.67 < 1.71$$

This surprising result (it was expected that adaptation to user makes the automatic controller less energy efficient) is explained in the next section.

6.1.2 Analysis per Season

An analysis of energy consumption of the different systems is done depending on the season.

6.1.2.1 Winter

Table 6.2 shows relative energy consumption for winter months. It confirms the two results already mentioned: automatic controllers reduce the energy consumption of 26% compared to the manual control and differences between the two automatic controllers are not significant.

Controller type	C^x_{tot} [MJ/(m^2·month)]	C^x_{rel} [-]	$C^x_{rel/room}$ [-]	$C^x_{rel/month}$ [-]
Manual	20.3	0.407	0.412	0.395
Automatic without user adaptation	14.7	0.295	0.289	0.294
Automatic with user adaptation	14.9	0.298	0.299	0.311

Table 6.2: *Energy consumptions in winter*

A previous study [Guillemin and Morel, 2002b] has determined that the implementation of a night setback in the conventional controller only reduces the total energy consumption by 5% for standard room of LESO. These rather low benefits may be explained by the fact that heating energy represents only 30% of the total energy consumption in the LESO building (see Section 5.2), while appliances and electric lighting represent the remaining 70%. So, energy savings concerning the heating system do not much influence the total energy consumption even if the heating system is very efficient. Moreover, the thermal mass of the building being large, a night setback applied to the heating system may only lead to a limited reduction of the heating energy consumption.

Table 6.3 gives different average measurements on the winter period and provides interesting clues to explain the remaining 21% of energy savings.

Controller type	Indoor temperature [°C]	Anidolic blind position [-]	Normal blind position [-]	Windows opening [time fraction]
Manual	20.6	0.94	0.96	0.012
Automatic without u. a.	20.5	0.93	0.95	0.008
Automatic with u. a.	20.5	0.86	0.90	0.007

Blind position = opening fraction [0;1]

Table 6.3: *Averaged measurements over the winter period*

Surprisingly, blind positions provided by the automatic controllers are lower than the ones chosen by users with the manual control. Thus, the difference in energy consumption between automatic and manual control systems may not be explained by a more extensive use of solar gains. On the other hand, the prediction capability of the heating controller (see Section 3.3.3) allows to reduce the heating power during the night and the morning when solar gains are predicted to provide a large amount of solar energy in the afternoon. Thus, heating energy consumption is reduced and overheating are avoided. This last point is confirmed by the fact that windows are more often open in rooms with manual control than in rooms with automatic controllers. Moreover, these windows opening may lead to additional heating loads if users let the windows open during a too long time and let the indoor temperature falling too low.

An other interesting fact is shown by Table 6.3. The automatic controller with user adaptation provides blind position lower than the one without user adaptation. This difference was mainly observed when user is absent, which is an evidence of the effect of the limitation introduced in the blind controller for the user absent case. This limitation was set to prevent the blind controller to accept too large solar gains when indoor temperature is already high (see Section 3.3.1.2). Histograms of temperatures for both controllers are shown in Figures 6.2 and 6.3. The effect of the limitation is clearly visible: the histogram is narrower in the case with the user adaptive controller.

Comparing these histograms with the one measured with the manual control system (see Figure 6.1), shows that overheatings around 23°C are much more frequent with the latter system, confirming the usefulness of predictive systems.

6.1.2.2 Mid-Season

Table 6.4 shows relative energy consumption for the mid-season months. The indicator $C^x_{rel/room}$ gives very different results from the others. This shows that results are biased by the room allocation.

The higher energy consumption of the manual controller can be explained by the fact that rooms with higher average energy consumption have been allocated to the manual controller and not to the automatic controller without user adaptation. This bias is unfortunately due to the missing November month. For mid-season (from September to

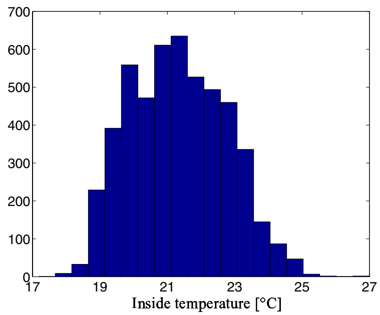


Figure 6.1: *Histogram of temperatures for the manual control system in winter*

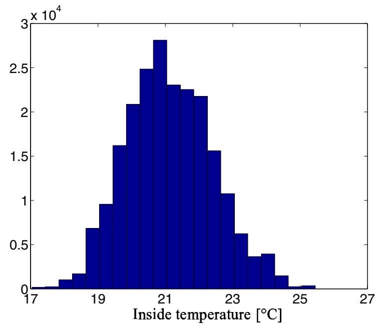


Figure 6.2: *Histogram of temperatures for the automatic control system* ***without*** *user adaptation in winter*

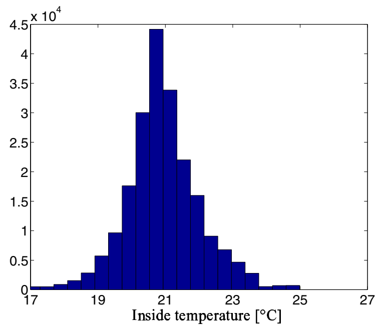


Figure 6.3: *Histogram of temperatures for the automatic control system* ***with*** *user adaptation in winter*

Controller type	C^x_{tot} [MJ/(m^2·month)]	C^x_{rel} [-]	$C^x_{rel/room}$ [-]	$C^x_{rel/month}$ [-]
Manual	7.4	0.469	0.300	0.463
Automatic without user adaptation	3.7	0.233	0.338	0.235
Automatic with user adaptation	4.7	0.298	0.362	0.302

Table 6.4: *Energy consumptions in mid-season*

Controller type	Indoor temperature [°C]	Anidolic blind position [-]	Normal blind position [-]	Presence [time fraction]
Automatic without u. a.	21.3	0.70	0.83	0.234
Automatic with u. a.	22.2	0.68	0.78	0.284

Table 6.5: *Averaged measurements over the mid-season period*

November) not all controllers have been applied to all rooms. Thus, it is harder to draw conclusions about energy consumptions. Nevertheless, the four indicators are in accordance to show that the automatic controller with user adaptation leads to higher energy consumption than the one without user adaptation. Table 6.5 provides a possible explanation. The averaged indoor temperature is higher in the case of the user adaptive controller, which could be explained by a higher user presence, and therefore a higher setpoint of temperatures (when user is absent the heating controller reduce the temperature setpoint of at least 0.5°C, see Section 3.3.3). In mid-season, some heating energy may occasionally be needed, and a higher temperature setpoint is leading to larger energy consumption during this period.

The observed discrepancy in user presence may come from the fact that controllers were not applied to the same rooms, and thus different presence patterns may have been encountered by them.

6.1.2.3 Summer

In summer, there is no heating energy used and energy consumption only involves appliances and electric lighting.

Table 6.6 gives the energy consumption during the summer months for the different controllers. The different indicators do not fully correspond concerning the manual and automatic without user adaptation systems. C^x_{tot} and C^x_{rel} show that the energy consumed by the automatic system was higher than the one consumed by the manual system. But

Controller type	C^x_{tot} [MJ/(m^2·month)]	C^x_{rel} [-]	$C^x_{rel/room}$ [-]	$C^x_{rel/month}$ [-]
Manual	5.6	0.349	0.410	0.376
Automatic without user adaptation	5.5	0.344	0.294	0.330
Automatic with user adaptation	4.9	0.307	0.296	0.294

Table 6.6: *Energy consumptions in summer*

$C^x_{rel/room}$ and $C^x_{rel/month}$ indicate the opposite and this shows that results are probably biased by the rooms allocation. That means the automatic system was applied in rooms that consume more energy (probably rooms with users present later in the evening or sooner in the morning) during months that lead to higher energy consumption (probably months with less daylighting available in the morning and evening). Nevertheless, histograms of workplane illuminances during the summer months (see Figures 6.4 and 6.5) seem to explain a higher energy consumption of the automatic system; indeed the histogram of the manual control system shows a higher occurrence of very low indoor illuminance (0-80 lux), whereas the histogram of the automatic without adaptation shows that indoor illuminance is almost never lower than 240 lux. The automatic control of electric lighting thus leads to an extensive use of electric lighting energy, since it switches on the lights in conditions where users would have not acted so, in case of a manual control system. Moreover, the benefit of the automatic control that switches off the lights, as soon as the user leaves the room, does not appear anymore since this feature is also implemented in the manual control system.

The user adaptive system seems to be a good compromise, since it also provides an automatic control for electric lighting but with a lower setpoint (observed in average at 165 ± 70 lux) compared to the one of the automatic control without user adaptation (constant at 400 lux). This is confirmed by the different histograms of illuminances (see the second slot corresponding to illuminances from 80 to 160 lux in Figures 6.5 and 6.6).

Finally, the lower energy consumption of the automatic control with user adaptation compared to the manual control system may be explained by a more efficient management of the electric lighting: with the manual system, user may switch on the lights on arrival and "forgets" to switch them off when daylighting becomes sufficient. Thus, electric lighting remains uselessly switched on or at a too high power.

6.1.2.4 Summary

Automatic controllers allow 26% of energy savings compared to the manual system, mainly due to the prediction capability of the heating controller and a more efficient management of electric lighting. On the whole experimental period, the energy consumption of the user adaptive system is not significantly higher than the one of the non-adaptive system.

6.2 Users Comfort

The users comfort has been assessed through daily questionnaires (see Section 5.5.2). A total amount of 3367 daily questionnaires have been filled by users during the monitoring period. This section presents the results of analysis for both thermal and visual comfort.

6.2.1 Thermal Comfort

Since energy consumption was reduced by using automatic controllers (see Section 6.1), it is important to check if thermal comfort was maintained. Figure 6.7 shows the user

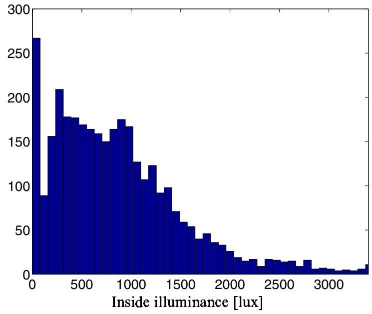


Figure 6.4: *Histogram of illuminances (when user present) for the manual control system in summer - each slot corresponds to 80 lux*

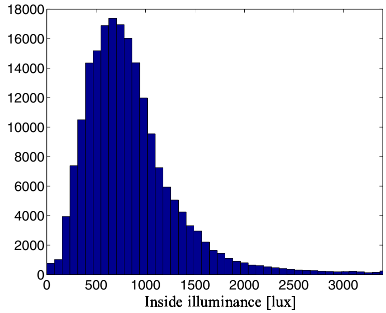


Figure 6.5: *Histogram of illuminances (when user present) for the automatic control system **without** user adaptation in summer - each slot corresponds to 80 lux*

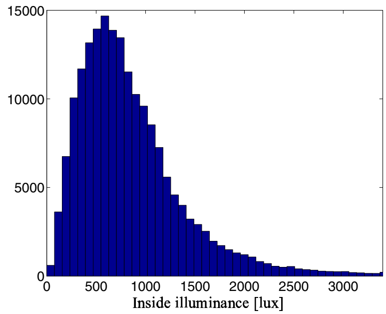


Figure 6.6: *Histogram of illuminances (when user present) for the automatic control system **with** user adaptation in summer - each slot corresponds to 80 lux*

thermal votes on the Fanger's scale for the whole experimental period, depending on the controller installed. The comfort votes for all controllers are very similar. On the whole period, the automatic controllers have provided conditions that user felt as comfortable as the ones with the manual control. Even a slight improvement is noticeable for the automatic controller with user adaptation (Higher frequency of votes 0). This is mainly due to a reduction of the overheating occurrence (less votes +1 and +2 compared to the manual system).

Analyzing comfort per season shows that the narrower distribution of temperature in winter provided by the user adaptive controller (see Section 6.1.2.1) do not improve the thermal comfort felt by users (see the similarity of the three controllers in Figure 6.8). In the other hand, the main advantage of the automatic controllers is pointed out in mid-season, where a better management of solar gains reduces perceptibly the overheating (see Figure 6.9). In summer, automatic controllers also avoid overheating in comparison to the manual system, but it sometimes leads to a slight cold discomfort (see votes -1 on Figure 6.10). The automatic controller with user adaptation avoids temperature to be too low and then gives slightly better results than the controller without user adaptation.

To summarize, more than 90% of votes are within the range [-1,+1] for all controllers, except in summer where significant overheating (+2 and +3) appears for all controllers. In mid-season, the overheating is often avoided by automatic controllers compared to the manual system. In winter, the comfort is comparable for all controllers, even if the automatic controller with user adaptation provides a narrower distribution of temperature. On the whole period, automatic controllers can be considered as comfortable for thermal aspects (and even slightly better for the one with user adaptation) as the manual control system.

6.2.2 Visual Comfort

Visual comfort is assessed using both glare and illuminance aspects. First, results of the daily questionnaires are presented for the whole experimental period on Figure 6.11 for glare and Figure 6.12 for illuminance. Considering glare aspects, the three controllers have quite similar results, with a slight reduction of glare by the automatic controllers. This obsrvation is a bit disappointing since avoiding glare should be a main benefit of the automatic blinds controller. It may be explained by the fact that users with the manual control system move blinds sufficiently often to cut direct solar radiation (see Section 6.3.1.1). Concerning illuminance, the automatic controller with user adaptation provides the most comfortable conditions, mainly by avoiding too high workplane illuminances.

Results for the winter months only (see Figures 6.13 and 6.14) show that the automatic controller with user adaptation and the manual control system give identical results for both glare and illuminance. The automatic control without user adaptation manages to avoid some "low glare" votes compared to the other systems and slightly reduces the number of "too dark" votes . The latter point is easily explained by its relatively high setpoint of the electric lighting system.

Figures 6.15 and 6.16 confirm that, in mid-season, the controller with user adaptation

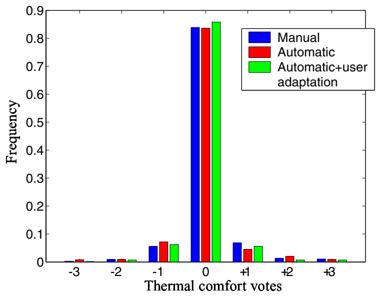


Figure 6.7: *Thermal comfort votes on a Fanger's scale for the whole period*

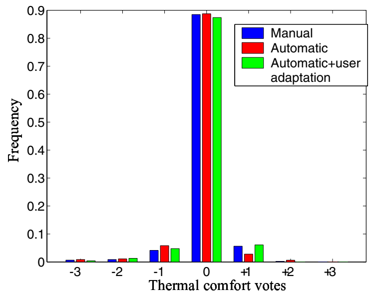


Figure 6.8: *Thermal comfort votes on a Fanger's scale for the winter period*

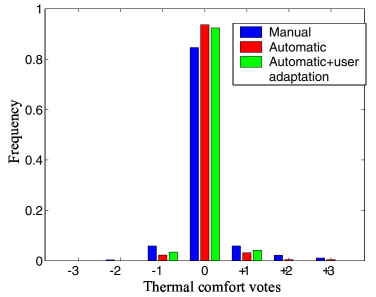


Figure 6.9: *Thermal comfort votes on a Fanger's scale for the mid-season period*

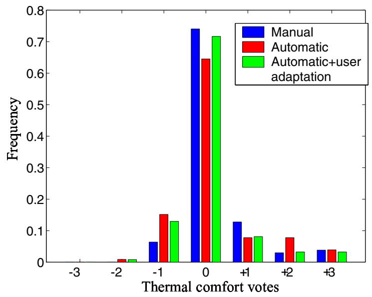


Figure 6.10: *Thermal comfort votes on a Fanger's scale for the summer period*

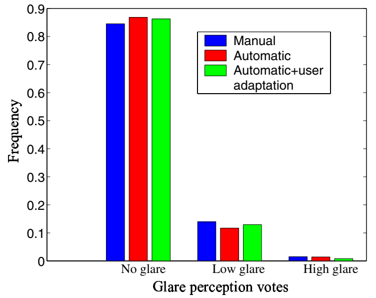


Figure 6.11: *Glare perception votes on the whole experimental period*

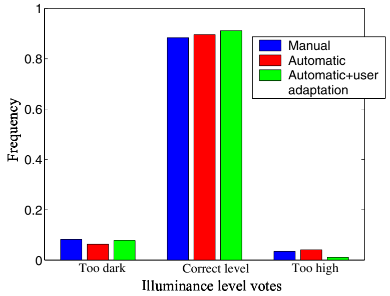


Figure 6.12: *Illuminance votes on the whole experimental period*

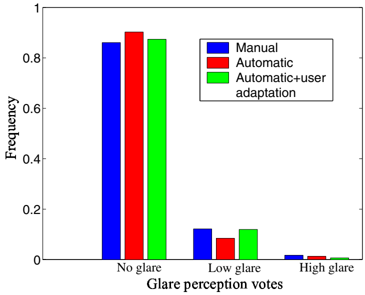


Figure 6.13: *Glare perception votes on the winter period*

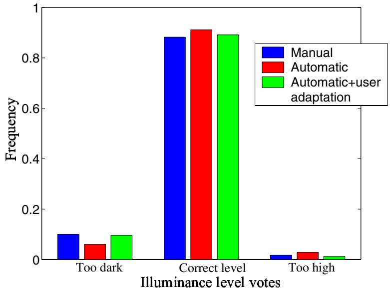


Figure 6.14: *Illuminance votes on the winter period*

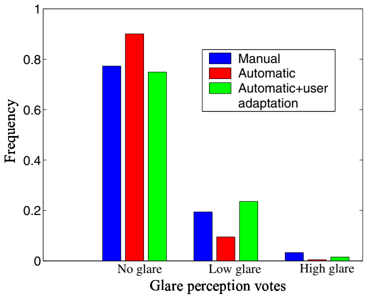


Figure 6.15: *Glare perception votes on the mid-season period*

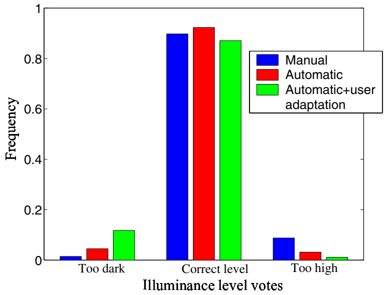


Figure 6.16: *Illuminance votes on the mid-season period*

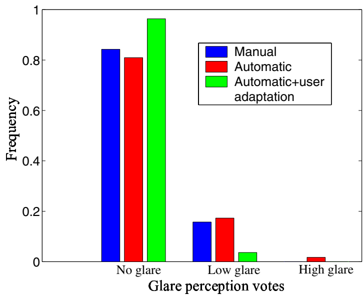


Figure 6.17: *Glare perception votes on the summer period*

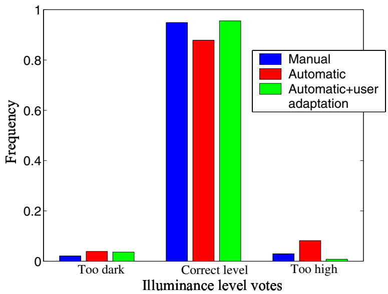


Figure 6.18: *Illuminance votes on the summer period*

provides sometimes too low illuminances, and also that its management of glare issue is not fully appropriate.

In summer, Figures 6.17 and 6.18 show that the situation is inverted, the automatic controller with user adaptation is quite better than the one without user adaptation for both glare and illuminance. Regarding illuminance, the automatic controller without user adaptation is even worse than the manual control system.

In summary, visual comfort conditions provided by the automatic controllers are similar or slightly better than the ones with the manual system on the whole experimental period, but some significant differences appear depending on the season: in summer, the automatic controller with user adaptation performs better than the one without user adaptation whereas in mid-season the situation is inverted. It seems to indicate that the user adaptation has particularly well performed in summer and not in mid-season. The next section deals with this issue.

6.3 Effect of the Adaptation to User

The effect of the adaptation to user (extensively described in Chapter 4) is studied in this section, through the evolution of the number of interactions with blinds and electric lighting over a month. In addition, evolution of the illuminance and temperature setpoints is also analyzed.

6.3.1 Number of Interactions Evolution during a Month

The number of interactions with the system may indicate if the automatic controller has adapted to user wishes. If the adaptation is efficient and conditions correspond better and better to the ones desired by the user, the number of interactions should decrease over the month.
First, interactions with the blinds are studied and then interactions with electric lighting are discussed.

6.3.1.1 Shading Device Controller

Figures 6.19 to 6.24 plot the number of interactions with blinds during the different seasons. In general, the number of interactions is higher with the automatic controller than with the manual system. It shows that users do not agree with the blind positions provided by the automatic controllers and consequently move them.

Due to technical problems, the number of interactions at the end of the month is not available for the manual system during summer months.

Concerning the anidolic blind, the number of interactions clearly decrease in the second half of the month during winter and summer when the user adaptive system is applied. In summer, the number of interactions with anidolic blinds is even lower than the ones with the manual system. It indicates that the user adaptation is working efficiently. In the other hand, in mid-season, the number of interactions do not decrease during the month. The adaptation seems not to converge, which may explained the disappointing results obtained by the user adaptive controller regarding visual comfort in mid-season (see Section 6.2.2).

Concerning the lower blind (normal window), conclusions are not so obvious. Nevertheless, in winter and summer, during the first part of the month the user adaptive controller leads to more interactions (blind positions do not suit users) but in the second part the number of interactions tends to decrease and to become lower than the ones with the non-adaptive controller. Again in mid-season, adaptation seems not to work properly.

The difficulty of the adaptation is probably due to the fact that there are no specific rules for mid-season in the controllers (see Section 3.3.1.1). Thus, the adaptation process has to act on values related to summer and winter conditions in order to learn user wishes: this makes the adaptation task very difficult. But results show that even it was probably fair regarding energy consumption, removing mid-season rules prevents a correct control during these months, and therefore prevents a correct adaptation to user.

Since user adaptation process is daily carried out, it was expected that user wishes would be learned in few days as soon as different sky conditions were encountered. But the number of interactions shows that it takes at least one or two weeks for the system to learn user wishes. Thus, applying the control system only during one month is just sufficient to show a significant difference between automatic controllers.

6.3.1.2 Electric Lighting Controller

Figure 6.25 shows the cumulated number of interactions with the electric lighting system during a month (average on the whole experimental period). Automatic controllers drastically reduce the total number of interactions compared to the manual system. This shows that it is easier to fulfill user needs and wishes dealing with electric lighting than the ones dealing with blinds (number of users interactions with blinds were not reduced by automatic controllers).

The user adaptive controller leads to less user interactions compared to the non-adaptive one. This is not due to an adaptation effect as it can be seen on Figure 6.26: the largest part of interactions consists of switch off interactions. Since the user adaptive electric lighting system has a lower illuminance setpoint (see next section) than the non-adaptive system, the electric lighting system is less often switched off by users with the adaptive controller. Moreover, this explanation is confirmed by the fact that number of switches on is higher with the adaptive system, surely because users experienced too low illuminances in their office.

The effect of the adaptation is not visible on these figures: lines related to the user adaptive system do not show any decreasing trend at the end of the month.

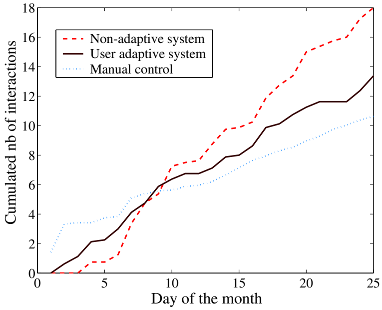


Figure 6.19: *Evolution of the number of interactions with anidolic blind in winter*

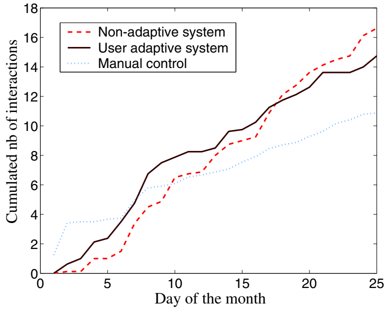


Figure 6.20: *Evolution of the number of interactions with normal blind in winter*

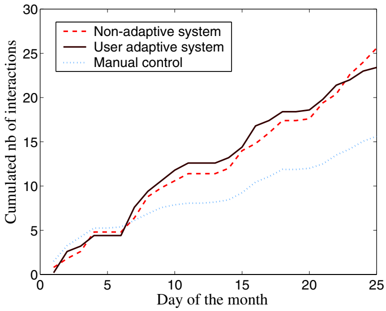


Figure 6.21: *Evolution of the number of interactions with anidolic blind in mid-season*

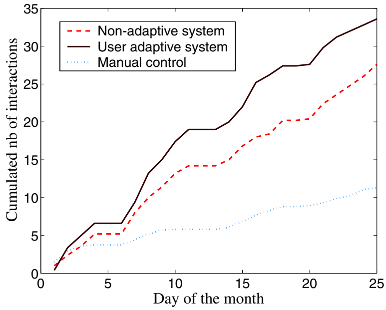


Figure 6.22: *Evolution of the number of interactions with normal blind in mid-season*

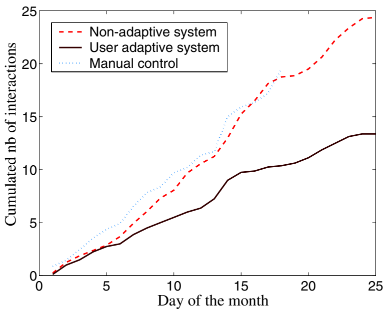


Figure 6.23: *Evolution of the number of interactions with anidolic blind in summer*

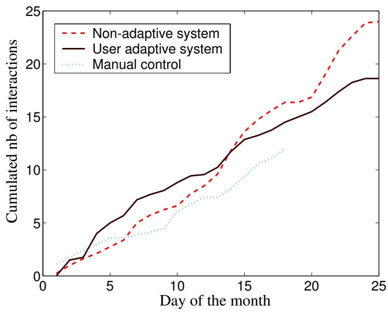


Figure 6.24: *Evolution of the number of interactions with normal blind in summer*

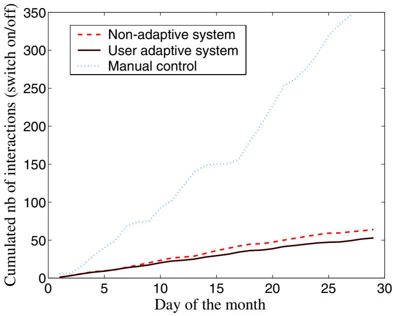


Figure 6.25: *Evolution of the number of interactions with electric lighting on the whole experimental period*

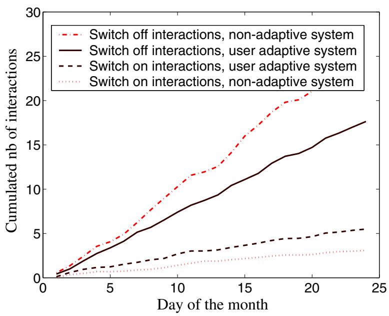


Figure 6.26: *Evolution of the number of interactions (depending on the action) with electric lighting on the whole experimental period*

6.3.2 Setpoints Evolution during a Month

An other way to see the user adaptation effect is to observe the evolution of the different setpoints over a month.

First, the illuminance setpoints evolution (averaged on the different corresponding months and on the different rooms) are given in Figures 6.27 to 6.29 for each season. In winter and summer, the illuminance setpoints do not much vary and have the same kind of lower (about 75 lux) and upper (about 400 lux) limits. In average, the setpoint value is higher in winter (195 ± 70 lux) than in summer (165 ± 70). This difference is not significant according to a Student t-test with a level of significance of 0.05. Nevertheless, it is quite probable that the season has an effect on the setpoint desired by the user. In particular, it is possible that users compensate the usual darkness of winter months by requesting higher illuminance setpoint.

During mid-season, the average setpoint value shows a clear increasing trend, confirmed by an associated increasing of the maximum setpoint value. First, it should be noticed that the average values at the end of the month (255 ± 120 lux) is absolutely not excessive and far below the setpoint applied in the rooms without adaptive system (400 lux). Secondly, this behaviour confirms the fact that user adaptation do not converge to a satisfactory configuration during mid-season.

The evolution of the temperature setpoint over a month[1] is given in Figure 6.30. These results are the average on the whole experimental period but the standard deviations given remain quite large. The plots for the season taken individually have higher standard deviation and are not given here.

[1]The setpoint of temperature is also used in summer for the management of solar gains (see Section 3.3.1.2).

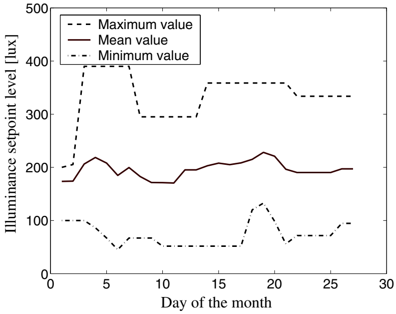


Figure 6.27: *Illuminance setpoint evolution during winter months (values on all rooms)*

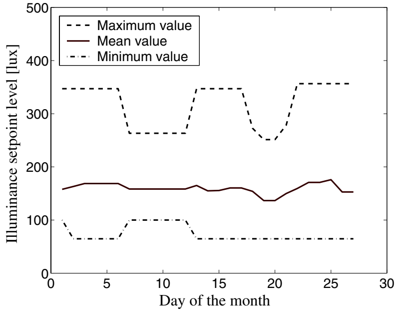


Figure 6.28: *Illuminance setpoint evolution during summer months (values on all rooms)*

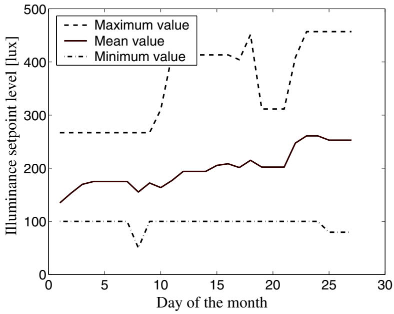


Figure 6.29: *Illuminance setpoint evolution during mid-season months (values on all rooms)*

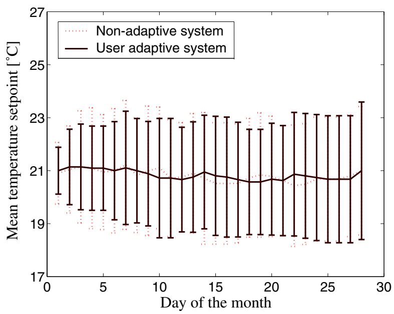


Figure 6.30: *Temperature setpoint evolution during a month, averaged on the whole experimental period*

Even if standard deviations are quite large, the setpoints seem to be kept constant over the month. At least, no clear trend is shown by these results. Moreover, no differences are noticeable between the user adaptive and non-adaptive controllers.

6.4 Users Acceptance of Automatic Controllers

The users acceptance of automatic controllers have been assessed through the twice-monthly questionnaires (see Section 5.5.2). 270 questionnaires are usable for the analysis.

6.4.1 Users Description

There are 23 users who have participated to the field study, 8 women and 15 men. 10 users wear glasses, 13 not. 6 users are less than thirty years old, 8 are between thirty and thirty-nine, 3 between forty and forty-nine and 6 are more than fifty years old.

In order to have a better statistic, users are grouped in two age classes: 14 users less than thirty-nine years old and 9 users are older than forty.

Three different room occupancy exist in the LESO offices: 1 person per room (6 concerned users), 2 persons per room (13 concerned users) and 3 persons per room (3 concerned users). In offices with several users, questionnaires show that the blind position and electric lighting power are chosen on the basis of a compromise between all occupants.

6.4.2 Overall Results

The last question of the twice-monthly questionnaire is:

> *After the last two weeks, do you prefer to come back to the manual system or keep the current control system you have?*

The proposed answers are:

◯	◯	◯
No more automatic control (reject)	*keep current system* (accept)	*No opinion*

Table 6.7 gives results related to this question for both automatic controllers (with and without user adaptation).

After two weeks, a difference between controllers appear: the percentage of rejection is lower with the user adaptive system (about 13%) than with the non-adaptive system (about 20%). The acceptance percentage is also slightly larger for the user adaptive system (68% compared to 64%).

After four weeks, the difference is drastically enlarged: the percentage of unsatisfied people with the non-adaptive system is increased and reaches 25% whereas only 5% of the users remain unsatisfied with the adaptive system.

System type	Reject	Accept	No opinion	Nb of questionnaires
After two weeks with the system				
Non-adaptive	20.5%	63.6%	15.9%	44
User adaptive	12.8%	68.1%	19.1%	47
After four weeks with the system				
Non-adaptive	**25.0%**	55.0%	20.0%	40
User adaptive	**4.8%**	71.4%	23.8%	42

Table 6.7: *Users acceptance of the automatic controllers after two and four weeks*

A Chi-Squared test (see Appendix C) for 2 degrees of freedom confirms, with a significance level of 0.05, that the variables "controller" and "acceptance" are not independent:

$$P_{obs} > q\chi_2^2(95\%) \quad , \quad (11.36 > 5.99)$$

Thus, acceptance is proven to be significantly and positively influenced by the user adaptation feature.

Then, several Chi-Squared tests are performed in order to assess the independence of the answers percentage with other variables (room occupancy, gender, age). Results of the tests on all questionnaires (both after two and four weeks) are summarized in Table 6.8. It shows that acceptance of the automatic controllers does not depend on the room occupancy. This proves that the user adaptive controller is also very beneficial with several users in a room. In particular, the fact that users choose the indoor conditions based on a compromise with all occupants in a room make their interactions consistent and this allows the adaptive system to converge to a suitable control strategy.

P_{obs}	rejection answers	acceptance answers	no opinion answers	Chi test degree of freedom (k_L)	Chi-Squared value $q\chi^2_{k_L}(95\%)$
Occupancy	1.39	2.82	1.68	2	5.99
Gender	0.81	0.00	0.04	1	3.84
Age	0.01	5.24	0.93	1	3.84

Table 6.8: *Chi-Squared independence test values with different variables - Variables are independent when values are lower than the last column*

There is no relation between gender and acceptance. Women and men accept and reject the automatic controllers in the same way.

The *rejection* of automatic controllers is not related to the age, but a significant dependence exist between the *acceptance* of a controller and the age. The same Chi-Squared test applied only on the questionnaires after four weeks show that the dependence is not anymore significant (P_{obs} = 0.79). Tables 6.9 and 6.10 show the acceptance percentage of both classes of age after two weeks and after four weeks with the control system.

	Non-adaptive controller	User adaptive controller
Age < 40	46%	70%
Age ≥ 40	85%	65%

Table 6.9: *Acceptance percentage after two weeks*

	Non-adaptive controller	User adaptive controller
Age < 40	50%	71%
Age ≥ 40	63%	71%

Table 6.10: *Acceptance percentage after four weeks*

These tables show that opinion of "young" users (less than 40 years old) about automatic controllers is already established after two weeks and do not change afterwards. They definitely accept more easily the controller with user adaptation than the one without user adaptation. On the opposite, "older" users (more than 40 years old) change their opinion towards automatic control during the month. They accept more largely the non-adaptive controller after the two first weeks, but they prefer the user adaptive system in the questionnaires after four weeks. In particular, the acceptance percentage of the non-adaptive system strongly decreases between two and four weeks (from 85% to 63%).

At the beginning, "older" users are more tolerant towards the non-adaptive controller compared to "young" users, who seem to be quite demanding. But at the end, both classes of age agree; they accept more the user adaptive control system.

Since it is shown in the next section that the adaptation effect is perceived by the users, results may be interpreted as follows: "young" users are more receptive to new features. As soon as they perceive the adaptation effect, they accept the control system even if it has not perfectly learned their wishes. In the other hand, "older" users also perceive the adaptation effect, but do not accept the control system until it has largely adapted to their wishes.

6.4.3 Users Perception of the Adaptation Effect

One question of the twice-monthly questionnaire allows assessing the user perception of the adaptation effect. The results are given in Figure 6.31 per type of control (blinds, electric lighting or heating system).

Concerning daylighting (blinds control), users strongly perceive the adaptation effect: Cumulating answers percentage for "completely" and "largely" adapted, a value of 55% is obtained for the user adaptive system and only 35% for the non-adaptive system.

For electric lighting, users also perceive the adaptation effect (50% for the adaptive system compared to 35% for the non-adaptive one, with cumulated "completely" and "largely" answers). But regarding the temperature, differences in the users perception are not significant. As mentioned in Section 6.2.1, the differences between automatic controllers in temperature conditions provided are too small to have an impact on thermal comfort and thus, they are not significantly perceived by users.

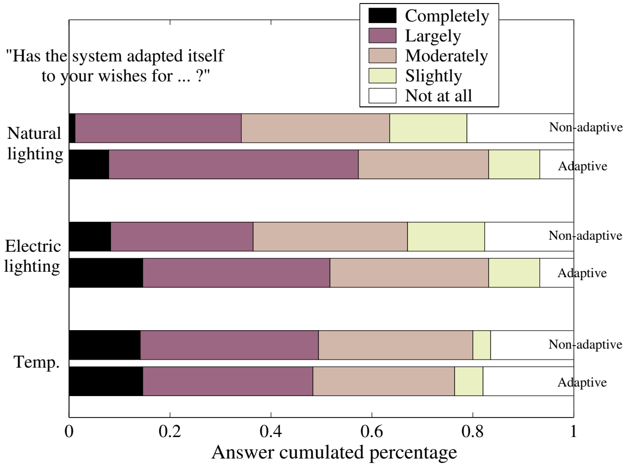


Figure 6.31: *User assessment of the adaptation effect*

6.4.4 Reasons of Rejection

Questions 6,7 and 8 of the twice-monthly questionnaires (see Appendix D) provide clues about reasons of rejection of the automatic controllers. Table 6.11 summarized the results for the rejection reasons.

System type	Answer percentage			
	"ineffective"	"stupid"	"irritating"	"going against my wishes"
Blinds controller				
Non-adaptive	8.2%	7.1%	21.2%	28.2%
User adaptive	4.5%	7.9%	12.4%	18.0%
Electric lighting control				
Non-adaptive	5.9%	7.1%	11.8%	17.7%
User adaptive	3.3%	2.3%	5.6%	6.7%
Heating control				
Non-adaptive	1.2%	0%	0%	2.4%
User adaptive	2.3%	0%	0%	2.3%

Table 6.11: *Reasons of rejection*

Two answers are mostly cited by users to describe the negative aspects of the automatic control for both blinds and electric lighting installed in their room: it "goes against my wishes" and it is "irritating". Concerning blinds, both answers are cited more than 20% of time with the non-adaptive control but these percentages are almost divided per two for the user adaptive system. Concerning electric lighting control, conclusions are

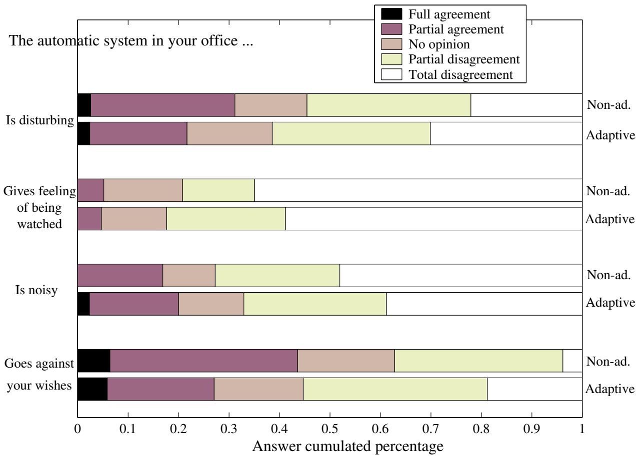


Figure 6.32: *User negative opinions on the automatic control*

similar, the adaptive control system reducing even more largely the answers percentage. Thus, the main reasons of rejection (system "goes against my wishes" and "is irritating"), were largely reduced by the adaptive control system and this explains the lower rejection percentage of the user adaptive system.

Concerning the heating control, all percentages are very low, attesting sufficient thermal comfort conditions in the rooms.

Figure 6.32 summarizes negative answers of question 9, which deals with general opinions about the controller installed in the room. The main drawback of automatic controllers is confirmed, users found that automatic controllers go against their wishes mainly when the controller installed is not adaptive (43% compared to 27% for user adaptive).

There is less than 5% of the users who feel being watched with both type of controllers. That excludes this aspect from the reasons of rejection.

6.4.5 Reasons of Acceptance

Questions 6,7 and 8 of the twice-monthly questionnaires (see Appendix D) provide also clues about the reasons of acceptance of the automatic controllers. Table 6.12 summarized the results for the acceptance reasons.

The answer mostly cited for all control types is clearly the "proper working" of the automatic control system. Regarding blinds control, the user adaptation has a strong effect on the answers percentages. Every positive aspects is enhanced with the user adaptive system. In particular, the answer "adapted to my wishes" is cited two times more with the user adaptive system together with the answer "intelligent". This confirms the user per-

System type	Answer percentage			
	"work properly"	"intelligent"	"pleasant"	"adapted to my wishes"
Blinds controller				
Non-adaptive	49.4%	16.5%	17.7%	15.3%
User adaptive	62.9%	30.3%	21.4%	27.0%
Electric lighting control				
Non-adaptive	51.8%	11.8%	10.6%	17.7%
User adaptive	52.8%	25.8%	15.7%	16.9%
Heating control				
Non-adaptive	43.5%	8.2%	5.9%	8.2%
User adaptive	44.9%	8.0%	2.3%	7.9%

Table 6.12: *Reasons of acceptance*

ception of the user adaptation feature. For electric lighting also, the answer "intelligent" is cited two times more with the adaptive system. But in this case, the adaptive system is not felt more "adapted to my wishes" by users, which may be explained by the fact that electric lighting setpoint has probably not sufficiently converged to the value desired by user (see Section 6.3.1.2).

For the heating control, no noticeable difference exist between controllers.

Considering all types of control (heating, lighting and blinds), about 50% of the users answer that the system "work properly", but only 8% to 20% answer that the system is "adapted to their wishes". This may be explained by the fact that users probably consider a system "working properly" as soon as it acts in a way they understand, and consider a system "adapted to their wishes" only when it acts in the same way as they would have acted. Thus, in order to get a system accepted (instead of a "no opinion" answer), a "proper working" is probably sufficient and it does not necessarily need to be "adapted to my wishes".

Figure 6.33 summarizes positive answers of question 9, which deals with general opinions about the controller installed in the room. It shows additional reasons of acceptance of the automatic controllers: energy savings, reduction of the number of interactions and improvement of comfort are all considered as existing aspects of the controllers they have (more than 60% of agreement). Moreover, the reduction of number of interaction and the improvement of comfort are clearly enhanced with the user adaptive system. The improvement of comfort with the user adaptive system confirms the slight effect observed in the daily comfort questionnaires (see Section 6.2) for both thermal and visual comfort. Regarding the reduction of the number of interactions, it has been actually observed that the adaptive system reduces it compared to the non-adaptive system. But for blinds, even the adaptive control system increases the number of interactions compared to the manual control (see Section 6.3.1.1). Nevertheless, the fact that automatic controllers largely reduce the number of interactions with electric lighting system seems to compensate, for users opinion, the corresponding increase number of interactions with blinds.

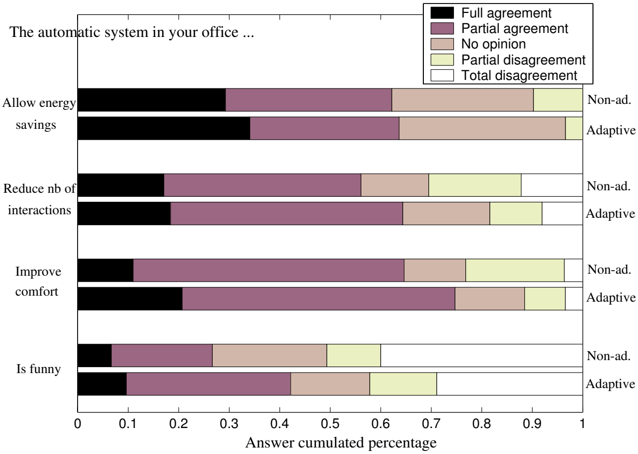


Figure 6.33: *User positive opinions on the automatic control*

6.4.6 Users Opinion Evolution

Personal questionnaires (see Section 5.5.2) have been submitted before and after the experimental period. Analysis of answers pointed out some differences that show evidence of an evolution of the user opinion.

Some questions ask the user to choose the three most relevant answers and classify them from 1 to 3. In the questionnaires analysis, a weight of 3 is given to the most relevant answer, a weight of 2 for the second one and a weight of 1 for the third one. Answers not chosen have a weight of 0. Then, the sum of all weights for an answer is divided by the total sum of all weighted answers for the considered question, in order to obtain a "relative weighted number of answers".

First, Figure 6.34 gives the user opinion before and after the experiments about the most important characteristics to make a room to his liking. "Efficient lighting" and "view of outside" are definitely more cited after the experiments. Indeed, introduction of automatic control has particularly an effect on lighting conditions, because of the blinds and electric lighting control. Moreover, some users realize that view of outside is very important, since they have observed that automatic blinds control may prevent it (at least when they enter the room with closed blinds in summer).

In Figures 6.35 and 6.36 the main positive and negative aspects of automatic controllers given by users are detailed before and after experiments. Concerning positive aspects, only slight differences in opinions are visible. Answers "increase of comfort" and "reduction of number of interactions" are more cited after the experiments, which shows that experiments have strengthened these positive opinions among users about automatic controllers. "Energy savings" and especially "control is funny" are considered

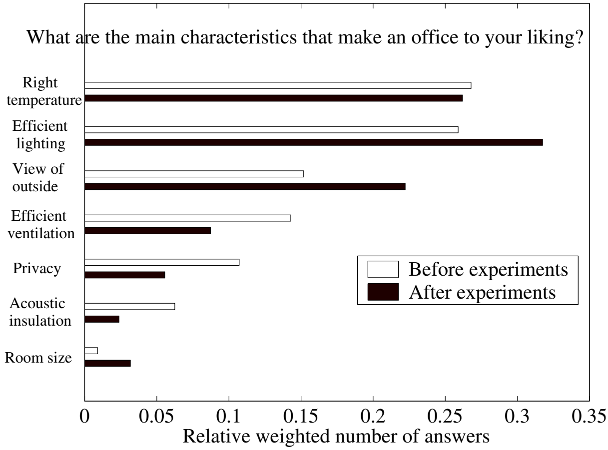


Figure 6.34: *Users opinion about the main characteristics to make a room to their liking*

relatively less relevant after experiments. The latter point shows a kind of demystification of automatic controllers after experiments.

About the negative aspects, the importance of "control goes against wishes" is almost doubled after the experiments and reaches more than 50%. This shows one more time that the main drawback and the main reason of rejection of automatic controllers is that they do not take into account user wishes. This also confirms and validates the opportunity of the present work.

Figure 6.37 shows the self-evaluation of the users concerning their sensitivity to glare before and after experiments. The same percentage of users consider themselves particularly and not particularly sensitive to glare. The situation is identical after experiments, except the fact that the number of users without opinion is clearly lower. The introduction of automatic control in their room probably gives users the feeling that an entity decides for them if situation is comfortable or not. Thus, they become more aware of what comfort means for themselves and which needs they have.

At the end of experiments, users could choose which system they wanted to be applied in their office rooms in the future. 21 users have requested the best available automatic system (i.e. the adaptive one) and 2 have requested the manual control. One of these two answers is related to the workshop (which have been observed to give disappointing results, see Section 6.5.2), so only one user in a standard office still rejects all automatic systems after the experiments. This corresponds to about 5% of the users who would probably reject automatic control in all forms.

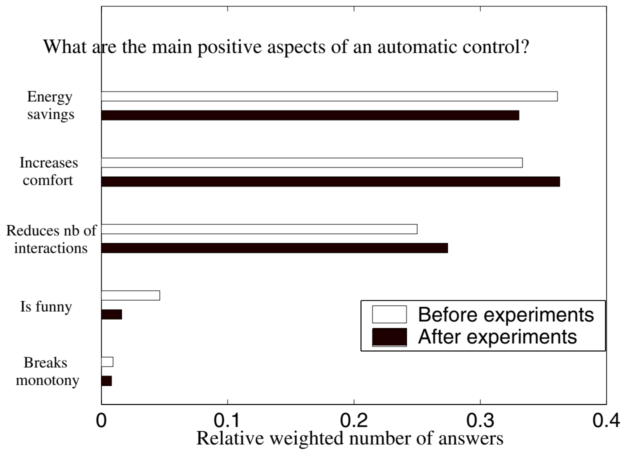


Figure 6.35: *User opinions evolution about the main positive aspects of automatic control systems*

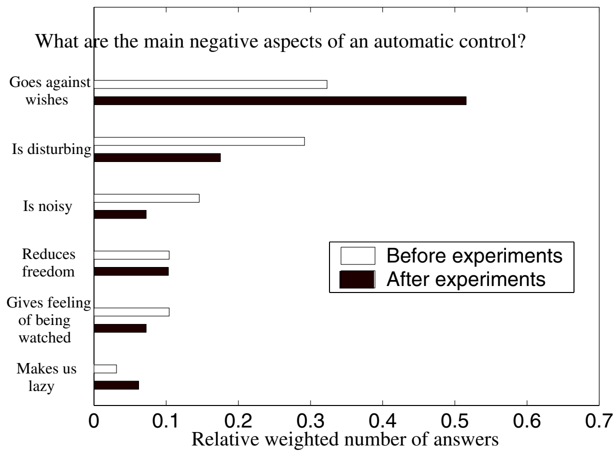


Figure 6.36: *User opinions evolution about the main negative aspects of automatic control systems*

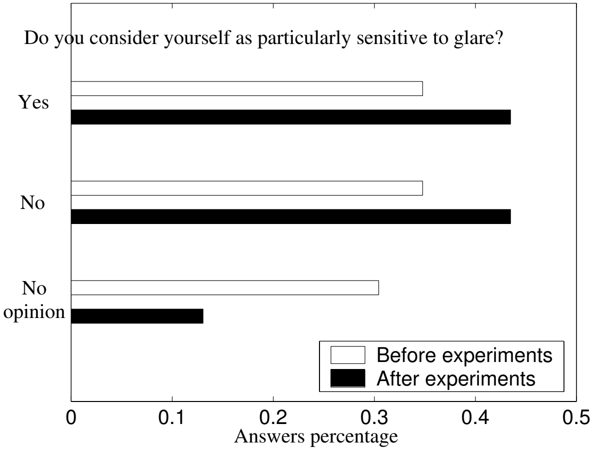


Figure 6.37: *User self-evaluation of his sensitivity to glare*

6.5 Additional Results

This section discusses the quality of the RI model results and explains the user adaptation problem observed in a special room of the LESO building.

6.5.1 RI Model Assessment

This section provides a comparison between measurements of indoor illuminance and values given by the RI model (described in Section 3.4.2).

Figure 6.38 shows a histogram of the relative error of the RI model in all rooms, the relative error being defined as:

$$\text{RI model relative error} = \frac{\text{model value} - \text{measurement}}{\text{measurement}}$$

Relative error is centered on zero but a high peak exists for a relative error equal to -1 and no relative errors appear below -1. This is explained by the fact that the RI model cannot give negative values. Indeed, the worst cases (cases corresponding to a relative error equal to -1) are when the RI model calculates a zero value for illuminances when measured values are not zero.

Frequencies observed in the range [-1,-0.5] are not equal to frequencies in the symmetric positive range [0.5,1]. This may indicate some cases in which RI model underestimates illuminances. It is discussed later in this chapter.

Table 6.13 shows the percentage of observed values for different boundaries. For this determination, null values of the RI model are removed (i.e. the peak at -1 in Figure 6.38

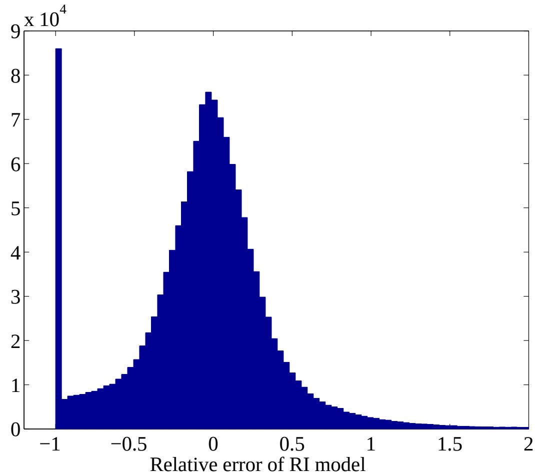


Figure 6.38: *Histogram of relative error of the RI model on all rooms*

is not taken into account). It is observed that only 40% of values provided by the RI model are comprised in the relative error boundaries of $\pm$ 0.15, which is the assumed relative error of the measured illuminances. The ratio reaches 65% when boundaries are enlarged to $\pm$ 0.3 and 83% with boundaries of $\pm$ 0.5. It means that in 17% of the cases values calculated by the RI model are more than 50% different from measurements. Some explanations of this discrepancy may be found in Figure 6.39. It depicts the RI model error in function of the illuminance measured in a standard room. At high illuminances (above 1500 lux) a trend of underestimation by the RI model is visible. This underestimation may be partly explained by the overestimation of illuminance of the EIB sensors. Even if these sensors were calibrated and an attempt to correct this overestimation was performed, they still gave slightly overestimated values (see Figure 5.16 on page 105).

Relative error boundaries	$\pm$0.15	$\pm$0.30	$\pm$0.50	$\pm$1.00
Percentage of observed values	40%	65%	83%	97%

Table 6.13: *RI model error assessment*

A malfunctioning of the RI model is visible on Figure 6.40, which depicts the RI model error in function of the illuminance measured in a not standard room. This room (room 205) is a large room grouping two standard rooms together with two illuminance sensors (with two associated and independent RI models) and four blinds to control. In this room, the RI model gives sometimes largely overestimated values when the measured values are around 750 lux. It indicates that the RI model is sometimes misleaded by the additional illuminance coming from the other windows of the double-room. For instance, it fits some measurements with blinds of the other windows completely open and then

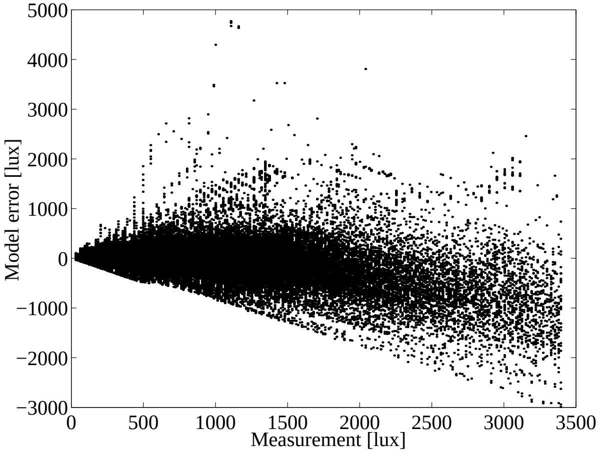


Figure 6.39: *RI model error in function of the illuminance, in a standard room (room 201)*

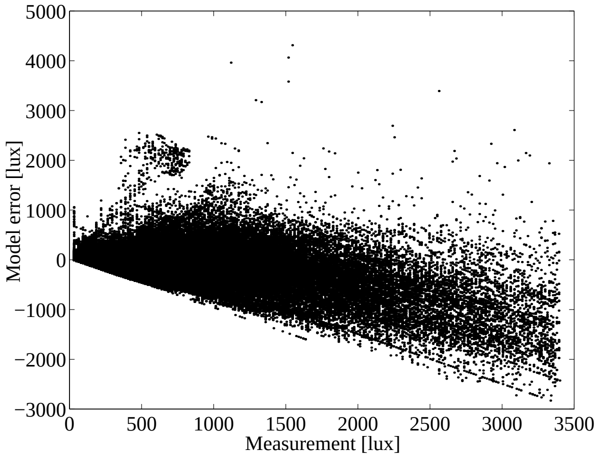


Figure 6.40: *RI model error in function of the illuminance, in a “special” room (room 205)*

overestimates indoor illuminances when blinds of the other windows are closed.

To summarize, the RI model is not very accurate (less than 40% of values comprised in the 0.15 of measurement relative errors) but provides reasonable values (relative errors less than 0.5) in 83% of the cases. Larger errors appear in non-standard rooms, and when the illuminance is high (RI model underestimate values measured by the EIB sensors).

6.5.2 Special Case of Workshop

The field study also included the workshop of the LESO building. This room (room 005) has two particularities: it is a large room grouping two standard rooms together and up to 10 different persons were working occasionally in this room. Questionnaires were filled by the main user of the workshop. At the end of experiments, it was obvious that the adaptive system proposed was not appropriate to the workshop case. Since a room with the same configuration (room 205) has given satisfactory results regarding acceptance, the difficulty should have come from the large number of users. In fact, different reasons explain why the user adaptation has failed in this room:

- Many different indoor conditions are irregularly requested, since users vary and are not regularly present. This lack of regularity prevents the adaptive system to converge.
- Various tasks were performed in the workshop, requesting very different indoor lighting conditions: tasks involving computers (requiring dark indoor conditions), general tasks such as readings (mainly requiring to avoid glare) and high precision manufacturing tasks (requiring high illuminance). The adaptive system do not manage to find a compromise between all these requirements.
- The electric lighting setpoint was not adapted correctly. It was observed that the adapted setpoint tends to be too low. In fact, frequent wrong adaptations occur when a user switches off the lights at his departure and when an other user enters the workshop just afterwards. Thus, the adaptive system considers that user is still present and that the switch off was a wish for lower illuminance.

Extrapolating from this result, it may be assumed that user adaptive systems are probably not appropriate for places with irregular users, such as workshop, library, corridors and in general all public spaces.

Chapter 7

Conclusions

"*The best way to predict the future is to invent it.*" (Alan Kay)

7.1 Achievements

The objective of this work was to develop and test user adaptive controllers for blinds, electric lighting and heating. For this purpose, an integrated control system that adapts to the environment and building characteristics was developed and successfully implemented. This system was built on three nested control loops: level 1 translating physical values into actuator commands, level 2 being the fuzzy logic controllers and level 3 dealing with adaptation aspects.

User adaptation was achieved by means of Genetic Algorithms that optimize parameters of the fuzzy logic controllers. GAs have been seen to be the most efficient optimization method for this task. They ensure a 100% convergence whereas standard search methods such as Gauss-Newton and Nelder-Mead converge in less than 25% of the time and the Simulated Annealing converges in about 75% of the time.

Simulations with a consistent virtual user (who permanently requires an opening fraction of blind of 20% in winter, and 80% in summer) have shown that the user adaptive controller is capable of anticipation. The control system manages to provide blind positions desired by the user in conditions not yet encountered.

The experimental tests were carried out in the LESO building, in 14 rooms with a total of 23 users. Three controllers were compared: a manual control system, an automatic controller without user adaptation and an automatic controller with user adaptation. Tests were conducted in a similar fashion as *clinical randomized trials* are carried out: control systems are randomly attributed to rooms and users do not know which system they have (single-blind study). The most important results are summarized in Table 7.1.

The main benefit of automatic controllers is the reduction of the total energy consumption: 26% energy savings compared to the manual control system. These large energy savings are reached without impairing indoor comfort. The thermal comfort is kept at a

Controller type	Energy savings	Thermal comfort satisfaction	Visual comfort* satisfaction	Rejection after 4 weeks
Manual	0%	84%	86%	–
Non-adaptive system	**26%**	84%	88%	25%
User adaptive system	26%	**86%**	**89%**	**5%**

* average values for both glare and illuminance assessment

Table 7.1: *Results on the whole experimental period*

high level and visual comfort is even slightly improved by the automatic controllers.

The most interesting result is the large reduction of the automatic control rejection percentage with the user adaptive system. Indeed, after four weeks with an automatic control, 25% of the users with the non-adaptive system rejected the automatic control, whereas only 5% of the users with the user adaptive system rejected it. Moreover, energy savings were not reduced by the user adaptive system.

It has been shown that the rejection percentages of automatic control do not depend on the gender or number of occupants in a room. On the other hand, an interesting dependence has been found between the age and the acceptance percentage. After two weeks, “older” users (more than 40 years old) are more likely to accept the non-adaptive system than the adaptive one. They only change their mind after four weeks and at the end, both classes of age agree: they prefer the user adaptive control system.

The main reason for rejection has been determined to be the fact that automatic control may go against user wishes. This validates the aim of the present work, which was to take into account user wishes on a long-term basis. Indeed, users with an adaptive control system complain considerably less about the control system going against their wishes.

An other interesting result is that the user adaptive control system slightly improves both thermal and visual comfort compared to the non-adaptive system. The performance of the user adaptive control would probably be even better if the adaptation performed better in mid-season. Indeed, during mid-season it has been observed that the adaptation does not properly converge for both electric lighting and blinds control. The reason for this is probably that there are no specific rules for mid-season in the controllers. Thus, the adaptation process has to act on rules set for summer and winter in order to correctly learn user wishes. This makes the adaptation task very difficult. An important improvement may thus be to include mid-season specific rules in the control system.

In addition, it was noticed that the user adaptive system did not converge properly in the case of a workshop, probably because of the numerous different users and tasks involved. It has been concluded that user adaptive systems are probably not appropriate for places with irregular users, such as public spaces.

7.2 Outlook

This work has shown that the user adaptation process takes quite a long time to be effective. For instance, at least one or two weeks are needed to see an effect on the number of interactions. Moreover, it has been noticed that the differences in user acceptance between the adaptive and non-adaptive control systems were only significant after four weeks with the control system.

In fact, there are no clues that adaptation has finished converging. Experiments should be carried out during several months with the same control system, in order to assess the user adaptation over a longer period. An extended period might lead to even better results, with a rejection percentage even lower than 5% and with better comfort conditions. On the other hand, adaptation might also become unstable and spoil the results obtained during the first month. Only experiments over a longer period would answer these questions.

An other promising approach is the integration of user presence prediction in the control system. When the user is absent, additional energy savings and better management of solar gains may be expected with an accurate presence prediction. For instance, the duration of the predicted absence may determine the management of solar gains: for a long absence, mainly thermal aspects are considered but for a shorter absence a compromise between thermal and comfort aspects should be made, in order to provide fair thermal comfort conditions at the user's arrival.

Finally, in order to investigate commercial applications, a more global approach to the building is needed. Interactions between rooms should be studied (in relation with thermal aspects or localization within the building), users should be recognized in different rooms (for instance using smart cards) and security aspects might also be considered (fire or intrusion detection). The most promising way is to combine the integrated control concept presented in this work with the Distributed Artificial Intelligence technique, which allows intelligence to be distributed among devices throughout the building.

Hence, several improvements can still be expected in the field of automatic control in buildings. However, this work has shown that the addition of an user adaptive feature was a very important step, and user needs should therefore always remain a major concern in any further development.

Appendix A

Shading Device Fuzzy Logic Controllers

A.1 User Present, “Glare” Fuzzy Rule Base

The innovative idea to take into account not only the incidence angle of the solar radiation on the facade but the exact position of the sun relatively to the facade. It is depicted on Figure A.1. This allows having different behaviours for different kind of direct sun penetration. In particular, it gives the opportunity to adapt the system (through the user wishes) depending on the user position in the room.

Inputs (fuzzy values):

- Direct vertical illuminance (Ev_{dir})
- Solar altitude ($Altitude$)
- Solar azimuth (relative to the facade orientation) ($Azimuth$)

Output (crisp value):

- Maximum blind position (α_{max})

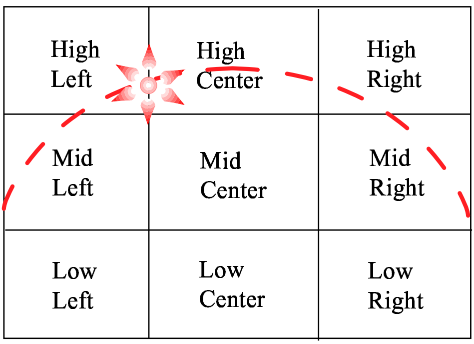


Figure A.1: *Sun position relatively to the facade*

Complete rule base (10 rules):

1. If "Ev_{dir} is high" and "$Altitude$ is low" and "$Azimuth$ is right" then "α_{max} = 0.4"

2. If "Ev_{dir} is high" and "$Altitude$ is low" and "$Azimuth$ is center" then "α_{max} = 0.4"

3. If "Ev_{dir} is high" and "$Altitude$ is low" and "$Azimuth$ is left" then "α_{max} = 0.4"

4. If "Ev_{dir} is high" and "$Altitude$ is mid" and "$Azimuth$ is right" then "α_{max} = 0.6"

5. If "Ev_{dir} is high" and "$Altitude$ is mid" and "$Azimuth$ is center" then "α_{max} = 0.6"

6. If "Ev_{dir} is high" and "$Altitude$ is mid" and "$Azimuth$ is left" then "α_{max} = 0.6"

7. If "Ev_{dir} is high" and "$Altitude$ is high" and "$Azimuth$ is right" then "α_{max} = 0.8"

8. If "Ev_{dir} is high" and "$Altitude$ is high" and "$Azimuth$ is center" then "α_{max} = 0.8"

9. If "Ev_{dir} is high" and "$Altitude$ is high" and "$Azimuth$ is left" then "α_{max} = 0.8"

10. If "Ev_{dir} is low" then "α_{max} = 1"

Fuzzy input variables are depicted on Figures A.2 to A.4. The output crisp variable α_{max} is shown in Figure A.5.

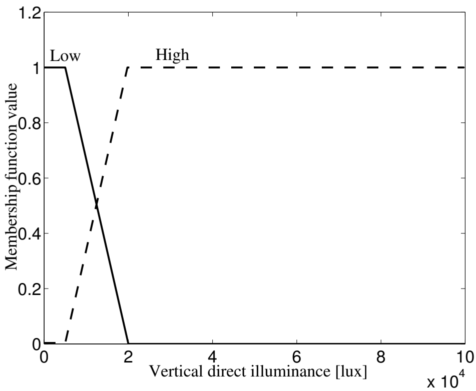


Figure A.2: *Fuzzy variable Ev_{dir}*

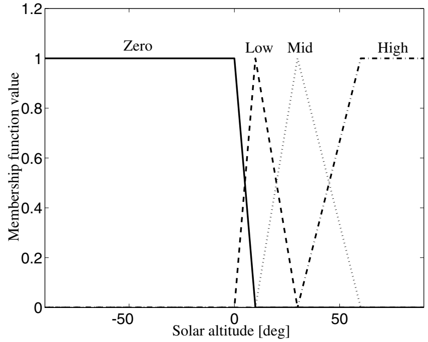


Figure A.3: *Fuzzy variable* $Altitude$

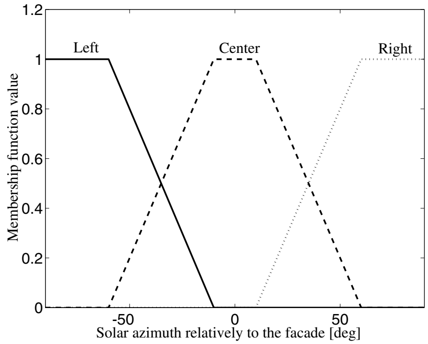


Figure A.4: *Fuzzy variable* $Azimuth$

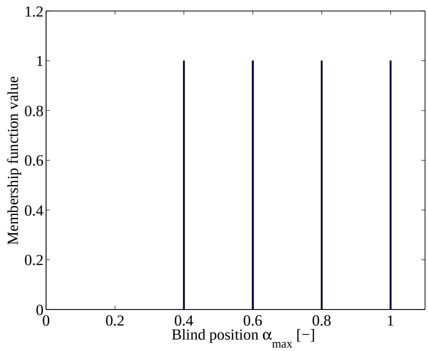


Figure A.5: *Output crisp value* α_{max}

A.2 User Present, "Illuminance" Fuzzy Rule Base

Inputs (fuzzy values):

- Global vertical illuminance (Ev_{glob})
- Outdoor average temperature on the last 24 hours ($Season$)

Output (crisp value):

- Maximum blind position (α_{ill})

Complete rule base (8 rules):

1. *If "Season is winter" and "Ev_{glob} is night" then "α = 1"*
2. *If "Season is winter" and "Ev_{glob} is high" then "α = 0.6"*
3. *If "Season is winter" and "Ev_{glob} is mid" then "α = 0.8"*
4. *If "Season is winter" and "Ev_{glob} is low" then "α = 1"*
5. *If "Season is summer" and "Ev_{glob} is night" then "α = 1"*
6. *If "Season is summer" and "Ev_{glob} is high" then "α = 0.3"*
7. *If "Season is summer" and "Ev_{glob} is mid" then "α = 0.5"*
8. *If "Season is summer" and "Ev_{glob} is low" then "α = 0.7"*

Fuzzy variables are depicted on Figures A.6 and A.7.

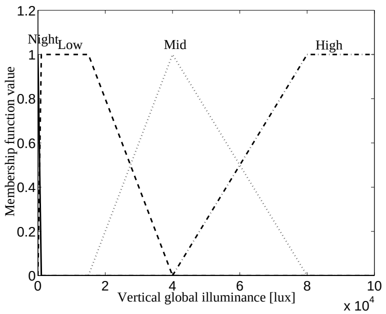


Figure A.6: *Fuzzy variable Ev_{glob}*

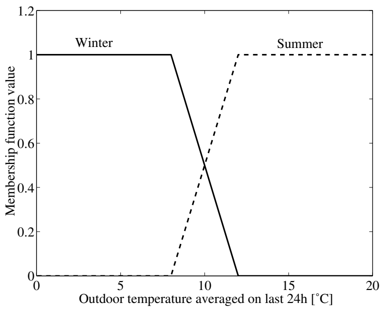


Figure A.7: *Fuzzy variable $Season$*

A.3 Genetic Algorithms Encoding

The encoding of the two fuzzy rule bases for Genetic Algorithms is realized by regrouping the two fuzzy rule bases in one individual, whose genes are representing variations of the crisp output values. An individual (chromosome) is built as follows:

"Glare" fuzzy rule number										"Illuminance" fuzzy rule number							
1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8

The rules numbers are given in previous sections.

A.4 User Absent Fuzzy Rule Base

Inputs (fuzzy values):

- Outdoor average temperature on the last 24 hours ($Season$)
- Horizontal global solar radiation (Qh_{glob})
- Difference between current room temperature and setpoint temperature (T_{diff})

Output (crisp value):

- Blind position (α)

Complete rule base:

If "Season is winter" and "Qh_{glob} is night" and "T_{diff} is zero" then "α = 0"

If "Season is winter" and "Qh_{glob} is shinyday" and "T_{diff} is zero" then "α = 1"

If "Season is summer" and "Qh_{glob} is night" and "T_{diff} is zero" then "α = 1"

If "Season is summer" and "Qh_{glob} is shinyday" and "T_{diff} is zero" then "α = 0"

If "Qh_{glob} is night" and "T_{diff} is too cold" then "α = 0"

If "Qh_{glob} is night" and "T_{diff} is too hot" then "α = 1"

If "Qh_{glob} is shinyday" and "T_{diff} is too cold" then "α = 1"

If "Qh_{glob} is shinyday" and "T_{diff} is too hot" then "α = 0"

If "Qh_{glob} is darkday" then "α = 1"

The last rule is not quite optimal for thermal aspects but it allows to illuminate corridors with daylight when office doors are open. It has been seen to reduce the use of electric lighting in corridors during dark day. Fuzzy variables are depicted on Figures A.8 and A.9. The fuzzy variable T_{diff} is less severe with too high temperature than too low temperature. It is due to the fact that it is less energy consuming to cool an office in winter (i.e. opens the windows) if there is overheating than to heat an office in summer (i.e. applies heating power) if there is overcooling. It would not be the case if a cooling system was installed in the LESO-PB building.

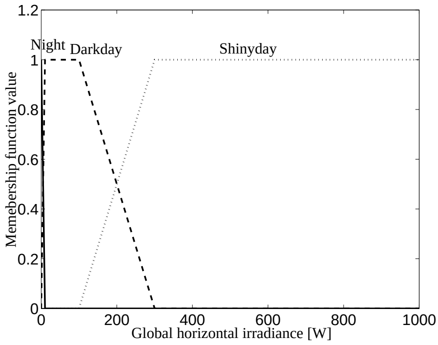


Figure A.8: *Fuzzy variable* Qh_{glob}

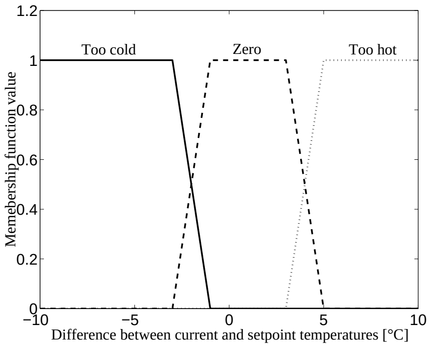


Figure A.9: *Fuzzy variable* T_{diff}

Appendix B

Venetian Blinds Controller

Controlling venetian blinds is more complex than tissue blinds since it deals with two variables: the vertical position (α) and the slats angle (β).

The venetian blinds controller developed in this work is divided into two controllers depending on whether the user is present or not (similarly to the standard blinds controller). If the user is absent the automatic control is performed identically to the tissue blind control system (the slats are simply closed and only the vertical position is regulated). The controller for the user present case is different and is described below.

The main difference compared to the tissue blind controller presented in Section 3.3.1.1 lies in the fact that the additional slats regulation is performed in a way to just completely cut the direct solar radiation. Thus, the main task is to determine the *critical slats angle* that just obstruct sufficiently the visible sky in order to cut the direct solar radiation.

Let x denotes the slat width, y the distance between two slats, β the slats angle as defined on Figure B.1 and θ the solar altitude projected on the vertical plan perpendicular to the facade.

Figure B.1 shows an illustration of two slats of a venetian blind.

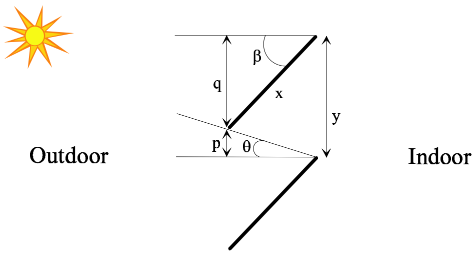


Figure B.1: *Lateral view of two slats of a venetian blind*

Defined on the figure, p and q can be easily calculated:

$$p = x \cdot \cos\beta \cdot \tan\theta$$

$$q = x \cdot \sin\beta$$

In addition, one has:

$$y = p + q$$

So,

$$y = x \cdot (\sin\beta + \cos\beta \cdot \tan\theta)$$

Then, defining $d = y/x$, the solar radiation is just cut when:

$$d = \sin\beta + \cos\beta \cdot \tan\theta \qquad \text{for} \quad \beta = \beta_c$$

with β_c being the critical slats angle.

Finally, using the relative azimuth a (angle between the perpendicular to the facade and the direction of the sun projected on a horizontal plane, positive towards the East direction) and the real solar altitude of the sun h instead of the projected sun height θ, it comes:

$$\tan\theta = \frac{\tan h}{\cos a}$$

and

$$d = \sin\beta + \cos\beta \cdot \frac{\tan h}{\cos a} \qquad \text{for} \quad \beta = \beta_c$$

This equation is solved for β_c using the Matlab Symbolic Calculation Toolbox. There are two solutions, only one of them has a physical meaning:

$$\beta_c = \left(\frac{1 - \sqrt{1 + \frac{\tan h}{\cos a} - d^2}}{\frac{\tan h}{\cos a} + d} \right)$$

Since β_c is determined, the venetian blind controller works as the tissue blind controller. With the slats regulated to reach the critical slats angle β_c, the vertical position α of the blind is determined using the “Glare” and “Illuminance” fuzzy rule bases as explained in Section 3.3.1.1.

A version of this venetian blind controller has been successfully implemented in the LESO building during an other research project, dealing with blind control, called SMARTWINDOW [Bakker et al., 2001].

Appendix C

Statistics Definition Reminder

The different definitions presented here are extensively discussed in the book of Morgenthaler [Morgenthaler, 1997].

C.1 Basic Definitions

Given a distribution of a variable x, the *expected value* of a function $f(x)$ is defined as:

$$\langle f(x) \rangle \equiv \sum_x f(x)P(x)$$

with $P(x)$ being the probability that a trial X takes on the value x.

The *arithmetic mean* denoted μ, commonly called *mean* or *average*, is defined by:

$$\mu_x \equiv \langle x \rangle = \sum_x xP(x)$$

For N samples of a variable x having a distribution with a known mean μ_x, the *variance* is defined as follows:

$$\text{var}(x) \equiv \langle (x - \mu_x)^2 \rangle = \langle x^2 \rangle - {\mu_x}^2$$

Note that the *standard deviation* denoted σ is simply equal to:

$$\sigma \equiv \sqrt{\text{var}(x)}$$

The *covariance* of two variables x and y, with their associated means μ_x and μ_y, is defined as:

$$\text{cov}(x, y) \equiv \langle (x - \mu_x)(y - \mu_y) \rangle = \langle xy \rangle - \langle x \rangle \langle y \rangle$$

Finally, the *statistical correlation* of two variables x and y is given by:

$$\text{cor}(x, y) \equiv \frac{\text{cov}(x, y)}{\sigma_x \sigma_y}$$

This value gives the strength of the relationship between variables.

C.2 Student t-Test for Two Samples

This test is used for comparing the means of two samples. These samples may be correlated or not.

Let x and y denotes two variables from two normal distributions with mean μ_x, μ_y and standard deviation σ_x, σ_y, respectively. And let m and n be the sample sizes for variables x and y, respectively.

Let assume that hypothesis H_0 is $\mu_y \leq \mu_x$ and thus alternative hypothesis H_1 is $\mu_y > \mu_x$.

First, the two standard deviations are combined:

$$\sigma_p^2 = \frac{(m-1)\sigma_x^2 + (n-1)\sigma_y^2}{m+n-2}$$

Then, the t-value is defined as:

$$t\text{-value} = \frac{\mu_y - \mu_x}{\sqrt{\sigma_p^2(m+n)/(m\,n)}} \qquad \text{for testing } H_0$$

Thus, H_0 is rejected at a significance level of 0.05 if

$$t\text{-value} > qt_{n+m-2}(95\%)$$

Where $qt_{n+m-2}(95\%)$ is the t-value in a t-table for $n+m-2$ degrees of freedom with a significance level of 0.05.

A *significance level* of 0.05 indicates that the probability of the observed data being due to pure chance is less than 5%. The *confidence level* is often mentioned in statistical tests. It is simply related to the significance level as follows:

$$\text{confidence level} = (1 - \text{significance level})$$

If H_0 is rejected, the means μ_y is *significantly higher* than μ_x.

C.3 Chi-Squared Test

This test allows to assess if two variables are independent or related. It is equivalent to the correlation but with variables that are categorical or ordinal. It is often used in questionnaires analysis.

Let observe a sample of n couple of discrete variables (Y,Z). Possible values for Y and Z are $y_1, \ldots, y_i, \ldots, y_I$ and $z_1, \ldots, z_j, \ldots, z_J$. Thus, there are $I \cdot J$ possible couples of values (Y,Z), that may be arranged in a *contingency table*, with I lines and J columns, each cell (x_i,y_j) displaying the number of occurrence n_{ij}.

Assuming Y and Z independent, one may calculate the probability p_{ij} observing each couple of values:

$$p_{ij} = P\{Y = y_i \text{ and } Z = z_j\} = P\{Y = y_i\} \cdot P\{Z = z_j\}$$

With

$$P\{Y = y_i\} = \frac{\sum_{j=1}^{J} n_{ij}}{\sum_{i=1}^{I}\sum_{j=1}^{J} n_{ij}}$$

$$P\{Z = z_j\} = \frac{\sum_{i=1}^{I} n_{ij}}{\sum_{i=1}^{I} \sum_{j=1}^{J} n_{ij}}$$

Then, a theoretical contingency table (if Y and Z were really independent) may be determined, each cell filled with:

$$n \cdot P\{Y = y_i\} \cdot P\{Z = z_j\}$$

Now, the independence test may be applied depending on a Chi-Squared distribution. The Pearson statistic test value P_{obs} is the sum of the $I \cdot J$ squared differences between theoretical and observed values in the contingency table, each squared difference being divided by the theoretical value.

The degree of freedom k_L is equal to $(I - 1) \cdot (J - 1)$.

Finally, the hypothesis of independence is rejected if

$$P_{obs} > q\chi^2_{k_L}(95\%)$$

Where $q\chi^2_{k_L}(95\%)$ is the test value for k_L degrees of freedom in a Chi-Squared distribution with a level of significance of 0.05.

Appendix D

Questionnaires

D.1 Personal Questionnaire

Projet AdControl – Questionnaire Général

Nom : ……………… Local : ……………. Date : ………………..

Votre nom est uniquement utilisé pour comparer les résultats avec les autres questionnaires que vous pourriez remplir.

1. Combien de personnes occupent-elles votre bureau ou votre espace de travail ?

1 personne	2 personnes	3-4 personnes	Plus de 4 personnes
o	o	o	o

2. Si vous n'êtes pas seul(e) dans votre bureau, qui choisit les conditions intérieures (stores, lumière artificielle et consigne de température) ?

Vous-même	Les autres	Compromis entre tous les occupants
o	o	o

3. Depuis combien de temps occupez-vous ce même bureau dans le bâtiment LESO ?

Moins d'un mois	Entre 1 et 6 mois	Entre 6 mois et 2 ans	Entre 2 et 5 ans	Plus de 5 ans
o	o	o	o	o

4. Notez par ordre d'importance les trois caractéristiques physiques qui vous paraissent les plus pertinentes pour rendre un bureau à votre goût (de 1 à 3, 1 = le plus important).

_ température agréable
_ bon éclairage
_ aération efficace
_ vue sur l'extérieur
_ agréments généraux (couleurs des revêtements, etc.)
_ insonorisation
_ espace privatif
_ grandeur du local
_ autre (spécifiez s.v.p.) …………………

5. Utilisez-vous une lampe de bureau supplémentaire comme appoint d'éclairage?

Oui	Non
o	o

6. D'une manière générale, préférez-vous travailler à la lumière naturelle, à la lumière artificielle ou avec une combinaison des deux ?

Lumière naturelle	Lumière artificielle	Combinaison des deux	Ne sais pas
O	O	O	O

7. Vous considérez-vous comme quelqu'un de très sensible à l'éblouissement ?

Oui	Non	Ne sais pas
O	O	O

8. Vous considérez-vous comme quelqu'un de très sensible ou au contraire résistant au froid ?

Sensible au froid	Résistant au froid	Indifférent ou ne sais pas
O	O	O

9. Vous considérez-vous comme quelqu'un de très sensible ou au contraire résistant à la chaleur ?

Sensible à la chaleur	Résistant à la chaleur	Indifférent ou ne sais pas
O	O	O

10. Portez-vous des lunettes ou des lentilles de contact pendant votre travail ?

Oui	Non
O	O

11. Sexe

Femme	Homme
O	O

12. Age

Moins de 30 ans	Entre 30 et 39 ans	Entre 40 et 49 ans	Entre 50 et 59 ans	Plus de 60 ans
O	O	O	O	O

13. Notez les trois avantages d'un système de contrôle automatique qui vous semblent le plus appréciable (de 1 à 3, 1 = le plus appréciable).

_ permet des économies d'énergie
_ limite le nombre d'interactions nécessaires avec les stores et la lumière artificielle
_ augmente le confort
_ permet de s'adapter à la cybernétique
_ casse la monotonie
_ est amusant
_ autre (précisez s.v.p.) ………..

14. Notez les trois inconvénients d'un système de contrôle automatique qui vous semblent le plus pénalisant (de 1 à 3, 1 = le plus pénalisant).

_ déconcentre
_ donne le sentiment d'être surveillé
_ est bruyant
_ entrave la liberté
_ rend fainéant
_ va à l'encontre des souhaits de l'utilisateur
_ autre (précisez s.v.p.) ………..

D.2 Twice-Monthly User Satisfaction

Projet AdControl – Questionnaire d'évaluation sur les 2 dernières semaines

Nom : ……………… Local : ……………. Date : ………………..

Votre nom est uniquement utilisé pour comparer les résultats avec les autres questionnaires que vous pourriez remplir.

1. De manière générale, comment estimez-vous la quantité de lumière artificielle et naturelle combinées, à votre place de travail ?

Trop clair	Clair	Correcte	Sombre	Trop sombre
o	o	o	o	o

2. L'éclairage artificiel dans ce local entraîne-t-il, pour vous, des gênes visuelles ?

Souvent	De temps en temps	Occasionnellement	Jamais
o	o	o	o

3. La lumière naturelle dans ce local entraîne-t-elle, pour vous, des gênes visuelles ?

Souvent	De temps en temps	Occasionnellement	Jamais
o	o	o	o

4. S'il y a des gênes visuelles, où se manifestent-elles généralement (plusieurs réponses possibles) ?

- ☐ éblouissement direct depuis la fenêtre
- ☐ éblouissement direct depuis le système anidolique
- ☐ éblouissement direct depuis les luminaires
- ☐ reflets sur l'écran d'ordinateur
- ☐ reflets sur du papier brillant
- ☐ autre (précisez s.v.p.) ……………………………

5. De manière générale, comment estimez-vous la température du local ?

Trop froid	Froid	A peine froid	Neutre	A peine chaud	Chaud	Très chaud
o	o	o	o	o	o	o

6. Le système de contrôle de stores vous a semblé … (plusieurs réponses possibles)

- ☐ absent
- ☐ inutile
- ☐ inefficace
- ☐ stupide
- ☐ énervant
- ☐ aller à l'encontre de vos souhaits
- ☐ fonctionner correctement
- ☐ performant
- ☐ adapté à mes besoins
- ☐ intelligent
- ☐ agréable
- ☐ autre (précisez s.v.p.) …………

7. Le système de contrôle de la lumière artificielle vous a semblé … (plusieurs réponses possibles)

- ☐ absent
- ☐ inutile
- ☐ inefficace
- ☐ stupide
- ☐ énervant
- ☐ aller à l'encontre de vos souhaits
- ☐ fonctionner correctement
- ☐ performant
- ☐ adapté à mes besoins
- ☐ intelligent
- ☐ agréable
- ☐ autre (précisez s.v.p.) ………..

8. Le système de contrôle du chauffage vous a semblé … (plusieurs réponses possibles)

- ☐ absent
- ☐ inutile
- ☐ inefficace
- ☐ stupide
- ☐ énervant
- ☐ aller à l'encontre de vos souhaits
- ☐ fonctionner correctement
- ☐ performant
- ☐ adapté à mes besoins
- ☐ intelligent
- ☐ agréable
- ☐ autre (précisez s.v.p.) ………..

9. Pour chacun des aspects suivants, jugez le système de contrôle qui a été installé dans votre bureau.

	Tout à fait d'accord	Plutôt d'accord	Ne sais pas	Plutôt pas d'accord	Désaccord total
Permet des économies d'énergie	○	○	○	○	○
Limite le nombre d'interactions	○	○	○	○	○
Augmente le confort	○	○	○	○	○
Permet de s'adapter à la cybernétique	○	○	○	○	○
Casse la monotonie	○	○	○	○	○
Est amusant	○	○	○	○	○
Déconcentre	○	○	○	○	○
Donne le sentiment d'être surveillé	○	○	○	○	○
Est bruyant	○	○	○	○	○
Entrave la liberté	○	○	○	○	○
Rend fainéant	○	○	○	○	○
Va à l'encontre des souhaits	○	○	○	○	○
autre (précisez s.v.p.) ………..	○	○	○	○	○

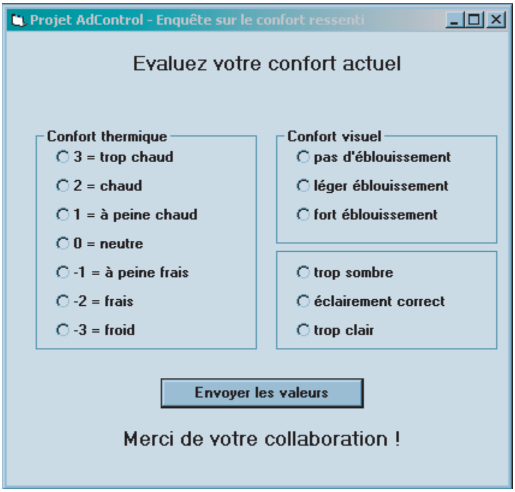
10. De manière générale, le système semble-t-il s'être adapté à vos goûts particuliers ?

	Totalement	Largement	Moyennement	Faiblement	Pas du tout
Pour l'éclairage naturel	○	○	○	○	○
Pour l'éclairage artificiel	○	○	○	○	○
Pour la température	○	○	○	○	○

11. Dans l'état actuel, préfériez-vous retourner à un système sans aucun contrôle automatique, ou conserver le système ?

Aucun contrôle automatique	Système actuel	Ne sais pas
○	○	○

D.3 Daily Comfort



Bibliography

[Abbod et al., 1998] Abbod, M., Mahfouf, M., and Linkens, D. (1998). Multi-objective genetic optimisation for self-organising fuzzy logic control. In *Proceedings of UKACC International Conference on CONTROL*, pages 1575–1580, University of Wales Swansea, UK.

[Altherr and Gay, 2002] Altherr, R. and Gay, J. (2002). A low environmental impact anidolic facade. *Building and Environment*, 37(12):1409–1419.

[Arabshahi et al., 1993] Arabshahi, P., II, R. M., and Reed, R. (1993). Adaptation of fuzzy inferencing: a survey. In *Proceedings of the IEEE/Nagoya University Workshop*, pages 7–14, Nagoya, Japan.

[Aronoff and Kaplan, 1997] Aronoff, S. and Kaplan, A. (1997). *Total Workplace Performance: Rethinking the Office Environment*. WDL Publications, Ottawa, Canada.

[ASE8912, 1977] ASE8912 (1977). *Eclairage Intérieur par la Lumière Artificielle, Recommendations de l'Union Suisse pour la Lumière*. Association Suisse des Electriciens, Zürich, Switzerland.

[Aström, 1970] Aström, K. (1970). *Introduction to Stochastic Control Theory*. Academic Press, New York, USA.

[Bagley, 1967] Bagley, J. (1967). *The Behavior of Adaptive Systems which Employ Genetic and Correlation Algorithms*. PhD Thesis, University of Michigan, Michigan, USA.

[Bakker et al., 2001] Bakker, L., Heimonen, I., Morel, N., Molteni, S., and Priolo, C. (2001). *SMARTWINDOW: an Innovative, Adaptive, Independently Controlled Window System with Smart Controlled Solar Shading and Ventilation*. EU Final Report CT98 0095, TNO, Delft, Netherlands.

[Bauer, 1998] Bauer, M. (1998). *Gestion biomimétique de l'énergie dans le bâtiment*. PhD Thesis, Swiss Federal Institute of Technology, Lausanne, Switzerland.

[Bauer et al., 1996] Bauer, M., Geiginger, J., Hegetschweiler, W., Sejkora, G., Morel, N., and Wurmsdobler, P. (1996). *DELTA, a blind controller using fuzzy logic*. OFEN Final Report 50.943, Solar Energy and Building Physics Laboratory, EPFL, Lausanne, Switzerland.

[Begemann et al., 1997] Begemann, S., den Beld, G. V., and Tenner, A. (1997). Daylight, artificial light and people in an office environment, overview of visual and biological responses. *International Journal of Industrial Ergonomics*, 20:231–239.

[Bellman, 1957] Bellman, R. (1957). *Dynamic Programming*. Princeton University Press, Princeton, New Jersey, USA.

[Birnbaum et al., 1997] Birnbaum, L., Lieberman, H., Horvitz, E., Marks, J., Kurlander, D., and Roth, S. (1997). Compelling intelligent user interfaces - how much ai. In *Proceedings of the 2nd International Conference on Intelligent User Interfaces*, pages 173–175, Orlando, Florida, USA. ACM Press.

[Bordass and Leaman, 1997] Bordass, W. and Leaman, A. (1997). From feedback to strategy. In *Proceedings of the Buildings in Use Conference*, London, UK.

[Brager and de Dear, 1998] Brager, G. and de Dear, R. (1998). Thermal adaptation in the built environment: a literature review. *Energy and Buildings*, 27(1):83–96.

[Brooks, 1997] Brooks, R. (1997). Intelligent room project. In *Proceedings of the 2nd International Cognitive Technology Conference*, Aizu, Japan.

[Burghes and Graham, 1980] Burghes, D. and Graham, A. (1980). *Introduction to Control Theory including Optimal Control*. Ellis Horwood Ltd.

[Chen, 2001] Chen, T. (2001). Real-time predictive supervisory operation of building thermal systems with thermal mass. *Energy and Buildings*, 33(2):141–150.

[Chow et al., 2002] Chow, T., Zhang, G., Lin, Z., and Song, C. (2002). Global optimization of absorption chiller system by genetic algorithm and neural network. *Energy and Buildings*, 34(1):103–109.

[Coen, 1997] Coen, M. (1997). Building brains for rooms: Designing distributed software agents. In *Proceedings of the 14th National Conference on Artificial Intelligence and 9th Innovative Applications of Artificial Intelligence Conference*, pages 971–977, Rhode Island, USA.

[Courret et al., 1998] Courret, G., Scartezzini, J., Francioli, D., and Meyer, J. (1998). Design and assessment of an anidolic light-duct. *Energy and Buildings*, 28(1):79–99.

[Cuenca and Heudin, 1997] Cuenca, C. and Heudin, J. (1997). An agent system for learning profiles in broadcasting applications on the internet. In *Proceedings of the 3rd European Artificial Evolution Conference*, pages 109–122, Nimes, France.

[Dadone and Vanlandingham, 1998] Dadone, P. and Vanlandingham, H. (1998). Genetic-based fuzzy adaptation. In *Proceedings of the 1998 IEEE World Congress on Computational Intelligence*, pages 1094–1099, Anchorage, Alaska, USA.

[de Dear, 1998] de Dear, R. (1998). A global database of thermal comfort field experiments. *ASHRAE Transactions*, 104(1b):1141–1152.

[Duffie and Beckman, 1974] Duffie, J. and Beckman, W. (1974). *Solar Energy Thermal Processes*. John Wiley and Sons, New York, USA.

[Elder and Tibbott, 1981] Elder, J. and Tibbott, R. (1981). *User acceptance of an Energy Efficient Office Building - A Study of the Norris Cotton Federal Office Building*. National Bureau of Standards, Washington, USA.

[Fanger, 1982] Fanger, P. (1982). *Thermal Comfort - Analysis and Applications in Environmental Engineering*. Krieger Publishing Company, Florida, USA.

[Fisk and Rosenfeld, 1997] Fisk, W. and Rosenfeld, A. (1997). Estimates of improved productivity and health from better indoor environments. *Indoor Air*, 7(3):158–172.

[Fletcher, 1980] Fletcher, R. (1980). *Practical Methods of Optimization*, volume Vol. 1, Unconstrained Optimization. John Wiley and Sons, New York, USA.

[Fraisse et al., 1997] Fraisse, G., Virgone, J., and Roux, J. (1997). Thermal control of a discontinuously occupied building using a classical and a fuzzy logic approach. *Energy and Buildings*, 26(3):303–316.

[Gelinas et al., 2001] Gelinas, J., Bernier, M., and Bilodeau, G. (2001). Optimisation de l'opération d'une centrale de production d'eau refroidie à l'aide des algorithmes génétiques. In *Actes du 5eme Colloque Interuniversitaire Franco-Quebecois, Thermique des Systêmes*, pages 281–288, Lyon, France.

[Geman and Geman, 1984] Geman, S. and Geman, D. (1984). Stochastic relaxation, gibbs distribution and the bayesian restoration of images". *IEEE Trans. Pattern Analysis and Machine Intelligence*, 6:721–741.

[Goldberg, 1989] Goldberg, D. (1989). *Genetic Algorithms in Search, Optimization, and Machine Learning*. Addison-Wesley, Massachusetts, USA.

[Guillemin and Molteni, 2002] Guillemin, A. and Molteni, S. (2002). An energy-efficient controller for shading devices self-adapting to the user wishes. *Building and Environment*, 37(11):1091–1097.

[Guillemin et al., 2001] Guillemin, A., Molteni, S., and Morel, N. (2001). Application of genetic algorithms to adapt an energy efficient blinds controller to the user wishes. In *Proceedings of CISBAT 2001*, pages 331–336, Lausanne, Switzerland.

[Guillemin and Morel, 1999] Guillemin, A. and Morel, N. (1999). A self-adaptive and smart system for blinds control. In *Proceedings of CISBAT'99*, pages 143–148, Lausanne, Switzerland.

[Guillemin and Morel, 2001] Guillemin, A. and Morel, N. (2001). An innovative lighting controller integrated in a self-adaptive building control system. *Energy and Buildings*, 33(5):477–487.

[Guillemin and Morel, 2002a] Guillemin, A. and Morel, N. (2002a). Application of genetic algorithms to adapt an energy efficient shading device controller to the user wishes. In *Proceedings of the 3rd European Conference on Energy Performance and Indoor Climate in Buildings*, pages 809–814, Lyon, France.

[Guillemin and Morel, 2002b] Guillemin, A. and Morel, N. (2002b). Experimental results of a self-adaptive integrated control system in buildings: a pilot study. *Solar Energy*, 72(5):397–403.

[Guth, 1966] Guth, S. (1966). Computing visual comfort ratings for a specific interior lighting installation. *Illuminating Engineering*, 61:634–642.

[Harris et al., 1993] Harris, C., Moore, C., and Brown, M. (1993). *Intelligent Control: Aspects of Fuzzy Logic and Neural Networks*. World Scientific Press, London, UK.

[Haykin, 1999] Haykin, S. (1999). *Neural Networks: a Comprehensive Foundation*. Prentice-Hall Inc., Upper Saddle River, New Jersey, USA, 2nd edition.

[Heerwagen and Diamond, 1992] Heerwagen, J. and Diamond, R. (1992). Adaptations and coping: Occupant response to discomfort in energy efficient buildings. In *Proceedings of ACEEE 1992 Summer Study on Energy Efficiency in Buildings*, pages 10.83–10.90, Berkeley, California, USA.

[Herrera et al., 1995a] Herrera, F., Lozano, M., and Verdegay, J. (1995a). *A Learning Process for Fuzzy Control Rules Using Genetic Algorithms*. Technical Report DECSAI-95108, Department of Computer Science and Artificial Intelligence, Granada, Spain.

[Herrera et al., 1995b] Herrera, F., Lozano, M., and Verdegay, J. (1995b). Tuning fuzzy logic controllers by genetic algorithms. *International Journal of Approximate Reasoning*, 12(3-4):299–315.

[Holland, 1975] Holland, J. (1975). *Adaptation in Natural and Artificial Systems*. Ann Arbor: The University of Michigan Press, Michigan, USA.

[Houck et al., 1995] Houck, C., Joines, J., and Kay, M. (1995). *A Genetic Algorithm for Function Optimization: a Matlab Implementation*. Technical Report NCSU-IE-TR-95-09, North Carolina State University, Raleigh, North Carolina, USA.

[Huang and Lam, 1997] Huang, W. and Lam, H. (1997). Using genetic algorithms to optimize controller parameter for hvac systems. *Energy and Buildings*, 26(3):277–282.

[Hygge and Löfberg, 1997] Hygge, S. and Löfberg, H. (1997). User evaluation of visual comfort in some buildings of the daylight europe project. In *Proceedings of the 4th European Conference on Energy-Efficient Lighting, Volume 2*, Copenhagen, Denmark.

[Inoue et al., 1988] Inoue, T., Kawase, T., Ibamoto, T., Takakusa, S., and Matsuo, Y. (1988). The development of an optimal control system for window shading devices based on investigations in office buildings. *ASHRAE Transactions*, 104:1034–1049.

[Jadad, 1998] Jadad, A. (1998). *Randomised Controlled Trials: A User's Guide*. BMJ Books, London, UK.

[Kalman, 1960] Kalman, R. (1960). A new approach to linear filtering and prediction problems. *Journal of Basic Engineering, Transactions of the ASME, Series D*, 82(1):35–45.

[Kemmoku et al., 1999] Kemmoku, Y., Orita, S., Nakagawa, S., and Sakakibara, T. (1999). Daily insolation forecasting using a multi-stage neural network. *Solar Energy*, 66(3):193–199.

[Kolokotsa et al., 2001] Kolokotsa, D., Tsiavos, D., Stavrakakis, G., Kalaitzakis, K., and Antonidakis, E. (2001). Advanced fuzzy logic controllers design and evaluation for buildings' occupant thermal-visual comfort and indoor air quality satisfaction. *Energy and Buildings*, 33(6):531–543.

[Krauss et al., 1998] Krauss, J., Bauer, M., Morel, N., and El-Khoury, M. (1998). *NEUROBAT, a Neuro-Fuzzy Expert System in Building Control*. OFEN Final Report 51.565, Swiss Center for Electronics and Microtechnology, Neuchâtel, Switzerland.

[Kummert et al., 2000] Kummert, M., André, P., and Nicolas, J. (2000). Optimal heating control in a passive solar commercial building. In *Proceedings of the EUROSUN 2000 Congress*, Copenhagen, Denmark.

[Lagarias et al., 1998] Lagarias, J., Reeds, J., Wright, M., and Wright, P. (1998). Convergence properties of the nelder-mead simplex method in low dimensions. *SIAM Journal on Optimization*, 9(1):112–147.

[Lam, 1993] Lam, H. (1993). Stochastic modelling and genetic algorithm-based optimal control of air conditioning systems. In *Proceedings of the 3rd International Building Performance Simulation Association Conference*, pages 435–441, Adelaide, Australia.

[Leaman and Bordass, 2001] Leaman, A. and Bordass, W. (2001). Assessing building performance in use 4: The probe occupant surveys and their implications. *Building Research and Information*, 29(2):129–143.

[Lee et al., 1999] Lee, E., DiBartolomeo, D., and Selkowitz, S. (1999). The effect of venetian blinds on daylight photoelectric control performance. *Journal of the Illuminating Engineering Society*, 28(1).

[Leigh et al., 1997] Leigh, J., Markowitz, S., Fahs, M., Shin, C., and Landrigan, P. (1997). Occupational injury and illness in the united states - estimates of costs, morbidity, and mortality. *Archives of Internal Medicine*, 157(14):1557–1568.

[LHC, 1990] LHC (1990). *Sick Building Syndrome: causes, effect and control*. London Hazards Centre Ltd, London, UK.

[Liker and Sindi, 1997] Liker, J. and Sindi, A. (1997). User acceptance of expert systems: a test of the theory of reasoned action. *Journal of Engineering and Technology Management*, 14(2):147–173.

[Liu and Jordan, 1960] Liu, B. and Jordan, R. (1960). The interrelationship and characteristic distribution of direct, diffuse and total solar radiation. *Solar Energy*, 4(3).

[McIntyre and Sterling, 1982] McIntyre, E. and Sterling, E. (1982). Building environment modification: An experimental study. In *Proceedings of the Indoor Air Conference*, pages 1:1067–1072, Washington, Seattle, USA.

[MeteoTest, 1996] MeteoTest (1996). *Meteonorm 95, V 2.0*. Bundesamt für Energiewirtschaft (BEW), Bern.

[Meyer et al., 1997] Meyer, C., Akoulchina, I., and Ganascia, J.-G. (1997). Two approaches of human behavior anticipation. In *Proceedings of the 9th International Conference on Tools with Artificial Intelligence*, pages 19–22, Newport Beach, California, USA.

[Mills and Borg, 1999] Mills, E. and Borg, N. (1999). Trends in recommended lighting levels: An international comparison. *Journal of the Illuminating Engineering Society*, 28(1):155–163.

[Minorsky, 1922] Minorsky, N. (1922). Directional stability of automatic steered bodies. *Journal of the American Society of Naval Engineers*, 34(2):280–309.

[Minsky, 1986] Minsky, M. (1986). *The Society of Mind*. Simon and Schuster, New York, USA.

[Mitchell, 1996] Mitchell, M. (1996). *An Introduction to Genetic Algorithms*. MIT Press, Cambridge, Massachusetts, USA.

[Moore et al., 2002] Moore, T., Carter, D., and Slater, A. (2002). User attitudes toward occupant controlled office lighting. *Lighting Research and Technology*, 34(3):207–219.

[Morel et al., 2001] Morel, N., Bauer, M., El-Khoury, M., and Krauss, J. (2001). Neurobat, a predictive and adaptive heating control system using artificial neural networks. *International Journal of Solar Energy*, 21:161–201.

[Morgenthaler, 1997] Morgenthaler, S. (1997). *Introduction à la statistique*. Presses Polytechniques et Universitaires Romandes, Lausanne, Switzerland.

[Morris and Dillon, 1997] Morris, M. and Dillon, A. (1997). How user perceptions influence software use. *IEEE Software*, 14(4):58–65.

[Mozer, 1998] Mozer, M. (1998). The neural network house: An environment that adapts to its inhabitants. In *Proceedings of the American Association for Artificial Intelligence Spring Symposium on Intelligent Environments*, pages 110–114, Menlo Park, USA.

[Muneer et al., 1998] Muneer, T., Gul, M., and Kinghorn, D. (1998). Development of a meteorological illuminance model for daylight computations. *Applied Energy*, 59(4):235–260.

[Nicol, 2001] Nicol, J. (2001). Characterising occupant behaviour in buildings: Towards a stochastic model of occupant use of windows, lights, blinds, heaters and fans. In *Proceedings of the 7th International IBPSA Conference*, pages 1073–1078, Rio de Janeiro, Brazil.

[Nicol and Humphreys, 2002] Nicol, J. and Humphreys, M. (2002). Adaptive thermal comfort and sustainable thermal standards for buildings. *Energy and Buildings*, 34(6):563–572.

[Nygard, 1990] Nygard, A. (1990). *Predictive Thermal Control of Building Systems*. PhD Thesis, Swiss Federal Institute of Technology, Lausanne, Switzerland.

[Pargfrieder, 2001] Pargfrieder, J. (2001). *Development of Intelligent Control Algorithms Optimising the Energy Consumption and the User Comfort in Buildings*. PhD Thesis, Technical University of Vienna, Vienna, Austria.

[Pham and Karaboga, 1998] Pham, D. and Karaboga, D. (1998). Cross breeding in genetic optimisation and its application to fuzzy logic controller design. *Artificial Intelligence in Engineering*, 12(1-2):15–20.

[Pigg et al., 1996] Pigg, S., Eilers, M., and Reed, J. (1996). Behavioral aspects of lighting and occupancy sensors in private offices: A case study of a university office building. In *Proceedings of the 1996 ACEEE Summer Study on Energy Efficiency in Buildings*, pages 8.161–8.168, Asilomar, California, USA.

[Priolo et al., 2001] Priolo, C., Sciuto, S., and Sperduto, F. (2001). *EDIFICIO: Efficient Design Incorporating Fundamentals Improvements for Control and Integrated Optimisation*. EU Final Report CT97 0069, Conphoebus, Catania, Italy.

[Reinhart, 2001] Reinhart, C. (2001). *Daylight Availability and Manual Lighting Control in Office Buildings - Simulation Studies and Analysis of Measurement*. PhD Thesis, Fraunhofer Institute for Solar Energy systems, Freiburg, Germany.

[Reinhart and Voss, 2002] Reinhart, C. and Voss, K. (2002). Monitoring manual control of electric lighting and blinds. *Lighting Research and Technology*, 34(4).

[Rochet, 1997] Rochet, S. (1997). Epistasis in genetic algorithms revisited. *Information Sciences*, 102(4):133–155.

[S. Kirkpatrick and Vecchi, 1983] S. Kirkpatrick, C. D. G. and Vecchi, M. P. (1983). Optimization by simulated annealing. *Science*, 220(4598):671–680.

[Scartezzini et al., 1990] Scartezzini, J.-L., Fritsch, R., Kohler, A., and Nygard, A. (1990). *Étude stochastique du comportement de l'occupant*. OFEN Final Report 339.5, Solar Energy and Building Physics Laboratory, EPFL, Lausanne, Switzerland.

[Scherz, 2003] Scherz, M. (2003). *A Heating Controller Based on User Presence Prediction*. Diploma Thesis, Solar Energy and Building Physics Laboratory, EPFL, Lausanne, Switzerland.

[Sharples et al., 1999] Sharples, S., Callaghan, V., and Clarke, G. (1999). A multi-agent architecture for intelligent building sensing and control. *International Sensor Review Journal*, 19(2):135–140.

[Shoureshi et al., 1992] Shoureshi, R., Torcellini, P., and Rahmani, K. (1992). *Intelligent Occupant Comfort Control System*. ASME Winter Annual Meeting DSC-45, Intelligent Control Systems.

[Takahara and Wakamatsu, 1997] Takahara, K. and Wakamatsu, H. (1997). Human friendly control system of alveolar co2-concentration based on adaptive control theory. In *Proceedings of the 6th International Workshop on Robot and Human Communication*, pages 432–437, Sendai, Japan.

[Teeter and Chow, 1998] Teeter, J. and Chow, M.-Y. (1998). Application of functional link neural network to hvac thermal dynamic system identification. *IEEE Transactions on Industrial Electronics*, 45(1):170–176.

[Timofeyev and Yusupov, 1996] Timofeyev, A. and Yusupov, R. (1996). Intelligent automatic control systems. *Journal of Computer and Systems Sciences International*, 34(1):129–140.

[Vine et al., 1998] Vine, E., Lee, E., Clear, R., DiBartolomeo, D., and Selkowitz, S. (1998). Office worker response to an automated venetian blind and electric lighting system: a pilot study. *Energy and Buildings*, 28(2):205–218.

[Willey, 1997] Willey, H. (1997). Energy-efficient people: Redefining energy-efficient lighting in terms of support for human activity. In *Proceedings of the 4th European Conference on Energy-Efficient Lighting*, pages 213–217, Copenhagen, Denmark.

[Winkelmann and Selkowitz, 1985] Winkelmann, F. and Selkowitz, S. (1985). Daylighting simulation in the doe-2 building energy analysis program. *Energy and Buildings*, 8:271–286.

[Wright, 1995] Wright, M. (1995). Direct search methods: Once scorned, now respectable. *Numerical Analysis (D. F. Griffiths and G. A. Watson, eds.) Pitman Research Notes in Mathematics*, pages 191–208.

[Wyon, 1996] Wyon, D. (1996). Individual microclimate control: Required range, probable benefits and current feasibility. In *Proceedings of the Seventh International Conference on Indoor Air Quality and Climate*, pages 1:1067–1072, Nagoya, Japan.

[Zadeh, 1965] Zadeh, L. (1965). Fuzzy sets. *Information and Control*, 8:338–353.

[Zhang and Kim, 2000] Zhang, B.-T. and Kim, J.-J. (2000). Comparison of selection methods for evolutionary optimization. *Journal of Evolutionary Optimization*, 2(1):55–70.

[Zimmermann, 1991] Zimmermann, H.-J. (1991). *Fuzzy Set Theory and its Application*. Kluwer Academic Publishers, Hingham, Massachusetts, USA, 2nd edition.

Antoine Guillemin

Birth : October 16, 1974 in Lausanne (CH). Swiss & French.

Diploma in physical engineering, EPF Lausanne, 1998

Teaching and Research Assistant
Solar Energy and Building Physics Laboratory

Professional Experience

2002-2003 : PhD Candidate at the Solar Energy and Building Physics Laboratory (LESO-PB)
2001 : Grant-holder at the Swiss Center for Electronics and Microtechnology (CSEM)
1998-2000 : Research fellow and lecturer at the Solar Energy and Building Physics Laboratory (LESO-PB)
1996 : Work placement at the Department of Rural Engineering (EPFL), with specialisation in ecology

Research

Participation to the Swiss project PROTEUS: Implementation of numerical tool for nuclear reactor simulation
Participation to the European project EDIFICIO (DG XII): R&D on "smart" control systems in buildings
Participation to the European project SMARTWINDOW (DG XII): R&D on advanced window component
Swiss Academy of Engineering Sciences (SATW) project: Development of an innovative visual comfort sensor
Participation to the EPFL project AdControl: R&D on bio-mimetic control in buildings using genetic algorithms

Services and Professional Organizations

Reviews for international journals (*Solar Energy* and *Energy and Buildings*)
Member of the USO-Built network

Teaching

2002-2003 : Follow up of student diploma thesis in physics
1998-2002 : Assistant lecturer for the building physics course
1996-1997 : Student assistant for practical work in physics

Publications

3 international journal papers
3 peer-reviewed conference papers

Languages

French: Native language
English: Fluent
German: Fair

Special Skills

In the technical computing tool MATLAB®
In artificial intelligence techniques (Artificial Neural Networks, Fuzzy Logic, Evolutionary Algorithms)