APPLICATION OF GENETIC ALGORITHMS TO ADAPT AN ENERGY EFFICIENT SHADING DEVICE CONTROLLER TO THE USER WISHES

A. Guillemin and N. Morel

Solar Energy and Building Physics Laboratory (LESO-PB), Swiss Federal Institute of Technology (EPFL), CH-1015 Lausanne, Switzerland

ABSTRACT

In order to improve the user acceptance of an automatic shading device controller, user wishes concerning the blind position are learned and integrated in the automatic controller through an innovative adaptation system developed with the use of Genetic Algorithms. Simulations with virtual users have shown learning and anticipating capabilities of the system. This paper explains in detail the adaptation process and shows one typical example of simulation results.

KEYWORDS

Building services control system, User adaptation, Genetic Algorithms

INTRODUCTION

Automatic controllers for building services are more and more used. The newly developed automatic controllers offer very promising possibilities to improve the energy efficiency, commissioning and maintenance. But nowadays, the main drawback of these controllers is that they do not take into account the user wishes on a long-term basis, and thus, all the benefits of the automatic system are lost since the user rejects it (Vine et al. (1998)). User-adaptive controllers remain to be elaborated. In particular, the capability of adaptation to the user's preferences is the necessary condition to lead to a wide acceptance of the automatic control systems among the users.

The aim of our research is to use an energy efficient blind fuzzy logic controller and to adapt it to the user wishes. The chosen fuzzy controller has been developed by Guillemin and Morel (2001) in a previous research project and its performance and efficiency have already been validated with experimental tests in several occupied offices. Few studies have been done in the issue of user acceptance of automated control system in buildings, but in the field of Artificial Intelligence Birnbaum et al. (1997) lists the main necessary points for a wide acceptance: the user should always keep the complete control of the system, the system should operate in real time and the user interactions should be taken into account. The automatic blind controller and its adaptation process have been developed taking into account these three points.

ADAPTATION ALGORITHM

The adaptation has two aims concerning 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 previously learned wishes and the energy efficient control. Therefore, the GAs are applied on two learning 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

The adaptation 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 learn the user wishes immediately (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 chosen by the user. The current conditions and the corresponding blind position wanted by the user are stored in the "wishbase" (see Table 1). The blind position is between 0 and 1, with 0 meaning blind completely closed and 1 meaning blind completely open.

TABLE 1
Example of a "wishbase" matrix (two wishes expressed in this example)

Conditions					User wishes
Season [°C]	Direct vertical illuminance [lux]	Global vertical illuminance [lux]	Sun height [deg]	Sun azimuth [deg]	Blind position
17	1000	13000	18	-75	0.5
21	34000	58000	51	11	0.8

Each night (at midnight for instance), all the new wishes expressed during the day are filtered before the adaptation is undertaken. If a wish is very bad 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 1.

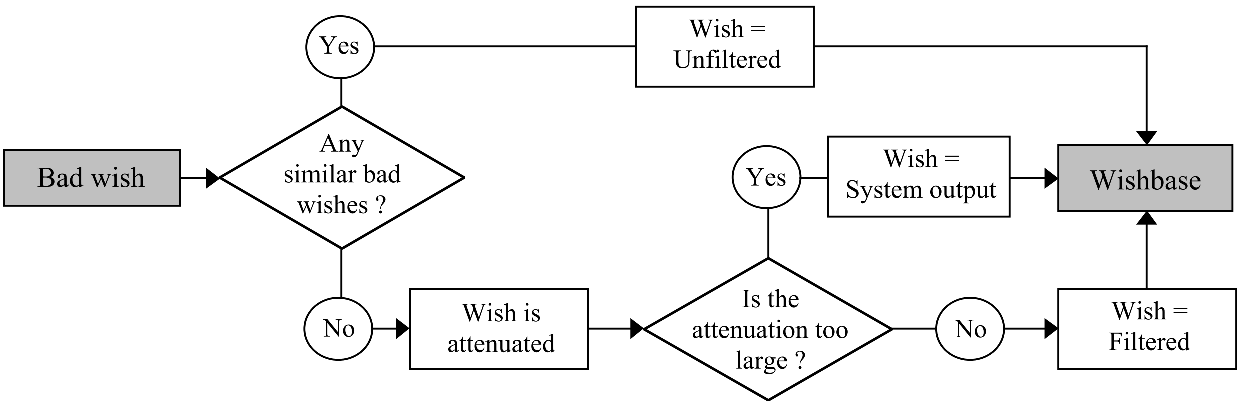

Figure 1: Operation diagram of the "wish pre-processing filter". This filter is applied when the wish is detected as being bad from an energetic point of view.

The filter is applied in the two situations in which wishes may be very bad from an energetic point of view: in summer, when the vertical illuminance is high, a large opening of the blinds would quickly lead to overheating in the room. In winter, also when the vertical illuminance is high, closing too much the blinds corresponds to a loss of large free solar gains that would greatly reduce the auxiliary heating demand of the day. The energetically bad wishes expressed during the day are compared to the wishes of the ten last days, and they are attenuated only if no similar wishes have already been expressed. This method ensures that the “wrong” wishes (not really asked 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. When all the bad wishes have been filtered, the "wishbase" is ready to be used by the genetic algorithms.

The contbase

The second aim of the adaptation is to keep the experience accumulated with 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, outside illuminances, sun position). The only difficulty is to choose the set of different conditions in order to fill at best the space of all the possible situations. A fixed set of values for each input of the fuzzy systems has been chosen in order to have every fuzzy membership functions individually matching. For instance, the fuzzy variable “sun radiation” has a fuzzy set of three membership functions (“low”, “medium” and “high”), so only three values are necessary to describe completely this variable. The chosen set of values contains in total 111 different conditions. "Contbase" has the same structure as "wishbase" (see Table 1). Since each night the controller is adapted and then changed, this "contbase" should be re-filled daily with the latest controller before carrying out the GAs adaptation.

Genetic algorithms adaptation

GAs are optimisation techniques based on the concepts of natural selection and genetic operators (recombination and mutation) and they may easily be applied to fuzzy logic controllers (f.i. see Herrera et al. (1995)). The variables are represented as genes on a chromosome. Each gene characterizes a change in one fuzzy rule of the controllers. Since there are 18 rules in the system, the total length of the chromosome is 18. Each chromosome corresponds to one controller. There is a population of individuals (chromosomes) on which the genetic operators are applied. The natural selection ensures that chromosomes with the higher fitness (measure of how good a specific controller is) will propagate themselves in next generations. Genetic operators allow exploring the whole search space. The fitness of an individual (that means a tested controller) is calculated using both bases. A good 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 calculated as follows:

$$\text{fitness}\ (c_i) = 1 \Big/ \left[\sum_j \left(\alpha_j(c_i) - \alpha_j(\text{contbase})\right)^2 + W \cdot \sum_k \left(\alpha_k(c_i) - \alpha_k(\text{wishbase})\right)^2 \right] \quad (1)$$

where

$\alpha\ (c_i)$ = blind position provided by the controller (individual) c_i

c_i = the evaluated individual (during the GA process)

j = index of the “contbase” conditions (1 to 111)

k = index of the “wishbase” conditions (1 to K = the total number of wishes in "wishbase")

W = weight for “wishbase” relatively to the “contbase”

Since there are normally much less wishes expressed than the 111 different conditions contained in "contbase", a weight W larger than 1 is necessary to ensure a good adaptation to the user wishes even if there are only few wishes expressed.

Sensitivity filter

At the end of the GA process, a "best chromosome" corresponding to the best individual is obtained. A sensitivity filter is applied on this new chromosome in order to avoid having a slight shift of the controller (due to the fact that GA is not an exact optimisation method). It tests each gene of the new chromosome separately by forcing the value of the gene to zero and 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.

SIMULATION EXAMPLES

In a previous author's paper (Guillemin and Molteni (2002)), the system had been tested with several sets of synthetic wishes and had shown a powerful ability to find solutions, even with complex combination of wishes. But in order to test the learning capability of the system on a year time basis, a simulation has been done with a virtual user whose wishes are consistent and only season dependent. This hypothetical user requests blind almost completely closed (0.2) in winter and almost completely open (0.8) in summer. During the simulation all the different possible conditions (defined by the membership functions of the fuzzy logic controller) are encountered. The Figures 2 to 4 show that the conditions go from "Winter with Glare risk and low sun radiation" to "Summer with No glare risk and high sun radiation". Each area on the figure defined by the vertical lines includes in fact 9 different conditions that correspond to 9 different sun positions relatively to the façade. The simulation is run sequentially on the different conditions by step of 3 conditions. That means it works as if there are 3 conditions encountered per day with the three associated wishes expressed by the virtual user. The adaptation process occurs at each step (=each day) on these 3 wishes. The Figures 2 to 4 describe the effect of the adaptation and the associated evolution of the controller at different time during the simulation. The bar at the top of the graphics spread over the cases where an adaptation has already been done.

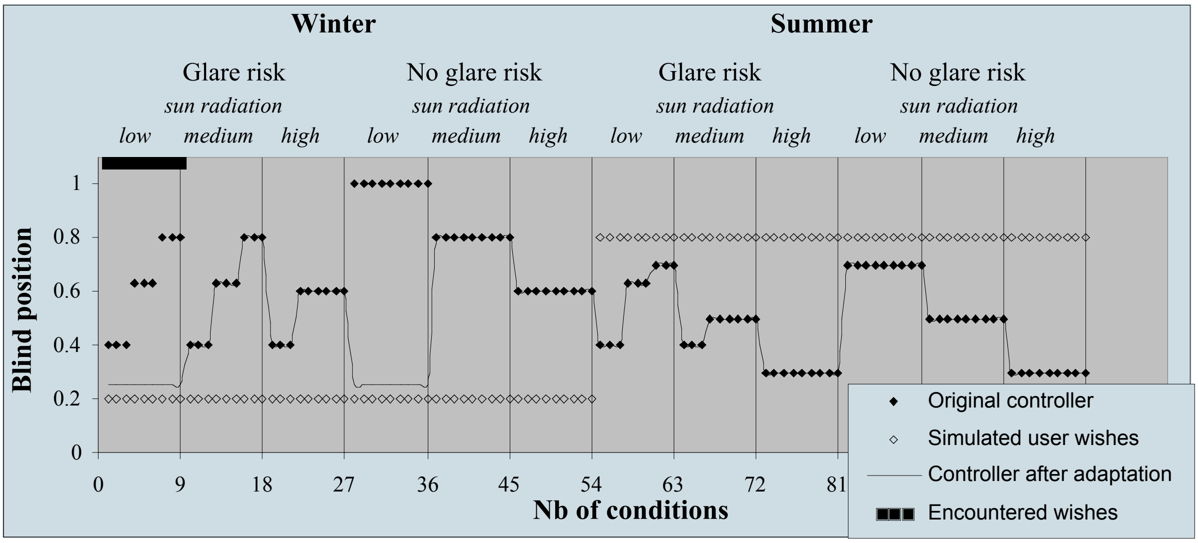

Figure 2: Effect of the adaptation after 3 time steps of simulation.

Figure 2 shows that thanks to the GAs, the system has widely learned what the user wants in the encountered conditions (the controller after adaptation curve is very near from the simulated user wishes in comparison with the original controller dots) and has kept the original controller for the not encountered conditions. There is only one exception for the not encountered "Winter with No glare risk and low sun radiation" which has also been changed by the adaptation. This behaviour may be explained as follows: the system has "understood" that the user has not reacted towards a glare risk because its reactions were not related to the sun position (same value of blind for every sun position). Thus, if the user is consistent, the system knows that the user should react in the same way in similar conditions (at least when the sun radiation is low) without glare risk.

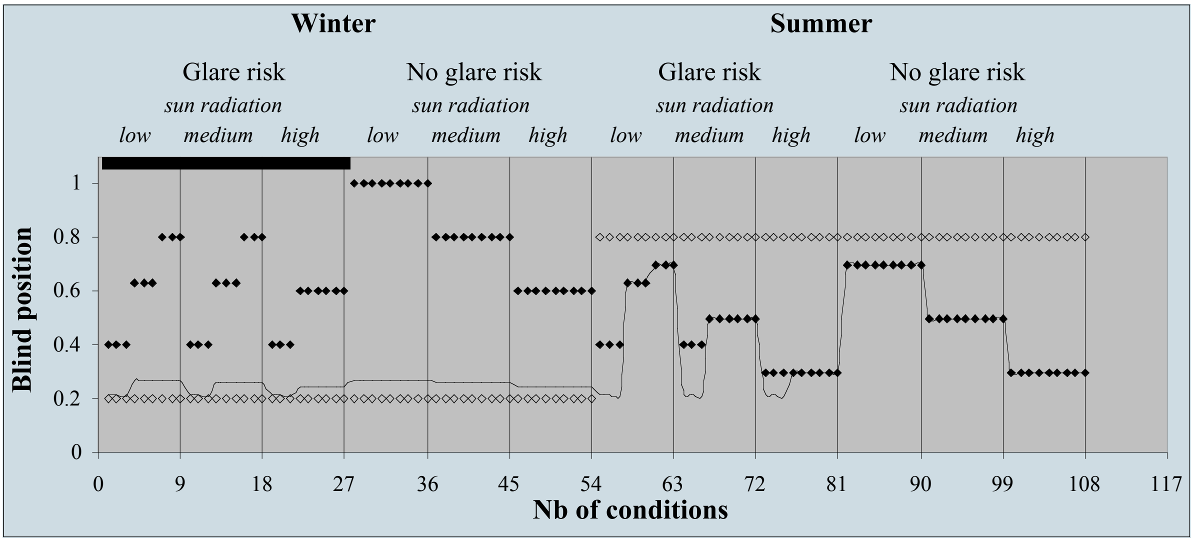

Figure 3: Effect of the adaptation after 9 time steps of simulation.

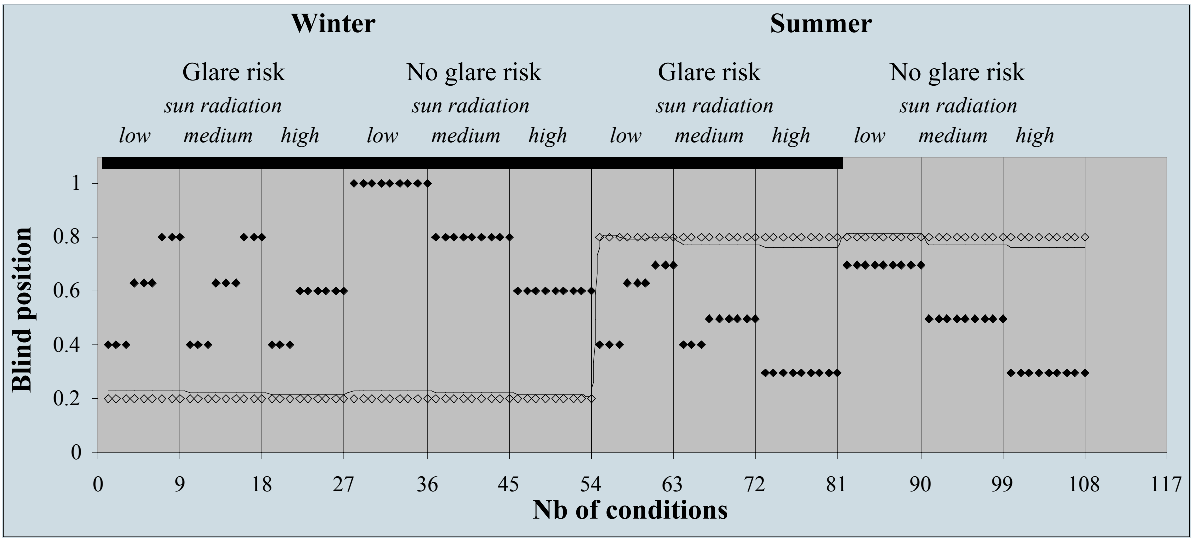

Figure 4: Effect of the adaptation after 27 time steps of simulation.

Figure 3 confirms the extrapolation capability of the system. After 27 time steps, 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 at this point, it was really plausible that the user wanted the same blind position during the whole year.

Figure 4 shows that, at this stage, the system has perfectly learned the user wishes in winter, and has corrected the wrong extrapolations in summer. Moreover, the system has again adequately extrapolated to the not encountered “No glare risk” conditions. At the end of the simulation, the results are quite similar to the ones shown on Figure 4. The small discrepancy between the user wishes and the adapted controller comes from the wish-filter (described on Figure 1). It tries to reduce over-heating in summer (lower blind positions) and accept more solar gains in winter (higher blind positions). The effect of this filter is strongly reduced in this simulation because the user has repeated many times the wishes in similar conditions. Several other simulations have been done with more complex, but always consistent, user behaviours, and the system has always managed, at least at the end, to almost perfectly learn the user wishes.

CONCLUSION AND FUTURE PROSPECTS

The simulation example has shown that the conditions concerned by the wishes are changed correctly by the adaptation process, and that the others are protected from unwanted modifications. Two choices have ensured this quality of the adaptation process: there is a rather slow adaptation of the controller to the user wishes in order to keep the experience of the controller and the wishes that are not energetically favourable are filtered. The changes observed in conditions not encountered by the system have been explained by an extrapolation of the user wishes. This emerging anticipation behaviour is a very promising feature for the implementation in real cases, with real users. User behaviours towards blinds are often very complex and hardly predictable but our system seems to have the ability to learn the user preferences, at least when they are consistent, and to take them into account on a long-term basis. The next step for our study is to undertake experimental tests with real users. That means to implement the self-adapting automatic blinds control in real office buildings and study the user acceptance of the system compared to an automatic blinds control without user adaptation.

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