OPTIMIZATION OF A FUZZY CONTROLLER USING GENETIC ALGORITHMS FOR THE INDOOR COMFORT CONTROL IN BUILDINGS

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Abstract –

The aim of this paper is the application of fuzzy control techniques coupled with Genetic Algorithms for preservation of air quality, thermal and visual comfort for buildings occupants. A fuzzy controller is developed for the control of the environmental parameters at the building zone level. The occupants' preferences are monitored via a smart card unit. Genetic Algorithm optimization techniques are applied to shift the membership functions of the fuzzy controller in order to satisfy the occupants preferences while minimizing energy consumption. Simulations using MATLAB/SIMLULINK demonstrate that energy conservation reaches 22%.

1. Introduction

Optimal control of indoor environment requires preservation of comfort conditions for buildings' occupants and minimization energy consumption and cost. Standards regarding indoor comfort are defined in international bibliography stating indoor conditions that satisfy users requirements [1-3]. The standards mainly correspond to average user requirements without taking into account occupants' particularities and buildings specificities. Moreover, artificial intelligence techniques are applied in a significant number of cases in the Building Energy Management Systems. (BEMS). Fuzzy techniques are tested for indoor thermal comfort, visual comfort or indoor air quality [4-7].

An integrated approach for indoor comfort and energy consumption is required to achieve optimal results. The present paper describes an optimization algorithm that integrates in a Genetic Algorithm (GA), both indoor comfort users requirements along with energy consumption. The GA targets to satisfy users requirements and simultaneously minimize energy consumption. The solution of the Genetic Algorithm provides optimal indoor comfort settings. A fuzzy controller is developed that reaches the default user requirements and default indoor comfort settings. After extraction of optimal indoor comfort settings by the Genetic Algorithm, the fuzzy controller is tuned to reach new indoor comfort settings.

The developed algorithms are parts of a distributed energy management system, which consists from the following components: (i) A smart card system, which collects the users preferences;(ii) A PLC or Local Operating Network (LON) module running the fuzzy controller that retains indoor thermal comfort, visual comfort and indoor air quality by regulating the PMV index, the indoor illuminance and the CO_2 concentration respectively; (iii) The central PC, which is responsible for monitoring the overall system performance and adaptation of the control strategy of the fuzzy controller using the output of the Genetic Algorithm [8]. The control architecture is depicted in Fig. 1.

2. The fuzzy controller

A fuzzy controller is developed to maintain indoor comfort in the zone level based on default user requirements. The main parameters that influence the users comfort are mentioned elsewhere and are: (i) Thermal comfort, (ii) Visual comfort and (iii) Indoor air quality. Normally, thermal comfort depends upon a great number of parameters such as air velocity, mean radiant temperature, people's activity, etc. For that reason, the controlled variable for thermal comfort is the Predicted Mean Vote (PMV) index [9]. The variable for controlling visual comfort is the illuminance level, measured in lux. Finally the indoor air quality controlled variable is the CO_2 concentration (measured in ppm) as it reflects the presence of users as well as various sources of pollutants in the building [5].

The fuzzy controller has five inputs and four outputs as tabulated in Table 1. The input–output universe of discourse is covered using triangular and trapezoidal membership functions. The rules are designed in such way as to give priority to passive techniques for reaching indoor comfort. The membership functions for the indoor thermal comfort inputs (PMV index) and the output (heating) are illustrated in Fig. 2 and 3, respectively.

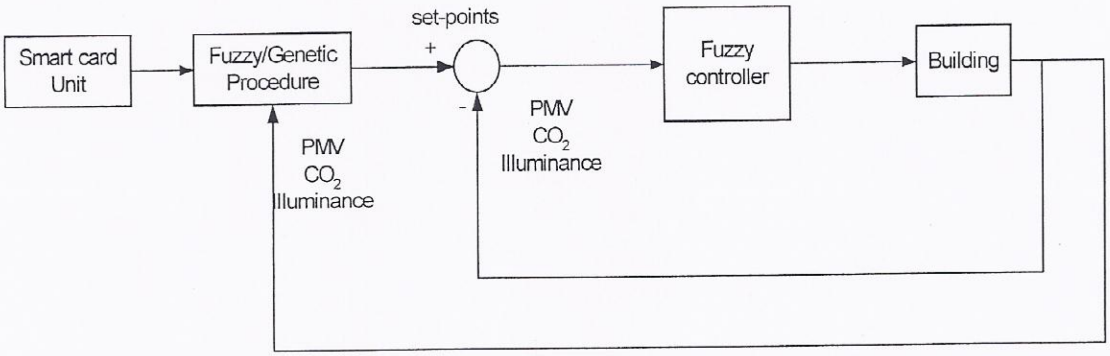

Fig. 1. The control architecture

Table 1						
Fuzzy controller inputs	PMV	Outdoor temperature	CO_2 concentration	The rate of change of CO_2 concentration	Indoor illuminance
Fuzzy controller outputs	Heating / Cooling		Window opening	Shading	Electric lighting

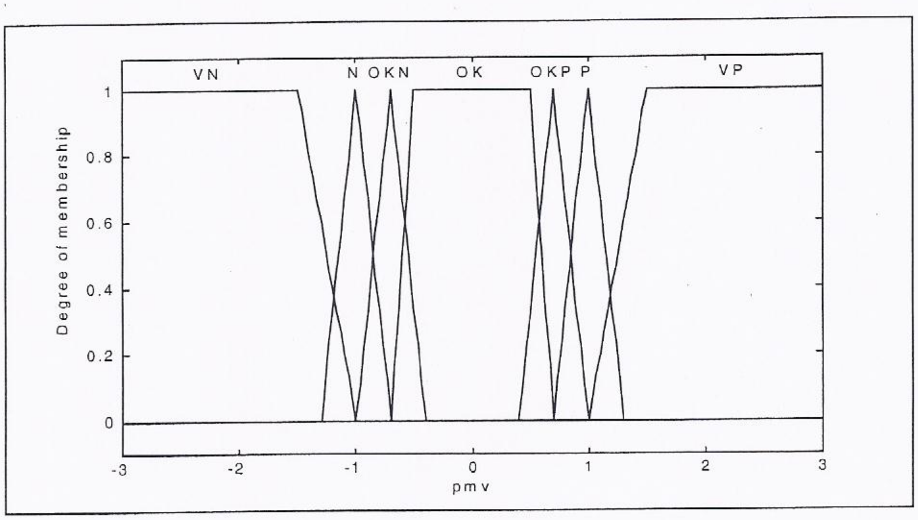

Fig. 2. The PMV membership functions

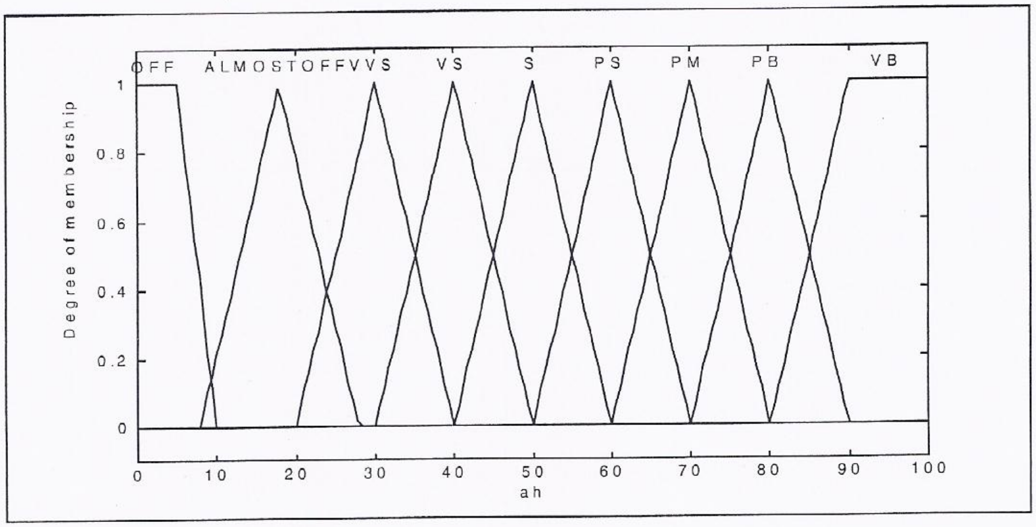

Fig. 3 The output heating membership functions

Concerning thermal comfort, the related fuzzy rules are such as to allow natural cooling through window openings and reach thermal comfort using natural ventilation techniques during moderate seasons. During winter and summer, windows are kept closed to avoid thermal losses. Sun penetration is controlled as to allow passive heating during winter and cut-off excessive heating during summer.

The membership functions of CO_2 concentration and window opening are illustrated in Figures 4 and 5, respectively. The desired CO_2 concentration is 800 ppm corresponding to 1 of the OK membership function.

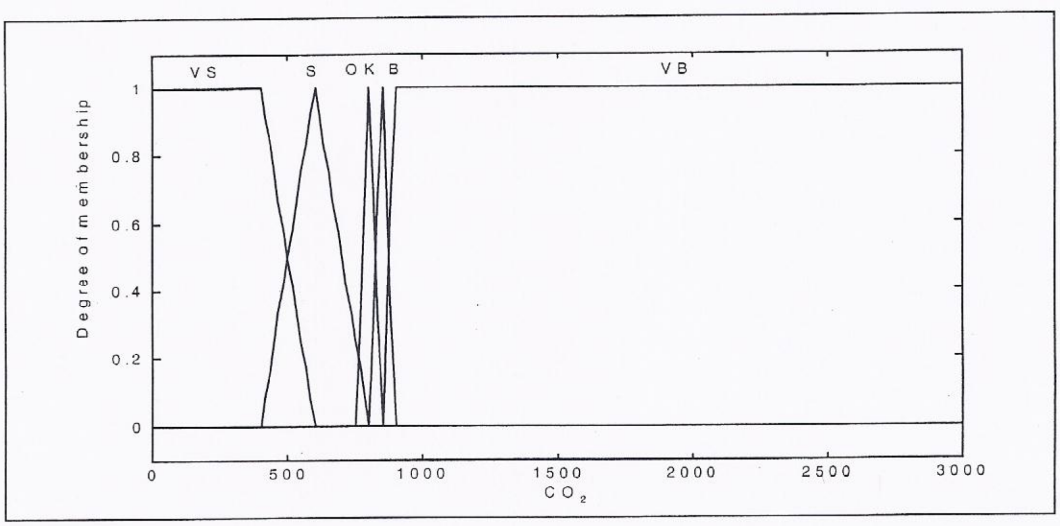

Fig. 4. The CO_2 concentration membership functions

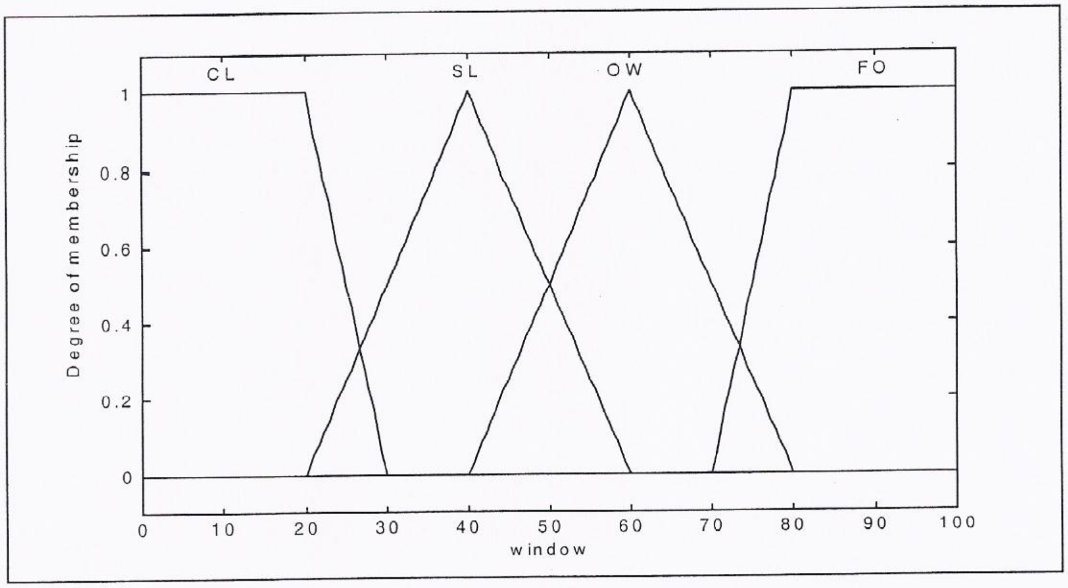

Fig. 5. The window opening membership functions

The indoor illuminance membership functions are illustrated in Fig. 6. The rules are such to allow the electric lighting to be on, when the indoor illuminance is zero, i.e. during nighttime and during cloudy conditions. When the indoor illuminance is increased, immediately the electric lighting is turned off and the shading regulates the indoor visual comfort.

The fuzzy controller is designed to reach specific set points for the controlled variables corresponding to the indoor comfort for an average user. The users requirements are taken into account by shifting the membership functions accordingly.

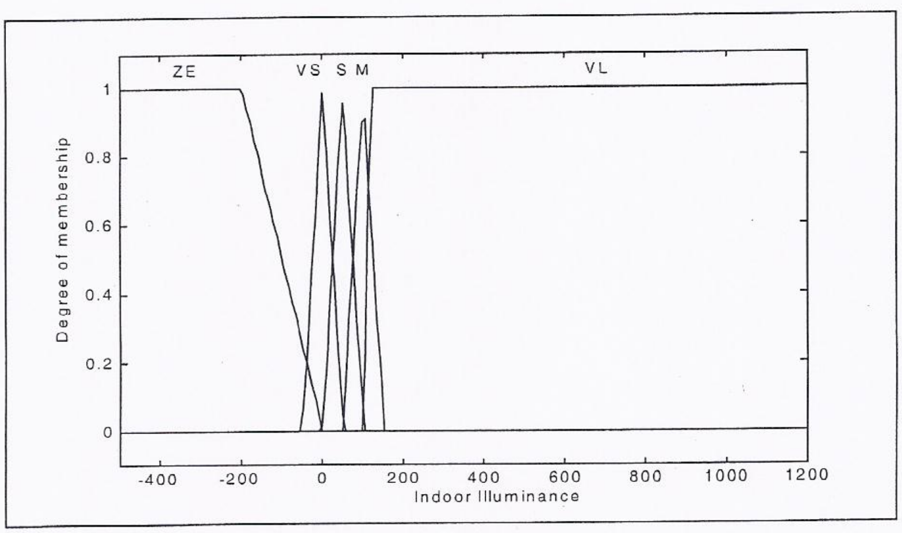

Fig. 6 The indoor illuminance membership functions

3. The Genetic Algorithm

The objectives of the Genetic Algorithm optimization technique are: (i) occupants' preferences satisfaction on a long-term basis and (ii) minimization of energy consumption for heating/cooling and electric lighting [10].

The multi-objective optimization is achieved minimizing the cost function satisfying the following constraints:

$$
\begin{aligned}
&-3 < PMV_{GA} < 3 \\
&400\ \text{ppm} < [CO_2]_{GA} < 1000\ \text{ppm} \\
&500\ \text{lux} < ILL_{GA} < 1000\ \text{lux}
\end{aligned}
\tag{1}
$$

where:

PMV_{GA} is the new thermal comfort setting to be reached by the zone level controllers

$[CO_2]$ is the new indoor air quality setting

ILL is the new visual comfort setting

The cost function is defined as:

$$
\begin{aligned}
\text{costF}= &\left[(PMV_{user}-PMV_{GA})^2+([CO_2]_{user}-[CO_2]_{GA})^2+(ILL_{user}-ILL_{GA})^2\right](1-\lambda)+ \\
&+\lambda\left[\text{Energy}^2_{heat/cool}(PMV_{GA},[CO_2]_{GA})+\text{Energy}^2_{light}(ILL_{GA})\right]
\end{aligned}
\tag{2}
$$

The costF parameters are normalized in the range [0-1] and are always positive.

Real-Coded Genetic Algorithms (GA) techniques are introduced for the solution of the optimization problem based on the mechanism of natural selection and natural genetics. Each 'chromosome' consists from three 'genes' corresponding to the PMV index, the CO_2 concentration and the indoor illuminance levels, respectively. The genes are real values of these variables. An initial population of 100 chromosomes is generated randomly. The fitness function of the GA chromosomes is the following:

$$
\text{fitF} = 1/\text{costF} \tag{3}
$$

The GA algorithm attempts to maximize its fitness function, thus minimizing the cost function of the system [11].

4. Results

The controller's initial set points are: PMV = -0.5, $[CO_2]$ = 800 ppm and Indoor Illuminance = 500 lux. If the users' requirements are: PMV_{user} = -0.5, $[CO_2]_{user}$ = 700 ppm and $\text{Illuminance}_{user}$ = 600 lux the resulting optimal set points corresponding to the maximum fitness extracted by the GA are: PMV = -1, $[CO_2]$ = 723 ppm and Indoor Illuminance = 520 lux

The fuzzy controller is adapted to the new settings by shifting its membership functions. The PMV response before and after adaptation is depicted in Fig. 6. All simulation results concern a 15 m^2 building in Athens Greece for a specific winter day.

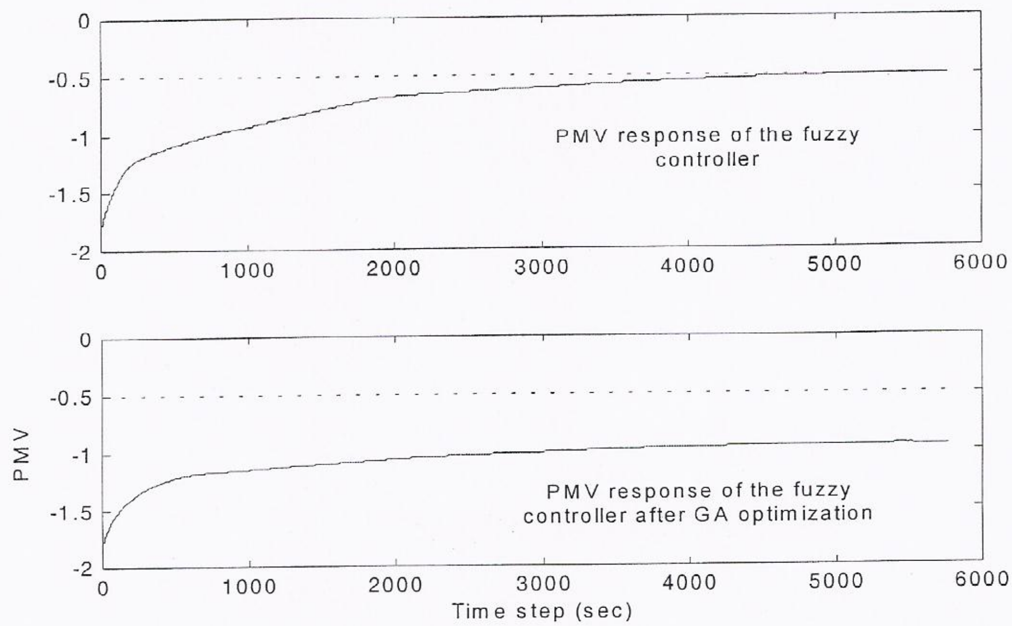

Fig. 6. The PMV response of the fuzzy controller before and after GA optimization

The $[CO_2]$ response, after shifting the membership functions, is closer to the setting defined by the GA, as depicted in Fig.7, compared to the initial response.

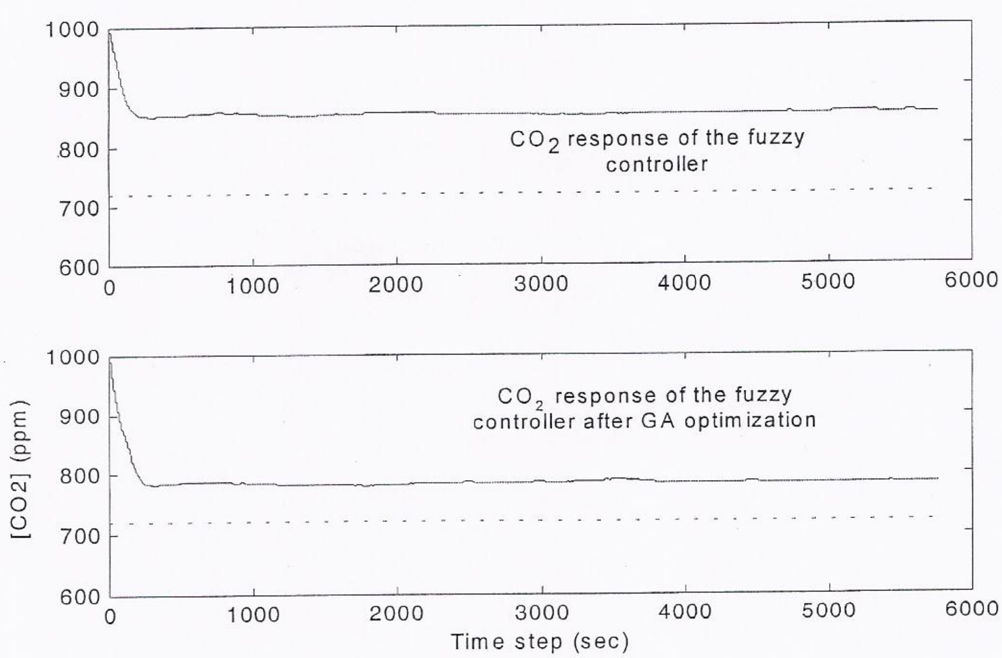

Fig. 7. The CO_2 concentration response of the fuzzy controller before and after GA optimization

The same observations apply to the indoor illuminance response illustrated in Fig. 8.

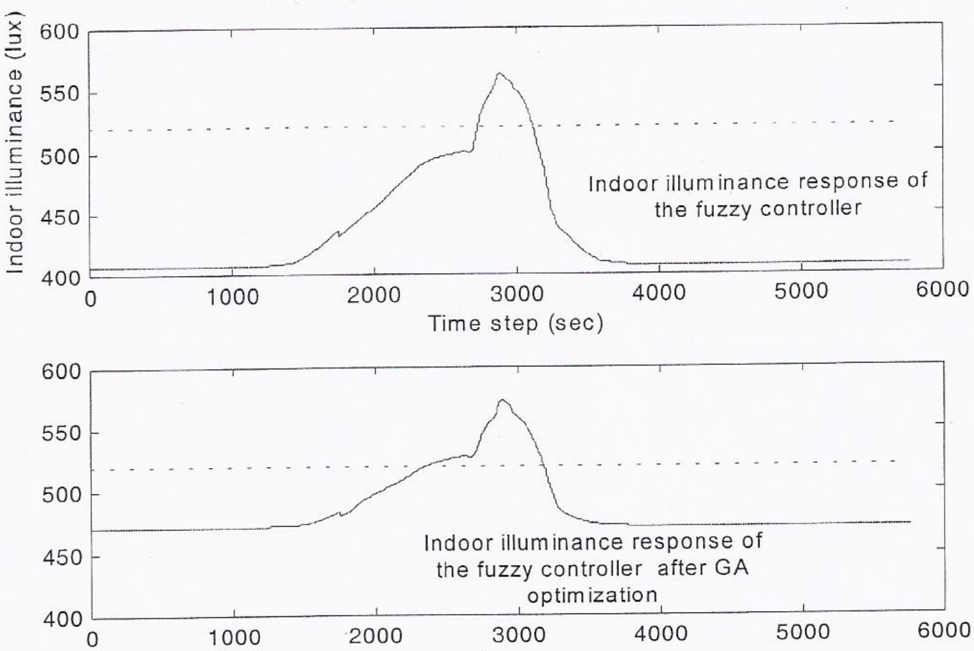

Fig. 8. The indoor illuminance response of the fuzzy controller before and after GA optimization

The performance criteria are tabulated in Table 2.

Table 2					
	Energy consumption		**Steady state error**		
	Heating	Lighting	PMV	CO2 (ppm)	Illuminance (lux)
Before GA	1.62	0.15	0	~150	~100
After GA	1.12	0.18	0.5	~80	~80

The energy consumption for electric lighting is increased after the GA algorithm is applied if it is compared to the 'Before GA' energy consumption. If it is compared to the reference requested by the user, then reduction of the energy consumption is achieved. From Table 2 can be calculated that the reduction of the energy use is up to 30% for the heating.

5. Conclusion

The reduction of the energy consumption has a direct impact on the steady state error. While the steady state error is increased the energy consumption is decreased.

The steady state error tolerance is influenced by the cost function's weight λ. If indoor comfort is more weighted than the energy consumption then the steady state error is decreased.

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