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Genetic algorithms optimized fuzzy controller for the indoor environmental management in buildings implemented using PLC and local operating networks

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Abstract

In this paper, an optimized fuzzy controller is presented 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 properly the membership functions of the fuzzy controller in order to satisfy the occupants' preferences while minimizing energy consumption. The implementation of the system integrates a smart card unit, sensors, actuators, interfaces, a programmable logic controller (PLC), local operating network (LON) modules and devices, and a central PC which monitors the performance of the system. The communication of the PLC with the smart card unit is performed using an RS 485 port, while the PLC-PC communication is performed via the LON network. The integrated system is installed and tested in the building of the Laboratory of Electronics of the Technical University of Crete.

Keywords: Fuzzy controller; Genetic algorithms; Control networks; PLC; Local operating networks (LON); Building indoor environment management system

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 occupants' requirements (Fanger, 1972; CIBSE Code for Interior Lighting, 1994; Allard, 1998). 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 indoor environment management systems (BIEMS). Fuzzy techniques are tested for indoor thermal comfort, visual comfort or indoor air quality (Fraisse et al., 1997; Kolokotsa et al., 2002; Bruant, 1997; Dounis et al., 1995).

An integrated approach for indoor comfort and energy consumption is required to achieve optimal results. The present paper describes a genetic algorithm (GA) optimization technique that integrates in its fitness function the indoor comfort occupants' requirements and the corresponding energy consumption. The GA targets to satisfy occupants' requirements and simultaneously minimize energy consumption. The solution of the GA 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 GA, the fuzzy controller is tuned to reach the 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 occupants' preferences, (ii) A PLC or local operating network (LON) module running the optimized fuzzy controller that retains indoor thermal comfort, visual comfort and indoor air quality, (iii)

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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 GA (Wang and Jin, 2000).

Normally thermal comfort depends on a great number of parameters such as air velocity, mean radiant temperature, people's activity, etc. For this reason, the controlled variable for thermal comfort is the predicted mean vote (PMV) index which depends upon the temperature of the zone, the relative humidity, the mean radiant temperature, the air velocity, the users activity level and the clothing parameter (Fanger, 1972).

Visual comfort, on the other hand, depends upon a number of parameters (subjective and objective) such as the illuminance levels and their spatial distribution, the glare, the colour rendering, the view, etc. The most suitable variable for controlling visual comfort is the illuminance level, measured in lux, as all other parameters are strongly subjective and difficult to measure (Baker et al., 1993).

The indoor air quality is mainly influenced by the concentration of pollutants in the controlled space. There is a wide range of indoor pollutants and specific sensors are required to measure each one of them. The CO_2 concentration (measured in ppm) is one of the most representative controlled variable to measure the indoor air quality, as it reflects the presence of users as well as various sources of pollutants in the building.

The proposed system architecture is depicted in Fig. 1.

2. The optimized fuzzy controller using GA

2.1. The fuzzy logic 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 occupants' comfort are: (i) thermal comfort, (ii) visual comfort and (iii) indoor air quality. Normally, thermal comfort depends on a great number of parameters such as air velocity, mean radiant temperature, people's activity, etc. For this reason, the controlled variable for thermal comfort is the PMV index (Fanger, 1972). 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 occupants as well as various sources of pollutants in the building (Kolokotsa et al., 2002).

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 a 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 Figs. 2 and 3, respectively.

Concerning thermal comfort, the related fuzzy rules are such as to allow natural cooling through window openings and reach thermal comfort using natural

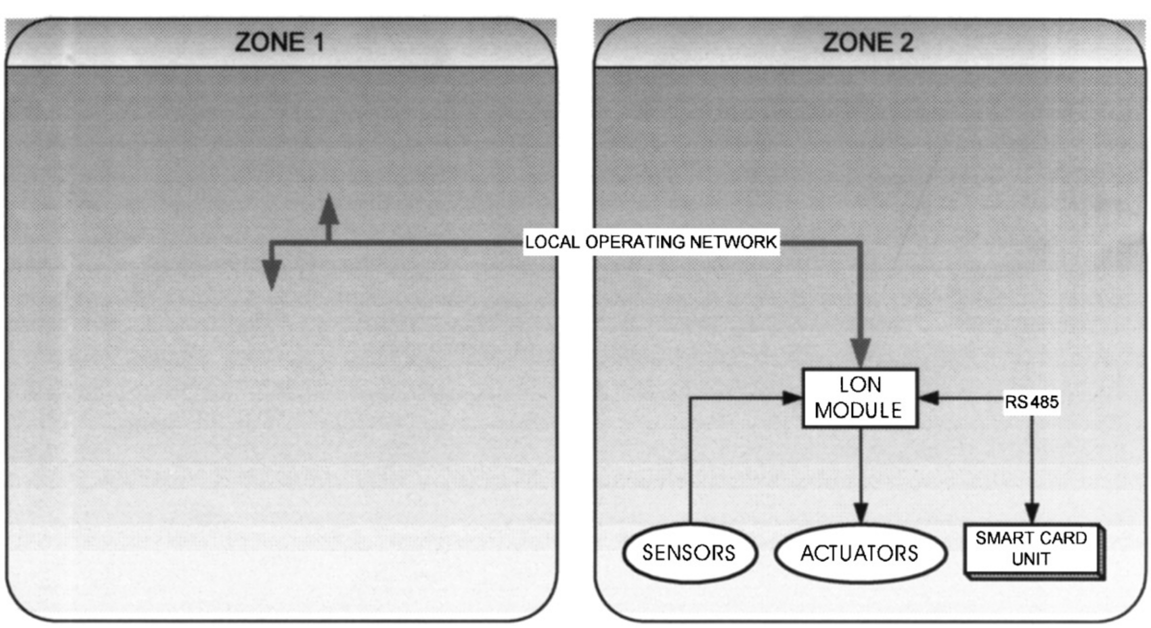

Fig. 1. The architecture of the proposed BIEMS for two building zones (*LONNY* or *LOONY device*: a LON node equipped with an EIA-232C serial interface to enable any Host or PC-based program to perform network management or download custom applications).

Table 1
Fuzzy controller's inputs and outputs

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

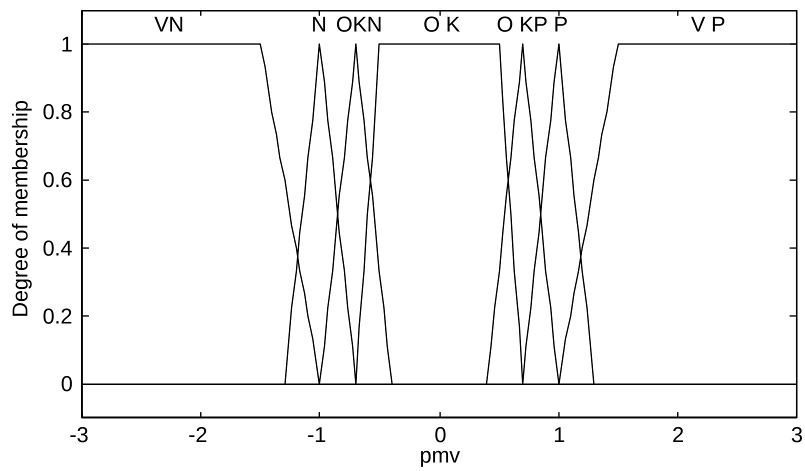

Fig. 2. The PMV membership functions.

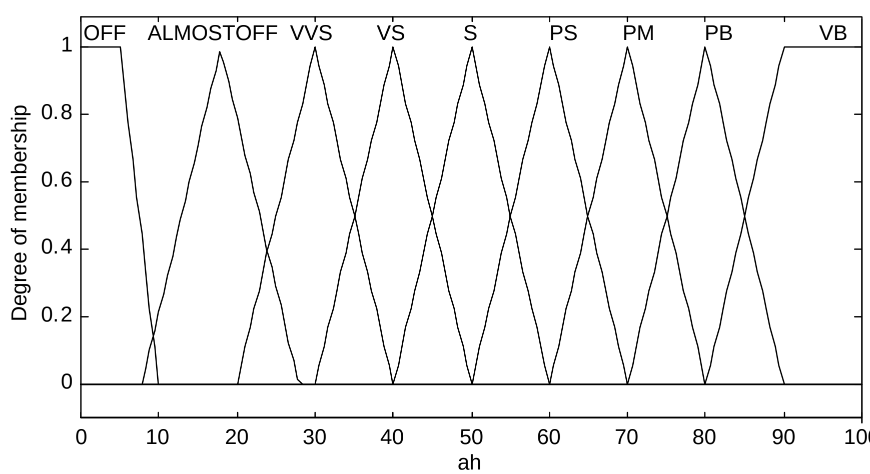

Fig. 3. The output heating membership functions.

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 shape and position of the thermal comfort membership functions are initially defined based on the related bibliography (Fanger, 1972) where, while PMV fluctuates between –0.5 and 0.5, 90% of the occupants are satisfied.

The membership functions of CO_2 concentration and window opening are illustrated in Figs. 4 and 5, respectively. The desired CO_2 concentration is 800 ppm corresponding to 1 of the OK membership function (Batterman and Peng, 1995). The shape and limits of the membership functions are defined based on bibliographic guidelines (CIBSE Guide Section A4, Air Infiltration and Natural Ventilation, 1994).

The indoor illuminance membership functions are illustrated in Fig. 6. The rules are such that they 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

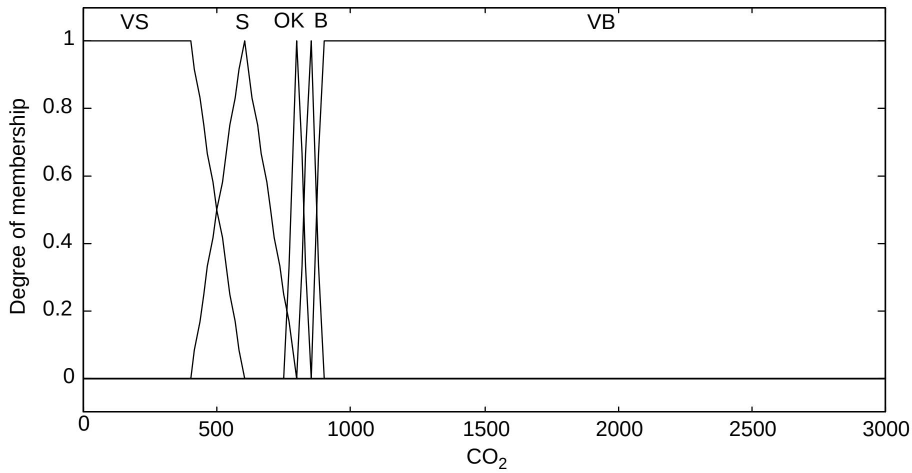

Fig. 4. The CO_2 concentration membership functions.

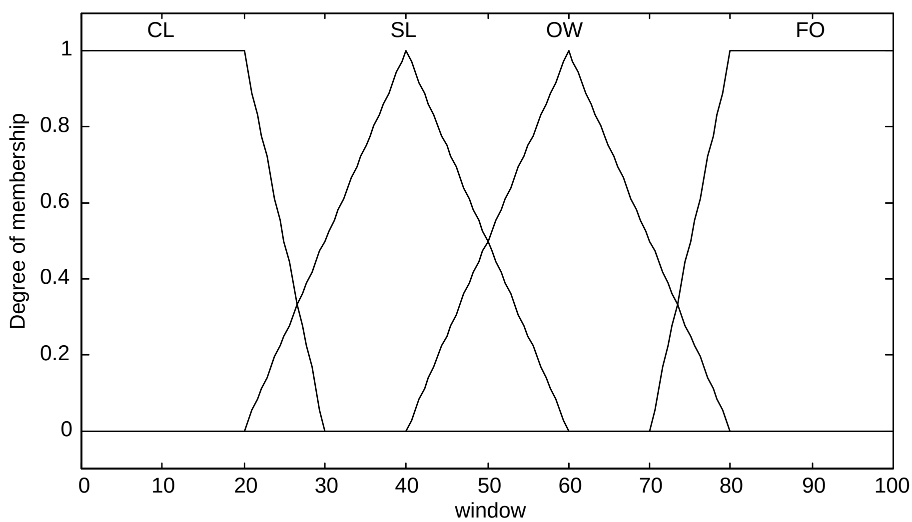

Fig. 5. The window opening membership functions.

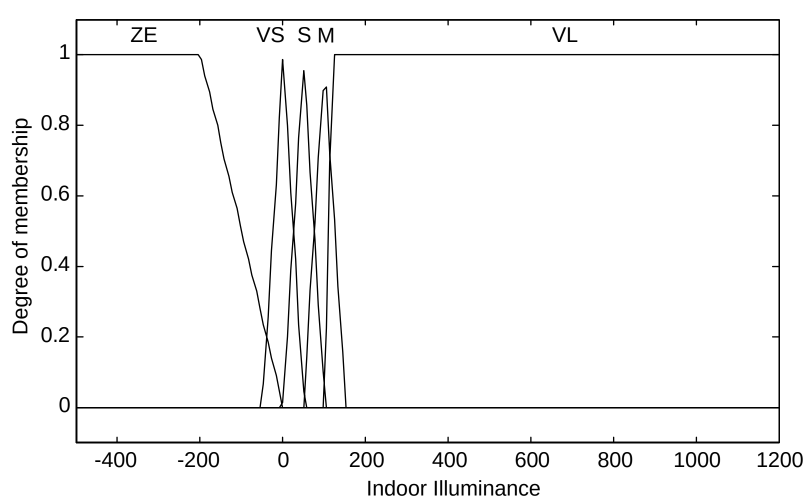

Fig. 6. The indoor illuminance membership functions.

increased, immediately the electric lighting is turned off and the shading regulates the indoor visual comfort. The indoor illuminance universe of discourse is covered based on international organizations' guidelines (CIBSE Code for Interior Lighting, 1994).

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

2.2. The GA optimization procedure

The objectives of the GA optimization technique are: (i) occupants' preferences satisfaction on a long-term basis and (ii) minimization of energy consumption for heating/cooling and electric lighting (Kolokotsa et al., 2001).

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

$$\begin{aligned} &-3 < \mathrm{PMV}_{\mathrm{GA}} < 3, \\ &400\,\mathrm{ppm} < [\mathrm{CO_2}]_{\mathrm{GA}} < 1000\,\mathrm{ppm}, \\ &500\,\mathrm{lx} < \mathrm{ILL}_{\mathrm{GA}} < 1000\,\mathrm{lx}, \end{aligned} \tag{1}$$

where $\mathrm{PMV}_{\mathrm{GA}}$ is the new thermal comfort setting to be reached by the zone level controllers, $[\mathrm{CO_2}]_{\mathrm{GA}}$ is the new indoor air quality setting and $\mathrm{ILL}_{\mathrm{GA}}$ is the new visual comfort setting.

The cost function is defined as

$$\begin{aligned} \mathrm{cost}\,F = {} & w_1(\mathrm{PMV}_{\mathrm{user}} - \mathrm{PMV}_{\mathrm{GA}})^2 \\ & + w_2\big([\mathrm{CO_2}]_{\mathrm{user}} - [\mathrm{CO_2}]_{\mathrm{GA}}\big)^2 \\ & + w_3(\mathrm{IIL}_{\mathrm{user}} - \mathrm{ILL}_{\mathrm{GA}})^2 + w_4\mathrm{Energy}^2_{\mathrm{heat/cool}} \\ & + w_5\mathrm{Energy}^2_{\mathrm{light}}, \end{aligned} \tag{2}$$

where subscript 'GA' denotes the new comfort settings that will be extracted by the GA, 'USER' subscript denotes the occupants' comfort preferences and w_1, w_2, w_3, w_4, w_5 are the weights for the cost function's terms varying from 0 to 1.

$\mathrm{Energy}_{\mathrm{heat/cool}}$ and $\mathrm{Energy}_{\mathrm{light}}$ are the energy for heating/cooling and lighting that will be consumed for a specific building in order to reach 'GA' settings and maintain them for 1 day. $\mathrm{Energy}_{\mathrm{heat/cool}}$ depends upon the building properties, the 'GA' settings, solar incidence angle, casual gains, ventilation, heating system, ventilation system, etc. It is calculated using the building model SIBIL developed under MATLAB/SIMULINK (Eftaxias et al., 1999). The $\mathrm{Energy}_{\mathrm{light}}$ depends upon the SIBIL daylight model.

The cost function's parameters are normalized in the range [0–1] and are always positive.

Real-Coded Genetic Algorithms 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:

$$\mathrm{fit}\,F = 1/\mathrm{cost}\,F. \tag{3}$$

The GA algorithm attempts to maximize its fitness function, thus minimizing the cost function of the system (Michalewicz, 1994).

The selection of the parents is based on the roulette wheel method (Michalewicz, 1994; Herrera and Verdegay, 1996). The crossover probability is set equal to 0.6 and the mutation probability is set equal to 0.1. The heuristic crossover method is used, where a random number λ is generated ranging from 0 to 1. Each new gene is extracted using the following equation:

$$\begin{aligned} \mathrm{gene\_new}_{\mathrm{cross}} = {} & \lambda \cdot \mathrm{cross\_parent}(i) \\ & + (1-\lambda) \cdot \mathrm{cross\_parent}(j), \end{aligned} \tag{4}$$

where cross_parent(i) and cross_parent(j) are the parents selected for crossover and λ takes values in the range [0, 1].

The genes are mutated using the following equation:

$$\mathrm{gene\_new}_{\mathrm{mute}} = \mathrm{gene\_old} + N(m, \sigma) \tag{5}$$

where $N(m, \sigma)$ is a normal distribution with centre m and deviation σ. The centre and deviation are set according to the range of each parameter.

The energy consumption necessary to reach the settings by means of the controlled variables, i.e. the PMV index, the $[CO_2]$ and the illuminance, is evaluated for the building, whose characteristics are presented in Table 2.

Table 2
Building envelope characteristics

Area (m^2)	Wall	Roof	Floor	No. of openings	Openings area (m^2)
15	200 mm light concrete 25 mm polystyrene 19 mm finishing	200 mm concrete 25 mm polystyrene 19 mm finishing	200 mm concrete 25 mm polystyrene 19 mm finishing	1	1

3. The integrated system implementation using central PC, smart card unit, PLC and LON technologies

3.1. The smart card unit

The default values of the control variables are stored in the smart card of each unit. The PMV represents the thermal comfort variable (Fanger, 1970), the indoor illuminance represents the visual comfort variable and the CO_2 concentration represents the indoor air quality variable (Batterman and Peng, 1995). When the smart card is inserted in the unit, the system detects the presence of the user and starts its operation. The system aims to reach the set-points. The set-points are either the default values of the control variables stored in the smart card (during the initialization of the BIEMS operation) or the short term preferences (STP) which correspond to the occupants' temporary requirements or the long term preferences (LTP) that are evaluated by the central PC taking into account the STP (monitoring the user behaviour for a specific time period, e.g. weekly). The LTP replace the defaults on the smart card. The LTP concept minimizes the communication between the smart card unit and other components of the system.

The sensors and actuators installed for the measurement of the environmental parameters at each zone are presented in Table 3.

3.2. The LON

The LonTalk protocol ensures the communication of the various components as well as the applicability of the system in existing buildings.

The LON (Echelon Corporation, 1995a, b), is formed by a number of nodes communicating over a variety of media such as twisted pair, power lines, radio frequency, fibre optics, etc., using an event driven protocol named LonTalk protocol. The LON nodes are intelligent devices that can be connected with sensors (temperature, humidity, illuminance, etc.), actuators (HVAC, lighting, alarms, etc.), interfaces (displays, terminals, PCs, etc.) and can run the relevant application program. The LON network is suitable for distributed control applications and is featured by simple integration of different devices, higher performance due to peer-to-peer communications and low installation and reconfiguration costs.

The LonTalk protocol, which follows the reference model for Open Systems Interconnection (OSI) providing services at all 7 layers, addresses its components using domain, subnet and node IDs. This simplifies replacement of nodes in an operating network. Free topology connection (ring, bus or star and all combinations of the above) is allowed.

3.3. The LON node

The node's hardware incorporates the Neuron Chip, which is fully programmable using the Neuron-C language. Each node has a number of I/O connectors where the sensors and actuators can be connected using a suitable interface. The integration of the node with the interfaces forms the LON module. Furthermore, each node supports 62 network variables which can be bound with other nodes variables to perform a specific task as soon as new information arrives (event driven) (Echelon Corporation, 1995a, b). The fuzzy controller application is programmed in the node using an appropriate development tool. In this case, the LON Builder Development Tool is used. A flash EEPROM programmer is used to download the application program to the node.

Table 3
Sensors and actuators

Sensor type	Range	Output type	Function
Mean radiant temperature	−30–50°C	0–5 V	Linear
Indoor temperature	−10–40°C	0–10 V	Linear
Relative humidity	0–100%	0–10 V	Linear
Air flow/hotwire anemometer	0–8 m/s	0–10 V	Linear
CO_2 sensor	0–2000 ppm	0–10 V	Linear
Illuminance sensor	0–4000 lx	0–10 V	Linear
Outdoor temperature	−10–40°C	0–10 V	Linear
Outdoor humidity	0–100%	0–10 V	Linear

Actuator type	Input	Function
Relay for the air conditioning system and the electric lighting	24 V DC	ON/OFF
Window opening/closing motors	24 V DC	Linear
Shading opening/closing motors	220 V AC	Linear
Damper motor	0–10 V	Linear

3.4. The PLC

The PLC, developed by the Greek company AMBER S.A. (Kolokotsa et al., 2002), is built around a central processing unit (CPU) which receives signals from a number of input interface cards that handle the various types of signals, processes them according to the logic that the user has input during system programming, and outputs a number of commands, to cards that handle output signals, to control the Automated Process.

In the specific application PLC performs the following operations:

- Reads the sensors data through its analogue input channels.
- Runs the fuzzy decision support algorithm for the adjustment of indoor thermal-visual comfort and air quality levels.
- Drives the actuators through its digital and analogue outputs.
- Communicates with the smart card unit using an RS485 connection.
- Communicates with the PC as slave via an RS232 port through the LOONY (see also Fig. 1).

4. Numerical results

The fuzzy controller's initial set points are PMV = –0.5, $[CO_2]$ = 800 ppm and Indoor Illuminance = 500 lx.

The GA is tested for one winter day. The occupants' requirements are supposed to be the following:

$$\begin{aligned} &\mathrm{PMV_{user}} = -0.5, \\ &[\mathrm{CO_2}]_{\mathrm{user}} = 700\,\mathrm{ppm}, \\ &\mathrm{ILL_{user}} = 600\,\mathrm{lx}. \end{aligned} \tag{6}$$

It should be noted here that the occupants' input their preferences through the smart card unit in a relevant form, i.e. 'more' or 'less' heat, light, etc. The occupants' inputs are translated into real values using a fuzzy algorithm. The inputs to the fuzzy algorithm are:

- The relative values of the smart card unit.
- The difference between the zone controller's set-points and current values of the environmental variables at the zone level.

The output of the fuzzy algorithm is the change of user's preferences in real values.

The cost function's weights are all set equal to 1. The GA converges after 35 generations.

The new settings values, corresponding to the maximum fitness function and consequently to the minimum cost function (near optimal solution), are:

$$\begin{aligned} &\mathrm{PMV_{GA}} = -1.7, \\ &[\mathrm{CO_2}]_{\mathrm{GA}} = 723\,\mathrm{ppm}, \\ &\mathrm{ILL_{GA}} = 519\,\mathrm{lx}. \end{aligned} \tag{7}$$

The GA algorithm results are quite satisfactory and close to the occupants' preferences for the CO_2 concentration and illuminance levels. The resulting PMV value of –1.7 (Eq. 7) corresponds to an average temperature of 16.8°C and is out of the comfort range based on the percentage of people dissatisfied (PPD) index introduced by Fanger (1972).

The fitness function corresponding to user settings is equal to 2.63 while the maximum extracted by the GA is equal to 11.35. The energy consumption, with respect to PMV, CO_2 user settings, is calculated to 27.6 kWh (1.84 kWh/m^2) for heating and 1.07 kWh (0.071 kWh/m^2) for electric lighting if the fuzzy non-adaptive controller is applied. The GA algorithm settings lead to a 3.5 kWh (0.23 kWh/m^2) energy consumption for heating and 0.9 kWh (0.06 kWh/m^2) for electric lighting. The energy savings when the GA algorithm is applied reaches 87% for heating and 15% for electric lighting. But, taking into consideration the fact that the indoor thermal comfort is not satisfied, more adjustments are required to the fitness function to overcome this issue.

Modifications in the cost function's weights cause optimization of the results versus the indoor thermal comfort. The weighted cost function has the form displayed in the following equation:

$$\begin{aligned} \text{cost}\,F = {} & 0.9(\mathrm{PMV_{user}} - \mathrm{PMV_{GA}})^2 + 0.5([\mathrm{CO_2}]_{\mathrm{user}} \\ & - [\mathrm{CO_2}]_{\mathrm{GA}})^2 + 0.5(\mathrm{IIL_{user}} - \mathrm{ILL_{GA}})^2 \\ & + 0.1\mathrm{Energy}^2_{\mathrm{heat/cool}} + 0.5\mathrm{Energy}^2_{\mathrm{light}}, \end{aligned} \tag{8}$$

where energy consumption for heating/cooling is less weighted than the indoor thermal comfort. This fitness function results in the following optimum chromosome:

$$\begin{aligned} &\mathrm{PMV_{GA}} = -1.0, \\ &[\mathrm{CO_2}]_{\mathrm{GA}} = 771\,\mathrm{ppm}, \\ &\mathrm{ILL_{GA}} = 510\,\mathrm{lx}. \end{aligned} \tag{9}$$

This chromosome is within the comfort range. 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. 7. All simulation results concern a 15 m^2 building in Athens, Greece for a specific winter day.

The $[CO_2]$ response, after shifting the membership functions, is closer to the setting defined by the GA, as depicted in Fig. 8, compared to the initial response.

The same observations apply to the indoor illuminance response illustrated in Fig. 9.

The performance criteria are tabulated in Table 4.

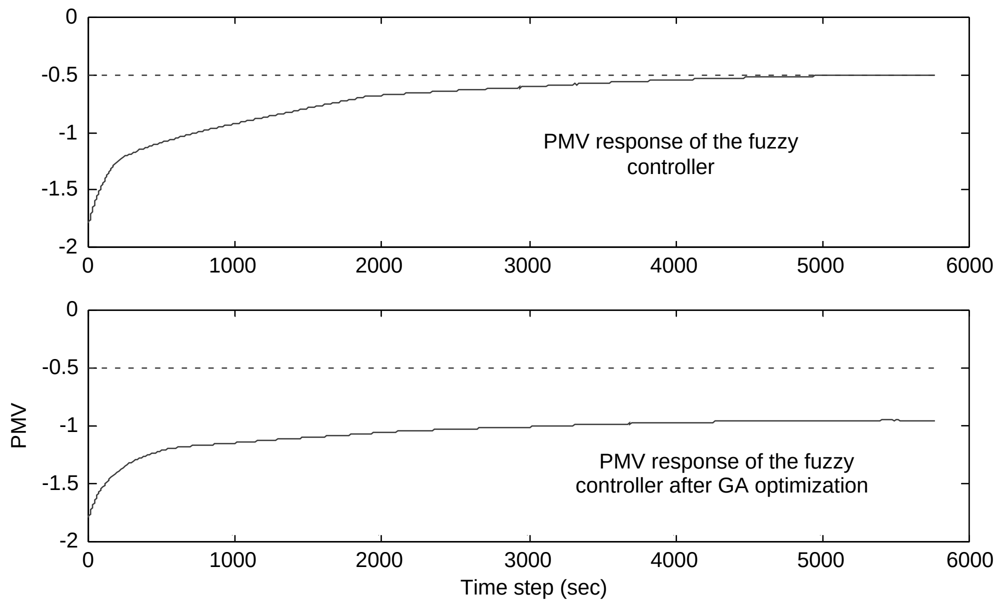

Fig. 7. The PMV response of the fuzzy controller before and after GA optimization.

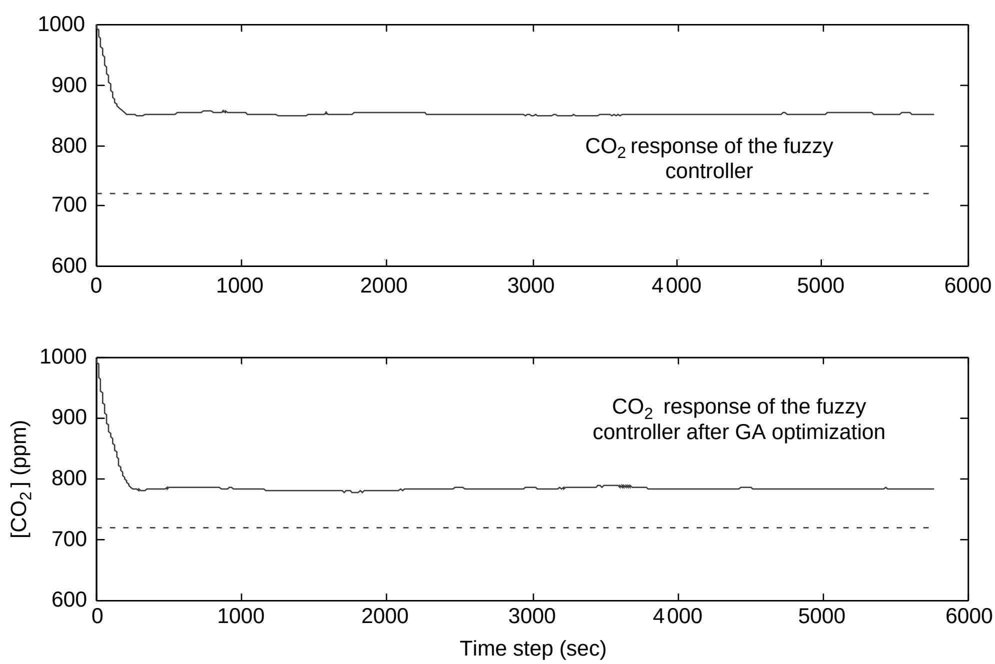

Fig. 8. The CO_2 concentration response of the fuzzy controller before and after GA optimization.

5. Implementation results

The system is installed in the Electronics laboratory of the Technical University of Crete. The evaluation of the system's performance is based on the following methodology:

A data set is prepared for the Electronics Laboratory measuring the environmental parameters of the building without the installation of the system. The measured environmental parameters are:

- Indoor and outdoor temperature
- Indoor humidity
- Mean radiant temperature
- Indoor air velocity
- CO_2 concentration
- Indoor illuminance

This data set calibrates a model of the Electronics Laboratory of the Technical University of Crete

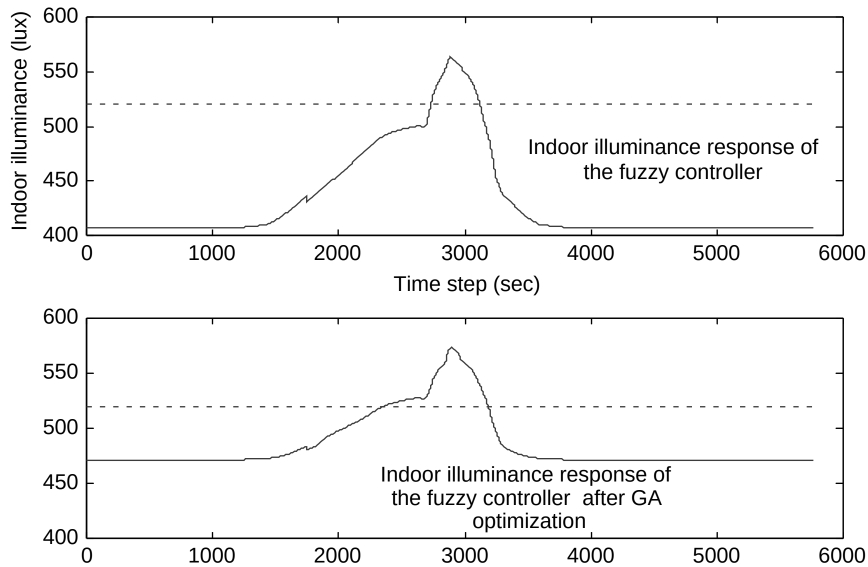

Fig. 9. The indoor illuminance response of the fuzzy controller before and after GA optimization.

Table 4
Performance criteria

	Energy consumption		Steady-state error		
	Heating	Lighting	PMV	CO_2 (ppm)	Illuminance (lx)
Before GA application	1.62	0.15	0	~150	~100
After GA application	1.12	0.18	0.5	~80	~80

based on Matlab/Simulink (Eftaxias et al., 1999). The calibrated building model is used to simulate the performance of the building with on–off and fuzzy controller.

The fuzzy controller's performance is evaluated by comparing the energy consumption for cooling/heating and lighting when using the fuzzy controller and the conventional control system for the Electronics Laboratory of the Technical University of Crete. The building's previous (conventional) control system is

- On–off for heating and cooling
- No control for electric lighting

The analysis is performed for two representative months of a test reference year (January and July). The system's PMV response for 10 winter and 10 summer days is depicted in Figs. 10 and 11, respectively. The analysis gave the following results:

- Energy savings for the heating period: 26.5%
- Energy savings for the cooling period: 14%
- Energy savings on annual basis (heating and cooling season: 20.5%)
- Energy savings for lighting: 66%.
- Overall energy savings: 35%

The energy savings for lighting are quite high due to the lack of lighting control in the previous control system. This fact increases significantly the overall energy savings.

6. Guidelines

The behaviour of the occupant for the energy conservation is of particular importance:

- An occupant who turns down the set temperature significantly wants a large cooling effect. Hence most people turn the setting down lower than necessary, for example when they first enter the room. Generally, they forget to turn the temperature up again if the proper temperature is reached and hence the room is cooled more than necessary.
- An occupant who adjusts only very slightly the thermostat is not interested in a quick response, but in accurate temperature. Over reactive control can cause the air-conditioner to overshoot the desired room temperature.
- When an occupant adjusts the temperature very often, the control should respond exactly and carefully.

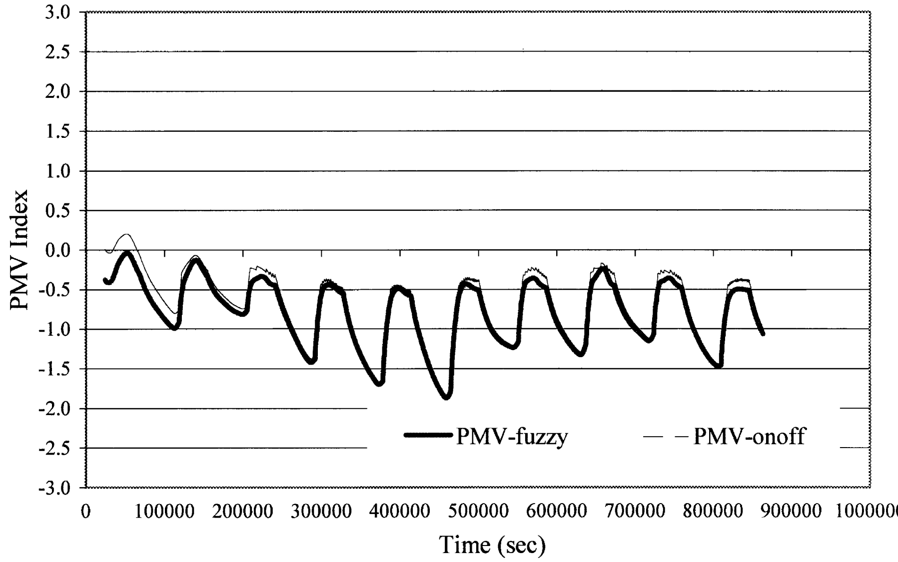

Fig. 10. The PMV index response with the fuzzy and the on–off controller for 10 winter days.

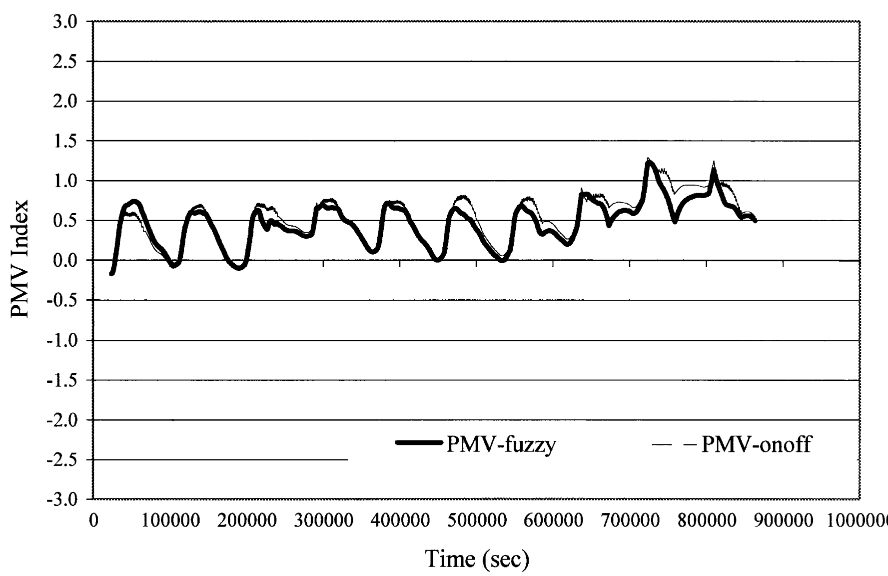

Fig. 11. The PMV index response with the fuzzy and the on–off controller for 10 summer days.

- If the room temperature changes a lot (due to doors or windows being opened or closed throughout the day, for example), the control should respond sensibly.

In order to improve the performance of an energy management system to satisfy more readily the occupant preferences, it is necessary to integrate in the design the different environmental conditions and the current needs of the user. Knowledge of the different situations such as those described above must be implemented in the system. Since this kind of knowledge is hard to model mathematically as well as to code in a conventional algorithm, fuzzy logic can be used for implementation:

- *Difference between set temperature and room temperature*: When the difference between the set temperature and the room temperature is very large, the fuzzy logic system increases the signal so the desired temperature is reached faster. At the same time a large hysterisis is used, so disturbances do not cause unnecessary on/off switching.
- *Time differentiated set temperature*: The set temperature is differentiated with a time constant of 30 min. The system uses this term to understand if the user wants the room to cool down quickly. Also the

hysterisis is set to large, so that disturbances do not interrupt the cooling process. As this signal is differentiated it disappears after some time if the set temperature is not changed again.

- *Number of set temperature changes*: This input signal is used to identify a user who tries to set the temperature very accurately. To satisfy this user, the hysterisis is set to small. This variable counts each time the user moves the dial. Every 6 h this variable is counted down until zero is reached.
- *Brightness in the room*: If direct sunlight hits the room, the set temperature is automatically reduced. During the day or when the lights are on in the room, the set temperature is slightly increased and the hysterisis is set to small.

7. Conclusion

The BIEMS integrates recent technological developments such as LON modules with mature components such as PLCs. One of the major advantages of the architecture is the incorporation of the smart card unit acting as user machine interface. The occupants' discomfort, which usually arises when tight control of the indoor comfort is applied, is diminished as the occupants' interact with the system.

The architecture as well as the communication could be made simpler if only local operating nodes are used, because the PLC complicates the communication and increases the number of components required (i.e. the LOONY device). The PLC controller can be used only if the disposal of a PC is not desirable. Furthermore, already existing PLCs in various zones, that are used for other purposes, can be used for indoor comfort control, with some modifications. The LON devices used are not of commercial type, but they are custom developed.

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