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Fuzzy Comfort and its Use in the Design of an Intelligent Coordinator of Fuzzy Controller-Agents for Environmental Conditions Control in Buildings*

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Abstract

The theme of this paper is the design of an intelligent coordinator (IC) of fuzzy controller-agents (FCAs) to control indoor environmental conditions in buildings by using a 3-D fuzzy comfort set. The basic factors that participate in the control of indoor environmental conditions are the controllers and users' comfort requirements. Harmonization of these factors results in energy saving, and occupants' comfort, both very significant. Synchronization of the control system is obtained by the design and implementation of an intelligent coordinator, which is a centralized one. It consists of a master agent and a slave agent that are both implemented by fuzzy logic theory. Master agent evaluates the energy efficiency of the building and comfort of occupants. A fuzzy inference mechanism produces signals that activate the slave agent and change the set points of the controllers. The slave agent is a fuzzy negotiation machine (FNM), which synchronizes the interaction of the FCAs and manages to avoid conflicts between them. When some conditions determined by the slave agent are satisfied FCAs are activated, otherwise they stay inactive. The ultimate goal is the harmonization of all factors that contribute for control of ambient intelligent environments. In addition, the hardware architecture that implements the proposed intelligent system for multi zone buildings is presented. Finally, the applicability of the suggested system is demonstrated via TRNSYS-MATLAB computer simulation.

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Keywords: intelligent coordinator, fuzzy negotiation machine, fuzzy cube, grey predictor, fuzzy controller-agent, environmental intelligent control, intelligent building, α-level fuzzy set

1. Introduction

The problem of energy saving and the achievement of comfort conditions in the interior environment of a building is multidimensional. Scientists from a variety of fields have been working on it for quite a few decades, but it still remains an open problem. International Energy Agency (http://www.iea.org) has found that buildings in Europe use effectively about 35% of the total energy consumed. European Union has recently issued a new directive regarding energy conservation in buildings. This directive dictates member countries to adopt stricter specifications and regulations for efficient use of energy in buildings.

People spend about 80% of their time inside buildings. So, achieving comfort conditions in a building is very important. The comfort conditions have direct implication to the productivity of the occupants and indirect implication to the energy efficiency of the building.

The quality of occupants' living conditions, in other words the comfort conditions, is determined by three basic factors: thermal comfort (TC), Visual Comfort (VC), and Indoor Air Quality (IAQ) (ASHRAE, 2005). Thermal comfort is specified by index PMV (Predictive Mean Vote). The PMV index has adopted by ISO7730 standard and ISO recommends maintaining PMV at 0 with tolerance of 0.5 as the best thermal comfort. Visual comfort is specified

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by the level of indoor Illumination (CIBSE). Indoor air quality is mainly affected by CO_2 concentration in the building (ASHRAE standard 62-1999). The minimum mechanical ventilation requirements are 20cfm/person (ASHRAE standard 62-1999). CO_2 comes from the presence of occupants and from a variety of pollutants inside the building.

The aforementioned reasons led researchers to the development of building intelligent management systems (BIEMS), mainly for big buildings like offices, hotels, and commercial buildings. BIEMS have been introduced in order to monitor and control the environmental parameters of a building and to minimize energy consumption and cost. Fuzzy techniques have been applied to a significant number of cases in buildings (Dounis et al, 1996; Guilemin and Morel, 2001; Kolokotsa, 2003) demonstrating a significant reduction of total energy consumption compared to the existing control system.

There are many sources uncertainties that arise from real-world applications and user behaviors. We can separate the sources of uncertainty in two categories. The first category of uncertainties arises from dynamic real-world unstructured environments (buildings). Some of them are:

a. Uncertainties in inputs and control outputs of a FLC. These uncertainties (high noise level, environmental changes, change in the operation conditions, etc) are appeared in the antecedents' and consequents' membership functions of the FLC (Hagras, 2007).
b. Uncertainties in the linguistic labels of the IF and THEN parts of rules, as words mean different things to different people (Mendel, 2003). Also, there are uncertainties in the structure of the rules.

The second category of uncertainties derives due to changes in the environmental conditions and the user behavior. Some of them are:

a. Change of outdoor environmental conditions (illuminance level, temperature, air velocity, etc.) which generate uncertainties.
b. Uncertainties coming from the fact that user behaviors that are dynamic and unpredictable (Hagras, 2007).

In this paper the comfort is considered as a concept with uncertainty. The word "comfort" is modeled by a 3-D fuzzy set in a fuzzy cube.

Many times, control engineers are faced with complicated control problems, where they have to design and implement real time control systems that involve a network of controllers instead of a single one. Also, the human factor is involved in the feedback loop of the control system, thus the occupants will be treated as an element of the closed loop system (Dounis and Caraiscos, 2005; Hagras et al, 2003). Here, the control engineer has one more job to do: that of breaking the problem in a number of simple sub-problems. So, the multi-controller system is designed and implemented on a more general framework, based on controller-agents (Breemen and Vries, 2001). For optimal operation, the controller-agents are guided by the intelligent coordinator that consists of the Master Agent (MA) and the Slave Agent (SA). The intelligent coordinator coordinates the operation of the sub-systems which are local PI-like Fuzzy Logic Controller (FLC) (Dounis and Caraiscos 2007).

The main objectives of this study are: i) to demonstrate the uncertainties related to the concept of comfort; ii) to determine the discrete comfort fuzzy set in fuzzy cube and define the membership grade using fuzzy equality measure; iii) to pursue the systematic development of intelligent coordinator; iv) to test the IC in the environmental conditions control in buildings.

The paper is organized in the following manner. Section 2 presents the associated uncertainties with the concept of comfort. Section 3 describes the comfort as a discrete fuzzy set in a fuzzy cube. The structure of a Fuzzy Controller-Agent is presented in Section 4. Section 5 proposes the architecture of an intelligent coordination. In section 6, we present the hardware implementation of the proposed system for multi zone buildings and the simulation results are described in Section 7. Conclusions follow in Section 8.

2. Uncertainties Associated with Information Granularity of Comfort

The collection of complex information entities (thermal comfort, visual comfort and indoor air quality) represents an information granule of comfort. The mapping

$$\{TC, VC, IAQ\} \rightarrow Comfort$$

signifies a different level of granularity information granules that gives rise to the conceptual extension of fuzzy sets.

The attribute of information granule of comfort is the uncertainty. Uncertainty is one of the basic facets of human cognition. However, the word comfort means different things to different people. Using a type-1 fuzzy set is completely determined with regard to shape and parameters to model the word comfort there is nothing uncertain (Mendel, 2003). When any type-1 fuzzy set is used to model the word "comfort" then the uncertainty is lost. In section 3 we define the comfort as a fuzzy set in a fuzzy cube by using the α-level fuzzy set.

2.1. Relationships between: Information Granule, Granularity and Uncertainty

Comfort is an information granule. Comfort granulation (fuzzy quantization) produces granules of comfort, that is, linguistic variables, which are fuzzy sets. Now, uncertainty is appeared in the membership functions of linguistic variables (Zadeh, 2005). So, the uncertainty lies into fuzzy sets.

2.2. Uncertainty about Comfort

The uncertainty about the word “comfort” is of two kinds: 1) Uncertainty a user has about the word, and this kind is called intra-uncertainty (Mendel, 2003), and 2) Uncertainty that a team of users have about the comfort. This kind is called inter-uncertainty (Mendel, 2003). Intra-uncertainty of comfort can be modeled using a type-1 fuzzy set equipped by α-level fuzzy set for each information entity (TC, VC, IAQ). Inter-uncertainty can be modeled by means of lower and upper bounds of a fuzzy comfort set. These two kinds of uncertainty can be modeled by using a 3-D uncertain fuzzy comfort set in a fuzzy cube, thus permitting us to include all uncertainties that users have about comfort. Also, another way to design fuzzy sets for words is the so called type-2 fuzzy set.

2.3. Uncertainty in User Preferences Using A α-level Fuzzy Set

The desired value or set point is chosen as a trapezoidal fuzzy interval whose membership function is illustrated in Figure. 1. The trapezoidal type-1 fuzzy set equipped by an a-cut level can effectively model the uncertainty of comfort.

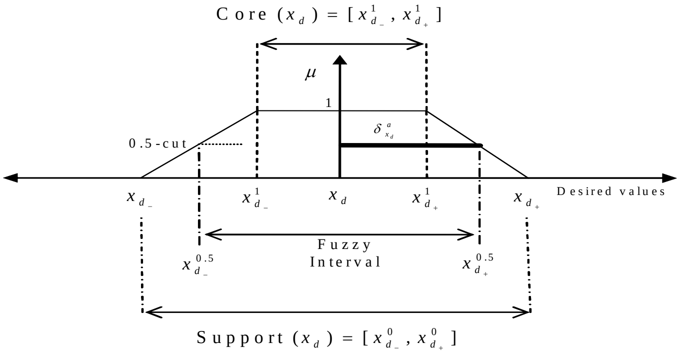


Figure 1: Trapezoidal fuzzy interval desired values.

The core is composed of the most acceptable user’s preferences, and the fuzzy interval is defined as:

$$[x^a_{d_-}, x^a_{d_+}] = [x_{d_-} + a(x^1_{d_-} - x_{d_-}), x_{d_+} - a(x_{d_+} - x^1_{d_+})]$$

The desire values belong to interval $[x_d - \delta^a_{x_d}, x_d + \delta^a_{x_d}]$, $x = \{PMV, CO_2, ILL\}$, where x_d is the set point, x_{d_-} and x_{d_+} denote the upper and lower bounds of x, respectively, and $\delta^a_{x_d} = (x_{d_+} - x_d) - a(x_{d_+} - x^1_{d_+})$ is the band around of the desired value; with $\lim_{a \to 1} \delta^a_{x_d} = x^1_{d_+} - x_d = \frac{Core(x_d)}{2}$ $\lim_{a \to 0} \delta^a_{x_d} = x_{d_+} - x_d = \frac{Support(x_d)}{2}$. If the fuzzy set is triangular then $x^1_{d_+} = x_d$ and hold the above formulas. $x^1_{d_+} = x_{d_+} - \text{uncertainty} = 0.3$ where $\text{uncertainty} = \beta \frac{(x_{d_+} - x_{d_-})}{2}$ with $\beta \in [0,1]$ and $\delta = \frac{\text{Fuzzy interval}}{2} = \frac{\text{Support}(x_d)}{2} - \alpha \cdot \text{uncertainty} \cdot$

The α-cut of fuzzy desired values is the set of all values of x_d satisfying the user's preferences at least with a degree of preference α=0.5. For the PMV are defined: $x_d = PMV_d = 0$ (desired value), $x_{d_+} = 0.5$ (Fanger, 1972) and $x^1_{d_+} = 0.3$ where $\text{uncertainty} = 0.2$ with $\beta = 0.4$. The user defines the α-cut generated the fuzzy interval $\delta^{0.5}_{PMV_d}$ =0.4. For the illumination and CO$_2$ the band δ are: $\delta^{0.5}_{ILL_d}$ =75lux with $\beta = 0.5$ and $\delta^{0.5}_{CO_{2_d}}$ =50ppmv with $\beta = 1$, respectively.

3. Comfort as A Discrete Fuzzy Set in A Fuzzy Cube

The unit cube geometry of discrete fuzzy sets assists us when we define fuzzy concepts. Information granule is the comfort; the size of granules is problem-oriented and user-depended; the size of information granule of the comfort consists of three parts (PMV, ILL, CO$_2$), and the formal representation of this information granule is a fuzzy set in a fuzzy cube (Kosko, 1996).

Let Ω be a set of three elements $\Omega = \{PMV_d, CO_{2_d}, ILL_d\}$. The nonfuzzy power set 2^{Ω} contains eight sets. These sets correspond respectively to the eight bit vectors (0, 0, 0), … ,(1, 1, 1). Empty set $\varnothing$ lies at the origin (0, 0, 0) of the cube, and space Ω lies at vertex (1,1,1). The 1s and 0s indicate the presence or absence of the ith element in the subset. A fuzzy subset $c \subset \Omega$ defines the fuzzy unit (fit) or fit vector

$$c = (\mu_{PMV_d}, \mu_{CO_{2_d}}, \mu_{ILL_d}) \in I^3 = [0,1]^3$$

$$\mu_c = [\underline{c}, \overline{c}] \subseteq [0,1]$$

where the membership grades $\mu_{PMV_d}, \mu_{CO_{2_d}}, \mu_{ILL_d} \in [0,1]$ and the three variables PMV_d, ILL_d, CO_{2_d} lie in the support set of desired values as illustrated in Figure 1. $\underline{c}$ and $\overline{c}$ denote lower and upper bounds, and μ_c denotes an interval set, that is, the set of the real numbers from $\underline{c} = \alpha$ to $\overline{c} = 1$. The fuzzy α-cut or α-level fuzzy set of A characterized by

$$\tilde{A}_\alpha = \begin{Bmatrix} A(x) \text{ if } A(x) \geq \alpha \\ 0 \quad \text{otherwise} \end{Bmatrix} \text{ or } \tilde{A}_\alpha \equiv \{(x, \mu_A(x)) \mid x \in A_\alpha\}$$

Based on above definition, we can conclude that α-level fuzzy set is obtained by reducing part of fuzziness in the original fuzzy set (Tsoukalas and Uhrig, 1997). The fuzzy α-cut or α-level fuzzy set of variables PMV_d, ILL_d, CO_{2_d} defines a 3-D fuzzy comfort set c with membership function μ_c . If α=0.5 then the 3-D fuzzy set is a cube with origin (0.5, 0.5, 0.5) and the optimal comfort value corresponds to the vertex (1, 1, 1). Using the symmetric fuzzy equality measure (Kosko, 1996) we measures the degree to which fuzzy set c matches fuzzy set Ω , that is, the membership grade of 3-D fuzzy comfort set.

$$E(c,\Omega) = \mu_{c(k)} = Degree(c = \Omega) = \frac{cardinality(c \cap \Omega)}{cardinality(c \cup \Omega)} = \frac{\sum_{i=1}^{3} \min(c_i, \Omega_i)}{\sum_{i=1}^{3} \max(c_i, \Omega_i)}$$

where k is the discrete time step. The fuzzy equality measure $E(c,\Omega)$ measures the degree to which fuzzy set c equals fuzzy set Ω. If c and Ω are nonempty then $E(c,\Omega) = E(\Omega,c) \in [0,1]$, $E(c,c) = 1$ and $E(c,\varnothing) = 0$. The fuzzy equality measure gives a value near 1 if the two fuzzy sets equal well. It gives a value near 0 if they equal poorly. The fuzzy comfort set in fuzzy cube membership function is a new representation for the word "comfort".

4. Structure of A Fuzzy Controller - Agent

The building control system that we present in this paper contains five PI-like FLC. Each PI-like FLC stands for a fuzzy controller-agent (FCA) that adjusts some actuator as a function of various sensor outputs. The action of one such fuzzy controller-agent changes the physical quantities (temperature, humidity, air velocity etc) and affects the behavior of other FCAs in the system. These FCAs can be viewed as agents that each one communicates with the upper level module (the slave agent). Quantities $w_i(k)$ and $a_i(k)$ are the activation and acknowledgement signals, respectively. The communication signals of FCA are shown in Figure 2. The five controllers of our control system denoted as $a_i, i = 1,2,3,4,5$, are shading, artificial lighting, heating, cooling, and ventilation controllers.

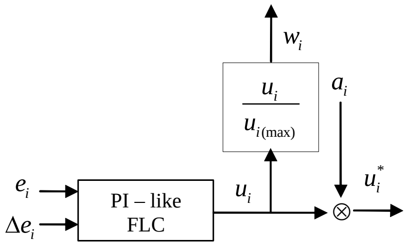


Figure 2: Communication signals of a FCA.

4.1. Incremental PI – Like FLC

A conventional digital fuzzy controller has two inputs, the error $e_i(k) = r_i(k) - y_i(k)$ and its derivative $\Delta e_i(k) = e_i(k) - e_i(k-1)$, where r_i and y_i denote the desired and the actual system output, respectively. Indexes *k* and *k-1* indicate the present and the previous state of the process. The output of the FLC is of incremental type. The control signal $u_i(k)$ will be the sum of $u_i(k-1)$ and $\Delta u_i(k)$.

The change of control action $\Delta u_i(k)$ is calculated from the two inputs using a fuzzy inference mechanism. The inputs $e_i(k)$ and $\Delta e_i(k)$ of the controller are actual values. Fuzzification converts a numerical value into a linguistic variable. In this fuzzy controller we adopt singleton fuzzification which transforms a crisp value in a fuzzy singleton value. All membership functions of the FLC inputs $e_i(k)$, $\Delta e_i(k)$, and the output are defined and normalized in the interval [-1,1]. Also, the linguistic variables NB→{E_{-3}, U_{-3}}, NM→{E_{-2}, U_{-2}}, NS→{E_{-1}, U_{-1}}, ZE→{E_0, U_0}, PS→{E_1, U_1}, PM→{E_2, U_2}, PB→{E_3, U_3} represent negative big, negative medium, negative small, zero, positive small, positive medium, and positive big, respectively. Triangular MFs are chosen for NM, NS, PS, PM fuzzy sets and trapezoidal mfs are chosen for fuzzy sets NB, ZE and PB. The fuzzy sets of the output space are fuzzy singletons. Fuzzy singletons for shading and artificial lighting controllers are: NB=-1, NM=-0.5, NS=-0.25, ZE=0, PS=0.25, PM=0.5, and PB=1, and fuzzy singletons for heating and cooling controllers are: NB=-1, NM=-0.5, ZE=0, PS=0.5, and PB=1, fuzzy singletons for mechanical ventilation controller are NB=-1, NS=-0.125, ZE=0, PS=0.5, and PB=1. The fuzzy control rule for each controller is in the form of:

FCA_1: If $e_{l_1}(k)$ is E_i and $\Delta e_{l_1}(k)$ is E_j Then $u_{l_1}(k)$ is $U_{(i+j)}$,

FCA_2: If $e_{l_1}(k)$ is E_i and $\Delta e_{l_1}(k)$ is E_j Then $u_{l_1}(k)$ is $U_{-(i+j)}$,

$$if \begin{cases} i+j > 3 \Rightarrow i+j \leftarrow 3 \\ i+j < -3 \Rightarrow i+j \leftarrow -3 \end{cases} \quad l_1 = 1,2 \text{ and } i,j \in \{-3,-2,-1,0,+1,+2,+3\}$$

$FCA_{3,4}$: If $e_{l_2}(k)$ is E_i and $\Delta e_{l_2}(k)$ is E_j Then $u_{l_2}(k)$ is $U_{(i+j)}$,

FCA_5: If $e_{l_2}(k)$ is E_i and $\Delta e_{l_2}(k)$ is E_j Then $u_{l_2}(k)$ is $U_{-(i+j)}$,

$$if \begin{cases} i+j > 2 \Rightarrow i+j \leftarrow 2 \\ i+j < -2 \Rightarrow i+j \leftarrow -2 \end{cases} \quad l_2 = 3,4,5 \text{ and } i,j \in \{-2,-1,0,+1,+2\}$$

The use of normalized domain requires input and output normalization, which maps the physical values of the state variables on the interval [-1,1]. The scaling factors which describe the particular normalization play a role similar to that of the gains of a conventional controller. The scaling factors are chosen via the design procedure to be

$$g_{e_i} = \frac{1}{\max(e_i)}, g_{\Delta e_i} = \frac{1}{\max(\Delta e_i)}, g_{\Delta u_i} = 1$$

where $\max(e_i)$ and $\max(\Delta e_i)$ have been found via simulations (trial and error) (Passino and Yurkovich, 1998).

The incremental type of the proposed PI-like FLC is suitable to our problem because in the building control systems there are actuators with continuous output such as variable speed fans, hot water heating systems, electrical heaters, air inlets, and integral-type actuators (e.g. step motors), etc.

5. Intelligent coordinator

In order to achieve intelligent coordination, we design a special coordinator agent which is responsible for detecting interdependencies (e.g. conflicts) between of local FCAs actions (Fig. 3). The operation state of FCAs is determined by Fuzzy Negotiation Machines (FNM). This coordination model leads to a hierarchical integration of control plans as determined by the upper level functions. From an abstract point of view, the centralized coordination seems more reliable with respect to operation (Weiss, 1999). The centralized approach provides a model of predictable behavior where all possible cases of inconsistencies are analyzed a priori and taken into account by the upper level modules (Master-Slave control concepts).

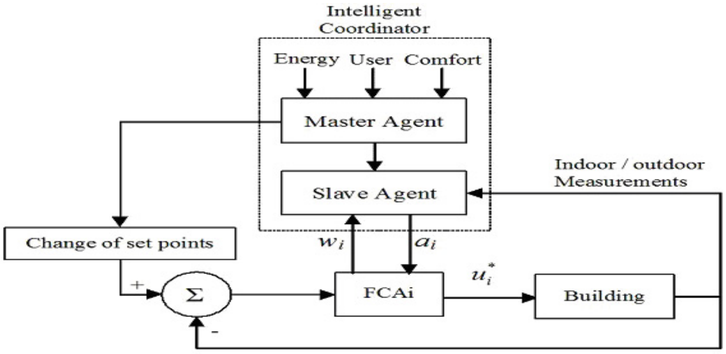


Figure 3: Architecture of proposed control system.

5.1. Grey Energy Predictor

A grey system is a system which is not completely known, that is, the knowledge of the system is partially known and partially unknown. The grey system theory can estimate an unknown system by using only a few data and can characterize the unknown system by using a first order differential equation (Liu and Lin, 2006). The energy is considered as a sequence of discrete data $E^{(0)}(k)$ where $E^{(0)}(k) = [E^{(0)}(1), E^{(0)}(2), ..., E^{(0)}(n)]$ $n \geq 4$, n samples, is a time sequence data and the superscript (0) represents the original series of energy.

Algorithm of Grey energy predictor

$$E^{(1)}(k) = \sum_{m=1}^{k} E^{(0)}(m),\ k = 1, 2, \ldots, n$$

$$E^{(1)}(k) = [E^{(1)}(1), E^{(1)}(2), \ldots, E^{(1)}(n)]$$

$$E^{(0)}(k) + a_g \frac{[E^{(1)}(k) + E^{(1)}(k-1)]}{2} = u_g, k \geq 2$$

$$\begin{bmatrix} a_g \\ u_g \end{bmatrix} = (B^T \cdot B)^{-1} \cdot B^T \cdot E$$

$$B = \begin{bmatrix} -\frac{E^{(1)}(1) + E^{(1)}(2)}{2} & 1 \\ -\frac{E^{(1)}(2) + E^{(1)}(3)}{2} & 1 \\ . & \\ . & \\ . & \\ -\frac{E^{(1)}(n-1) + E^{(1)}(n)}{2} & 1 \end{bmatrix}$$

$$E = [E^{(0)}(2), E^{(0)}(3), \ldots, E^{(0)}(n)]^T$$

$$E^{(0)}(k+1) = (1 - e^{a_g})(E^{(0)}(1) - \frac{u_g}{a_g})e^{-a_g(k-1)}$$

The prediction of accumulated consumed energy is a very important element for the proposed system.. The goal is to predict $\hat{E}^{(0)}(k+1)$. As shown in Figure 4 a grey model of first order and one variable, the so-called GM(1,1) model, is used (Dounis and Caraiscos, 2007).

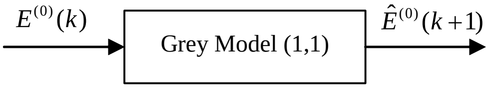


Figure 4: The block diagram of Grey Model

5.2 Master Agent

The master agent is an economy behavior fuzzy system that is shown in Figure 5. This fuzzy system has two inputs: the predicted energy consumption $\hat{E}(k+1)$ and the membership grade of comfort $\mu_{c(k)}$. Output of the master agent is the change of the controller set points. Master Agent activates Slave Agent with software signal when modification in set points to be done. The input and output MFs are shown in Figure 6.

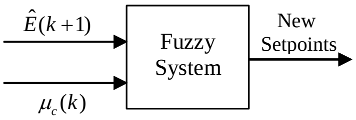


Figure 5: The block diagram of master agent.

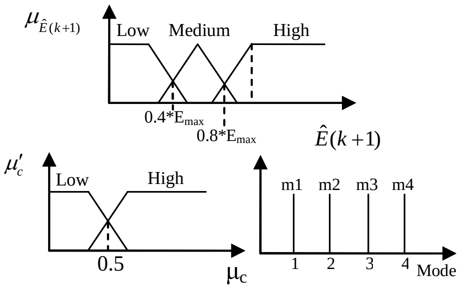


Figure 6: The membership functions of master agent.

The economy behavior fuzzy rules of master agent are:

$R^{(1)}$: If $\hat{E}(k+1)$ is Low and μ_c is Low then Mode is m1.

$R^{(2)}$: If $\hat{E}(k+1)$ is Low and μ_c is High then Mode is m2.

$R^{(3)}$: If $\hat{E}(k+1)$ is Medium and **(**μ_c is Low or μ_c is High) then Mode is m3.

$R^{(4)}$: If $\hat{E}(k+1)$ is High and **(**μ_c is Low or μ_c is High) then Mode is m4, where

Mode m1: $(ILL_d)_{new} = (ILL_d)_{initial}$, $(PMV_d)_{new} = (PMV_d)_{initial}$.

Mode m2: $(ILL_d)_{new} = (ILL_d)_{initial} \cdot 0.98$, $(PMV_d)_{new} = (PMV_d)_{initial} \pm 0.1$.

Mode m3: $(ILL_d)_{new} = (ILL_d)_{initial} \cdot 0.96$, $(PMV_d)_{new} = (PMV_d)_{initial} \pm 0.2$.

Mode m4: $(ILL_d)_{new} = (ILL_d)_{initial} \cdot 0.94$, $(PMV_d)_{new} = (PMV_d)_{initial} \pm 0.3$.

where plus (+) → cooling and the minus (−) → heating.

5.3. Slave Agent

As illustrated in Figure 7, the slave agent comprises of two fuzzy negotiation machines (FNMs) and one critique unit. Each FNM has two inputs and its output is the $a_i^{NP}(k)$ signal. The critique unit consists of five decision blocks. Each decision block makes decision as follows:

$$\mu_{a_i}(k) = w_i(k)\cdot a_i^{NP}(k)\text{, If } \mu_{a_i}(k) > 0 \text{ then } a_i(k)=1 \text{ else If } \mu_{a_i}(k)=0 \text{ then } a_i(k)=0\text{,}$$

where $a_i^{NP}(k)$ are the output from FNM 1 and FNM 2, $w_i(k)$ is the activation signal, and $a_i(k)$ is the acknowledgement signal (Figure 2).

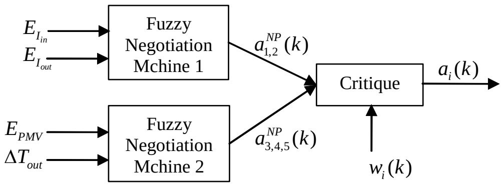


Figure 7: The block diagram of slave agent.

where $E_{I_{in}}$ is the indoor error illuminance, $E_{I_{out}}$ is the illuminance reference minus outdoor illuminance, E_{PMV} is the error of PMV and $\Delta T_{out} = 23^0 - T_{out}$, where T_{out} is the outdoor ambient temperature. All MFs of FNM 1 and FNM 2 are shown in Figures 8-9.

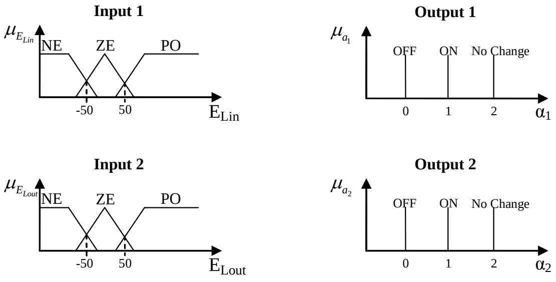


Figure 8: The membership functions of FNM 1.

The fuzzy negotiation rules of machine 1 for the computation of a_1^{NP} and a_2^{NP} are:

R$^{(1)}$: If E$_{Lin}$ is (NE or PO) and E$_{Lout}$ is (NE or ZE) then a_1^{NP} is OFF and a_2^{NP} is ON.

R$^{(2)}$: If E$_{Lin}$ is ZE and E$_{Lout}$ is (NE or PO) then a_1^{NP} is No Change and a_2^{NP} is No Change.

R$^{(3)}$: If E$_{Lin}$ is ZE and E$_{Lout}$ is ZE then a_1^{NP} is OFF and a_2^{NP} is OFF.

R$^{(4)}$: If E$_{Lin}$ is (NE or PO) and E$_{Lout}$ is PO then a_1^{NP} is ON and a_2^{NP} is OFF.

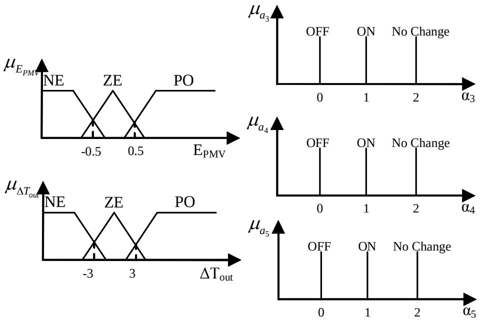


Figure 9: The membership functions of FCM 2.

The fuzzy negotiation rules of machine 2 for the computation of a_3^{NP} , a_4^{NP} and a_5^{NP} are:

$R^{(1)}$: If E_{PMV} is NE and ΔT_{out} is NE then a_3^{NP} is OFF and a_4^{NP} is ON and a_5^{NP} is ON.

$R^{(2)}$: If E_{PMV} is (NE or PO) and ΔT_{out} is ZE then a_3^{NP} is OFF and a_4^{NP} is OFF and a_5^{NP} is ON.

$R^{(3)}$: If E_{PMV} is PO and ΔT_{out} is NE then a_3^{NP} is OFF and a_4^{NP} is OFF and a_5^{NP} is ON.

$R^{(4)}$: If E_{PMV} is NE and ΔT_{out} is PO then a_3^{NP} is OFF and a_4^{NP} is OFF and a_5^{NP} is ON.

$R^{(5)}$: If E_{PMV} is ZE and ΔT_{out} is (NE or ZE or PO) then a_3^{NP} is No Change and a_4^{NP} is No Change and a_5^{NP} is ON.

$R^{(6)}$: If E_{PMV} is PO and ΔT_{out} is PO then a_3^{NP} is ON and a_4^{NP} is OFF and a_5^{NP} is ON.

6. Hardware Architecture for Spatial Distributed Control

Although the present paper describes the intelligent coordinator for the control of single zone building, its hardware has to be designed to accommodate multiple zone buildings. In this respect, a network of small embedded processors is used, forming a decentralized architecture, supervised by a central computer.

Each building is divided into zones (physical units), which are space with similar environmental characteristics, i.e. thermal behaviour, lighting and indoor air quality requirements. At the zone level the designed intelligent agent incorporates all necessary items to ensure indoor comfort interacting with the zone occupants using artificial intelligence techniques. Each room contains sensors and output devices, which are monitored and controlled locally by an intelligent agent. All these intelligent agents are connected together via a network (Rutishauer). The cmmunication network needs to be real time and to have simple device interfaces. This has led to the development of specialist networks. Such intelligent buildings networks are: The serial field bus network (Local Operating Network, which ensures interoperability and expandability (Kolokotsa 2002)), EHSA, X10, BACnet, see (Snoonian) for the LON and other field-bus standards. The proposed distributed architecture encompasses networks, agent technologies, and general embedded intelligent controllers and processors. This architecture constitutes a pervasive computing environment (Doctor). Figure 10 shows an overview of our hardware architecture for distributed control in multi zone buildings.

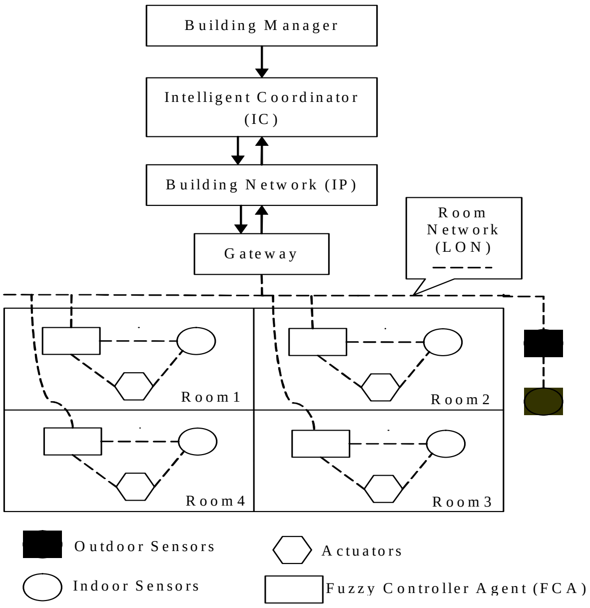


Figure 10: Overview of hardware architecture. The intelligent coordinator monitors and controls the building environment via FCAs, sensors, and actuators attached to a common field-bus room network. A gateway allows the IC to access the room network.

7. Simulation Results

The model of the building implemented in TRNSYS (TRNSYS 16, 2006) and the control system is implemented in Matlab. This software environment combines TRNSYS and Matlab package (Figure 10). For simplicity, the sampling period of the controller is the same with the time step of TRNSYS simulation algorithm. Sampling period is 6 min. Communication between TRNSYS and Matlab is realized by a TRNSYS TYPE calling the Matlab Engine Library. Controllers outputs u_i^* belong to interval [0,1] and Φ_i is the maximum power of each actuator.

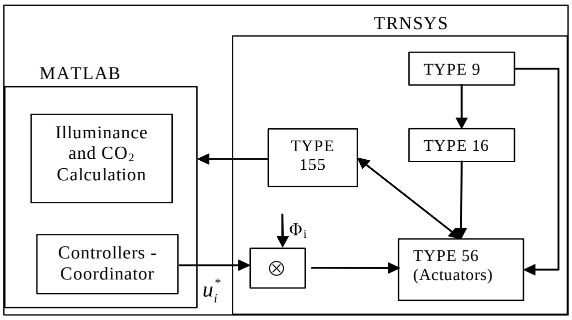


Figure 11: Simulation block diagram.

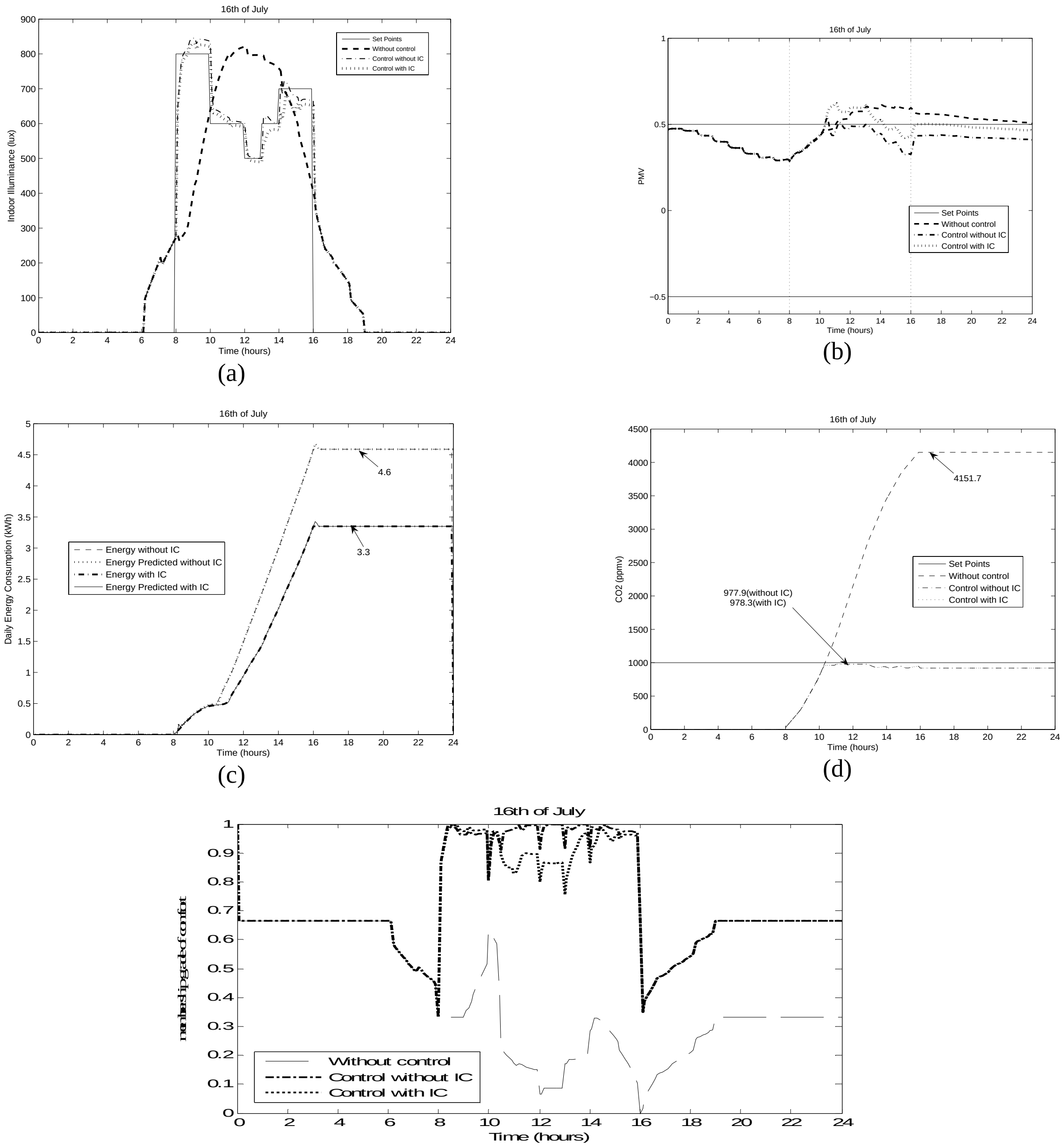
All simulations concerned a passive single zone solar building characterized by an south-facing window glazed area (3m^2), area 45 m^2, volume 135 m^3 and by a high thermal inertia. In TRNSYS there exist an auxiliary heating/cooling actuator (4kW), electric lighting (10 lamps, 0-1000 lux, 800 W total), and a shading device (curtain). The building space has a mechanical ventilation system, regulated to provide 100% non-recycled air at a constant rate of 2 air changes per hour or about 159cfm. The outdoor CO_2 concentration is considered to be constant at any time step and equal to 370 ppmv. CO_2 emission rate inside the zone is taken equal to 0.036 kg.h^{-1}.person^{-1}. The number of occupants every two hours is 2,3,4,5,5,4,3,2, and the initial indoor air temperature is 25^{o}C. Algorithms for calculation of illuminance and CO_2 concentration are taken from (Aydinli and Krochmann, 1983; ASHRAE, 2005; Li and Lam, 2000; Littlefair et al, 1993; Perraudeau, 1994). The controllers' initial set points are: PMV=0, [CO_2]=1000 ppmv, and indoor Illuminance= {800-600-500-800}lux. In a real system the sensors are measuring the following environmental variables: a) mean radiant temperature; b) indoor temperature; c) relative humidity; d) air velocity; e) CO_2 concentration; f) indoor illuminance; g) outdoor temperature and illuminance. The sensors a to d are used for the evaluation of the PMV index. PMV depends upon clothing parameter and activity level.

Two cases were simulated: (i) without the IC, that is, only with use of four FCAs, and (ii) with the IC together with the FCAs. Some selected results (one summer day – 16 July) are shown in Figure 11. Figures 12a, 12b, and 12c show the indoor illuminance, PMV and CO_2 responses of the system with (dotted line) and without IC (dot-dashed line), and without control (dashed line). Figure 12d gives the curves of the daily energy consumption with IC (dot-dashed line) and without IC (dashed line), respectively, and predicted daily energy consumption with IC (solid line), and without IC (dotted line), respectively. Figure 12e shows the time evolution of the new information granule of comfort.

From the above simulations we observe that: a) using only the FCAs without IC, index PMV is maintained within the acceptable limits (-0.5 to +0.5), and indexes ILL and CO_2 successfully approach the set points, b) by appending the IC to the FCAs, the controlled variables are maintained in acceptable limits. Particularly, PMV index is maintained within the new thermal zone [-0.5, +0.6], and the upper limit of thermal comfort zone was increased by master agent (Mode m2). Thereby we ensure energy saving of about 28%, c) during the control with IC, the comfort variable lies within the 3-D fuzzy comfort set with degree of acceptance greater than 0.75. However, the energy saving that was obtained caused reduction of the acceptance degree of comfort concerning, compared to the case of control without IC.

8. Conclusions

The proposed intelligent control system is open architecture. It incorporates fuzzy controllers, intelligent coordinator and the behavior of occupants. In this paper the uncertainty of comfort is considered as a discrete fuzzy set and is represented as a point in the fuzzy cube. The membership grade of comfort is computed by fuzzy equality measure. A new approach has been presented for the design of an intelligent coordinator. The coordinator is comprised by two hierarchical subsystems the master and slave agent that are two fuzzy negotiation machines. The negotiation lies in the successful avoidance of the conflicts between the controllers and in the management of the interaction between user’s preference and energy consumption. Simulation results show that the proposed intelligent control system successfully manages to satisfy the multiple objectives which are the buildings’ users comfort requirements and energy conservation.



(a) (b)

(c) (d)

(e)

Figure 12: Time evolution, (a) Indoor illuminance, (b) PMV, (c) CO_2, (d) Real and predicted daily energy consumption, (e) Comfort (membership grade using fuzzy equality measure).

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