Investigation of Using Fuzzy Logic to Model Occupant Satisfaction and Behavior in a Building

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Abstract.

Occupant satisfaction with indoor environmental conditions are in close relation to energy consumption in buildings. Despite the increasing efforts to maintain thermal comfort conditions in buildings with control strategies, occupants are not usually satisfied, and, thus, change their behavior which generally interfere with building operation systems. Therefore, modeling and characterizing occupant satisfaction and behavior are important considerations in the building energy use. However, occupant satisfaction and behavior as well as indoor environmental conditions have serious amount of uncertainty, and, thus, it is difficult to simulate them via traditional techniques. In this study, a total of 8 tests were conducted to monitor indoor environmental conditions in an educational building. A questionnaire was distributed during the monitoring period in order to understand the satisfaction level of occupants as well as their behavior preference. The results are utilized to model occupant behavior where fuzzy logic is preferred to tackle the uncertainty in the model parameters. Results denote that there is a significant potential of utilizing fuzzy logic to model occupant behavior under uncertain conditions similar to the real life.

Keywords: Indoor environmental conditions; occupant satisfaction; behavior; modeling; fuzzy logic.

1 Introduction

Energy efficiency in buildings has emerged as a vital concept in energy conservation during the past few decades. As a sector, buildings consume approximately 40% of total energy consumption and the gap between predicted and actual building energy performance is indicated to be up to 100% [1]. Not being able to predict the building energy performance not only affects energy policies but also increases the expenditures in the operation stage, adversely affect thermal comfort conditions, and, thus, user productivity. Thermal comfort is of crucial importance due to the fact that it characterizes the response of users in order to increase their satisfaction with the environment. It is therefore undoubtedly among one of the most influential factors affecting building energy consumption within its operational phase. Although, it is possible to control the operation of energy systems and to monitor the energy consumption via Building Management Systems, these systems cannot include occupant behavior in their operating systems due to the complexity of modelling occupant behaviour. In addition, smart meter technology is one of the most important advancements in helping reductions in energy consumption; however, Armel et.al.

claim that the full potential of the new smart meter technology cannot be exploited if human factors are not considered; that is, a complete exploitation of smart grid has to consider human in the loop [2].

The influence of occupant behaviour is under-recognized due to the complexity and the great district discrepancy of occupant behaviour, which are not always reasonable and often spontaneous [3]. As most of the existing studies on occupant behaviour are carried out mainly from the perspective of sociology, they lack in in-depth quantitative analysis, which is crucial in terms of developing any model. On the other hand, the traditional approaches consider human behavior almost in a deterministic way; however, many parameters influencing indoor environmental conditions and occupant behavior vary significantly and cannot be predicted. Fuzzy logic is a technique which enables to tackle the uncertainty in the model parameters (i.e. indoor environmental conditions and occupant behavior). In addition, fuzzy rule-base systems (FRBS) has the ability to simulate nonlinear behaviors by means of fuzzy logic as well as fuzzy rules. Therefore, fuzzy logic is a promising technique to model occupant satisfaction and behavior, which are unpredictable and that are not linear.

In this study, a total of 8 tests were conducted to monitor indoor environmental conditions in an educational building. A questionnaire was distributed during the monitoring period in order to understand the satisfaction level of occupants as well as their preference of behavior in terms of changing indoor environmental conditions. The data obtained by setting up the measurement campaign along with questionnaires given to and answered by the occupants are utilized to model occupant behavior. Fuzzy logic is preferred to tackle the uncertainty in the model parameters including indoor air temperature, relative humidity, air velocity, air pressure and CO_2 concentration, as well as occupant satisfaction levels with indoor environmental conditions and their preference of behavior (action). The following sections present the literature review, describe test bed building and data collection, introduce the application of the methodology and present findings and conclusion.

2 Literature Review

Modeling occupant behaviour with respect to energy consumption in buildings mainly aims at revealing the interaction between human and energy use. There are several models that can be used for occupant behaviour. Action based models define "occupant behaviors" as actions. These studies focus on either occupant presence, which are typically kept at an aggregate level [4-9] (e.g. occupied/unoccupied) or typical activities such as the control of window openings or sun-shading devices [10-15]. Probability theory [16-18] and stochastic models [19-23] are also among the most commonly used techniques to predict the occupant behavior. Deterministic models use predefined typologies whereas probabilistic models define parameters and equations to calculate the probability of an occurrence. Studies utilizing deterministic and stochastic models generally focus on simulating lighting energy use patterns [19, 21] and window openings. Zhou et. al. used stochastic modelling to simulate occupants' lighting energy use patterns [19] whereas Li et. al. investigated window-opening behavior of occupants by using probability [20]. Palacios-Garcia et. al. proposed a model to simulate the lighting's electricity consumption in the residents [21]. Chen et. al. modeled occupancy in commercial buildings by using markov chain [22] and McKenna et. al. presented a four-state model domestic building occupancy model for energy demand simulations by markov chain outputs [23]. Despite their potential in modeling occupant behavior, deterministic and probabilistic models are based on assumptions and data. Deterministic models reveal one outcome at a time for each assumed type of behavior and thus various calculations have to be done to model each behavior. Probabilistic models yield the probabilities of a behavior and the distribution of behaviors. Recently agent based models are also considered as an alternative methodology in which behaviors of occupants are mimicked based on rules and memory. Although these methodologies are widely used to model occupant behavior, other influencing factors (i.e. indoor environmental conditions), which contribute to the variation in building energy consumption, and, thus, occupant behavior, are mostly ignored or assumed to be steady.

Fuzzy logic is a promising technique to model occupant satisfaction and behavior. It is based on fuzzy sets instead of classical crisp sets which use crisp boundaries. Thus, partially belongingness concept is considered in fuzzy sets by means of real continuous interval [0, 1]. In fuzzy set theory, each point in the set belongs to the set with a membership value, and closer values to 1 increase the strength of belongingness. In this manner, fuzzy logic enables to reason not only by means of discrete symbols and numbers but also using ambiguous information. Fuzzy logic is a formal characterization of fuzzy set theory with logical expressions to make heuristic inference possible by linguistic rules. Therefore, in fuzzy logic, the system's complexity, which arises from the uncertainty in the form of ambiguity, is considered by allowing intermediate values and outcomes are regions instead of a single point in the universe. Consequently, fuzzy logic is a powerful tool to model human behavior and enables human-like inferences in an environment with uncertainty, vagueness, and data imprecision [24-26].

Fuzzy rule-base systems (FRBS) can be used the simulation of nonlinear behaviors by means of fuzzy logic as well as fuzzy rules. There are different inference techniques which are used in FRBSs, such as, Mamdani [27], Sugeno [28], Tsukamoto [29] systems. Mamdani system is the first inference implemented fuzzy inference methodology, in which the variables are used in fuzzy relational equations in the canonical form. The linguistic rules are associated with logical connectives namely, *and*, *or*, *else*. Since the outcome is an area (or a region) in the output space, defuzzification process is usually carried out to calculate a single value as an output [24, 28]

Fuzzy logic was applied for modelling human behavior in several studies. In order to model pedestrian walking path and behavior, fuzzy system and its hybrid models were implemented [30, 31]. Another study revealed that by using fuzzy systems, human behavior could be modeled more accurately [32]. Moreover, fuzzy ontology was used for identification of human behavior [33]. Fuzzy logic system was also used to simulate the behavior of residential occupants in terms of electricity use and lights in the houses [34]. In recent studies, fuzzy controllers were applied to smart buildings in which HVAC systems are regulated. Marvuglia et. al. developed a combined neuro-fuzzy model, which produces indoor temperature forecasts that are used to feed a fuzzy logic control unit that simulates switching the heating, ventilation and air conditioning (HVAC) system on and off according to the indoor temperature [35]. Nowadays, fuzzy logic based controllers were able to control the HVAC and A/C systems [36-43]. These studies show that fuzzy logic has potential to be used in modelling occupant behavior which are unpredictable and that are not linear.

3 Test Building Description and Data Collection

The study was carried out at the Department of Civil Engineering, Ege University located in Izmir, which is at Turkey's western coastline characterized by long, hot and dry summers. Subsequently, reducing energy consumption for cooling and ensuring thermal comfort conditions constitute the main concerns in this climatic zone. A total of 8 tests were carried out in two periods spanning 2 and 3 days in June and July, 2014 respectively. These days were selected as there was high attendance to classes. Physical and subjective measurements were conducted to obtain quantitative data on the prevailing actual conditions. Data collection methods included: (1) a physical measurement of certain parameters that influence the occupant satisfaction and behavior, (2) a questionnaire as the subjective measurement.

Test bed building was constructed in 2002 and has no insulation on the exterior walls. Heating and cooling are maintained via a centralized system. The building has double glazed windows with aluminum frames. Four different classrooms, which are located on the south, were selected for the case studies. These classrooms were selected as (1) they are the most commonly used ones and (2) they are the most affected ones by the sun due to their location. The floor plans and the selected classrooms are presented in Figure 5.

Fig. 5. a) 1st Floor plan, b) 2nd Floor plan, c) 3rd Floor Plan

Field measurements were taken every minute at a height of 1.1 m from the ground level as advised in the prescriptions of the ASHRAE Standard 55-2010 [44]. Indoor air temperature (T), relative humidity (RH), air velocity (V), air pressure (P) and CO_2 concentrations were measured via the TESTO Thermo-Anemometer Model 435-2. The subjective study involved collecting data via questionnaires. The questionnaire was developed to gauge how occupants are feeling in terms of thermal comfort and what they would like to do to feel more comfortable. The options for the first question varied from very comfortable to very uncomfortable, whereas the options for the latter question were window opening/closing, door opening/closing, cloth adjustment, curtain closing, using air conditioning and no change. Details of the test design and number of participants are presented in Table 1.

Table 1. Test design of the case study

Test No	Measurement Date	Time interval	Classroom	Floor	Area	Number of Participants
Test 1	18.06.2014	14:25-15:20	D104	1st Floor	136.6 m2	50
Test 2	19.06.2014	13:05-13:50	D104	1st Floor	136.6 m2	43
Test 3	18.06.2014	08:50-10:20	D204	2nd Floor	136.6 m2	43
Test 4	19.06.2014	13:50-14:20	D204	2nd Floor	136.6 m2	46
Test 5	23.07.2014	13:20-14:15	D209	2nd Floor	70.4 m2	30
Test 6	23.07.2014	14:35-15:15	D209	2nd Floor	70.4 m2	32
Test 7	24.07.2014	13:00-13:55	D209	2nd Floor	70.4 m2	30
Test 8	25.07.2014	13:35-14:40	D309	3rd Floor	70.4 m2	30

Table 2 presents the statistical summaries of indoor measurements. Indoor air temperature values ranged between 30.3 and 25 ^{0}C with mean values of 30.15 and 26.86 ^{0}C and standard deviations (STD) of 0.10 and 0.55, which indicate that indoor air temperatures were relatively stable during the tests. Relative humidity values ranged between 55.4 – 39.1%, with mean values of 51.12 and 40.35% and STDs of 2.04 and 0.46. Air velocities ranged between 0.3 and 0.01 with mean values of 0.04 and 0.01 whereas the STDs ranged between 0.09 and 0.01. CO_2 concentrations ranged between 4130 and 646 ppm with mean values of 3108.55 and 1128.25 ppm whereas the STDs ranged between 37.4 and 600.88, which indicate large deviations between measurements.

Table 2. Descriptive statistics of indoor environmental conditions

	Test 1	Test 2	Test 3	Test 4	Test 5	Test 6	Test 7	Test 8
Indoor air temperature (^{0}C)								
Mean	30.15	28.37	28.93	28.76	27.87	26.86	25.97	29.36
Std. Dev.	0.16	0.51	0.34	0.32	0.55	0.10	0.34	0.49
Minimum	29.7	27.10	28.4	28.6	27.3	26.5	25	28.2
Maximum	30.3	28.80	29.4	30	29.1	27	26.3	29.9
Relative Humidity (%)								
Mean	40.35	42.30	51.12	41.68	47.49	43.6	47.69	43.44
Std. Dev.	0.66	2.04	4.16	0.79	1.34	0.50	0.54	0.46
Minimum	39.1	40.20	42.2	40.3	43.2	42.9	45.7	42.7
Maximum	41.7	47.20	55.4	43.4	48.9	44.9	48.3	44.8
Air Velocity (m/sec)								
Mean	0.02	0.05	0.03	0.01	0.18	0.12	0.12	0.04
Std. Dev.	0.02	0.07	0.02	0.01	0.07	0.09	0.07	0.03
Minimum	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.01
Maximum	0.1	0.3	0.1	0.04	0.27	0.28	0.25	0.16
Air Pressure (kPa)								
Mean	100.95	100.45	101.05	100.41	100.16	100.16	100.29	100.16
Std. Dev.	0.02	0.03	0.03	0.01	0.01	0.00	0.00	0.00
Minimum	100.89	100.43	101.01	100.38	100.16	100.16	100.29	100.15
Maximum	100.97	100.51	101.1	100.43	100.19	100.18	100.31	100.17
CO_2 Concentration (ppm)								
Mean	1555.91	1426.44	1128.25	1136.37	1487.44	1406.63	1167.69	3108.55
Std. Dev.	149.93	177.84	187.85	132.42	541.07	37.4	148.96	600.88
Minimum	1221	1156	646	973	566	1358	877	2054
Maximum	1806	1766	1315	1383	2351	1528	1374	4130

The results of the questionnaires are shown in Table 3. A total of 304 responses were received and all of them were valid. The gender ratio of respondent students was 16% female and 84% male. Majority of the students were seniors in the age range of 20-27. Approximately thirty percent of participants stated that they feel “light annoyance” and 73% of these occupants indicated that they would prefer to use air conditioning to feel comfortable whereas window opening was ranked the second. Occupants who stated their thermal satisfaction as “comfortable” and “annoyance” had almost the same ratio of 24%. Majority of these respondents indicated that using air conditioning would be their first choice to prevent an uncomfortable indoor environment. In summary, using air condition was the first choice of respondents whereas “no change” and “window opening” were ranked the second and third, respectively. Although “closing curtains” could have prevented direct sunlight, it was the least preferred behaviour among respondents.

Table 3. Questionnaire results

Behavior Preferences	Thermal Satisfaction					TOTAL	Percentage (%)	Rank Order
	V.C*	C*	L.A*	A*	H.A*			
Window-Opening	1	2	8	9	5	**25**	8.2	3
Window-Closing	1	0	2	2	0	**5**	1.6	7
Door-Opening	3	3	2	4	3	**15**	4.9	4
Door-Closing	1	2	3	2	1	**9**	3.0	5
Cloth Adjustment	1	4	2	1	0	**8**	2.6	6
Curtain-Closing	1	1	2	0	0	**4**	1.3	8

Using Air-conditioning	8	51	67	56	14	**196**	64.5	1
No change	26	10	6	0	0	**42**	13.8	2
TOTAL	**42**	**73**	**92**	**74**	**23**	**304**	100	
Percentage (%)	13.8	24.0	30.3	24.3	7.6	100		

*V.C: very comfortable, C: comfortable, L.A: light annoyance, A: annoyance, H.A: heavy annoyance.

4 Application of the Methodology

In this section, results of questionnaires, which were conducted to understand occupant satisfaction and behavior during cooling season, are applied to fuzzy model. The numerical example aims at showing the approximation ability of the fuzzy model in terms of characterizing occupant satisfaction with the indoor environment. In addition, assessing average occupant satisfaction level and estimating the occupant behavior are targeted.

Firstly, indoor air temperature, relative humidity, air velocity, air pressure and CO_2 concentration variables that are measured in the indoor environment are characterized with fuzzy variables as well as triangular membership functions. It should be noted that mapping of a fuzzy set to the universe is represented by the membership function concept. Then, if the universe of discourse is represented by X, the fuzzy set $\underline{A}$ can be given by the following expression (Equation 1) [28]:

$$\underline{A} = \left\{ \frac{\mu_{\underline{A}}(x_1)}{x_1} + \frac{\mu_{\underline{A}}(x_2)}{x_2} + \ldots \right\} = \left\{ \sum_i \frac{\mu_{\underline{A}}(x_i)}{x_i} \right\} \tag{1}$$

Triangular membership function (Fig.1) can be given with the expression below (Eq.2):

$$\mu(x) = \begin{cases} 0 & x \le a \\ \dfrac{x-a}{b-a} & a \le x \le b \\ \dfrac{c-x}{c-b} & b \le x \le c \\ 0 & c \le x \end{cases} \tag{2}$$

Therefore, a fuzzy relation can be inferred by means of max-min composition rule for a triangular fuzzy membership function as follows:

$$\mu(x; a, b) = \max\left[\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b} \right), 0 \right] \tag{3}$$

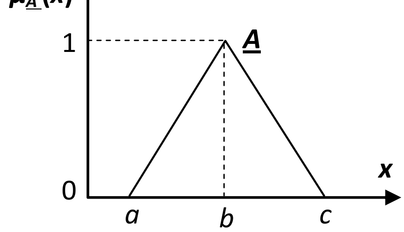

Fig. 1. Representation of a triangular membership function

In a fuzzy rule-based system, each logical proposition in the universe of discourse is characterized by a fuzzy set and the outcome of a rule is obtained by an implication technique, which is referred to as an extension principle or approximate reasoning. In this study, Mamdani's implication method is applied and a fuzzy relation ($\underline{R}$) is

(Eq.4):

$$\mu_{\underset{-}{R}}(x, y, \ldots) = \min\left[\mu_{\underset{-}{A}}(x), \mu_{\underset{-}{B}}(y), \ldots\right] \tag{4}$$

Obviously, fuzzy rule-based systems consist of several rules, which involve antecedents, namely conjunctives (AND) and disjunctives (OR). The inference is made by a decomposition method. Basically, decomposition can be made for conjunctives as given by the following expression:

$$\mu_{\underset{-}{B}^S}(y) = \min\left[\mu_{\underset{-}{A}^1}(x), \mu_{\underset{-}{A}^2}(x), \ldots, \mu_{\underset{-}{A}^L}(x)\right] \tag{5}$$

Analogously, decomposition is done for disjunctive antecedents as follows:

$$\mu_{\underset{-}{B}^S}(y) = \max\left[\mu_{\underset{-}{A}^1}(x), \mu_{\underset{-}{A}^2}(x), \ldots, \mu_{\underset{-}{A}^L}(x)\right] \tag{6}$$

A graphical representation of a Mamdani fuzzy inference system is shown in Figure 2. As can be derived from the figure that the outcome is a region; thus, it is required to make a defuzzification in order to get single output value. There are several defuzzification techniques in the literature; nevertheless, in this study, centeroid method is preferred, and the formulation is as follows:

$$x^* = \frac{\int \mu_{\underset{-}{A}}(x)\, x\, dx}{\int \mu_{\underset{-}{A}}(x)\, dx} \tag{7}$$

In which, $\underline{A}$ is fuzzy set, $\mu_{\underline{A}}$ is membership function, x is input variable, and x^* is single output value.

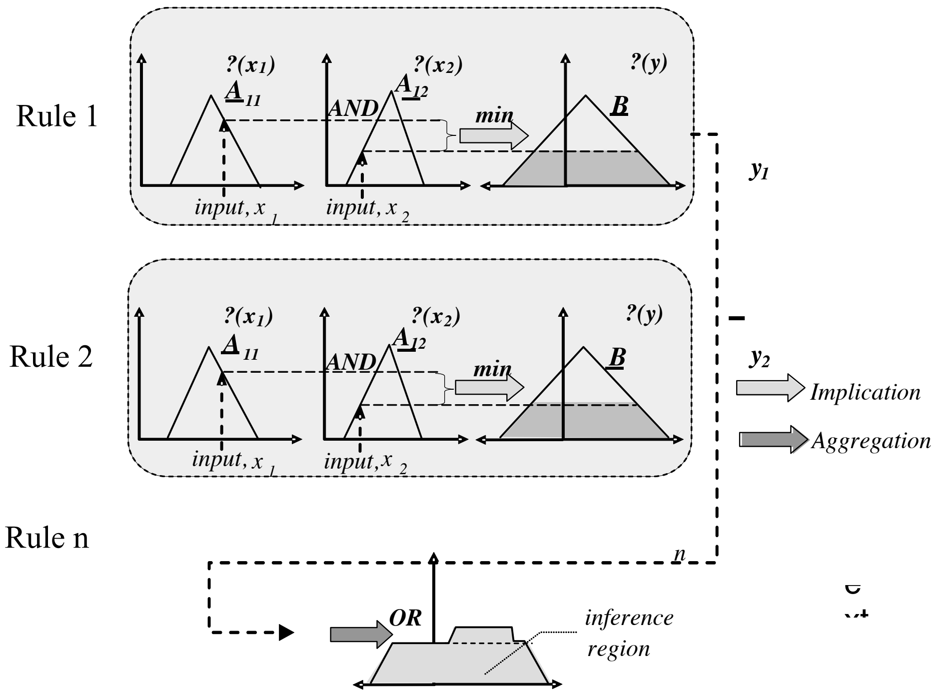

Fig. 2. Schematic representation of the fuzzy inference methodology

Fig.3 shows the input fuzzy variables (indoor air temperature (T); relative humidity (RH); air velocity (V); air pressure (P); CO_2 concentrations(C)) and associated triangular membership functions. As can be derived from the figures, fuzzy variables have different partitioning from 3 to 5.

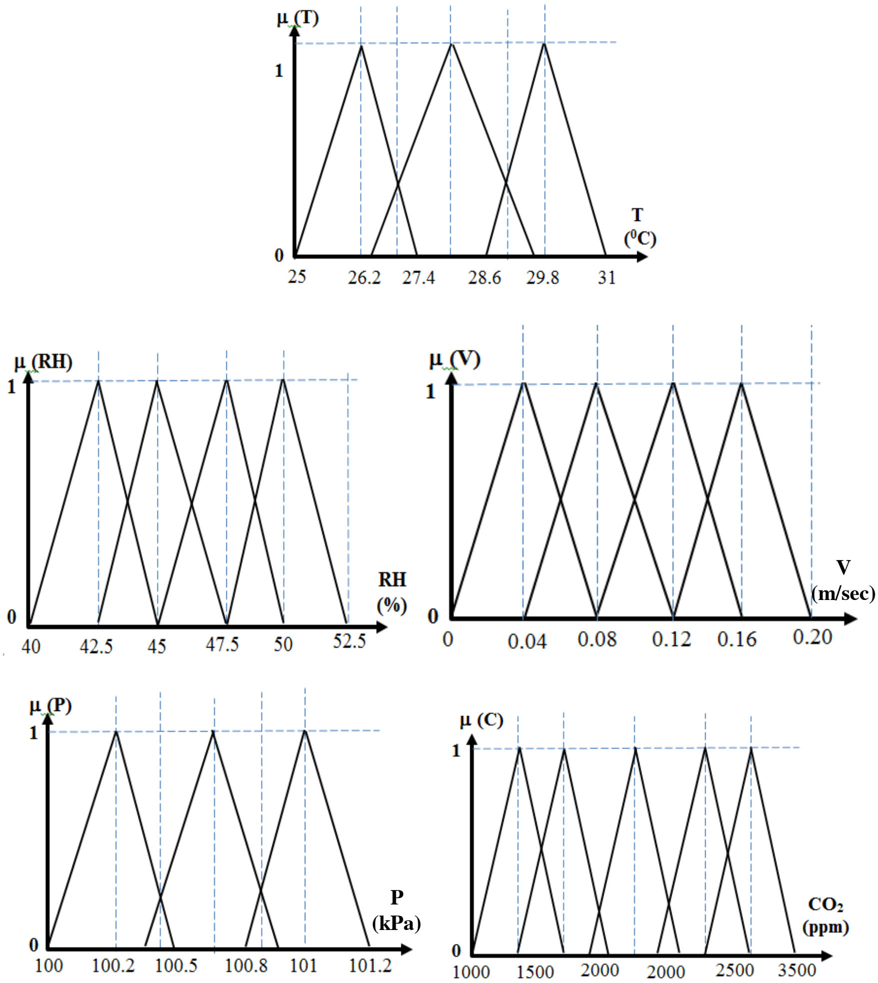

Fig. 3. Membership functions of the fuzzy input variables

Output variable of the model which characterizes the satisfaction of an occupant is considered by Satisfaction Index (SI) variable. In Fig.4, membership function of SI variable is shown. In order to quantify and model the occupant satisfaction, the results of the questionnaires are graded per answers in the questionnaires. In other words, each response of the occupants is quantified with a relative scale within [0,100], which is a percentage indicating the satisfaction with the indoor environment.

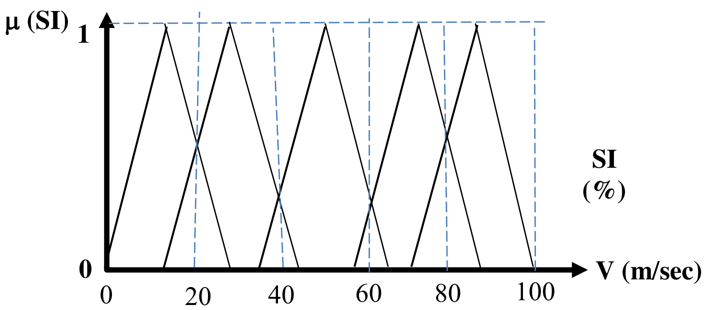

Fig. 4. Membership function of the fuzzy output variable, SI

In the next step, fuzzy rule-base is established using grid partitioning technique. Namely, each rule is associated with each possible variation for considered fuzzy input parameters; thus, totally 720 (5 x 3 x 3 x 3 x 4) different rules are included in the fuzzy rule-base. It should be noted that the fuzzy partitioning of each variable is done according to the range of the variable, and then the rules are developed while ensuring enough precision in the inference. A sample rule from the rule base is given below.

IF CO_2 is C^2 AND T is T^2 AND P is P^2 RH is RH^3 AND V is V^3 THEN SI is SI^3 (8)

5 Findings

Matlab and Fuzzy Logic Toolbox software packages are used to develop the presented model. Next, the developed fuzzy model is employed with the test data that was obtained from the measurement campaign which is explained in Section 3. In order to observe the performance of the fuzzy model, the outcomes are compared with the results of the questionnaires that were conducted in accordance with the measurements. In this context, firstly, SIs are calculated over 100% per responses of the occupants. After this, in order to calculate the combined satisfaction of all occupants simultaneously; weighted averages, Performance Points (PP) are calculated over 2 000. Then, establishing fuzzy inference according to performance points is aimed. Fig. 6 shows a sample relationship among some model parameters and SI.

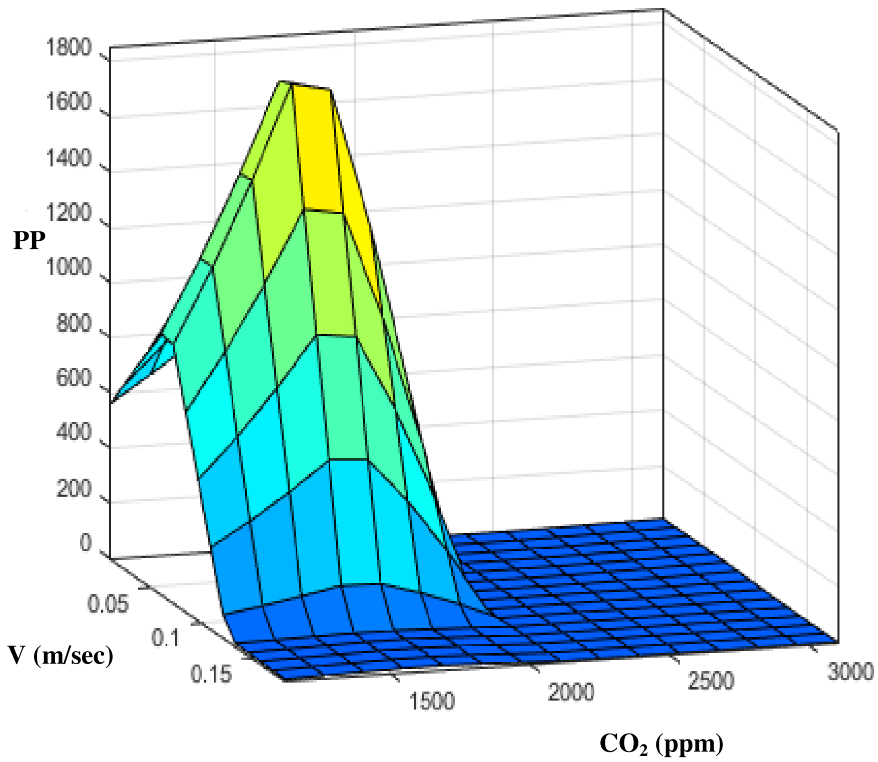

Fig. 6. Relationships between model parameters

Inference mechanism during the calculation of the output of fuzzy model using rule-base is presented in Fig. 7.

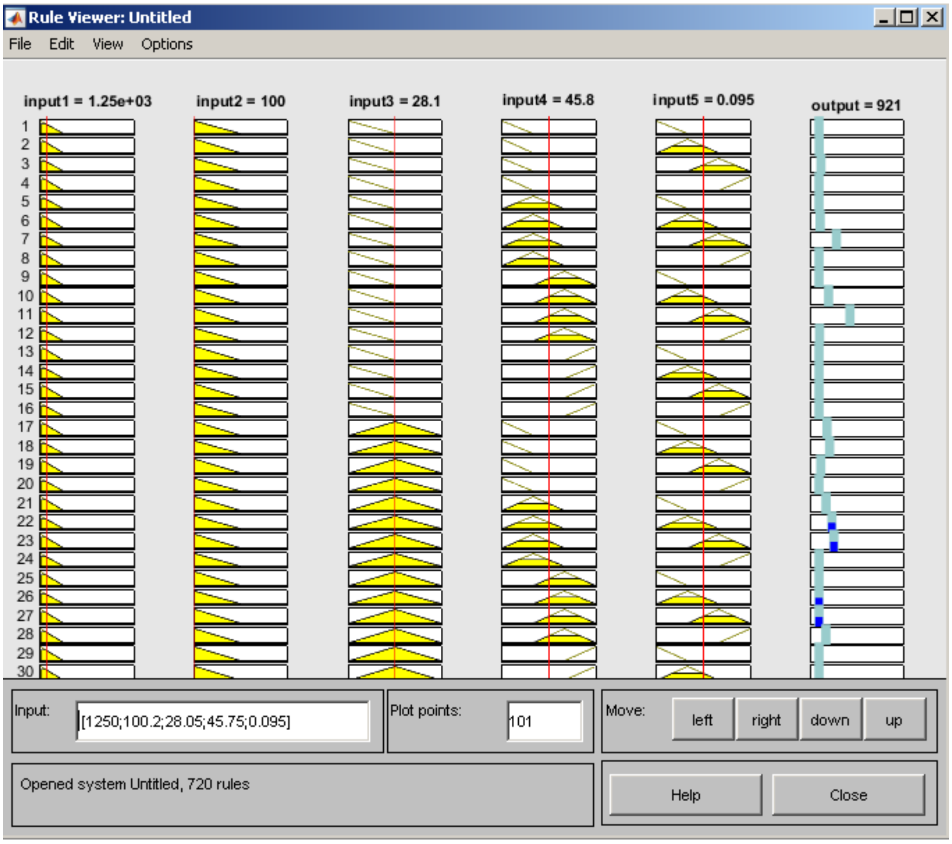

Fig. 7. Fuzzy inference with rule-base

Finally, the results of the fuzzy model developed for occupant satisfaction are compared to the actual questionnaire data. The closeness of the fuzzy model to the actual data can be seen in the scatter plot given in Fig.8. It should be noted that the PP value is a weighted average of the occupants of which maximum value is considered as 2000 in this study. Any other formulation can be used to calculate such a value analogously.

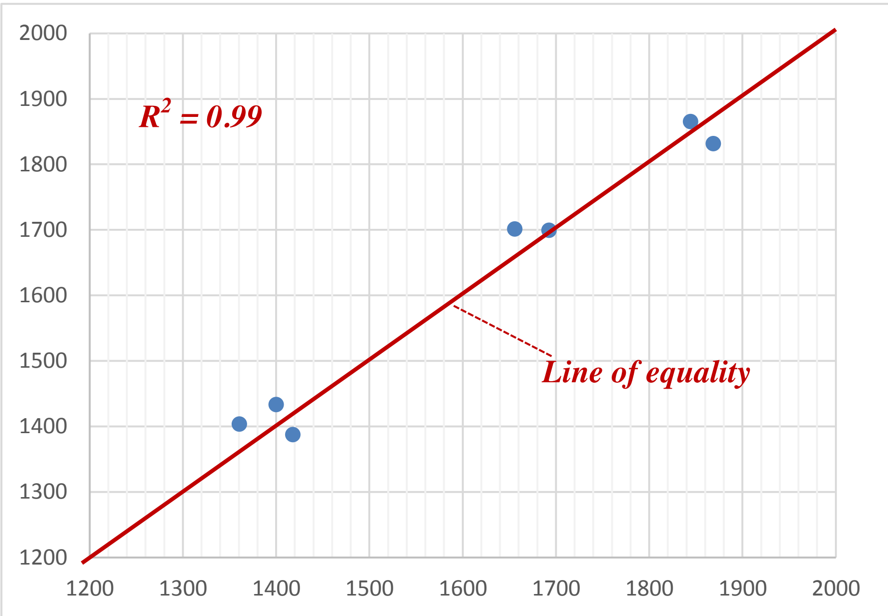

Fig. 8. Scatter plot between fuzzy model outputs and questionnaire results

As can be derived from Fig. 8, results of the developed fuzzy model are successful, and easily capable of simulating the occupant satisfaction and behavior. The R^2 value is calculated as 0.99, which indicates an outstanding correlation between the model and the questionnaire results. The R^2 value also highlights the potential to tackle the uncertainty with fuzzy logic.

6 Conclusion

This study aims at investigating the approximation ability of the fuzzy approach in terms of characterizing occupant satisfaction with the indoor environment as well as predicting occupant behavior. The results show that the developed fuzzy model is capable of estimating the satisfaction levels of occupants when indoor environmental conditions (i.e. indoor air temperature, relative humidity) are known. Considering the fact that buildings are becoming more equipped with technologies that enable real time monitoring, understanding and predicting occupant satisfaction and behaviors will be achieved via the developed fuzzy model. In addition, the simulation of occupant behavior provides a valuable chance to model the interaction with building operation systems (i.e. HVAC). Consequently, the developed model enables to develop energy efficient systems in the buildings with lower energy consumptions considering the effect of human behavior as well as the uncertainty in the model parameters.

Results indicate that there is a great potential to use fuzzy models for such behavioral simulations and such a fuzzy system can be used to achieve successful occupant behavior models for increasing occupant satisfaction as well as helping facility managers to optimize operation strategies of the buildings. In further studies, existing uncertainties and correlations should be evaluated with a larger database. Furthermore, future studies could focus on incorporating such fuzzy inferences in the energy efficiency problems directly. This study basically aims to show the potential of using fuzzy logic to model occupant behaviors and related responses that can be utilized in such efficiency optimization systems.

References

1. U.S. Department of Energy. March 2012. “Buildings Energy Data Book: 1.1 Buildings Sector Energy Consumption”, `http://buildingsdatabook.eren.doe.gov/docs/xls_pdf/1.1.3.pdf` (accessed February 8, 2015)
2. Armel, K.C., Gupta, A., Shrimali, G., Albert, A.: Is disaggregation the holy grail of energy efficiency? The case of electricity. Energy Policy. Volume 52. (2013) 213–234.
3. `http://performer-project.eu/insight-on-intrinsic-in-use-building-energy-simulation/`
4. Stoppel, C.M., Leite, F.: Integrating probalistic methods for describing occupant presence with building energy simulation models. Energy and Buildings. Volume 68. (2014) 99-107.
5. Andersen, P. D., Iversen, A., Madesen, H., Rode, C.: Dynamic modeling of presence of occupants using inhomogeneous Markov chains. Energy and Buildings. Volume 69. (2014) 213-223.
6. Page, J., Robinson, D., Morel, N., Scartezzini, J.L.: A generalized stochastic model for the simulation of occupant presence. Energy and Buildings. Volume 40 (2). (2008) 83-98.
7. Yang, Z., Becerik-Gerber, B.:The coupled effects of personalized occupancy profile based HVAC schedules and room reassignment on building energy use. Energy and Buildings. Volume 78. (2014) 113-122.
8. Kwok, S.S.K., Lee, E.W.M.: A study of the importance of occupancy to building cooling load prediction by intelligent approach. Energy Conservation and Management. Volume 52. (2011) 2555-2564.
9. Yang, Z., Becerik-Gerber, B.: Modeling personalized occupancy profiles for representing long term patterns by using ambient context. Building and Environment. Volume 78. (2014) 23-35.
10. Reinhart, C.F.: Lightswitch-2002: A model for manual and automated control of electric lighting and blinds. Solar Energy. Volume 77(1). (2004) 15–28.
11. Haldi, F., Robinson, D.: Interactions with window openings by office occupants. Building and Environment. Volume 44(12). (2009) 2378-2395.
12. Rijal, H.B., Tuohy, P., Humphreys, M.A., Nicol, J.F., Samuel, A., Clarke, J.: Using results from field surveys to predict the effect of open windows on thermal comfort and energy use in buildings. Energy and Buildings. Volume 39(7). (2007) 823–836.
13. Fabi, V., Andersen, R.V., Corgnati, S., Olesen, B.W.: Occupants’ window opening behavior: A literature review of factors influencing occupant behavior and models. Building and Environment. Volume 58. (2012) 188-198.
14. Hoes, P., Hensen, J.L.M., Loomans, M.G.L.C., De Vries, B., Bourgeois, D.: User behavior in whole building simulation. Energy and Buildings. Volume 41(3). (2009) 295–302.
15. Bourgeois, D., Reinhart, C., Macdonald, I.: Adding advanced behavioural models in whole building energy simulation: a study on the total energy impact of manual and automated lighting control. Energy and Buildings. Volume 38(7). (2006) 814–823.
16. Hunt, D.: The use of artificial lighting in relation to daylight levels and occupancy. Building and Environment. Volume 14. (1979) 21–33.
17. Reinhart, C.F.: Lightswitch 2002: A model for manual control of electric lighting and blinds. Solar Energy. Volume 77. (2004) 15–28.
18. Joakim, W., Nilsson, A.M., Wäckelgård, E.: A combined Markov-chain and bottom-up approach to modelling of domestic lighting demand. Energy and Buildings, Volume 41. (2009) 1001–1012.
19. Zhou, X., Yan, D., Hong, T., Ren, X.: Data analysis and stochastic modeling of lighting energy use in large office buildings in China. Energy and Buildings. Volume 86. (2015) 275–287.

20. Li, N., Li, J., Fan, R., Jia, H.: Probability of occupant operation of windows during transition seasons in office buildings. Renewable Energy. Volume 73. (2015) 84-91.
21. Palacios-Garcia, E.J. , Chen, A., Santiago, I., Bellido-Outeiriño, F.J., Flores-Arias, J.M., Moreno-Munoz, A.: Stochastic model for lighting's electricity consumption in the residential sector. Impact of energy saving actions. Energy and Buildings. Volume 89. (2015) 245–259.
22. C., Xu, J., Soh, Y.C.; Modeling regular occupancy in commercial buildings using stochastic models. Energy and Buildings. Volume 103. (2015) 216–223.
23. McKenna, E., Krawczynski, M., Thomson, M.: Four-state domestic building occupancy model for energy demand simulations. Energy and Buildings. Volume 96. (2015) 30-39.
24. Ross, T.J.: Fuzzy Logic with Engineering Applications, 3rd Ed., McGraw Hill Co. (2009)
25. Cox, E.: Fuzzy Modeling Tools for Data Mining and Knowledge Discovery. Elsevier Science & Technology Books (2005)
26. Klir, G.J.: Fuzzy Sets and Fuzzy Logic: Theory and Applications. Prentice Hall. (1995)
27. Mamdani, E.H., Assilian, S.: An experiment in linguistic synthesis with a fuzzy logic controller. Int. Journ. of Man-Machine Studies. Volume 7(1). (1975) 1-13.
28. Takagi, T., Sugeno, M.: Fuzzy identification of systems and its applications to modeling and control. IEE Trans. Sys. Man and Cybern. Volume 15. (1985)116-132.
29. Tsukamoto, Y.: An approach to reasoning method. In: Gupta M, Ragade RK, Yager RR, editors. Advances in Fuzzy Set Theory and Applications. Amsterdam. (1979)137-149.
30. Nasir, M., Lim, C.P., Nahavandi, S., Creighton, D.: Inclusion of environmental effects in steering behaviour modelling using fuzzy logic. Expert Systems with Applications. Volume 41(4). (2014) 1901-1914.
31. Nasir, M., Lim, C.P., Nahavandi, S., Creighton, D.: A genetic fuzzy system to model pedestrian walking path in a built environment. Simulation Modelling Practice and Theory. Volume 45. (2014) 18-34.
32. Leon, E., Clarke, G., Callaghan, V., Doctor, F.: Affect-aware behaviour modelling and control inside an intelligent environment. Pervasive and Mobile Computing. Volume 6(5). (2010) 559-574.
33. Rodríguez, N.D., Cuéllar, M.P., Lilius, J., Calvo-Flores, M.D.: A fuzzy ontology for semantic modelling and recognition of human behavior. Knowledge-Based Systems. Volume 66. (2014) 46-60.
34. Zúñiga, K.V., Castilla, I., Aguilar, R.M.: Using fuzzy logic to model the behavior of residential electrical utility customers. Applied Energy. Volume 115. (2014) 384-393.
35. Marvuglia, A., Messineo, A., Nicolosi, G.: Coupling a neural network temperature predictor and a fuzzy logic controller to perform thermal comfort regulation in an office building. Building and Environment. Volume 72. (2014) 287- 299.
36. Ghadi, Y.Y., Rasul, M.G., Khan, M.M.K.: Potential of Saving Energy Using Advanced Fuzzy Logic Controllers in Smart Buildings in Subtropical Climates in Australia. Energy Procedia. Volume 61. (2014) 290-293.
37. Li, Z., Xu, X., Deng, S., Pan, D.: A novel neural network aided fuzzy logic controller for a variable speed (VS) direct expansion (DX) air conditioning (A/C) system. Applied Thermal Engineering. Volume 78. (2015) 9-23.
38. Preglej, A., Rehrl, J., Schwingshackl, D., Steiner, I., Horn, M., Škrjanc, I.: Energy-efficient fuzzy model-based multivariable predictive control of a HVAC system. Energy and Buildings. Volume 82. (2014) 520-533.
39. Marvuglia, A., Messineo, A., Nicolosi G.: Coupling a neural network temperature predictor and a fuzzy logic controller to perform thermal comfort regulation in an office building. Building and Environment. Volume 72. (2014) 287-299.

40. Ghadi, Y.Y., Rasul, M.G., Khan, M.M.K.: Recent Developments of Advanced Fuzzy Logic Controllers Used in Smart Buildings in Subtropical Climate. Energy Procedia. Volume 61. (2014) 1021-1024.
41. Bermejo, P., Redondo, L., Ossa, L., Rodríguez, D., Flores, J., Urea, C., Gámez, J.A., Puerta, J.M.: Design and simulation of a thermal comfort adaptive system based on fuzzy logic and on-line learning. Energy and Buildings. Volume 49. (2012) 367-379.
42. Parameshwaran, R., Karunakaran, R., Kumar, C.V.R., Iniyan, S.: Energy conservative building air conditioning system controlled and optimized using fuzzy-genetic algorithm. Energy and Buildings. Volume 42. (2010) 745–762.
43. Karunakaran, R., Iniyan, S., Goic. R.: Energy efficient fuzzy based combined variable refrigerant volume and variable air volume air conditioning system for buildings. Energy and Buildings. Volume 87. (2010) 1158–1175.
44. ANSI/ASHRAE Standard 55-2010.Thermal comfort conditions for human occupancy. Atlanta: ASHRAE; 2010.