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FUZZY RULE BASED PREDICTION OF IAQ CHARACTERISTICS IN AIR CONDITIONED CAR*

P. THIRUMAL**[1], K. S. AMIRTHAGADESWARAN[2] AND S. JAYABAL[3]

[1]Dept. of Mechanical Engineering, Government College of Engineering, Bargur, India
Email: ptml76@gmail.com
[2]Dept. of Mechanical Engineering, Government College of Technology, Coimbatore, India
[3]Dept. of Mechanical Engineering, A.C. College of Engineering Technology, Karaikudi, India

Abstract– Air conditioning is widely applied for the improvement of standard of living in human life. This present investigation focused on the prediction of indoor air quality characteristics of air conditioned car using fuzzy logic algorithm. The conditioned space was selected and the experiments were planned as per design of experiments to study the effect of human load, fresh air supply and air velocity on the human comfort conditions. The mathematical models were developed to predict the comfort conditions, namely temperature, CO_2 level and relative humidity over a specified range of input conditions. Carbon dioxide exhalation rate differs person to person based on their body weight and burning rate of calories, etc. Fuzzy logic predicted the intermediate response of IAQ parameters for varying input conditions in this present investigation. The proposed multi response fuzzy model predicted better results comparing with nonlinear regression models. The absolute error percentage of fuzzy model for carbon dioxide level, temperature and relative humidity is 2.05%, 3.81 % & 2.24 % respectively.

Keywords– Indoor air quality, temperature, relative humidity, carbon dioxide, Fuzzy logic

1. INTRODUCTION

The human comfort conditions were affected by various Indoor Air Quality parameters in an air conditioned space. Du et al. [1] state that increments in the fresh air volume can develop the indoor air quality, and the rate at which outdoor air is supplied to a building is specified by the building code. Kong et al. [2] analyzed the main influencing factors on IAQ of the air conditioning system and put forward some measures to improve indoor IAQ of modern building. Jayabal et al. [3] have used Response Surface Methodology (RSM) techniques for the modeling and optimization of performance characteristics of composites. Palanikumar [4] presented a detailed procedure for mathematical modeling by correlating the interactions of drilling parameters and the optimum values of responses by RSM. A modified evolutionary strategy algorithm was developed for optimal decision making in ventilation control by Kusiac et al. [5] who applied soft computing techniques on IAQ prediction and optimization in the year of 2010 and 2011.

An Artificial neural network (ANN) with multi-layer preceptor algorithm was used to build virtual IAQ sensors for online monitoring in HVAC system by Kusiac et al. [6]. The neural network based predictive model was optimized with a Strength Multi-Objective Particle-Swarm Optimization (S-MOPSO) algorithm by Kusiac et al. [7] in another work. The relation between energy consumption and thermal comfort measured with temperature and humidity were discussed. An artificial neural network model was developed to predict the effect of volume fraction, compact pressure and milling time on green

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**Corresponding author

density, sintered density and hardness of Al-Al2O3 metal matrix composites (MMCs). The three input parameters in the proposed ANN were the volume fraction, compact pressure and duration of the milling process. Green density, sintered density and hardness of the composites were the outputs obtained from the proposed ANN. Canakci et al. [8] found ANN was successful in predicting the green density, sintered density and hardness of Al-Al2O3 MMCs.

In another study artificial neural network (ANN) approach was used for the prediction of effect of physical and mechanical properties of Al2024–B4C composites produced by powder metallurgy. Effects of reinforcement size and content (weight %) on the physical and mechanical properties of composites were determined by measuring the density, hardness and tensile strength values. The outputs obtained from the proposed ANN were density, hardness and tensile values strength of the composites. Temel Varol et al. [9] demonstrated that the well-trained feed forward back propagation ANN model is a powerful tool for prediction of effect of physical and mechanical properties of composites. Velimir et al. [10] used Genetic algorithms (GA) for operating standard HVAC systems in order to optimize performance, primarily with regard to power saving.

Kusiac et al. [11] using S-MOPSO algorithm demonstrated how much power can be saved by the method of carbon dioxide concentration control in a standard HVAC system. The solutions derived by the S-MOPSO algorithm point to a large number of control alternatives for an HVAC system, representing a range of trade-offs between thermal comfort and energy consumption. Kusiac et al. [12] have provided initiative ideas for the development of IAQ models. Based on above studies, an automobile with air conditioning facility was selected and experiments were conducted to study the IAQ parameters focusing mainly the Carbon dioxide level, Temperature and Relative humidity.

Karunakaran et al. [13] described the thermal comfort and energy conservation potential of the VAV system utilizing a fuzzy logic controller (FLC) that enhances the system performance substantially. The results shown that the energy saving potential of the variable air volume system was 27% at part load conditions, compared with the constant air volume system. Experimental results show that the required thermal comfort was achieved using FLC. Kolokotsa et al. [14] achieved optimum indoor environmental conditions with minimized energy costs using a bilinear model-based predictive control. Feriadi et al. [15] used Fuzzy logic approach to model an appropriate Thermal Comfort (TC) standard for tropical naturally ventilated houses. The complexities of the human cognitive process and the vagueness of linguistic expression are considered. Mendes et al. [16] developed a simulation tool based on the Matlab computational environment for building temperature performance analysis with automatic control. Angelov et al. [17] proposed a methodology for the development of self-structuring fuzzy rule-based (FRB) models of HVAC components. Roberto et al. [18] presented a work focusing on the study of indoor thermal comfort control problem in buildings equipped with HVAC systems. The occupants' thermal comfort sensation is addressed here by the well-known comfort index known as PMV (Predicted Mean Vote) and by a comfort zone defined in a psychometric chart. Rafael et al. [19] proposed the use of weighted linguistic fuzzy rules in combination with a rule selection process to develop accurate fuzzy logic controllers dedicated to the intelligent control of heating, ventilating and air conditioning systems concerning energy performance and indoor comfort requirements.

Based on previous research work studies, the present work aims to study the IAQ parameters and to develop a fuzzy model to predict the intermediate responses focusing mainly the Carbon dioxide level, Temperature and Relative humidity inside an air-conditioned car.

2. EXPERIMENTAL PROCEDURE

a) Experimental setup

A common passenger car with air conditioning facility was selected to conduct the Indoor Air Quality Assessment. The vehicle is selected with the controls, to vary fan speed and fresh air vent opening. An IAQ probe with sensors was used to record the responses, namely CO_2 level, Temperature, and Relative Humidity. Dual Channel NDIR sensor with a measuring range of 0 to 5000 ppm for measuring Carbon dioxide level, LM35 precision Centigrade temperature sensor for measuring Indoor Temperature and HIH-4010 Humidity sensor for measuring Relative Humidity were used in this present investigation. These entire sensors were calibrated before conducting the experiments. The air velocity from vent was measured using Anemometer and the response variables such as Temperature (t), Relative humidity (h) and Carbon dioxide (c) were recorded for 80 runs as per design matrix using IAQ probe as shown in Fig. 1.

Fig. 1. Experimental setup

b) Design of experiments

Design of experiments, or experimental design, is the design of all information-gathering exercises where variation is present, whether under the full control of the experimenter or not. Based on previous works reported in literature, the levels of input variables were confirmed. The assigned levels of input parameters are given in Table 1.

Table 1. Input Variables and their levels

Level	Human load (Nos.)	Fresh air supply (%)	Air velocity (m/s)
Very low	1	25	2
Low	2	50	4
Medium	3	75	6
High	4	100	8
Very high	5	-	-

As per full factorial Design of experiments, 80 sets of readings were recorded and they were grouped into five levels for developing multipurpose fuzzy model (Table 2).

Table 2. Output variables and their levels

Level	Carbon dioxide level (ppm)	Temperature (^{0}C)	Relative humidity (%)
Very low	up to 1000	up to 21.5	up to 52
Low	1001 to 1600	21.6 to 23	52.1 to 56
Medium	1601 to 2200	23.1 to 24.5	56.1 to 60
High	2201 to 2800	24.6 to 26	60.1 to 64
Very high	above 2800	above 26	above 64

c) Nonlinear regression analysis

In statistics, nonlinear regression is a form of regression analysis in which observational data are modeled by a function which is a nonlinear combination of the model parameters and depends on one or more independent variables. The relationship between the input parameters and the responses is given as

$$y_u = \varphi\,(x_{1u}, x_{2u}, \ldots, x_{ku}) + \varepsilon_u \tag{1}$$

where u=1, 2, 3, k and k represents the number in the factorial experiment. The term x_{iu} represents the level of the i^{th} factor in the u^{th} experiment. The function φ is called the response surface. The residual ε_u measures the experimental error in the u^{th} observation. The first order polynomials have the form:

$$y_u = \beta_0 + \beta_1 x_{1u} + \beta_2 x_{2u} + \cdots + \beta_k x_{ku} + \varepsilon_u \tag{2}$$

The second order polynomial, specifically known as the Quadratic response surface has 3−x variables, and takes the form:

$$y_u = \beta_0 + \beta_1 x_{1u} + \beta_2 x_{2u} + \beta_3 x_{3u} + \beta_{11} x_{1u}^{2} + \beta_{22} x_{2u}^{2} + \beta_{33} x_{3u}^{2} + \beta_{12} x_{1u} x_{2u} + \beta_{23} x_{2u} x_{3u} + \beta_{13} x_{3u} x_{1u} + \varepsilon_u \tag{3}$$

ε_u is a term that represents other sources of variability not accounted for. It includes measurement error on the response, other sources of variation that are inherent in the process or system and so on. Quadratic design models were selected based on better value of coefficient of correlation and F-test for all the responses in this study using statistical software.

d) Fuzzy logic algorithm

Fuzzy logic mimics the way humans make decisions using linguistic reasoning. It is based on mathematical theory combining multi-valued logic, probability theory and artificial intelligence methods and can be used to tackle complex problem. Mamdani FIS was used in this present investigation and the structure of the fuzzy logic system used in this present investigation is shown in Fig. 2.

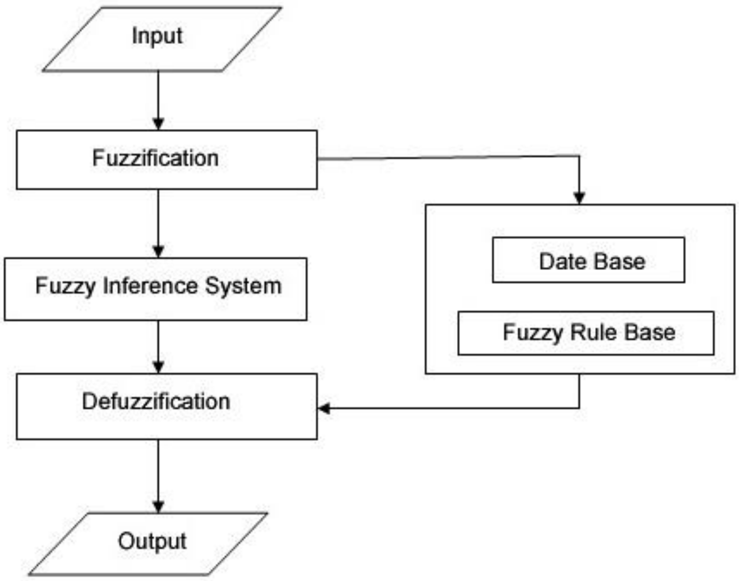

Fig. 2. Fuzzy model for IAQ parameters

The meaningful linguistic statements are selected for each variable and are expressed by appropriate fuzzy sets such as low, medium, and high. The concept of fuzzy reasoning for three-input–three-output multi response fuzzy logic model is described as follows. The fuzzy rule base consists of a group of IF–THEN statements with three inputs, x_1, x_2, and x_3 and three outputs y_1, y_2, and y_3,

Rule 1: if x_1 is A_1 and x_2 is B_1 and x_3 is C_1 then y_1 is P_1 and y_2 is Q_1 and y_3 is R_1
Rule 2: if x_1 is A_2 and x_2 is B_2 and x_3 is C_2 then y_1 is P_2 and y_2 is Q_2 and y_3 is R_2

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Rule n: if x_1 is A_n and x_2 is B_n and x_3 is C_n then y_1 is P_n and y_2 is Q_n and y_3 is R_n (4)

A_i, B_i and C_i are input membership functions for the fuzzy models whereas P_i, Q_i and R_i are output membership functions for the multi response fuzzy models. The triangular and trapezoidal membership functions were used for input and output conditions in fuzzy model. The generated membership function plots for input and out variables are shown in Figs. 3 and 4 respectively. The triangular membership function (trimf) is the simplest one formed by a collection of three points forming a triangle. The trapezoidal membership function (trapmf) is a truncated triangle formed by four points.

Fuzzy rule editor is used to construct 80 sets of rules based on the input and output variables defined with the FIS editor. By constructing these rules in Fuzzy model, the first three columns refer to the input variables and the remaining refer to the output variables. By these rules, Fuzzy Inference System is completely defined using variables, membership functions, and the rules necessary to calculate intermediate IAQ parameters are in place.

Fuzzy rule viewer gives whole fuzzy inference process and every row in rule viewer is formed by *if-then* rule as per the syntax. Every column represents a variable and the rule numbers are displayed adjacent to each row. Micro view of the Fuzzy interference system is given in the rule viewer, which shows each calculation in great detail. The surface viewer shows the entire output of the fuzzy system based on entire span of input set.

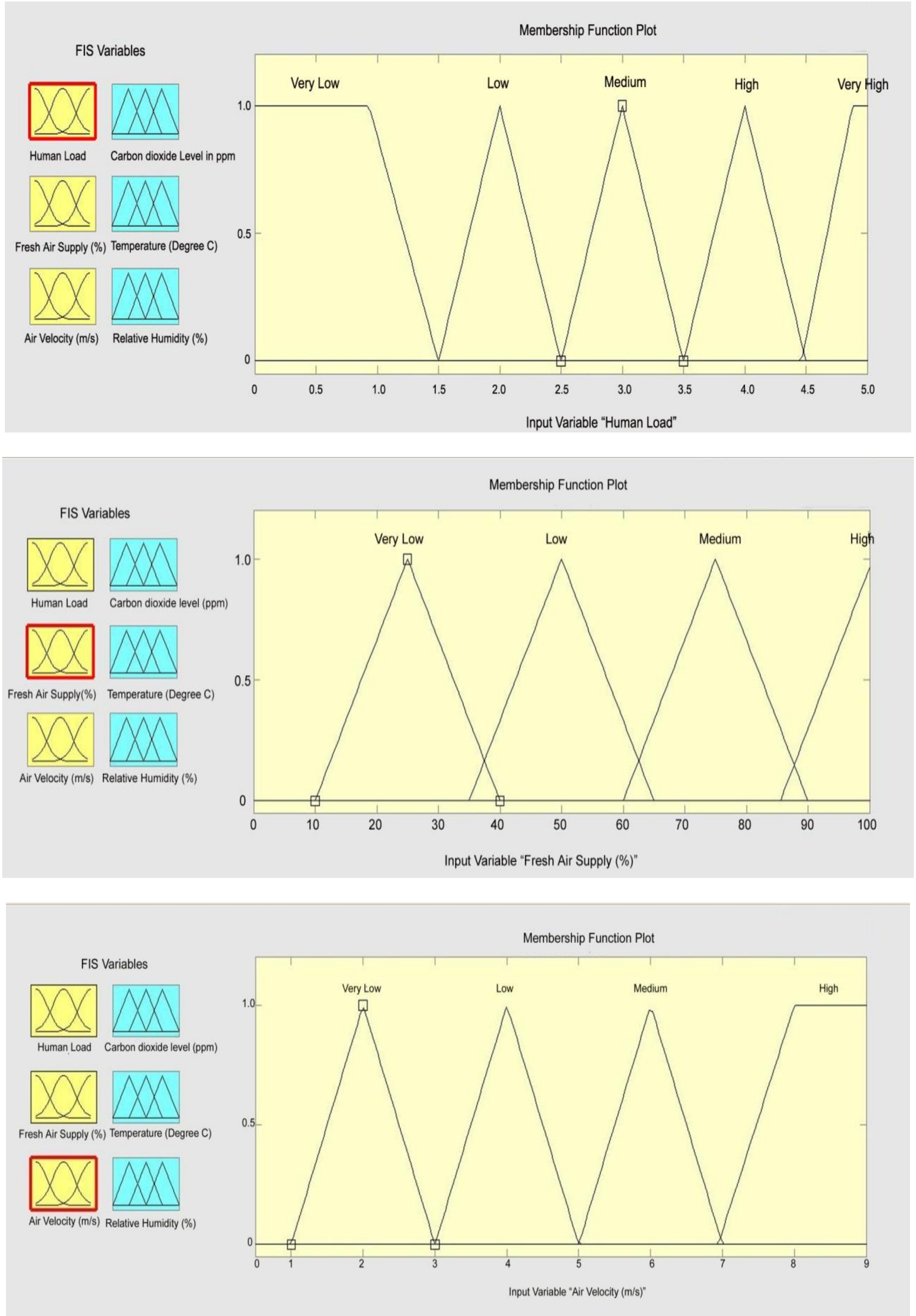

Fig. 3. Input parameters and their membership plots

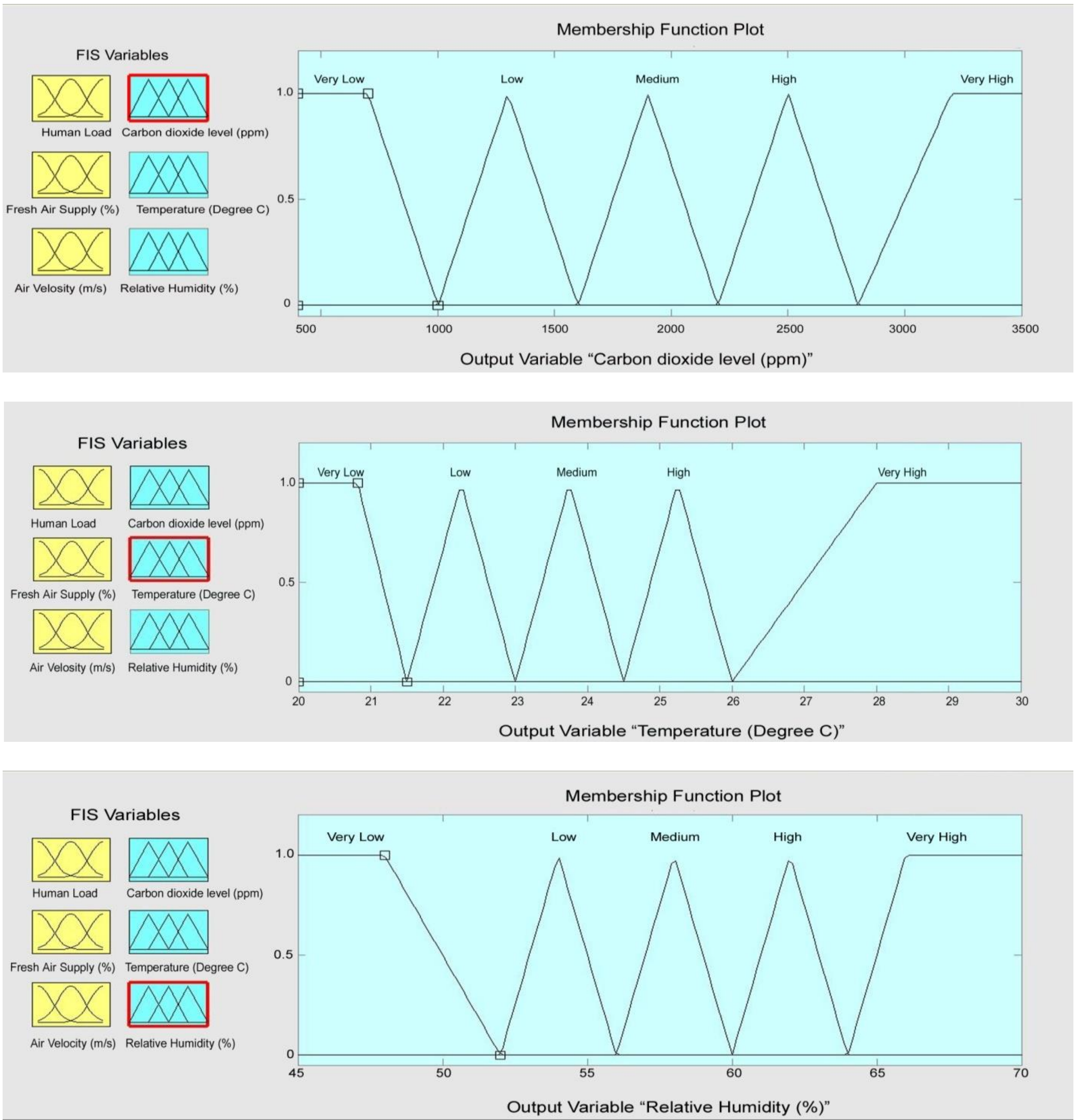

Fig. 4. Output parameters and their membership plots

3. RESULTS AND DISCUSSION

a) Prediction using NLRM

In statistics, the coefficient of determination, R^2, is the proportion of variability in a data set that is accounted for by the statistical model. The R^2 values of 0.90, 0.98 and 0.94 were obtained for Temperature, Relative humidity and Carbon dioxide level models respectively. The mathematical relationship for correlating the CO_2 level and the considered process variables is obtained from the coefficients resulting from the Design Expert 8 software output. The terms *l*, *s* and *v* are human load, Fresh air supply and Air Velocity respectively whereas *c*, *t* and *h* represent CO_2 level, Temperature and Relative Humidity respectively.

$$c = 1294.309+713.1889\,l-11.6435s-21.7709\,v-2.3997\,l\,s - 43.7519lv+1.5311\,sv-21.6889l^2+0.02244s^2+23.9105v^2 \quad (5)$$

The best model for the given set of data was suggested on the basis of fit summary (F-probability). The F-value was used to test the significance of adding new model terms to those terms already in the model. A small p-value (Probability > F) indicated that adding second order terms had improved the model. The mathematical relationship for correlating temperature and the considered process variables is obtained from the coefficients resulting from the Design Expert 8 software output:

$$t = 26.277 - 0.703l + 0.0197s - 0.5794v - 0.0003ls + 0.0206\,lv - 0.00063sv + 0.146l^2 - 0.00109s^2 + 0.00795\,v^2 \tag{6}$$

The mathematical relationship for correlating the relative humidity and the considered process variables is obtained from the coefficients resulting from the Design Expert 8 software output:

$$h = 46.705 + 0.1596l + 0.017045s + 1.2606\,v + 0.0003ls + 0.04371l\,v - 0.002133sv + 0.08022l^2 + 0.00012s^2 - 0.0255v^2 \tag{7}$$

b) Prediction using Fuzzy Logic

The input and output variables are fuzzified and represented by means of membership function. The output variables are grouped together for five levels each and 80 fuzzy rules were formulated (Table 3).Table 3. Fuzzy rules

Rule number	Human load	Fresh air supply	Air velocity	Carbon dioxide level	Temperature	Relative humidity
1	Very low	Very low	Very low	Very low	Medium	Very low
2	Very low	Very low	Low	Very low	Medium	Very low
3	Very low	Very low	Medium	Very low	Low	Low
4	Very low	Very low	High	Very low	Very low	Low
5	Very low	Low	Very low	Very low	High	Very low
6	Very low	Low	Low	Very low	Medium	Low
7	Very low	Low	Medium	Very low	Medium	Low
8	Very low	Low	High	Very low	Low	Medium
9	Very low	Medium	Very low	Very low	High	Very low
10	Very low	Medium	Low	Very low	High	Low
11	Very low	Medium	Medium	Very low	Medium	Low
12	Very low	Medium	High	Very low	Low	Medium
13	Very low	High	Very low	Very low	Very high	low
14	Very low	High	Low	Very low	High	low
15	Very low	High	Medium	Very low	Medium	Medium
16	Very low	High	High	Very low	Medium	Medium
17	Low	Very low	Very low	Very low	High	low
18	Low	Very low	Low	Very low	Medium	low
19	Low	Very low	Medium	Very low	Low	low
20	Low	Very low	High	Very low	Low	Medium
21	Low	Low	Very low	low	High	Very low
22	Low	Low	Low	low	Medium	Low
23	Low	Low	Medium	Very low	Low	Low
24	Low	Low	High	Very low	Low	Medium
25	Low	Medium	Very low	Very low	High	Very low
26	Low	Medium	Low	Very low	Medium	Low

Table 3 continued.

27	Low	Medium	Medium	Very low	Medium	Medium
28	Low	Medium	High	Very low	Low	Medium
29	Low	High	Very low	Very low	Medium	Low
30	Low	High	Low	Very low	Low	Low
31	Low	High	Medium	Very low	Low	Medium
32	Low	High	High	Very low	Very Low	Medium
33	Medium	Very Low	Very low	Medium	High	Very low
34	Medium	Very Low	Low	Low	High	Low
35	Medium	Very Low	Medium	Very low	Medium	Low
36	Medium	Very Low	High	Very low	Low	Medium
37	Medium	Low	Very low	Medium	High	Low
38	Medium	Low	Low	Low	Medium	Low
39	Medium	Low	Medium	Very low	Medium	Medium
40	Medium	Low	High	Very low	Low	High
41	Medium	Medium	Very low	Low	High	Low
42	Medium	Medium	Low	Low	Medium	Low
43	Medium	Medium	Medium	Very low	Medium	Medium
44	Medium	Medium	High	Low	Low	Medium
45	Medium	High	Very low	Low	Medium	Low
46	Medium	High	Low	Very low	Low	Medium
47	Medium	High	Medium	Very low	Low	Medium
48	Medium	High	High	Very low	Low	Medium
49	High	Very Low	Very low	Medium	Very High	Very Low
50	High	Very Low	Low	Medium	High	Low
51	High	Very Low	Medium	Low	High	Low
52	High	Very Low	High	Low	Medium	Medium
53	High	Low	Very low	High	High	Low
54	High	Low	Low	High	Medium	Low
55	High	Low	Medium	Low	High	Medium
56	High	Low	High	Very low	Medium	Medium
57	High	Medium	Very low	Medium	High	Low
58	High	Medium	Low	Low	Medium	Low
59	High	Medium	Medium	Very low	Medium	Medium
60	High	Medium	High	Very low	Low	Medium
61	High	High	Very low	Low	Very High	Medium
62	High	High	Low	Very low	High	Medium
63	High	High	Medium	Very low	High	Medium
64	High	High	High	Very low	Medium	Medium
65	Very high	Very Low	Very low	Very high	High	Low
66	Very high	Very Low	Low	Medium	Medium	Low
67	Very high	Very Low	Medium	Low	Medium	Medium
68	Very high	Very Low	High	Low	Low	Medium
69	Very high	Low	Very low	Medium	High	Low
70	Very high	Low	Low	Low	Medium	Medium
71	Very High	Low	Medium	Low	Medium	Medium
72	Very High	Low	High	Very low	Low	High
73	Very High	Medium	Very low	Medium	Very High	Low
74	Very High	Medium	Low	Low	High	Medium
75	Very High	Medium	Medium	Very low	Medium	Medium
76	Very High	Medium	High	Very low	Medium	High
77	Very High	High	Very low	Medium	Very High	Low
78	Very High	High	Low	Very low	High	Medium
79	Very High	High	Medium	Very low	Medium	Medium
80	Very High	High	High	Very low	Medium	High

The fuzzy decision will depend on the input values given to the system. The input variables and their current output values are displayed on top of each column. After training the fuzzy interference system, the effectiveness of fuzzy models was tested using confirmation experiments.

Six confirmation tests were conducted and experimental and predicted values using fuzzy model were compared. The fuzzy rule viewer for a confirmation test is shown in Fig. 6. For example, validation of the fuzzy system an experimental value (Human Load 2, Fresh Air Supply 100% and Air Velocity 4 m/s) was given and the nearer values to experimental results (Carbon dioxide level 628 ppm, Temperature 22°C and Relative Humidity 54%) was obtained as output.

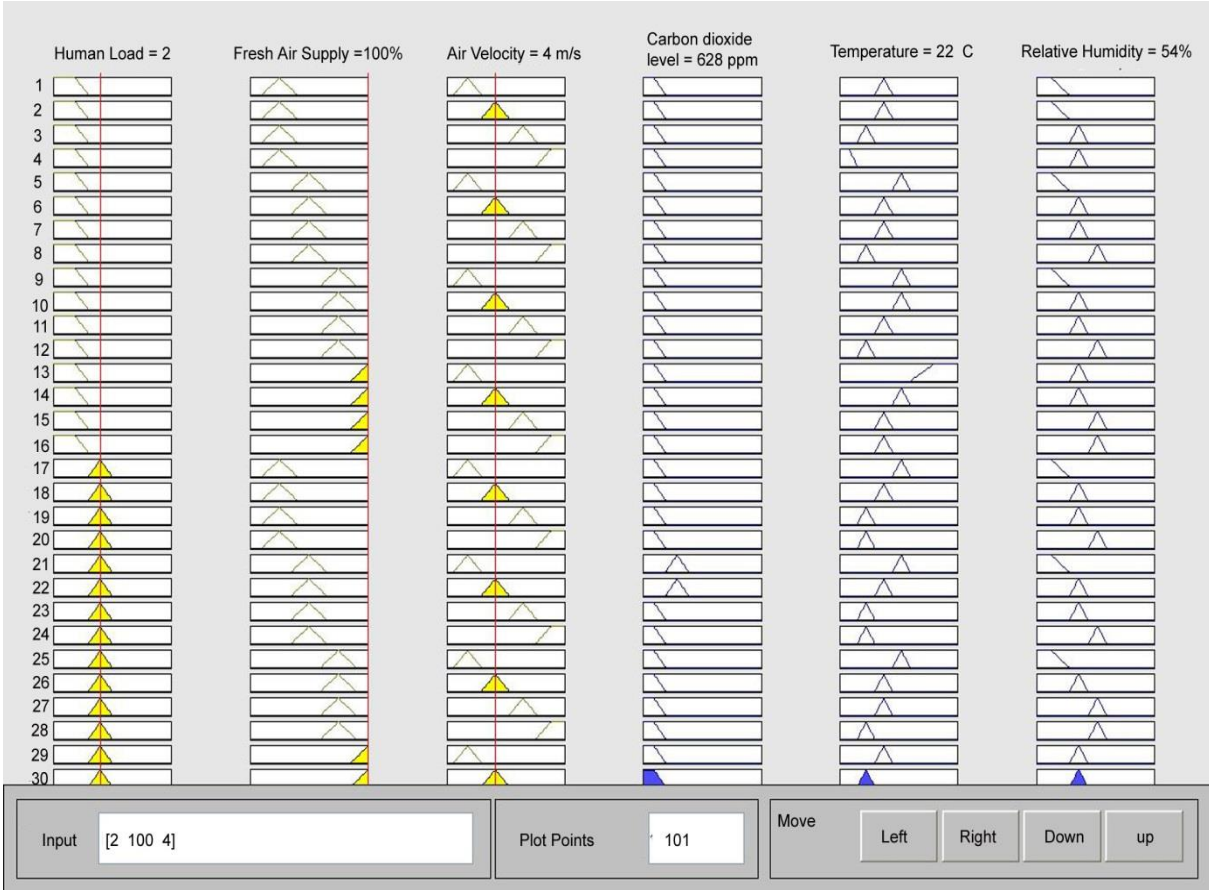

Fig. 6. Fuzzy rule viewer for IAQ parameters

Figure 7 shows the 3D fuzzy surface viewer for entire output values of Carbon dioxide level, Temperature and Relative Humidity against the combinations of Fresh air supply -Human load and Air velocity - Human load. The interaction effect of input parameters on the responses were studied with the help of surface plots.

The interaction effects of human load - fresh air supply, human load -air velocity on Temperature, Carbon dioxide level and Relative Humidity are shown in Fig. 7. The CO_2 level is directly related with human load because the polluted air is exhaled by the humans inside. The interaction plot shows the level of CO_2 can be brought down by increase in air velocity and fresh air supply.

The interaction effect for Temperature & Human load with various air velocity and fresh air supply shows the increase in the air velocity will improve the cooling rate and the thermal comfort can be achieved. But the amount of fresh air supply will have direct impact on the temperature. When fresh air supply is at 100%, the plot shows wide variations in the temperature plot which means the outdoor temperature is influenced the thermal comfort.

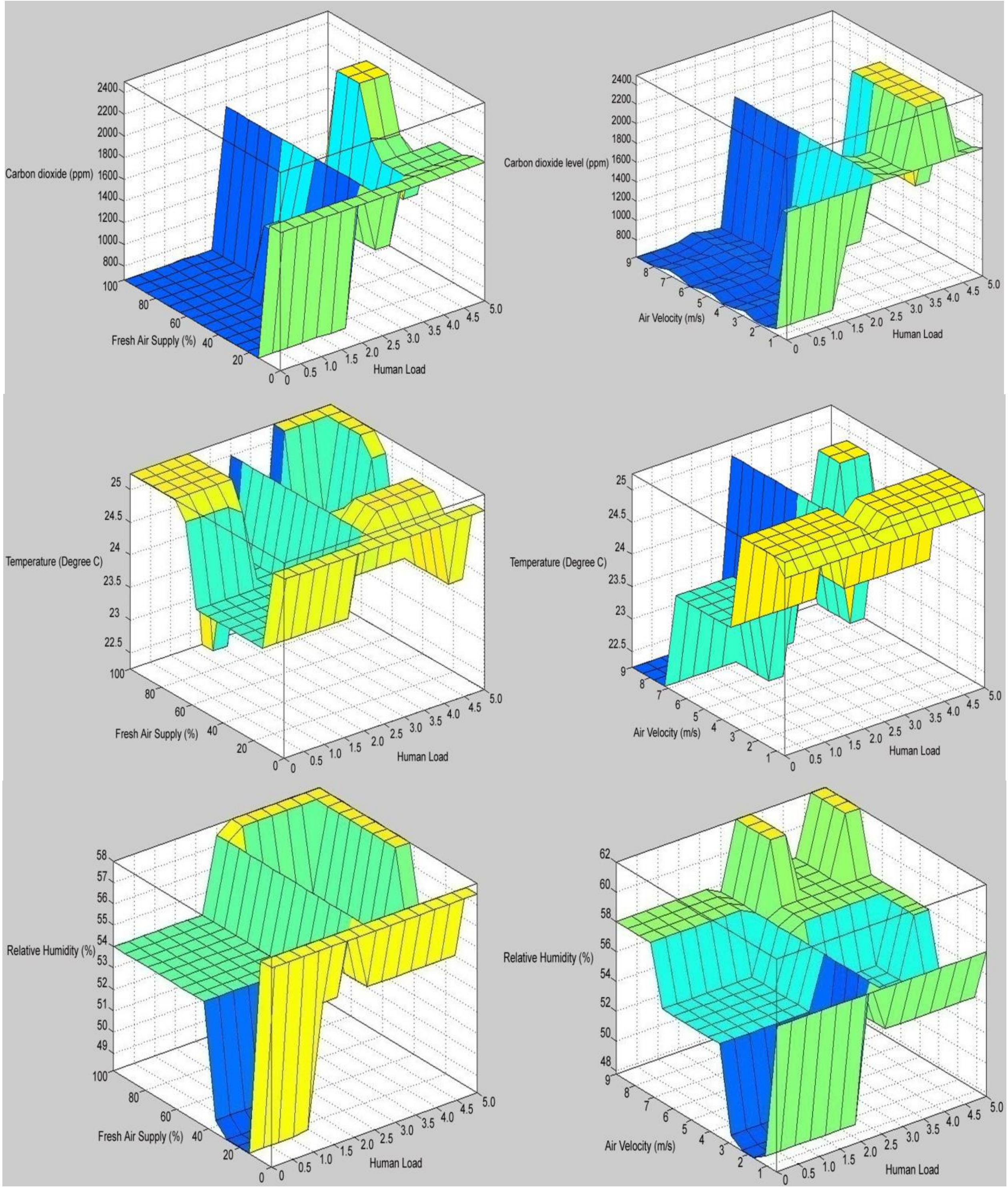

Fig. 7. Surface viewer for IAQ responses

c) Validation of Fuzzy models

Confirmation experiments were conducted for six sets of input conditions. The experimental values and the predicted values obtained from mathematical model and Fuzzy logic were compared (Table 4).

Table 4. Comparison of experimental results with predicted results

Run	Human load (Nos)	Fresh air supply (%)	Air velocity (m/s)	Experimental values			Predicted values using NLRM			Predicted values using fuzzy model		
				c	*t*	*h*	*c*	*t*	*h*	*c*	*t*	*h*
1	2	100	4	640.12	23	55	571.9	22.09	54.44	628	22	54
2	4	100	8	779.49	23.34	56.95	681.07	20.74	59.8	788	22.2	55.8
3	5	50	6	1195.29	23.38	57.88	1268.93	23.41	58.05	1177	22.8	56.3
4	2	100	4	622.56	22.95	55	571.9	22.09	54.44	648	23.4	56.2
5	3	100	8	754.97	23	55.83	709.7	20.29	58.69	766.8	22	54.5
6	4	100	8	781.71	23.64	57.92	681.07	20.74	59.8	798.3	22.5	56.6

$$\% \text{ of error} = (\text{Experimental value} - \text{Predicted value}) \times 100 / \text{Experimental value} \quad (8)$$

From the Table 5, it was observed that the average absolute error percentages for IAQ characteristics in nonlinear regression Model is as follows

Carbon dioxide level = 9.41 %,
Temperature = 7.17 %
Relative humidity = 2.62 %

The fuzzy model predicted with better accuracy compared with nonlinear regression models. The average absolute error percentages in Fuzzy model are as follows

Carbon dioxide level = 2.05 %,
Temperature = 3.81 %
Relative humidity = 2.24 %

Table 5. Comparison of Error Percentages

Run	Human load (Nos)	Fresh air supply (%)	Air velocity (m/s)	NLRM percentage of error			Fuzzy percentage of error		
				c	*t*	*h*	*c*	*t*	*h*
1	2	100	4	10.66	3.96	1.02	1.89	4.35	1.82
2	4	100	8	12.63	11.14	-5.00	-1.09	4.88	2.02
3	5	50	6	-6.16	-0.13	-0.29	1.53	2.48	2.73
4	2	100	4	8.14	3.75	1.02	-4.09	-1.96	-2.18
5	3	100	8	6.00	11.78	-5.12	-1.57	4.35	2.38
6	4	100	8	12.87	12.27	-3.25	-2.12	4.82	2.28
Average error percentage				9.41	7.17	2.62	2.05	3.81	2.24

The comparisons of experimental and predicted values of Carbon dioxide level, Temperature and Relative Humidity are shown in Figs. 8, 9 and 10, respectively. The accuracy of fuzzy prediction compared with NLRM (Non Linear Regression Model) prediction was studied using these validation plots.

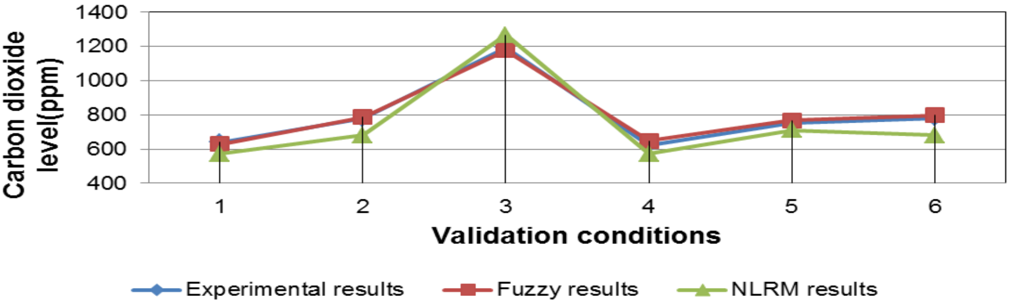

Fig. 8. Comparison of experimental and predicted values of Carbon dioxide level

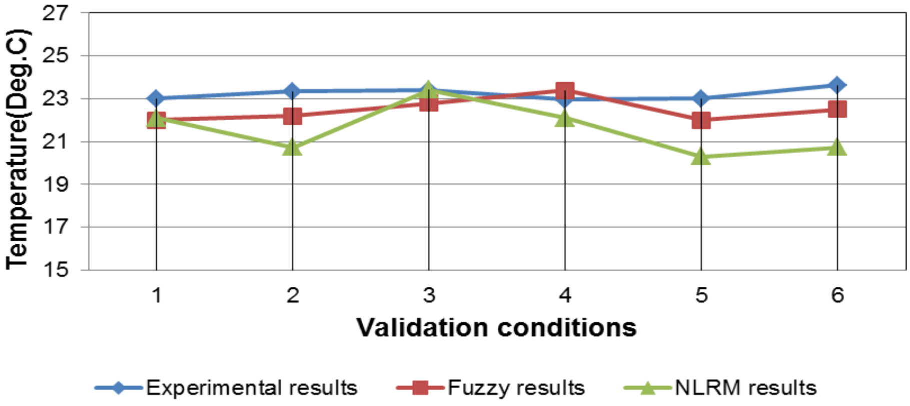

Fig. 9. Comparison of experimental and predicted values of Temperature

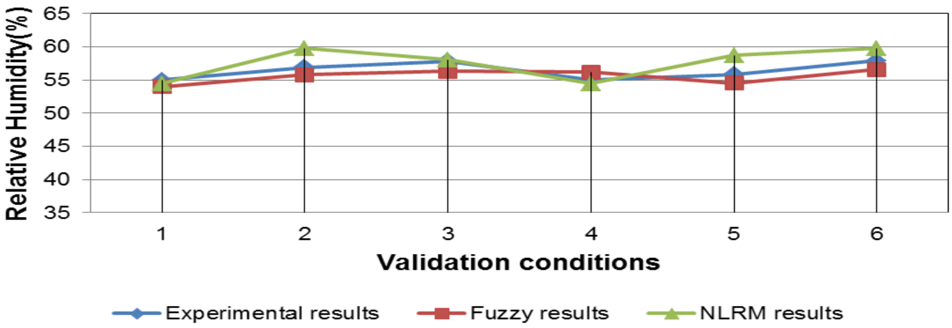

Fig. 10. Comparison of experimental and predicted values of Relative Humidity

4. CONCLUSION

The prediction of IAQ characteristics of an air conditioned car under varying human load, Fresh air opening and air velocity were studied using Fuzzy logic approach in this present investigation. The effect of input parameters on responses was studied and the relationship between input and output parameters was mathematically formulated by nonlinear regression analysis. The interaction effect of variables and their significance on outputs were studied using surface plots and systematic fuzzy model was developed to predict the responses in the specified range of conditions. Fuzzy logic predicted the IAQ characteristics accurately and the validation reported that the error percentage is below 4 % for all the models whereas the error percentage varies up to 9.4 % in NLRM.

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