



Experimental and Statistical Analysis of Indoor Air Quality Characteristics in an Air Conditioned Car

P. Thirumal*, **K.S. Amirthagadeswaran**** and **S. Jayabal*****

*Deptt. of Mechanical Engg., Government College of Engineering, Bargur-635 104, T.N., India (Corresponding Author)

**Deptt. of Mechanical Engg., Government College of Technology, Coimbatore- 641 013, T.N., India

***Deptt. of Mechanical Engg., A.C. College of Engineering & Technology, Karaikudi 630 004, T.N., India

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ABSTRACT

The present investigation was focused on the analysis of indoor air quality characteristics of an air conditioned car using statistical approach. 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 nonlinear regression models were developed to predict the comfort conditions namely temperature, CO₂ level and relative humidity over a specified range of input conditions in this investigation.

INTRODUCTION

The human comfort conditions were affected by various indoor air quality (IAQ) parameters in an air conditioned space. Du et al. (2008) stated 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 & Wan (2008) analysed the main influencing factors on IAQ of the air conditioning system and put forward some measures to improve indoor IAQ of modern building. Jayabal & Natarajan (2011) have used Response Surface Methodology (RSM) techniques for the modelling and optimization of performance characteristics of composites. Palanikumar (2009) presented a detailed procedure for mathematical modelling 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 Andrew & Mingyang (2009) and they applied soft computing techniques on IAQ prediction and optimization in the year of 2010 and 2011.

Andrew et al. (2010) simulated and demonstrated how much power can be saved by using the M-PSO method for carbon dioxide concentration control in a standard HVAC system. Andrew et al. (2011) have provided initiative ideas for the development of IAQ models. Based on the 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. (2009) 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 have shown that the energy saving potential of the VAV system was 27% at part load conditions, compared with the CAV system. Experimental results expressed that the required thermal comfort was achieved using FLC. Kolokotsa et al. (2009) worked on a bilinear model-based predictive control utilized in conjunction with BEMS, so as to achieve optimum indoor environmental conditions while minimizing energy costs. The bilinear modelling procedure is selected as it is the simplest extension of linear modelling and offers simplicity in the prediction algorithms' calculation procedure. The overall system predicts the indoor environmental conditions of a specific building and selects the most appropriate actions so as to reach the set points and contribute to the indoor environmental quality by minimizing energy costs.

Thermal comfort has a great influence on the productivity and satisfaction of indoor building occupants. The majority of heating, ventilation and air conditioning (HVAC) systems for thermal comfort are based either on a single temperature control loop or, in some cases, on a multivariable

temperature and relative humidity control loop. However, as far as thermal comfort optimization is concerned, other parameters should be considered in order to provide thermal satisfaction to the occupants. The interactions between people and the thermal environment are complex and have been the subject of much study; therefore, the science of thermal comfort is taking into account all these considerations. Roberto et al. (2008) 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. The first set of strategies is related to the thermal comfort optimization and the second one includes energy consumption minimization, while maintaining the indoor thermal comfort criterion at an adequate level. The methods are based on the model predictive control scheme and simulation results are presented.

HVAC systems are equipments usually implemented for maintaining satisfactory comfort conditions in buildings. The energy consumption as well as indoor comfort aspects of ventilated and air conditioned buildings are highly dependent on the design, performance and control of their HVAC systems and equipments. Wright & Zhang (2008) worked on experimental results for the optimization of a two-zone HVAC system of a building located in a continental climate. The indoor pollutants created by the human beings and the rate of ventilation required to dilute the pollutant levels to meet ASHRAE standards was discussed in our previous work (Thirumal et al. 2010).

Based on the previous literature, it is observed that Non Linear Regression Models (NLRM) can be used to predict the intermediate responses based on varying human load. The focus of this paper is further extended to study the CO₂ level inside the car, rate of fresh air supply and air velocity required to maintain the comfort conditions inside the passenger car.

MATERIALS AND METHODS

Experimental setup: A common passenger car with an air conditioning facility was selected to conduct the indoor air quality assessment. The vehicle is selected in such a way that the controls to vary fan speed and fresh air vent opening are available. The maximum seating capacity of the car is five. An IAQ probe with sensors was used to record the responses. Dual Channel NDIR sensor with a measuring range of 0 to 5000 ppm was used to record CO₂ level. LM35 precision Centigrade temperature sensor was used for measuring indoor temperature, and HIH-4010 humidity sensor was used for relative humidity. The sensors were calibrated before



Fig.1: Block diagram of experimental setup.

conducting the experiments and all the sensors were housed in IAQ probe as shown in Fig. 1. 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.

Assumptions: The following assumptions were made for the controlled environment inside the vehicle.

- When the doors of the vehicle are closed, the leakage is negligible.
- The CO₂ emission, Dubois's surface area of human and oxygen consumption rate per person are constant.
- There are no volatile organic component emissions inside the vehicle.
- The inside controlled environment is allowed to attain equilibrium with outdoor conditions before starting the experiment.
- Other pollutants like pollen, dander and suspended particles are not considered.
- The conditioned space is free from tobacco smoke, dust and other foreign particles.
- Air velocity will change with respect to engine rpm and supply current rating to the fan motor. Hence, average speeds were fixed as 2, 4, 6 and 8m/s.

Experimental conditions: The experimental condition levels were determined by user defined experimental design. In the current work human load can be varied from 1-5. But fresh air supply (%) and air velocity (m/s) can be varied in 4 levels. Hence, 80 combinations can be derived.

Statistical analysis: Statistics is the study of the collection, organization, analysis and interpretation of data. ANOVA is a collection of statistical models and their associated procedures, in which the observed variance is partitioned into components due to different explanatory variables. Degrees of freedom are used to describe the number of values in the final calculation of a statistic that are free to vary. Estimates of statistical parameters were based on different amounts of information or data. The number of independent pieces of information that go into the estimation of a parameter is called the degrees of freedom. The mean squared error or MSE of an estimator is one of many ways to quantify the amount by

which an estimator differs from the true value of the quantity being estimated. As a loss function, MSE is called squared error loss. MSE measures the average of the square of the 'error'. The error is the amount by which the estimator differs from the quantity to be estimated. The difference occurs because of randomness or because the estimator does not account for information that could produce a more accurate estimate. Mathematically, degrees of freedom are the dimension of the domain of a random vector, or essentially the number of 'free' components: how many components need to be known before the vector is fully determined. This design consisted of three factors, each at three levels.

RESULTS AND DISCUSSION

Effect of input parameters: The recorded response readings at 80 different input settings as per design of experiments for CO₂ level, temperature and relative humidity are shown in Figs. 2, 3 and 4 respectively. The maximum CO₂ level of 3353.45 ppm occurs at full load condition with air velocity of 2m/s and fresh air vent opening of 25%. The minimum level of 439.77 ppm is recorded for minimal load of single person with full fresh air vent opening and air velocity of 6m/s. ASHRAE recommends that the air conditioned spaced to be maintained at 23°C and 55% RH for thermal comfort. The temperature and relative humidity variations are within the acceptable limits to maintain thermal comfort inside the air conditioned car in this investigation.

Prediction using NLRM: In statistics, the coefficient of determination, R² is the proportion of variability in a data set that is accounted for by the statistical model. It provided a measure of how well future outcomes are likely to be predicted by the model. The R² values of 0.90, 0.98 and 0.94 were obtained for temperature, relative humidity and carbon dioxide level models respectively.

Mathematical model of CO₂ concentration level: The mathematical relationship for correlating the CO₂ 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* represents CO₂ level, temperature and relative humidity respectively.

$$c = 1294.309 + 713.1889l - 11.6435s - 21.7709v - 2.3997ls - 43.7519lv + 1.5311sv - 21.6889l^2 + 0.02244s^2 + 23.9105v^2 \dots (1)$$

Mathematical model of temperature: 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 one of the responses

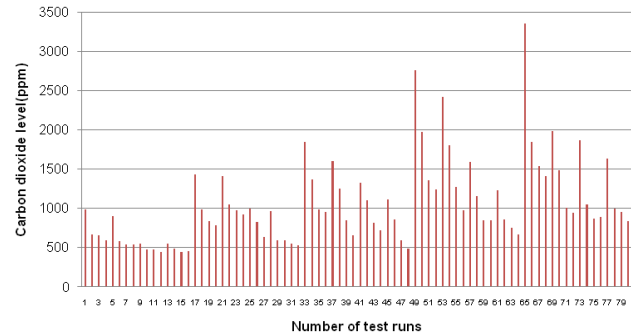


Fig. 2: Influence of input conditions on carbon dioxide level.

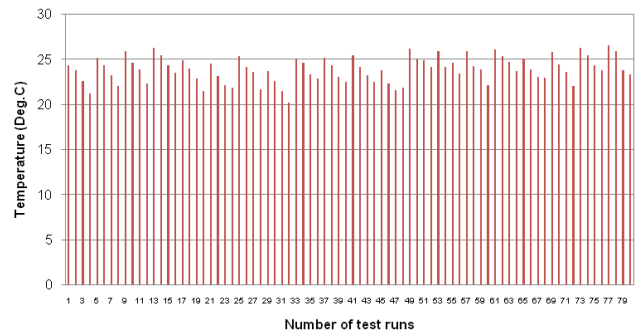


Fig.3: Influence of input conditions on temperature.

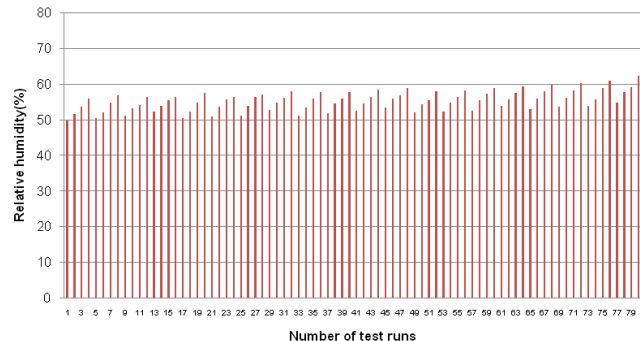


Fig. 4: Influence of input conditions on relative humidity.

temperature and the considered process variables were obtained from the coefficients resulting from the Design Expert 8 software output.

$$t = 26.277 - 0.703l + 0.0197s - 0.5794v - 0.0003ls + 0.0206lv - 0.00063sv + 0.146l^2 - 0.00109s^2 + 0.00795v^2 \dots (2)$$

Mathematical model of relative humidity: The best model for the given set of data was suggested on the basis of fit summary and the better value of coefficient of correlation. 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.

Table 1: Experimental results.

Runs	Human load	Fresh air supply (%)	Air velocity (m/s)	CO ₂ level (ppm)	Temperature (°C)	Relative humidity (%)
1	1	25	2	979.33	24.37	49.68
2	1	25	4	669.36	23.77	51.52
3	1	25	6	652.98	22.59	53.67
4	1	25	8	596.32	21.20	55.81
5	1	50	2	899.43	25.15	50.32
6	1	50	4	583.13	24.35	52.09
7	1	50	6	542.00	23.21	54.81
8	1	50	8	537.87	22.02	56.82
9	1	75	2	551.23	25.91	51.08
10	1	75	4	473.90	24.64	53.17
11	1	75	6	469.45	23.83	54.14
12	1	75	8	447.22	22.27	56.41
13	1	100	2	551.13	26.28	52.31
14	1	100	4	480.93	25.42	53.75
15	1	100	6	439.77	24.33	55.42
16	1	100	8	455.11	23.46	56.35
17	2	25	2	1432.32	24.88	50.38
18	2	25	4	979.74	23.97	52.35
19	2	25	6	835.84	22.83	54.68
20	2	25	8	787.00	21.50	57.50
21	2	50	2	1406.00	24.50	50.94
22	2	50	4	1049.35	23.16	53.59
23	2	50	6	978.36	22.11	55.62
24	2	50	8	925.55	21.88	56.47
25	2	75	2	999.02	25.38	51.15
26	2	75	4	822.38	24.12	53.88
27	2	75	6	635.56	23.56	56.26
28	2	75	8	958.64	21.68	57.06
29	2	100	2	588.00	23.65	52.61
30	2	100	4	589.24	22.59	54.70
31	2	100	6	553.25	21.50	56.23
32	2	100	8	528.37	20.16	57.86
33	3	25	2	1845.00	25.08	51.05
34	3	25	4	1369.43	24.56	53.50
35	3	25	6	980.11	23.34	55.85
36	3	25	8	949.06	22.83	57.76
37	3	50	2	1605.2	25.16	51.79

Table cont....

...Table cont.

38	3	50	4	1255.35	24.36	54.60
39	3	50	6	842.47	23.03	55.90
40	3	50	8	656.50	22.48	57.68
41	3	75	2	1324.71	25.39	52.42
42	3	75	4	1100.00	24.10	54.58
43	3	75	6	815.76	23.22	56.32
44	3	75	8	720.15	22.48	58.35
45	3	100	2	1107.12	23.81	53.32
46	3	100	4	853.48	22.35	55.92
47	3	100	6	592.98	21.61	56.90
48	3	100	8	489.35	21.85	58.85
49	4	25	2	2756.67	26.21	51.95
50	4	25	4	1970.66	25.05	54.20
51	4	25	6	1357.61	24.85	55.37
52	4	25	8	1237.8	24.10	57.90
53	4	50	2	2421.87	25.87	52.18
54	4	50	4	1798.90	24.11	54.80
55	4	50	6	1267.92	24.64	56.47
56	4	50	8	973.86	23.44	58.14
57	4	75	2	1588.99	25.90	52.41
58	4	75	4	1154.35	24.22	55.42
59	4	75	6	848.60	23.89	57.17
60	4	75	8	841.88	22.09	58.81
61	4	100	2	1232.58	26.04	53.91
62	4	100	4	855.25	25.38	55.75
63	4	100	6	751.75	24.70	57.42
64	4	100	8	666.90	23.71	59.35
65	5	25	2	3353.45	25.03	52.99
66	5	25	4	1847.28	23.85	55.93
67	5	25	6	1538.00	23.02	57.88
68	5	25	8	1406.90	22.92	59.81
69	5	50	2	1985.00	25.80	53.53
70	5	50	4	1485.70	24.42	56.21
71	5	50	6	1001.19	23.62	58.08
72	5	50	8	943.06	22.02	60.18
73	5	75	2	1862.68	26.22	53.93
74	5	75	4	1050.47	25.44	55.57
75	5	75	6	869.50	24.37	58.88
76	5	75	8	883.64	23.79	60.95
77	5	100	2	1630.20	26.57	54.86
78	5	100	4	998.07	25.89	57.64
79	5	100	6	952.00	23.82	59.02
80	5	100	8	838.32	23.28	62.23

$$h = 46.705 + 0.1596l + 0.017045s + 1.2606v + 0.0003ls + 0.0437lv - 0.002133sv + 0.08022l^2 + 0.00012s^2 - 0.0255v^2 \quad \dots(3)$$

ANALYSIS OF VARIANCE (ANOVA)

ANOVA for CO₂ model: The ANOVA for carbon dioxide model is listed in Table 2. The model F-value of 84.00749 implied that the model was significant. In this case *l*, *s*, *v* have the individual significant effect on the model. However the interaction effects of *l-s*, *l-v*, *s-v* and the second order effect of *v*² were also significant.

ANOVA for temperature model: The ANOVA for temperature model is listed in Table 3. The model F-value of

17.41535 implied that the model was significant. There was only < 0.0001 chance that a ‘model F-value’ this large could occur. Values of ‘Probability > F’ less than 0.0500 indicated that the model terms were significant. In this case *l*, *v* has the individual significant effect on the model and second order effect of *l*² is also significant.

ANOVA for relative humidity model: The ANOVA for relative humidity model is listed in Table 4. The model F-value of 317.0236 implied that the model was significant. In this case *l*, *s*, *v* have the individual significant effect on the model. The interaction effects of *l-v*, *s-v* and the second order effect of *l*² were also significant.

Table 2: ANOVA for carbon dioxide model.

Source	Sum of Squares	Degrees of Freedom	Mean Square	F Value	P-Value Prob>F	Remarks
Model	21168361	9	2352040	84.00749	< 0.0001	Significant
<i>l</i>	7348594	1	7348594	262.4687	< 0.0001	
<i>s</i>	4391908	1	4391908	156.8652	< 0.0001	
<i>v</i>	5591135	1	5591135	199.6978	< 0.0001	
<i>l-s</i>	719864.9	1	719864.9	25.71131	< 0.0001	
<i>l-v</i>	1531383	1	1531383	54.69621	< 0.0001	
<i>s-v</i>	732582.1	1	732582.1	26.16553	< 0.0001	
<i>l²</i>	105371.9	1	105371.9	3.763555	0.0564	
<i>s²</i>	15730.97	1	15730.97	0.561861	0.4560	
<i>v²</i>	731791.6	1	731791.6	26.1373	< 0.0001	
Residual	1959859	70	27997.98			
Corrected Total	23128220	79				

Table 3: ANOVA for Temperature model.

Source	Sum of Squares	Degrees of Freedom	Mean Square	F Value	P-Value Prob>F	Remarks
Model	108.5361	9	12.05957	17.41535	< 0.0001	Significant
<i>l</i>	10.63528	1	10.63528	15.35853	0.0002	
<i>s</i>	0.181945	1	0.181945	0.262749	0.6099	
<i>v</i>	91.98632	1	91.98632	132.8385	< 0.0001	
<i>l-s</i>	0.012633	1	0.012633	0.018243	0.8929	
<i>l-v</i>	0.339117	1	0.339117	0.489723	0.4864	
<i>s-v</i>	0.137332	1	0.137332	0.198323	0.6575	
<i>l²</i>	4.787933	1	4.787933	6.914307	0.0105	
<i>s²</i>	0.374695	1	0.374695	0.541102	0.4644	
<i>v²</i>	0.080836	1	0.080836	0.116736	0.7336	
Residual	48.47273	70	0.692468			
Corrected Total	157.0088	79				

Table 4: ANOVA for relative humidity model.

Source	Sum of Squares	Degrees of Freedom	Mean Square	F Value	P-Value Prob>F	Remarks
Model	563.1875	9	62.57639	317.0236	< 0.0001	Significant
<i>l</i>	123.6401	1	123.6401	626.3839	< 0.0001	
<i>s</i>	31.1364	1	31.1364	157.7428	< 0.0001	
<i>v</i>	402.7246	1	402.7246	2040.278	< 0.0001	
<i>l-s</i>	0.012246	1	0.012246	0.062041	0.8040	
<i>l-v</i>	1.528626	1	1.528626	7.744304	0.0069	
<i>s-v</i>	1.421511	1	1.421511	7.20164	0.0091	
<i>l²</i>	1.441611	1	1.441611	7.30347	0.0086	
<i>s²</i>	0.45000	1	0.45000	2.279784	0.1356	
<i>v²</i>	0.83232	1	0.83232	4.216688	0.0438	
Residual	13.8171	70	0.197387			
Corrected Total	577.0046	79				

INTERACTION AND TREND ANALYSIS PLOTS

The generated interaction and trend plot of CO₂ level, temperature and relative humidity for varying human load, fresh air supply and air velocity are shown in Figs. 5 and 6 respectively. When the effect of one factor depends on the level of

other factor, interaction plot is used to visualize possible interactions. The interaction effect of human load-fresh air supply, human load-air velocity and fresh air supply-air velocity on CO₂ level, temperature and relative humidity were studied using these plots. Trend analysis plot evaluates patterns and behaviour in data over experimental range and dis-

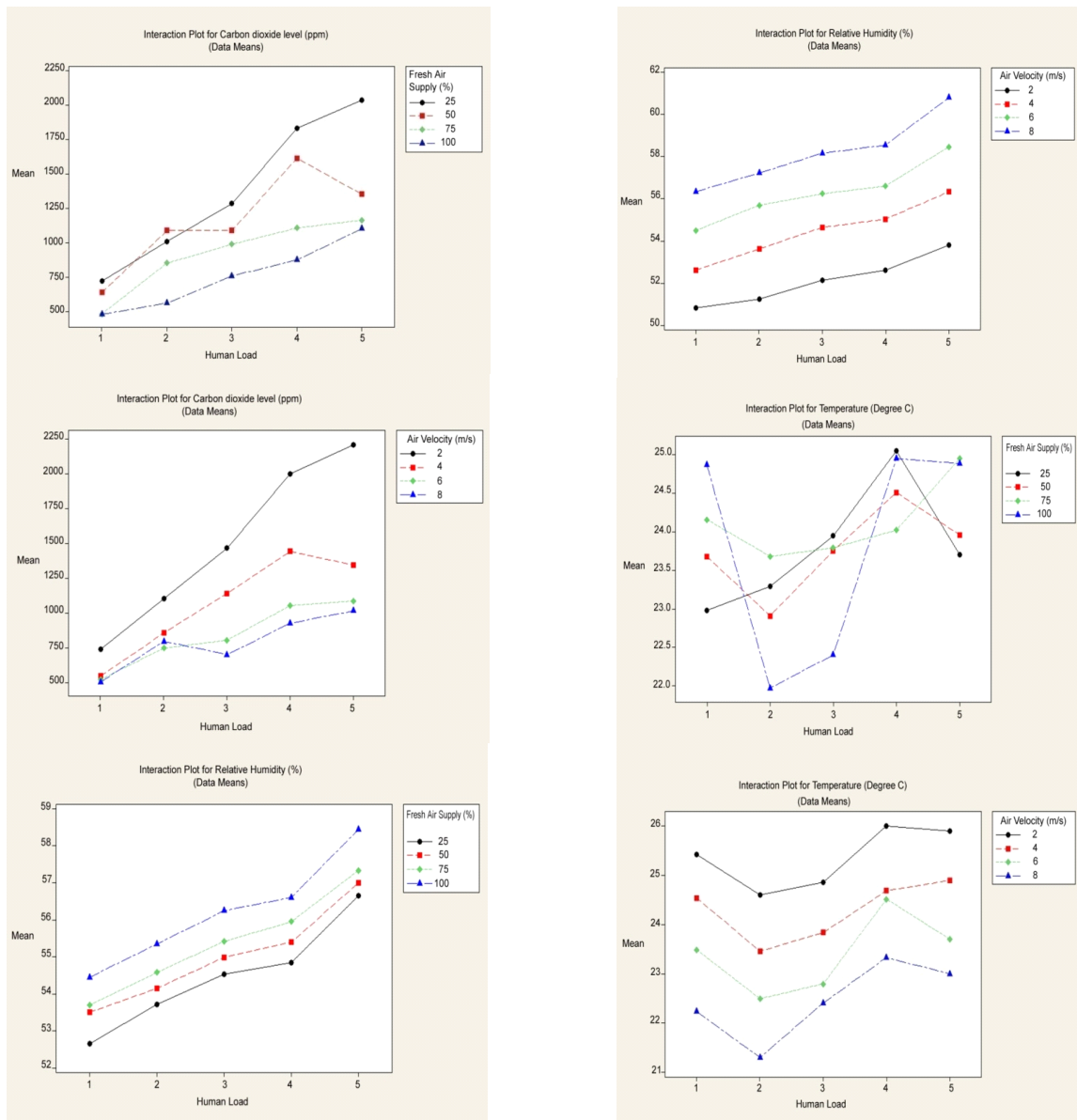


Fig. 5: Interaction plots of IAQ responses.

Table 5: Validation of regression models.

Run	Human load (Nos.)	Fresh air supply (%)	Air velocity (m/s)	Experimental values			Predicted values using NLRM			Percentage of Error			
				<i>c</i>	<i>t</i>	<i>h</i>	<i>c</i>	<i>t</i>	<i>h</i>	<i>c</i>	<i>t</i>	<i>h</i>	
1	2	100	4	640.12	23.00	55.00	571.90	22.09	54.44	10.66	3.97	1.02	
2	4	100	8	779.49	23.34	56.95	681.07	20.74	59.80	12.63	11.12	-5.00	
3	5	50	6	1195.29	23.38	57.88	1268.93	23.41	58.05	-6.16	-0.14	-0.29	
4	2	100	4	622.56	22.95	55.00	571.90	22.09	54.44	8.14	3.76	1.02	
5	3	100	8	754.97	23.00	55.83	709.70	20.29	58.69	6.00	11.78	-5.14	
6	4	100	8	781.71	23.64	57.92	681.07	20.74	59.80	12.87	12.25	-3.25	
Average Absolute Error Percentage									9.41	7.17	2.62		

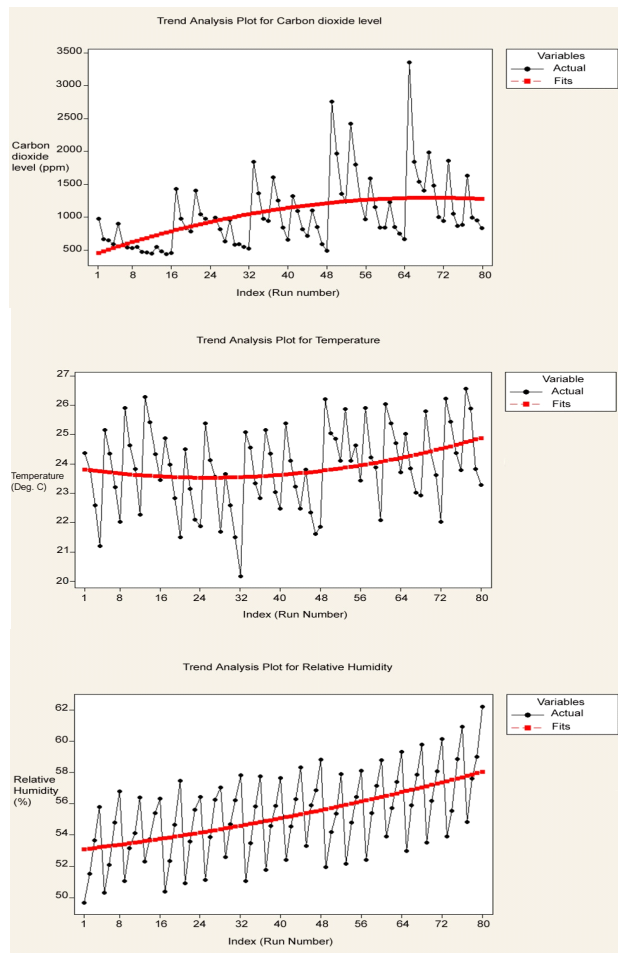


Fig. 6: Trend analysis plots for IAQ responses.

plays observation of responses against equally spaced input set points in x axis. In trend analysis and the experimental variables were represented using black dots and lines and average fit was represented using red lines.

COMPARISON OF EXPERIMENTAL AND PREDICTED VALUES

Confirmation experiments were conducted for six set of conditions. The experimental values and the predicted values obtained from mathematical model were compared. The percentage of error was calculated using the following formula for the validation of mathematical model.

$$\% \text{ of error} = \frac{(\text{Experimental value} - \text{Predicted value}) \times 100}{\text{Experimental value}} \quad \dots(4)$$

From the Table 5, it was observed that the average absolute error for Carbon dioxide level = 9.41%, temperature = 7.17% and relative humidity = 2.62% and better accuracy was obtained using the developed mathematical models.

CONCLUSION

The comfort conditions of an air conditioned car under varying human load, fresh air opening and air velocity were studied using statistical approach in the 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 was studied using ANOVA tables, interaction and trend analysis plots. The developed non linear regression models predicted the comfort conditions accurately and the validation reported that the error percentage is within 10% for all the models.

NOMENCLATURE

ANOVA	-	Analysis of Variance
ASHRAE	-	American Society of Heating Refrigeration and Air Conditioning Engineers
HVAC	-	Heating Ventilation Air Conditioning
MSE	-	Mean Square Error
IAQ	-	Indoor Air Quality
NDIR	-	Non Dispersive Infrared Sensor
t	-	Temperature ($^{\circ}\text{C}$)
l	-	Human Load
h	-	Relative Humidity (%)
s	-	Fresh Air Supply (%)
c	-	Carbon Dioxide Level (ppm)
v	-	Air Velocity (m/s)

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