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Optimization of in-Vehicle Carbon Dioxide Level in a 5-Seat Car

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The air quality in a car's cabin can be five times worse than that of residential and non-residential buildings, resulting in a variety of health issues, such as headache, sore throat, and nausea, which are all symptoms of in-vehicle air pollution. The monitoring of carbon dioxide, which is one of the principal pollutants in car cabins, is required before regulating it. The current research is focused on the recording of carbon dioxide levels for different levels of human load, air speed, and temperature. A statistical analysis and plots were obtained for recorded responses to determine air quality parameters for a minimum value of carbon dioxide level in a five-seat car cabin. Three algorithms (generalized reduced gradient (GRG), response surface methodology (RSM), and genetic algorithm (GA)) were successfully used in a 5-seat car to optimize the in-vehicle carbon dioxide level. The GRG method provided the minimum carbon dioxide level of 471.531 ppm for a one-human load at an air speed of 2 m/s and a temperature of 24 °C. For varying human loads of 2,3,4, and 5, the GRG and GA methods provided carbon dioxide levels of 508.785 ppm, 580.722 ppm, 659.839 ppm and 769.016 ppm, respectively. Comparing all three techniques, the RSM provided carbon dioxide levels of 471.876 ppm, 508.865 ppm, 580.79 ppm, 659.905 ppm, and 769.362 ppm for human loads of 1, 2, 3, 4, and 5, respectively. This study will provide a platform for the researchers working on indoor air quality characteristics to apply soft computing techniques effectively for the evaluation of comfortable healthy environments and for the benefit of the passengers in car cabins.
Keywords: carbon dioxide, five-seat car, genetic algorithm, in-vehicle air quality, response surface methodology

Highlights
- *Carbon dioxide level for varying human loads, air speeds, and temperatures in a 5-seat car are studied.*
- *Influence of air quality parameter on response is studied with the help of ANOVA and statistical plots.*
- *Statistical analysis and regression equation are developed for the prediction of carbon dioxide levels.*
- *Air quality characteristics for minimum values of response are obtained through familiar optimization algorithms.*

0 INTRODUCTION

Human beings spend almost 80 % to 90 % of their time in confined spaces [1], such as houses, workplaces, classrooms, shopping malls, and theatres, as well as vehicles like cars. As a result, the indoor air quality (IAQ) of living spaces has become a matter of concern. The in-vehicle air quality (IVAQ) of automobiles, where pollution levels are much higher than the living indoor environments [2] to [4] is one such occupied space that has not been studied. The need for optimal indoor environmental quality (IEQ) is especially vital in all living and working places with vulnerable populations [5]. This is an area that needs to be seriously researched and studied to ensure better in-vehicle air quality for the passengers. Particulate matter (PM), carbon dioxide (CO_2), carbon monoxide (CO), volatile organic compounds (VOCs), and other pollutants impair the IVAQ of the cabins. People employ varying degrees of temperature, velocity, and air-circulation modes for their preferences while commuting in a car with an air-conditioning system, without realizing the deleterious repercussions of those settings. The levels of pollutant concentration have higher values in indoor environments that use mechanical ventilation compared to natural ventilation [6]. These factors may lead to an increase in PM, the particle-health correlation has been thoroughly investigated and found to be both valid and confirmatory [7]. The carbon dioxide concentrations within inhabited living spaces are more than such concentrations outdoors, as people generate and exhale CO_2.

The levels of the indoor-outdoor CO_2 concentration differential grow as the ventilation rate (i.e., supply of fresh air into the house) per individual reduces [8], As a result of the limited and closed aspect of public transit, contaminants accumulate and lead to rises in concentrations [9]. There is no major change in indoor CO_2 levels with changes in the average outdoor temperature [10]. There are a few factors that lead to the increase in cabin CO_2 levels. Various ventilation fan speeds may lead to variations in cabin CO_2 concentrations [11]. The month of the year when testing is being conducted will also have a significant impact on CO_2 levels in vehicles [12]. When the mode of travel is a subway rather than normal open roads the concentration levels will be high [13]. The CO_2 that the inhabitants breathe enters their bloodstream and creates respiratory problems, harms their health, and even leads to premature deaths [14] and [15]. This not only affects human health; it also triggers nutrition imbalances in plants that are exposed to higher levels of CO_2 [16]. As the amount of CO_2 inside the vehicle

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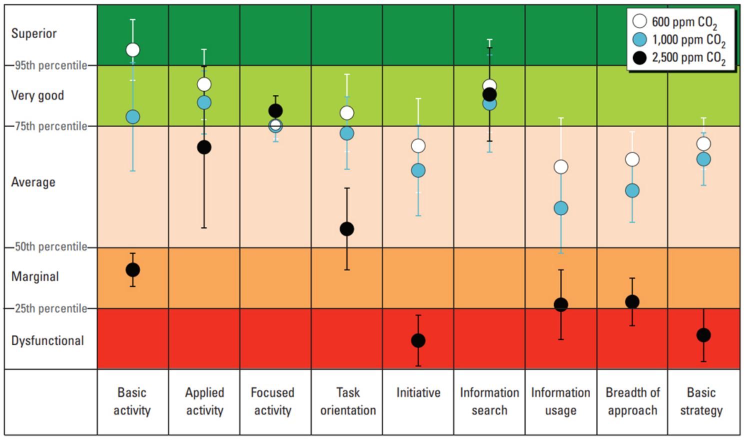

Fig. 1. *CO_2's effect on human decision-making*

cabin rises, so does the danger of an accident caused by the driver's tiredness and reduced agility [17]. Fig. 1 sourced from the research article documented by Satish et al. [18] shows the influence of the increase in CO_2 levels in human decision making.

CO_2 is a widely used and practical metric for determining air quality [19]. As of September 2021 [20], the worldwide average ambient CO_2 concentration level was at 413.30 ppm. The permissible amounts of CO_2 in air-conditioned space for human beings are defined by ASHRAE Standard-62 [21]. According to ASHRAE (American Society of Heating, Refrigerating, and Air-Conditioning Engineers), the maximum CO_2 level limit is 700 ppm over ambient surroundings continuously. Even though the value does not apply to CO_2 levels inside cars, it is still significant because a car is a confined space. In comparison to other small environments, automobile exposure is more difficult to comprehend because it is influenced by several interconnected factors, such as ventilation, motorway type, vehicle type, and self-pollution [22].

Many strategies are used to improve the IAQ for the inhabitants, and many researchers [23] and [24] have sought to optimise heating, ventilation, and air-conditioning (HVAC) systems for indoor conditions. Researchers have proved that productivity has a significant relationship with indoor air quality [25]. Different monitoring techniques should be applied for natural and mechanical ventilation, as both have different characteristics [26]. Prior research in IVAQ optimization has been documented, but the optimization of input parameters for the vehicle cabin to minimize CO_2 levels concerning occupants in a subcompact car is very limited. In this article, algorithms were used for optimization.

1 EXPERIMENTS

1.1 Air Quality Parameters and their Characteristics

In the modelling process, some parameters gathered are irrelevant or redundant. As a result, before constructing the predictive model, parameter selection is critical. In data mining, the availability of irrelevant or redundant parameters can obscure primary patterns [27], As a result, before beginning an experiment, identifying the right parameters is essential. On indoor air quality metrics, the Environmental Protection Agency (EPA), ASHRAE, and Leadership in Energy and Environmental Design (LEED) are all interrelated. The conditions for a healthy environment of particulate matter are 10 micrometres or less in diameter of 50 µg/m³ and 2.5 micrometres or less in diameter of 15 µg/m³. The humidity is below 60 %, ideally ranging from 30 % to 50 % (EPA). CO concentration should be less than 9 ppm and CO_2 is about 700 ppm above open-air air levels, and it is about 1000 ppm to 1200 ppm, and the temperature is 20.3 °C to 23.3 °C in winter and 23.9 °C to 26.9°C in summer (ASHRAE). The air quality parameters, such as air speed and temperature, were varied at different levels for varying human loads and CO_2 characteristics were measured accordingly.

1.2 Assumptions

To avoid ambiguity and maintain a regulated atmosphere inside the vehicle, the following assumptions were made, and similar ones were proposed to be applicable by Thirumal et al. [28] for optimizing IAQ characteristics using a multi-objective genetic algorithm.

- When the car's doors were closed, the leak is negligible. The air-conditioning is set in fresh air supply mode.
- The CO_2 may vary based on location and environmental conditions. Within the car, volatile organic component pollutants are not present.
- Before beginning the experiment, the indoor regulated space is allowed to reach equilibrium with the outdoor circumstances.
- Pollen, dander, dust solids, and particulate matter are not considered.
- Tobacco smoking, dust particles, and further unknown elements are not present in the space.
- The fan motor's input current and air speed will change when the engine rpm changes. Hence, the average air speeds were approximated as (1, 2, 3, 4, 5, 6, 7 and 8) m/s.

1.3 Experimental Set-Up

1.3.1 Description of Locale

The assessment was recorded in an important roadway of the Karaikudi municipality, which is the 20th highest urban accumulation of Tamilnadu with a population of 106,714 (2011 census survey data). It is a heritage town situated in Sivagangai District, Tamilnadu, India. Fig. 2 shows the location of the town. This place can be accessible by the Tiruchirappalli–Rameswaram highway that passes through Karaikudi. This locus is located at 10.07° N latitude and 78.78° E longitude. The average maximum temperature is about 34° C (~93° F), and the average lowest temperature is about 24° C (~75° F); the twelve-monthly middling rainfall in Karaikudi is about 920 millimetres, the topography of the place is predominantly flat and some gravel areas are also found in the surroundings. The area of the municipality is about 33.75 km².

1.3.2 Measurements

To measure in-vehicle carbon dioxide concentration a portable IAQ CO_2 meter, the Extech device (Model CO250) by FLIR commercial systems Inc., USA, has been utilized. A similar experimental setup and equipment were used by Ayyakkannu et al. [29] for measuring in-vehicle pollutants. This measuring device works with the theory of the non-dispersive infrared (NDIR) technique. The device can assess up to a maximum range of 5000 ppm with 1 ppm resolution. The device was positioned in the centre of the car cabin at breathing level. The instrument was

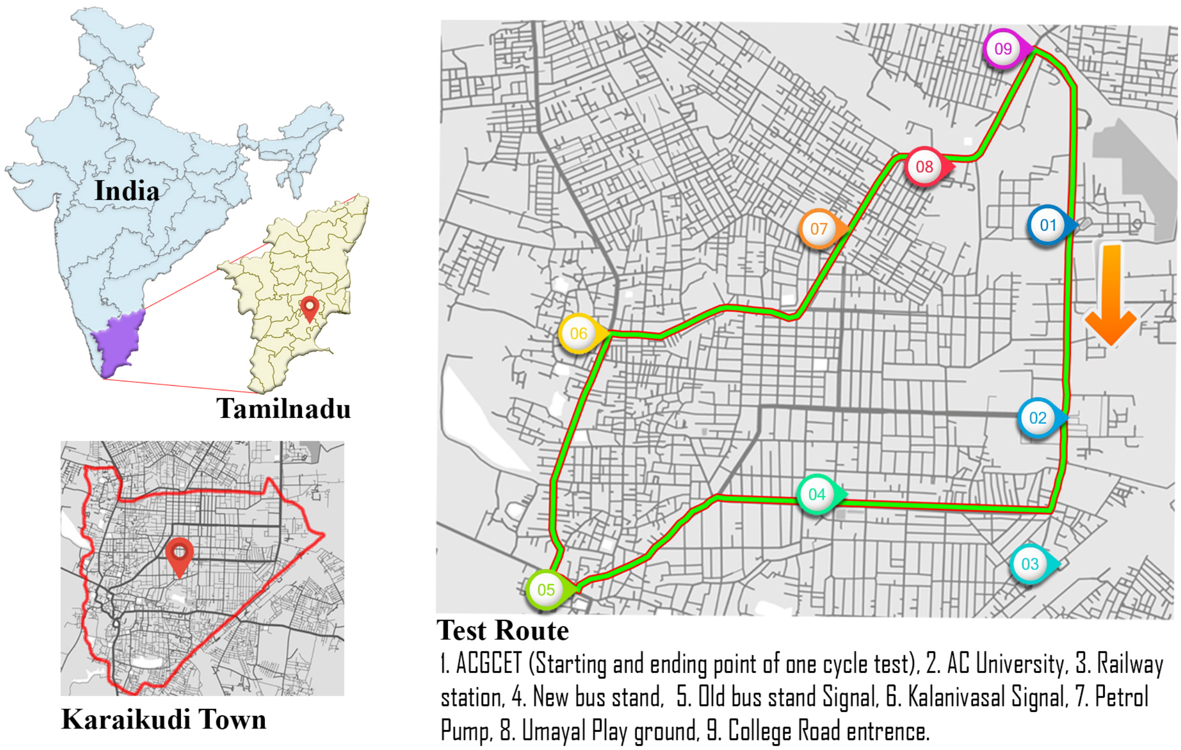

Fig. 2. *Location of Karaikudi town and experimental test route*

calibrated and field-tested before the measurement of CO_2. The measuring instrument is set to record data at a one-minute time interval; the data is then transferred to a laptop PC with an acquisition software provided by the device manufacturer to record the CO_2 values from the instrument. The schematic sketch is shown in Fig. 3, this set-up is used for carrying out our research. A five-seat hatchback car was chosen; it has air-conditioning with a variable temperature from 18 °C to 25 °C and with recirculation modes.

Three tests are carried out for each human load varying from one to five, as the CO_2 concentration will significantly increase according to the number of passengers **[30]**. The mean values of three tests were considered for the final optimization of the parameters. The route at Karaikudi, where the test was carried out was about 13 km per cycle, which includes a college road with trees, traffic signals, a petrol station, road junctions, and a bus stand. The test route is shown in Fig. 2.

1.3.3 Design of Experiments and Regression Line

The design of experiments for the study was designed using full factorial design and regression modelling in statistical software. In each comprehensive trial run or repetition of the studies, the full factorial design establishes experimental points utilizing all feasible combinations of the levels of the components. The vertices of a hypercube in the n-dimensional design space are determined by the least and highest values of each of the factors. These factors are the experimental design points in a full factorial design; therefore, these experimental points are also known as factorial points.

Regression analysis is a type of predictive modelling approach that focuses on the correlation between a dependent (target) and an independent variable (predictor). This technique is used for the prediction of the finding of the fundamental effect relationship between the variables. The quartic non-linear regression model was suggested due to the better value of correlation coefficient and fitting to the data points. The refined model is also developed for predicting carbon dioxide levels for various human loads, which are further used for finding the better value of air quality parameters.

1.4 Search Optimization Methods

Among the various algorithms, the statistical, gradient, and metaheuristic algorithms are popularly used by most researchers for finding the optimum value of responses. The familiar algorithms in the above three categories are effectively chosen for finding indoor air quality characteristics in the present investigation. Response surface methodology (RSM) is based on indirect optimization self-organization; GRG is the most commonly used reduced gradient method to solve nonlinear problems, which finds a local optimal solution; genetic algorithm (GA solves optimization problems based on a natural selection process derived form biological evaluation; it uses high-level search procedures for minimization of response variables.

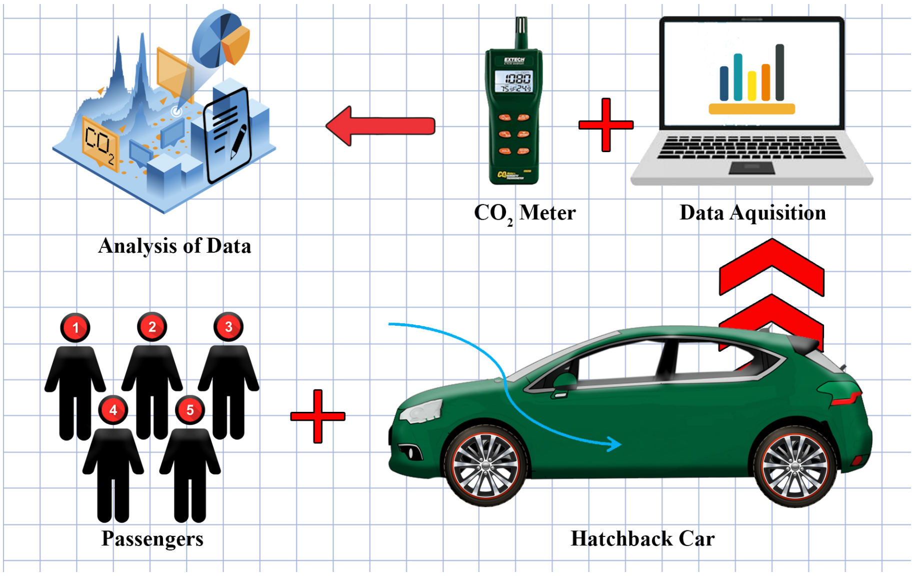

Fig. 3. *Schematic sketch of the experimental setup*

1.4.1 Response Surface Method

The RSM is a commonly used arithmetical and mathematical approach for developing and evaluating a process in which many factors impact the response of interest. This strategy aims to optimize the response time. The development of an approximation model for the true response surface is required for the RSM to be used in reality [31]. The RSM searches for a suitable approximation relationship between input and output variables to find the best operating conditions for a system or a portion of the factor field that complies with the requirements. The RSM was used to optimize the conditions of the experiment by the author Yan et al. [32] for the optimization and analysis of CO_2 surface assimilation by imidazole and tetraethylenepentamine operative sorbent material.

The RSM includes three stages (i.e., design, analysis, and optimization) using statistical software; a non-linear regression equation was developed and optimized using this approach for varying human loads in the present investigation. The ANOVA Table and statistical plots were also generated to study the individual, interaction, and higher-order effects of air quality parameters.

1.4.2 Generalized Reduced Gradient

The generalized reduced gradient (GRG) method is a nonlinear inequality constraint-aware expansion of the reduced gradient method. In this method, a quest path is found in which the current dynamic limitations remain precisely effective for any move. Microsoft Excel uses three solving methods such as GRG Nonlinear for problems that are smoothing nonlinear, LP Simplex for problems that are linear, and Evolutionary for non-smooth problems. GRG is used to find the optimum CO_2 level for various human loads by setting quadratic estimates, forward derivatives, and Newton search in the solver option. The max time was set to 100 seconds for 100 iterations with the precision value of 0.000001, the tolerance was set to 5 % and the convergence was 0.0001in the Microsoft Excel Solver.

1.4.3 Genetic Algorithm

A genetic algorithm is a search heuristic based on Charles Darwin's natural-evolution hypothesis. This algorithm mimics natural selection, in which the fittest individuals are chosen for reproduction to create the next generation. GA have been used to solve a wide variety of systematic, engineering, and financial problems. GA are robust because they can find the global optimum in a multimodal landscape [33]. The initial population, fitness function, selection, crossover, and mutation are the five phases considered in a genetic algorithm.

MATLAB's R2016a graphical user interface was used to find the minimum value of the function. The double vector population type opted with the population type was left to default at 50 for five or fewer variables; otherwise, it was 200. The creation function was constrained dependent on keeping the initial population, initial scores, and initial range as default. For the fitness-scaling function, rank was chosen. The stochastic uniform was set for the selection function. In the reproduction section, elite count and cross-over fraction were default. Mutation and crossover functions are constraint-dependent. Migration direction is forward keeping fraction and interval values as default 0.2 and 20, respectively. For the constraint parameters, the nonlinear constraint algorithm Augmented Lagrangian is used with an initial penalty and penalty factor as default. The hybrid function was set to none, and the stopping criteria were completely used with default settings.

2 RESULTS AND DISCUSSION

2.1 Experimental Observation of Air Quality Characteristics

The three factors that are varied in three levels ($5 \times 8 \times 8 = 320$) contributed 320 experimental runs as per full factorial design. The standard deviation for human load, air speed, and temperature are 1.42, 2.29 and 2.29, respectively. A minimum value of 460 and a maximum value of 949 were observed in carbon dioxide level. The mean and standard deviations for the recorded value of responses are 633 and 128.9, respectively (Eq. (1)).

$$\bar{x} = \frac{\sum x}{n}, \quad \sigma = \sqrt{\frac{\sum\left(x-\bar{x}\right)^2}{n}}, \tag{1}$$

where $\bar{x}$ is mean, n number of observations, x individual observations, and σ standard deviation. The observation of the highest frequency for 320 data in 18 bins was obtained, which is shown in Fig. 4. The frequency is calculated using number of counts in the histogram range specified in x axis whereas proportion is calculated using the Eq. (2).

$$\text{Proportion} = \frac{\text{Frequency}}{n}. \tag{2}$$

The proportion and density plots are also obtained in correlation with recorded values of carbon dioxide levels. The CO_2 level is ranged from 460 ppm to 949 ppm and the corresponding frequency values up to 60 and proportion up to 0.2 are plotted.

2.2 Development of NLRM for Carbon Dioxide Level

The design is built, and response data is added to formulate a polynomial model of response design by including individual, interaction, and lower and higher-order terms. The polynomial degree of four, which is in the form of a quartic function was observed based on the best fit and the coefficient of correlation of 0.9975. The statistical summary of factors and response are in Table 1.

$$f\left(x\right)=ax^4+bx^3+cx^2+dx+e. \quad (3)$$

The adjusted R^2 associates the explanatory power of regression replicas with varying numbers of predictors, whereas the projected R^2 shows how well a regression model predicts fresh observations' responses. The predicted R^2 of 0.9968 is in satisfactory agreement with the adjusted of 0.9972 due to the variance of less than 0.2. The subgroup sample standard deviation divided by the subsection mean, multiplied by 100, yields the percentage of the CV plot point. In practice, the percentage of CV is the proportion of the mean that the standard deviation.

The model F-value of 3389.3 shows the model is considerable. There is only a 0.01 per cent probability that an F-value of this massive might appear due to noise. Model terms with P-values less than 0.0500 are noteworthy. x_1, x_3, $x_1 x_2$, $x_1 x_3$, x_1^2, x_3^2, $x_1 x_2 x_3$, $x_1^2x_2$, $x_1^2x_3$, x_1^3, $x_1^2 x_2^2$, $x_1^2 x_3^2$, $x_1^3x_2$, $x_1^3 x_3$, $x_1 x_2^3$, $x_1 x_3^3$, x_1^4, x_3^4 are significant model terms in this scenario. The model terms are not significant if the value is larger than 0.1000. The model decrease may enhance your model if there are several irrelevant model terms (not involving those necessary to support hierarchy). The nonlinear regression model was developed using statistical software, as given in Eq. (4).

$$\begin{aligned}f(x) = &+ 10021.14279 + 1030.93478\times x_1\\ &- 254.83387\times x_2 - 1784.46657\times x_3\\ &- 2.82325\times x_1\times x_2 - 213.63461\times x_1\times x_3\\ &+ 32.61305\times x_2\times x_3 + 261.08873\times x_1^2\\ &+ 10.19365\times x_2^2 + 130.89552\times x_3^2\\ &-1.15965\times x_1\times x_2\times x_3 + 4.79252\times x_1^2\times x_2\\ &+ 0.610780\times x_1^2\times x_3 + 0.559092\times x_1\times x_2^2\\ &+ 10.14499\times x_1\times x_3^2 - 0.205609\times x_2^2\times x_3\end{aligned}$$

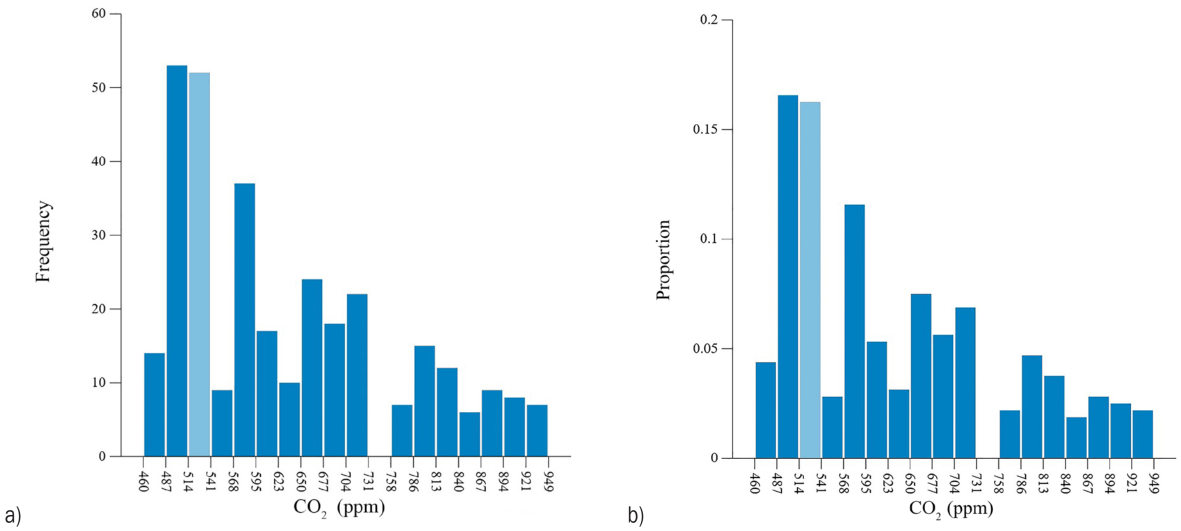

Fig. 4. *Histogram for response; a) frequency, and b) proportion*

Table 1. *Statistical summary of factors and response*

Factor/ Response	Name	Minimum	Maximum	Coded Low	Coded High	Mean	Std. Dev.
Factor 1	Human load [No.]	1	5	-1 ↔ 1.00	+1 ↔ 5.00	3.00	1
Factor 2	Air speed [m/s]	1	8	-1 ↔ 1.00	+1 ↔ 8.00	4.50	2
Factor 3	Temperature [°C]	18	25	-1 ↔ 18.00	+1 ↔ 25.00	21.50	2
Response	CO_2 [ppm]	460	949	-	-	632.88	128.87

$$- 1.43142 \times x_2 \times x_3^2 - 62.51457 \times x_1^3$$
$$-1.24080 \times x_2^3 - 4.31326 \times x_3^3 - 0.192815 \times x_1^2 \times x_2^2$$
$$+ 0.012856 \times x_1^2 \times x_2 \times x_3 - 0.172513 \times x_1^2 \times x_3^2$$
$$- 0.030896 \times x_1 \times x_2^2 \times x_3 + 0.028628 \times x_1 \times x_2 \times x_3^2$$
$$+ 0.005322 \times x_2^2 \times x_3^2 - 0.448041 \times x_1^3 \times x_2$$
$$+ 0.803695 \times x_1^3 \times x_3 + 0.090972 \times x_1 \times x_2^3$$
$$- 0.143119 \times x_1 \times x_3^3 + 0.004359 \times x_2^3 \times x_3$$
$$+ 0.020725 \times x_2 \times x_3^3 + 4.00456 \times x_1^4$$
$$+ 0.048793 \times x_2^4 + 0.053101 \times x_3^4 \ . \quad (4)$$

The sequential p-value is less than 0.0001 and the difference between the adjusted and predicted coefficient of correlation is 0.0004 which indicated the best fit of the quartic model for 320 values of carbon dioxide level (Table 2). The sequential p-value is < 0.0001 for linear, two-factor interaction, quadratic, cubic, quartic, and quintic models. The best fit is selected based on the higher value of coefficient of correlation.

Table 2. *Fit summary and selection of model*

Source	Sequential p-value	Adjusted R^2	Predicted R^2	Remarks
Linear	< 0.0001	0.891	0.8889	-
2FI	< 0.0001	0.9197	0.917	-
Quadratic	< 0.0001	0.9935	0.9933	-
Cubic	< 0.0001	0.9942	0.9938	-
Quartic	< 0.0001	0.9972	0.9968	Suggested
Fifth	< 0.0001	0.9985	0.9981	Aliased

2.3 ANOVA, Diagnostics and Statistical Plots

The model includes the overall model test for significance and how much variance in the reaction is described by the model. Individual factors are removed from the model and tested separately. The residual indicates how much variation in the response remains unaccounted for. The degree to which the model predictions differ from the observed is referred to as “lack of fit”. The amount of variation between replicate runs is known as “pure error”. The degree of variation around the mean of the observations is shown by the corrected total. The individual effect of human load and temperature, combined effect of air speed and temperature, are significant terms in ANOVA listed in Table 3. The second-order effect of human load with air speed and temperature is also significant.

The normal probability plot shows whether the residuals have a normal distribution and, as a result, follow a straight line. For better analysis, scatter with normal data in an s-shaped curve showed the transformation response as shown in Fig. 5a. A graph of anticipated response values versus actual response values can be used to spot a value, or a collection of values, that the model cannot predict is shown in Fig. 5b. The assumption of constant variance is tested by plotting the residuals against the ascending expected response values as shown in Fig. 5c. A studentized residual is calculated by dividing the residual by an estimate of its standard deviation. The standard deviation for each residual is computed with the observation excluded. A plot of the residuals against the experimental run order to look for hidden variables that could have influenced the response during the experiment is shown in Fig. 5d. Internally studentized residuals are defined for each observation as an ordinary residual divided by an estimate of its standard deviation.

Cook’s distance is a measurement of how much the entire regression function changes when the i^{th} point is removed from the model fitting (Fig. 6a). The plot of the residuals versus any factor if the variation not accounted for by the model varies depending on the level of the factor is in Fig. 6b. The response surface plot and contour plot for the interaction of variables are shown in Figs. 6c and d, respectively. Surface plots are diagrams of three-dimensional data that shows a functional relationship between a designated dependent variable and two independent variables. A contour plot is a graphical technique for representing a 3-dimensional surface by plotting constant z slices called “contours”.

2.4 Optimization of Carbon Dioxide Level

2.4.1 RSM Optimization for Minimum Value of Carbon Dioxide Level

The human load is set to 1, 2, 3, 4, and 5, whereas the air speed and temperature are set in range as criteria and the minimization of carbon dioxide was carried out using response surface methodology. The minimum value of carbon dioxide levels for various human loads in accordance with air speed and temperature are given in Table 4. The optimization looks for a set of factor values that satisfies all the criteria for each of the responses and factors at the same time. The desirability function indicates the desirable limits for each response. The maximum value of air speed and low value of temperature is needed for getting the minimum value of CO_2 level in a 5-seat car. The minimum value of air speed and upper limit of temperature provided a minimum value of carbon dioxide of 472. The setting of air speed and

Table 3. *ANOVA for response and significance of factors*

Source	Sum of Squares	df	Mean Square	*F*-value	*p*-value	Remarks
Model	5.29E+06	34	1.55E+05	3389.3	< 0.0001	Significant
x_1	3.76E+05	1	3.76E+05	8202.13	< 0.0001	
x_2	145.96	1	145.96	3.18	0.0755	
x_3	6182.8	1	6182.8	134.82	< 0.0001	
$x_1 \times x_2$	851.29	1	851.29	18.56	< 0.0001	
$x_1 \times x_3$	5184.82	1	5184.82	113.06	< 0.0001	
$x_2 \times x_3$	31.56	1	31.56	0.6882	0.4075	
$x_1{}^2$	461.81	1	461.81	10.07	0.0017	
$x_2{}^2$	33.99	1	33.99	0.7412	0.39	
$x_3{}^2$	532.36	1	532.36	11.61	0.0008	
$x_1 \times x_2 \times x_3$	296.12	1	296.12	6.46	0.0116	
$x_2{}^2 \times x_3$	2296.85	1	2296.85	50.08	< 0.0001	
$x_1{}^2 \times x_3$	1101.23	1	1101.23	24.01	< 0.0001	
$x_1 \times x_2{}^2$	15.47	1	15.47	0.3374	0.5618	
$x_1 \times x_3{}^2$	0.7741	1	0.7741	0.0169	0.8967	
$x_2{}^2 \times x_3$	3.98	1	3.98	0.0867	0.7686	
$x_2 \times x_3{}^2$	54.02	1	54.02	1.18	0.2787	
$x_1{}^3$	594.83	1	594.83	12.97	0.0004	
$x_2{}^3$	0.4001	1	0.4001	0.0087	0.9256	
$x_3{}^3$	162.26	1	162.26	3.54	0.061	
$x_1{}^2 \times x_2{}^2$	699.53	1	699.53	15.25	0.0001	
$x_1{}^2 \times x_2 \times x_3$	4.08	1	4.08	0.089	0.7657	
$x_1{}^2 \times x_3{}^2$	559.98	1	559.98	12.21	0.0006	
$x_1 \times x_2{}^2 \times x_3$	67.35	1	67.35	1.47	0.2266	
$x_1 \times x_2 \times x_3{}^2$	57.83	1	57.83	1.26	0.2624	
$x_1{}^2 \times x_3{}^2$	4	1	4	0.0871	0.768	
$x_1{}^3 \times x_2$	971.26	1	971.26	21.18	< 0.0001	
$x_1{}^3 \times x_3$	3125.25	1	3125.25	68.15	< 0.0001	
$x_1 \times x_2{}^3$	393.27	1	393.27	8.58	0.0037	
$x_1 \times x_3{}^3$	973.35	1	973.35	21.22	< 0.0001	
$x_2{}^3 \times x_3$	2.37	1	2.37	0.0517	0.8203	
$x_2 \times x_3{}^3$	53.58	1	53.58	1.17	0.2807	
$x_1{}^4$	8445.27	1	8445.27	184.15	< 0.0001	
$x_2{}^4$	172.39	1	172.39	3.76	0.0535	
$x_3{}^4$	204.18	1	204.18	4.45	0.0357	
Residual	13070.01	285	45.86			

temperature for an intermediate value of human loads are effectively determined using response surface optimization. The maximum value of air speed and lower limit of temperature provided a minimum value of carbon dioxide of 769.362 ppm for the maximum capacity of the vehicle.

2.4.2 GRG Optimization for Minimum Value of Carbon Dioxide Level

The minimum CO_2 concentration value of 471.537 ppm was achieved in accordance with air speed and temperature of 2 m/s and 24 °C, respectively, for a single human load using the GRG technique. In a comparison of the three optimization methods utilized for one human load, among RSM (471.876), GRG (471.537), and GA (471.611), the lowest CO_2 level

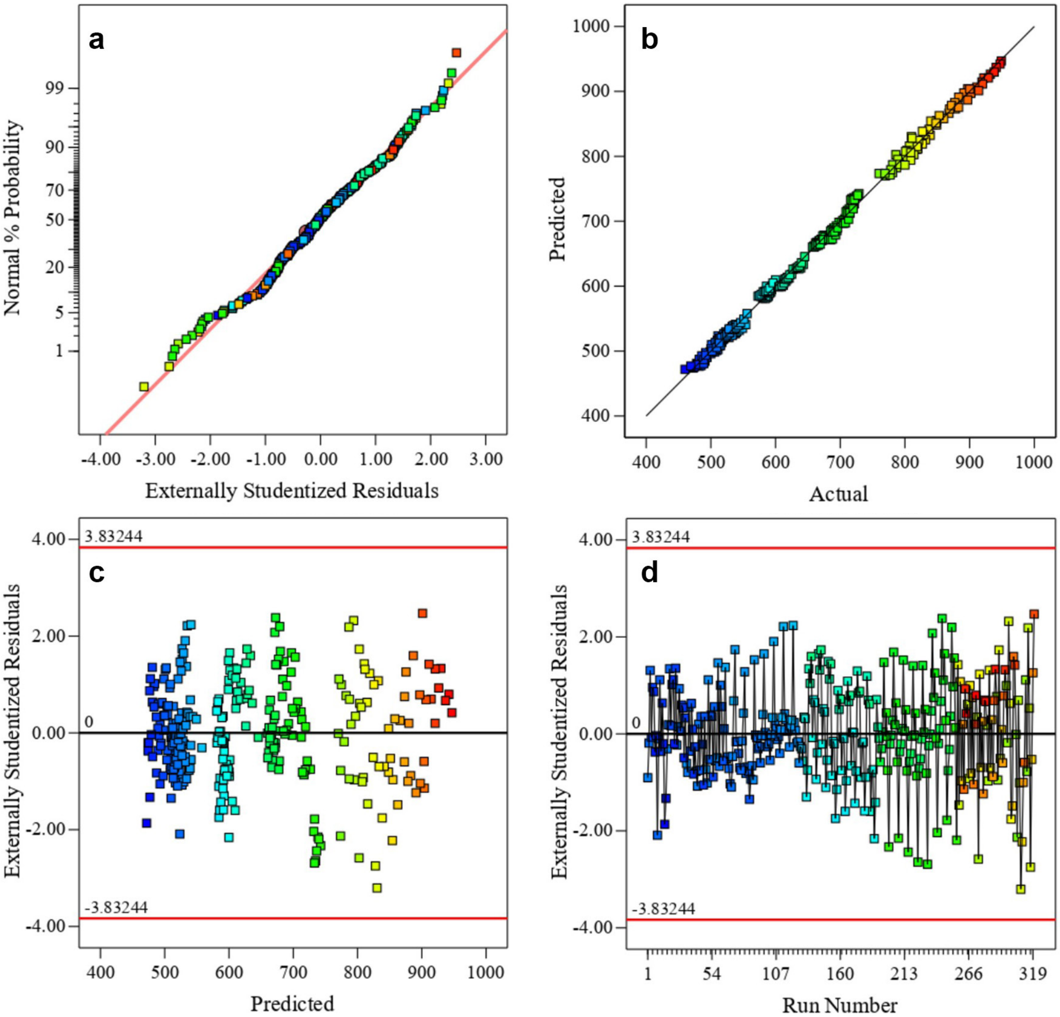

Fig. 5. *Plot of residuals; a) normal % probability, b) predicted vs. actual, c) residuals vs. predicted, and d) residuals vs. run*

was attained in GRG methods. The carbon dioxide levels of 508.785 ppm, 580.722 ppm, 659.839 ppm and 769.016 ppm were obtained for human loads 2, 3, 4 and 5, respectively.

When compared with RSM, GRG provided a minimum value of carbon dioxide level for all levels of human load. The search procedure in GRG found a better value of results when compared with statistical-based optimization. RSM is a mathematical and statistical technique for the empirical model building which predicted better value of responses using indirect optimization based on self-organization whereas the Newton method used a root-finding approach by polynomial approximation using Taylor's series. The air speed of 7 m/s and temperature of 18 °C were obtained for a minimum value of carbon dioxide level of 769.016 ppm in GRG and GA methods.

2.4.3 GA Optimization for Minimum Value of Carbon Dioxide Level

The minimum CO_2 concentration of 471,611 ppm for one human load was obtained for the air speed of 2 m/s and a temperature of 24 °C using the GA method, which was slightly higher than the optimum value (471.537 ppm) obtained using the GRG method. The lowest ideal value for a five-person capacity is 769,016 at an air speed of 7 m/s and a temperature of 18 °C, respectively. The carbon dioxide levels of 508.785 ppm, 580.722 ppm, 659.839 ppm and 769.016 ppm were obtained for human loads 2, 3, 4, and 5 respectively which is the same as the results obtained using the GRG method. When comparing the results acquired using the GA method in MATLAB software to the obtained results using RSM optimization in Design-Expert software, the GA approach produced

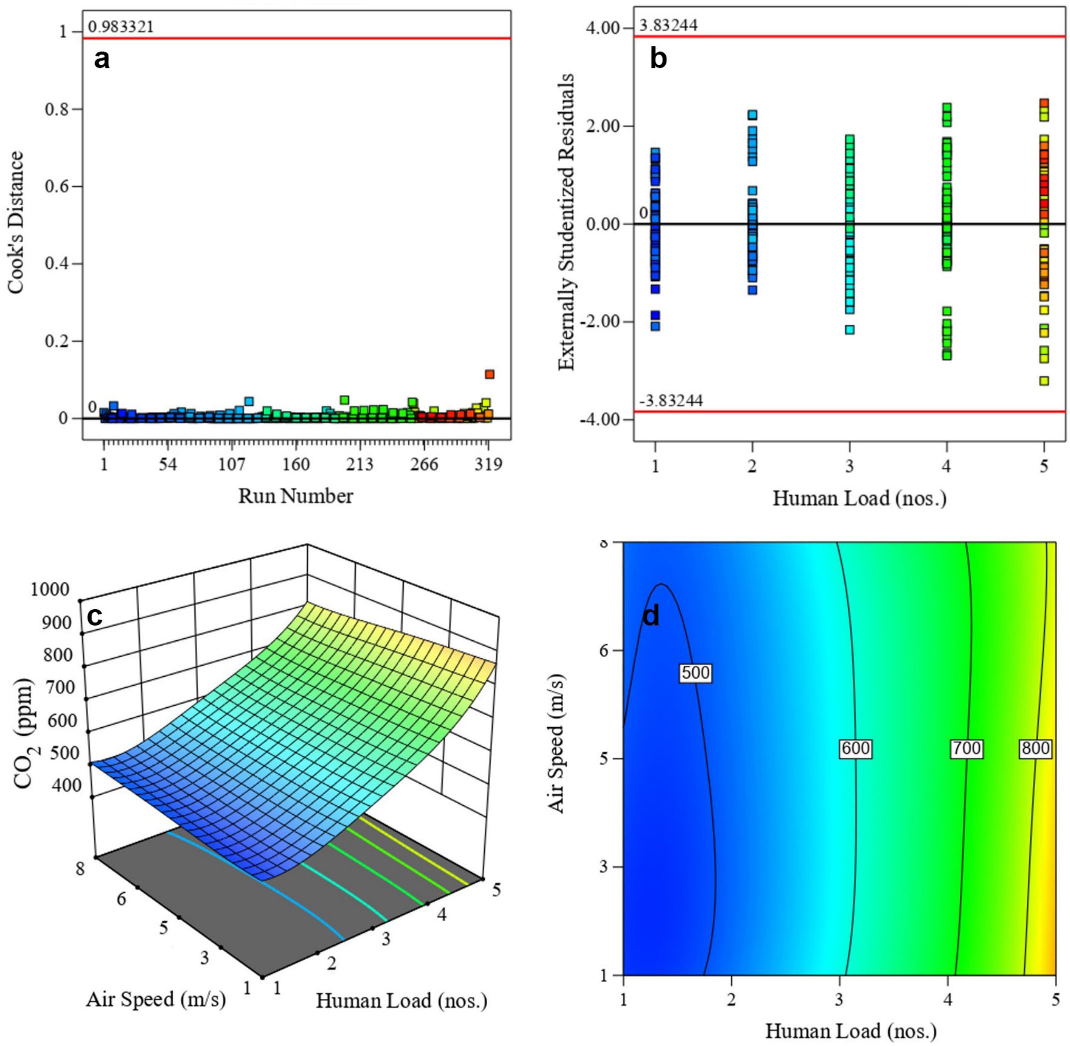

Fig. 6. *Design plots; a) Cook's distance, b) residual vs. factor, c) 3D surface plot, and d) contour plot*

Table 4. *Optimum values of CO_2 level for various human loads and confirmation of responses*

Sl. No.	Algorithm	Factors		CO_2 [ppm]		Absolute percentage of error
		Airspeed [m/s]	Air temp. [°C]	Predicted response	Experimental response	
1	RSM	2	24	471.876	479.983	1.7
2		3	21	508.865	503.832	0.2
3		3	20	580.79	586.231	0.9
4		6	19	659.905	671.376	1.7
5		8	18	769.362	752.263	2.2
6	GRG	2	24	471.537	479.983	1.8
7		3	21	508.785	503.832	0.9
8		3	19	580.722	586.231	0.9
9		6	19	659.839	671.376	1.7
10		7	18	769.016	777.847	1.1
11	GA	2	24	471.611	479.983	1.3
12		3	21	508.785	503.832	0.9
13		3	20	580.722	589.124	0.9
14		6	19	659.839	671.376	1.7
15		7	18	769.016	777.847	1.1

lower results due to the metaheuristic approach (High-level search procedure). In addition, when compared to RSM, the air velocity for the five human load conditions is lowered by one level in the GA optimization technique. The GA plots for optimization plotting fitness value vs. generation are shown in Fig. 7. The values are obtained in between 50 to 100 generations for the better value of fitness. The same value of best fitness and mean fitness was obtained which indicated the minimum value of carbon dioxide level for various human loads.

2.4.4 Confirmation of Optimum Conditions

The experiments were conducted for the optimum conditions obtained using RSM, GRG, and GA methods; the carbon dioxide levels values were reordered and compared with the optimum values. The comparison graph of experimental results and predicted results are shown in Fig. 8. The blue, green, and yellow lines indicated the optimum value of carbon dioxide levels for RSM, GRG, and GA, respectively, whereas the orange, red, and violet lines indicated the experimental value of carbon dioxide levels for RSM, GRG, and GA, respectively. RSM predicted carbon dioxide levels of 471.876 ppm, 508.865 ppm, 580.79 ppm, 659.905 ppm, and 769,362 ppm for human loads 1, 2,3,4, and 5 and the same is confirmed with experimental values of 479.983 ppm, 503.832 ppm, 586.231 ppm, 671.376 ppm, and 752.263 ppm. The absolute percentage error of values 1.8, 0.9, 0.9, 1.7, and 1.1 for human loads 1, 2, 3, 4, and 5 were obtained using the GRG method. GA predicted carbon dioxide levels of 471.611 ppm,

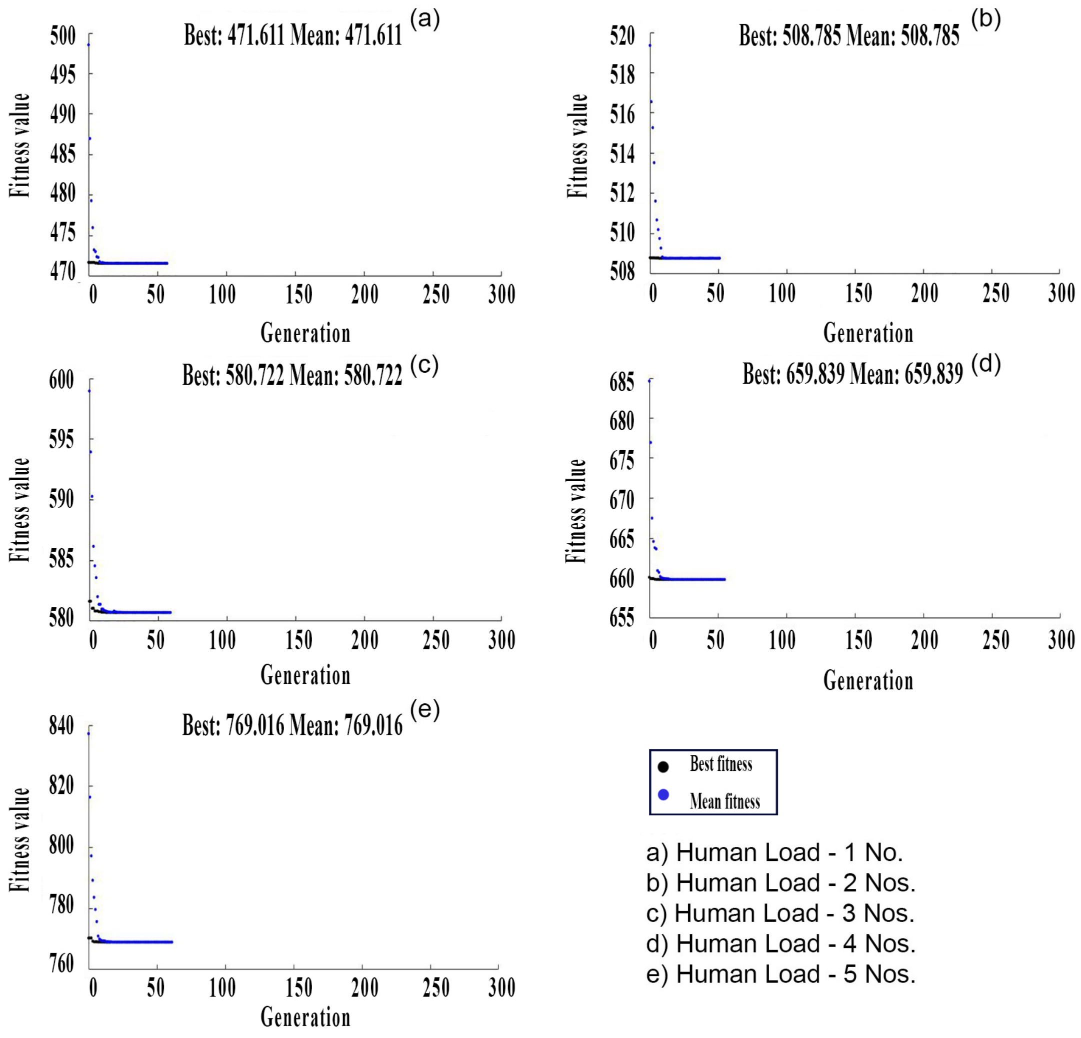

Fig. 7. *GA plot for optimization of carbon dioxide level for different human load*

508.785 ppm, 580.722 ppm, 659.839 ppm, and 769.016 ppm for human loads 1,2,3,4, and 5 and the same is confirmed with experimental values of 479.983 ppm, 503.832 ppm, 589.124 ppm, 671.376 ppm, 777.847 ppm, respectively.

The absolute ratio of error is determined using the following formulation.

$$\text{Percentage of error} = \frac{(\text{Experimental value} - \text{Optimum value})}{\text{Experimental value}}. \quad (5)$$

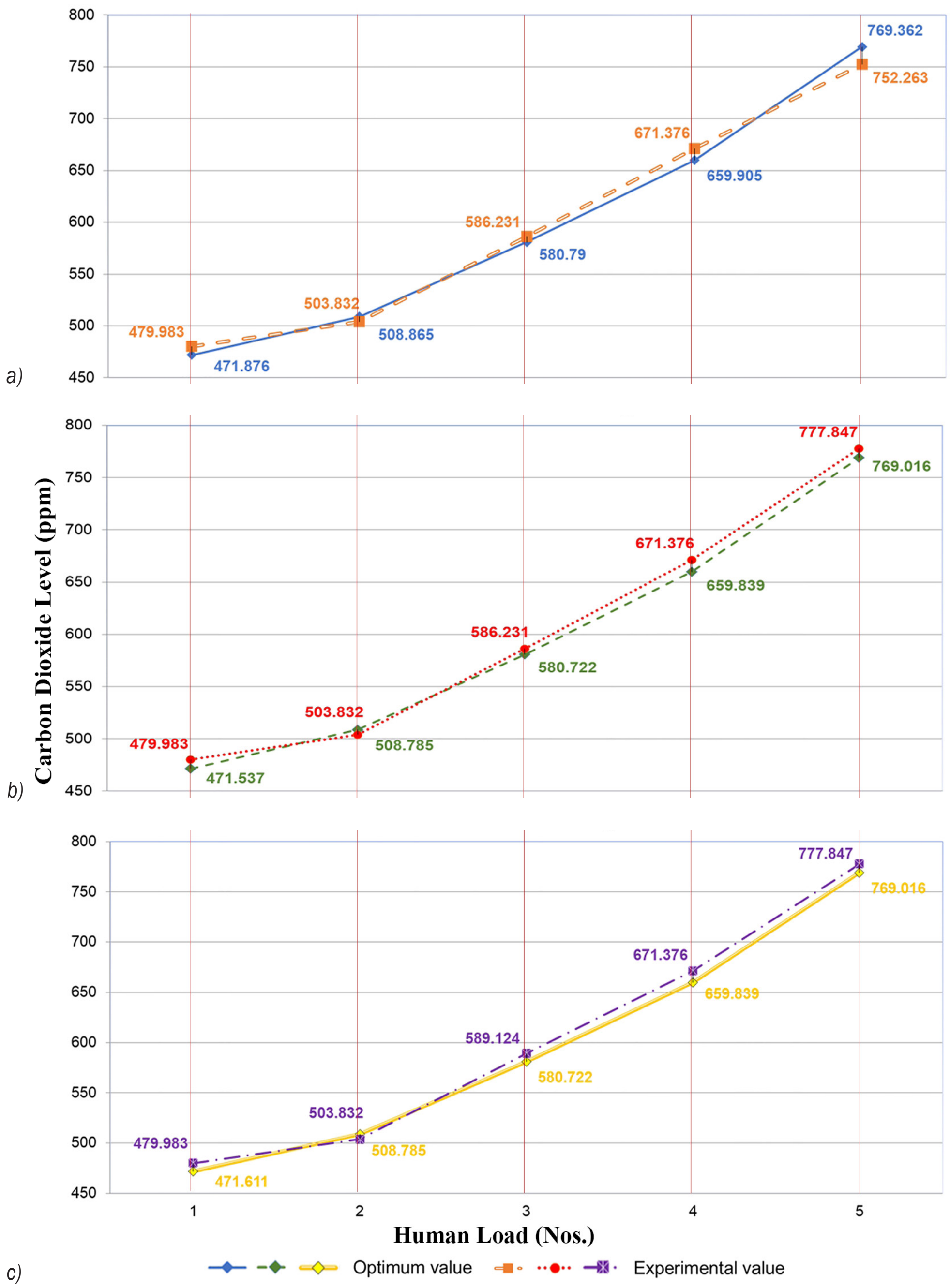

Fig. 8. *Confirmation testing comparative graph between optimum and experimental value for all three algorithms; a) RMS, b) GRG, and c) GA*

The absolute percentage of error is less than 2.5, indicating good level of accuracy in the confirmation of results the maximum absolute percentage of error of 2.2 in RSM, 1.8 in GRG and 1.7 in GA were obtained. The close prediction of experimental value with the predicted value was obtained.

3 CONCLUSION

Experimental runs were carried out for different values of human load, air speed, and temperature, and the observed value of carbon dioxide levels were recorded. Response surface design, analysis, and optimization were done to find the minimum value of carbon dioxide levels for various human loads and corresponding air velocity and temperature. In addition, with response surface methodology, the generalized reduced gradient and genetic algorithm are also used to find the minimum value of carbon dioxide levels in the present investigation. The minimum carbon dioxide level of 471.531 ppm for one human load was obtained for the air speed of 2 m/s and a temperature of 24 °C using the GRG method. The carbon dioxide levels of 508.785 ppm, 580.722 ppm, 659.839 ppm and 769.016 ppm were obtained for human loads 2, 3, 4 and 5, respectively, using GRG and GA methods. The experiment was conducted for the optimum value of IVAQ parameters, and the corresponding CO_2 level was measured. The absolute percentage of error was found for all three algorithms, which resulted in the genetic algorithm providing a better value of results for the current problem. Other indoor air quality characteristics, such as relative humidity, particulate matter, carbon monoxide level, and oxygen level may be optimised using the optimization techniques, and the optimal value for comfort and healthy living in an enclosed environment can be found. These methods can be used to determine the optimal inlet HVAC parameters such as inlet velocity, the quantity of fresh air supply, type of filtration, and required temperature for various human loads in a confined area. This application could lead to a better and healthier indoor living environment. Even though this method has a wide range of applications, the IAQ characteristics vary from place to place, and values in different countries may deviate at a significant pace depending on the environmental circumstances and abrupt climate changes of that country as well as the region under study. In the future, the same study can be extended to other vehicle cabins, such as those of SUVs or seven-seat cars, trucks, buses and even trains by varying different passenger loads, elevation of location under study, ventilation type, and outside environmental weather conditions. It is also concluded that breathing clean air is a vital aspect of investigation for enhanced human health during the Covid-19 pandemic.

4 REFERENCES

[1] Gladyszewska-Fiedoruk, K. (2011). Concentrations of carbon dioxide in a car. *Transportation Research Part D: Transport and Environment*, vol. 16, no. 4, p. 166-171, **DOI:10.1016/j.trd.2011.01.005**.

[2] Kaur, S., Nieuwenhuijsen, M.J., Colvile, R.N. (2007). Fine particulate matter and carbon monoxide exposure concentrations in urban street transport microenvironments. *Atmospheric Environment*, vol. 41, no. 23, p. 4781-4810, **DOI:10.1016/j.atmosenv.2007.02.002**.

[3] El-Fadel, M., Abi-Esber, L., (2009). In-vehicle Exposure to Carbon Monoxide Emissions from Vehicular Exhaust: A Critical Review. *Critical Reviews in Environmental Science and Technology,* vol. 39, no. 8, p.585-621, **DOI:10.1080/10643380701798264**.

[4] Knibbs, L.D., Cole-Hunter, T., Morawska, L. (2011). A review of commuter exposure to ultrafine particles and its health effects. *Atmospheric Environment*,vol. 45, no. 16, p. 2611-2622, **DOI:10.1016/j.atmosenv.2011.02.065**.

[5] Dovjak, M., Slobodnik, J., Krainer, A. (2019). Deteriorated indoor environmental quality as a collateral damage of present day extensive renovations. *Strojniški vestnik - Journal of Mechanical Engineering*, vol. 65, no. 1, p. 31-40, **DOI:10.5545/sv-jme.2018.5384**.

[6] Yin, H., Zhai, X., Ning, Y., Li, Z., Ma, Z., Wang, X., Li, A. (2022). Online monitoring of $PM_{2.5}$ and CO_2 in residential buildings under different ventilation modes in Xi'an city. *Building and Environment*, vol. 207, art. ID 108453, **DOI:10.1016/j.buildenv.2021.108453**.

[7] Dab, W., Ségala, C., Dor, F., Festy, B., Lameloise, P., Le Moullec, Y., Quénel, P., Wallaert, B., Zmirou, D. (2001). Air pollution and health: Correlationor causality? The case of the relationship between particle exposure and cardiopulmonary mortality. *Journal of the Air & Waste Management Association*, vol. 51, no. 2, p. 203-235, **DOI:10.1080/10473289.2001.10464267**.

[8] Persily, A., Dols, W.S. (1990). The relation of CO_2 concentration to office building ventilation. *Air Change Rate and Air tightness in Buildings*. Sherman, M.H. (ed.), ASTM International, West Conshohocken, p. 77-92, **DOI:10.1520/STP17206S**.

[9] Kim, H.H., Park, G.Y., Lee, J.H. (2019). Concentrations of particulate matter, carbon dioxide, VOCs and risk assessment inside Korean taxis and ships. *Environmental Science and Pollution Research*, vol. 26, no. 10, p. 9619-9631, **DOI:10.1007/s11356-019-04361-5**.

[10] Muhič, S., Muhič, T. (2022). Measurements of air quality in kindergartens and schools in the republic of Slovenia before the COVID-19 epidemic. *Strojniški vestnik-Journal of Mechanical Engineering*, vol. 68, no. 4, p. 290-299, **DOI:10.5545/sv-jme.2022.13**.

[11] Grady, M.L., Jung, H., Kim, Y.C., Park, J.K., Lee, B.C. (2013). Vehicle cabin air quality with fractional air recirculation. *SAE Technical Paper*, no. 01-1494, **DOI:10.4271/2013-01-1494**.

[12] Kadiyala, A., Kumar, A. (2013). Quantification of in-vehicle gaseous contaminants of carbon dioxide and carbon monoxide under varying climatic conditions. *Air Quality, Atmosphere & Health*, vol. 6, no. 1, p. 215-224, **DOI:10.1007/s11869-011-0163-2**.

[13] Ren, J., He, J., Kong, X., Xu, W., Kang, Y., Yu, Z., Li, H., (2022). A field study of CO_2 and particulate matter characteristics during the transition season in the subway system in Tianjin, China. *Energy and Buildings*, vol. 254, art. ID 111620, **DOI:10.1016/j.enbuild.2021.111620**.

[14] Mathur, G.D. (2018). Effect of cabin volume on build-up of cabin carbon dioxide concentrations from occupant breathing in automobiles. *SAE Technical Paper*, no. 2018-01-0074, **DOI:10.4271/2018-01-0074**.

[15] Kumar, S., Jain, M.K., (2022). Exposure to particulate matter and CO_2 in indoor conditions at IIT (ISM) Dhanbad. *Materials Today: Proceedings*, vol. 49, p. 3469-3473, **DOI:10.1016/j.matpr.2021.04.496**.

[16] Kundu, P., Goel, K., Zinta, G. (2022). Nutritional imbalance in plants under rising atmospheric CO_2. *Plant Nutrition and Food Security in the Era of Climate Change*, p. 513-536, **DOI:10.1016/B978-0-12-822916-3.00006-8**.

[17] Chang, T.B., Sheu, JJ., Huang, J.W., Lin, Y.S., Chang, C.C. (2018). Development of a CFD model for simulating vehicle cabin indoor air quality. *Transportation Research Part D: Transport and Environment*, vol. 62, p. 433-440, **DOI:10.1016/j.trd.2018.03.018**.

[18] Satish, U., Mendell, M.J., Shekhar, K., Hotchi, T., Sullivan, D., Streufert, S., Fisk, W.J. (2012). Is CO_2 an indoor pollutant? Direct effects of low-to-moderate CO_2 concentrations on human decision-making performance. *Environmental Health Perspectives*, vol. 120, no. 12, p. 1671-1677, **DOI:10.1289/ehp.1104789**.

[19] Kusiak, A., Li, M. (2009). Optimal decision making in ventilation control. *Energy*, vol. 34, no. 11, p. 1835-1845, **DOI:10.1016/j.energy.2009.07.039**.

[20] Trends in Atmospheric Carbon Dioxide (2021). Global Monitoring Laboratory, Global average CO_2 level, NOAA, from *https://gml.noaa.gov/ccgg/trends/*, accessed on 2021-11-10.

[21] ANSI, Standard 62-1999. *Ventilation for Acceptable Indoor Air Quality*. American Society of Heating Refrigerating and Air Conditioning Engineers, Inc., Atlanta.

[22] Abi-Esber, L., El-Fadel, M. (2013). Indoor to outdoor air quality associations with self-pollution implications inside passenger car cabins. *Atmospheric Environment*, vol. 81, p. 450-463, **DOI:10.1016/j.atmosenv.2013.09.040**.

[23] Alcalá, R., Benítez, J.M., Casillas, J., Cordón, O., Pérez, R. (2003). Fuzzy control of HVAC systems optimized by genetic algorithms. *Applied Intelligence*, vol. 18, no. 2, p. 155-177, **DOI:10.1023/A:1021986309149**.

[24] Congradac, V., Kulic, F. (2009). HVAC system optimization with CO_2 concentration control using genetic algorithms. *Energy and Buildings*, vol. 41, no. 5, p. 571-577, **DOI:10.1016/j.enbuild.2008.12.004**.

[25] Fanger, P.O. (2000). Good air quality in offices improves productivity. *Strojniški vestnik - Journal of Mechanical Engineering*, vol. 46, no. 7, p. 408-412.

[26] Zhang, D., Ding, E., Bluyssen, P.M. (2022). Guidance to assess ventilation performance of a classroom based on CO_2 monitoring. *Indoor and Built Environment*, vol. 31, no. 7, p. 1107-1126, **DOI:10.1177/1420326X211058743**.

[27] Kusiak, A., Tang, F., Xu, G. (2011). Multi-objective optimization of HVAC system with an evolutionary computation algorithm. *Energy*, vol. 36, no. 5, p. 2440-2449, **DOI:10.1016/j.energy.2011.01.030**.

[28] Thirumal, P., Amirthagadeswaran, K.S., Jayabal, S. (2014). Optimization of indoor air quality characteristics in an air-conditioned car using multi-objective genetic algorithm. *Arabian Journal for Science and Engineering*, vol. 39, no. 11, p. 8307-8317, **DOI:10.1007/s13369-014-1392-0**.

[29] Ayyakkannu, R.K., Subbaian, J., Pandian, M., Iruthayaraj, D.L. (2021). Commuter exposure to fine particulate matter in private road transport modes in Salem, India. Thermal Science, vol. 26, no. 2, p. 1695-1708, **DOI:10.2298/TSCI200629214A**.

[30] Goh, C.C., Kamarudin, L.M., Shukri, S., Abdullah, N.S., Zakaria, A. (2016). Monitoring of carbon dioxide (CO_2) accumulation in vehicle cabin. *3rd International Conference on Electronic Design*, p. 427-432, **DOI:10.1109/ICED.2016.7804682**.

[31] Węglowski, M.S. (2014). Experimental study and response surface methodology for investigation of FSP process. *Archive of Mechanical Engineering*, vol. 61, no. 4, p. 539-552, **DOI:10.2478/meceng-2014-0031**.

[32] Yan, H., Zhang, G., Liu, J., Li, G., Wang, Y. (2021). Highly efficient CO_2 adsorption by imidazole and tetraethylenepentamine functional sorbents: Optimization and analysis using response surface methodology. *Journal of Environmental Chemical Engineering*, vol. 9, no. 4, art. ID 105639, **DOI:10.1016/j.jece.2021.105639**.

[33] Huang, W., Lam, H.N. (1997). Using genetic algorithms to optimize controller parameters for HVAC systems. *Energy and Buildings*, vol. 26, no. 3, p. 277-282, **DOI:10.1016/S0378-7788(97)00008-X**.