

Response Surface Methodology based optimization of emission characteristics of SI engine fueled with blends of ethanol and Graphene oxide nanoparticles

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Abstract: This study investigates the performance and emission characteristics of a spark-ignition (SI) engine operating on ethanol-gasoline blends, with the addition of graphene oxide (GO) nanoparticles, to enhance engine performance and reduce emissions. The research examined the effects of varying ethanol blend ratios and GO nanoparticle concentrations on key engine parameters, specifically brake thermal efficiency, brake specific fuel consumption, and emissions of carbon monoxide (CO), hydrocarbons (HC), and nitrogen oxides (NOx). Statistical models were developed using response surface methodology (RSM) to accurately predict engine responses based on the input parameters. The optimization process identified specific combinations of ethanol blend ratios and GO nanoparticle levels that achieved a favorable balance between improved efficiency and lower emissions. The results indicated that the lowest emissions were achieved with 60 ppm GO concentration in E20 fuel, at a load of 10 kg and a speed of 2400 rpm, yielding a desirability value of 0.949, as determined by Design Expert software, including ANOVA analysis. In conclusion, this research demonstrates the potential of RSM to optimize SI engine performance with ethanol-GO blends, offering insights for more sustainable engine operation.

Keywords: SI engine 1; ethanol 2; graphene oxide nanoparticles 3; emissions 4; blends 5; optimality 6; response surface methodology 7.

Nomenclature

1. ICE - Internal Combustion Engine
2. E20 - Ethanol-blended fuel containing 20% ethanol and 80% gasoline
3. GO - Graphene Oxide
4. MPFI - Multi-Point Fuel Injection
5. SI Engine - Spark Ignition Engine
6. CO - Carbon Monoxide
7. CO₂ - Carbon dioxide
8. HC - Hydrocarbon
9. NOx - Nitrous Oxide
10. [A] - model term matrix
11. [B] - coefficient matrix
12. [C] - response matrix
13. Adjusted R₂ - adjusted coefficient of determination
14. MS - mean square
15. PR - predicted responses
16. Predicted R₂ - predicted coefficient of determination
17. R₂ - coefficient of determination
18. Residual - error sum of squares
19. X - sum of all recorded responses
20. y_i / AR - actual responses
21. p - ANOVA assessment value
22. PRESS - predicted error sum of squares
23. d_i - individual desirability
24. r - weights assigned to response
25. L - lower value of response
26. U - upper value of response
27. T - target value of response
28. dc - composite desirability
29. k - number of responses to be optimized

1. INTRODUCTION

With increasing environmental awareness and the adverse effects of fossil fuel consumption on global climate, the automotive industry is compelled to seek alternative fuels and cleaner combustion strategies. Traditional petroleum-based fuels, although highly efficient, are major contributors to air pollutants such as carbon monoxide (CO), hydrocarbons (HC), carbon dioxide (CO₂), and nitrogen oxides (NOx), which pose significant threats to both human health and the environment (Alsultan et al. 2019). As a result, researchers are exploring renewable and sustainable biofuels to address these challenges. Ethanol has emerged as a promising biofuel alternative due to its renewable nature, high oxygen content, and potential to reduce greenhouse gas emissions when blended with gasoline. Ethanol blends, especially E20 (20% ethanol and 80% petrol), have been shown to improve combustion characteristics and reduce tailpipe emissions in internal combustion engines (Raheman and Phadatar 2004). Its application in spark-ignition (SI) engines improves anti-knock properties, allows higher compression ratios, and reduces net carbon emissions due to its biogenic origin. Parallel to biofuel development, advancements in nanotechnology have introduced new possibilities in enhancing fuel properties and combustion efficiency. Graphene oxide (GO), a derivative of graphene, has attracted attention due to its high surface area, exceptional thermal conductivity, and oxygen-containing functional groups. These properties enable GO nanoparticles to act as combustion catalysts, improving the fuel-air mixing and oxidation reactions, thereby reducing CO and HC emissions (Kumar et al. 2019; Sadiq Basha et al. 2018). Furthermore, GO nanoparticles assist in improving thermal stability and promoting cleaner combustion by enhancing fuel atomization and vaporization processes (Selvan et al. 2020). However, the influence of GO nanoparticles on emissions such as NOx remains complex. While GO enhances combustion efficiency, it may also raise in-cylinder temperatures, which can contribute to higher NOx formation (Subramanian et al. 2018). Therefore, a balance between reduced emissions and optimized engine performance is essential.

To address these intricacies, multi-objective optimization methods are required. Response Surface Methodology (RSM) is a statistical technique used for modeling and analyzing problems in which several independent variables influence a response variable. It is particularly effective for experimental design, process optimization, and predictive modeling in engineering applications (Khuri and Mukhopadhyay 2010; Montgomery 2017).

This study aims to investigate the combined impact of ethanol-GO nanoparticle fuel blends on the emission characteristics of a spark-ignition engine. The specific objectives are as follows:

1. To analyze the effects of GO nanoparticle concentration on CO, CO₂, HC, and NOx emissions.
2. To use RSM in developing empirical models that predict emission behavior based on GO concentration, engine load, and speed.
3. To optimize engine operating conditions to achieve minimal emissions using Design Expert Software.

This investigation provides valuable insights into the synergy between biofuels and nanotechnology and emphasizes the practical utility of RSM in formulating strategies for sustainable and efficient engine operation.

2. MATERIALS AND METHODS

2.1. Fuel Preparation: The fuel preparation process for this investigation involved the meticulous blending of various fuel types with graphene oxide (GO) nanoparticles to assess their impact on combustion performance. The study utilized three distinct fuel types: standard petrol as the control, Speed Petrol, and an ethanol blend (E20), which comprises 20% ethanol and 80% petrol. For each fuel type, graphene oxide nanoparticles were incorporated at concentrations of 20 ppm, 40 ppm, and 60 ppm, enhancing the potential for improved combustion characteristics. The blending process employed was low shear mixing using an agitator, selected for its effectiveness in achieving uniform dispersion of the nanoparticles within the fuel matrix. The duration of the mixing process ranged from 30 minutes to 1 hour, allowing for optimal distribution of the GO nanoparticles to promote enhanced atomization and combustion efficiency. This systematic approach aimed to leverage the unique properties of graphene oxide to foster better engine performance and reduced emissions during combustion.

2.2. Test setup and methodology of experiment: The experimental setup for this study involved a four-stroke, multi-point fuel injection (MPFI) petrol engine, selected for its relevance and efficiency in real-world applications. The engine specifications included a bore diameter of 66.5 mm, a stroke length of 72 mm, and

a compression ratio of 9.2:1, contributing to a cubic capacity of 800 cc. With a rated power output of 27.6 kW at 5000 RPM and a rated torque of 59 N-m at 2500 RPM, manufactured by Maruti, this engine provided a solid foundation for analyzing combustion performance when blended with graphene oxide nanoparticles. The testing was designed to operate under constant speed conditions while systematically varying the load from zero to its maximum limit. This approach necessitated the careful adjustment of the fuel supply, ensuring that the engine maintained a constant speed despite fluctuations in load. For each specific load setting, a range of critical performance metrics were calculated, including brake power (BP), brake specific fuel consumption (BSFC), brake mean effective pressure (BMEP), air-fuel ratio (A/F), and mechanical efficiency. These parameters were essential for evaluating how effectively the engine performed compared to the manufacturer's specifications. The engine was coupled with a hydraulic dynamometer, a crucial component of the setup for the accurate measurement of brake power. This type of dynamometer works by dissipating power through fluid, rather than relying on dry friction, thus facilitating a more reliable assessment of engine performance. The hydraulic dynamometer consisted of an inner rotating impeller linked to the engine output shaft, contained within a fluid-filled casing. This design allowed for efficient power dissipation, with measurements of frictional forces accounted for by a spring balance fitted on the casing.



Fig. 1: Multi Point Fuel Injection Engine (MPFI)

In addition to the dynamometer, the setup incorporated a load cell, which recorded the load applied to the engine and displayed it on a control panel for real-time data monitoring. An RPM sensor was also installed on the dynamometer shaft to continuously track engine speed, which was displayed alongside load measurements.

Fuel consumption was meticulously quantified using a calibrated glass tube connected to the fuel tank and a stopwatch, ensuring precise volumetric measurements. Air consumption, known to be more challenging to measure due to the pulsating flow in IC engines, was monitored by connecting the engine intake to an airbox. This airbox was designed to dampen pressure pulsations, and it was fitted with an orifice at its top, coupled with a U-tube water manometer to enable accurate pressure difference readings. Through this setup, flow velocity could be calculated, providing comprehensive data regarding air intake during the test.

The procedural steps were clearly delineated to ensure reliability in results. Initially, fuel supply, lubrication oil, and cooling water availability were checked before starting the engine. The dynamometer was then set to zero load, and the engine was allowed to run until it reached a stable working temperature and operating condition. The dynamometer load was adjusted to achieve the desired engine speed, and fuel consumption rates were recorded. This process was repeated with varying loads, ensuring that the necessary adjustments in fuel consumption were made to maintain a constant engine speed. After all tests were conducted, the dynamometer was disengaged, and the engine was stopped, allowing for subsequent calculations and data analysis to assess engine performance comprehensively. Overall, this comprehensive experimental setup was crucial for examining the effects of graphene oxide nanoparticles on engine performance, facilitating a thorough investigation into the emissions and efficiency parameters critical to advancing combustion technologies.

Table 1: Characteristics of GO nanoparticles

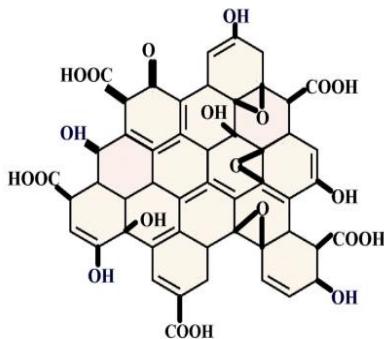


Fig. 2: Representation of GO chemical structure
Engine Technical Specifications:
Observations:

Description	GO
Purity	99%
Number of layers	2 to 6
Average thickness	0.5 to 2 nm
Surface area	110 to 250 m ² /g
Thermal conductivity	11 W/mK
Carbon %	60 to 80%
Oxygen %	15 to 32%
Nitrogen %	1 to 2%
Sulphur %	<1%
Bulk Density	0.5 g/cm ³

- Density of air: 1.16 kg/m³
- Diameter of Orifice: 35 mm
- Coefficient of Discharge for Orifice (Cd): 0.64
- Specific gravity of fuel: 0.764
- Calorific value of fuel: 44240 kJ/kg
- Dynamometer arm length: 200 mm

3. LITERATURE REVIEW

The increasing concerns regarding environmental pollution and the depletion of fossil fuel reserves have driven extensive research into alternative fuels and advanced combustion technologies. Among these, ethanol and nano-additives, particularly graphene oxide (GO) nanoparticles, have garnered significant attention due to their potential to enhance engine performance and reduce emissions. This literature review aims to synthesize existing research on the application of Response Surface Methodology (RSM) for optimizing engine performance and emission characteristics, focusing on the utilization of ethanol blends and GO nanoparticles in Spark Ignition (SI) engines.

3.1. Alternative Fuels and Nano-Additives in SI Engines: Ethanol, as a renewable fuel, offers a promising alternative to gasoline due to its higher octane number and oxygen content, which can improve combustion efficiency and reduce emissions [36, 23]. However, challenges such as lower energy density and potential engine modifications need careful consideration. The use of nano-additives, especially GO, has shown potential in mitigating these challenges. GO, known for its high surface area and catalytic properties, can enhance fuel combustion and improve engine performance [14, 31, 33, 35, 38].

Reviews by Sharma et al. [8] and Lv et al. [10] highlight the significant impact of nanoparticles on fuel properties, combustion, and emission characteristics in internal combustion engines. They emphasize that nano-additives can improve fuel atomization, enhance combustion rates, and reduce particulate matter emissions. Furthermore, Dehghani et al. [19] specifically reviewed the effects of nano-additives on SI engines, focusing on the health impacts of emissions and concluding that careful optimization is crucial. The synthesis and characterization of GO, along with its applications in various fields, have been extensively studied, as demonstrated by Kusrini et al. [6] and Al-Gaashani et al. [28], providing a foundation for its application in fuel enhancement.

3.2. Response Surface Methodology (RSM) for Optimization: RSM is a statistical and mathematical technique used for modeling and optimizing processes by analyzing the relationships between input variables and output responses [22, 11]. It allows for the identification of optimal operating conditions and the understanding of interaction effects between variables. This methodology has been widely applied in engine performance and emission optimization studies.

Table 2: Engine Technical Specifications

Make	Maruti
Bore Diameter	66.5 mm
Stroke Length	72 mm
Compression Ratio	9.2:1
Cubic Capacity	800 cc
Rated Power in kW	27.6 at 5000 RPM
Rated Torque in N-m	59 at 2500 RPM
Fuel	Petrol

Anderson and Whitcomb [2] and Montgomery [20] provide comprehensive guides on RSM, detailing its principles and applications. The application of RSM in optimizing engine performance and emissions has been demonstrated in several studies. For instance, Alsultan et al. [1] utilized RSM to optimize diesel engine performance and emissions, showcasing its effectiveness in identifying optimal operating parameters. Similarly, Atmanli et al. [3] optimized diesel-n-butanol-cotton oil blends using RSM, achieving significant improvements in engine performance and emission characteristics. Yadav and Sawant [44] also employed RSM for optimizing vehicle performance parameters with oxy-hydrogen blending. RSM has also been compared to other optimization techniques. Sarve et al. [32] compared RSM with artificial neural networks (ANN) for biodiesel production, demonstrating the strengths and limitations of both methods. Other optimization methods like Taguchi techniques have also been discussed and applied in engine optimization [7, 12, 42, 43]. The desirability function, as discussed by Wu [41], is also a relevant tool for optimizing multiple correlated quality characteristics.

3.3. Nano-Additives and Biofuel Blends in Engine Applications: The combination of nano-additives with biofuels has been explored to further enhance engine performance and reduce emissions. Basha et al. [9, 17] provided comprehensive reviews on the applications of nano-additives in internal combustion engines, focusing on their effects on stability, engine performance, and emission characteristics. Mofijur et al. [15] analyzed the impact of nanoparticle-based fuel additives on biodiesel combustion, highlighting improvements in fuel properties, engine performance, and emission characteristics.

Kumar et al. [13, 30] and Singh et al. [45] have also investigated the effects of nanoparticles as fuel additives in diesel engines, emphasizing their potential to improve performance and reduce emissions. Research focusing on GO nano-additives in particular has shown promising results. For example, Kumar et al. [14] and Selvan et al. [33] investigated the effect of GO nano-additives on diesel-biodiesel blends, demonstrating improvements in performance and emission characteristics. Similarly, Subramanian et al. [35] explored the influence of GO on a DI diesel engine fueled with diesel and biodiesel blends, further validating its potential. Agbulut et al. [38] also explored the synthesis of GO nanoparticles and their influence as fuel additives on CI engine behaviors.

3.4. Emission Characteristics and Environmental Impact: Reducing engine emissions is a critical aspect of research in this field. Merola et al. [18] discussed the impact of nanoparticles from engine exhaust on urban areas, highlighting the importance of emission control. Khan et al. [30] and Haq et al. [21] further examined the influence of nano-additives on diesel-biodiesel blends in terms of spray, performance, and emissions.

Research by Kül et al. [39] on aluminum particles and engine emissions and Agbulut et al. [37] on metal-oxide nanoparticles and biodiesel blends also contribute to understanding the impact of nano-additives on emission characteristics. The tribological properties of lubricants with nano-additives, as reviewed by Ali et al. [46], also play a role in engine efficiency and emission reduction.

3.5. Statistical Modeling and Experimental Design: The statistical design of experiments and the analysis of the resulting data are crucial for the successful application of RSM. Kutner et al. [4] and De Gryze et al. [3] provide foundational knowledge on linear statistical models and prediction intervals, which are essential for accurate modeling and interpretation of experimental results. Cavazzuti [2] and Ross [5] offer insights into optimization methods and Taguchi techniques, respectively, which can complement RSM.

3.6. Conclusion: This literature review highlights the potential of ethanol blends and GO nano-additives in improving SI engine performance and reducing emissions. RSM is a powerful tool for optimizing engine parameters and understanding the interaction effects between variables. Future research should focus on further optimizing the combination of ethanol and GO nano-additives, exploring different engine operating conditions, and conducting comprehensive emission characterization studies to ensure the environmental sustainability of these fuel blends.

4. MULTI-OBJECTIVE OPTIMIZATION OF VEHICLE EMISSION PARAMETERS

Multi-objective optimization is an essential strategy in the automotive sector to address intricate engineering challenges that involve competing objectives, such as enhancing performance, safety, and efficiency concurrently. This method enables engineers to identify optimal trade-offs in the design of various vehicle components—ranging from powertrain parts like connecting rods to structural elements like body frames and thin-walled tubes, as well as in the refinement of manufacturing processes like machining and additive manufacturing. By taking multiple objectives into account, this approach fosters innovation and aids in developing vehicles that satisfy increasingly rigorous performance, environmental, and economic standards. To validate the experimental results, investigate the interaction effects between GO nanoparticles and E20 blends, and formulate mathematical models for predicting responses based on specific factor levels, experiments were constructed using response surface methodology (RSM) through the Design Expert software package. Researchers frequently employ RSM for optimizing various engine parameters, as this methodology employs regression analysis to model responses. The most common variants of the models are Linear, 2FI, Quadratic, and Cubic. The methodology is outlined with a flowchart in Figure 2. The modeling of emission parameters in relation to GO nanoparticles, load, and speed involves expressing the performed experiments in terms of three matrices: the model term matrix [A], the coefficient matrix [B] containing the model term coefficients, and the response matrix [C], represented mathematically as follows:

$$[A] \times [B] = [C] \quad \dots(1)$$

The model preferred for modeling CO, CO₂, HC and NO_x are:

$$CO = B_0 + B_1 \times GO + B_2 \times Load + B_3 \times Speed + B_4 \times GO \times Load + B_5 \times Load^2 \quad \dots(2)$$

$$CO_2 = B_0 + B_1 \times GO + B_2 \times Load + B_3 \times Speed - B_4 \times GO \times Load + B_5 \times Load^2 \quad \dots(3)$$

$$HC = B_0 + B_1 \times GO + B_2 \times Load + B_3 \times Speed + B_4 \times GO \times Load + B_5 \times Load \times Speed + B_6 \times Load^2 + B_7 \times Speed^2 \quad \dots(4)$$

$$NO_x = B_0 + B_1 \times GO + B_2 \times Load + B_3 \times Speed + B_4 \times GO \times Load + B_5 \times GO^2 + B_6 \times Load^2 \quad \dots(5)$$

After multiple iterations, these models were selected based on their adequacy, confirmed by the values of R², predicted R², and adjusted R². The model with the highest values for these coefficients was ultimately chosen. To derive the coefficients in the equations, the following matrix operations were executed:

$$[B] = [A^T A]^{INV} \times [A^T C] \quad \dots(6)$$

In this equation, the superscripts T and INV denote the transpose and inverse operations of the matrix, respectively. Following these matrix operations, model term coefficients were obtained, and the equations were revised accordingly.

$$CO = 1.58834 - 0.005915 \times GO - 0.221672 \times Load - 0.000308 \times Speed - 0.000482 \times AB + 0.000084 \times BC \quad \dots(7)$$

$$CO_2 = 15.44839 - 0.129389 \times GO - 0.016389 \times Load + 0.001854 \times Speed - 0.016674 \times AB \quad \dots(8)$$

$$HC = 146.01860 - 1.31826 \times GO + 0.957812 \times Load + 0.001834 \times Speed - 0.072795 \times AB \quad \dots(9)$$

$$NO_x = -2426.50031 - 4.06671 \times GO + 315.24273 \times Load + 1.10921 \times Speed - 4.90070 \times AB \quad \dots(10)$$

ANOVA (Analysis of Variance) was conducted to assess the significance of both the model and the individual model terms. Given the unbalanced nature of the data and the expectation of interactions, type-III sum of squares, also known as partial sum of squares, was employed during the ANOVA. The corrected total sum of squares (CorTotal) was calculated using the provided formula.

$$CorTotal = \sum_{i=1}^N y_i^2 - \frac{X^2}{N} \quad \dots(11)$$

where y_i is the recorded/actual responses (AR) of FAP and WP, X is the sum of all recorded values of response and N is the total number of experiments. For CO, CorTotal is obtained as:

$$CorTotal(CO) = (0.013^2 + 0.4^2 + 0.79^2 + 0.805^2 + 0.676^2 + 0.53^2 + 0.79^2 + 0.7^2 + 0.4^2 + 0.676^2) - \frac{6.715^2}{12}$$

$$CorTotal(CO) = 0.80856$$

Using the model equations, predicted responses for each experiment were derived, as detailed in the accompanying table. The error sum of squares, or residual, was determined through the specified equation.

$$Residual = \sum_{i=1}^N (AR_i - PR_i)^2 \quad \dots(12)$$

$$Residual(CO) = (0.013 - 0.00432)^2 + \dots + (0.676 - 0.6986)^2 = 0.0167466$$

Model sum of squares is obtained by subtracting residual from corrected total sum of squares (SS).

$$Model SS (CO) = CorTotal - Residual = 0.80856 - 0.0167466 = 0.7918134$$

To calculate the factor sum of squares, each model term is sequentially removed from the model term matrix [A], which also leads to a reduction in the coefficient matrix. After this adjustment, all matrix operations described in Equation (6) are repeated to derive updated model term coefficients and equations. New predicted responses are then generated using these revised equations. The updated residual is computed as explained previously and is then subtracted from the residual containing all model terms to determine the sum of squares (SS) for the removed term. This process continues iteratively to identify the SS for the remaining factors. The total degrees of freedom (df) are defined as the total number of experiments conducted minus one, resulting in a total of 11. Each model term is

allocated one degree of freedom. In the case of the CO model, which consists of 5 model terms, the model degrees of freedom totals 5. By subtracting the model df from the total df, we arrive at a residual df of 11-5 = 6. The mean square (MS) is calculated by dividing SS by the corresponding df. The F-value is determined by dividing MS by the error df. Confidence levels (CL) and p-values for the model are sourced from the F-distribution table, utilizing the model F-value along with the model and error df.

$$R^2 = 1 - \frac{Residual}{CorTotal} = 1 - \frac{0.0167466}{0.080856} = 0.98033 \quad \dots(13)$$

$$Adjusted R^2 = 1 - \frac{Residual / Residual df}{(Residual + SS Model) / (Residual df + Model df)}$$

$$= 1 - \frac{0.0167466/6}{(0.0167466+0.7927)/(6+5)} = 0.9653 \quad \dots(14)$$

$$Predicted R^2 = 1 - \frac{PRESS}{Residual + SS Model} = 1 - \frac{0.0686}{0.0167466+0.7927} = 0.9152 \quad \dots(15)$$

To derive the predicted error sum of squares (PRESS), each individual experiment is removed from the total dataset. Following similar processes, a new model is created. The predictions from this new model are subtracted from the 'deleted' observation to yield the predicted residual for each data point. These predicted residuals are then squared and summed to calculate PRESS. The percentage contribution of each factor is calculated by dividing the factor sum of squares by the combined sum of squares of all factors and the residual. For example, the percentage contribution of GO in response CO is calculated as:

$$\% Contribution of GO = \frac{SS of GO}{SS (all factors) + Residual} = \frac{0.5897}{1.5885 + 0.0167466} = 0.36735 \quad \dots(16)$$

Likewise, the percentage contributions of all other factors are computed. Similar calculations are conducted to generate the ANOVA table for various parameters. In ANOVA Table 4, the Model F-values for CO, CO₂, HC, and NO_x indicate that the models are statistically significant. A 'Prob > F' value of less than 0.0500 signifies that the model terms are significant, with all terms in both models displaying significance. Additionally, the calculated R², predicted R², and adjusted R² values demonstrate that the model accurately represents the data and can effectively predict responses. It is also noted that there exists a significant interaction among GO nanoparticles, Load, and Speed for all responses, which will be further explored using 3D interaction plots. For optimization the desirability approach proposed by Derringer and Suich in 1980 is used. Each response is converted into a desirability value (d). Desirability function assesses how well the combination of input variables satisfies the goal defined for the selected response. Desirability has a value between 0 and 1. With desirability equal to 1 the selected combination of independent factors satisfies the goal defined for the response best and vice versa for desirability equal to zero. If the response value goes beyond acceptable limit the desirability value becomes zero. Desirability is to be calculated for each experimental run and called individual desirability (d_i). For maximizing the goals RSM uses equation;

$$d_i = \begin{cases} \frac{(PR - L)^r}{(T - L)^r} & PR < L \\ \frac{(U - PR)^r}{(U - T)^r} & L \leq PR \leq T \\ 0 & PR > T \end{cases} \quad \dots(17)$$

where r is the weight assigned to the response according to its importance (unit in present study), L is the lower value of response amongst all responses, U is the upper value of response amongst all responses and T is the target value of the response. While maximizing the response if PR is greater than T, desirability will have a value = 1 and if less than L then will have a zero value. For any value of PR between L and U, the individual desirability is to be calculated using Equation (17). Finally the composite desirability is calculated using Equation 8 (Anderson and Whitcom 2017) wherein k is the total number of responses to be optimized, 4 in this case.

$$dc = (d_1 \times d_2 \times \dots \times d_n)^{\frac{1}{k}} \quad \dots(18)$$

The total degrees of freedom (df) are defined as the total number of experimental runs minus one, and the degrees of freedom for each model term are determined based on the number of parameters that contribute to that term. After identifying the sum of squares for each factor and the residuals, F-values can be calculated to determine the significance of each term in the model. The F-value is computed by dividing the mean square of each factor by the mean square of the residuals. Suppose the F-value exceeds a critical value from the F-distribution table. In that case, the null hypothesis (that the factor does not significantly affect the response) can be rejected, suggesting that the factor plays a significant role in influencing the emissions. This comprehensive analysis not only aids in validating the model but also guides engineers in making informed decisions for further optimizing vehicle designs to reduce emissions while enhancing overall performance. Through this iterative and rigorous approach, multi-objective optimization allows for continuous improvements in vehicle technology, ultimately leading to more sustainable and efficient automotive solutions.

Fig. 3: Flow Chart of Response Surface Methodology [44]

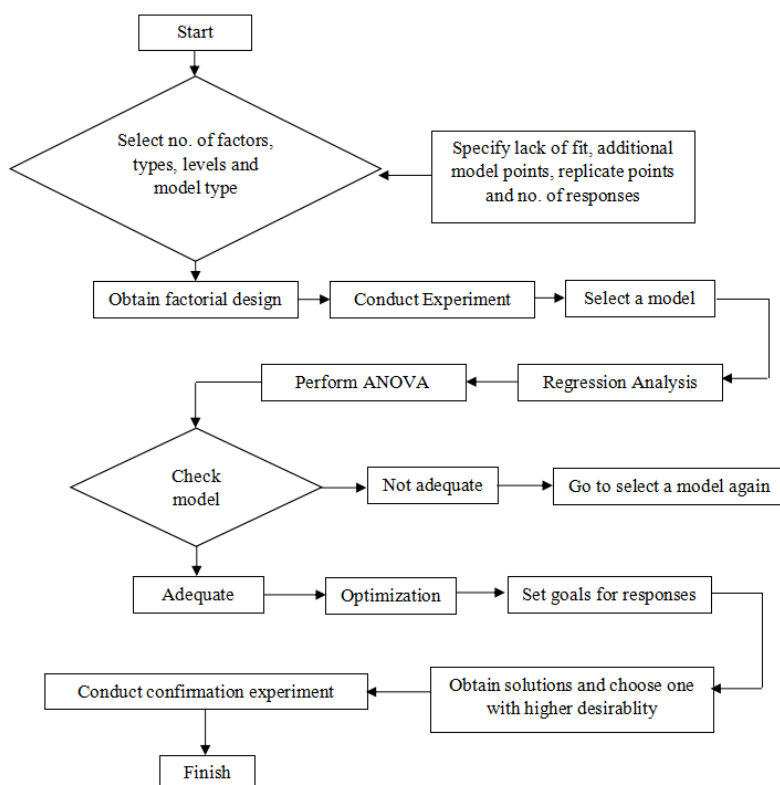


Table 3: Experimental Design with Actual, Predicted Response

Run	Factor 1 A:GO (ppm)	Factor 2 B:load (kg)	Factor 3 C:speed (rpm)	Actual Response CO	Predicted Response	Actual Response CO2	Predicted Response	Actual Response HC	Predicted Response	Actual Response NOx	Predicted Response
1	60	10	2400	0.013	0.00432	0.41	1.96636	26	37.22572	180	203.65409
2	60	0	2700	0.4	0.40184	12.2	12.69085	70	71.8748	308	324.36409
3	0	0	2600	0.79	0.78754	19.99	20.26879	149	150.787	452	457.44569
4	0	10	2700	0.805	0.80802	20.19	20.2903	158	160.54852	3729	3720.83969
5	60	10	2700	0.13	0.16392	4.08	2.52256	49	37.77592	560	536.41709
6	0	10	2700	0.805	0.80802	20.19	20.2903	158	160.54852	3729	3720.83969
7	0	7.5	2400	0.676	0.6986	19.91	19.7750725	161	157.60379	2589	2599.95844
8	40	0	2400	0.53	0.61254	13.49	14.72243	80	97.6898	59	72.93529
9	0	0	2600	0.79	0.78754	19.99	20.26879	149	150.787	452	457.44569
10	40	0	2400	0.7	0.61254	17.43	14.72243	121	97.6898	136	72.93529
11	60	0	2700	0.4	0.40184	12.2	12.69085	70	71.8748	308	324.36409
12	0	7.5	2400	0.676	0.6986	19.91	19.7750725	161	157.60379	2589	2599.95844
			U	0.805	0.80802	20.19	20.2903	161	160.54852	3729	3720.83969
			L	0.013	0.00432	0.41	1.96636	26	37.22572	59	72.93529
			T	0.805	0.80802	20.19	20.2903	161	160.54852	3729	3720.83969
			PR	0.013	0.00432	0.41	1.96636	26	37.22572	180	203.65409

Table no: 4: ANOVA table for CO, CO₂, HC and NOx

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Response 1: CO						
Model	0.7927	5	0.1585	59.77	< 0.0001	significant
A-GO	0.5897	1	0.5897	222.30	< 0.0001	
B-Load	0.1296	1	0.1296	48.86	0.0004	
C-Speed	0.0026	1	0.0026	0.9910	0.3579	
AB	0.0426	1	0.0426	16.07	0.0071	
BC	0.0313	1	0.0313	11.81	0.0139	
Residual	0.0159	6	0.0027			
Lack of Fit	0.0015	1	0.0015	0.5069	0.5083	not significant
Pure Error	0.0144	5	0.0029			
Cor Total	0.8086	11				
R ² = 0.9803 Adjusted R ² = 0.9636 Predicted R ² = 0.9151 Adequate Precision= 22.0300						
Response 2: CO₂						
Model	493.48	4	123.37	60.01	< 0.0001	significant
A-GO	392.87	1	392.87	191.09	< 0.0001	
B-Load	67.19	1	67.19	32.68	0.0007	
C-Speed	0.7575	1	0.7575	0.3684	0.5630	
AB	51.25	1	51.25	24.93	0.0016	
Residual	14.39	7	2.06			
Lack of Fit	6.63	2	3.31	2.14	0.2136	not significant
Pure Error	7.76	5	1.55			
Cor Total	507.87	11				
R ² = 0.9717 Adjusted R ² = 0.9555 Predicted R ² = 0.9002 Adequate Precision= 19.7980						
Response 3: HC						
Model	26606.90	4	6651.73	40.22	< 0.0001	significant
A-GO	24560.88	1	24560.88	148.50	< 0.0001	
B-Load	378.45	1	378.45	2.29	0.1741	
C-Speed	0.7408	1	0.7408	0.0045	0.9485	
AB	976.85	1	976.85	5.91	0.0454	
Residual	1157.77	7	165.40			
Lack of Fit	317.27	2	158.63	0.9437	0.4490	not significant
Pure Error	840.50	5	168.10			
Cor Total	27764.67	11				
R ² = 0.9583 Adjusted R ² = 0.9345 Predicted R ² = 0.8755 Adequate Precision= 14.8555						
Response 4: NOx						
Model	2.320E+07	4	5.800E+06	6490.16	< 0.0001	significant
A-GO	7.084E+06	1	7.084E+06	7927.75	< 0.0001	
B-Load	7.125E+06	1	7.125E+06	7972.88	< 0.0001	
C-Speed	2.711E+05	1	2.711E+05	303.34	< 0.0001	
AB	4.427E+06	1	4.427E+06	4954.43	< 0.0001	
Residual	6255.25	7	893.61			
Lack of Fit	3290.75	2	1645.37	2.78	0.1546	not significant
Pure Error	2964.50	5	592.90			
Cor Total	2.320E+07	11				
R ² = 0.9997 Adjusted R ² = 0.9996 Predicted R ² = 0.9992 Adequate Precision= 189.0473						

5. RESULTS AND DISCUSSIONS

Experimental data was carefully examined through analysis of variance (ANOVA), which helped establish mathematical models for predicting emission characteristics.

5.1. Carbon Monoxide (CO) analysis

5.1.1. ANOVA results for CO

Model f-value: 59.77 (p < 0.0001, highly significant)

Significant factors:

- GO concentration (A): strong negative effect on co emissions.
- Load (B): as load increases, co decreases.
- Interaction (AB, BC): statistically significant effects on co emissions.

5.1.2. Regression model for CO

$$CO = 1.58834 - 0.005915 \times GO - 0.221672 \times LOAD - 0.000308 \times SPEED - 0.000482 \times AB + 0.000084 \times BC$$

Effect of load:

Increased loads lead to reduced co emissions because of increased air-fuel mixing.

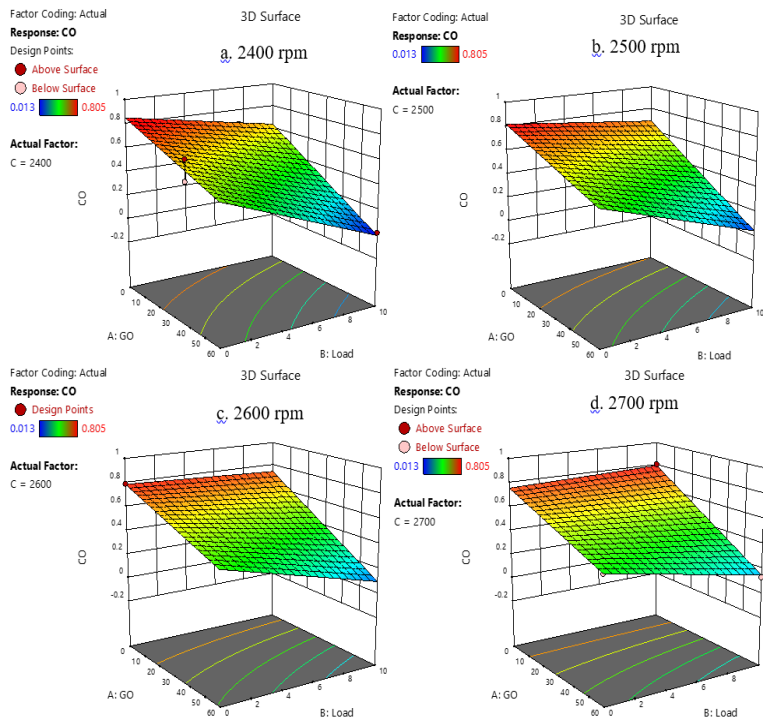
5.1.3. Discussion and Implications

1. GO is a catalyst and improves complete combustion, thereby inhibiting CO formation.
2. At increased loads, increased air flow into the combustion chamber leads to better oxidation and reduced CO emissions.

Fig. 4: 3D Interaction plot for CO showing interactions between GO, Load and speeds at different rpms (a: 2400 rpm, b: 2500 rpm, c: 2600 rpm and d: 2700 rpm)

5.2. Carbon Dioxide (CO₂) Analysis

5.2.1. ANOVA Results for CO₂



Model F-value: 60.01 (p < 0.0001, highly significant)

Significant Factors:

- GO concentration (A): Reduces CO₂ emissions.
- Load (B): Load negatively impacts CO₂ emissions.
- Interaction (AB): Affects CO₂ significantly.

5.2.2. Regression Model for CO₂

$$CO_2 = 15.44839 - 0.129389 \times GO - 0.016389 \times Load + 0.001854 \times Speed - 0.016674 \times AB$$

Impact of GO:

GO contributes to the reduction of CO₂ emissions, indicating improved fuel oxidation.

5.2.3. Discussion and Implications

1. GO facilitates better air-fuel mixing, reducing incomplete combustion.
2. At higher speeds, combustion instability increases CO₂ emissions slightly.

5.3. Hydrocarbons (HC) Analysis

5.3.1. ANOVA Results for HC

Model F-value: 40.22 (p < 0.0001, highly significant)

Significant Factors:

- GO (A): Highly significant in reducing HC.
- Interaction (AB): Also significant.

5.3.2. Regression Model for HC

$$HC = 146.01860 - 1.31826 \times GO + 0.957812 \times Load + 0.001834 \times Speed - 0.072795 \times AB$$

Impact of Engine Speed:

- Load has a mild effect on HC emissions.
- Increased engine speed correlates with higher HC emissions, signaling incomplete combustion.

5.3.3. Discussion and Implications

1. GO enhances atomization, leading to less unburnt hydrocarbons.
2. Higher speeds cause minor increases in HC emissions due to incomplete combustion

Fig. 5: 3D Interaction plot for CO₂ showing interactions between GO, Load and speeds at different rpms (a: 2400 rpm, b: 2500 rpm, c: 2600 rpm and d: 2700 rpm)

5.4. Nitrogen Oxides (NOx) Analysis

5.4.1. ANOVA Results for NOx
 Model F-value: 6490.16 (p < 0.0001, extremely significant)

Significant Factors:

GO (A), Load (B), Speed (C), Interaction (AB).

5.4.2. Regression Model for NOx

$$NOx = -2426.50031 - 4.06671 * GO + 315.24273 * Load + 1.10921 * Speed - 4.90070 * AB$$

Impact of GO:

1. Load and speed also significantly increase NOx.
2. The presence of GO marginally increases NOx emissions, indicating a trade-off between lowering CO and increasing NOx.

5.4.3. Discussion and Implications

- GO enhances combustion, increasing flame temperature and NOx formation.
- EGR (Exhaust Gas Recirculation) could be implemented to counteract NOx formation.

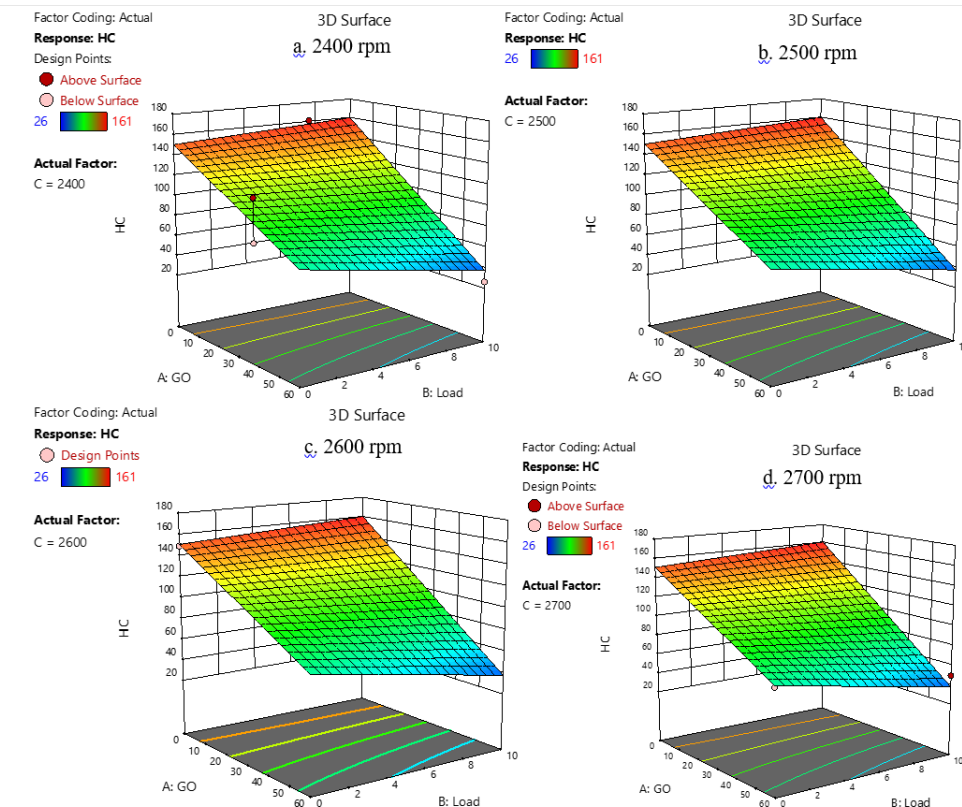


Fig. 6: 3D Interaction plot for HC showing interactions between GO, Load and speeds at different rpms (a: 2400 rpm, b: 2500 rpm, c: 2600 rpm and d: 2700 rpm

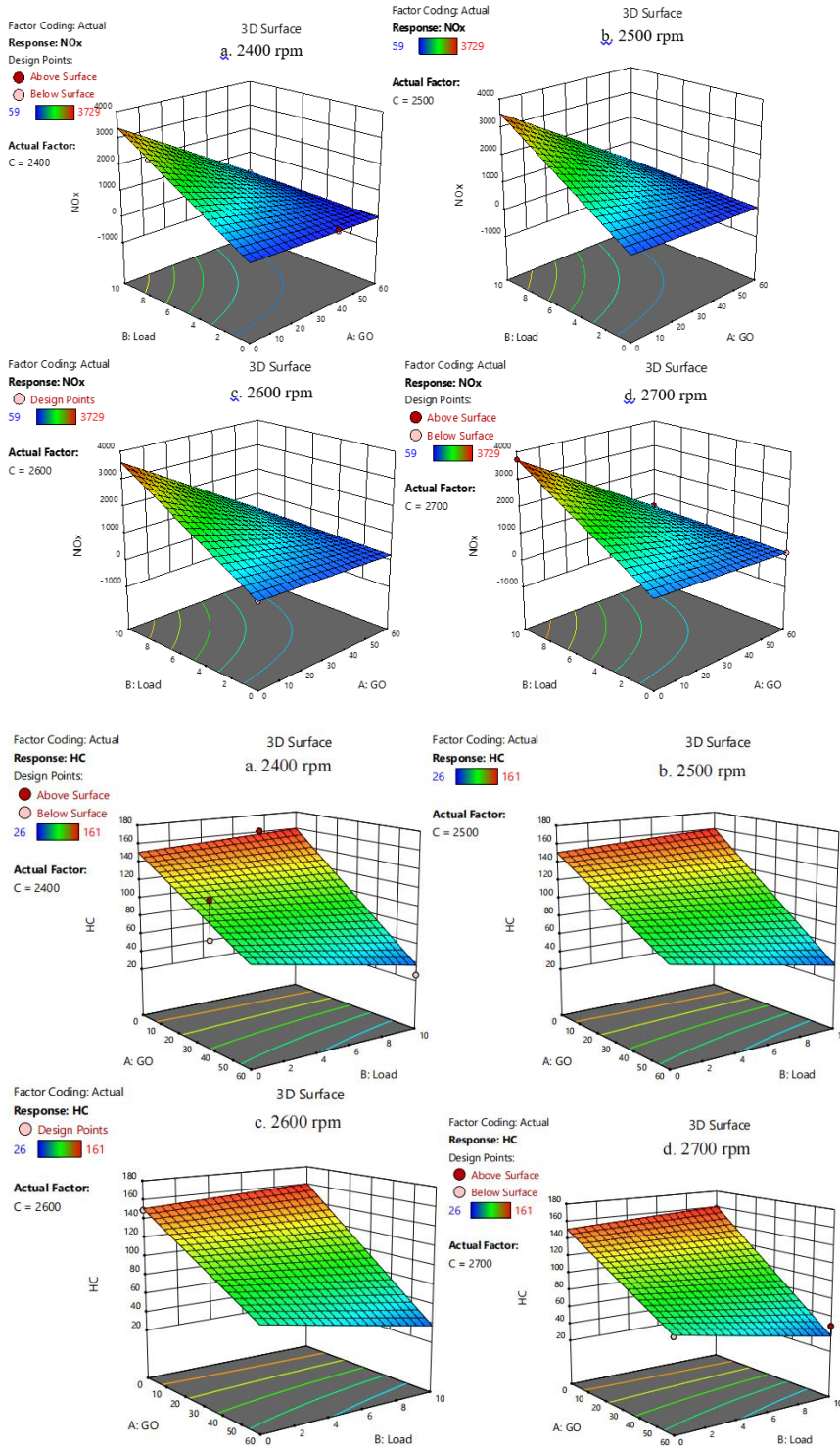


Fig. 7: 3D Interaction plot for NOx showing interactions between GO, Load and speeds at different rpms (a: 2400 rpm, b: 2500 rpm, c: 2600 rpm and d: 2700 rpm
Table no. 5: Solutions obtained for desirability

Number	GO	Load	Speed	CO	CO2	HC	NOx	Desirability
1	60.000	10.000	2400.000	-0.008	1.967	37.225	203.618	0.949
2	60.000	10.000	2401.307	-0.007	1.969	37.228	205.071	0.949
3	60.000	10.000	2402.477	-0.006	1.972	37.230	206.368	0.949
4	60.000	10.000	2407.246	-0.004	1.980	37.239	211.658	0.948
5	60.000	9.944	2400.004	-0.005	2.024	37.416	202.437	0.948
6	60.000	9.993	2410.952	-0.001	1.994	37.269	215.621	0.948
7	60.000	10.000	2413.206	-0.001	1.991	37.249	218.271	0.948
8	60.000	10.000	2416.359	0.001	1.997	37.255	221.767	0.947
9	60.000	10.000	2417.529	0.002	1.999	37.257	223.064	0.947
10	60.000	10.000	2419.714	0.003	2.003	37.261	225.489	0.947
11	60.000	9.999	2421.040	0.004	2.007	37.266	226.941	0.947
12	60.000	9.857	2400.018	-0.000	2.112	37.711	200.620	0.946
13	60.000	10.000	2425.819	0.006	2.015	37.273	232.257	0.946
14	59.743	10.000	2400.011	-0.005	2.043	37.751	217.271	0.946
15	60.000	10.000	2433.927	0.010	2.030	37.288	241.251	0.946
16	59.676	10.000	2402.154	-0.003	2.067	37.892	223.208	0.945
17	60.000	10.000	2438.386	0.013	2.038	37.295	246.196	0.945

18	60.000	9.883	2428.357	0.013	2.139	37.678	232.589	0.944
19	60.000	9.692	2400.000	0.008	2.280	38.276	197.085	0.943
20	60.000	9.620	2401.047	0.012	2.355	38.523	196.734	0.942
21	60.000	10.000	2452.566	0.020	2.064	37.321	261.925	0.942
22	60.000	10.000	2455.862	0.022	2.070	37.327	265.581	0.941
23	60.000	10.000	2457.426	0.023	2.073	37.330	267.317	0.940
24	60.000	10.000	2459.570	0.024	2.077	37.334	269.694	0.940
25	59.316	10.000	2427.742	0.014	2.221	38.675	270.685	0.938
26	60.000	10.000	2466.229	0.027	2.090	37.347	277.085	0.938
27	60.000	10.000	2467.809	0.028	2.093	37.349	278.832	0.938
28	60.000	9.427	2400.000	0.021	2.550	39.179	191.472	0.936
29	60.000	10.000	2473.675	0.031	2.104	37.361	285.343	0.936
30	60.000	10.000	2475.578	0.032	2.107	37.364	287.451	0.936
31	58.795	10.000	2400.002	0.005	2.324	39.691	267.576	0.935
32	60.000	10.000	2478.660	0.034	2.113	37.370	290.867	0.935
33	60.000	10.000	2485.025	0.037	2.125	37.381	297.937	0.933
34	58.563	9.962	2400.028	0.010	2.430	40.290	278.864	0.932
35	58.406	10.000	2400.017	0.010	2.439	40.488	288.261	0.931
36	60.000	10.000	2494.169	0.042	2.142	37.398	308.076	0.931
37	60.000	10.000	2505.143	0.048	2.162	37.418	320.247	0.928
38	60.000	9.116	2400.001	0.037	2.866	40.240	184.889	0.926
39	60.000	10.000	2521.657	0.057	2.192	37.448	338.563	0.923
40	60.000	10.000	2526.244	0.059	2.201	37.457	343.653	0.922
41	60.000	10.000	2529.764	0.061	2.207	37.463	347.557	0.921
42	60.000	10.000	2554.073	0.074	2.253	37.508	374.520	0.915
43	60.000	10.000	2573.375	0.084	2.288	37.543	395.930	0.910
44	60.000	10.000	2577.402	0.086	2.296	37.550	400.395	0.908
45	60.000	10.000	2591.893	0.094	2.323	37.577	416.470	0.905
46	60.000	10.000	2593.297	0.094	2.325	37.580	418.025	0.904
47	60.000	10.000	2599.419	0.098	2.337	37.591	424.818	0.903
48	60.000	8.385	2400.023	0.073	3.609	42.732	169.403	0.901
49	60.000	10.000	2608.478	0.102	2.353	37.607	434.867	0.900
50	60.000	8.294	2400.017	0.078	3.702	43.042	167.472	0.897
51	60.000	10.000	2646.669	0.122	2.424	37.677	477.226	0.890
52	60.000	9.992	2661.696	0.131	2.460	37.731	493.735	0.885
53	60.000	10.000	2674.132	0.137	2.475	37.728	507.692	0.882
54	60.000	10.000	2675.209	0.137	2.477	37.730	508.886	0.882
55	60.000	10.000	2678.137	0.139	2.483	37.735	512.131	0.881
56	60.000	10.000	2679.722	0.140	2.486	37.738	513.888	0.881
57	60.000	10.000	2684.488	0.142	2.494	37.747	519.177	0.879
58	60.000	10.000	2686.689	0.144	2.498	37.751	521.618	0.879
59	60.000	10.000	2699.999	0.151	2.523	37.776	536.382	0.875
60	60.000	7.531	2400.000	0.116	4.477	45.644	151.277	0.871
61	59.642	10.000	2700.000	0.154	2.629	38.507	555.372	0.870
62	60.000	7.477	2400.001	0.119	4.533	45.830	150.121	0.869
63	59.131	10.000	2699.304	0.160	2.779	39.552	581.723	0.863
64	52.706	9.999	2400.008	0.071	4.127	52.151	590.695	0.849
65	60.000	8.525	2699.945	0.188	4.022	42.803	505.063	0.837
66	60.000	7.646	2699.974	0.210	4.916	45.800	486.456	0.813
67	60.000	6.513	2700.000	0.238	6.069	49.667	462.446	0.783
68	56.236	8.186	2700.000	0.233	5.369	51.167	664.224	0.779
69	60.000	6.274	2699.989	0.244	6.312	50.482	457.368	0.776
70	60.000	4.271	2400.009	0.280	7.792	56.761	82.165	0.751
71	60.000	3.663	2400.001	0.310	8.410	58.832	69.276	0.728
72	60.000	1.840	2699.996	0.355	10.820	65.598	363.388	0.646

Table no. 6: Confirmation Experiment

Two-sided Confidence = 95%

Analysis	Actual Response	Predicted Mean	Predicted Median	Predicted Response	Std Dev	n	SE Pred	95% PI low	95% PI high
CO	0.013	-0.00756112	-0.00756112	0.00432	0.0515024	1	0.0673761	-0.172425	0.157302
CO2	0.41	1.96687	1.96687	1.96636	1.43385	1	1.8149	-2.32469	6.25843
HC	26	37.2249	37.2249	37.22572	12.8606	1	16.2783	-1.26717	75.7171
NOx	180	203.618	203.618	203.65409	29.8933	1	37.8374	114.147	293.089

6. Confirmation Experiment

Final step in the analysis is to perform confirmation experiments at the optimized levels of factors. Initially confidence interval for each response is to be calculated for the confirmation experimentation. The procedure is different than the one described in case of Taguchi's DOE process and is explained for RGN. In case of regression analysis confidence interval is calculated using formula (De Gryze et al. (2007),

$$CI = \hat{y}_0 \pm t_{(\frac{\alpha}{2}, Residual\ df)} \times SE_{mean}$$

$$where, SE_{mean} = S \times \sqrt{x_0(X^T X)^{-1} x_0^T}$$

$$S = \sqrt{Residual\ Mean\ Square}$$

\hat{y}_0 = Predicted mean response at optimum levels of factors in coded form and

$$\alpha = Risk = (1 - CL) = (1 - 0.95) = 0.05$$

x_0 = Single row matrix with column equal to number of predicted variables (coded form) at optimum levels of factor

X = Matrix with all model terms (coded form) for all recorded responses

Following steps are used to calculate the confidence interval for regression analysis of RGN –

1. Calculate \hat{y}_0 using model equation coded form with optimum factor levels in coded form.
2. Calculate $t_{(\frac{\alpha}{2}, Residual\ df)}$
3. Obtain Matrix x_0
4. Perform matrix operations. $x_0(X^T X)^{-1} x_0^T$
5. Obtain SE_{mean}

6. Calculate CI

Values of actual responses at optimum levels are in close agreement with predicted responses. The error between predicted and actual response is also well within acceptable range. Hence the experimentation is confirmed with 95% confidence level

7. Conclusion

- 1. The analysis demonstrates stable performance across various operational parameters, characterized by minimal fluctuations in key metrics, indicating reliable system functionality.
- 2. Initial desirability values start high as (at 60 ppm GO, 10 kg Load and 2400 rpm) of 0.949 as the optimized response but show a progressive decline, suggesting diminishing returns as operational parameters are increased, which warrants careful consideration in future adjustments.
- 3. There is a distinct correlation between elevated loads and speeds and the resultant increase in emissions of CO, CO₂, HC, and NO_x, highlighting the environmental implications of performance enhancements.
- 4. The observed decline in desirability scores points to significant opportunities for optimizing performance while concurrently striving to reduce harmful emissions, thus encouraging more efficient operational strategies.
- 5. Specific operational conditions lead to notably lower desirability, indicating important areas that necessitate further investigation to enhance overall system performance without compromising environmental standards.
- 6. This study underscores the necessity of balancing performance metrics with environmental sustainability, emphasizing the need for integrating desirability assessments into future development efforts to achieve both operational efficacy and compliance with regulatory requirements.

Design Expert Software

Factor Coding: Actual

All Responses

Actual Factors: GO: 60 ppm

Load: 10 kg

Speed: 2400 rpm

Coded Factors: GO: 1

Load: 1

Speed: 0

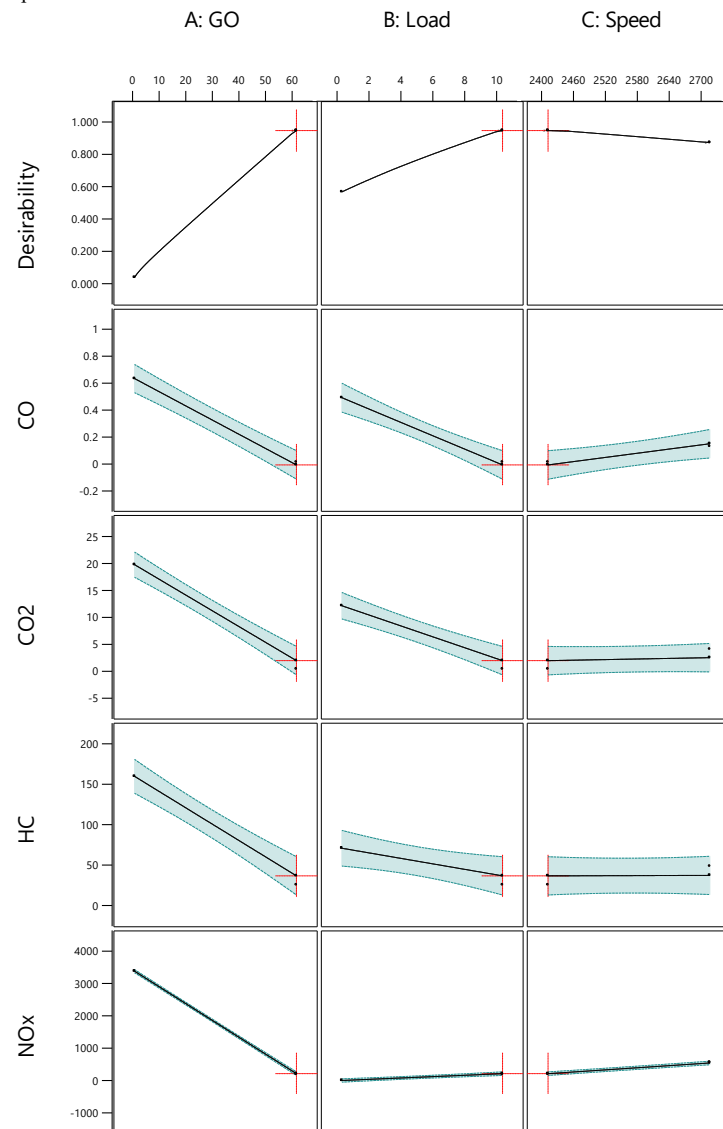


Fig. 8: Response optimizer plot