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Analysis of NOx, HC, and CO Emission Prediction in Internal Combustion Engines by Statistical Regression and ANOVA Methods

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Abstract
This study investigates the impact of engine operating parameters on exhaust emissions, mainly nitrogen oxides (NOx), hydrocarbons (HC), and carbon monoxide (CO), using a statistical regression modelling approach. The analysis employs the Analysis of Variance (ANOVA) method to assess model accuracy and sensitivity. The results indicate that the developed regression models exhibit high predictive accuracy, with the CO model demonstrating the best performance. The NOx model achieved an R-squared value of 0.9827, explaining 98.27% of data variation, but showed the highest standard deviation (35.14) and PRESS value (1.549E+005), indicating more significant data variability. The HC model performed slightly better with an R-squared value of 0.9865, a standard deviation of 3.68, and the lowest coefficient of variation (C.V.%) at 1.68%, ensuring high stability. The CO model outperformed both, with the highest R-squared value (0.9910), the lowest standard deviation (0.11), and a moderate C.V.% of 3.70%, making it the most reliable. Additionally, the Adeq Precision values for NOx, HC, and CO models were 45.791, 51.764, and 66.569, respectively, confirming strong signal-to-noise ratios. The findings indicate that increasing engine speed and throttle opening significantly influences emissions. Higher speeds increase NOx emissions but reduce HC and CO emissions, while larger throttle openings increase CO levels. These results provide valuable insights into optimizing engine parameters for reducing emissions. The developed models can be practical tools for emission predictions and mitigation strategies, contributing to environmentally friendly combustion technologies.

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1. Introduction
In recent decades, attention has been paid to exhaust emissions from internal combustion engines, considering their impacts on the environment and human health. One of the emissions of significant concern is nitrogen oxides (NOx), which contribute to the formation of tropospheric ozone and acid rain (Erdiwansyah et al., 2019; Kern, 2021; Nguyen et al., 2022; Rosdi, Erdiwansyah, Ghazali, & Mamat, 2025). Studies have shown that engine operating parameters, such as temperature and in-

cylinder pressure, significantly affect NOx formation. Statistical analysis using the ANOVA method shows that the regression model has an R-squared value of 0.9827, indicating the model's ability to explain data variations well (Almardhiyah, Mahidin, Fauzi, Abnisa, & Khairil, 2025; Dastkhoon et al., 2017; Khan & Singh, 2024; Prasad, Murugan, Wincy, & Sekhar, 2021). Increasing engine speed and throttle tend to increase NOx emissions, as shown by the scatter and three-dimensional graphs depicting the relationship between these variables.

In addition to NOx, hydrocarbons (HC) are one of the emissions produced due to incomplete combustion. The presence of hydrocarbons in the exhaust gas is related to the stoichiometric conditions of the air and fuel mixture in the engine, as revealed by (Alenezi, Erdiwansyah, Mamat, Norkhizan, & Najafi, 2020; İlhak, Tangöz, Akansu, & Kahraman, 2019; Muzakki & Putro, 2025; Rosdi, Maghfirah, Erdiwansyah, Syafrizal, & Muhibbuddin, 2025; Yana, Mufti, Hasiany, Viena, & Mahyudin, 2025). Based on the ANOVA analysis, the regression model for hydrocarbons has an R-squared value of 0.9865, indicating that this model can explain data variations accurately. The results of this study also show that increasing engine speed and throttle can reduce hydrocarbon emissions, which is in line with the theory that more complete combustion occurs in more optimal engine operating conditions. In addition, carbon monoxide (CO) results from incomplete combustion due to oxygen deficiency in the fuel and air mixture (Alenezi et al., 2021; Gani et al., 2025; Valdés-López, Mason, Shearing, & Brett, 2020). Based on the ANOVA results, the regression model used to analyze CO has the highest R-squared value of 0.9910, indicating excellent model suitability in explaining data variations. Increasing engine speed causes a decrease in CO emissions while increasing throttle tends to increase CO levels in exhaust gas. This indicates that the air-fuel ratio plays a vital role in determining the level of CO produced by the engine.

Comparison of regression models for NOx, HC, and CO shows that the model for CO has the best performance with higher accuracy and stability compared to other models. The coefficient of variation (C.V.%) value for the CO model is relatively small (3.70%), indicating that the data is more centred around the mean value (Schägner, Brander, Maes, Paracchini, & Hartje, 2016). In contrast, the NOx model has a higher level of variation with the most significant standard deviation (35.14), indicating that the data fluctuation is more critical. Hence, the model prediction is more susceptible to uncertainty. Overall, the model developed in this study has a relatively good sensitivity in analyzing exhaust emissions from internal combustion engines. The high Adeq Precision value, especially for the CO model (66.569), indicates that this model has an excellent signal-to-noise ratio, so it can be relied on to predict exhaust emissions (Fitriyana, Rusiyanto, & Maawa, 2025; Irhamni, Kurnianingtyas, Muhtadin, Bahagia, & Yusop, 2025; Najafi et al., 2016; Silitonga et al., 2018). These findings provide further insight into how engine operating parameters can be optimized to reduce harmful emissions.

This study contributes to a deeper understanding of the factors affecting exhaust emissions and can form the basis for developing emission reduction strategies in future engine designs. By understanding how engine speed and throttle affect NOx, HC, and CO emissions, more effective mitigation measures can be designed to improve combustion efficiency and reduce the environmental impact of motor vehicles. Furthermore, the novelty of this study lies in the developed simulation modelling approach, which not only allows an in-depth analysis of the factors affecting emissions but also provides more accurate predictions regarding engine parameter optimization to reduce environmental impacts significantly.

2. Methodology

Research Approach

This study uses a simulation modelling approach to analyze the impact of engine operating parameters on exhaust emissions, especially nitrogen oxides (NOx), hydrocarbons (HC), and carbon monoxide (CO). Simulations are carried out using a statistical approach using the Analysis of Variance (ANOVA) method to test the significance of the developed regression model.

Variables and Simulation Models

The independent variables in this study include engine speed and throttle opening, while the dependent variables are the concentrations of NOx, HC, and CO in exhaust gas. A regression model is developed to describe the relationship between engine operating parameters and exhaust emissions, with the calculation of R-squared, Adjusted R-squared, and Predicted R-squared values to evaluate model performance.

Simulation Procedure

a) **Data Collection**: Data is obtained from experimental results and simulations based on internal combustion engine (ICE) combustion characteristics.
b) **Statistical Analysis**: The regression model for each exhaust gas is analyzed using ANOVA to measure the model's suitability to the data obtained.
c) **Data Visualization**: The simulation results are visualized using scatter plots and 3D plots to clarify the relationship between engine speed, throttle, and exhaust emissions.
d) **Model Performance Evaluation**: The developed model is evaluated with statistical parameters such as standard deviation, coefficient of variation (C.V.%), PRESS value, and Adeq Precision to ensure the accuracy and sensitivity of the model in predicting emissions.

Model Calculation and Validation

a) The NOx model shows R-Squared = 0.9827, with Adeq Precision 45.791, indicating a reasonably sensitive model in predicting NOx emissions.
b) The HC model has R-Squared = 0.9865, with Adeq Precision 51.764, indicating a more stable performance in predicting hydrocarbon emissions.
c) The CO model shows the best performance with R-squared = 0.9910 and Adeq Precision 66.569, indicating this model is the most accurate and stable in predicting carbon monoxide emissions.

The modelling method used in this study shows that the regression model can explain the variation of exhaust emission data. The CO model performs best, followed by HC, while the NOx model has higher data variability and is therefore susceptible to prediction uncertainty. These results provide a strong basis for developing engine parameter optimization strategies to reduce the impact of emissions on the environment.

3. Result & Discussion

The temperature and pressure inside the cylinder significantly impact the formation of nitrogen oxide (NOx) emissions. The presence of hydrocarbons in the exhaust gas is related to the stoichiometric conditions of the air and fuel mixture in the engine, as revealed by (Sagna et al., 2017). These hydrocarbons contribute to air pollution because engines emit this dangerous gas as a byproduct of incomplete combustion, potentially leading to adverse environmental and health effects (Efremov & Kumarasamy, 2025; Ogunkunle & Ahmed, 2021). The nitrogen oxide ANOVA response is displayed in **Table 1**. It stated that the R-squared value is 0.9827, nearly equal to 1. Additionally, significant model terms are indicated by Prob > F values less than 0.0500. The relationships between NOx, engine throttle, and engine speed are given in **Eq. 1**. A graph of NOx emissions as a function of engine speed, and throttle is displayed in **Fig. 1 (a)** as a scatter plot and **(b)** as a three-dimensional plot. It explained that as engine speed and throttle increased, so did NOx emissions.

$$NOx = 658.23+133.09 * A+237.90 * B+67.54 * C[1]+15.57 * C[2]-21.57 * C[3]-54.21 * C[4]+34.18 * C[5]-4.74 * C[6]+32.23 * AB-13.19 * AC[1]-1.34 * AC[2]+0.014 * AC[3]+9.16 * AC[4]-6.67 * AC[5]-0.39 * AC[6]+20.52 * BC[1]+0.77 * BC[2]-6.27 * BC[3]-20.11 * BC[4]+12.81 * BC[5]+2.98 * BC[6]-37.55 * A^2+24.89 * B^2 \quad (1)$$

Table 1 shows the ANOVA results for nitrogen oxides, which illustrate the performance of the statistical model in explaining data variation. The standard deviation value of 35.14 indicates a reasonably significant data variation from the average of 653.96. The coefficient of variation (C.V.%) of 5.37% suggests that the model has a moderate level of relative variation. The high PRESS value (1.549E+005) indicates a relatively large model prediction error, which wider data fluctuations may influence. However, the R-squared value of 0.9827 indicates that the model is still able to explain 98.27% of the data variation well, supported by the Adjusted R-squared (0.9760) and Predicted R-squared (0.9638) values, which indicate the stability of the model in fitting and prediction. In addition, the Adeq Precision of 45.791 demonstrates that this model's signal-to-noise ratio is quite good, indicating that the model still has adequate sensitivity for nitrogen oxide analysis and prediction.

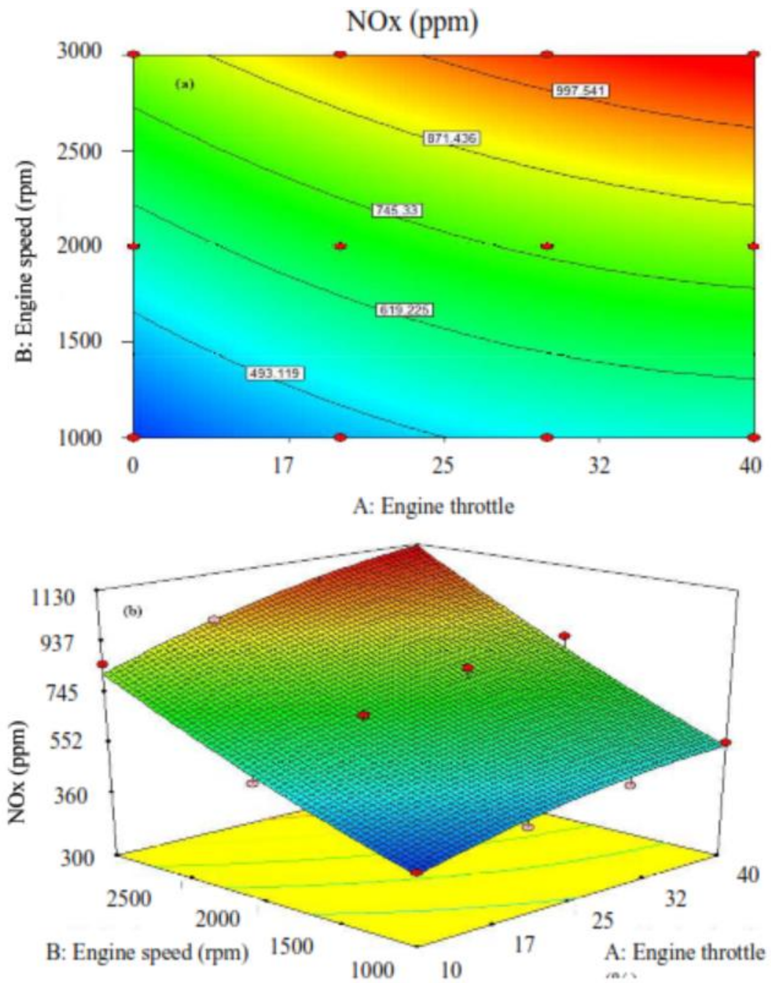

Fig. 1. Graph of NOx emission as a function of engine speed and engine throttle (a) scatter (b) 3D

Table 1. ANOVA response for Nitrogen oxide

Parameter	Value
Std. Dev.	35.14
Mean	653.96
C.V. %	5.37
PRESS	1.549E+005
R-Squared	0.9827
Adj R-Squared	0.9760
Pred R-Squared	0.9638
Adeq Precision	45.791

Incomplete combustion produces hydrocarbons, which occur when the stoichiometry of engine emissions is reached (Chen, He, & Zhong, 2019; Krishnamoorthi, Malayalamurthi, He, & Kandasamy, 2019). The hydrocarbon ANOVA results are displayed in **Table 2**. The model is considered significant when the R-squared value is 0.9865 and near 1. Additionally, considerable model terms are indicated by Prob > F values less than 0.0500. **Eq. 2** illustrates the relationship between engine speed, throttle, and hydrocarbon. The (a) scatter graph and (b) three-dimensional graph for hydrocarbons as a function of engine speed and throttle are displayed in **Fig. 2**. It said that as engine speed and throttle increase, hydrocarbon drops.

$$HC = 208.65-31.84 * A-5.24 * B+14.05 * C[1]+3.55 * C[2]-4.84 * C[3]-12.23 * C[4]+7.69 * C[5]+0.37 * C[6]+1.51 * AB-2.07 * AC[1]-0.97 * AC[2]+1.73 * AC[3]+2.46 * AC[4]-2.49 * AC[5]-1.10 * AC[6]-2.80 * BC[1]-1.05 * BC[2]+1.40 * BC[3]+1.99 * BC[4]-0.76 * BC[5]+0.49 * BC[6]+15.00 * A2+2.66 * B^2 \quad (2)$$

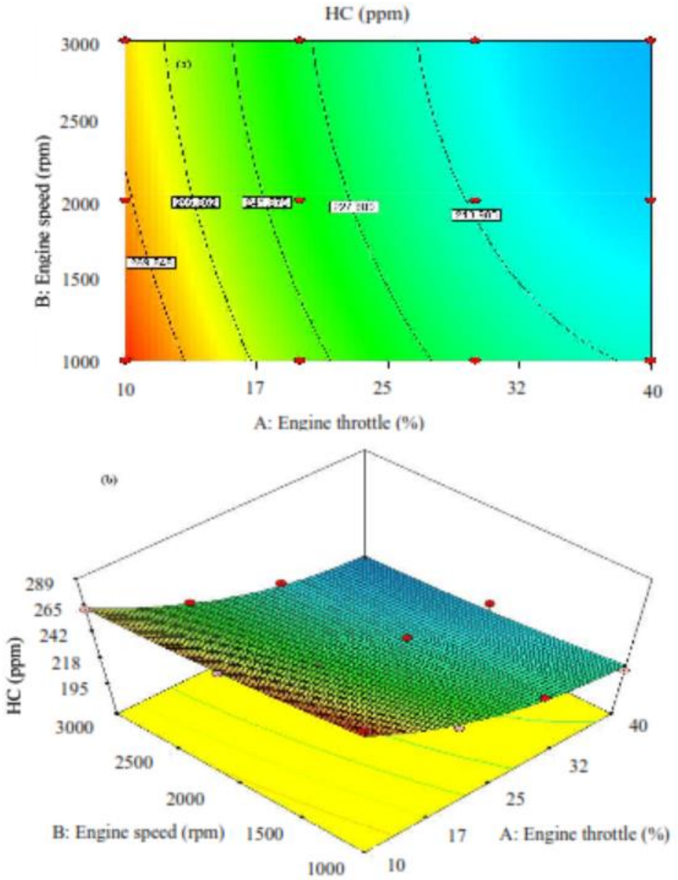

Fig. 2. Graph HC emission as a function of engine speed and engine throttle (a) scatter graph (b) 3D graph

Table 2 presents the ANOVA results for hydrocarbons, which show the performance of the statistical model in analyzing the data. The standard deviation value of 3.68 reflects the level of data variation from the average of 218.76, with a low coefficient of variation (C.V.%) of 1.68%, indicating that the model has good stability. The PRESS value is relatively high (1749.70), indicating residuals in the model prediction. The coefficient of determination (R-squared) of 0.9865 suggests that the model can explain about 98.65% of the data variation, supported by the Adjusted R-squared (0.9813) and Predicted R-squared (0.9709), which are also high, confirming the reliability of the model both in fitting and prediction. In addition, the Adeq Precision of 51.764 shows a reasonably good signal-to-noise ratio, indicating that this model has adequate sensitivity and is suitable for hydrocarbon analysis and prediction with high accuracy.

Table 2. ANOVA results for hydrocarbon

Parameter	Value
Std. Dev.	3.68
Mean	218.76
C.V. %	1.68
PRESS	1749.70
R-Squared	0.9865
Adj R-Squared	0.9813
Pred R-Squared	0.9709
Adeq Precision	51.764

When rich mixes are burned, carbon monoxide results from incomplete combustion with inadequate oxygen (Baskar & Senthilkumar, 2016; Wang, Liu, Long, Wang, & He, 2015). The hydrocarbon ANOVA results are displayed in **Table 3**. When R-squared is 0.9910 and near 1, the model is considered significant. Additionally, considerable model terms are indicated by Prob > F values less than 0.0500.

Eq. 3 illustrates the relationship between engine speed, throttle, and carbon monoxide. A scatter graph and a three-dimensional graph of carbon monoxide as a function of engine speed and throttle are displayed in **Fig. 3**. According to the article, carbon monoxide drops as engine speed rises. In contrast, it falls when the engine throttle increases.

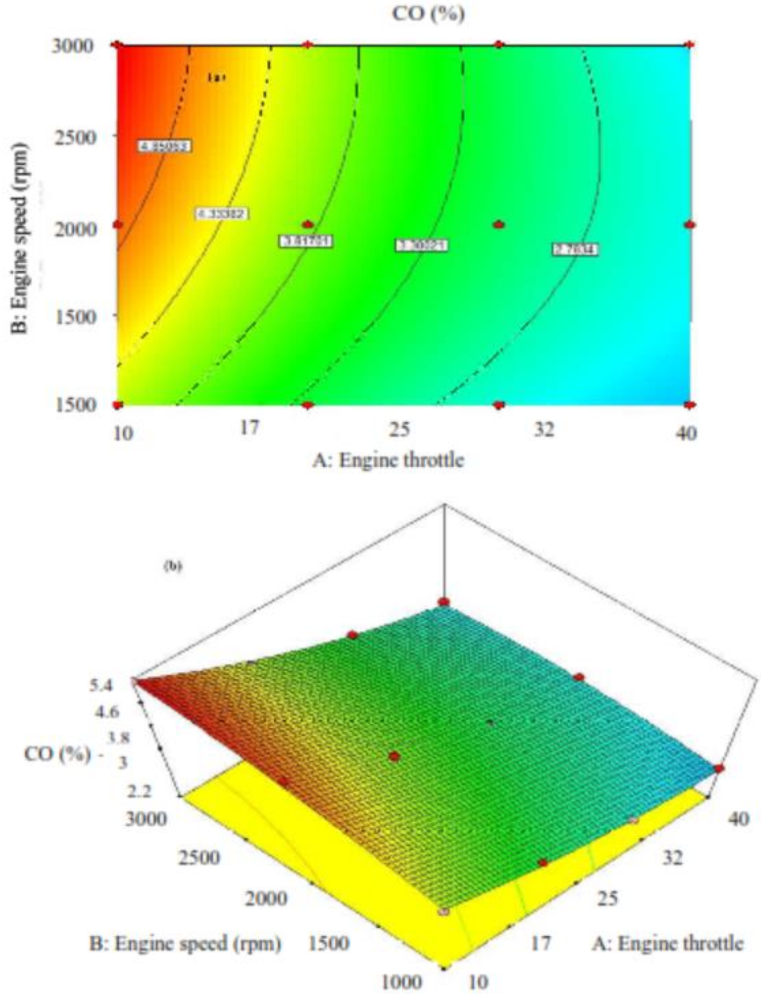

Fig. 3. Graph CO emission as a function of engine speed and engine throttle (a) scatter graph (b) 3D graph

$$CO = 2.95 - 1.18 * A + 0.30 * B + 0.48 * C[1] + 0.097 * C[2] - 0.13 * C[3] - 0.41 * C[4] + 0.24 * C[5] - 0.023 * C[6] - 0.27 * AB - 0.024 * AC[1] + 0.025 * AC[2] - 6.559E{-}003 * AC[3] - 0.013 * AC[4] + 0.053 * AC[5] - 0.024 * AC[6] + 0.048 * BC[1] + 0.025 * BC[2] - 0.025 * BC[3] - 0.063 * BC[4] + 0.081 * BC[5] - 6.488E{-}003 * BC[6] + 0.31 * A^2 - 0.20 * B^2 \quad (3)$$

Table 3 presents the ANOVA results for carbon monoxide, which include various statistical parameters that assess the quality of the regression model. The standard deviation value (0.11) indicates a relatively small level of data dispersion from the mean (2.99), while the coefficient of variation (C.V.%) of 3.70% suggests relative variation in the data. The PRESS (Predicted Residual Sum of Squares) value of 1.42 illustrates the model's predictive ability. The high coefficient of determination (R-squared) (0.9910) indicates that the model has a perfect fit to the data, supported by the Adjusted R-squared (0.9876) and Predicted R-squared (0.9827) values , which are also high, which confirms the stability of the model both in adjustment and prediction. In addition, the Adeq Precision of 66.569 indicates that the model has a perfect signal-to-noise ratio, which means that the model can be used to make predictions with a high level of accuracy.

Table 3. ANOVA results for carbon monoxide

Parameter	Value
Std. Dev.	0.11
Mean	2.99
C.V. %	3.70
PRESS	1.42
R-Squared	0.9910
Adj R-Squared	0.9876
Pred R-Squared	0.9827
Adeq Precision	66.569

Based on the ANOVA results presented in Table 1-3, the performance of the models for carbon monoxide, hydrocarbons, and nitrogen oxides can be compared in terms of stability, accuracy, and sensitivity. The model for carbon monoxide showed the best performance with the highest R-squared (0.9910) and consistently high Adjusted R-squared (0.9876) and Predicted R-squared (0.9827) values, indicating a highly accurate and stable model. In addition, the smallest standard deviation value (0.11) and low coefficient of variation (3.70%) indicate that the data are more concentrated around the mean, resulting in more reliable predictions. The model for hydrocarbons also showed good performance with an R-squared of 0.9865. However, the PRESS value was quite significant (1749.70), indicating a higher prediction error level than carbon monoxide. However, the lowest C.V. % (1.68%) suggests the hydrocarbon model has high stability.

Meanwhile, the model for nitrogen oxides has a lower R-squared value than the other two gases (0.9827), as well as the highest standard deviation (35.14) and the largest PRESS (1.549E+005), indicating that the data has more significant variability and the model prediction is more susceptible to uncertainty. However, the Adeq Precision values are still relatively high for all models, with carbon monoxide (66.569) having the highest value, followed by hydrocarbons (51.764) and nitrogen oxides (45.791), indicating that the carbon monoxide model has the best signal to noise ratio. Overall, the model for carbon monoxide has the best performance in terms of fit and sensitivity, followed by hydrocarbons. In contrast, the model for nitrogen oxides has higher data variability, which can affect the accuracy of prediction.

4. Conclusion

This study successfully analyzed the impact of engine operating parameters on exhaust emissions, mainly nitrogen oxides (NOx), hydrocarbons (HC), and carbon monoxide (CO), using a statistical regression modelling approach. The findings indicate that the developed models exhibit high accuracy in predicting emissions, with the CO model demonstrating the best performance.

a. The NOx model achieved an R-squared value of 0.9827, explaining 98.27% of the data variation. However, it has the highest standard deviation (35.14) and PRESS value (1.549E+005), reflecting more significant data variability and susceptibility to uncertainty. The Adeq Precision of 45.791 suggests that the model is sufficiently sensitive for NOx emission predictions.

b. The HC model performed slightly better, with an R-square value of 0.9865, capturing 98.65% of the data variation. The standard deviation was relatively low (3.68), and the coefficient of variation (C.V.%) was the smallest among the three models (1.68%), indicating high stability. The Adeq Precision of 51.764 confirms that the model maintains a good signal-to-noise ratio.

c. The CO model exhibited the best overall performance, with the highest R-squared value (0.9910), explaining 99.10% of the data variation. It also had the lowest standard deviation (0.11) and a moderate C.V.% (3.70%), ensuring stable and precise predictions. The Adeq Precision of 66.569 further demonstrates the strong reliability of the model in CO emission analysis.

d. An increase in engine speed and throttle leads to higher NOx emissions, while it reduces HC emissions due to more complete combustion. CO emissions decrease with higher engine speed but increase with more significant throttle opening due to air-fuel ratio imbalances.

e. The CO model is the most robust in predicting emission levels, followed by the HC model, whereas the NOx model exhibits higher variability, making its predictions slightly less reliable.
f. These findings highlight the potential for optimizing engine parameters to minimize harmful emissions, contributing to cleaner combustion technologies and improved environmental sustainability.

This study provides a strong foundation for optimizing engine operations and developing future emission control strategies. The high accuracy of the models, particularly for CO and HC, indicates their potential use in real-world applications to mitigate the environmental impact of internal combustion engines.

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