# Modeling of emissions characteristics of a diesel engine fueled by Jatropha Diestrol

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**Abstract:** This paper uses a multi-objective based on the genetic algorithm and support vector machine to optimize the engine operating parameters of a single-cylinder diesel engine. Jatropha Diesterol fuel blends underwent testing in a single-cylinder air-cooled diesel engine, operating at full load and four engine speeds (i.e., 1600, 2000, 2400, and 2800 rpm). The emitted pollutants, namely CO, $CO_2$, HC, $O_2$, and HC, were analyzed and recorded. Subsequently, the data was modeled using the support vector machine method, incorporating genetic algorithm optimization to predict engine-out emissions simultaneously. The findings of this investigation demonstrated that the technique employed could predict the data from this experiment with high accuracy. Therefore, this modeling approach can be utilized for future research in this field, obviating the need for costly and time-consuming experiments and evaluations of advanced alternative fuel blends.
**Keywords:** emissions, diesel engine, Jatropha, Genetic Algorithm, Support vector machine

**Citation:** Kazemi, N., N. Alizadehbehbahani, and S. M. Safieddin Ardebili. 2025. Modeling of emissions characteristics of a diesel engine fueled by Jatropha Diestrol. Agricultural Engineering International: CIGR Journal, 27(2):171-180.

## 1 Introduction

The dominance of fossil fuels in global energy supply, as reported by the International Energy Agency, stands at around 80% (Wang et al., 2022). However, fossil fuels suffer from inherent limitations, including their non-renewable nature, depletion of resources, environmental pollution, and susceptibility to price volatility linked to crude oil markets (Aghbashlo et al., 2021; Geetha et al., 2020). The adverse effects of greenhouse gases on the environment and human health are far-reaching, encompassing both short-term and long-term consequences (Perera and Nadeau, 2022; Wang et al., 2023; Benevolenza and DeRigne, 2019; Coulibaly et al., 2020).

Biodiesel is derived from renewable and sustainable sources, making it an environmentally friendly option (Sultana et al., 2022). Biodiesel can be described as fatty acid monoalkyl esters obtained from plant oils, animal fats, and other lipids (Rizwanul Fattah et al., 2020). Notably, biodiesel exhibits favorable properties such as oxygen content, absence of sulfur, and non-toxicity [8]. Vegetable oils serve as the primary source for biodiesel production, with approximately 95% of global biodiesel currently being derived from edible oils (Kazemi et al., 2020; Mathew et al., 2021).

**Received date:** 2024-06-08 **Accepted date:** 2024-11-21
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Jatropha seeds contain an oil content of approximately 30 to 35%, making them well-suited for conversion into high-quality biodiesel using conventional methods (Becker, 2009). Direct utilization of plant oils in diesel engines is limited due to in incomplete combustion and fuel deposits in injectors (Almasi et al., 2021). To overcome these limitations, various methods have been developed to enhance the properties of plant oils and convert them into biodiesel (Kazemi et al., 2020; Almasi et al., 2021). To address these issues, the use of ethanol and catalysts in biodiesel production offers a solution. Ethanol and catalysts can effectively reduce the density, viscosity, and emissions of NOx, and smoke compared to diesel fuel (Shekofteh et al., 2020). Biodiesel can be blended with diesel fuel at any desired ratio, allowing for flexibility in fuel utilization (Noorollahi et al., 2018). However, diesel fuel itself also experiences increased viscosity in cold weather conditions, requiring additional equipment for engine startup, for which ethanol serves as a suitable solution (Kazemi et al., 2020). Consequently, ethanol can improve the challenges associated with both biodiesel and diesel fuel (Kazemi et al., 2020; Noorollahi et al., 2018). Ethanol is a renewable fuel alternative with an oxygen content, and it necessitates an intermediary such as biodiesel for blending with diesel fuel (Noorollahi et al., 2018). Extensive research has been conducted to develop an improved fuel with properties similar to diesel fuel, leading to the creation of an advanced fuel known as "diesterol", which is registered with the number 39407 in Iran (Noorollahi et al., 2018). Diesterol is a modern fuel composition comprising biodiesel, diesel, and ethanol. It boasts notable features such as renewability, an energy value equivalent to fossil fuels, environmental friendliness, and desirable lubrication properties (Shirneshan et al., 2021).

Research findings suggest that the use of diesterol fuel leads to reduced emissions of hydrocarbons (HC), carbon monoxide (CO), particulate matter (PM), and smoke in comparison to diesel fuel. However, results regarding nitrogen oxides (NOx) emissions vary (Shirneshan et al., 2021). Given the numerous advantages offered by diesterol fuel, further extensive research in this field is warranted. However, conducting comprehensive studies on the production and evaluation of a new fuel blend with various compositions requires substantial resources and involves considerable costs. These limitations pose challenges to extensive research efforts. To overcome these constraints, the application of artificial intelligence (AI) methods for modeling, optimization, and prediction can be employed, effectively addressing the limitations associated with experimental investigations. In Iran, significant progress has been made in recent years in utilizing AI methods to study the behavior of diesel engines when operating with biofuels (Solmaz et al., 2021). SVR (support vector regression) is a powerful method for modeling and prediction that has found applications in various fields (Ji et al., 2021). The effectiveness of SVR heavily relies on the proper determination of its parameters, which significantly influence its performance. Therefore, achieving an optimized model requires tuning all the meta-parameters using an algorithm (Sultana et al., 2022). Researchers employ various methods to determine these parameters, which vary depending on the research problem and the available data (Ji et al., 2021). Each method has its own strengths and limitations, and thus far, no comprehensive method has been universally established (Ji et al., 2021). Empirical parameter tuning is one commonly used approach, but it requires expertise and in-depth knowledge, and there is no guarantee that it will identify the best parameter settings (Ji et al., 2021). Another approach involves employing different algorithms, with the genetic algorithm being one of them (Sultana et al., 2022). The genetic algorithm is a metaheuristic algorithm introduced by J.H. Holland in 1992, inspired by evolutionary techniques observed in biology, particularly Darwinian evolution (Abdolkarimi and Mosavi, 2022). In this study, the genetic algorithm has been utilized to determine the parameters of SVR and perform optimization. The objective of the present study is to obtain the best operating condition of a single cylinder diesel engine fueled with Diesterol fuel. Besides, the predicting models based on the GA and SVM for predicting the emissions parameters suggested to find the best blend at different engine operating conditions.

## 2 Methodology

### 2.1 Production of biodiesel

The entire research process, encompassing the production, testing, and fuel analysis in the engine, was conducted at the Renewable Energy Institute's pilot biodiesel facility, situated at the Faculty of Agriculture, Tarbiat Modares University. Pure Jatropha oil, sourced from India, was utilized as the primary feedstock for the production of biodiesel, possessing a molecular weight of 900 grams. The transesterification method employing a KOH catalyst (at a weight ratio of 1% with respect to the oil) and methanol (at a molar ratio of 1:6) was employed to produce biodiesel. This production process involved the utilization of a double-walled reactor equipped with a standard heater, and the reaction was allowed to proceed for a duration of 1 hour. The biodiesel underwent tests to assess its viscosity and density, and the results confirmed that it met the required standards.

### 2.2 Experimental procedure

A blend of Jatropha diesterol fuel was obtained by combining varying proportions of biodiesel, ethanol, and diesel. Each fuel blend was denoted by an abbreviation. For instance, the fuel blend $E_XB_YD_Z$ denoted a composition comprising X% ethanol, Y% biodiesel, and Z% diesel.

Through an extensive series of preliminary experiments and rigorous performance and load tests conducted on the engine, suitable fuel blends were meticulously chosen. These selected diesterol fuels encompassed 3% ethanol content and different ratios of Jatropha biodiesel, namely 10%, 20%, and 30%.

In the present study, experiments were conducted using a single-cylinder, air-cooled Lombardini diesel engine model 3LD510, manufactured in Italy. To measure the engine's performance parameters such as torque, rotational speed, and power, a vortex flow dynamometer model WE400 with a power capacity of 70 kW, produced by Mobtakeran Pars Andish (MPA), was employed. The engine was subjected to testing with Jatropha diesterol fuel blends at four different speeds: 1600, 2000, 2400, and 2800 rpm, while also being evaluated under full load conditions. To analyze the engine's exhaust pollutants, an AVL MDS418 emissions analyzer from AVL Austria was utilized. This emissions analyzer is capable of measuring five gases: carbon monoxide (CO), carbon dioxide ($CO_2$), hydrocarbons (HC), oxygen ($O_2$), and nitrogen oxides (NOx). All the data obtained from the dynamometer and emissions analyzer were meticulously recorded in the central control system, employing an Excel program for data management and analysis purposes.

### 2.3 Modeling of the engine-out emissions parameters

For the purpose of data modeling and prediction in this research, the support vector regression (SVR) method was employed. SVR is a powerful technique that can predict a specific set of data based on other data and compare the predicted values with the actual values. The accuracy of SVR predictions can be assessed by measuring the difference between the predicted and actual data. A smaller difference indicates a higher accuracy of the SVR predictions. If the prediction accuracy is deemed acceptable, it allows for further and more extensive research to be conducted while reducing costs and resource requirements. SVR, along with various algorithms, has been widely used by researchers for modeling biofuels under different conditions (Sultana et al., 2022). One notable method is the hybrid SVR-BOH model, which has demonstrated exceptional accuracy in estimating the efficiency of microalgae biodiesel (Sultana et al., 2022). In another study, SVR was employed to predict exhaust pollutants and evaluate the performance of a Hyundai D4CB 2.5 diesel engine using fuel blends B0, B10, and B20 (Do et al., 2021). The results, based on metrics such as root mean square error (*RMSE*), mean absolute percentage error (*MAPE*), Mean absolute error (*MAE*), and *R*-squared ($R^2$) values, indicated that SVR exhibited acceptable accuracy for prediction and model expansion in that context (Do et al., 2021).

In the following, the overall structure of the SVR neural network that has been optimized by the genetic algorithm has been provided (Figure 1).

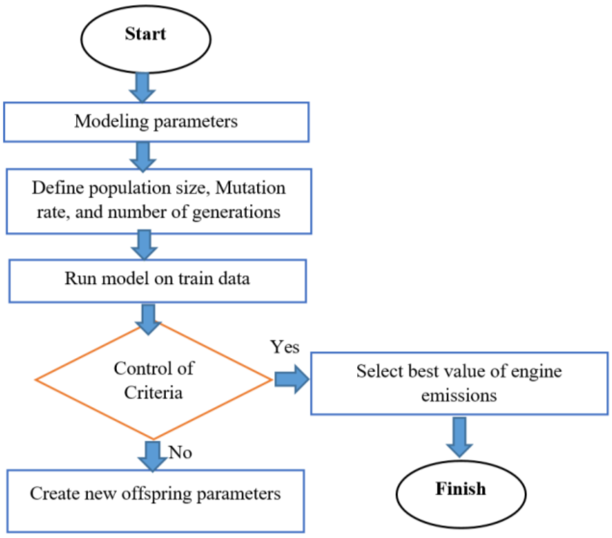


Figure 1 Overall structure of SVR-GA (Luo et al., 2021)

**Table 1 Values obtained by GA for SVR optimization**

| Parameters | GA | | |
|---|---|---|---|
| | Epsilon | C | Sigma |
| CO | 0.097896893 | 331.3840263 | 0.523671046 |
| $CO_2$ | 0.008801832 | 564.0089947 | 0.291865028 |
| HC | 0.000290682 | 365.4489337 | 2.22045E-16 |
| $O_2$ | 0.008602623 | 670.0199036 | 0.180008496 |
| NOx | 0.012554871 | 815.9556438 | 0.108307138 |

The neural network formulation is as follows (Aslipour and Yazdizadeh, 2020):

$$\hat{y} = \sum_{i=1}^{N} \omega_i^T (x \cdot x_i) \varphi_i(x) + b \quad (1)$$

$$e = y - \hat{y} \quad (2)$$

In this formulation, $y$ represents the system output, $\hat{y}$ is the model's output, $\omega_i^T$ denotes the neural network weights, $\varphi_i(x)$ represents the input function of the system, $b$ is the bias value, and $e$ is the modeling error (Aslipour and Yazdizadeh, 2020).

In the present study, five groups of output engine pollutants, including CO, $CO_2$, HC, $O_2$, and NOx, were selected for modeling and prediction. The genetic algorithm was used for optimization. The values obtained for C, SIGMA, and Epsilon through the genetic algorithm for optimizing the SVR method for each group of data are shown in Table 1.

To assess the performance of the SVR method, a comprehensive evaluation was conducted by comparing the predicted data with the corresponding actual data. Several evaluation metrics were employed, including the $R^2$, mean squared error (*MSE*), *RMSE*, and *MAE*. These metrics provide insights into the accuracy and quality of the SVR model's predictions.

$R^2$, calculated using Equation 4, is a measure ranging from 0 to 1 that indicates the accuracy of the model. A value closer to 1 signifies a highly accurate model, while a value closer to 0 suggests lower accuracy (Shi et al., 2023).

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - y_i)^2}{\sum_{i=1}^{n} (Yi - \underline{y})^2} \quad (3)$$

*RMSE*, as shown in Equation 5, and *MAE*, as shown in Equation 6, quantify the disparities between the predicted values and the actual values. Lower values of *RMSE* and *MAE* indicate a more accurate model, and as they approach zero, the model's predictions become more precise (Shi et al., 2023).

$$MSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (Yi - y_i)^2} \quad (4)$$

$$MAE = \sum_{i=1}^{n} \left| \frac{Yi - y_i}{n} \right| \quad (5)$$

*MSE*, as expressed in Equation 7, provides information about the level of modeling error. A lower *MSE* value indicates less modeling error (Shi et al., 2023).

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (Yi - y_i)^2 \quad (6)$$

In the above equations, $Y_i$ represents the measured (actual) data, $y_i$ represents the predicted data, $\underline{y}$ denotes the mean of the data, and $n$ signifies the number of data points (Shi et al., 2023).

In the subsequent sections, the values of *MSE*, *RMSE*, and $R^2$, along with the corresponding graphs generated by the SVR model, are presented for each specific group of data. These graphical representations illustrate both the actual data (depicted by solid black lines) and the predicted data (represented by dashed red lines) in both the test and train datasets.

## 3 Results and discussion

The modeling and prediction results for the CO data are presented in Table 2, along with Figures 2 and 3. The accuracy of the modeling was assessed based on the criteria of $R^2$, *MSE*, *RMSE*, and *MAE*. Upon evaluation, it can be concluded that the CO data has been predicted with high accuracy, as indicated in Table 2. Figure 2 illustrates the performance of the model on the training data, while Figure 3 depicts the performance on the testing data. Both figures show that the predicted values closely align with the actual data points, indicating a strong agreement between the model predictions and the observed values.

The same evaluation approach, utilizing the aforementioned criteria, has been applied to all subsequent tables and figures to assess the accuracy of the modeling for each respective group of data.

Table 3 presents the metrics for modeling $CO_2$ data in Figures 4 and 5.

Table 4 shows the metrics for modeling HC data in Figures 6 and 7.

Table 5 displays the metrics for modeling $O_2$ data in Figures 8 and 9.

Table 6 exhibits the metrics for modeling NOx data in Figures 10 and 11.

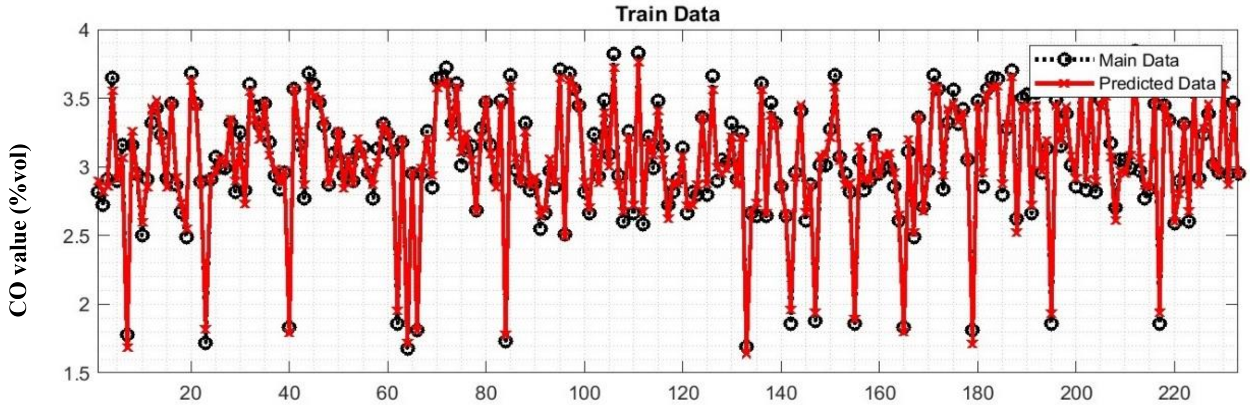


Figure 2 Modeling of actual and predicted CO data (Train)

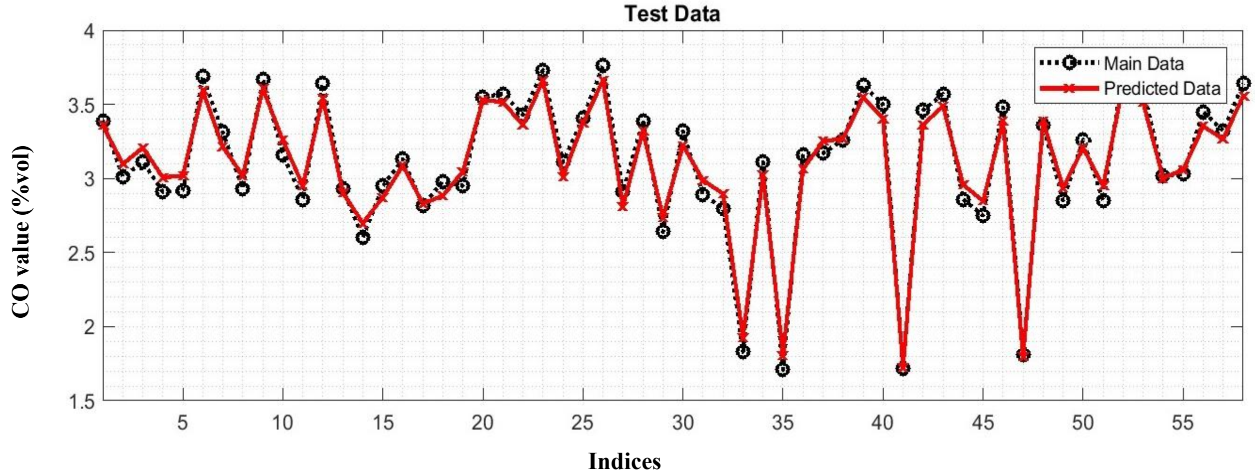


Figure 3 Modeling of actual and predicted CO data (Test)

**Table 2 Modeling values for CO data**

| Parameters | Train data | Test data |
|---|---|---|
| *MSE* | 0.004352369 | 0.00664505 |
| *MAE* | 0.056639774 | 0.07584724 |
| *RMSE* | 0.065972483 | 0.065972483 |
| $R^2$ | 0.990156856 | 0.988793929 |

**Table 3 Modeling values for $CO_2$ data**

| Parameters | Train data | Test data |
|---|---|---|
| *MSE* | 6.98968E-05 | 7.61941E-05 |
| *MAE* | 0.008175095 | 0.008681702 |
| *RMSE* | 0.00836043 | 0.00836043 |
| $R^2$ | 0.999991197 | 0.999993065 |

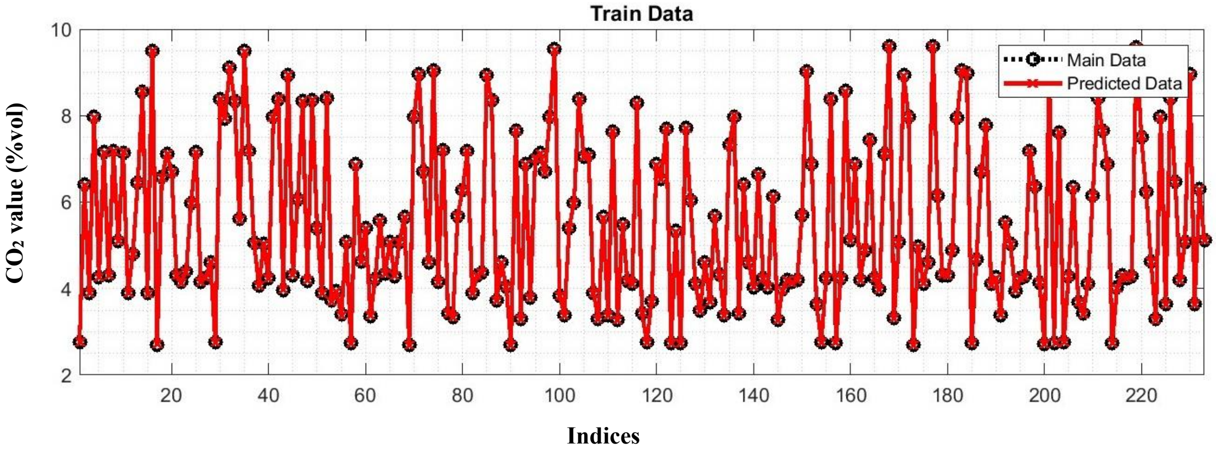


Figure 4 Modeling of actual and predicted $CO_2$ data (Train)

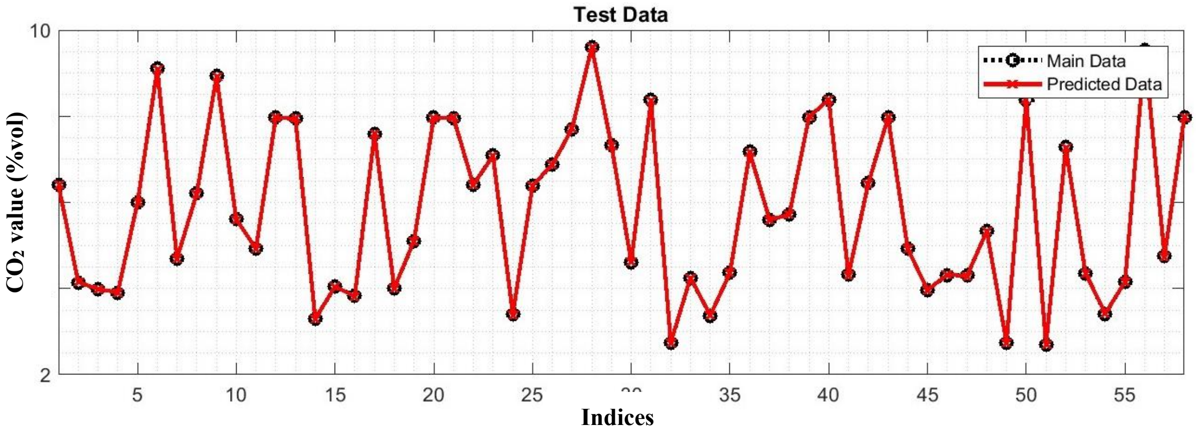


Figure 5- Modeling of actual and predicted $CO_2$ data (Test)

**Table 4 Modeling values for HC data**

| Parameters | Train data | Test data |
|---|---|---|
| *MSE* | 8.44955E-08 | 8.44958E-08 |
| *MAE* | 0.000290681 | 0.000290682 |
| *RMSE* | 0.000290681 | 0.000290681 |
| $R^2$ | 1 | 1 |

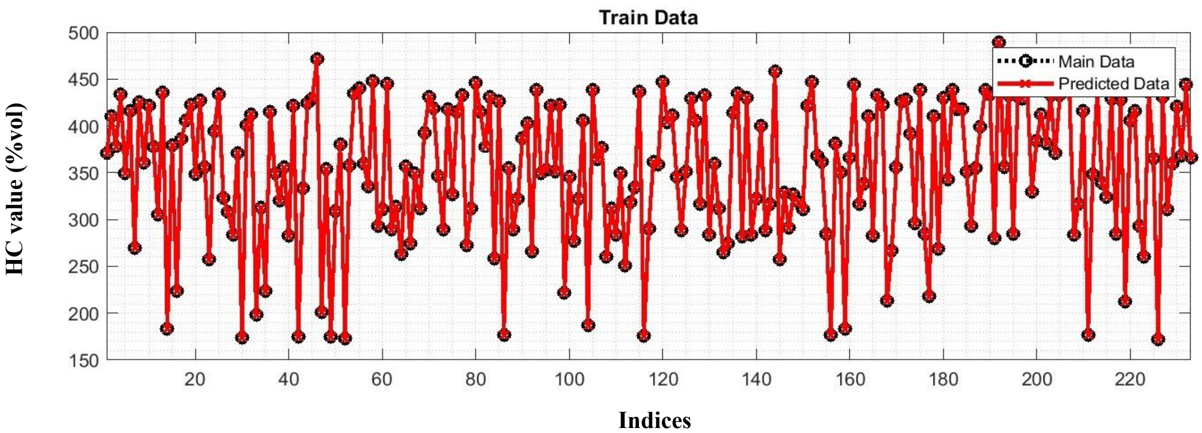


Figure 6- Modeling of actual and predicted HC data (Train)

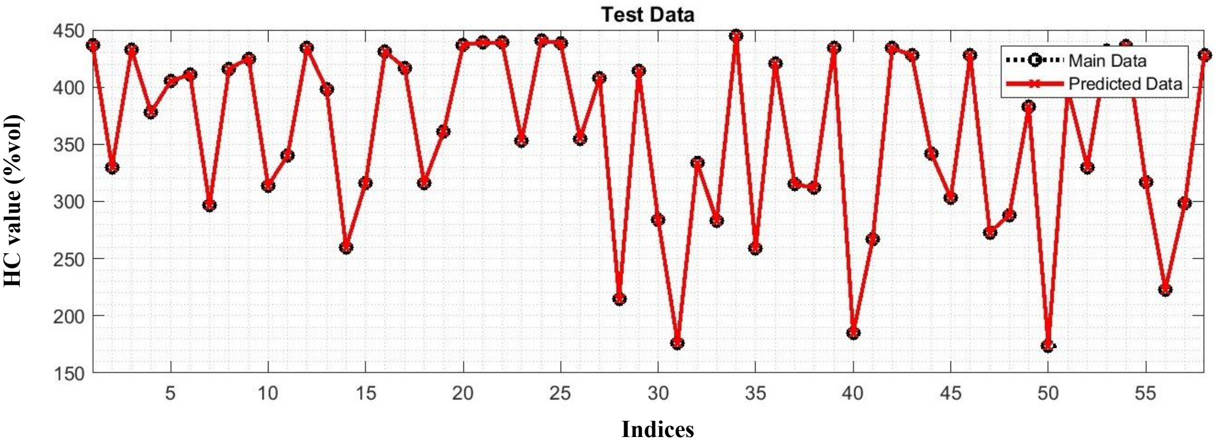


Figure 7- Modeling of actual and predicted HC data (Test)

**Table 5- Modeling values for $O_2$ data**

| Parameters | Train data | Test data |
|---|---|---|
| *MSE* | 0.000111068 | 7.29535E-05 |
| *MAE* | 0.009034132 | 0.008516498 |
| *RMSE* | 0.010538888 | 0.010538888 |
| $R^2$ | 0.999995326 | 0.999998592 |

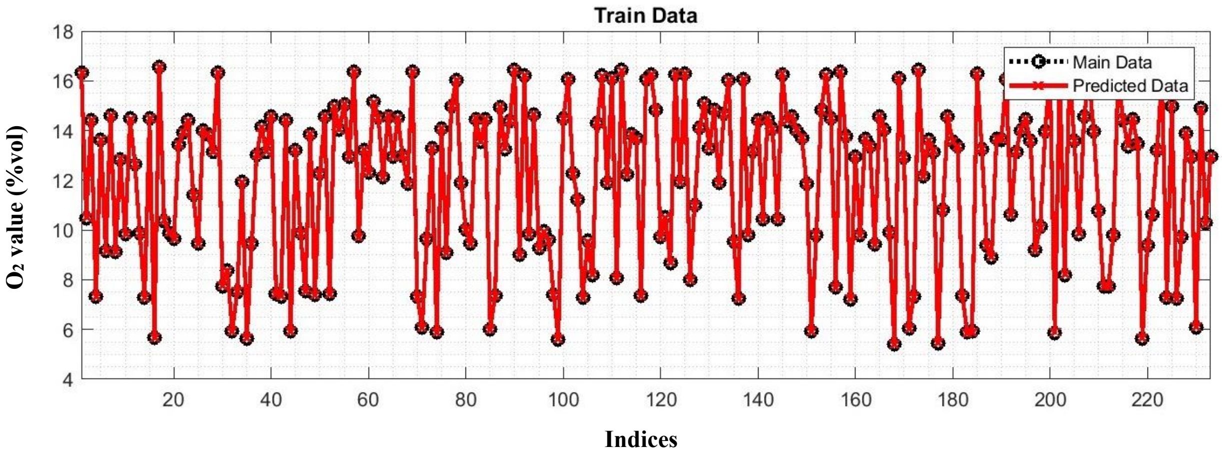


Figure 8 Modeling of actual and predicted $O_2$ data (Train)

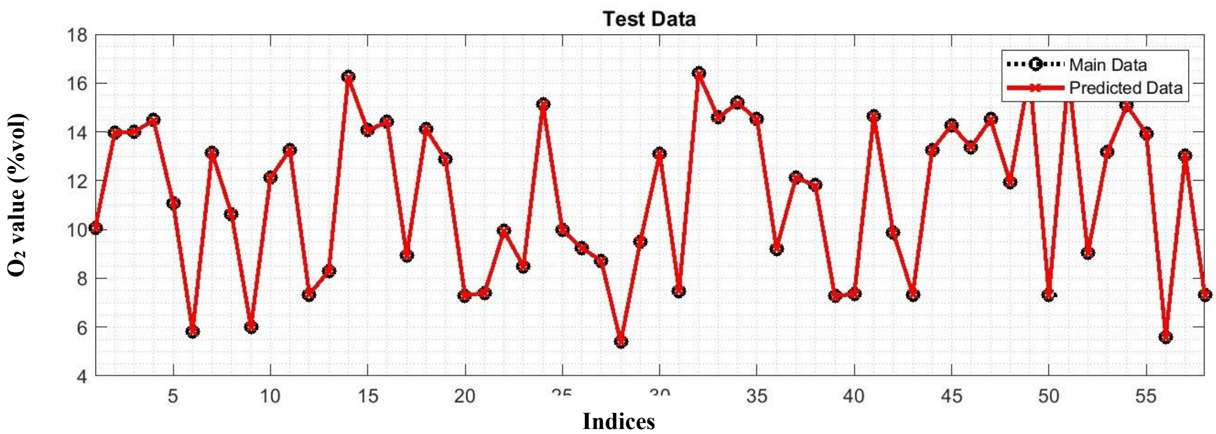


Figure 9 Modeling of actual and predicted $O_2$ data (Test)

**Table 6 Modeling values for NOx data**

| Parameters | Train data | Test data |
|---|---|---|
| *MSE* | 1.338370737 | 0.000178219 |
| *MAE* | 0.266553297 | 0.012973035 |
| *RMSE* | 1.156879742 | 1.156879742 |
| $R^2$ | 0.999921254 | 0.999999994 |

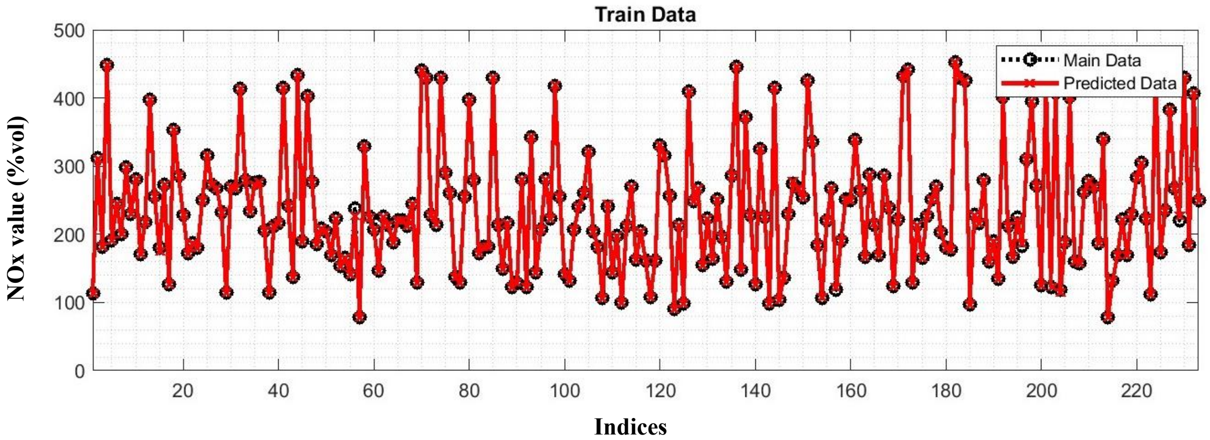


Figure 10 Modeling of actual and predicted NOx data (Train)

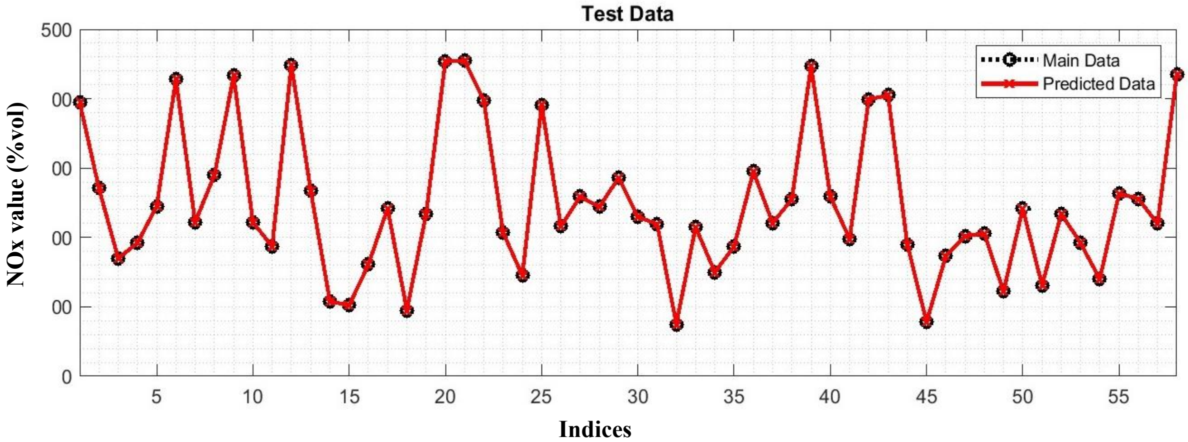


Figure 11 Modeling of actual and predicted NOx data (Test)

## 4 Conclusion

The SVR+GA modeling approach has demonstrated exceptional accuracy in predicting pollutant emissions from Jatropha biodiesel when utilized in a single-cylinder diesel engine. The results obtained from the modeling process, as depicted in the Tables and corresponding Figures for each data group of emitted pollutants, have shown a high level of agreement between the predicted values and the actual data. Notably, the $R^2$ values reached 1 in certain cases, indicating a perfect match between the predicted and actual values, thus attesting to the reliability and accuracy of the SVR combined GA modeling method. This suggests that the SVR+GA approach can serve as a valuable tool for predicting pollutant emissions when using Jatropha biodiesel in diesel engines. By employing this modeling approach, researchers can save significant costs, resources, and time that are typically associated with practical experiments. Furthermore, further investigations using this modeling approach can help identify the optimal combinations of renewable and alternative fuels, addressing concerns and advancing the field of biofuels. In light of these findings, it is essential for researchers in the field of biofuels and renewable energies to persist in their dedicated efforts and continue their research endeavors.

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## Abbreviations section

| Support Vector Machine | SVM |
|---|---|
| Genetic Algorithm | GA |
| $R^2$ | r-square |
| *MSE* | mean square error |
| *MAE* | mean absolute error |
| *RSME* | root mean square error |
| *MAPE* | absolute percentage error |
| NOX | nitrogen oxides |
| BSFC | brake-specific fuel consumption |
| CO | carbon monoxide |
| UHC | unburned hydrocarbons |
| PM | particulate matter |
| $\hat{y}$ | model's output |
| $\omega_i^T$ | Weights |
| b | bias value |
| E | modeling error |