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PREDICTION OF THE MAIN ENVIRONMENTAL AND ENERGY CHARACTERISTICS OF DIESEL ENGINES USING AN ARTIFICIAL NEURAL NETWORK IN A WIDE RANGE OF DIESEL AND HVO FUEL MIXTURES

Summary. This research assesses the influence of different quantities of Hydrotreated Vegetable Oil (HVO) in diesel fuel on the performance of the engine and the emissions it produces. The particular areas of interest are the level of smoke emitted and the Brake Thermal Efficiency (*BTE*). A series of engine experiments were undertaken to quantify emissions and performance characteristics under various operating regimes using three distinct fuel blends: D100 (pure diesel), HVO50 (50% HVO mixture), and HVO100 (pure HVO). The experimental findings showed a conspicuous decline in smoky emissions as the proportion of HVO rose, with HVO100 exhibiting the most notable drop. Similarly, it was shown that the stability and performance of *BTE* increased marginally with increasing concentrations of HVO. In order to forecast emissions and performance indicators under different operating scenarios, we used Artificial Neural Networks (ANNs). The ANNs demonstrated excellent prediction accuracy, exhibiting robust linear correlations between the expected and real values for all fuel types. This research emphasises the advantages of utilising HVO in diesel engines for both environmental impact and performance. It also emphasises the usefulness of ANNs in optimising engine settings to improve efficiency and minimise emissions. The results endorse the further use of HVO as a viable substitute for conventional diesel, leading to less ecological consequences and enhanced engine efficiency.

1. INTRODUCTION

In transportation, usage of HVO (Hydrotreated Vegetable Oil) in diesel is very important for several reasons: due to regulatory compliance (1), for environmental benefits (2), for improved performance (3), and due to marked demand (4). Many countries (for example, in EU) have governmental regulations for: i) reducing the greenhouse gas emissions; and ii) promoting the use of ecologically friendly products (5). As renewable alternative to traditional diesel fuel, HVO emits the lower level of technical pollutants such as carbon monoxide (CO) and hydrocarbons (HC) in outcomes (6). For environmental sustainability, increasing the amount of HVO in diesel allows reducing emissions. Mixing HVO and fossil fuels allows compliance with these rules over a wide range of applications (7). In the framework of improved performance of diesel engines, usage of HVO can significantly increase the power output and engine longevity (8). Due to higher cetane number compared to traditional diesel, HVO containing fuel burns more cleanly, resulting in smoother engine operation and better fuel economy (9,10). Consumer demand for organic products (including transport fuel) is growing (11,12). By offering the mixtures of diesel with higher HVO content, transport companies can meet this demand and increase their market competitiveness.

Generally, adjusting the amount of HVO in diesel for transportation purposes can bring about a range of benefits, including improved performance, environmental protection, regulatory compliance. Amount of HVO in diesel is not solved problem. Usage of commercially available diesel containing 10%, 30%, 40%, 50% HVO supplement (HVO10, HVO30, HVO40, HVO50) shows several benefits in plane of ecology (decreased amounts of pollutants), however, different energetical regimes of diesel engine could not be related to the linear dependence of outcome distributions. Taking more strictly, prognosis and prediction of pollutants of diesel engine working at large interval of different regimes is very complicated task which could be solved in approximating way using Artificial Neural Netwok (ANN) algorithms (13).

This work is devoted to estimate the quality of ANN prognosis for several type pollutants (smokiness, CO_2, NO_x) in the diesel outcomes when diesel engine works in vide range of regimes using different commercial fuels: D100 (pure diesel), HVO50 (containing 50% HVO supplement), HVO100 (pure HVO).

a) To establish relationship for chemical parameters (smokiness, CO_2, NO_x) related to diesel working regime and fuel type (D100, HVO50, HVO100).
b) To establish relationship for energetic parameter (*BTE*) related to diesel working regime and fuel type (D100, HVO50, HVO100).
c) To estimate the parameters of ANN architecture and training regime for such type tasks of prognosis,

to estimate the prognosis precision for HVO containing fuels.

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Recent advancements in predictive modeling for engine emissions have been significant. A study by (13) explores the relationship between engine power, vibrational and sound pressure levels, and exhaust emissions. It was found that engine power and the type of fuel significantly influence these variables, enhancing predictive models' capabilities for exhaust emissions. The root mean square (RMS) related function T11 was identified as a potent predictor within these models. Adding vibration data to these models not only enriched the dataset but also improved the accuracy of predicting emissions from biodiesel fuels.

In another study, the effectiveness of different predictive models was assessed on a single-cylinder four-stroke engine, with findings highlighting the model's accuracy (MAPE < 1%) across most engine emission parameters such as max_press, CA05, and CO, among others. However, certain emissions like NO_X remained challenging to predict, underscoring the need for developing new predictive techniques (14).

The role of machine learning, specifically ANNs, in predicting engine emissions has been increasingly recognized (15–17). A particular study developed a 3-7-7-6 ANN model, integrating key combustion parameters to predict engine efficiency and emissions. This model demonstrated high accuracy with an R^2 close to unity and a low RMSE, indicating its potential in aiding engine design and development (18). Despite its efficacy, the need for updating neural network algorithms as engine parameters evolve remains a critical consideration.

Buscema (19) represents an overview of Feed Forward Back Propagation (BP) ANN. Buscema claims that BP consisting of single hidden layer is sufficient for mapping of any function $y=f(x)$. Practically, deviations from target value are too big, and sometimes is necessary to expand the architecture of ANN: to use ANN consisting of double hidden layers. It happens when the functions to simulate are too complex. Sekhar et al (20) observe the working of BP by approximating the non-linear association between the data and the yield by changing the weight regards inside. Murat (21) presented mostly used learning/training algorithm of BP ANN. Zhang et al (22) described the feed-forward neural networks with random weights (FNNRWs). The main behaviour is related to the clusterization: FNN divides large-scale data into subsets of the same size, and each subset derives the corresponding sub-model. Presented approach demonstrates the successful acceptance in processing huge datasets.

The environmental implications of engine emissions are profound, contributing to natural disasters and climatic anomalies such as El Niño and forest fires. A broader perspective provided by (23) discusses the role of sustainable development goals set by the United Nations, emphasizing the importance of improving engine performance and reducing emissions through advanced machine learning techniques. These include not only ANNs but also other methods such as the relevance vector method, support vector machine, and genetic algorithms, which could further refine predictive accuracy and environmental sustainability.

2. METHODS AND MATERIALS

The experimental engine tests shall be carried out using the engine load bench and additional equipment as shown in Figure 1. The engine used is the 1.9 TDI (VW) with compression ignition, compression ratio 19.5, maximum power 66 kW (4000 rpm), maximum torque 180 Nm (2000-2500 rpm).

Engine load bench (KI-5543) torque measurement accuracy ±1.2 Nm, fuel consumption scale (SK-5000) measurement accuracy ±1.0 g, air mass meter (BOSCH HFM 5) accuracy ±2%, exhaust gas analyser (AVL DiCom 4000) measurement accuracy ±0.1% for CO_2, ±0.01% for CO, ±1 ppm for CH, ±1 ppm for NO_x and ±0.01% for smokiness (opacity).

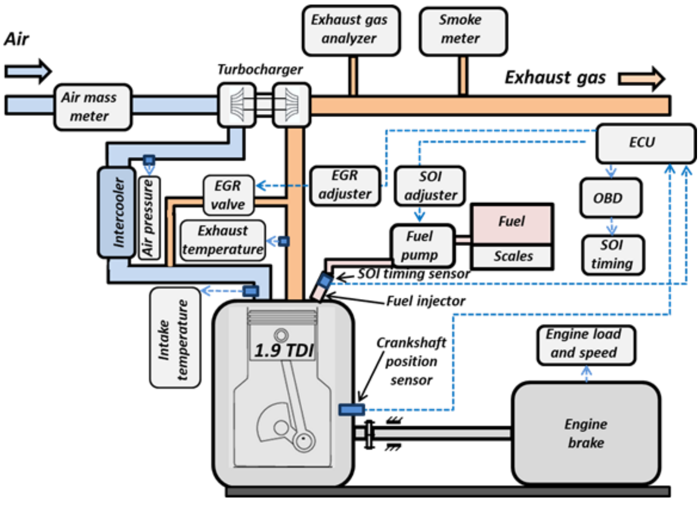


Fig. 1. Layout of engine performance test equipment

In order to investigate the wide range of engine performance, the tests are carried out with the engine running in different regimes where Start of Injection (*SOI*) and Exhaust Gas Recirculation (EGR) were adjusted by the electronic control unit (ECU), with the additional adjustments of *SOI* and EGR. *SOI* was measured with an accuracy of ±1.0 Crank Angle Degree (CAD) by connecting Vag-Com diagnostic equipment to the on-board diagnostic port. The EGR ratio was determined by calculating the change in mass of air intake by the engine. During the test the engine speed was n = 2000 pm and n = 2500 rpm, torque M_B = 30; 60; 90 and 120 Nm, *SOI* = 0–16 CAD before Top Dead Centre (bTDC), EGR = 0–0.4. The conditions of the different regimes of testing are described in Figure 2.

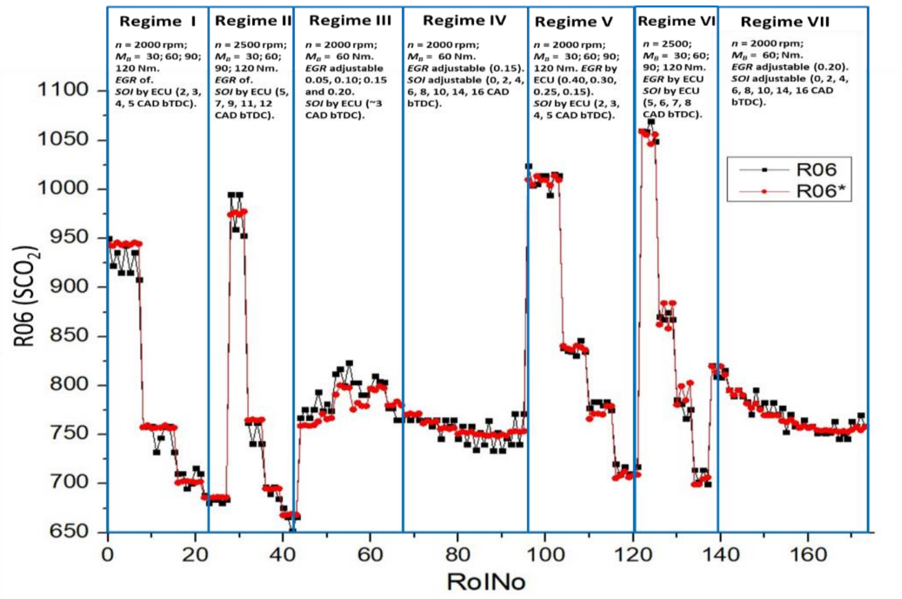


Fig. 2. Engine test regimes

The tests used pure diesel (D100), pure biodiesel - hydrotreated vegetable oil (HVO100) and a mixture of diesel (50% by volume) and HVO (50% by volume), labelled HVO50. The physical and chemical properties of the fuels were tested in the laboratory and the results are shown in Table 1.

Table 1

Fuel properties

Properties	D100	HVO50	HVO100
Kinematic viscosity at 40 °C, cSt	3.948	3.000	2.959
Dynamic viscosity, mPa · s	3.271	2.365	2.2617
Density at 15 °C, g/mL	0.830	0.806	0.780
Cetane number	50.9	59.9	74.5
C/H ratio	6.80	6.22	5.60
Air to fuel ratio (stoichiometric), kg air/1 kg fuel	14.50	14.79	15.10
Lower Heating Value (*LHV*), MJ/kg	42.82	43.21	43.63

The specific carbon dioxide emissions (SCO_2) have been calculated by taking into account the carbon dioxide concentration in the exhaust gas, the mass of the exhaust gas and the engine power. The specific emissions of nitrogen oxides (SNO_x) were calculated in a similar way. Together with the smokiness characteristics, these parameters best represent the combustion chemistry and environmental parameters of the engine when operating on different fuel blends. Braking Thermal Efficiency (*BTE*) results are presented to evaluate the energy efficiency.

3. SIMULATION SETUP

3.1. ANN architecture

ANN architecture and dynamic training mode determine the final performance of ANN and following quality of validation/prediction (24). We have selected implementation of ANN consisting of input layer, single hidden layer, and output layer. Figure 3 represents the ANN schema in the framework of *VALLUM01* (25).

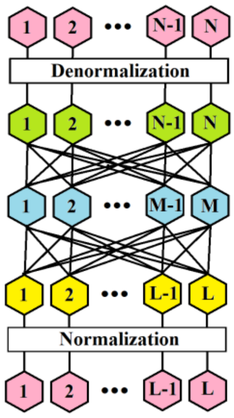


Fig. 3. ANN: input layer, number of units L = 12 (yellow); single-hidden layer, number of perceptrons M = 200 (blue); output layer, number of units N = 10 (green). Normalization/denormalization plugins were used for data conversion/deconversion. Flow from bottom to top

Due to adjusting possibilities, bias was included in the hidden layer. The programmed package *VALLUM01*, which contains a graphical, user-friendly interface for input, output, and control, was created using the JAVA *Eclipse* framework. Normalization plugin was used for conversion of any real value (pink) from requested interval into (0;1) interval. Denormalization plugin works in reversed order. Information flow is directed from bottom to top.

For ANN, two typical classes from Ref. (26) were used: *Matrix* and *NeuralNetwork*. As an *S*-shaped function, a sigmoidal function was used:

$$\sigma(x) = 1/(1+e^{(-x)}) \tag{1}$$

Four different organizational stages (a) selection of amount of input layer, b) establishing the number of hidden layers (single or double), c) adjusting the number of perceptrons in the single hidden layer (in this case), d) requested amount of output layer) are described in the previous work (27) and used without any changes.

3.2. Data collection

For data collections, we have used two data clusters for input (see Table 2) and three data clusters for output (see Table 3) according to the similar or related properties. This organizational trick allows decreasing the random fluctuations of Total Network Error (TNE). ANN consist of input layer, number of units L = 12 (yellow), single-hidden layer, number of perceptrons M (blue), output layer, number of units N = 10 (green) – see Figure 3.

First input cluster consist of parameters describing the technical conditions (P10, P03, P02, P11, P01) and second input cluster consist of parameters describing burning chemistry parameters (P09, P04, P05, P12, P06, P08, P07), see Table 3. First output cluster consists of: w SNO_x (R04). Second output cluster consists of: smokiness (R00), and brake thermal efficiency (*BTE*) (R02). Third output cluster consists of: SCO_2 (R06).

Table 2

Experimental parameters of diesel engine used for an ANN as the input parameters

Cluster	Index	Abbr.	Parameter	Units	Interval	
					X_{MIN}	X_{MAX}
1	0	P10	The excess air ratio ($\boldsymbol{\lambda}$)	-	1.0	10.0
1	1	P03	Brake mean effective pressure (*BMEP*)	MPa	0.0	1.2
1	2	P02	*EGR* ratio	-	0.0	0.5
1	3	P11	Start of injection (*SOI*)	CA bTDC	−3.0	18.0
2	4	P09	Cetane number	-	5.0	85.0
1	5	P01	Engine speed (*n*)	rpm	800.0	4000.0
2	6	P04	Volume fraction of HVO100	%	0.0	100.0
2	7	P05	Volume fraction of D100	%	0.0	100.0
2	8	P12	C/H ratio	-	5.0	7.0
2	9	P06	Stoichiometric air to fuel ratio ($\boldsymbol{l_0}$)	1 kg of air/1 kg of fuel	10.0	20.0
2	10	P08	Lower heating value (*LHV*)	$MJ{\cdot}kg^{-1}$	18.0	60.0
2	11	P07	Density	$kg{\cdot}m^{-3}$	600.0	900.0

Table 3

Experimental parameters of diesel engine used for ANN as the output parameters

Cluster	Index	Abbr.	Parameter	Units	Interval	
					Y_{MIN}	Y_{MAX}
1	8	R04	SNO_x	$g{\cdot}kWh^{-1}$	0.1	20.0
2	3	R00	Smokiness	m^{-1}	0.001	100.0
2	5	R02	Brake thermal efficiency (*BTE*)	-	0.01	0.5
3	2	R06	SCO_2	$g{\cdot}kWh^{-1}$	100.0	2000.0

3.3. Simulation routine

Table 4 describes the provided procedures of training as well as validation of ANNs. For validation procedure, separate files 0.csv (172 events), 50.csv (174 events), and 100.csv (195 events) were used in prediction regime using the same training stamp 200-050100.csv. Tables 6,7,8,9 represent distributions of R06, R04, R00, R02 parameters on experiment RolNo at different type of fuel mixture (D100, HVO50, HVO100). Selected parameters belong to two groups:

a) parameters of burning chemistry: R06 as SCO_2, R04 as $SNOx$, both in [$g{\cdot}kWh^{-1}$], R00 as smokiness, in [m^{-1}];
b) energetic parameter R02, *BTE*.

ANN consist of input layer, single-hidden layer, where number of perceptrons M = 200 (blue), output layer – see Figure 3. *VALLUM01* simulates the learning process adjusting the weights of the artificial synapses by the process of backpropagation. Table 4 represents the procedure of training and validation of ANNs.

Nomenclature of files were constructed according to type of the fuel mixture. 0.csv is related to the D100, 50.csv is related to the HVO50 (containing 50% HVO supplement), 100.csv is related to the HVO100 (pure HVO). Initially, training data file was formed by adding the content of files 0.csv, 50.csv, and 100.csv into new one 050100.csv without any selection, and all records were included. Finaly, number of events of training file 050100.csv distinguish 541 (172+174+195). Training procedure was provided using 160,000,010 epochs for ANN consisting of single hidden layer containing M=200 perceptrons (training project T0 only). Training stamp in form of file 200-050100.csv (***M***=200 , contains

0.csv, 50.csv, 100.csv) was obtained for following validations purposes. Figure 4 represents the TNE^2 dependence on epochs number as an evolution of the ANN training.

Table 4

The procedure of training and validation of ANNs. Input layer L = 12, output layer N = 10, amount of perceptron in the hidden layer M, learning rate 0.01

Project	One Hidden Layer	Training					Validation	
Name	*M*	Routine	File	Events	Epochs	TNE^2	File	Events
T0	200	T0	200-050100.csv	541	160,000,010	Figure 4		
T0	200		200-050100.csv				0.csv	172
T50	200		200-050100.csv				50.csv	174
T100	200		200-050100.csv				100.csv	195

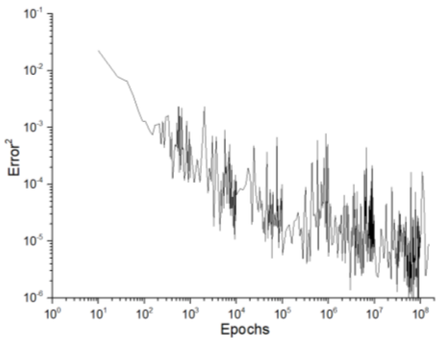


Fig. 4. TNE^2 dependence on epochs number. Evolution of the ANN training. Number of epochs 160,000,010. Number of training events -541. Number of perceptrons ***M***=200 in the single hidden layer.

4. RESULTS

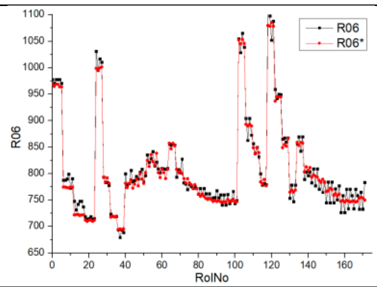
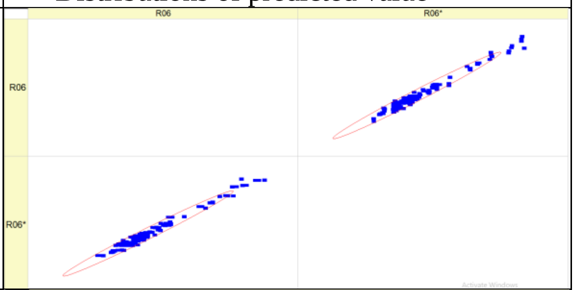
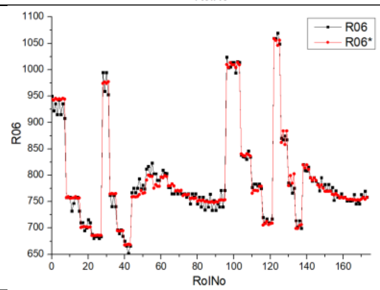
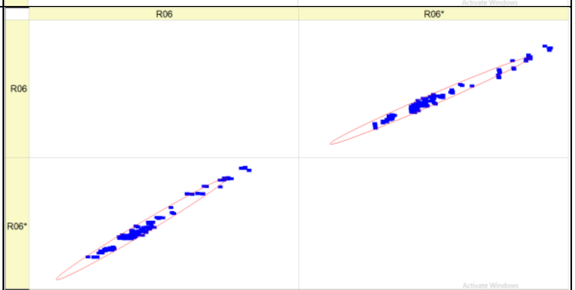
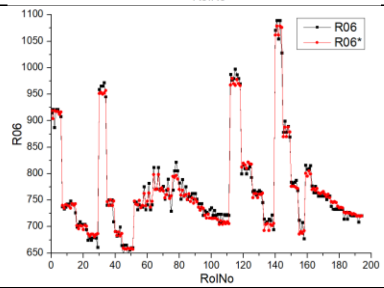
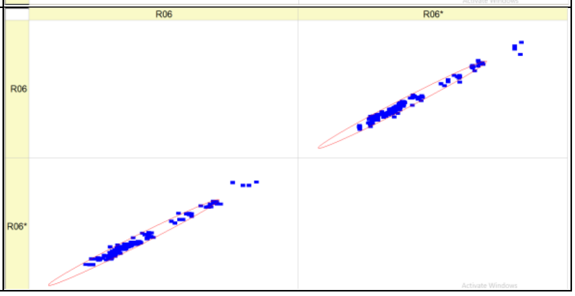
The Table 5 provided depicts a comparative examination specific CO_2 emission (SCO_2) of diesel engines using three distinct fuel mixtures: D100, HVO50, and HVO100. The data are divided into two main components for each kind of fuel: the distribution of actual values and the distribution of anticipated values generated by an ANN model. Every row represents a distinct fuel combination. The scatter plots on the left-hand side of each row show the trend or distribution of SCO_2 emissions over different experimental runs (referred to as "RoINo"), with red dotted lines representing this trend or distribution. These scatter plots display peaks and troughs, which may suggest fluctuations in emission rates caused by variations in operating circumstances or engine performance measures at various test points. The D100 exhibits changing amounts of SCO_2 emissions with many distinct peaks, indicating a significant degree of variability in emissions during the test cycles. The user's text is "HVO50". Like D100, the $SCO2$ emissions exhibit considerable fluctuation, but the general magnitude of the peaks is considerably mitigated, indicating a potential decrease in emission levels attributable to the presence of HVO. The user has entered the text "HVO100". The fluctuation is present, however, the peaks are much reduced in comparison to D100 and HVO50, suggesting that pure HVO has the potential to generate less emissions.

On the right side of each row, there are scatter plots that show the projected values of SCO_2 emissions compared to the actual values for each kind of fuel. These charts are essential for assessing the accuracy of the ANN predictions in comparison to the actual measured values. Each fuel type exhibits a set of graphs where data points are closely grouped around a line, indicating a significant connection between the anticipated and experimental values. This suggests that the ANN model is effectively estimating $_{SCO2}$ emissions for various kinds of fuel and operating circumstances. The density of the point clusters along the 45-degree line (representing the optimal prediction line) differs somewhat across the different fuel types: The D100 points exhibit a strong alignment with the line, suggesting a high level of prediction accuracy. The HVO50 and HVO100 exhibit a strong correlation, while there are some modest variances indicating minor inaccuracies in prediction, especially at higher emission levels.

The graphical data indicates that the use of HVO, whether in the form of a mix or in its pure form, in diesel engines may effectively decrease SCO_2 emissions, as seen by the observed emission patterns in the experiments. Moreover, the ANN model offers dependable forecasts of emissions, as seen by the robust correlation in the predictive graphs. This makes it a valuable tool for predicting emissions in various operating situations and with different fuel types. The efficacy of the model also underscores its potential usefulness in optimising engine efficiency and ensuring adherence to environmental rules.

Table 5

Distributions of R06 parameter (SCO_2, g·kWh^{-1}) on experiment RolNo at different type of fuel mixture (D100, HVO50, HVO100)

Fuel	Parameter	Distributions of predicted value
D100		
HVO50		
HVO100		

The Table 6 presents an ongoing investigation of emissions from diesel engines using various fuel combinations. The analysis specifically focuses on a parameter labelled "R04" which represents the specific NO_x emissions (SNO_x). Similar to the previous diagram, the study is divided between distributions of actual values and distributions of forecasted values using ANNs for three fuel types: D100, HVO50, and HVO100.

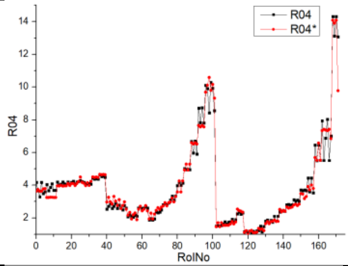
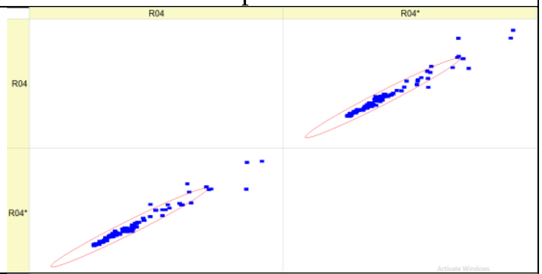
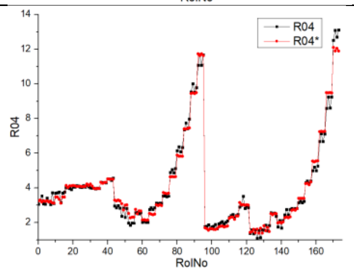
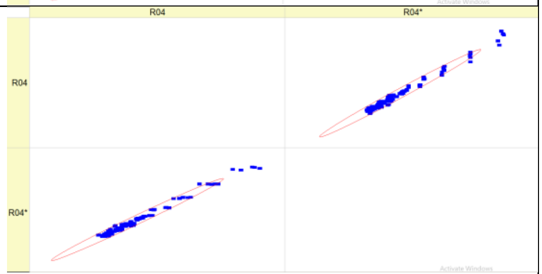
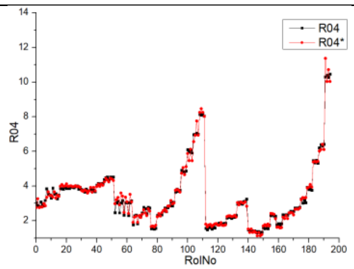
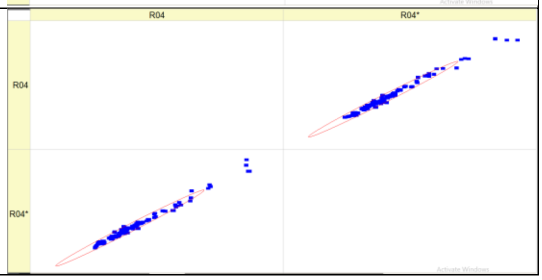
D100 has a discernible pattern of emissions characterised by many prominent peaks of SNO_x emissions. This pattern may suggest certain operating conditions in which SNO_x levels are elevated. The variations are significant and exhibit elevated peak values. The user's text is "HVO50". Like D100, the pattern exhibits distinct peaks, but with significantly lower intensity than pure diesel. This indicates that the addition of HVO assists in mitigating SNO_x emissions. HVO100 exhibits a substantial decrease in both the frequency and amplitude of peaks. The occurrence of peaks is much reduced in pure HVO compared to D100 and HVO50, suggesting a large decrease in SNO_x. The observed trends indicate that higher levels of HVO concentration in the fuel combination result in decreased of SNO_x, which is consistent with the anticipated advantages of using cleaner and sustainable fuel sources.

Graphs located on the right side each row represents a specific fuel type and displays scatter graphs comparing projected and experimental results for SNO_x emissions. Linear regression lines Each figure has a line, which may represent a linear regression fit, illustrating the relationship between the expected and experimental values. The graphs indicate that the points are typically closely aligned along the line for all fuel types, indicating that the artificial neural networks (ANNs) have the ability to reliably forecast SNO_x emissions under various scenarios.

Forecast Discrepancies D100 and HVO50 the scatter plots demonstrate a strong correlation along the line, with a few outlier points that vary from the expected trend, particularly at higher emission levels. The user's text is "HVO100". The forecast seems to be somewhat more dispersed in comparison to D100 and HVO50, perhaps indicating difficulties in estimating emissions for a fuel variant that deviates greatly from standard diesel fuels.

Table 6

Distributions of R04 parameter (SNO_x, g·kWh^{-1}**)** on experiment RolNo at different type of fuel mixture (D100, HVO50, HVO100)

<table>
<tr><th>Fuel</th><th>Parameter</th><th>Distributions of predicted value</th></tr>
<tr><td>D100</td><td></td><td></td></tr>
<tr><td>HVO50</td><td></td><td></td></tr>
<tr><td>HVO100</td><td></td><td></td></tr>
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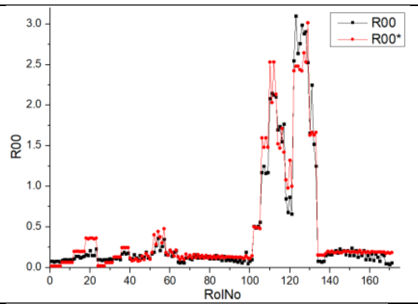
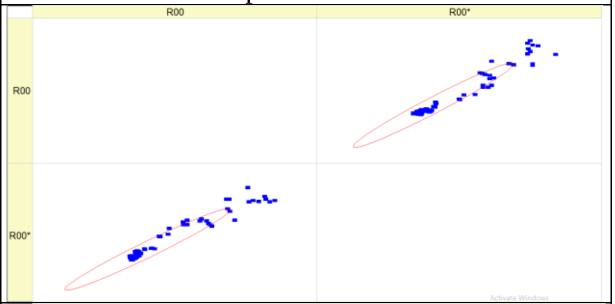
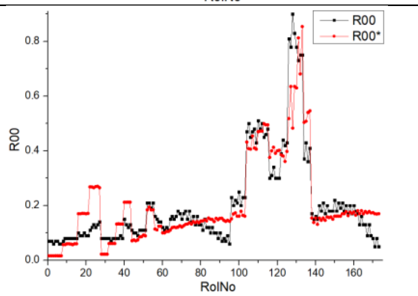
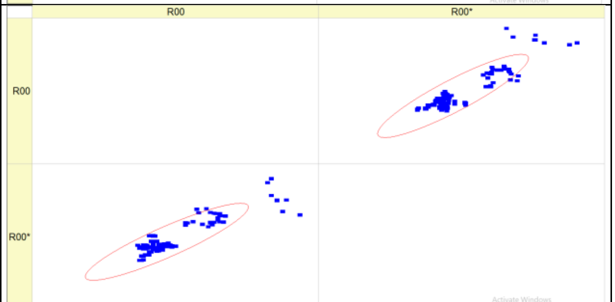
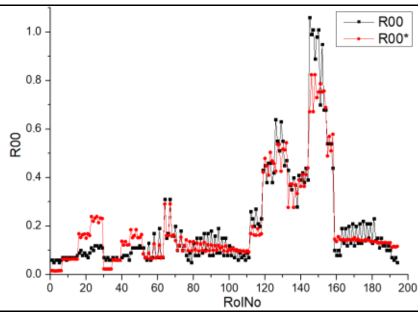
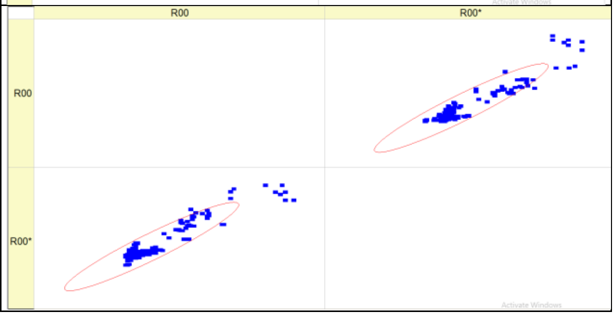
The graphical representations clearly demonstrate that the use of HVO leads to a significant decrease in smokiness emissions in diesel engines, particularly when pure HVO mixes are used. The ANN models exhibit a notable level of prediction precision, efficiently establishing the correlation between operational circumstances and emission levels. The results not only emphasise the positive impact of HVO on the environment, but also demonstrate the potential of ANN models in accurately forecasting engine emissions. This capability is essential for meeting regulatory requirements and optimising engine design.

The given Table 7 displays statistics on the emissions of smokiness from diesel engines while utilising various fuel mixtures: D100, HVO50, and HVO100. The content is divided into two main parts for each kind of fuel: the distribution of actual values and the distribution of anticipated values using ANNs.

Experimental Value Distributions The user's text is "D100". The data shows pronounced peaks in smoky emissions, suggesting substantial variability and instances of elevated emission levels. The distribution has many distinct peaks, which might indicate fluctuations in engine efficiency or variations in testing circumstances. The user's text is "HVO50". The figure demonstrates a significant drop in peak height when comparing it to D100, indicating that the presence of HVO leads to a reduction in emissions of smokiness. The number of peaks is reduced and their prominence is diminished. The HVO100 fuel has the least prominent peaks compared to the other two fuels, suggesting the lowest amounts of emissions related to smokiness. The general trend is less pronounced, indicating that pure HVO significantly decreases the variability of emissions and the amounts of peak emissions.

Table 7

Distributions of R00 parameter (*Smokiness, m^{-1}*) on experiment RolNo at different type of fuel mixture (D100, HVO50, HVO100)

Fuel	Parameter	Distributions of predicted value
D100		
HVO50		
HVO100		

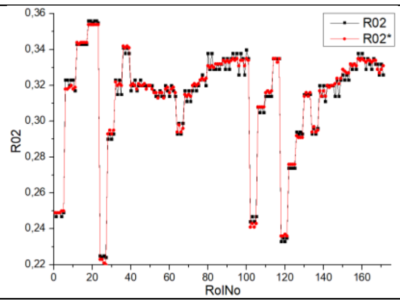
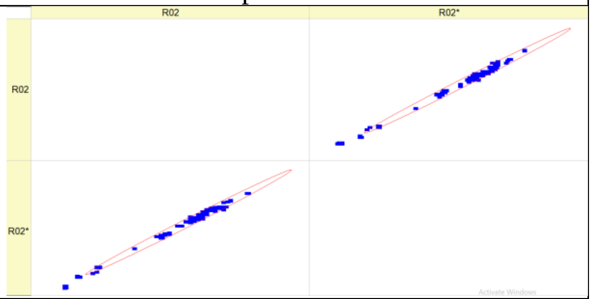
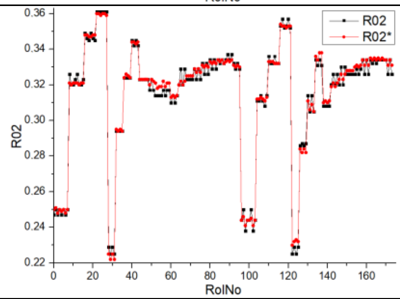
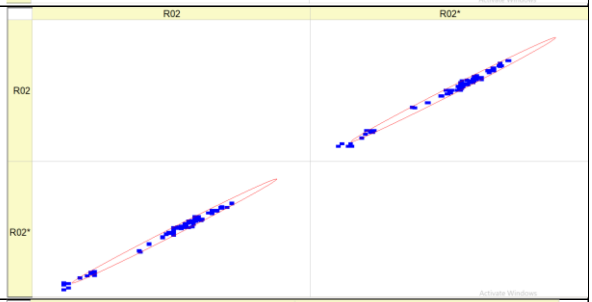
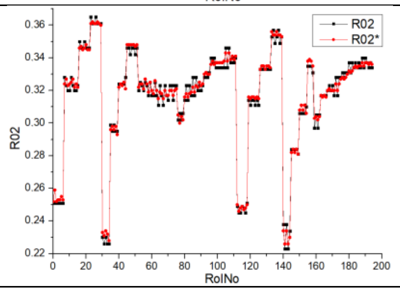
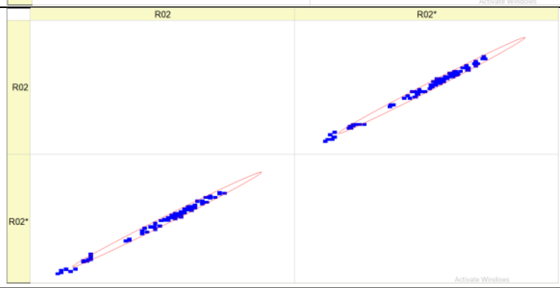
Forecasting Precision of Artificial Neural Network Models Graphs located on the right side Scatter graphs comparing projected and experimental results for smokiness emissions are shown for each fuel type. Correlation analysis each plot incorporates an oval shape that indicates the distribution and relationship of the data points, with the goal of visually showing the precision and consistency of the artificial neural networks' predictions. The D100 model has a robust linear correlation in its predictions, as seen by the dense clustering of data points along the trend line. However, a little dispersion may be noticed at higher emission levels. HVO50 has a strong prediction accuracy, as the majority of data points closely adhere to the trend line. The spread is somewhat wider, suggesting a little greater range of variability in forecast accuracy. HVO100 the predictions reported here exhibit the highest degree of variation across the three fuel types, suggesting that the model's predictive accuracy may be significantly worse for pure HVO. This might be attributed to the narrower range of emission levels or distinct behavioural patterns that are less prevalent in the training data.

The investigation unequivocally demonstrates a correlation between higher levels of HVO in diesel fuel and a substantial decrease in smokiness emissions from engines. The decrease is seen in both the empirical data and the artificial neural network forecasts. The ANN models exhibit strong performance in forecasting smokiness emissions, particularly with conventional diesel and HVO mixtures. However, they show somewhat higher variability when applied to pure HVO, indicating the need for further model tuning or more representative training data. This information is vital for promoting the use of HVO as a greener alternative to conventional diesel. It is backed by strong predictive models that guarantee compliance and enhance engine efficiency.

The distribution of Brake Thermal Efficiency (*BTE*) for diesel engines running with various fuel combinations, namely D100, HVO50, and HVO100, is shown in Table 8. Additionally, the table includes the predictions produced using ANNs for these parameters.

Table 8

Distributions of R02 parameter (*BTE)* on experiment RolNo at different type of fuel mixture (D100, HVO50, HVO100)

Fuel	Parameter	Distributions of predicted value
D100		
HVO50		
HVO10 0		

Comparisons Among Different Fuel Types The user's text is "D100". The figure illustrates that the *BTE* ranges mostly from roughly 0.26 to 0.34. The distribution has many peaks, which indicate the variability in efficiency across various operating points or engine settings. The user's text is "HVO50". Like D100, *BTE* has a broad range but demonstrates significantly more consistency across several test points, showing less abrupt declines compared to pure diesel. The user's text is "HVO100". The efficiency distribution closely resembles that seen with HVO50, with the majority of peaks occurring at comparable values. Nevertheless, it seems to have a little more consistent efficiency profile over its working range, suggesting superior performance stability.

These patterns suggest that including HVO, whether as a mixture or in its pure form, has a tendency to stabilise and perhaps improve the efficiency of the engine under different operating situations. Forecasting Precision of ANNs Models Graphs located on the right side Scatter plots show the projected *BTE* values versus the experimentally measured values for each fuel type. Linear trend lines the inclusion of these lines in each plot demonstrates the predictive pattern and signifies the level of agreement between the anticipated and actual values. There is a clear and direct relationship between the projected and actual values for each kind of fuel. The points exhibit a high degree of clustering along the line, which suggests that the ANNs have a high level of predicting accuracy. The D100, HVO50, and HVO100 samples have a comparable degree of correlation, indicating that the ANNs perform as well across various fuel compositions. The data points consistently form compact clusters along the linear trend lines, which suggests that the forecasts are accurate.

The statistics clearly indicate that including HVO into diesel fuel either preserves or improves the thermal efficiency of engines. Furthermore, the ANN models used for forecasting *BTE* demonstrate effectiveness across various levels of HVO concentrations, exhibiting a high degree of accuracy in their forecasts. The dependability of predictive modelling is essential for optimising engine performance and obtaining efficiency benefits in practical applications. The results emphasise the potential advantages of using higher HVO mixes, not just for environmental benefits, but also for improved engine performance.

5. CONCLUSIONS

1. Quality of ANN prognosis for several type pollutants (SCO_2, SNO_x and smokiness) in the diesel outcomes when diesel engine works in vide range of regimes using different commercial fuels: D100 (pure diesel), HVO50 (containing 50% HVO supplement), HVO100 (pure HVO) is very high.
2. Relationship for chemical parameters (SCO_2, SNO_x and smokiness) related to diesel working regime and fuel type (D100, HVO50, HVO100) is satisfied.
3. Relationship for energetic parameter (*BTE*) related to diesel working regime and fuel type (D100, HVO50, HVO100) is excellent.
4. For such type of data (input layer, number of units L = 12, output layer, number of units N = 4, number of events for training – 541), the empirically selected parameters of ANN architecture and training regime are sufficient: single-hidden layer, number of perceptrons M = 200, training regime using 160,000,010 epochs.
5. Prognosis of outcome parameters for fuels containing HVO is available, precision is high, deviations less 10 %.

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