Environmental Effects of Exhaust Emission from Spark Ignition Engine Fuelled with 4% HDPE Pyrolysis Oil-Gasoline Blend: Artificial Neural Network Modelling

Manickavelan Kolandasami, Kumaradhas Paulian, Venkatesan Tharanipathy, Mithun V.Kulkarni

Abstract: ***The present study investigates the environmental impacts of exhaust emissions from a spark-ignition (SI) engine fueled with a 4% High-Density Polyethene (HDPE) pyrolysis oil-gasoline blend. Using Artificial Neural Network (ANN) modelling, the research focuses on predicting and analysing key emissions parameters, including carbon monoxide (CO), nitrogen oxides (NOx), oxygen (O2), hydrocarbons (HC), and carbon dioxide (CO_2). A comprehensive dataset, encompassing various operational conditions, load, and speed, is collected from experiments. The analysis involves feature selection, data preprocessing, and the design of a feedforward backpropagation neural network architecture. The model is trained, tested, and validated on the dataset, with performance evaluated against environmental standards and regulations. Results from the trained ANN are then utilized to assess the environmental impact of the fuel blend under different scenarios. Sensitivity analysis identifies influential factors affecting emissions, providing insights into the complex relationship between input features and environmental effects. The study concludes with a detailed interpretation of findings, highlighting potential future considerations for mitigating environmental impacts associated with the use of HDPE pyrolysis oil-gasoline blends in SI engines. This research contributes to a deeper understanding of the interplay between fuel composition and environmental sustainability.***

Keywords: ***Spark-ignition, Comprehensive Dataset, Load Encompassing, Various Operational Conditions***

Nomenclature:
SI: Spark-Ignition
ANN: Artificial Neural Network
HDPE: High-Density Polyethene
IC: Internal Combustion
PPO: Plastic Pyrolysis Oil
RSM: Response Surface Methodology

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I. INTRODUCTION

Plastic oil generated from discarded plastics has been investigated as a potential alternative fuel source for internal combustion (IC) engines [1]. According to detailed research, plastic pyrolysis oil (PPO) might be a feasible alternative to petroleum diesel in CI engines [2]. Due to the scarcity of fossil fuels, researchers have investigated the use of waste plastic oil in automotive engines [3]. The use of plastic-derived fuel in internal combustion engines is viewed as a renewable and sustainable energy source, providing an effective method for recycling discarded plastics [4]. In addition, studies have shown that distilled waste plastic oil can replace diesel fuel in diesel engines. The growing use of plastics and the difficulty of plastic waste disposal have spurred studies into the reuse of trash [5][6].

High-density polyethene, a commonly used plastic, poses significant challenges for disposal and environmental impact. The conversion of HDPE into pyrolysis oil, a process that involves the thermal decomposition of plastic waste, presents an intriguing opportunity to transform a pollutant into a potential energy source [7][8]. Integrating this pyrolysis oil with gasoline aims to harness its energy content while potentially reducing the overall carbon footprint associated with transportation [9][10]. To comprehensively assess the environmental implications of adopting this fuel blend, it is imperative to scrutinise the exhaust emissions profile [11], [12]. The combustion of fuels in an internal combustion engine releases various pollutants, including carbon monoxide (CO), nitrogen oxides (NOx), hydrocarbons (HC), and carbon dioxide (CO2). Understanding how the introduction of HDPE pyrolysis oil to gasoline influences the emission characteristics of an SI engine is crucial for evaluating the viability of such a blend from an environmental standpoint [13][14]

Artificial neural networks (ANNs) have been employed to forecast and evaluate various attributes, such as efficiency, combustion behaviour, and emissions, of internal combustion (IC) engines, thereby improving time and energy utilisation. However, the intricate structure of ANNs can result in significant computational demands, energy consumption, and space requirements. Recent research has focused on altering network architectures, exploring deep learning methodologies, and refining ANN is designed to achieve optimal performance

[15][16]. Carbot-Rojasa et al. (2019) mathematically modelled an IC engine with a hydrogen-enriched E10 blend, revealing improved efficiency and torque. The optimal spark timing is 15.2° before BTDC at 1500 rpm [17]. Khatri et al. (2023) developed an Artificial Neural Network-based model for a micro-tri-generation system on a CI engine that predicts performance and emissions using data from multiple fuel blends. The model showed a higher correlation with observed values [18]. To extend the research, neural networks were employed to investigate the impact of cetane number on diesel engine emissions and to enhance performance [19], [20]. Ahmed et al. (2021) studied the performance and emissions of a four-stroke, single-cylinder SI engine using methanol-gasoline blends, and they found that adding methanol up to 12% improved engine performance but reduced emissions except for NOx [21]. Similar research has been conducted to predict performance and emission characteristics in SI engines fueled with different gasoline and other alternative-fuel blends, such as ethanol, isobutanol, and LPG [22].

Certain researchers are intrigued by Response Surface Methodology (RSM), which has diverse applications in engine research, notably in enhancing engine performance, minimising emissions, and refining combustion characteristics. RSM accurately predicts the relationship between input factors and output responses in engine tests, especially in ICE. It plays a crucial role in optimizing engine combustion, performance, and emissions. However, its application may have limitations, and integrating RSM with other optimization techniques can improve data learning and estimation accuracy [23]. Aydın et al. (2020) predicted and optimised the performance and emission characteristics of a single-cylinder diesel engine fueled with biodiesel-diesel fuel blends using ANN and RSM. Emissions and performance metrics were predicted with accuracy by the ANN model [24]. Dey et al. (2021) used RSM and ANN models to predict engine responses in a single-cylinder CI engine powered by biodiesel with ethanol (diesel-palm oil-ethanol) blends. Their ANN model showed lower prediction error and higher correlation, and the D75B20E5 blend was found to be best for optimizing BTE, BSEC, and NOx emissions [25]. Many research studies have been carried out to analyze the engine performance and emissions with different alternate fuel blends using ANN and RSM techniques [26]–[29].

The present investigation adopts a multidisciplinary approach, combining experimental data collection with advanced modelling techniques. The subsequent application of Artificial Neural Network (ANN) modelling enables the creation of a predictive tool capable of estimating exhaust emissions based on various input parameters, such as engine speed and load, and compared with RSM output. By focusing on a 4% HDPE pyrolysis oil-gasoline blend, this research aims to strike a balance between the benefits of incorporating bio-derived components and the potential challenges associated with altering the fuel composition. The study addresses key questions about the engine's performance under varying conditions, its compliance with environmental regulations, and its overall impact on air quality.

As the world transitions to a more sustainable, environmentally conscious energy landscape, the findings from this research contribute valuable insights to the ongoing dialogue on alternative fuels and their role in shaping the future of transportation. The exploration of unconventional fuel blends not only provides potential solutions to waste management challenges but also offers a pathway to reduce the carbon footprint of conventional internal combustion engines. Through a systematic analysis of the environmental effects, this study aims to inform decision-makers, researchers, and industry stakeholders about the potential benefits and challenges associated with adopting a 4% HDPE pyrolysis oil-gasoline blend in SI engines.

II. MATERIALS AND METHODS

ANN modelling is employed in this study to establish correlations between engine speed and load and emission traits. The chosen architecture for this task is a multi-layer feed-forward ANN, a robust technique for non-linear regression analysis. This architecture comprises an input layer with input variables, one hidden layer with 10 neurons, and an output layer with response variables. Each neuron in the hidden layer is connected to the input and output layers by weights. Neurons in the hidden layer may use linear activation functions, such as purelin, ReLU, etc., or nonlinear functions, such as logsig, tansig, etc. Biases are introduced to each neuron in the hidden and output layers for additional flexibility [30][31]. The training process adjusts the weights and bias tolerance parameters based on experimental data to minimise errors, using the backpropagation technique. The effectiveness of the ANN modelling is assessed using the correlation coefficient (R) to select the most effective configuration for training, adaptability, learning, and performance, including hidden layers, activation functions, and neurons [32].

Figure 1 illustrates the artificial neural network architecture used in the experiment. MATLAB R2022a is utilized for ANN modeling in this study, incorporating two input and five outputs (2-10-5 configuration) with feed-forward and backward propagation, utilizing the Levenberg algorithm, gradient descent, momentum weight, and bias learning functions. The error analysis is conducted using the TANSIG activation function for both output and hidden layers. The TANSIG activation function normalises the ANN output, restricting values to the range [-1, +1] [33]. Subsequently, training, testing, and validation are conducted in a 70:15:15 ratio based on the given data. The actual output is compared to the desired parameter, and an error value is calculated. The training process continues until the minimum error is achieved. Weights and biases are adjusted through additional iterations of training, testing, and validation.

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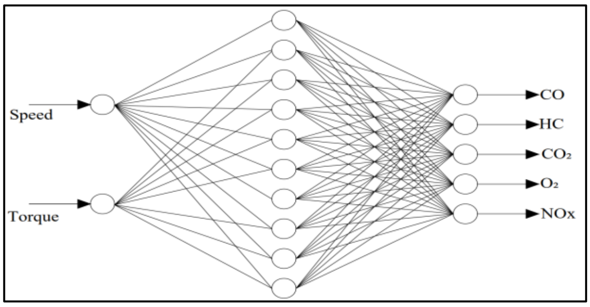


[Fig.1: ANN Architecture for Emission Traits of 4% HDPE Pyrolysis Oil-Gasoline Blends in SI Engine]

Weights, wij, represent the connectivity between the input layer and hidden layer, connecting input factors (i) to hidden layer neurons (j), with B_{1j} denoting the first bias to the j^{th} neuron of the hidden layer. The generalised equation from the hidden layers to the input is given in Equation (1).

$$H_j = \sum_{i,j=1}^{i,j=3,10} w_{ij} X_i + B_{1j} \qquad (1)$$

where Xi represents the i^{th} input factor.

The connection between the hidden layer and the output layer, represented by weights w_{jk}, is governed by Equation (2).

$$Y_k = \sum_{i=1}^{9} \tanh(H_j) * w_{jk} + B_{2k} \qquad (2)$$

where Y_k represents the k^{th} output factor. The training process adheres to the parameters and uses MATLAB's default settings without modification.

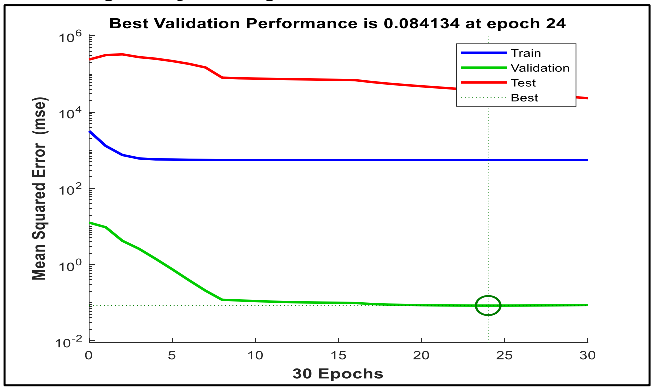
III. RESULTS AND DISCUSSION

Table I. presents the experimental and Artificial Neural Network (ANN) predicted values of response variables. The input layer comprises engine speed and load, while the output layer includes carbon monoxide (CO), nitrogen oxides (NOx), oxygen (O2), hydrocarbons (HC), and carbon dioxide (CO2) as response variables.

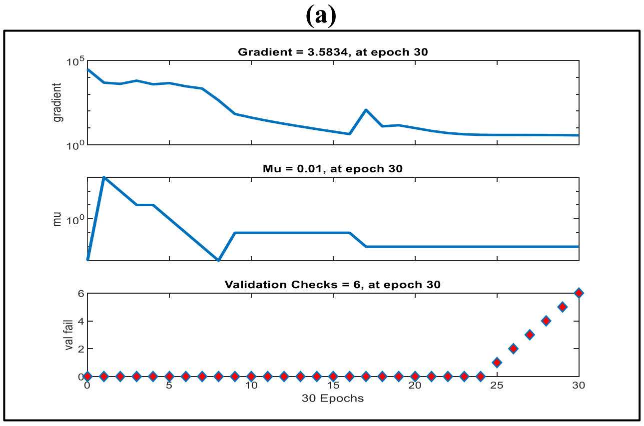
Table I: Effect of Engine Speed and Load on Experimental and ANN-Predicted Values of Emission

Speed (rpm)	Torque (Nm)	Experimental Values					ANN Predicted Values				
		CO	HC	CO_2	O_2	NOx	CO	HC	CO_2	O_2	NOx
2000	4.5	3.866	2123	1.6	14.08	136	3.955	2150	1.5	14.95	140
2200	5.8	4.492	1359	1.9	13.22	150	4.29	1340	1.8	13.32	156
2000	6.2	4.092	738	2.3	13.11	134	4.15	725	2.4	13.25	145
2500	8	4.763	612	2.5	12.25	151	4.69	618	2.6	12.35	140
3000	8.8	4.76	543	2.4	12.37	185	4.71	531	2.6	12.26	198
3200	9.5	3.895	411	3.8	11.36	239	3.81	420	3.6	11.28	225
3600	12	3.723	364	3.5	11.89	271	3.69	351	3.7	11.75	268

Figures 2(a) and (b) illustrate the progress of the ANN in predicting emission parameters from an SI engine loaded with 4% HDPE pyrolysis oil-gasoline blend using the Levenberg-Marquardt algorithm.



(a)



(b)

[Fig.2: Progress of the ANN in Predicting Emission Parameters]

The weights and biases from the training dataset used to develop the model are tabulated in Table II.

Table II: Weights and Bias from the Input to the Hidden Layer of the ANN Architecture for Prediction

Neuron	Speed	Torque	Bias to Layer 1
1	-3.8256	2.2196	4.4404
2	4.7237	-0.76012	-2.9272
3	-0.46822	-3.9442	3.6688
4	1.4336	-4.7132	-2.8202
5	-4.1471	1.6402	1.0993
6	-2.8697	-2.4591	-2.56
7	-2.4016	-4.6262	0.281
8	-4.9552	-4.1653	-1.405
9	5.406	2.7806	1.5233
10	2.9475	-7.3182	-3.8193

Table III. depicts the weights from the hidden layer to the output layer. The biases of the output layer are -1.6116, 1.2021, -0.55901, -0.47164, and -12.3847 for CO, HC, CO2, O2, and NOx, respectively.

Table III: Weights from the Hidden to the Output Layer of the ANN Architecture

Neuron	CO	HC	CO_2	O_2	NOx
1	0.51553	-0.21136	0.37175	-0.16834	-13.4998
2	-0.81924	-1.2441	-0.08835	-0.43945	14.712
3	0.14015	0.6638	-0.25814	0.70877	-16.2419
4	-0.0111	2.3216	-0.81252	0.10631	15.3626
5	-0.40579	-0.74459	-1.2487	0.93166	-21.6385
6	0.052651	0.34553	0.58225	0.038993	-20.9888
7	0.47265	3.8641	0.064396	0.62963	-8.0449
8	0.35339	7.7208	-0.23455	-0.70429	-4.0057
9	0.72073	11.0908	0.1379	-0.05218	5.284
10	-0.51896	1.471	-0.11937	1.1023	-0.65322

The error analysis of the ANN model is portrayed in Figure 3. Correlation

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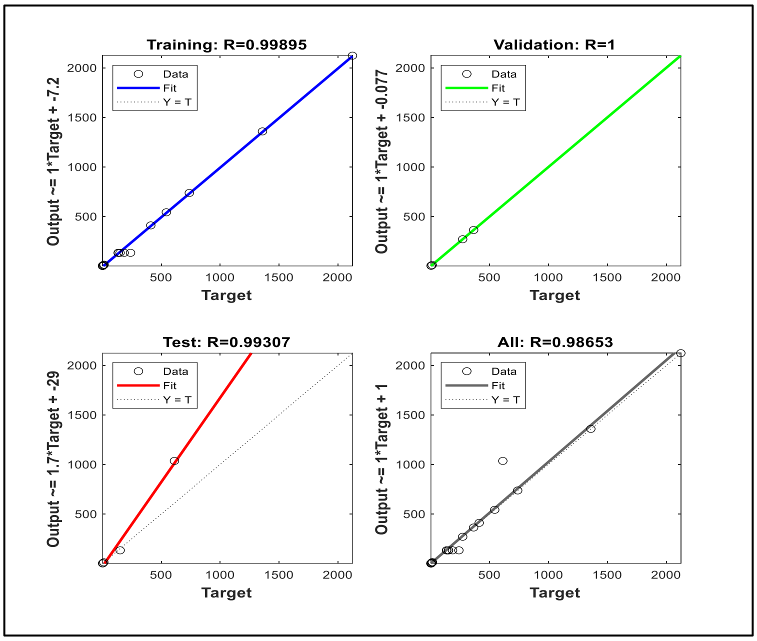
coefficients (R) for training, testing, and validation are 0.99895, 0.99307, and 1, respectively. The overall result is 0.98653, indicating a substantial and clear connection.

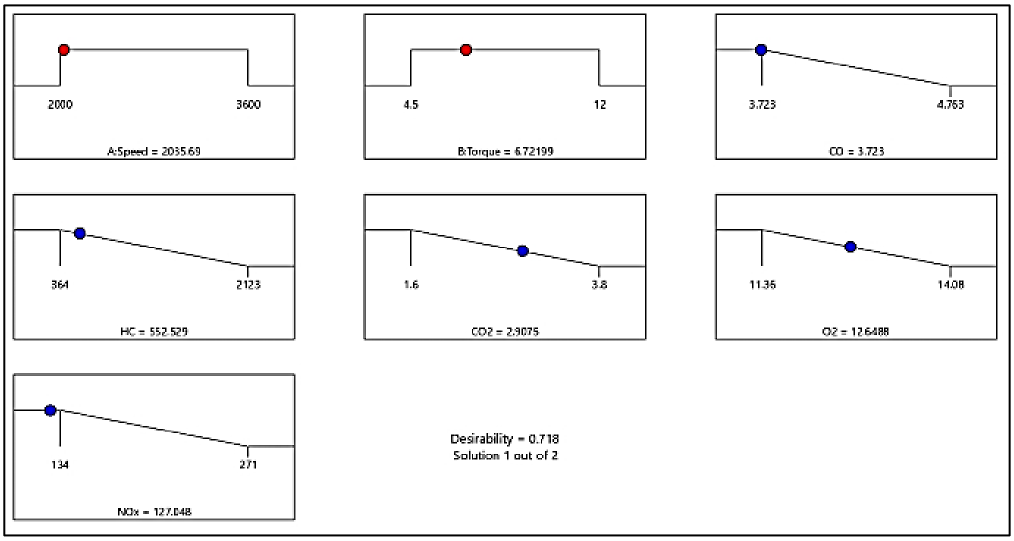


[Fig.3: Correlation Coefficients of Training, Testing, Validation, and the Entire Prediction Set of Emission Parameters]

The experimental values are optimized by Response Surface Methodology (RSM), and the results are listed below.

Table IV: Experimental Model Through RSM

	Factor 1 A: Speed RPM	Factor 2 A: Torque RPM	Response 1 CO %	Response 2 HC PPM	Response 3 CO_2 %	Response 4 O_2 %	Response 5 Nox %
1	2000	4.5	3.866	2123	1.6	14.08	136
2	2200	5.8	4.492	1359	1.9	13.22	150
3	2000	6.2	4.092	738	2.3	13.11	134
4	2500	8	4.763	612	2.5	12.25	151
5	3000	8.8	4.76	543	2.4	12.37	185
6	3200	9.5	3.895	411	3.8	11.36	239
7	3600	12	3.723	364	3.5	11.89	271
8	2000	6.2	4.092	738	2.3	13.11	134
9	2500	8	4.763	612	2.5	12.25	151



[Fig.4: Ramp Output from RSM]

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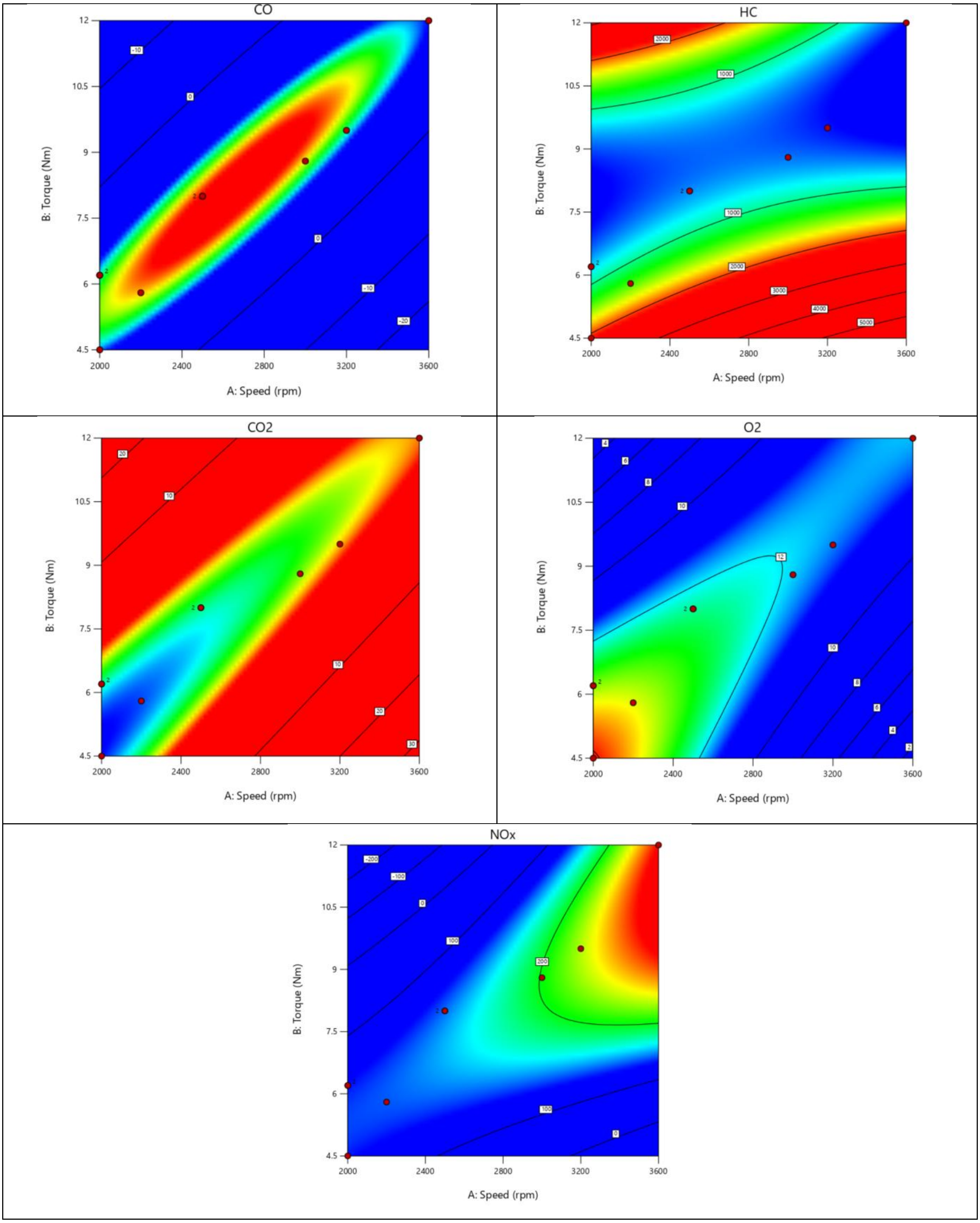

[Fig.5: Model Graphs of Responses from RSM]

IV. CONCLUSION

In conclusion, this study demonstrates that blending HDPE pyrolysis oil with gasoline in SI engines can significantly affect emissions, with ANN modelling proving effective for predicting key emissions parameters. Sensitivity analysis reveals critical factors affecting emissions, underscoring the complex interplay among operational conditions, fuel composition, and environmental impact. Findings suggest that HDPE-gasoline blends may be viable in reducing some emissions, though further exploration is needed to refine the blend ratio and engine settings for optimal environmental performance. This work provides valuable insights into sustainable fuel options and emissions-reduction strategies for automotive applications.

DECLARATION STATEMENT

Some of the cited references are older and are noted explicitly as [18]. However, these works remain significant for the current study, as they are pioneering in their fields.

As the article's author, I must verify the accuracy of the following information after aggregating input from all authors.

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- **Author's Contributions:** The authorship of this article is contributed equally to all participating individuals.

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