International Journal of Research Publication and Reviews

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

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A B S T R A C T

The present study investigates the environmental impacts of exhaust emissions from a spark-ignition (SI) engine fueled with a 4% High-Density Polyethylene (HDPE) pyrolysis oil-gasoline blend. Employing Artificial Neural Network (ANN) modeling, the research focuses on predicting and analyzing key emissions parameters such as carbon monoxide (CO), nitrogen oxides (NOx), oxygen (O2), hydrocarbons (HC), and carbon dioxide (CO2). 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 back propagation neural network architecture. The model is trained, tested, and validated, using the dataset, with performance evaluation 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 Engine, Artificial Neural Network , High-Density Polyethylene, neural network, emission

1. Introduction

Plastic oil generated from discarded plastics has been investigated for potential use as an alternative fuel source in internal combustion (IC) engines[1]. According to detailed researches, plastic pyrolysis oil (PPO) might be a feasible alternative to petroleum diesel in CI engines[2]. Because of 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 of recycling discarded plastics[4]. In addition, studies have revealed that distilled waste plastic oil has the potential to replace diesel fuel in diesel engines. The growing usage of plastics and the difficulty of waste plastic disposal have encouraged studies into reusing trash[5][6].

High-density polyethylene, a commonly used plastic, poses significant challenges in terms of disposal and environmental impact. The conversion of HDPE into pyrolysis oil, a process involving the thermal breakdown of plastic waste, presents an intriguing opportunity to transform a pollutant into a potential energy source.[7–9]. Integrating this pyrolysis oil with gasoline aims to harness its energy content while potentially reducing the overall carbon footprint associated with transportation[10,11]. To comprehensively assess the environmental implications of adopting this fuel blend, it is imperative to scrutinize the exhaust emissions profile[12,13]. The combustion of fuels in an internal combustion engine releases various pollutant, 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[14–16]

Artificial neural network (ANN) has been employed to forecast and evaluate various attributes such as efficiency, combustion behavior, and emissions of internal combustion (IC) engines, thereby offering efficiencies in time and energy utilization. However, the intricate structure of ANNs can result in significant computational demands, energy consumption, and space requirements. Recent research endeavors have focused on altering network architectures, exploring deep learning methodologies, and refining the design of ANNs to achieve optimal performance outcomes[17,18]. Jahirul et al. (2009) found that a neural network model accurately predicted experimental data for a modified multi-cylinder diesel engine, indicating potential improvements in future performance of NG-fueled engines.[19]. Carbot-Rojasa et al. (2019) mathematically modelled an IC engine with hydrogen-enriched

E10 blend, revealing improved efficiency and torque. The optimal spark timing is 15.2° before BTDC at 1500 rpm[20]. Khatri et al. (2023) developed an Artificial Neural Network-based model for a micro-tri-generation system on a CI engine, predicting performance and emissions using data from multiple fuel blends. The model showed a higher correlation with observed values[21]. To extend the research, neural networks were employed by researchers to investigate the impact of cetane number on diesel engine emissions and performance enhancement[22–24]. 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 [25]. Similar research have been carried out to predict the performance and emission characteristics in SI engines fueled with different gasoline and other alternate fuel blends like ethanol, I amyl alcohol, LPG etc[26–28].

Certain researchers are intrigued by Response Surface Methodology (RSM), which holds diverse applications within engine research, notably in enhancing engine performance, minimizing 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.[29,30]. Aydın et al. (2020) predicted and optimized the performance and emission characteristics of a single-cylinder diesel engine driven by mixes of biodiesel and diesel fuel by using ANN and RSM. Emissions and performance metrics were predicted with accuracy by the ANN model[31]. Dey et al. (2021) used RSM and ANN models to predict engine responses in a single-cylinder CI engine powered by bio-diesel with ethanol(diesel-palm oil-ethanol) blends. Their ANN model showed lower prediction error and higher correlation, and the D75B20E5 blend was found best for optimizing BTE, BSEC, and NOx emissions[32]. Many researches have been carried out to analyze the engine performance and emissions with different alternate fuel blends by ANN and RSM techniques[33–36].

The present investigation takes a multidisciplinary approach, combining experimental data collection and advanced modeling techniques. The subsequent application of Artificial Neural Network (ANN) modeling 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 regarding the performance of the engine under different conditions, compliance with environmental regulations, and the overall impact on air quality.

As the world transitions towards a more sustainable and 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.

2. Materials and Methods

ANN modeling is employed in this study to establish a correlation between engine speed and load with 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 is hidden layer is connected by weights between input and output layers. Neurons in the hidden layer may have linear activation functions, such as purelin, ReLU, etc, or nonlinear functions such as logsig, tansig, etc. Biases are introduced to each neuron in hidden and output layers for additional flexibility[37,38]. The training process involves adjusting the weights and bias tolerance parameters based on experimental data to minimize errors, achieved through the back-propagation technique. The effectiveness of the ANN modeling is assessed using the correlation coefficient (R), with the goal of selecting the most effective configuration for training, adaptability, learning, and performance, including hidden layers, activation functions, and neurons[39].

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 processing normalizes the ANN tool, restricting values between -1 and +1[40]. Subsequently, training, testing, and validation are conducted in the ratio of 70:15:15 based on 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[41].
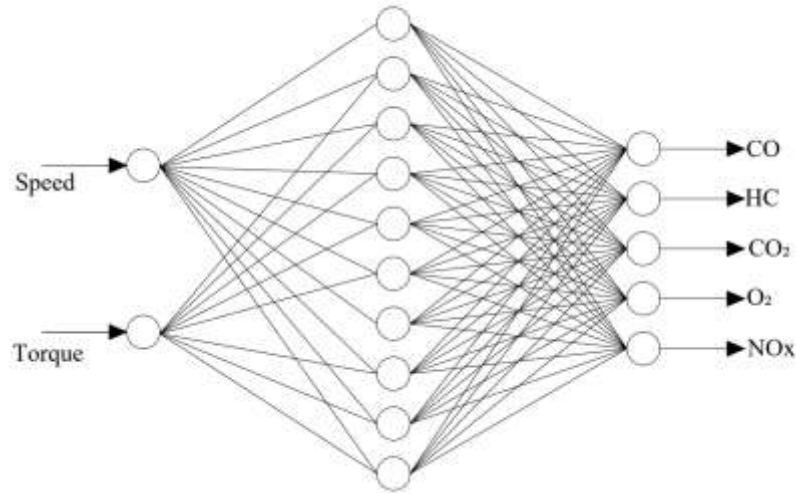
Figure 1- ANN architecture for emission traits of 4% HDPE pyrolysis oil-gasoline blends in SI engine

The connectivity between the input layer and hidden layer is represented by weights, w_{ij}, connecting input factors (i) to hidden layer neurons (j), with B_{1j} denoting the first bias to the jth neuron of the hidden layer. The generalized equation from hidden layers to input is expressed in Equation (1).

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

where, X_i represents 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 kth output factor. The training process adheres to the parameters using default settings of MATLAB without modifications.

3. Results and Discussion

Table 1 presents the experimental and Artificial Neural Network (ANN) predicted values of response variables. The input layer comprises speed and load of engine, while the output layer includes carbon monoxide (CO), nitrogen oxides (NOx), oxygen (O2), hydrocarbons (HC), and carbon dioxide (CO2) as response variables.

Table 1. 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

Figure illustrates the progress of the ANN in predicting emission parameters from SI engine loaded with 4% HDPE pyrolysis oil-gasoline blend using the Levenberg-Marquardt algorithm.
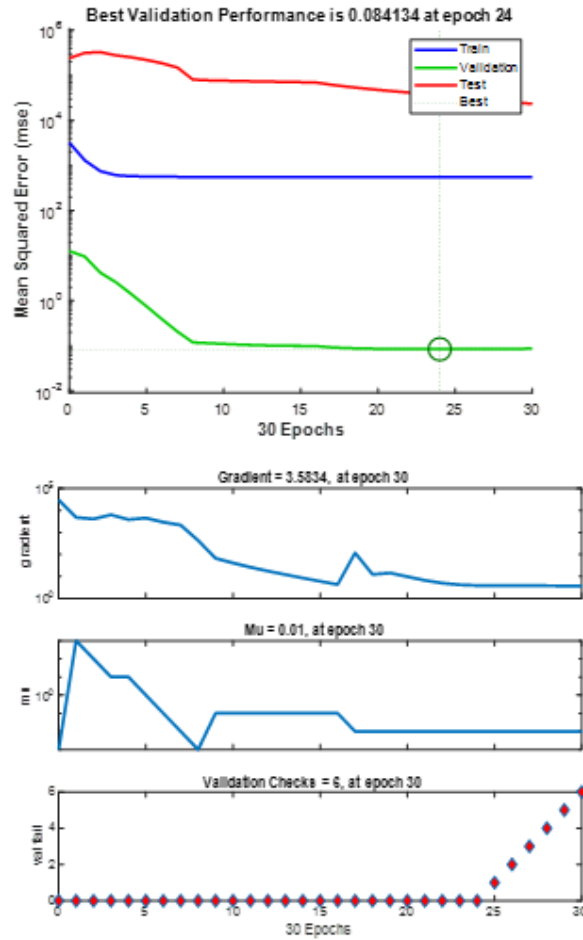
Figure 2 - Progress of the ANN in predicting emission parameters

The weights and bias from the training dataset, used to develop the model, is tabulated in table 2.

Table 2. Weights and bias from input to 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 3 depicts the weights from the hidden layer to the output layer. The bias to output layer are -1.6116, 1.2021, -0.55901, -0.47164, and -12.3847 for CO, HC, CO_2, O2 and NOx, respectively.

Table 3. Weights from hidden to 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 coefficients (R) for training, testing, and validation are 0.99895, 0.99307, and 1, respectively. The overall result is determined to be 0.98653, signifying a substantial and clear connection.
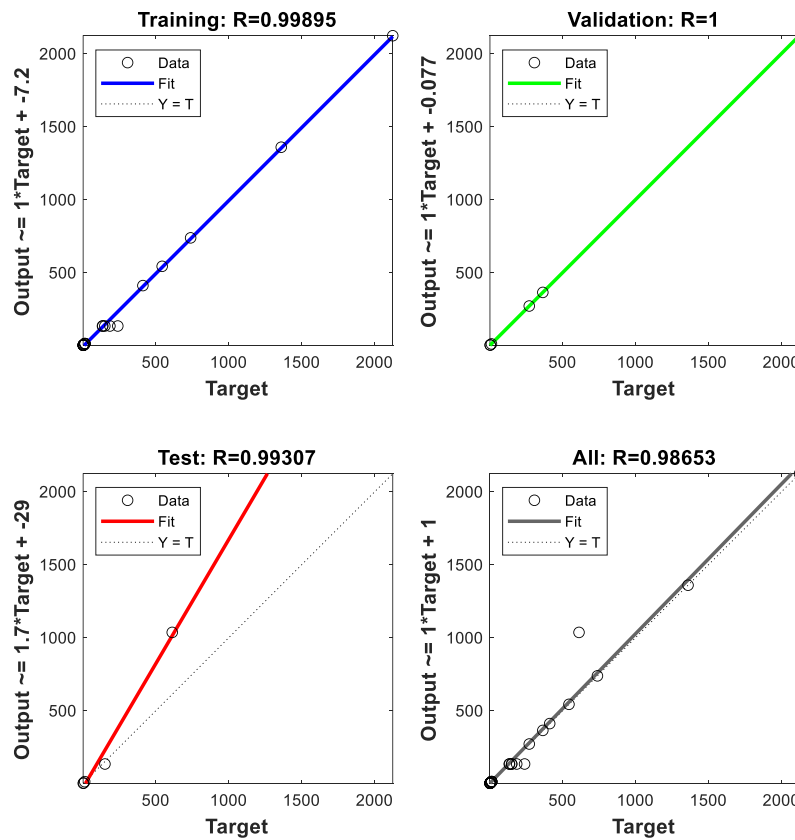
Figure 3 -Correlation coefficients of training, testing, validation, and all prediction set of emission parameters

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

Table 4. Experimental model through RSM

| Sl.No	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
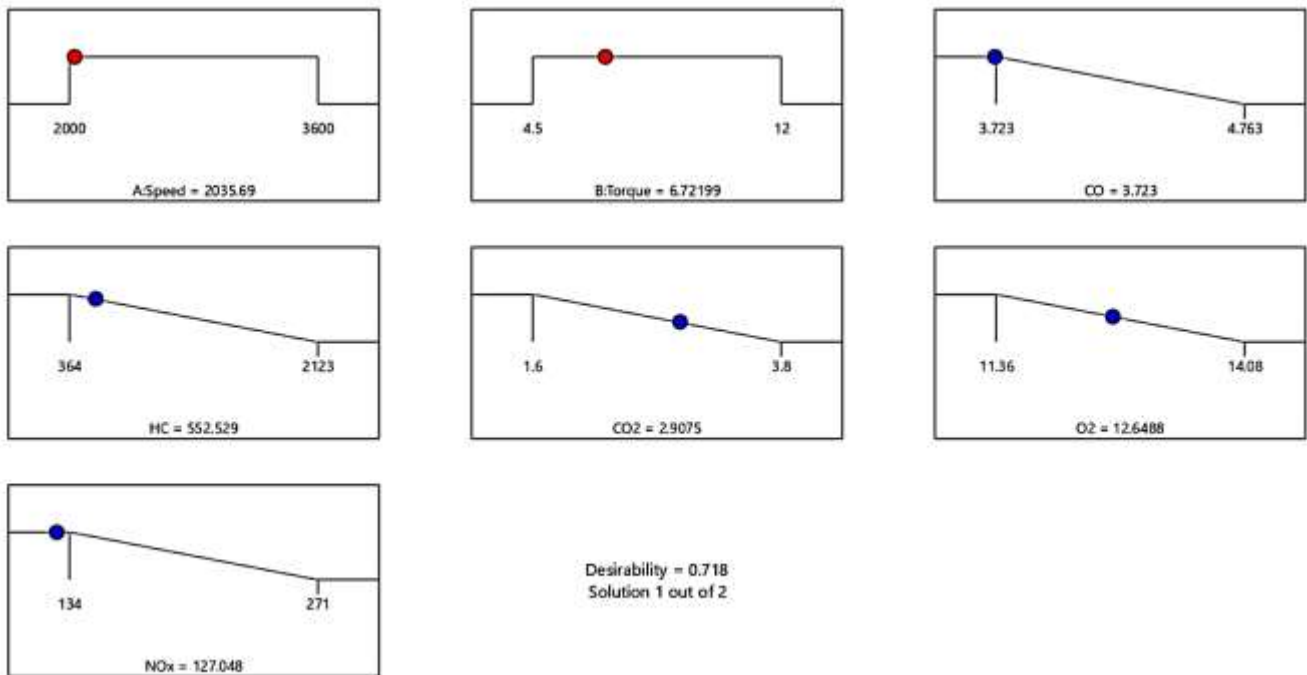
Figure 4 -Ramp output from RSM
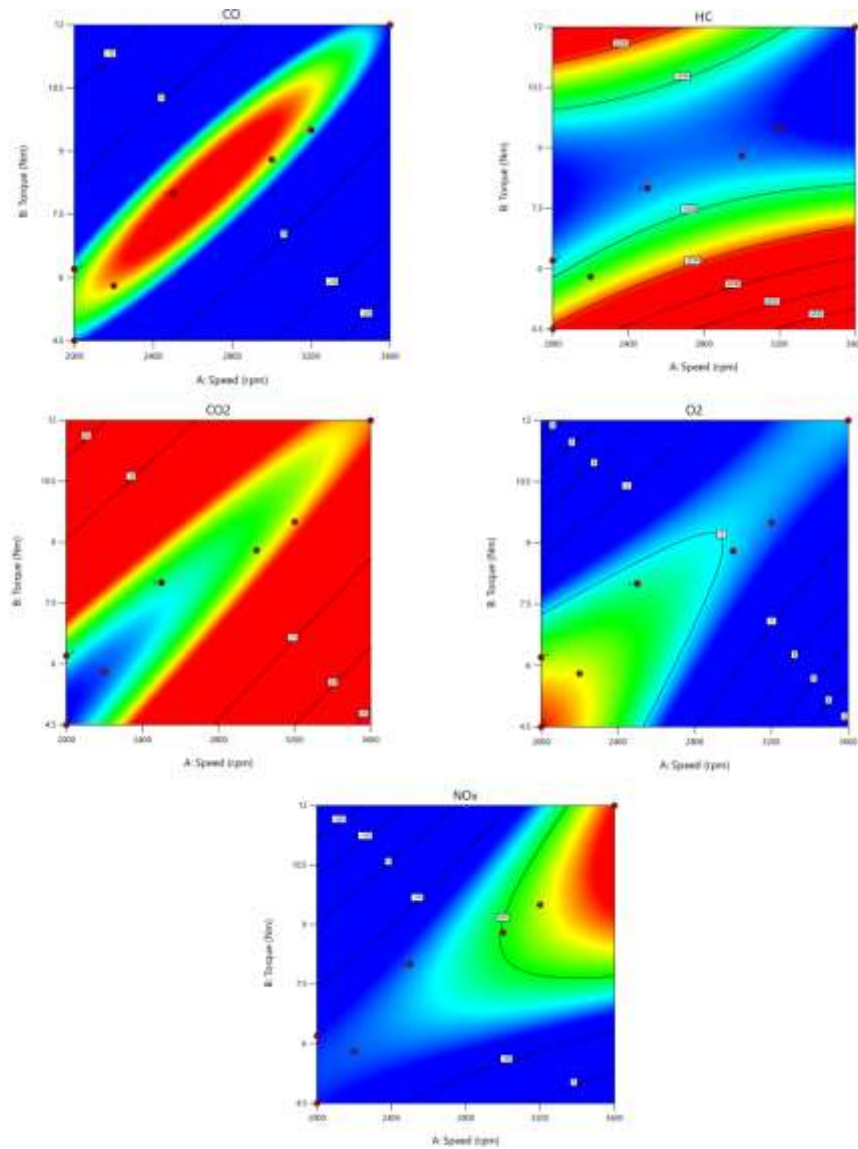
Figure 5- Model graphs of responses from RSM

4. Conclusion

This study highlights the feasibility of using a 4% HDPE pyrolysis oil-gasoline blend in SI engines, offering potential for reduced emissions and sustainable waste management. The integration of ANN modeling proved effective in accurately predicting emissions and identifying influential operational factors. The findings underscore the importance of optimizing fuel blends and engine configurations to balance performance with environmental compliance. This work contributes to the development of alternative fuels, addressing both energy demands and environmental challenges. Future studies could focus on refining blend ratios and exploring long-term impacts to ensure broader applicability and sustainability.

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