Investigation of a Compression Ignition Engine Run on Alternative Fuel Using Soft Computing Techniques

B. Tech Project Report

SUBMITTED BY

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ABSTRACT

The supply and demand of energy is a crucial concern that calls for optimized methods of harnessing new forms of energy. Finding sustainable green alternative fuels and optimizing operating parameters is currently a viable solution and a critical issue in the scientific community. It is known that fossil fuels are running low every day. With the increase in the number of vehicles, pollution has reached alarming levels. Engine experiments are complex, expensive, and time-consuming, significantly when the global economy has plummeted due to the COVID19 pandemic. The restriction is placed on social distancing, so soft computing techniques are used in this area. Soft computing is a set of algorithms, including neural networks, fuzzy logic, genetic algorithms etc. These algorithms are tolerant of imprecision, uncertainty, partial truth, and approximation.

This literature review consists of the applications of soft computing techniques in the field of Spark Ignition (S.I.) and Compression Ignition (CI) engines. Soft computing approaches were initially utilized mainly to estimate the performance and emission parameters. However, because of ongoing comprehensive research in this subject, similar methodologies are being used to investigate engine misfiring, fuel optimization, and ignition activation. These algorithms predicted engine parameter values that were found to be very near to the experimented values, making them a very reliable prediction tool.

This work aims to complement the research in internal combustion engines on waste cooking oil as fuel alternative engines using ANN and RSM technique applied to model and predict performance, exhaust, and combustion parameters of Compression Ignition engine.

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CHAPTER-1
INTRODUCTION

Internal Combustion engines are the most broadly used power-generating devices in the present time. Due to their less size as compared to external combustion engines and high power to weight ratio, they are widely used in combustion vehicles like motorcycles, automobiles, aircrafts, ships, etc. Based on the method of ignition, they are classified into two types, i.e., spark-ignition engine (S.I.) and compression ignition engine (CI). [1] Knowing that internal combustion engines are most used in the present time, they have their disadvantages. The demand for fossil fuels is increasing day by day as a result of rapid industrialization and modernization. It is also estimated that fossil fuel reserves will be depleted within 50 years, leaving a considerable gap between available and necessary energy. The number of automobiles is growing every day, and so is pollution caused by vehicle exhaust emissions. The significant pollutants for the exhaust of an internal combustion engine are carbon monoxide (C.O.), Sulphur Oxide (SOx), Hydrocarbons (H.C.), particulate matter (PM), and Nitrogen oxides (NO_x). [2]

Many researches are being conducted to reduce the exhaust emission from engines, improve performance, and find a suitable alternative fuel that is cheap and eco-friendly. But the performance and exhaust emission measuring experiments on an internal combustion engine is complex, time-consuming, and costly. Therefore, mathematical modeling can be employed to predict the performance and exhaust characteristics. However, their accuracy is not high enough. The current auto industry based on internal combustion engines is uncertain about future technology. Hydrogen, electricity, and biofuels are the future of transport. Future internal combustion engines must address emission requirements, energy security, energy efficiency, and consumer power requirements. The sustainable and inexpensive solution for using biofuel depends on the availability of local raw materials or residual biomass, the properties of the biodiesel, and production methods to improve the properties.

Lately, many soft computing (S.C.) techniques [3] have been used to predict and optimize engine performance parameters and exhaust emissions. It is an emerging approach to mathematical modelling that incorporates the remarkable ability of the human mind to argue and learn in the atmosphere of uncertainty and distrust. It plays a vital role in finding the solutions for various complex problems and has a wide range of applications. Computer science became a formal field of study in the early 1990s. In the past few years, some computer modeling techniques have been used to relate the various engine parameters and predict the multiple characteristics of internal combustion engines such as power, combustion, and emissions, and seem helpful because of their fair and precise predictions.

Various soft computing techniques used for analysing and optimization are as follows:

- Artificial Neural Network (ANN)
- Fuzzy Logic
- Adaptive Neuro-Fuzzy Inference System (ANFIS)
- Genetic Algorithm (G.A.)
- Particle Swarm Optimization (PSO)

1.1 Artificial Neural Network

Neural networks are computer algorithms that are nonlinear and can model complex and complicated systems. The structure and the work of ANN simulates a biological neural network that receives inputs from multiple sources, combines those inputs, performs nonlinear operations on the result, then gives the final output. It can learn very complex functions and fits data with high variance.

There are three types of layers in ANN:

- Input layer
- Hidden layer
- Output layer

ANN consists of interconnected processing nodes known as neurons. They accept weighted inputs and respond with an appropriate output. Each layer contains neurons connected to the neurons of the anterior and posterior layers. The experimental data determines the number of neurons in the input layer, while the output of the experimental data determines the number of neurons in the output layer.

Many training algorithms available are used in ANN modelling like Levenberg-Marquardt (L.M.), Scalar Conjugate Gradient (SCG), and others. These training algorithms are generally classified into two categories, i.e., heuristic techniques and standard numerical optimization techniques. Variable learning rate and resilient backpropagation algorithms fall under the heuristic technique while L.M. and SCG algorithms are standard numerical optimization techniques. Backpropagation neural network (BPNN) is the most used network. Figure 1.1 shows the architecture of an ANN model.

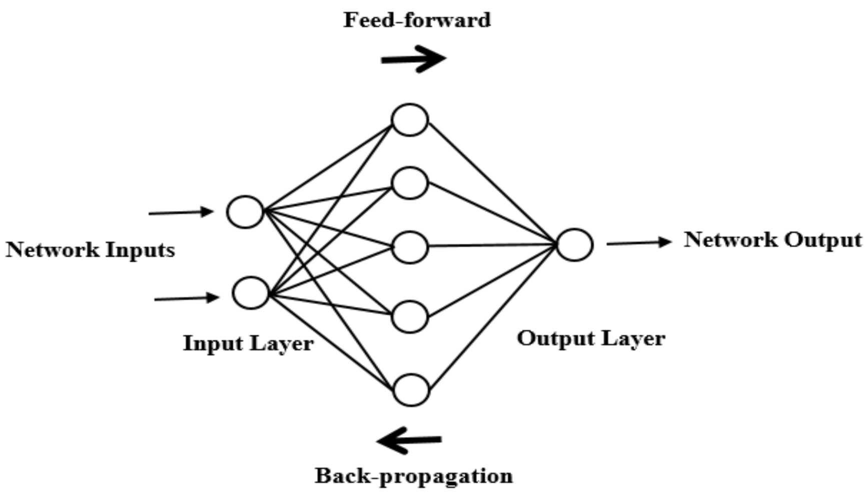


Figure 1.1: Structure of ANN [i]

1.2 Fuzzy Logic

Fuzzy logic is an expert system that uses fuzzy membership rules and functions instead of Boolean logic to infer data. The Fuzzy set has smoother boundaries that allow partial membership, unlike the Boolean set, which only allows 0 or 1 as values. FES consists of fuzzification, fuzzy inference engine, knowledge base, and defuzzification subsystems. In fuzzification, the membership functions are applied to their actual values. This is done to determine the degree of truth for each rule premise. The truth value for the assumption of each rule is computed in the inference and then applied to the conclusion part of each rule. It is also being used in various fields such as I.C. engine.

Fuzzy logic rules are used in the IF-THEN format. These rules can be written by a human or can be generated from numerical data. Defuzzification is the process that converts the fuzzy output set into a crisp number. Several forms of defuzzification process are available, including center of gravity (COG), mean of maximum (MOM), and center average methods. Mamdani and Takagi-Sugeno are the two major types of FIS. The adaptive abilities of fuzzy logic make it an ideal choice for applying it to real-life problems. Fuzzy logic applications are found in diverse areas like facial recognition, power systems, data classification, decision analysis, expert systems, and computer vision. The architecture of the fuzzy logic system is enumerated in Figure 1.2.

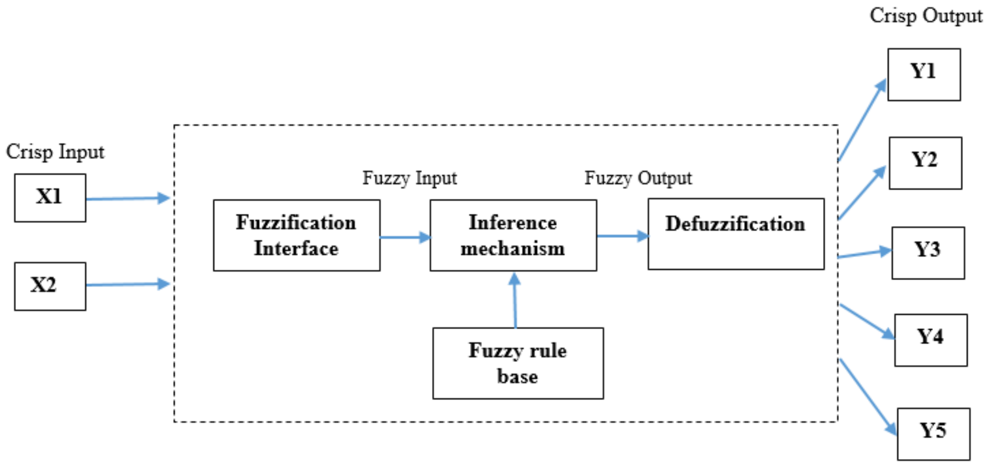


Figure 1.2: Structure of Fuzzy Logic [ii]

1.3 Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS is better than a simple fuzzy system and a neural network. ANFIS learns from the environment and then makes a decision. On the other hand, they can deal with inaccurate data and knowledge without problems and describe their results in the area where the facts are in the verb form but cannot learn from their surroundings. Therefore, these two technologies complement each other. A typical architecture of the ANFIS system is enumerated in Figure 1.3.

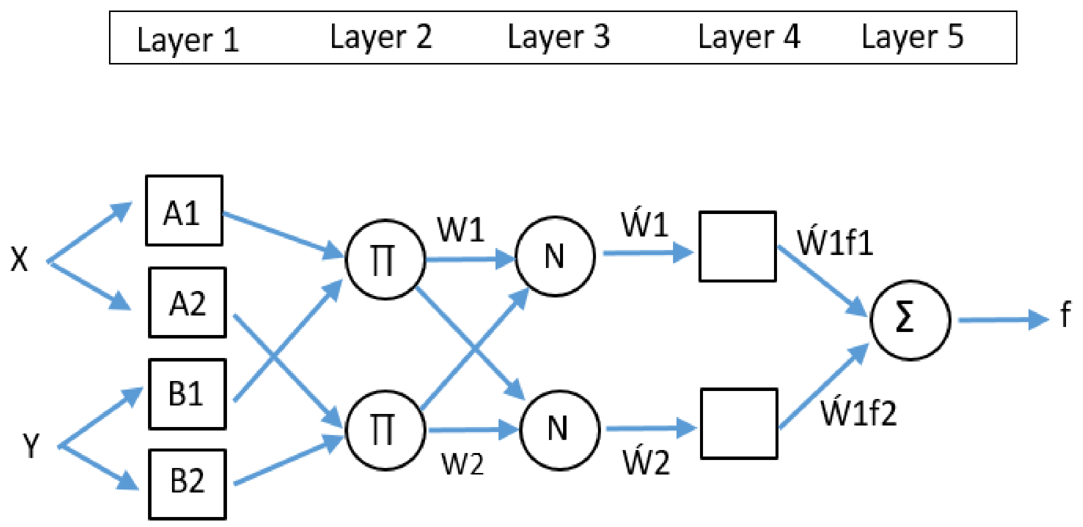


Figure 1.3: Typical ANFIS structure [iii]

It is a combination of a neural network and a fuzzy system based on the structure of the Takagi-Sugeno Type-Fuzzy-Inference system developed by Jang. It is a fuzzy expert system & runs in the form of an adaptive neural network. ANFIS has the hybrid learning algorithm, a fusion of least squares estimation learning and inverse propagation.

1.4 Genetic Algorithm (G.A.)

The Genetic Algorithm is a widely used technique for optimizing various engineering problems. It can be used to solve problems that are not suitable for standard optimization algorithms. The objective function is strongly nonlinear, stochastic, non-differentiable, and discontinuous. The Algorithm repeatedly modifies a population of individual solutions. Individuals are randomly selected from the current population at each step and then used as parents to father the next generation of children. With successive generations, the people "evolve" to achieve an optimal result.

G.A. applies to most real-life applications. Multi-modal, discontinuous, nonlinear problems can be handled by G.A. Along with these, variable and noisy search space problems can be addressed by this method. G.A. is an adaptive algorithm, and parallel computation is easier with computationally expensive problems. Figure 1.4 represents the flow diagram of G.A.

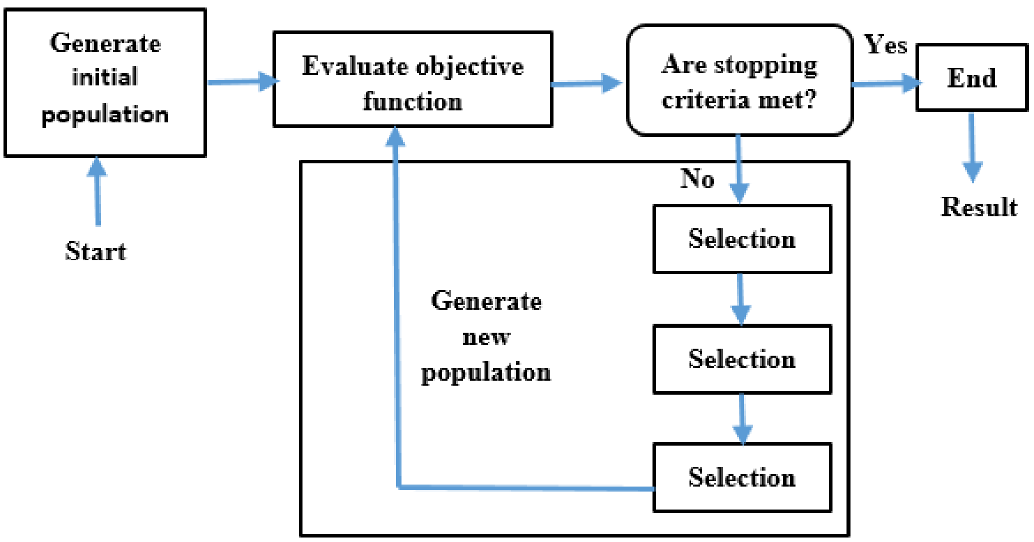


Figure 1.4: Genetic Algorithm structure [iv]

1.5 Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is a computational technique used to optimize a parameter by improving a solution concerning a given quality measure. Dr. Eberhart and Dr. Kennedy developed it in 1995. The working of PSO imitates the social behavior of the schools of fish or the flock of birds.

Each particle moves with adaptive probability to update its position and velocity from local best to global best known; thus, the entire swarm is directed in the international best direction by cumulative influence of parameters of all particles. In PSO, each particle's position is updated according to the best direction found by other particles in the swarm. Due to all the particles' communication, the overall optimized solution is obtained for an entire swarm. PSO does not require any prior assumption of the problem and also can cover an ample search space. Thus it is used by many researchers for optimizing their problem statements. Figure 1.5 represents the flow diagram of PSO.

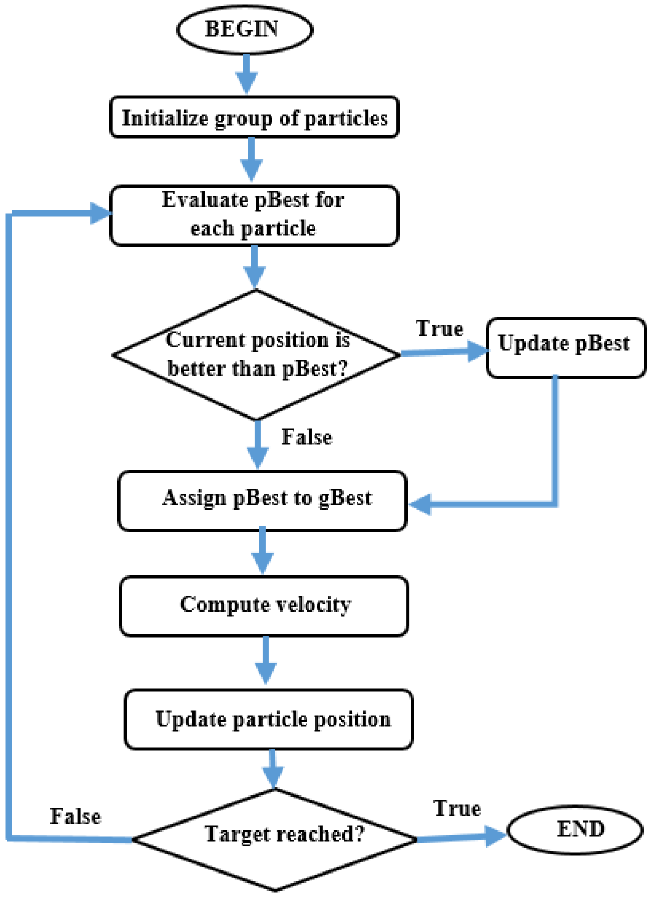


Figure 1.5: Particle swarm optimization algorithm [v]

1.6 Response Surface Methodology (RSM)

Response surface method (RSM) is one of the most promising statistical methods to the optimization of process parameters in biodiesel production. The primary advantage of RSM is reducing the number of experimental runs which is adequate to provide statistically acceptable results. It helps to reduce the computational required during experiments. RSM is used to find the best value of the response.

There are many studies in which optimize the process parameters in biodiesel production by using RSM. In addition, the ability of the usage of artificial intelligence techniques such as RSM to predict and optimize of a diesel engine operating parameter have not been adequately investigated in the literature. Therefore, in order to complete this space, the novelty of the present investigation is applied to RSM as an accurate step to optimize the operating parameters of diesel engine powered with biodiesel/diesel fuel blends regarding to best performance and exhaust emissions. Contour plot of RSM can be seen in Figure 1.6.

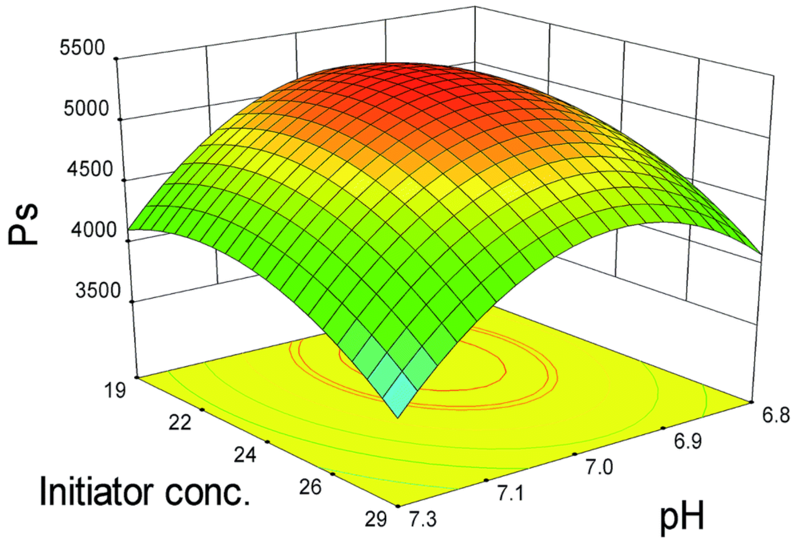


Figure 1.6: An example of RSM contour plot [vi]

CHAPTER-2
LITERATURE REVIEW

2.1 Soft Computing Techniques in Spark Ignition Engine

Togun and Baysec [4] used ANN modelling to predict brake specific fuel consumption (BSFC) & torque of S.I. engines with gasoline as fuel. Ignition advance throttling status and the engine speed were taken as input parameters. The test was performed using a four-cylinder four-stroke engine. For the prediction of engine torque, network 3-13-1 was chosen here. In the input layer, there were three parameters, while in the hidden layer, there were 13 parameters to give output. On the other hand, BSFC was predicted using a 3-15-1 network configuration. The Levenberg-Marquardt (L.M.) training algorithm was used for the network training. The model performed well with a correlation coefficient (R) of 0.99.

Cay [5] worked with four strokes and a four-cylinder S.I. engine using ethanol and gasoline as fuel. Using parameters such as fuel flow, speed, etc., the researchers predicted BSFC, EGT, and adequate power. The used Levenberg-Marquardt (L.M.) training algorithm with Scaled Conjugate Gradient (SCG) learning algorithm with different values of neuron in the hidden layer and finally 5-7-3 model gave the best results. For test data, mean error percentage (MEP) & root mean square error (RMSE) were less than 2.7% and 0.02, respectively, and finally, for training set & testing set data (R^2) value was 0.99.

Cay et al. [6] used backpropagation with Log-Sigmoid as an activation function to find the SFC, air-fuel ratio, and different exhaust parameters like H.C. and CO. Input parameters for this experiment were engine speed, torque. Different blends of methanol and gasoline were taken as the fuel for a four-stroke four-cylinder engine, with the help of other networks such as 4-7-1, 4-11-1, 4-14-1, 4-7-1, which gave the value of R^2 as 0.9.

The graphs for the same are shown in Figure 2.1. From the figure below we conclude that with increase in number of testing pattern the predicted value comes very close to the actual value. For Hydrocarbon and BSFC we can see that with increase in test size their prediction was very close to actual value. Thus, providing high regression value.

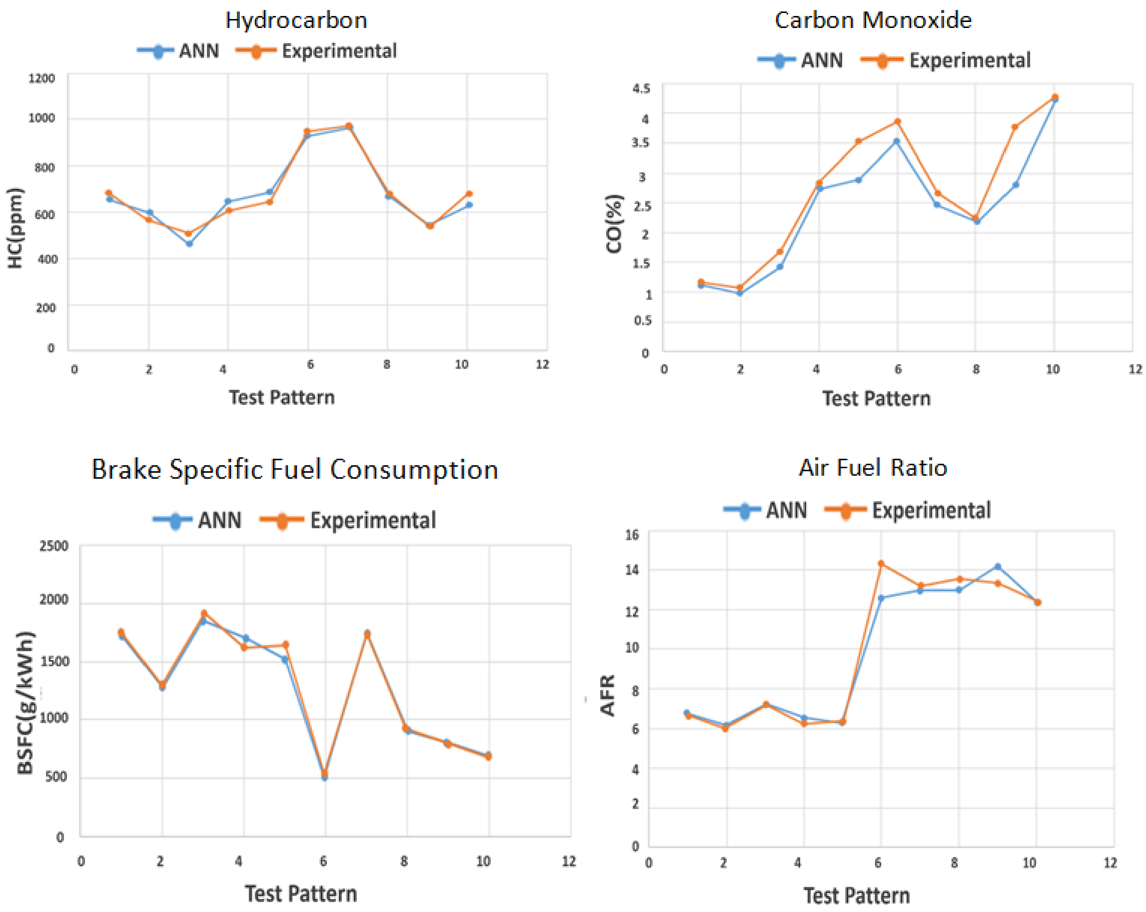


Figure 2.1: Comparison of the experimental and ANN values for testing sets of C.O., H.C., BSFC, and AFR [6]

Sahin et al. [7] investigated excess air coefficient, which is necessary for engine and emission performance. So, determination of this is essential for working of the engine. Sahin, in his study, used gasoline blends to determine excess air coefficient. Ignition angle, engine speed, peak ionization current with the location was taken as input parameters. Backpropagation algorithm and Scaled Conjugate Gradient (SCG) learning algorithm were used to train the data, with Log-Sigmoid as the activation function, and SCG was found to give better results. The (R^2) value for this experiment using SCG was 0.99, and MAPE was found to be 12.3.

Kapusuz et al. [8] analysed and studied to calculate the BSFC of four strokes four-engine cylinder. Kaspusuz used a backpropagation feedforward neural network model in his study. In this experiment, tan sigmoid is taken as the activation function. The network configuration used for this experiment was 3-10-1, 3-10-1, 3-7-1, 3-18-1. Input parameters for this experiment were taken as power, torque, and fuel consumption. Blends of methanol and ethanol with gasoline were taken as fuel. The result showed that 11% methanol and 1% ethanol gave the best result, while fuel having 2% ethanol gave minimum BSFC. ANN fetched the results with a R-value of close to 0.99 for all the above configurations.

Korkmaz et al. [6] modelled an ANN model which was used to predict the BSFC, CO, H.C., and AFR using methanol and gasoline fuels. Different training algorithms were used. The best results in predicting BSFC, CO, H.C., and AFR were obtained by network architecture of 4-7-1, 4-7-1, 4-14-1, and 4-11-1 and the SCG, L.M., R.P., and BFGS learning algorithms, respectively. In the ANN model, the coefficients of determination of the BSFC, CO, H.C., and AFR for both the training and the testing set were notably close to 1.

Wilson VH and Udayakumar [9] dealt with the use of neural networks for the estimation of performance and fuel consumption of a spark-ignition engine using different initial valve timings and engine speeds. The overall results show that the networks can be used as an alternative way for predicting the performances of these systems. It used 62 results as data sets to train the network, while 15 results were used as test data from the total of 77 experimental results. L.M. and SCG algorithms have been studied and the best results were obtained from the L.M. algorithm with 15 neurons and the mean absolute percentage error was limited to 7.2–8.8% for both the L.M. and SCG algorithm.

Kiani et al. [10] used different percentages of ethanol in the experimentation phase for data acquisition, in which torque, and exhaust emissions such as carbon dioxide, oxides of nitrogen were studied. There were three values in the given configuration of the input layer. In contrast, the number of elements in hidden layers was 25, giving six outputs. Blend percentage, load, engine speed was taken as input parameters. Here backpropagation algorithm was used with Tan-sigmoid as the activation function. This model helped to calculate the value of R as 0.98.

Najafi et al. [11] incorporated an ANN model with back propagation algorithm to predict various engine out parameters such as torque, power, BTE, BSFC, and various exhaust parameters. The input parameters were taken as different blends of ethanol which was fuel for the engine and the engine speed. For this experiment, there were three layers. In the input layer, there were two parameters, while in the hidden layer number of parameters increased to 23 and in the output layer there were nine outputs. The value of R was found to be 0.97.

Danaiah et al. [12] used tert-butyl alcohol as the fuel for the four stroke four cylinder engine, with varying blend percentage, load, and engine speed. For this experiment, a network configuration of 3-1-10 was used, so there were around three neurons in the input layer while one neuron in the hidden layer and the final layer had ten outputs. An ANN model with L.M. training algorithm was employed. The value of the Root Mean Square error calculated here was 0.999%.

Mehra et al. [13] investigated the optimum value of torque, BSFC, and other exhaust parameters that are essential for the good performance of the engine. Various parameters were considered like engine load, excess air ratio, spark timing, and Hydrogen-Enriched Compressed Natural Gas (HCNG) ratio, to calculate the output parameters. HCNG was taken as the fuel for the engine. Here, L.M. training algorithm was used to calculate values of output parameters. Tan-sig was used as the activation function. With the network configuration of 4-15-6, the value of R was found to be 0.999.

Tasdemir et al. [14] calculated the optimum values of H.C. (Hydrocarbon) emission, BSFC, torque, and power. A multilayer perceptron (MLP) network using Back-Propagation algorithm was developed and Tan-sigmoid was used as the activation function. Tasdemir used gasoline as the engine's fuel and controlled the parameters like intake valve advancement and speed to give optimum values of the output parameter. With the help of network configuration of 2-60-4, value of R equals to 0.999 was achieved.

Martinez et al. [15] measured the exhaust value of oxides of nitrogen. They used a gasoline-fueled engine with various input parameters like injection timing, torque, intake pressure, speed, ignition point, and throttle. With Backpropagation algorithm and Log-Sigmoid as the activation function, this model was modified with three objective functions using Ant colony optimization. The optimization involves the sensitivity analysis using the hyper volume metrics and VIKOR method for decision making. With the network configuration of 6-7-9-6-1, a value of R^2 equals 0.999 was achieved.

Uslu and Celik [16] used blends of gasoline and i-amyl alcohol and speed and compression ratio as the input parameters to calculate the optimum values of BTE, BSFC, BMEP, and other exhaust parameters. For the model's training, the L.M. training algorithm was used with Tan-sigmoid as the activation function. With the help of RSM optimization and the network configuration of 3 – 10 – 6, the model was trained and gave the value of R^2 as 0.94.

An ANN model was applied to test a single-cylinder four-stroke Common rail direct injection (CRDI) engine with EGR to predict performance and exhaust emission parameters by Roy et al. [17]. In this, an investigation was done for various alcohol–unleaded gasoline mixtures that can be used with no modifications in a spark-ignition engine. The mixtures consisted of 5%, 10%, and 15% ethanol, methanol together and separately. The input layer for this model consisted of engine load, fuel injection pressure, EGR, and fuel-injected per cycle. In contrast, the ANN model predicted brake-specific fuel consumption, thermal brake efficiency, CO2, NOx, and PM in the output layer. The feedforward network model used the gradient-descent method for minimizing the errors. The logistic sigmoid transfer function was utilized as an activation function, and mean square error (MSE) was employed as an error generation indicator.

The results are shown in Figure 2.2. The correlation coefficients ranged between 0.987-0.999 for exhaust emissions and performance parameters, and MAPE ranged between 1.1-4.57 %, which displayed good prediction values.

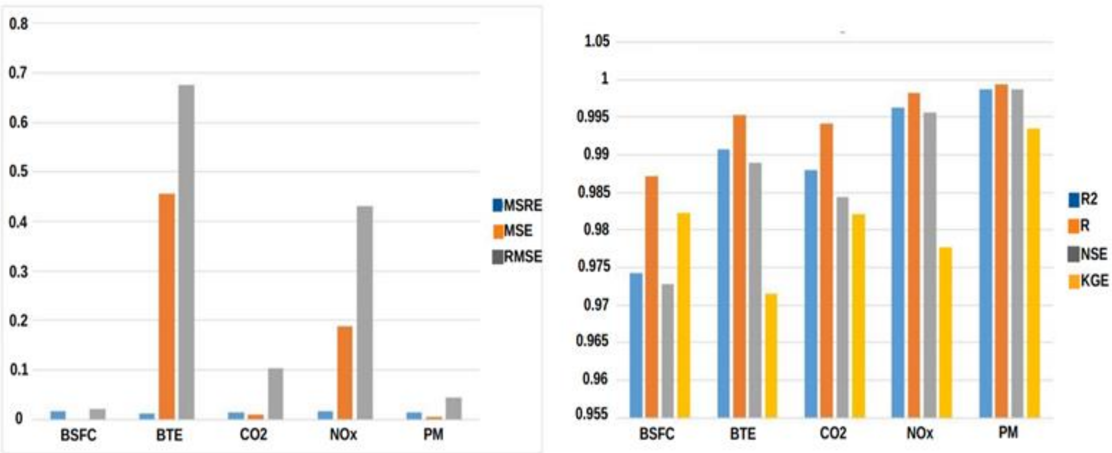


Figure 2.2: Error matrices and Correlation coefficients of ANN model [17]

Liu et al. [18] investigated that fuel consumption is a handy parameter to determine the engine's working. So, to measure the effect of compression ratio, speed, alcohol type on various parameters such as the torque, fuel consumption, and other exhaust parameters, Liu used gasoline, butanol, propanol, ethanol, and methanol as the fuel. The experiment was conducted and analyzed, taking back propagation as the learning algorithm, Tan-sigmoid as the activation function, and General Regression Neural Network (GRNN), Gaussian, and Linear as the transfer function. The network configuration of 4-18-5-2 was used. With the help of Multi-Output Least-square Support Vector Repressors (MLS-SVR), ANFIS as the optimization method, the value of R^2 was obtained as 0.93.

An ANN-based approach for modeling a four-stroke, four-cylinder gasoline engine with various octane numbers to foresee BSFC, exhaust gas temperature, brake thermal efficiency, and exhaust emissions was employed by Sayin et al. [19]. A three-layered feedforward network with a standard backpropagation algorithm with the Levenberg-Marquardt method was implemented for optimizing weights. Lower heating value, engine torque, engine speed, and air inlet temperature were utilized as the input layer, while BSFC, exhaust gas temperature, thermal brake efficiency, and exhaust emissions formed the output layer. The correlation coefficients for performance parameters ranged between 0.983-0.996, and mean relative errors ranged between 1.41-6.66 %. Overall, the ANN model displayed good prediction results.

Taghavifar et al. [20] investigated and analyzed the data obtained from the CFD code used to develop the ANN model for prognostication of the soot and nitrogen oxide production. Input parameters required for this were engine speed, heat release rate, equivalence ratio, turbulence kinetic energy, and temperature variance. Among the various learning algorithm, the L.M. training function with the network configuration of 5-19-17-2 was used to give the mean square error of 0.0004627.

Costa et al. [21] incorporated a robust design methodology for the four-stroke engine to reduce nitrogen oxide and soot emission. To ensure that emission reduces without decreasing the efficiency of the fuel, a Multi-Objective Genetic Algorithm is used. Best solutions were validated through actual C.F. three-dimensional calculations. It was seen that the decrease in soot emission and nitrogen oxide emission of around 36% were recorded.

Sakthivel and Gnanasekaran [22] dealt with ethyl ester of fish oil as biofuel. To predict the engine performance and emission by the use of fish oil, the ANN model was created. The network was trained with 70 % of the available data, and the remaining data were used to verify the model. The values of predicted and experimental data were very similar, with RMSE and MRE errors relatively low. It was seen that the BTE, CO, H.C., etc. value gradually decreased with an increase in smoke.

To study a new application in diagnosing the misfires in an internal combustion engine, Chen et al. [23] designed two feedforward MLPs. A Toyota 3S-FE, four-cylinder engine was used for experimentation and data acquisition. The data was obtained from simulation results for testing using LMS AMESim software package was used for training, and experimental results obtained were used for testing. Multiple multilayer perceptron (MLP) models and probabilistic neural networks were incorporated in MLP1 for the detection stage; Probability neural network (PNN) was used in the localization stage and MLP2 in the severity identification stage. Saturated linear transfer functions were used as activation functions. The ANN model was able to detect the misfires in actual tests efficiently.

2.2 Soft Computing Techniques in Compression-Ignition Engine

Muralidharan et al. [24] researched a model for predicting the engine's emission, performance, combustion parameters using biodiesel made from used cooking oil. The blends of fuel, load, compression ratio, and crank angle were taken as input parameters. With the help of the backpropagation algorithm BSFC, BTE, H.C., CO_2, CO, NO_X as output parameters were calculated. After testing, the R^2 was found out to be 0.9982.

Gurgen et al. [25] investigated the cyclic variability of diesel and butanol fuel blends. The observational datasets were integrated to design an ANN model to predict cyclic variability as output parameters with fuel mixtures and input speed. The SCG learning algorithm was used for the training was 2-11-1 ANN network architecture. The value of R^2 ranged between 0.737 and 0.9677.

Arumugam et al. [26] used an ANN for predicting the emission while using different fuel mixture. The R-value obtained was close to 1, and the MRE value was below 5%. The performance of diesel engines using preheated crude palm oil has been investigated by Yusaf et al. The parameters were comparable to diesel used in our daily routine, and the braking performance is slightly higher than that of diesel. BSFC, NO_x, CO, CO_2, and EGT were predicted by the neural network model using a different mixing percentage, engine speed as inputs, and a backpropagation algorithm to train the network. The log sigmoid function was selected for the hidden layer and a network configuration of 2-25-6. Mean squared error (MSE) as a result was 0.0004.

Kshirsagar and Anand [27] modelled variable injection time and pressure to predict engine performance with methyl ester from calophyllum inophyllum. Two different ANN models were developed; the first with the 4-16-3 architecture for predicting engine performance and the second with architecture 4-14-14-6 to predict the emission characteristics. Charge, fuel mixtures, injection pressure, and timing were the inputs for both models. R-value was predicted to be 0.999.

Kumar et al. [28] in their research investigated Pongamia Pinnata biodiesel using a backpropagation algorithm with Tan-Sigmoid as the transfer function for analysing BTE, BSFC, NO_x, H.C., and CO. Load and fuel type were taken as the input parameters. A 3-6-5 network configuration was used for the same. Final result predicted to be MSE equals 0.002 and MRE of 6.8%.

Ghobadian et al. [29] studied waste cooking oil as a fuel with blend percentage and engine speed as input parameters to predict torque, SFC, CO, H.C. They developed the model using Back Propagation algorithm with Log-Sig with activation function, finally model was preferred with 2-25-4 network architecture. This model predicted with R value close to 1 and MSE value of 0.0004.

Langkumaran et al. produced diethyl ether mixed with fish oil biodiesel. A model was developed to predict emission and performance parameters. The model had a hidden layer of 20 neurons. The different load and the percent mix were entered into the model. The correlation coefficients for BTE and EGT were 0.997 and 0.999, while exhaust emissions were 0.997 to 1.

ANN modelling was applied by Ismail et al. [30], with the motive of studying nine engine parameters with blends of various biodiesel. Pure Diesel, Palm oil blends, and Soybean oil blends were used for testing. The input layer consisted of four parameters; those are engine speed, engine torque, fuel mass flow rate, and various biodiesel samples, while the 15-output layer measured nine parameters like C.O., CO2, NO, UHC, the maximum pressure (Pmax), location of maximum pressure (CAD Pmax), maximum heat release rate (HRR max), location of maximum HRR (CAD HRR max) and cumulative HRR (Cu-HRR).

The correlation coefficient ranges between 0.939-0.987. Also mean square error (MSE) observed was between 0.017381-0.029287 which was within acceptable limits.

The graphs comparing measured and predicted values are given in Figure 2.3. From below graph we can see that with increase in measured value of Carbon Monoxide & Nitrogen Oxide their predicted value also increases. Thus, we see high correlation value for CO and NOx.

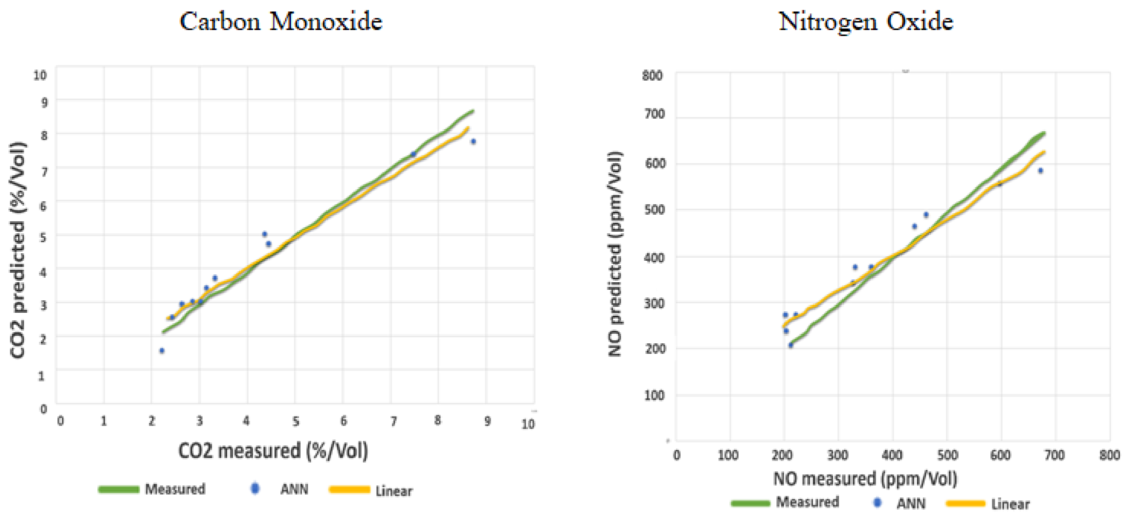


Figure 2.3: Comparison between measured and predicted output values of a CI engine using Soybean oil blends [30]

Manieniyan et al. [31] used Mahua biodiesel to predict R-value via input parameters as hot EGR, cetane number, cold EGR, time. A different algorithm was preferred here, i.e., PNN, RBFNN, and Gaussian functions were used. The output parameters were the wear value of Fe, Cu, CO, Zn, Pb, and Mg. Results predicting R-value ranged from 0.90 – 0.99.

Sakthivel et al. [32] analyzed the I.C. engine powered by fish oil-based biodiesel. With the use of the EGT, BTE, CO, NOx, H.C., CO_2, and smoke, final results were anticipated. The network configuration of the ANN model was 2-20-11. To train, a MLP model with backpropagation algorithm with the trainlm function was utilized. As inputs, the percentage of load and the types of fuel blends were used. The anticipated outcomes; mean relative error and correlation coefficient were determined to be 0.02–3.97 percent and 0.02–3.97 percent respectively. R-value 0.957–0.999, to be precise. Other researchers reached the same outcomes.

Shivakumar et al. [33] examined the consequences of varying the fuel injection timing and compression ratio in an engine running on kitchen waste. The BSFC and NO_X emissions of the biodiesel blended fuel were relatively higher than pure diesel, while the smoke and H.C. emissions were relatively lower. ANN model with backpropagation algorithm was used for the prediction of results. The input variables were selected as exhaust gas temperature, power consumption, thermal efficiency, mixing ratio, load, injection time, and compression ratio. The MRE for emission and performance characteristics were predicted as 8% and 5%, respectively.

As input parameters, Bahri et al. [34] investigated diesel – ethanol fuel blend with peak pressure and three pressures at a different crank angle. A 4-20-1 network architecture along with a backpropagation algorithm was used. The output parameter taken was noise level. The predicted result was found out to be R^2 equals 0.99.

The researcher mentioned above did another study. In this same fuel, the blend was used, but input parameters were taken as five different pressures. 5-10-10-10-10-1 network configuration was considered for the prediction of MSE. Output parameters included three misfires (low temperature, fuel cut off, high dilution). The final result was that MSE was 0.01.

Anarghya et al. [35] used methanol as fuel and analyzed the behavior, using input parameters air-fuel ratio, iso-octane with n-heptane(Primary reference fuel, PRF) percent, methanol, crank angle. A genetic Algorithm was preferred for the prediction of the final result. Here, the Gaussian activation function was used to train the model. Output parameters included heat release rate, pressure release rate, C.O., NO_x, and H.C. predicted error value was less than 0.9927.

Rezai et al. [36] researched a model using butanol and ethanol fuel mixture. Fuel blend and equivalence ratio were the input parameters. A 2-15-7 network system with a backpropagation algorithm was considered for the prediction. Output parameters were BTE, in-cylinder pressure, IMEP, HRR, NOx, CO, and H.C. MSE came out to be less than 4%.

Krishnamoorthi et al. [37] investigated straight vegetable oil using the RSM optimization method. Compression ratios, EGR rate, and engine speed were taken as input parameters. The backpropagation algorithm was chosen. A 3-12-7 network configuration was used to train the model. Output parameters included NO_x, smoke, C.O., H.C., CO_2, BTE and BSFC. The anticipated outcome of the R-value was 0.99.

Optimum biodiesel blends and speed ranges using a hybrid Artificial Neural Network and multi-objective optimization process were determined by Etghani et al. [38]. Initially a standard back propagation algorithm was used to predict the output values like BSFC, brake power and engine emissions with MLP network for nonlinear connection between input and output layer. The input layer was made up of engine speed and oil 17 blend percentage while the output layer consisted of brake power, brake specific fuel consumption, PM, NOx, CO and CO2. Correlation coefficient, RMSE and MAPE were used as three parameters for determining the most suitable ANN architecture. The multi objective optimization was then carried out by an evolutionary algorithm NSGA-II, these Pareto solutions were then ranked using TOPSIS.

Uludamar et al. [39] used biodiesel and OxyHydrogen (HHO) as fuel blend and considered cetane number, heating value, HHO %, and speed as input parameters followed by output parameters which included vibrations. Backpropagation algorithms with log-sigmoid and Purelin functions were used to train the model. A 4-2-1 network architecture was used for the same. The R^2 values predicted came out to be 0.9986.

A fuzzy expert system was developed to calculate the fuel consumption based on C.O., CO2, H.C., O2 and air ratio values in S.I. engine by Kilagiz et al. [40]. The fuel system faults, ignition system faults, intake valve and exhaust valve faults were calculated based on the emission and fuel consumption outputs and according solutions were advised. The advice given by the model has led to reduction in the emission at high ratio.

Marin et al. [41] investigated using fuzzy logics, the emission parameters of a gasoline engine and to optimise the injection parameters and the Air-Fuel ratio. A MATLAB application toolbox as used to model the system. The system used Mamdani fuzzy control. The fuzzy system was used to reduce C.O. emissions and also injection timing was improved with the help of a fuzzy logic controller.

2.3 Waste Cooking Oil as fuel in a Diesel Engine using ANN

Ghobadian et al. [42] used different blends of waste vegetable oil, methyl ester, and diesel as fuel. For the input parameters Load, Speed, and different fuel blends were considered to predict the Brake Power, Torque, SFC, and various exhaust parameters. Back Propagation was used to train the model, which gave the R values as 0.9487, 0.999, 0.929, and 0.999 for torque, SFC, CO, and HC emissions, respectively. The mean square error was 0.0004.

Fangfang et al. [43] used Biodiesel made from waste cooking oil. For making the ANN model, they used input parameters such as Load and Blend ratio, to predict the Thermal efficiency, SFC, NOX, and smoke opacity. To train the model Levenberg-Marquardt backpropagation algorithm was used. With these high R-value of 0.98192 and 0.99758 was achieved.

Gholamhassan et al. [44] used biodiesel from waste cooking and mixed it with methyl ester. To predict Brake Power, Torque, and various exhaust parameters, Engine Speed and various fuel blends were taken as the input. To train, this model Back Propagation method was used. R2 obtained was 0.99994, 1, 1 and 0.99998 for the engine torque, specific fuel consumption, CO and HC emissions, respectively.

Eminson et al. [45] took used cooking oil biodiesel as the fuel. In order to predict BTE, SFC, BP, mechanical efficiency, exhaust parameters and indicated mean adequate pressure: compression ratio, blend percentage and percentage load was taken as input. Feed-forward backpropagation was used to train the model.

Abed et al. [46] used waste sunflower oil for making Biodiesel to used as fuel for experiments. Different engine loads and engine speed was used to predict smoke opacity and exhaust gas concentration. To train the model Back Propagation method was used.

Karthikeyan et al. [47] used Chinensis oil methyl ester as fuel for the experiment. Input parameters to train the model was CA, CR, CI, and fuel blends. These were used to predict Exhaust Gas Temperature (E.G.T), Brake Specific Fuel Consumption (BSFC), and Brake Thermal Efficiency (B.T.E). To train the neural network model Levenberg-Marquardt backpropagation algorithm was used. From the model overall regression value of 0.99 was

Hoanga et al. [48] used Biodiesel as the fuel to generate the data for model. Input parametres for the model was taken as CR, IT, IP, load, speed to predict exhaust gas temperature (EGT), Brake Specific Fuel Consumption (BSFC), Brake Thermal Efficiency (BTE) and various exhaust parameters. To train he model Levenberg-Marquardt backpropagation algorithm was used. From predicted parameters Mean Square Error obtained was in range of 0.1479–0.00029 while R value obtained was in range of 0.84145–0.99988.

Narath et al. [49] used palm based Biodiesel with ethanol blend and diesel blend as fuel. To predict the BSEC, NOx, UHC & CO2 emissions different blends was taken as input and load was varied. To train the model Levenberg-Marquardt backpropagation technique was used. This model gave the MSE as 0.000179 and 0.000466. while MAPE was in range (2.32–4.54%) and R varied between (0.99329–0.99875).

2.4 Waste Cooking Oil as fuel in a Diesel Engine using RSM

Suleyman et al. [50] used Biodiesel based on canola, safflower, and waste vegetable oil as fuel to collect data. The input parameters were chosen as biodiesel ratio, injection pressure and engine load to predict BTE, EGT, NOx, CO2 and smoke. From the RSM model R2 values for BTE, EGT, NOx, CO2 and smoke were found as 99.81%, 99.36%, 98.31%, 99.00% and 98.84%, respectively.

Ceyla et al. [51] used waste cooking oil-based biodiesel. Different blends of Biodiesel with diesel was used along with various engine speed to predict power, torque, smoke opacity, and exhaust parameters. R2 for the biodiesel optimization model was 0.9596.

Shirneshan et al. [52] used waste cooking oil as fuel. The input parameters for a model as various engine speeds combined with engine loads. The output parameters were Brake power, Brake torque and BSFC.

Dey et al. [53] used different blends of diesel with waste cooking oil-based Biodiesel as the fuel. To predict the output parameter fuel consumption and thermal efficiency, various fuel combinations were used along with torque. The experimentally obtained FC and TE at recorded a value of 0.5094 kg/h and 23.70%, respectively.

CHAPTER-3

OBJECTIVES, METHODOLOGY AND WORK PLAN

3.1 Objectives

The main objective behind the project undertaken is to perform experiment and analyze the internal combustion engine to increase the modelling and prediction of performance, exhaust and combustion parameters of CI and S.I. engines using various alternative fuels like biodiesel, alcohol and gaseous fuels in dual fuelling. Our aim is to analyse and optimise the engine with the following ways:

- Using different S.C. techniques being used in this field such as Artificial Neural Network (ANN), Fuzzy Logic, Adaptive Neuro Fuzzy Inference System (ANFIS), Genetic Algorithm (G.A.), Response Surface Methodology (RSM) and Particle Swarm Optimization (PSO) for prediction of output parameters of a fuel.
- Training the model with the use of multi-input single-output and multi-input multi-output approach. This will help in developing methodology and statistical analysis for evaluation.
- To get optimum results, number of neurons in the range of 10 to 20 in a hidden layer and logarithmic sigmoid and tangent sigmoid transfer function will be taken into consideration.

3.2 Methodology

We begin with selecting the type of engine for our experiment. We then proceed to finalize the various input parameters like air-fuel ratio, type of fuel, composition of fuel etc. We also need to fix the output parameter for further experimentation. Once the input and output parameters are fixed, we proceed with the data acquisition process.

Performing numerous experiments, we collect data of various outputs given by engine while we vary the input parameters. After acquisition, we then need to preprocess the data. After preprocessing, we finally work in the development of ANN model to predict the output parameters.

We try to build model using different number of hidden layers and different number of neurons in those layers. We train our model with various learning algorithms in order to obtain the best results. At last, comparative analysis is done between various models to ensure efficient working by the prediction of complex engine performance, combustion, and emission characteristics and helps in cost-effective search for a sustainable alternative fuel with enhanced engine characteristics.

Next is using Response Surface Methodology (RSM) to optimize performance and exhaust parameters as this technique is more efficient. So, initially we choose type of RSM required for the analysis. After acquisition, we then need to preprocess the data. After preprocessing, we finally work in the development of RSM model to predict the output parameters. Further processing of data is done in Minitab software, selecting suitable levels, and aiming to optimize the engine parameters via various contour plot analyzation, regression analysis and error analysis.

3.3 Work Plan

This project will be completed in four semesters. Phase-1 work is already completed. The work is distributed in the following manner:

Phase-1:

- Conduct a thorough literature analysis and determine which areas of research require more Investigation.
- Among various alternative fuels, choosing a fuel to complement a compression ignition engine’s need and analysing the engine's operational parameters.
- To finalize the most efficient and suitable soft computing technique for predicting and optimizing the engine parameters that have been chosen.

Phase-2:

Various application studies involve performance and emission predictions, modeling for valve timing, knock intensity detection, noise prediction, misfire detection, engine wear determination, and optimization problems. We are planning to work on any of these problems. The prediction of engine characteristics with different test conditions using the Artificial Neural Network is decided for the time being.

- For data collection, perform trial runs on a CI engine with various biofuel blends.
- Using the data obtained from the engine run, modeling and building an appropriate ANN model.

Phase-3:

- Using Response Surface Methodology, performing the optimisation of various engine performance and exhaust parameters on CI engine run on diesel engine.
- Applying RSM technique on various engine load and fuel flow datasets and train our model to minimise the error in predicted and experimented values.

Phase-4:

- Using combined Response Surface Methodology and Artificial Neural Method to optimize the engine performance and performance parameters.
- Choosing waste cooking oil-based bio-diesel as an alternative fuel in compression ignition engine, to complement its need and analysing the engine's operational parameters.

CHAPTER-4

ANN MODELING

4.1 Experimental Setup

Experimental trials were carried out in a single cylinder engine test bench. This engine is water cooled with eddy current dynamometer of maximum loading capacity of 7.5 kW. The experiments were carried in diesel mode, so the compression ratio (CR) range used was between 12 and 17.5. Its characteristics are shown in Table 4.1. Performance and exhaust parameters of the engine were recorded using LABVIEW Software and Enginesoft for online performance evaluation. All acquired data was then coupled and pre-processed in Juypter to later enter it in the Artificial Neural Network model. Figure 4.1 shows the engine setup used for experimental tests.

Temperature was measured at the inlet and outlet of each element of the scheme as well as in the exhaust gas outlet in each cylinder of the engine. All in all, 104 different performance and emission parameters were acquired throughout the whole engine, which are listed as follows: temperature data, ambient conditions, engine torque, engine speed, fuel consumption and 3 emission parameters. Of these parameters, 8 were used as inputs and 10 were used as outputs for the neural network model.

Figure 4.1: Experimental Setup [54]

4.2 Data Acquisition Process

Many studies have used ANNs for diesel engine modelling, as seen in the literature review. Despite this, most of this research has concentrated on specific engine load and engine speed conditions. To accomplish this, various ‘load vs engine speed’ relationships were proposed and tested in order to later train, validate, and test the Artificial Neural Network.

Table 4.1: Specifications of Engine

Parameter	**Value**	**Unit**
Number of cylinders	1	[-]
Stroke	110	mm
Connecting rod	234	mm
Nominal Speed	1500	rpm
Nominal Power	3.5	kW
Compression ratio	12:1-17.5:1	[-]

The specifications of the engine which we used is mentioned in Table 4.1. The engine which we used was single cylinder 2 stroke engine with stroke length of 110mm. Power of engine was 3.5kW with nominal speed of 1500 rpm. The engine was tested in each performance curve for 0-12kg load conditions. After setting each load/engine speed condition, the engine was kept running for 20 min before data acquisition to ensure steady state of each point. Consequently, performance and emission data were acquired for 5 min; data acquisition frequency was 1 sample/second for both performance and emission parameters. From each measured point, 104 samples were acquired for the database to later train/validate the ANN. In order to analyse the regression capability of the ANN for unseen data, 10 additional points were randomly selected from the engine performance map. The experimental procedure of these 10 testing points was the same as the others (20 min to steady state, 5 min extraction), but these were not introduced in the training/validation phase of the ANN to later discuss the ANN prediction accuracy on them.

4.3 Selection of Input and Output Parameters

While selecting the input and output parameters, we wanted to choose the parameters that haven't been explored properly, apart from that we also wanted to be sure that our models still are useful even after introduction of the Electric Vehicles. We wanted to ensure that out model can be used even then. So, we decided to train our model to predict two parameters i.e. performance and exhaust.

It is an important step to firstly find the correlation between various engine parameters i.e. the input parameters must affect the output parameters. This has been done by finding correlation coefficients for each pair of datasets in Jupyter notebook.

Various correlation coefficients include Pearson moment correlation coefficient, Spearman correlation, Kendall correlation and null hypothesis.

- **Pearson moment correlation coefficient:** The advantage of using Pearson's r is that it is a straightforward way to assess the association between two variables; whether they share variance (covary), if the relationship is positive or negative, and the degree to which they correlate. The disadvantages of using Pearson's are that it cannot name relationships that are not linear, and may show a correlation of zero when the correlation has a relationship other than a linear one. Additionally, the types of variables that can be evaluated are limited. [56]
- **Spearman correlation:** It is right when one or both variables are skewed or ordinal and is robust when extreme values are present. For a correlation between variables x and y, the formula for calculating the sample Spearman's correlation coefficient is given by [57].

For selection of proper input variables, Pearson correlation test was applied to Performance and Exhaust, as these variables satisfied the assumptions of this test. While BSFC, CD and ID were treated with Spearman correlation test as this test has no assumption of linearity.

Figure 4.2 summarizes the correlation coefficient and probability values (p) between selected input and output parameters. A probability value of less than 5% is hypothesized as there is a significant relationship between input and output variables. This hypotheses states that there is a 95 % confidence that the relationship between two variables is not by chance or there is less than 5% probability that the relationship is by chance. It can be seen that for performance parameters Pe, BTHE and BSFC, load (kg), speed (rpm), exhaust temperature (˚C), torque (Nm) and fuel flow (kg/h) have high correlation coefficient and very less p-value thus the null hypotheses could be rejected with 95% confidence interval. Similarly, for the combustion parameters CD and ID the exhaust temperature (˚C) and CR display high correlation coefficient and low p-value.

BTHE Correlation Table

	r	p
CR	0.172000	0.097927
Load	0.973000	0.000000
Speed(rpm)	-0.935000	0.000000
T2 (deg C)	0.438000	0.000010
Air(mmWC)	-0.560000	0.000000
Fuel (cc/min)	0.854000	0.000000
Torque (Nm)	0.973000	0.000000

SFC Correlation Table

	r	p
CR	-0.177000	0.087976
Load	-0.972000	0.000000
Speed(rpm)	0.934000	0.000000
T2 (deg C)	-0.445000	0.000007
Air(mmWC)	0.563000	0.000000
Fuel (cc/min)	-0.852000	0.000000
Torque (Nm)	-0.972000	0.000000

IP Correlation Table

	r	p
CR	-0.224000	0.029921
Load	0.896000	0.000000
Speed(rpm)	-0.901000	0.000000
T2 (deg C)	0.167000	0.107304
Air(mmWC)	-0.412000	0.000037
Fuel (cc/min)	0.931000	0.000000
Torque (Nm)	0.897000	0.000000

CO Correlation Table

	r	p
CR	-0.799000	0.000000
Load	-0.238000	0.021078
Speed(rpm)	0.178000	0.085327
T2 (deg C)	-0.567000	0.000000
Air(mmWC)	0.291000	0.004377
Fuel (cc/min)	0.021000	0.841833
Torque (Nm)	-0.237000	0.021466

NOX Correlation Table

	r	p
CR	0.148000	0.153281
Load	0.835000	0.000000
Speed(rpm)	-0.798000	0.000000
T2 (deg C)	0.284000	0.005513
Air(mmWC)	-0.423000	0.000022
Fuel (cc/min)	0.774000	0.000000
Torque (Nm)	0.835000	0.000000

Figure 4.2: Correlation coefficients of engine-output parameters

We decided to use BTHE, SFC and IP as the output for our performance model. BTHE is one of the most important parameters of an engine it provides us with the information of how efficient our working engine is. Apart from BTHE: SFC & IP were chosen, IP represents the indicated power of engine while, SFC stands for specific Fuel Capacity. IP & SFC provide us with a value of energy produced in an engine while later one provides us with the information about how much of energy input is needed for generating unit output of energy. For the performance point of view this are the important parameters. For an emission model we decided to use NOX and CO as our output. This two are the most important exhaust parameter from an engine.

We must now choose the input for our models. To choose our input we considered various parameter like Speed, Load, Compression Ratio, engine waterflow etc. Artificial neural network tries to find the relation between the given input and output. It doesn't get affected by the type of input; all it does is tries to predict the relation between two numbers. So, to make our model more generalised it was needed to choose those input that would really affect our output parameters.

Few of such parameters which had potential to become our input were speed, load, compression ratio, torque. We wanted to keep the number of inputs minimum. So, we needed to choose the inputs that affected our output most. To find the most valid parameter we calculated the Pearson and Spearmen coefficient for all our outputs.

After calculating Pearson and Spearmen coefficient we concluded that for our performance model i.e. for BTHE, SFC, IP the suitable inputs are Load, speed and torque as they have coefficient value of greater than 0.95; for our emission model compression ratio, speed and load supplied good coefficient value. Since speed and load are depended on each other so it is advisable to drop one of the factors. Out of the above two parameters we decided to drop torque as calculating it is more complicated than the load.

So, we finalised inputs as load, speed and compression ratio with output as BTHE, SFC, IP, NO_X, CO.

4.4 Method: Artificial Neural Networks

In order to develop an artificial neural network (ANN) model to get the best prediction results, several architectures were estimated and trained using the experiment data. Firstly, a back-propagation algorithm was utilized for testing, training and validation processes. This algorithm is used to supervise the training technique, where the weight and biases of training networks are set randomly at the start of the training stage [55]. A gradient descent rule for the minimization process of error is achieved. In the network architecture, for performance parameter evaluation, there are two input and three output parameters in the experimental data evaluation and for exhaust parameters evaluation, there are two outputs. The two input variables for performance parameter evaluation are the load in kg and the engine speed in rpm with the conventional diesel engine and load and compression ratio for exhaust parameter evaluation.

Performance parameters- The two input variables are the load in kg and the engine speed in rpm with the conventional diesel engine The three output parameters include the indicated power in kW, brake specific fuel consumption in kg/kW-hr and brake thermal efficiency in percentage. Thus, the two input variables at the input layer consist of two neurons related to the load of the diesel engine and its engine speed.

Exhaust parameters- Input variable is load and compression ratio. The two outputs are NOx and CO_2. Therefore, the two input variables at the input layer consist of two neurons related to the load of the diesel engine and its compression ratio.

Figures 4.3 and 4.4 show the architecture of the ANN model for the prediction of engine performance and exhaust parameters using diesel as fuel. In first model we predicted the performance of engine while varying load and speed on the other hand to predict the exhaust parameters NOX and Co, we used compression ratio and load as input.

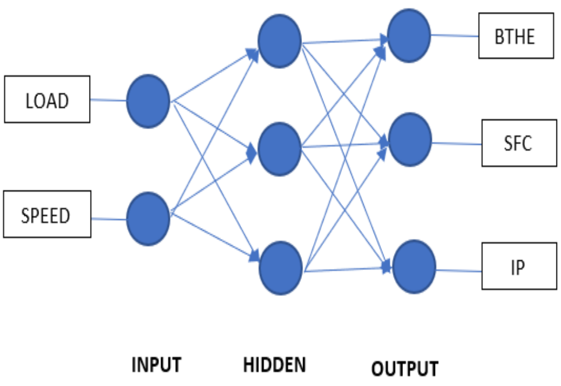


Figure 4.3: ANN structure for prediction of performance parameters

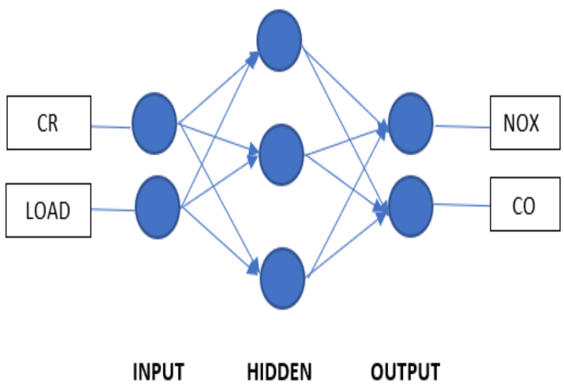


Figure 4.4: ANN structure for prediction of exhaust parameters

4.5 Data Scaling

Normalization of data is especially crucial step while training a model to predict output. During training phase of a model, we feed our model with the inputs and outputs. Now, we want our model to be generalised. To ensure need to normalize our data. During acquisition of data, it is not always possible that all the data obtained will be in same range. Some parameter might have high value while some may have low, so ensure homogeneity in model we normalize our data. Normalizing data ensures that our data is within a given range for all inputs and outputs, that is, data are in each range. We prefer use the range between 0-1. [58]

4.6 Results and Discussion

4.6.1 Evaluation of ANN model for Performance Parameters

The brake thermal efficiency is the kind of engine thermal efficiency which is the ratio of the brake power at the engine crankshaft to the power generated by the combustion of the fuel. The brake thermal efficiency shows the amount of power taken by the engine crankshaft out of total power generated by the combustion of the fuel. Specific fuel Consumption is the amount of fuel consumed by a vehicle for each unit of power output. The Indicated power of an I.C engine is total power developed within the cylinder in one complete cycle neglecting any losses.

BTHE is one of the important characteristics for deciding the performance of an engine. SFC and IP plays a significant role in performance of an engine.

To predict the performance of an engine we have developed a model. This model has an input, output layer apart from a hidden layer. With varying the number of neurons in the hidden layer we were able to get the correlation coefficient (R) of around 0.97 for all the three parameters.

During training of the model, it was seen that with increase in number of hidden layer neuron correlation coefficient increased then it reached a best value then started decreasing. For the configuration of 2-7-3 we have correlation coefficient of 0.975, 0.9984, 0.9968 for IP, BTHE and SFC respectively with this configuration value for MSE, RMSE. It is within acceptable limits. This shows good correlation between the experimental and ANN predicted values.

4.6.2 Evaluation of ANN model for Emission Parameters

NO_X & CO are harmful for the human body as well as for the environment. In recent years we had seen a strict measure against the exhaust released from the vehicles. So, we need to ensure that out exhaust parameters meet the standards. To predict the exhaust parameter, we have taken inputs as load and CR. While training the model it was seen that with increase in number of neurons in the hidden layer correlation between input and output increases.

We started training models with 3 input layer neurons and increased the number to 20, while increasing we analysed that error decreased and correlation got better. With 2-12-3 architecture, we got correlation of 0.98 and 0.99 for CO and NOX respectively. It is within the acceptable limits. This shows good correlation between the experimental and ANN predicted values. The mean squared error plot for CO and NOx are given in Figure 3. The experimental and ANN predicted values for CO and NO_X are given in Figure 4.

4.6.3 Modelling results for ANN models of Performance Parameters

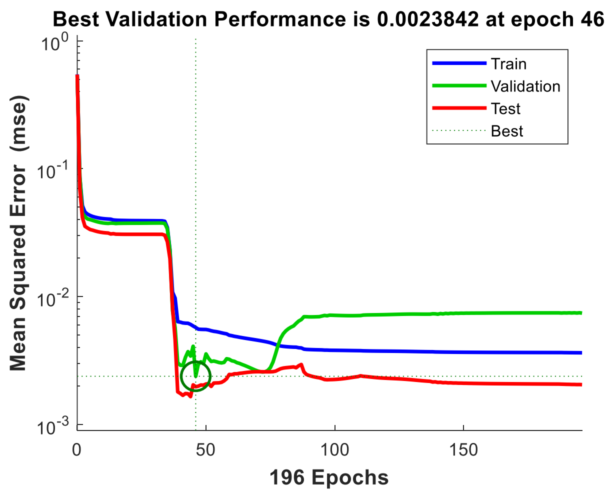
From the Table 4.2, Figure 4.5 we can see that for performance prediction model as the number of neurons in first hidden layer increases the mean of square error starts to decrease and correlation increases. MSE starts to decrease from 0.003 to 0.005 for training data when number of neurons is increased from 3 to 15. While during the same time corelation rises from 0.97 to 0.98.

For the optimization of the performance parameters, we had chosen two inputs load and speed to predict the BTHE, SFC and IP. To train the model we had used Levenberg-Marquardt algorithm. This algorithm has unique property, that it behaves like gradient descant when it is far from the optimum point while it acts as a Gauss Newton Method when it is close to the optimum point. (Gradient Descant is the method which is preferred when optima is far as when it is close to the optima there are chances of overshooting the optima. On the other hand Gauss Newton Method works very slowly when it is away from optima and when it gets close to optima its rate of convergence increases.)

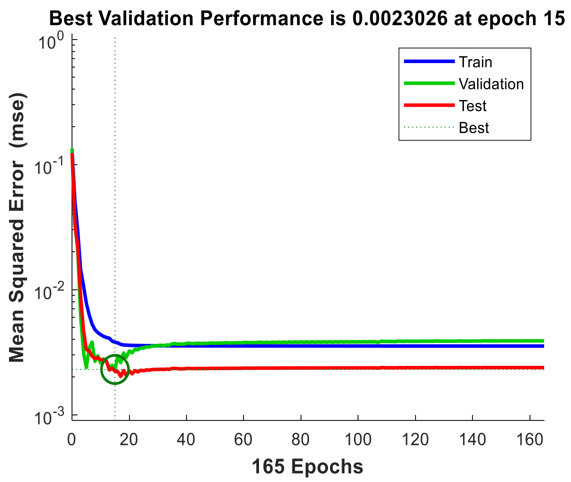
From the MSE plot below we can see that initially the value of MSE is very high and with each iteration there are lot of fluctuations in value of MSE. With increase in iterations fluctuation gets decreased and the value of MSE gets stable. This ensure that we have reached the optimum state for that configuration. After around 100 epochs we reached the stable state value of MSE for each configuration of Neural Network.

Table 4.2: Variation of MSE values and Corelation coefficient with increase in number of neurons in hidden layer for optimizing performance parameters.

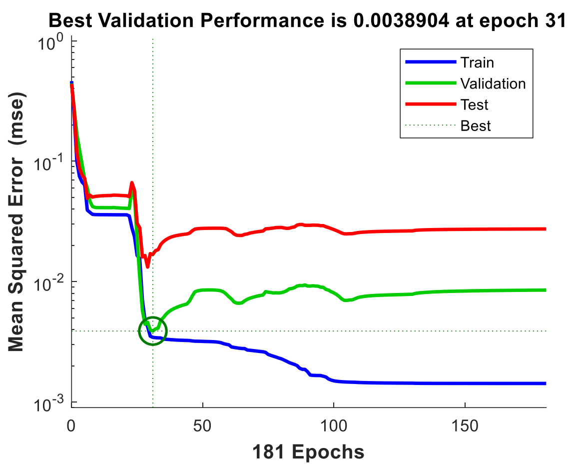
Training Algorithm	Network Structure	Epochs	MSE		R	
			Training	Testing	Training	Testing
L-M	2-3-3	196	0.003639	0.001652	0.97808	0.99238
	2-5-3	165	0.003542	0.002024	0.98523	0.99122
	2-7-3	181	0.001428	0.01321	0.9872	0.93015
	2-9-3	156	0.001666	0.001628	0.98174	0.99068
	2-12-3	256	0.001061	0.008448	0.96806	0.94978
	2-15-3	156	0.0005909	0.005131	0.98355	0.97605



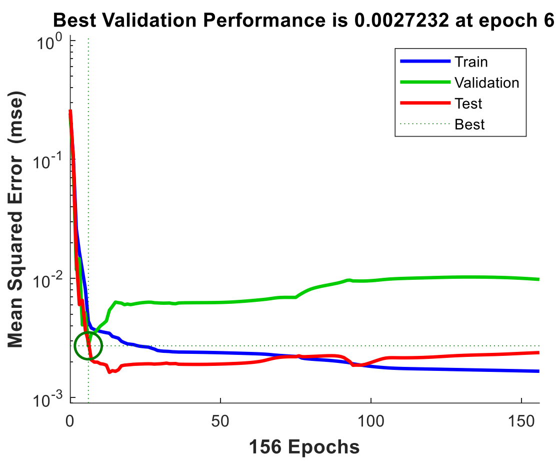
(a) MSE plot for 3 hidden neurons



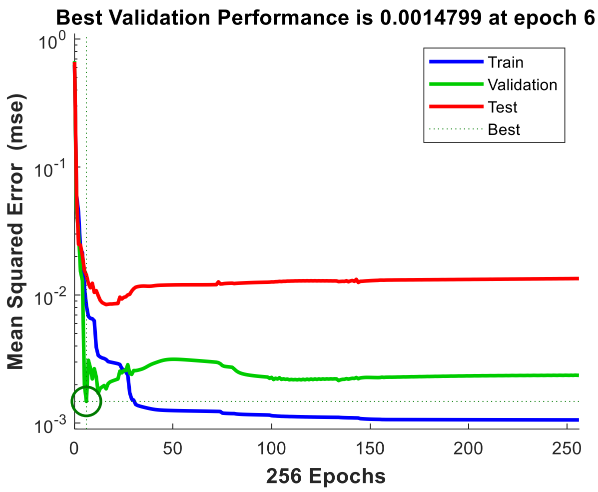
(b) MSE plot for 5 hidden neurons



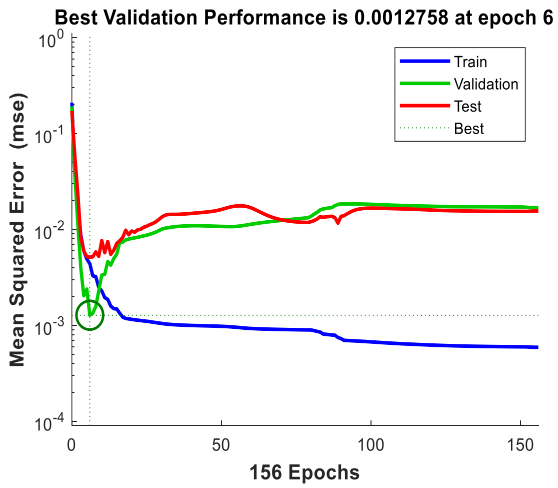
(c) MSE plot for 7 hidden neurons



(d) MSE plot for 9 hidden neurons



(e) MSE plot for 12 hidden neurons



(f) MSE plot for 15 hidden neurons

Figure 4.5: Mean squared error plot for network architecture: (a) 2-3-3, (b) 2-5-3, (c)2-7-3, (d) 2-9-3, (e) 2-12-3 (f) 2-15-3

4.6.4 Modelling results for ANN models of Emission Parameters

From the Table 4.3, Figure 4.6 we can see the various model to predict the exhaust parameters. From table below we can conclude that with increase in number of neurons in hidden layer prediction of model improved with MSE from 0.004 for 3 neurons to 0.0001 for 15 neurons. We also see strong corelation in with increase in number of hidden layer neuron. LM algorithm was used to train the model. After training the model we got the regression value of around 0.99 for various configuration.

Table 4.3: Variation of MSE values and Corelation coefficient with increase in number of neurons in hidden layer for optimizing exhaust parameters.

Training Algorithm	Network Structure	Epochs	MSE		R	
			Training	Testing	Training	Testing
L-M	2-3-2	122	0.004232	0.004326	0.93022	0.9379
	2-5-2	173	0.002059	0.003314	0.97883	0.95769
	2-7-2	101	0.001007	0.000769	0.99101	0.99055
	2-9-2	1000	0.0005586	0.001258	0.97478	0.99504
	2-12-2	1000	0.0009425	0.00209	0.99131	0.9798
	2-15-2	83	0.0001516	0.000180	0.99727	0.9954

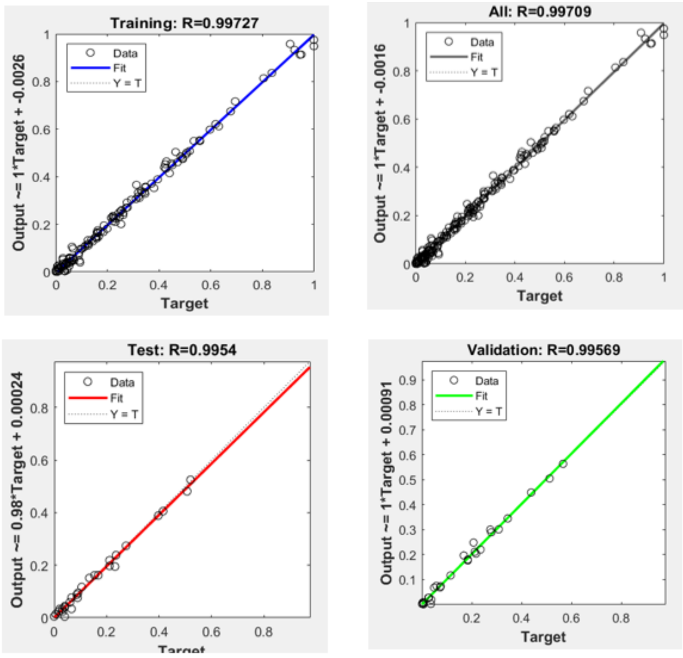


Figure 4.6: Regression plots for prediction of exhaust parameters.

4.6.5 Errors Analysis

By principle of trial and error, ANN modelling is processed in terms of figuring out the most suitable architecture for a given system. The R & σ test is one way of ascertaining the best network model. Another faster method is to compare the average or RMS error values. These values can be decided using following equations (1-4) by

$$Error\% = \frac{|\mathrm{A_e} - A_p|}{\mathrm{A_e}}$$

$$Error_{rms} = \sqrt{\sum_{i=1}^{N} \frac{1}{N}\left(\frac{|A_e - A_p|}{A_e}\right)^2}$$

$$R = \frac{1}{N}\sum_{i=1}^{N} \frac{A_e}{A_p}$$

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (R - R_i)^2}$$

Table 4.3: Root mean square error values for each output parameter

Neurons in Hidden Layer	%RSME				
	BTHE	**SFC**	**IP**	**CO**	**NOX**
3	0.0459	0.034401	0.074556	0.0771	0.0988
5	0.05942	0.02277	0.0949	0.06002	0.0299
7	0.054804	0.021298	0.068809	0.0468	0.0832
9	0.065006	0.030835	0.07668	0.0314	0.03623
12	0.05702	0.03293	0.13636	0.02599	0.02084
15	0.6140	0.024568	0.07067	0.01250	0.01042

From table 4.3, it can be seen that with the increase in number of neurons in hidden layer, %RSME for BTHE increased from 0.045 to 0.614 with as neurons in hidden layer changed from 3 to 15 respectively. Similarly, for SFC and IP we can see that the values of %RSME remained around 0.03 and 0.07 respectively. For CO it was found that %RSME values decreased from initial value of 0.07 to 0.01 and for NOx, %RSME values decreased from 0.09 to 0.01.

CHAPTER-5

RSM MODELING

5.1 Response Surface Methodology

Response Surface Methodology (RSM) is a collection of mathematical and statistical techniques which has proven itself in many disciplines, is a computer-based application for modeling and optimizing internal combustion engines. This method aims to determine and optimize the effects and degrees of effects of several input factors on the engine response parameters. Furthermore, experiments on internal combustion engines are incredibly time-consuming and costly. [58] By RSM, similar accuracy results can be achieved with fewer experiments, saving time and money. This method optimizes the responses according to the input factors by setting a relationship between the input and output parameters.

RSM uses the least squares technique. According to RSM, each of the engine input parameters is assumed to be computable and can be expressed as:

$$y = f(x_1, x_2, \cdots, x_n)$$

where $x1$, $x2 \ldots x_n$ are engine input parameters and y is engine output, respectively.

Response surfaces are usually approximated by a second-order regression model as the higher-order effects are usually unimportant. RSM is a very effective in terms of computational analysis. A second-order regression model (also known as the full quadratic) for k number of factors can be written as in equation given below. In addition to the most popular method, the central composite design, Central Composite Design, Box-Behnken Design will also be demonstrated in the following sections. [59]

$$y = \beta_0 + \beta_1 x_1 + ..\beta_k x_k + \ldots \beta^2{}_{11} x_1{}^2 + ..\beta^2{}_{kk} x_k{}^2 + \ldots \beta_{12} x_1 x_2 + ..\beta_{k-1,k} x_{k-1} x_k$$

5.2 Methods of RSM

There are two methods of RSM to obtain optimum response and we move towards our optimum point using these two methods:

- Method of steepest ascent
- Method of steepest descent

5.2.1 Steepest Ascent Method

This is the procedure for moving sequentially in the direction of maximum increase in the response getting optimum response. The initial estimate of the optimum operating condition for this will be far from the actual optimum. In such circumstances, the objective of the experimenter is to move rapidly to the general vicinity (nearest point) of the optimum. [60]

We wish to use a simple and economically efficient experimental procedure. When we remote from the optimum, usually assume the 1st order model is an adequate approximation to the true surface in a small region of the x's.

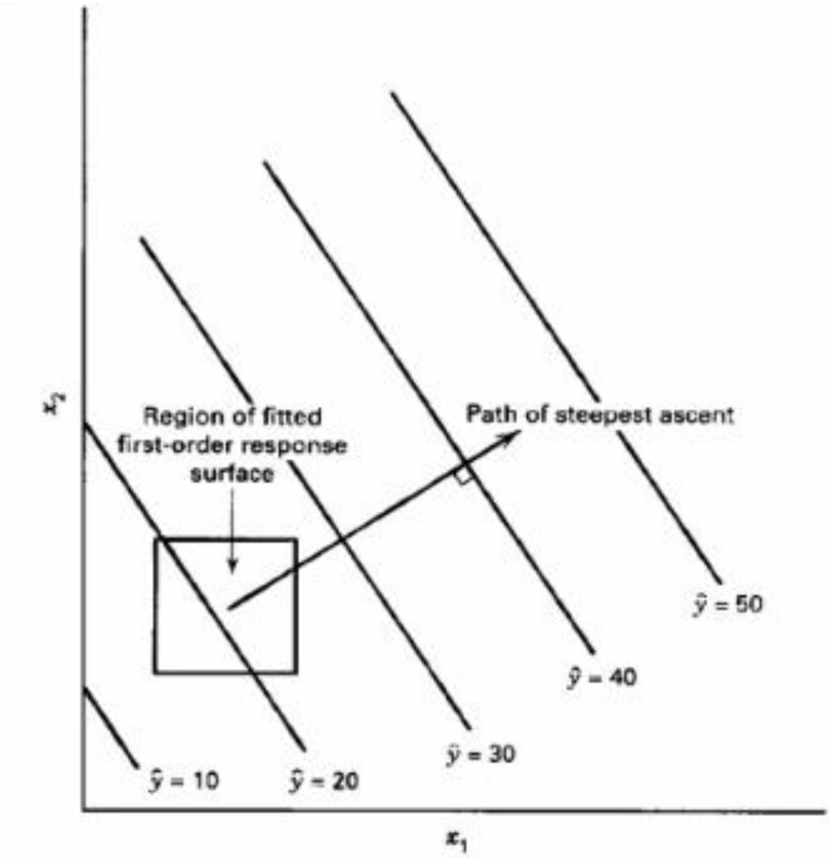


Figure 5.1: Plot showing path of steepest ascent [60]

5.2.2 Steepest Descent Method

If minimisation is desired then we call this technique the “method of steepest descent”.

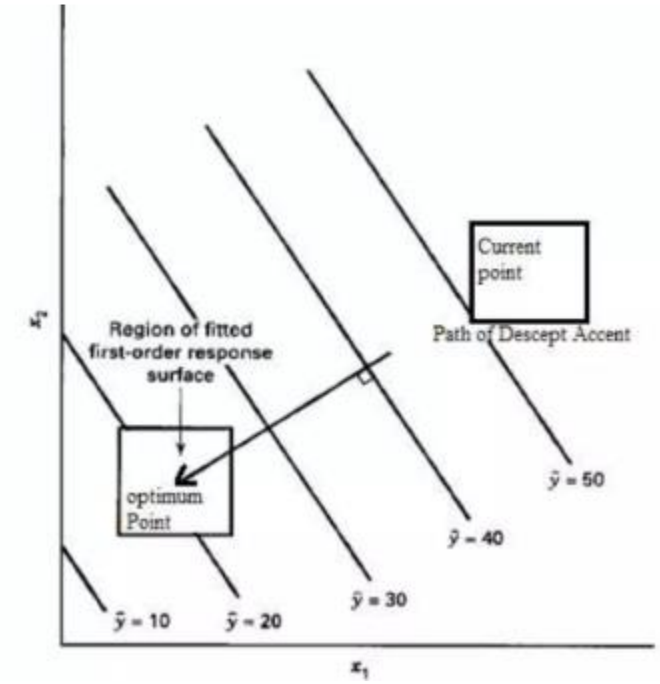


Figure 5.2: Plot showing path of steepest descent [60]

5.3 Types of Design

5.3.1 Central Composite Design (CCD)

The most popular method of response surface design is the Central Composite Design, CCD. The CCD is a two-level full factorial or fractional factorial design with added center points and the axial points (also known as star points) as shown in *Figure 5.3*. While the center point is added at the center, the axial points are applied in the middle of the levels of a factor for each level of the other factors. [61] Therefore, the coordinators for the axial points are (-1, 0), (1,0), (0, -1), and (0, 1). For this design in *Figure* 5.3(b), the axial (star) points are placed on the face of the square box of the 2^2 designs. Therefore, the design in *Figure 5.3* (b) becomes a 3^2 factorial for which a full quadratic model can be fitted for the response surface. With the addition of multiple center points, the lack-of-fit could also be tested. The distance from the center and the axial points are denoted by α (α=1 for this design in *Figure 5.3* (b)).

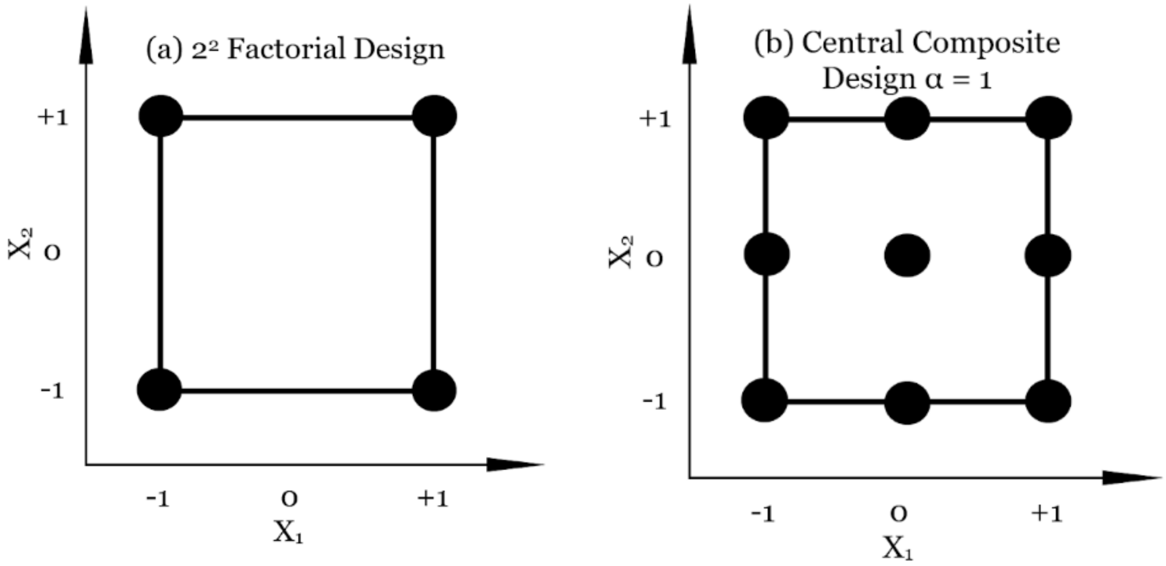


Figure 5.3: Central Composite Design, CCD (right) from the 2^2 Factorial Design (left) [60]

The CCD in Figure 5.3(b) is enough to develop a full quadratic model. However, the axial points can be designed more systematically to get even more information from the same number of experiments. For example, the CCD provides a couple of more advantages over the CCD in Figure 5.3(b). As compared to the CCD in Figure 5.3 (b) with only three levels for each factor allows only up to the full quadratic model, the CCD in Figure 5.4 consists of five distinctive levels for each factor model.

5.3.2 Box-Behnken Design (BBD)

Box-Behnken Design, BBD for the response surface methodology, RSM, is specially designed to fit a second-order model, which is the primary interest in most RSM studies. Box-Behnken designs (BBDs) are useful designs for fitting second-order response-surface models. They use only three levels of each factor (compared with 5 for central-composite designs) and sometimes fewer runs are required than a CCD. it only works for 3 to 7 factors.To fit a second-order regression model (quadratic model), the BBD only needs three levels for each factor (*Figure 5.5*), rather than five levels in CCD (*Figure 5.4*). The BBD set a mid-level between the original low- and high-level of the factors, avoiding the extreme axial (star) points as in the CCD. Moreover, the BBD uses face points, often more practical, rather than the corner points in CCD. The addition of the mid-level point allows the efficient estimation of the coefficients of a second-order model. The BBD is almost rotatable as the CCD. Moreover, often, the BBD requires a smaller number of experimental runs.

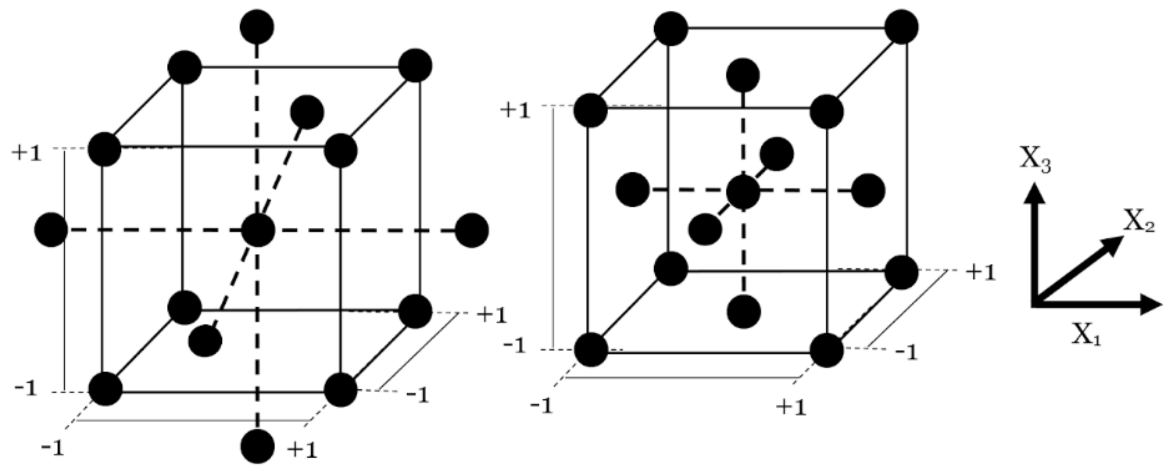


Figure 5.4: Two Representation of the Box-Behnken Design, BBD for RSM [60]

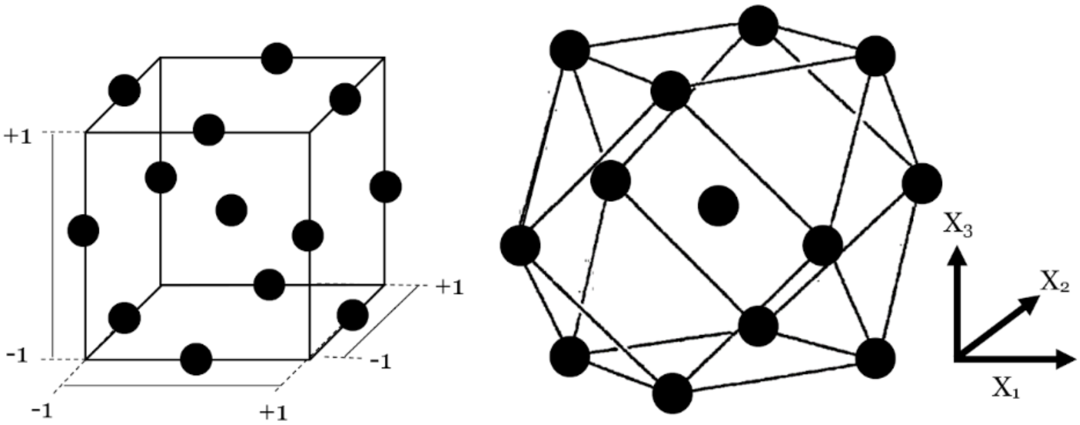


Figure 5.5: Central Composite Design, CCD For Rotatability (Left) And Face Center Design [60]

5.4 Design and Methodology

A Central Composite Design (CCD) of RSM with three variables was used to model diesel production. For prediction diesel yield output 105 experiments were performed for three levels of two different input parameters; Speed and Load.

A central composite design (CCD) was used to design and optimize the engine experiments. There are two independent variables namely load and engine speed was used for the prediction and optimization of engine outputs at levels. CCD is consisting of 13 experimental runs including 4 cube points, 4 axial points, and 5 center points to evaluate the pure error.

The objective of this work is to examine the optimized process parameters in biodiesel production by using CCD method on RSM. Moreover, optimize engine parameters as load and engine speed by using CCD based on RSM to maximize BTHE values and to minimize exhaust emissions. For the settled RSM model, BTHE, SFC, CO and NOx are selected as output parameters while speed, compression ratio and engine load are selected as input parameters.

The number of experimental sets was evaluated by given;

$$N = 2^k + 2*k + NC$$

where k is the number of independent variables and NC is the number of center points.

Response Surface Methodology (RSM) is employed to develop mathematical relationships between engine speed and engine load as the independent variables and BTHE,

specific fuel consumption (BSFC), CO and NOx as the responses. In addition, using response surface plots, the interaction effects of process parameters on the responses are analyzed and discussed. Minitab software was used to carry out three main steps: analysis of variance (ANOVA), regression analysis and graphical analysis of work data. The main dataset values taken of the analysis are provided in table 5.1.

Table 5.1: Design related to the experimented results

Speed	**Load**	**CR**	**SFC**	**CO**	**NOx**	**Run Order**	**Blocks**	**Ptype**
1562	0.088	15	24.66	428.67	1.18	1	1	0
1576	0.112	17	11.88	154.80	3.08	2	1	-1
1553	1.007	16	2.01	78.17	1.02	3	1	1
1542	2.011	15.5	1.01	100.50	0.87	4	1	1
1540	3.056	16	0.78	69.67	2.28	5	1	0
1521	4.954	16.5	0.52	44.33	7.17	6	1	-1
1521	5.935	17	0.46	61.00	29.65	7	1	0
1520	6.996	15	0.44	360.00	48.00	8	1	-1
1506	9.097	16	0.36	37.83	15.62	9	1	0
1496	12.007	16	0.34	57.83	33.60	10	1	0

5.5 Results and Discussion

The standard RSM design using central composite design (CCD) was employed to examine the relationship between the response variables and set of quantitative experimental factors. The independent variables were fuel (cc/min) (x1), engine speed (rpm) (x2) and engine load (x3). Each independent variable had coded levels of -1, 0 and 1. The two responses (Y) were BTHE and SFC for engine performance parameters while for the exhaust parameters CO and NOx, Compression ratio (CR) and load was chosen.

Minitab software was used to develop the mathematical models and to evaluate the subsequent regression analyses. The developed mathematical models were effectively used to predict the range of parameters used in the investigation. Based on these models, the main and interaction effects of the process parameters on the exhaust emissions characteristics were computed and plotted in contour plots as shown in Figs 5.8 and 5.9.

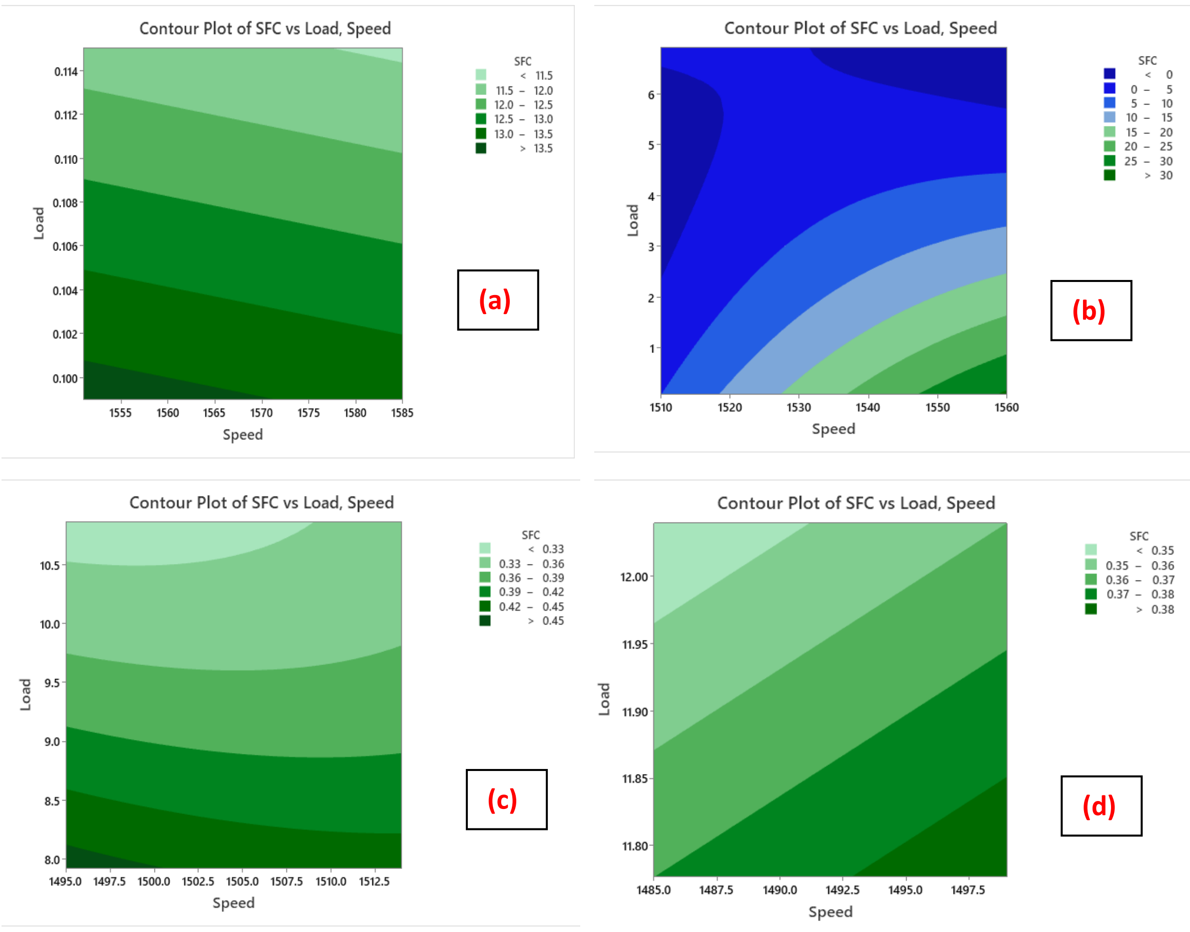


Figure 5.6: Effect of load and engine speed on SFC at 8 (a), 16 (b), 20 (c), 25 (d) engine fuel (cc/min)

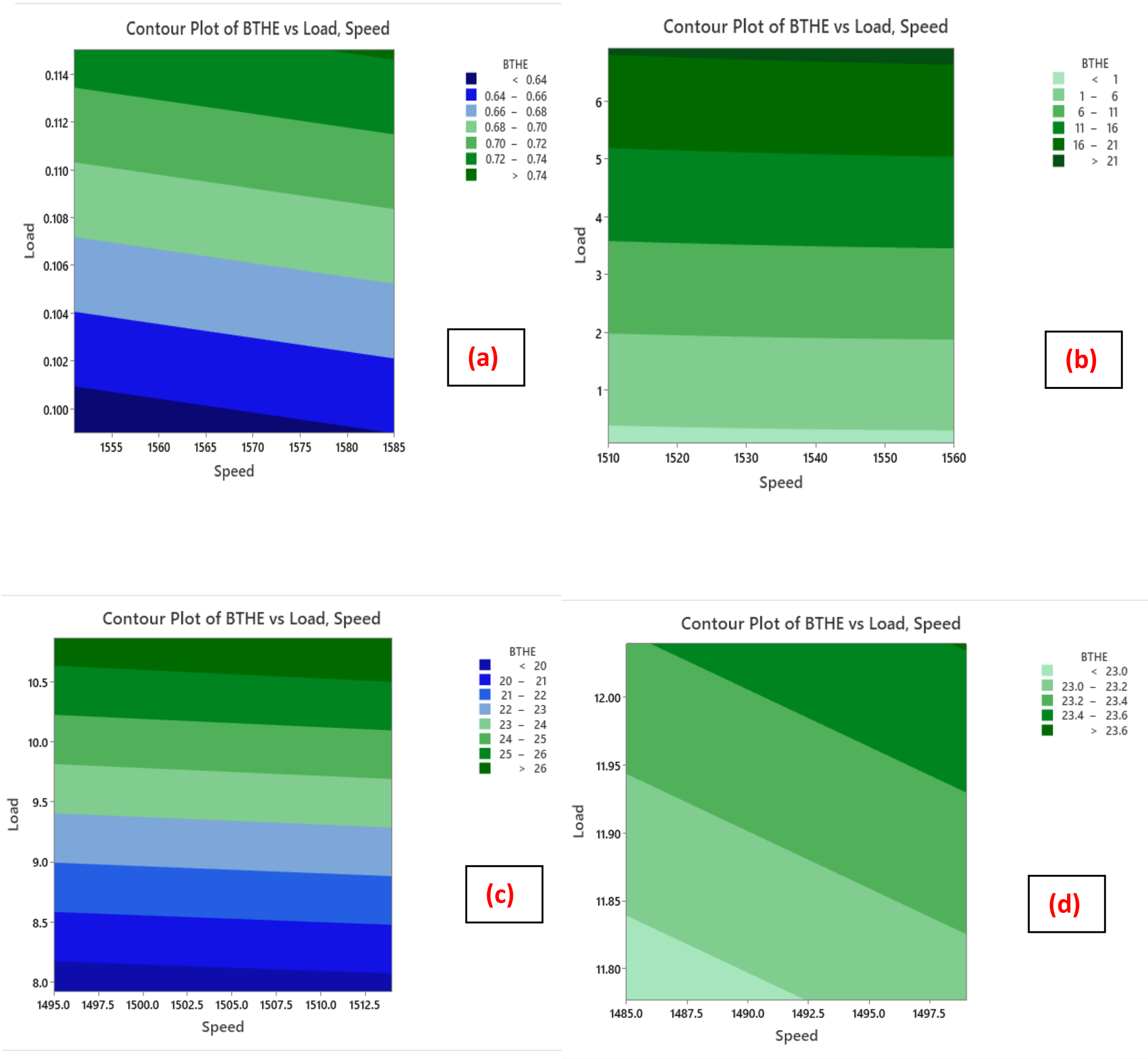


Figure 5.7: Effect of load and engine speed on BTHE at 8 (a), 16 (b), 20 (c), 25 (d) engine fuel (cc/min)

From figure 5.6 and 5.7, we can clearly see that the effect of load and engine speed on BTHE and SFC with the change in fuel flow. It can be concluded that with the increase in engine speed and engine load, BTHE values increases.

Now, the emission parameters such as NOx and CO were taken as output in another model and trained using RSM by taking input parameters as load and compression ratio (CR). Their respective contour plots are shown in figure 5.8. It can be seen that at a lower value of load, the NOx emissions are very less. While in CO emissions, in the range of 16.0-16.5 CR value, CR values are lower as compared to other values.

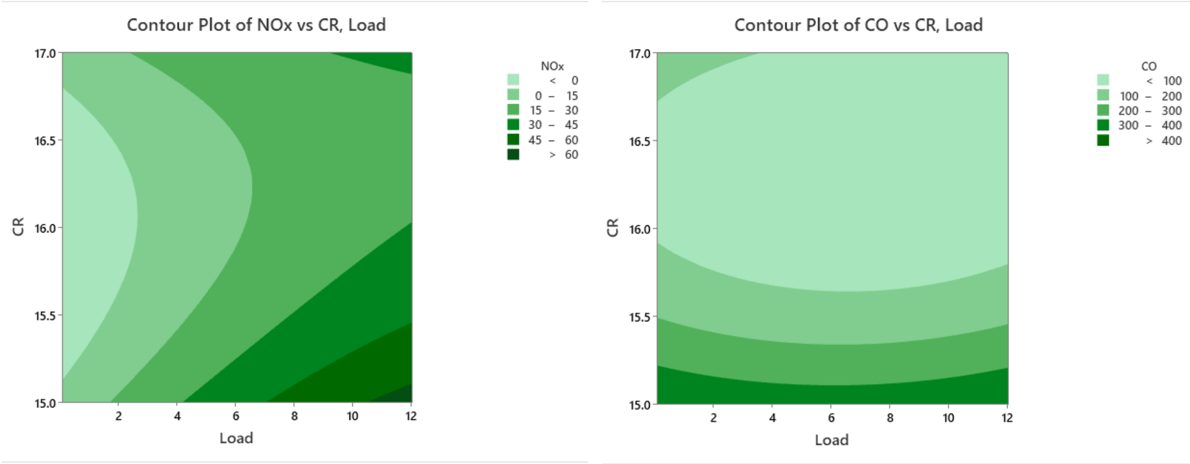


Figure 5.8: Contour plot for NOx and CO versus CR, Load

The models were also checked applying a numerical method utilizing the coefficient of determination R^2. The fact that R^2 values close to 1, which is an indicator of the compatibility of the experimental results with the results obtained from the model, means that the compatibility is high.

R^2 values were calculated as given in Eq.:

$$R^2 = 1 - \frac{SS_{error}}{SS_{model} + SS_{error}}$$

Where SS_{model} is the sum of the squares of the model and SS_{error} is the sum of the squares of the error.

Table 5.2: Assessment of model

Model	BTHE	SFC	CO	NOx
R^2 (%)	99.89	99.81	95.65	96.48
Adj. R^2 (%)	99.75	99.64	90.21	94.21
Pred. R^2(%)	90.93	99.87	89.43	93.32

From the Table 5.2, it is seen that 99.89%, 99.81%, 95.65% and 96.48% R^2 values are obtained for BTHE, SFC, CO and NOx respectively. R2 values are very close to 1, so that means the model gives good results. The second order equations generated by RSM to estimate output parameters based on input parameters are shown in Equations below:

$$\textbf{BTHE} = 9950 - 12.67\,\text{Speed} - 70.5\,\text{Load} + 0.00403\,\text{Speed*Speed} + 0.010\,\text{Load*Load} + 0.0472\,\text{Speed*Load}$$

$$\textbf{SFC} = -141606 + 181\,\text{Speed} + 1501\,\text{Load} - 0.0577\,\text{Speed*Speed} - 3.11\,\text{Load*Load} - 0.963\,\text{Speed*Load}$$

$$\textbf{CO} = 50689 + 18\,\text{Load} - 6202\,\text{CR} + 1.36\,\text{Load*Load} + 190.0\,\text{CR*CR} - 2.32\,\text{Load*CR}$$

$$\textbf{NOx} = 4665 + 29.6\,\text{Load} - 586\,\text{CR} - 0.148\,\text{Load*Load} + 18.36\,\text{CR*CR} - 1.51\,\text{Load*CR}$$

Surface plots are diagrams of three-dimensional data. In a surface plot, each point is defined by 3 points: its latitude, longitude, and altitude (X, Y and Z). Rather than showing the individual data points, surface plots show a functional relationship between a designated dependent variable (Y), and two independent variables (X and Z).

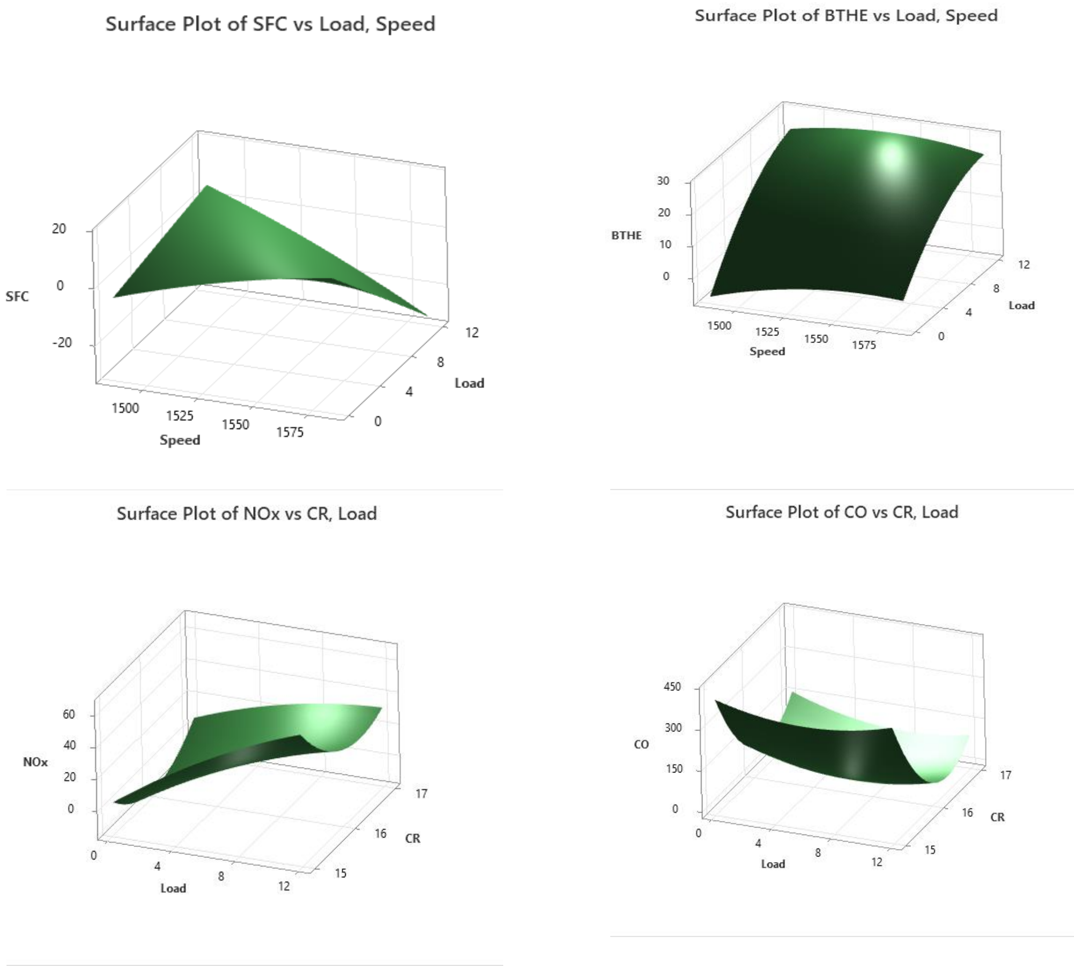
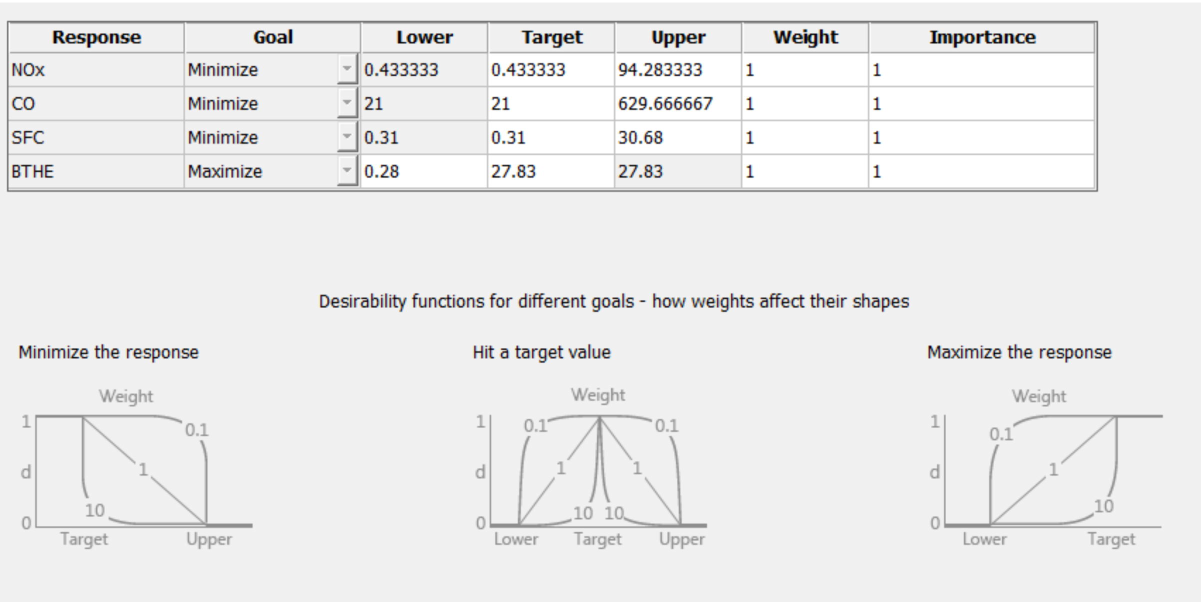


Figure 5.9: Surface plots of selected engine performance and exhaust parameters

5.6 Optimization and Validation

In this study, the RSM optimizer is applied to optimize the engine load and speed as the engine operating parameters and to achieve the best output factors according to the optimized operating factors. Fig. shows the optimization principles. While trying to achieve the highest level of engine efficiency, on the other hand, it has been tried to keep emissions to a minimum level.



Response	Goal	Lower	Target	Upper	Weight	Importance
NOx	Minimize	0.433333	0.433333	94.283333	1	1
CO	Minimize	21	21	629.666667	1	1
SFC	Minimize	0.31	0.31	30.68	1	1
BTHE	Maximize	0.28	27.83	27.83	1	1

Figure 5.10: Optimization principles

The optimized results from the optimization application are shown in Fig. 6.3. According to the results, optimum engine operating parameters found as 1487.0202 rpm engine speed, 8.5407 engine load and 16.0968 compression ratio while the best output parameters found as 1.7543 kg/kWh, 20.0162%, 0.210%, 0.208% for Specific fuel consumption (SFC), Brake thermal efficiency (BTHE) , NOx and CO respectively. In order to validate the optimized results, the optimized results were compared with the experimental results and the error rates was calculated.

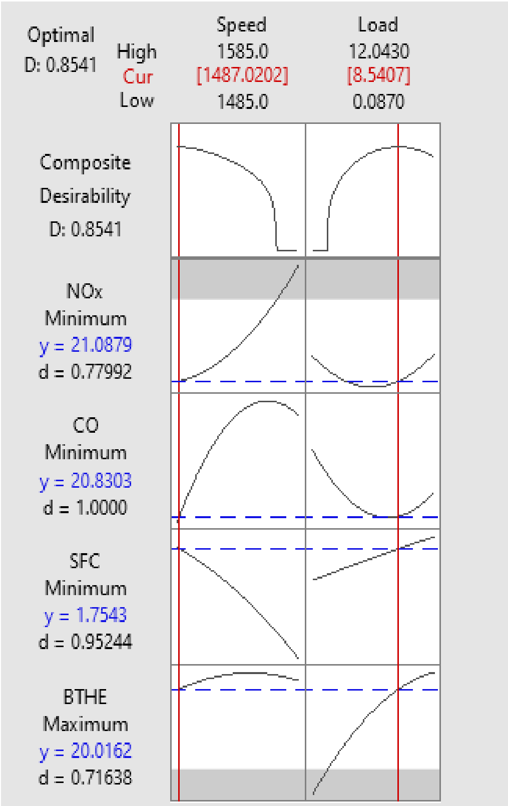


Figure 5.11: Optimization plots

5.6.1 Validation Tests for Predicted and Actual Values

Table 5.3: Values taken for a particular engine speed i.e., 1542 rpm and 15.5 CR

Value	**BTHE**	**SFC**	**CO**	**NOx**
Predicted	8.11	1.08	103.26	0.96
Experimental	8.45	1.01	100.50	0.87
Error (%)	4.19	6.48	2.67	9.37

From table 5.3, it can be seen that the predicted and experimental values are quite closer. For the experimental results, the average of 105 experiments were performed. The error between the predicted results and the experimental results was less than 10%, and close results were obtained. Graphs have also been plotted between experimented and predicted values as shown in figure. This means RSM models were found to be acceptable to find the effects of speed, engine load and CR on the engine performance and emission responses.

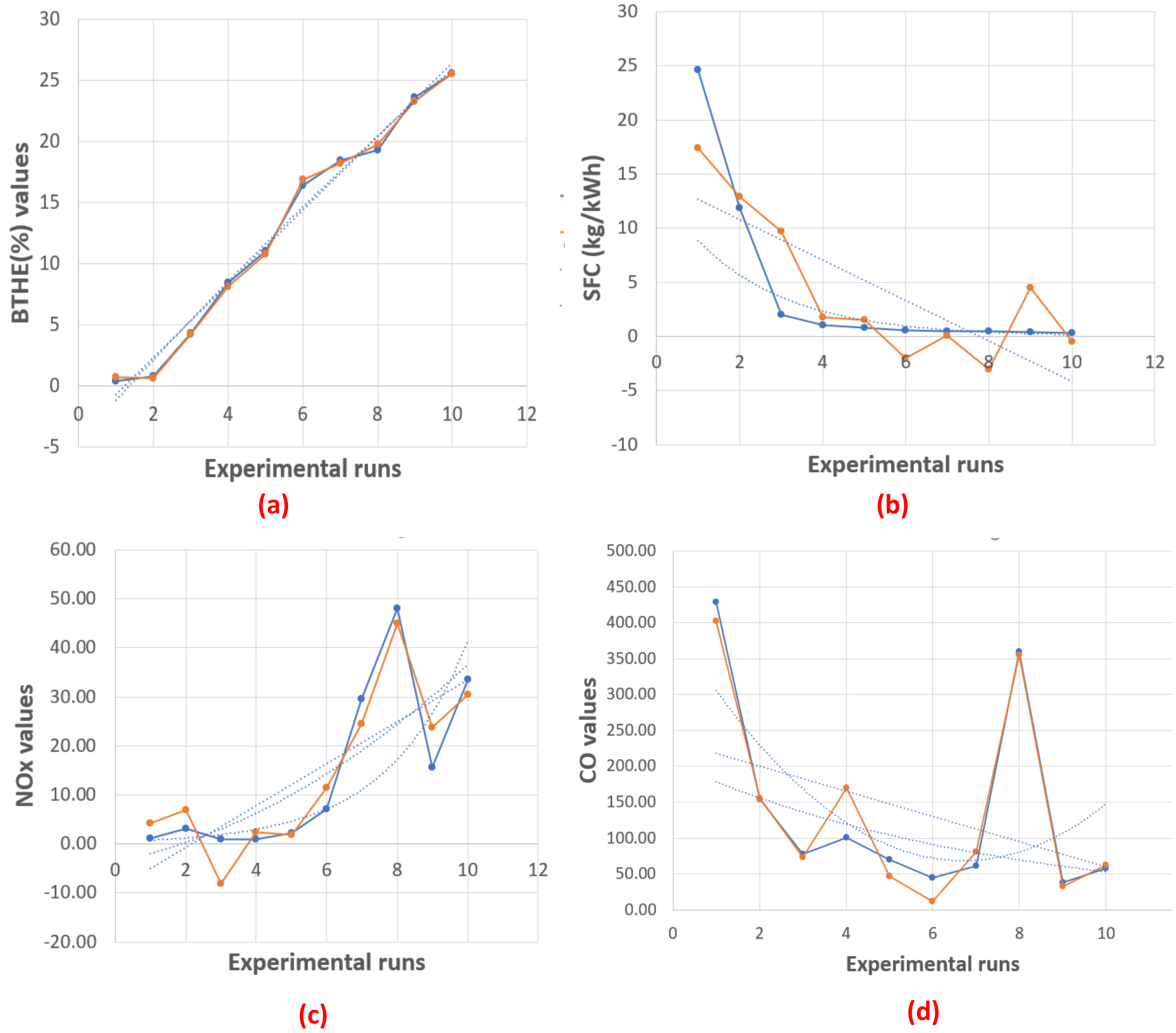
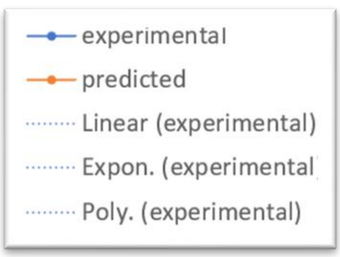


Figure 5.12: Plots of experimental and predicted values of BTHE, SFC, NOx and CO



For the validation of optimized results, experimental tests were conducted at optimum input parameters. The test results and the comparison of the obtained results with experimental results are given in Figure 5.12.

According to the validation results, RSM model is an extremely efficient method for optimization of engine performance and emission values.

CHAPTER-7
CONCLUSION

In the present report, we have seen the various applications of S.C. techniques in the field of I.C. engines. The problem was divided according to the engine type like S.I. (Spark Ignition), CI (Compression Ignition). Firstly, this paper reveals the contributions of researchers in the field of soft computing to enhance and perfect the S.I. and CI engine parameters. Secondly, the role of prediction algorithms and optimization algorithms can also be understood from the many studies made by the researchers. A comprehensive approach of contributions of different SC techniques can be understood from this review. The literature also emphasizes the application of the different pure and hybrid models in the evaluation of various engine parameters. We read and investigated various input parameters like fuel mixture, air-fuel mixture, engine speed, etc., considering the provided outputs like BSFC, SFC, and exhaust parameters. Among all the techniques, ANN was found out to be more efficient due to its property of providing multiple outputs using multiple input properties.

In this research, the effects of engine speed, compression ratio and engine load on the engine performance and emission parameters are examined by RSM. For the RSM model of performance parameters like BTHE and SFC, engine speed and load were selected as input factors while for emission parameters like NOx and CR and engine load were selected as inout parameters.

All the statistical models formed by RSM from the test data for performance and emission attributes were observed to be important with confident levels of 95%. 99.89%, 99.81%, 95.65% and 96.48% R^2 values are obtained for BTHE, SFC, CO and NOx respectively. The mean errors were obtained as 4.19%, 6.48%, 2.67%and 9.37% from the validation test for BTHE, SFC, CO and NOx respectively. In accordance with the RSM results, the best engine operating factors for engine speed, engine load and CR were found as 1487.0202 rpm, 8.5407 and 16.0968 respectively, while the best output parameters found as 1.7543 kg/kWh, 20.0162%, 0.210%, 0.208% for Specific fuel consumption (SFC), Brake thermal efficiency (BTHE) , NOx and CO respectively. When comparing the results obtained with optimization to experimental results, it was determined that RSM technique gave successful results with an acceptable error rate. Consequently, the RSM models can be applied successfully to define the best engine operating parameters for optimize the engine performance and emissions responses.

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