Effect of plastic oil addition on performance and emission characteristics of biogas-diesel dual fuel engine using taguchi method and prediction of performance parameter using artificial neural network

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Abstract. Ever increasing usage of fossil fuels and dwindling natural resources led researchers to concentrate on investigating other sources which can satisfy our demands and reduce pollution levels. Present research work aims to investigate the performance and emission characteristics of plastic, diesel and biogas as fuel blend operated in a dual-fuel engine with biogas as a primary fuel and plastic oil – diesel blends as secondary fuel and also predict the output variable using artificial neural network. A modified four-stroke single cylinder CI engine was used for experiments conducted at varying load, percentage of plastic oil percentage in diesel and biogas flow rate. Based on the levels and factors a Taguchi L9 orthogonal matrix was designed to find the optimal combination of input indices. The signal to noise ratios in taguchi method were applied based on the desired output characteristics and according to the respective SNR ratios an ANOVA table was created to determine the major contributor effecting output parameters such as brake thermal efficiency, CO, HC NOx and smoke emissions. ANN model helped to predict BTE with same input parameters but with an increased set of sample data. Based on Gradient descent and Levenberg-Marquardt algorithm the ANN architecture was trained, validated and tested to predict the response with least error.

1. Introduction

In present era, science and engineering have undergone many changes and is still in process of achieving a breakthrough new technology. Many engineering problems today are being solved with the simplest of ideas and innovations. To note there is one field which requires a rapid modernization and development which is waste management. Though there are many resources being deployed to reduce the rapidly increasing waste, but they are indeed causing pollution (land, water, air). Plastic is a major contributor to this daily increasing waste and enough measures are not being adapted to overcome problems. Artificial neural network is a field of AI useful in making time-forecasting, prediction of data and etc. As plastic causes a great harm to our nature converting them to fuel for usage in CI engine might help decrease demand for vehicle fuel and provides a solution for recycling plastic.

There are various research works conducted which provide evidence for plastic oil to be used in engines partly. Devaraj et al. [1] found reduction in smoke levels with that of baseline waste plastic pyrolysis oil. The BTE (brake thermal efficiency) increased when compared to pure plastic pyrolysis oil and diesel. Yuvarajan et al. [2] using taguchi found experiments reveal that Diglyme blended with 10% of diesel and injected at -21° crank angle is the optimum combination for simultaneous reduction of smoke and NOx. Gopinath et al. [3] experimented Low-Density Polyethylene (LDPE), catalyst:
Silica alumina (SA), and temperature: 500°C are optimized to get the better yield of oil. Vincent et al. [4] worked on DI engine to reduce Nox and improve fuel economy and results of confirmation tests showed good agreement with predicted results. Sharma et al. [5] has experimented using response surface methodology to analyze the performance of dual fuel operation in CI engine and soya biodiesel blend showed a better result. Nalbant et al. [6] has found the roughness parameter in the experiment using taguchi using ANOVA and SNR-analysis. Hosseini et al. and Abnisa et al. [7-8] former conducted experiment using MLP in ANN to predict responses and later used feed forward neural network. Samuel et al [9] have observed emission analysis from a CRDI engine and predicted them using ANN which had a good accuracy. Ghibadian et al.[10] has observed the performance and emission analysis for a biodiesel fuel and has also predicted the responses using ANN. Venkatesan et al. [11] has observed at plastic oil has improved break thermal efficiency. Gu et al. [12-13] has observed that plastic oil operation with diesel in CI engine had better performance when operated at higher loads and adding additives has further improved their efficiency. Karedula and Karedula [14] have observed ethanol with plastic in SI engine has controlled CO and NOx emissions. Hariram et al. [15] have analyzed that plastic oil had higher BTE and BSFC when operated in CI engine. Feroskhan & Ismail [16] have observed biogas-diesel fuel mode has relatively high unaccounted losses at low loads. Gnanamoorthi and Murugan [17] has observed that when MEA is used it relatively reduced CO, HC and Smoke emissions. Manjunath et al. [18] has used neem oil, biogas to predict BTE and BSFC using ANN and had least error when majority of data was used for training.

In this current analysis, the performance and emission characteristics of plastic oil-diesel biogas fuel proportions in a CI engine is analysed. Considering the parameters like break thermal efficiency, CO, NOx, HC and smoke emissions as output parameters, the experiments in dual fuel mode are performed. Also, analytical calculations are conducted to find the significance of variation in the input indices on the output parameters. Further artificial neural networks are incorporated in this analysis to predict the break thermal efficiency.

2. Experimental Setup
The water-cooled CI engine with specifications as shown in Table 1 has been modified to function in a dual fuel mode. The biogas constitutes of mainly CH4 and CO2, so they were supplied to intake manifold through separate sources. Their proportion of their supply is in the ratio 60/40, where methane and CO2 contribute to 60% and 40% of the total biogas flow rate. Their composition is kept constant throughout the experiment and their flow rate is measured using rotameters. The flow of gases is controlled through valves with pressure regulators to maintain the required flow rate of individual gas. The air present at atmospheric conditions enter the cylinder due to the suction stroke of the cylinder which creates a vacuum causing the air to enter. Air is taken in and stocked in a box equipped with an orifice meter connected to a water manometer enabling the air flow rate. The pilot fuel (blend of diesel and plastic oil) is supplied to the engine through a cylinder tank. A burette is used to find the flow rate of diesel-plastic oil blend. The properties of fuel were listed in Table 2. The load applied to the engine is done using an eddy current dynamometer. The emissions from the exhaust are assessed using AVL exhaust gas analyzers.

| Table 1: Engine specifications |
|--------------------------------|
| Parameters | Values |
| No.of strokes | 4 |
Table 2: Fuel properties

| Parameters                  | Diesel | WPO  | Biogas |
|-----------------------------|--------|------|--------|
| Cetane number               | 52     | 40   |        |
| Density(Kg/m3)              | 822    | 938.5| 1.2    |
| Kinematic viscosity(est)    | 3.2    | 7.27 |        |
| Auto ignition temperature( °C) | 215    | 700  |        |
| Calorific value(MJ/Kg)      | 40.447 | 42.1 | 35     |
| Acid number(mgKOH/gm)       |        |      | 7.27   |

3. Methodology
The process utilized to turn fuel out of plastics is pyrolysis, which involves heating the plastic in the absence of oxygen where the organic compounds are decomposed into much smaller and weaker bonds in the form of liquid and gas. Later they are separated using distillation process to get the respective fuel at varying condensate temperature. On the other side, the inorganic part remains as a solid waste which can be re-used in the process and utilized for other applications. Usually, pyrolysis is operated between a temperature range of 300-400°C. Being a renewable source biogas is produced in an oxygen free environment where organic matter breaks down into gas which mainly constitutes of CH₄ and CO₂. So, this experiment is conducted by supplying CH₄ and CO₂ at constant proportion with varying overall flow rate. This design of experiments involves a process called taguchi method developed by Dr. Genichi Taguchi aiming to produce a better-quality output at a lower cost, Jaharah A et al. [19]. This method investigates how certain parameters affect the performance of a task based on mean and variance. The taguchi method developed utilizes ‘orthogonal arrays’ to reduce the experimental trials by a significant amount providing optimum values which improve the quality of product/case. This method helps organize the varying input indices in a factorial approach instead of combination based, providing a sequential relationship between factors which impact a process and their output values. Factors and levels used in this study is shown in Table (3).

Table 3: Factors and Levels

| Parameters                  | Units | Parameter Labels | Levels |
|-----------------------------|-------|------------------|--------|
| Load                        | N m   | A                | 5      |
| Percentage of plastic oil in diesel | %     | B                | 20     |
|                             |       |                  | 10     |
|                             |       |                  | 15     |
|                             |       |                  | 20     |
|                             |       |                  | 35     |
|                             |       |                  | 50     |
Factors are variable inputs which can be of the type controllable or uncontrollable. Levels are settings which are related to the factor, for example in rising the temperature from 30 - 80°C temperature is considered to be a factor and the range at which it is operated are its levels. Finally, responses are the output of the experiment or the values we desire to obtain by conducting the experiment. The following notations are usually used in taguchi to design the orthogonal array matrix: LQ(W*R), where Q, is the overall experimental trials and W, R are the factors and levels respectively. The optimum results are defined based on a criterion known as signal to noise ratio, which provides a path to identify the control factors which can provide an optimum solution. There are certain indexes like higher the better values, normal the better and lower the better values which need to be finalized before conducting the experiment as these performance indexes define the optimum level for each input parameter. For example, having high thermal efficiency is desirable, so we would choose higher the better value to improve the performance, similarly based on the desired output respective indexes are chosen. There are different orthogonal arrays used like L4, L9, L16, L25 and etc. based on the levels and factors. The following indices have been used for the respective output parameters to calculate SNR ratios:

1. Larger the better ratio has been used for brake thermal efficiency, using the formula in eq(1).

\[ SNR = -10 \times \log \left( \frac{1}{n} \times \sum \frac{1}{y^2} \right) \]  

(1)

2. smaller the better ration has been used for CO,HC,Smoke and NOx emission, as given in eq(2).

\[ SNR = -10 \times \log \left( \frac{1}{n} \times \sum y^2 \right) \]  

(2)

where i=level in the matrix; n= no. of trials;
y= SNR response value Based on the obtained SNR values in the graph the highest value is considered to provide the best result.

Figure 1: Experimental setup

3.1 Artificial neural network

Artificial neural networks are applied for input-output curve fitting which is a data processing technique relating the predictor data to response data. ANN’s consist of neurons or nodes which connect the layers allowing for data to be distributed. These connections include three layers input, hidden and output layer which collectively define the architecture of ANN.

As this investigation consists of 3 factors namely load, percentage of plastic oil and biogas flow rate, the input layer consists of three neurons which are connected to the neurons in hidden layers. Each input is added with a random weight and a bias, the sum of these weights and bias are transferred to
the neuron in hidden layer. Then these layers are processed through the activation function which produces an output. There are variety of activation functions included the most popular ones are log-sigmoid, tan-sigmoid and linear transfer function. In this network, tan-sigmoid is used as the activation function for hidden layer. After the data from each neuron in hidden layer is processed through the activation functions, new weights and bias are again initialized and added for the data to transfer to hidden layer which has a single neuron. Since our response variable is brake thermal efficiency so the output layer consists of only single neuron. Further, the neuron connected to activation function - linear function yields the final response variable. Usually, linear functions are used as the activation function for the output layer to overcome the limited range of sigmoid functions. The overall network used is shown in Figure (2).

![Figure 2: ANN Architecture created with 8 neurons](image)

The network architecture is based on feed-forward-backpropagation neural network. There are various model parameters for each method which need to be defined while training a network. The MATLAB neural network toolbox is initiated when the respective commands for activation functions 'logsig', 'purelin' and training algorithm are used with the 'newff' command. There are numerous training algorithms available. Two algorithms 'Levenberg-Marquart' and 'Gradient descent' method which are named in MATLAB are used with the command 'trainlm' and 'traingd' respectively. The newff command automatically initializes the weights and biases depending on the neurons. Rezaei, J et al. [20] has experimented on using ANN with various training algorithms to determine 7 different output indices, with experiment being conducted using a HCCI engine with oxygenated fuels. XiaoHang et al. [21] has analyzed NOx emission from a diesel engine using levenberg and bayesian methods, also two filter techniques were used to optimize the performance. While training the respective weights and biases are updated based on the gradient or other named parameters for respective training method, they are iteratively adjusted to minimize the residual. Mean squared -error (MSE) and root mean squared - error are two main evaluating parameters to decide if the trained network is efficient or not. Based on these iterative methods the network finds the weights and bias which yield the minimum error. As there is no defined parameters to choose the number of neurons, the network is evaluated with different neurons ranging from 8 to 18. Similarly, a single hidden layer is chosen to reduce over fitting of network, as increased hidden layers increase the complexity and cause the data to yield less efficient predictions. The gradient descent backpropagation algorithm updates the weights and biases based on the learning rate. Learning rate is a hyper parameter which decides how the systems find the local minimum for a function. If the learning rate is too high then the gradient descent slope will increase which may lead to missing the minimum error point. So based on training for various learning rate usually from 0.0001 to 0.1. As sample data is relatively small consisting of 30 samples, the data is found to work at learning rate of 0.001. The max _fail condition was chosen to be 100, which indicates that if the networks error keeps on increasing for 100 iterations the system stops the iterations and yields the minimum error for that set of iterations. This method works on the equation (3) shown below,
Where \( k \) is the vector of weights, \( \alpha \) is the learning rate and \( \frac{\partial \text{Loss}}{\partial W} \) is the gradient. As it is known that the output layer is connected to 8 different neurons, each of these neurons is updated based on the differentiation chain rule. For the output layer, the weights are updated using the following equation (4),

\[
\frac{\partial \text{Loss}}{\partial W} = \frac{\partial \text{Loss}}{\partial \text{output}} * \frac{\partial \text{output}}{\partial W}
\]

Levenberg-marquardt algorithm is a second order derivative function using jacobian matrix. Moreover, it is an updated version of gauss-newton method. The gauss-newton equation (5) and the modified LM method in equation (6) below

\[
Y_{(n+1)} = Y_n - (J_n^T * J_n) - 1 * J_n^T * E_n
\]

\[
Y_{(n+1)} = Y_n - (J_n^T * J_n + \mu * I - 1) - 1 * J_n^T * E_n
\]

Here, \( \mu \) represents the scalar which controls the identity matrix I. The \( \mu \) parameter depends on \( Y(n+1) \), if it is less than \( Y_n \) then \( \mu \) reduces by a value depending on the mu-dec, usually it is reduced by half which is the default value. While, \( Y(n+1) \) is greater than \( Y_n \) then \( \mu \) increase by mu-inc, its default value being twice \( \mu \). The J-Jacobian matrix contains the derivative of error function with respect to the weight and the multiplication of JT with J yields the hessian matrix which involves the second-order derivative of error function with weights. Similar to network designed for gradient descent has also been utilized for LM method, but few additional parameters like \( \mu \) are included.

### 4. Results and Discussion

The experiments conducted to find the effect of 3 input parameters (Load, Percentage of plastic oil in diesel and Biogas flow rate) on 5 output parameters as shown in Table 4. The respective SNR ratios and ANOVA predictions for individual output parameters was also discussed. The calculated SNR ratios were plotted based on the indexes, for break thermal efficiency a larger-the-better ratio was used and for others a smaller-the better approach was applied. These values were calculated based on the calculations discussed in previous section. Under similar evaluation conditions, the response data for diesel fuel was obtained and listed in Table 5 for comparison purpose. For prediction a 30-sample data with 60% being considered for training and 20% for validation and testing each, are chosen randomly by the MATLAB software.

**Table 4: Input and Output parameters**

| Torque (N-m) | Plastic oil Percentage % | Bio Gas Flow Rate Lpm | Break Thermal Efficiency (%) | CO (%) | HC (ppm) | Smoke (%) | NOx (ppm) |
|-------------|--------------------------|-----------------------|-----------------------------|--------|---------|-----------|-----------|
| 5           | 20                       | 0                     | 16.51                       | 0.04   | 21      | 28.4      | 77        |
| 5           | 35                       | 12                    | 11.31                       | 0.18   | 395     | 36.9      | 27        |
| 5           | 50                       | 16                    | 10.21                       | 0.19   | 436     | 34.5      | 25        |
| 10          | 20                       | 12                    | 20.5                        | 0.17   | 298     | 27.4      | 48        |
| 10          | 35                       | 16                    | 18.64                       | 0.2    | 372     | 25.5      | 47        |
| 10          | 50                       | 0                     | 22.12                       | 0.02   | 30      | 55.2      | 174       |
| 15          | 20                       | 16                    | 25.55                       | 0.2    | 288     | 29.5      | 150       |
| 15          | 35                       | 0                     | 27                          | 0.01   | 33      | 43.6      | 270       |
| 15          | 50                       | 12                    | 25                          | 0.13   | 187     | 50.8      | 140       |
Table 5: Experimental data for Diesel as fuel

| Torque (N-m) | Brake Thermal Efficiency (%) | CO (%) | HC (ppm) | Smoke (%) | NOx (ppm) |
|--------------|------------------------------|--------|----------|-----------|-----------|
| 5            | 19.91496                     | 0.11   | 53       | 37.7      | 127       |
| 10           | 28.65653                     | 0.09   | 52       | 42.3      | 268       |
| 15           | 31.61                        | 0.08   | 51       | 46.8      | 599       |

4.1. Brake Thermal Efficiency

The brake thermal efficiency reveals the ratio of output power of engine to input power of fuel used in an engine. As indicated in Table 5, the BTE tends to increase as the load increases. But, increase in biogas flow rate hampers the brake thermal efficiency. Figure 3 shows SNR for brake thermal efficiency. A3-B1-C1 (High load-low plastic oil addition – low biogas flow rate) combination shows better combination for brake thermal efficiency. High biogas flow rate reduces efficiency. This decrease can be attributed to the less oxygen availability as biogas flow rates tend to increase, they displace the air entering the cylinder resulting in lesser air-fuel ratio, as lower air fuel ratio causes partial combustion to occur, they decrease the brake thermal efficiency [22,23]. Usually, CI engines operate at close to stoichiometric conditions where ample amount of air-fuel ratio is available for a complete combustion to occur. Furthermore, the calorific value of biogas is low which results in reduced break thermal efficiency. The SNR ratios indicated in the Figure 3 depicts that lower plastic oil and biogas flow condition to be the optimum for engine to provide better brake thermal efficiency. As the load increases break thermal efficiency tend to increase and 15 N-m seems to be an ideal condition. Similarly with the predictions from the ANOVA (Refer Table 6), load tend to be the major contributing factor for BTE with 85%, plastic oil and biogas have 4% and 9% respectively. The optimum combination for reducing the smoke emissions is A3-B1-C1 (Refer Figure 3).

![Figure 3: SNR for break thermal efficiency](image)

Table 6: ANOVA calculated for Break thermal efficiency

| Parameters   | Units  | Degree Of Freedom | Sum Of Squares | Mean Squares | Contribution |
|--------------|--------|------------------|----------------|--------------|--------------|
| Load         | N m    | 2                | 63.512         | 31.7560      | 85.21669127  |
4.2. Carbon Monoxide emissions

Percentage of contribution of the carbon monoxide emissions for each input parameter is shown in Table 7. It was stated that incomplete combustion results in CO emissions. According to the contributions based on ANOVA in Table 7, biogas seems to show a bigger impact on CO emissions followed by load and plastic oil which vary by 1%. It indicates that increase in biogas flow rate leads to an increase in percentage of CO emissions. From these results (Refer Figure 4), it can be deduced that the increase is due to the incoming biogas which displaces the air causing incomplete combustion. Moreover, the CO emissions tend to reduce as values of load and plastic oil increase which is due to a better combustion environment provided in contrast with increasing biogas flow which causes a deficiency in oxygen supply. As discussed in the literature Prabhu et al [24], CO emissions tend to increase with high biogas flow rate. This can be attributed to the existence of CO2 in biogas which has resulted in improper combustion and also due to plummeting oxygen content in the cylinder. Further, increase in percentage of plastic oil does not seem to impact CO performance in a negative way. The optimum combination for reducing the CO emissions is A3-B2-C1 (Refer Figure 4).

| Input Parameters | Break Thermal Efficiency | CO  | HC  | Smoke | NOx  |
|------------------|--------------------------|-----|-----|-------|------|
| Load             | 85.21                    | 4.38| 1.09| 11.17 | 62.93|
| Plastic oil percentage | 4.01                   | 3.03| 1.46| 55.56 | 1.08 |
| biogas Flow rate | 9.14                     | 90.32| 95.31| 26.26 | 34.25|
| Residual         | 1.62                     | 2.25| 2.12| 6.99  | 1.72 |
| Total            | 100                      | 100 | 100 | 100   | 100  |

4.3. Hydrocarbon emissions

The unburnt fuel in the cylinder which comes out from the exhaust are the hydrocarbons. There are various reasons for HC emissions to occur like flame quenching, fuel getting deposited into crevices.
The factor owing to increasing HC emissions are because of biogas supersedes the incoming air resulting in poor air fuel mixture Yilmaz, and Gumus [25]. Also, particles of hydrogen and carbon get stuck in the combustion chamber like crevices, so these particles do not take part in the combustion process properly causing the HC particle to discharge through exhaust, Mani et al. [26]. Further rise in engine load has caused HC emissions to decrease which can be related to increase cylinder temperature. According to the contributions based on ANOVA in Table 7 for HC emissions which indicate that biogas is the major factor causing HC emissions to occur with a staggering 95% followed by plastic oil and load at 1% approximately. The optimum combination for reducing the HC emissions is A3-B1-C1 (Refer Figure 5).

4.4. NOx emissions

NOx emissions are the harmful gas particles which are formed due to reaction of oxygen and nitrogen during combustion. Furthermore, high temperatures and unburnt combustion are favorable conditions for their formation Mani et al. [27]. Increasing plastic oil percentage has led to relative increase in its viscosity which has depleted the NOx formation. Also, the load plays an imperative role in controlling the NOx emissions as indicated by the percentage contributions based on ANOVA in Table 7. High load increases NOx emissions. This increase in NOx emissions during the 0Lpm biogas can be attributed to decrease in biogas and increase in load where there is higher oxygen content and higher temperature availability favoring its formation. The optimum combination which yields a better result is found to be A1-B2-C3 (Refer Figure 6).
4.5. Smoke emissions

Solid soot particles which are suspended from an exhaust gas due to low temperature and incomplete combustion causes smoke to accumulate in high amounts. Due to the heat loss from the cylinder walls, piston rings, during the time of injection reduces the mixture temperature and makes it highly difficult for fuel to completely evaporate and leads to production of smoke. When the plastic oil percentage is increasing the smoke emissions also increased due to increasing viscosity and low volatility leading to formation of non-homogeneous charge which results in incomplete combustion Ayodhya, A.S. et al. [28]. Moreover, due to the presence of aromatic compounds in plastic fuel causes poor spray characterization and improper air-fuel mixture resulting in combustion inefficiency, Barik, D. and Sivalingam, M [29]. The optimum combination for reducing the smoke emissions is A1-B1-C1 (Refer Figure 7). As seen from table 8 the optimum combination of trials are compared between L9 matrix and SNR ratio, there is a change in combination for BTE, smoke and NOx.

4.6. Gradient Descent method

The sample considered for training the dataset consists of 30 samples. When trained with different The sample considered for training the dataset consists of 30 samples. When trained with different neurons in the hidden layer, 8-neurons seems to give the least RMSE of all the data as shown in Table (8). So, these results were also displayed for the same network with a learning rate of 0.001. Moreover, the RMSE value obtained is approximately 0.66618 with most of the predicted values having a difference which is within a permissible limit unlike the linear regression model. With consecutive iterations based on epochs the local minimum with respective weights and bias are updated with output values. Most of the values seem predicted correctly with minimum error, as per the data BTE efficiency which is 0 at no load condition has been predicted to yield a difference of 0.2 for most anticipations compared to true value. Though these errors are minimal and have occurred due to smaller dataset, considering a larger sample data the efficiency would further increase with lesser residual. However, for this data the R2 value for training, validation and test set is approximately 0.99. Further the variation between experimental (true) data and Predicted data has been potted in MATLAB with X-axis being considered as the trial number for sample data and Yaxis for the output variable (BTE) as in Figure (8).

![Figure 6: SNR ratios plotted for Input parameters and NOx emissions](image)

![Figure 7: SNR ratios plotted for Input parameters and NOx emissions](image)

**TABLE 8: RMSE values for both Gradient descent and Levenberg-Marquardt method**

| No. of Neurons | RMSE values -LM | RMSE values -GD |
|----------------|-----------------|-----------------|
|                |                 |                 |

10
Compared to both the algorithm used LM method has produced better result with least RMSE value of 0.612738. The LM method is the recommended algorithm for supervised learning as it best suits for models with small and medium sized sample data. As seen from Table 3, the least RMSE value was obtained for ANN network with 8 neurons in hidden layer. Also, the network seems to overfit for data exceeding 12 neurons. From Table 4 the response values obtained were listed. For Instance, at 15 N-m of load, 0 lpm of biogas and 20% plastic oil the experimental value of BTE is 28.47% whereas the predicted value was found to be 27.42 with the residual being approximately 1, which seems to be small. Similarly, the confusion matrix helps for better visualization of data. The R2 value for the training, validation and test data was found to be 0.99, which shows a good fit for the data. Furthermore, experimental and predicted values are compared using a graph as shown in Figure (9).

**FIGURE 8: Experimental and Predicted data comparison for GD method**

### Table 4: Response Values Obtained

| Load (N-m) | Biogas (lpm) | Plastic Oil (%) | BTE (%) |
|------------|--------------|-----------------|---------|
| 8          | 0            | 0               | 27.42   |
| 10         | 0            | 0               | 26.84   |
| 12         | 0            | 0               | 26.466  |
| 14         | 0            | 20              | 25.7626 |
| 16         | 0            | 20              | 19.8388 |
| 18         | 0            | 20              | 19.65   |

4.7. Levenberg-Marquardt method

Compared to both the algorithm used LM method has produced better result with least RMSE value of 0.612738. The LM method is the recommended algorithm for supervised learning as it best suits for models with small and medium sized sample data. As seen from Table 3, the least RMSE value was obtained for ANN network with 8 neurons in hidden layer. Also, the network seems to overfit for data exceeding 12 neurons. From Table 4 the response values obtained were listed. For Instance, at 15 N-m of load, 0 lpm of biogas and 20% plastic oil the experimental value of BTE is 28.47% whereas the predicted value was found to be 27.42 with the residual being approximately 1, which seems to be small. Similarly, the confusion matrix helps for better visualization of data. The R2 value for the training, validation and test data was found to be 0.99, which shows a good fit for the data. Furthermore, experimental and predicted values are compared using a graph as shown in Figure (9).
4.8. Linear regression modelling

The linear regression model computes a relationship between the predictor and response variable, as there are more than 2 independent variables this is a multiple regression equation. It was calculated using MATLAB and the RMSE error was found to be 3.67 which when compared with ANN network is quite higher. As linear regression model does not take into account the uniformity of true values, it leads to significantly larger residuals. ANN prove their worthiness in such scenarios by providing better prediction. The error values predicted for LRM along with the best ANN parameters are given in table (9). The multi linear regression model uses the following equation (7) to predict the response:

\[
BTE = 7.13 + 1.3171 \times \text{load} - 0.1946 \times \text{plastic oil percentage} - 0.0394 \times \text{biogas flow}
\]  

(7)

| Load | Biogas flow (LPM) | Plastic oil (%) | BTE (%) | Predicted LRM | Predicted ANN-LM |
|------|-------------------|-----------------|---------|---------------|-----------------|
|      |                   |                 |         |               |                 |
5. Conclusion

Based on results comparing the diesel values with blended fuel mixture in this experiment, we were able to make the following conclusions:

1. The BTE was higher for diesel fuel when compared at different load conditions due to a negative impact of biogas.
2. The CO emissions were found to be better for blended fuel mixture at 0 lpm biogas flow. Similarly, HC emissions were better for blended mixture and found to be growing with increased biogas flow.
3. Further, NOx and Smoke emissions were found to be much lesser for blended mixture. However, increasing biogas gas has helped in reducing their values unlike the previous case.
4. Comparing the predicted values for any trial case the residual is found to be gradually higher and LRM model failed to predict the response variables better than ANN. Moreover, the RMSE values for ANN and LRM are 0.6128 and 3.67 respectively and $R^2$ value for LRM is 0.88.

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