

PREDICTIONS OF PERFORMANCE AND EMISSION PARAMETERS OF A BIOETHANOL BLENDED VCR SI ENGINE USING ARTIFICIAL NEURAL NETWORKS

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Abstract: The influence of alternate fuels in the place of fossil fuels play a prominent role in the automobile sector. This is due to combustion of fossil fuels; the emissions were coming out of the engine which affects the human health and the environment. In order to decrease the emissions (like CO and HC emissions) coming out of the SI engine, an oxygenated fuel (Bioethanol) is selected as an alternate fuel for the SI Engine. To decrease the complexity and to save the time with the thermodynamic calculations, Neural Networks are very useful for predicting the required targets. The performance and emission parameters data is selected from the base paper and are arranged accordingly inputs and targets for the training purpose of neural networks. The selected inputs are % of Gasoline, % of Bioethanol, Specific Gravity, Calorific value, Octane Number, Compression ratio, Brake Power, Mass of Fuel, EGT and the selected targets are BTE, % of CO Emissions, ppm of HC Emissions. The results obtained from the L-M Algorithm are correlated with the experimental results from the base paper using statistical tool such as MAPE and R^2 . The MSE Value of best validation performance is 0.010456 at the epoch 3 which is in acceptable limits. After observing the experimental and predicted results, it is clarified that the ANN is successful in simulating the engine model.

Keywords: VCR SI Engine, Performance and Emission parameters, ANN, L-M Algorithm, MAPE, R^2

I. Introduction

Artificial neural networks (ANN) have appeared as general mathematical modules simulating biological nervous systems. In a simplified mathematical model of the neuron, the effects of the synapses are represented by connection weights that modulate the effect of the associated input signals, and the nonlinear characteristic exhibited by neurons is represented by a transfer function, which is usually the sigmoid, Gaussian, trigonometric function, and so on.

The neuron impulse is then computed as the weighted sum of the input signals, being transformed by the transfer function. The learning capability of an artificial neuron is achieved by adjusting the weights in accordance to the chosen learning algorithm. Most applications of neural networks fall into the following categories:

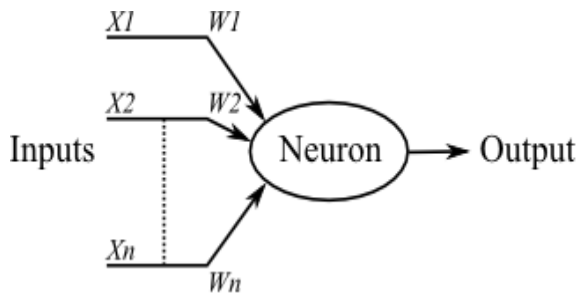
- **Prediction:** to predict the output variables using input values
- **Classification:** to process the classification stage using input values
- **Data Association:** it is as classification, plus recognizing data that has errors
- **Data conceptualization:** to analyze the inputs so that grouping relationships can be inferred

A typical multi-layered neural network and an artificial neuron are illustrated in Figure 1. Each neuron is characterized by an activity level (representing the state of polarization of a neuron), an output value (representing the firing rate of the neuron), a set of input connections (representing synapses on the cell and its dendrite), a bias value (representing an internal resting level of the neuron), and finally a set of output connections (representing a neuron's axonal projections). Those components of the unit are described mathematically by real values. Thus, each connection owns a synaptic weight (strength) that defines the effect of the incoming input on the unit activation limit. The negative and positive weights can be used. Referring to Figure 1, the signal flow from inputs $x_1...x_n$ is considered to be unidirectional, shown via arrows, like a neuron's output signal flow (O). The neuron output signal O is determined by the following expression:

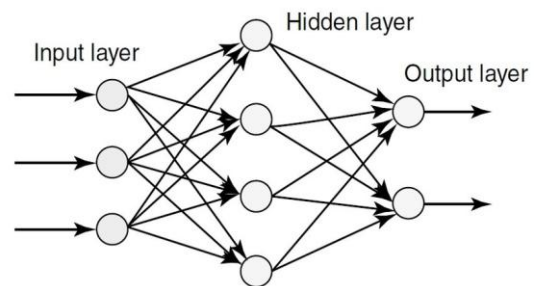
$$O = f(\text{net}) = f\left(\sum_{j=1}^n w_j x_j\right) \quad (1)$$

Where w_j is the weight vector and the function $f(\text{net})$ is referred to as an activation (transfer) function. The variable net is defined as a scalar product of the weight and input vectors.

$$\text{net} = \mathbf{w}^T \mathbf{x} = w_1 x_1 + \dots + w_n x_n \quad (2)$$



a) single-Layered Artificial Neural Network



b) Multi- Layered Artificial Neural Networks

Figure1 Architecture of an artificial neuron and a Multi-Layered Neural network

T is transpose of a matrix and in simple form the output O is

Computed as

$$O = f(\text{net}) = \begin{cases} 1 & \text{if } \mathbf{w}^T \mathbf{x} = \theta; \\ 0 & \text{Otherwise} \end{cases}$$

Where θ is called the threshold level and that kind of node is named as a linear threshold unit.

The feature of the neural network is significantly a function of the interaction between the different neurons. The main architecture contains three types of neuron layers: (1). Input, (2). Hidden, and (3). Output.

In feed-forward networks, the signal flow is directed from the input to output layers, by constraint of the feed-forward direction. The data processing can be distributed over the multiple layers, but no feedback connections are present, that is, connections extending from the outputs of units to inputs of units in the same layer or previous layers [2].

Recurrent networks contain feedback connections. Contrary to feed-forward networks, the dynamical properties of the network are important. In some cases, the activation values of the units undergo a relaxation process such that the network will evolve into a stable state in which these activations do not change anymore. In other applications, the changes of the activation values of the output neurons are significant, such that the dynamical behaviour constitutes the output of the network.

There are many other neural network architectures such as Elman network, adaptive resonance theory maps, competitive networks, and others, depending on the properties and requirement of the application.

A neural network has to be configured such that the application of a set of inputs produces the desired set of outputs. Various methods to set the strengths of the connections exist. One way is to set the weights explicitly, using a priori knowledge. Another way is to train the neural network by feeding it, teaching patterns and letting it change its weights according to some learning rule. The learning process of neural networks can be classified into three distinct sorts of learning: (1). Supervised, (2). Unsupervised, and (3) Reinforcement.

In supervised learning, an input vector is presented at the inputs together with a set of desired responses, one for each node, at the output layer. A forward pass is done and the errors or discrepancies, between the desired and actual response for each node in the output layer, are found. These are then used to determine weight changes in the network according to the prevailing learning rule. The term ‘supervised’ originates from the fact that the desired signals on individual output nodes are provided by an external teacher. The best-known examples of this technique occur in the back propagation algorithm, the delta rule, and perceptron rule.

In unsupervised learning (or self-organization), a (output) unit is trained to respond to clusters of pattern within the input. In this paradigm, the system is supposed to discover statistically salient features of the input population. Unlike the supervised learning paradigm, there is no a priori set of categories into which the patterns are to be classified; rather, the system must develop its own representation of the input stimuli.

Reinforcement learning is learning what to do – how to map situations to actions – so as to maximize a numerical reward signal. The learner is not told which actions to take, as in most forms of machine learning, but instead must discover which actions yield the most reward by trying them. In the most interesting and challenging cases, actions may affect not only the immediate reward but also the next situation and, through that, all subsequent rewards. These two characteristics, trial-and-error search and delayed reward, are the two most important distinguishing features of reinforcement learning (Bishop 1995, Abraham 2001).

G. Najafi, et al.[1] studies on Performance and exhaust emissions of a gasoline engine with ethanol blended gasoline fuels using artificial neural network (ANN). The major purpose of this study is to experimentally analyse the performance and the pollutant emissions of a four-stroke SI engine operating on ethanol–gasoline blends of 0%, 5%, 10%, 15% and 20% with the help of artificial neural network (ANN). The experimental results revealed that using ethanol–gasoline blended fuels increased the power and torque output of the engine slightly. An ANN model was developed to predict a correlation between brake power, torque, brake specific fuel consumption, brake thermal efficiency, volumetric efficiency and emission components using different gasoline–ethanol blends and speeds as inputs data. This study exhibits that ANN approach can be used to accurately predict the SI engine performance and emissions.

Yakup Sekmen et al.[3] investigate about the increase in the fuel injection pressure leads to the vaporization of diesel fuel spray quickly with the decrease in the diesel fuel particle diameter. To study about this effect ANN with LM (Levenberg-Maquardt) and SCG (Scaled Conjugate Gradient) Algorithms having 11 hidden neurons is taken as a base. Engine speed, injection pressure are the inputs and torque, injection pressure, specific fuel consumption are the outputs. MAPE and R^2 are the statistical tools to determine the relationship between the actual and predicted outputs. The MAPE and R^2 for different outputs are in acceptable limits and are considered as best results.

II. Collection of Data

Performance and emissions Data was collected from the base paper such that the data can be arranged accordingly inputs and targets. Almost 108 data samples were collected with 9 inputs and 3 targets. The inputs and targets are shown in the table 1. Out of the 108 data samples, 70% of data samples are taken for the training purpose, 15% of data samples are taken for the validation purpose and remaining 15% of data samples are taken for the testing purpose. This data is used for training the algorithm, validating the error and testing the algorithm of the Neural Networks.

Table-1 Input-Output mapping for ANN

<i>s.no.</i>	<i>Input Parameters</i>	<i>Output Parameters</i>
1	Percentage of Gasoline (%)	Brake Thermal Efficiency (%)
2	Percentage of Ethanol (%)	
3	Calorific Value (kJ/kg)	
4	Octane Number	Carbon monoxide Emissions (%)
5	Specific Gravity	
6	Compression Ratio	
7	Brake Power (kW)	Unburnt Hydrocarbons Emissions (ppm)
8	Mass of Fuel (kg/h)	
9	Exhaust Gas Temperature ($^{\circ}$ C)	

III. Neural Network Modelling

In the supervised learning, out of the Normalised data patterns, 70% of the inputs and targets are simultaneously given to the Neural Network tool such that it is trained well. The training of the data patterns were done with the help of 3 algorithms which are Levenberg-Marquardt (L-M), Bayesian Regularisation and Scaled Conjugate method (SCM) algorithms. After training, the testing of the algorithm is done with the help of 15% of the data patterns. The layout of the Neural Net Fitting is as shown in the figure 2.

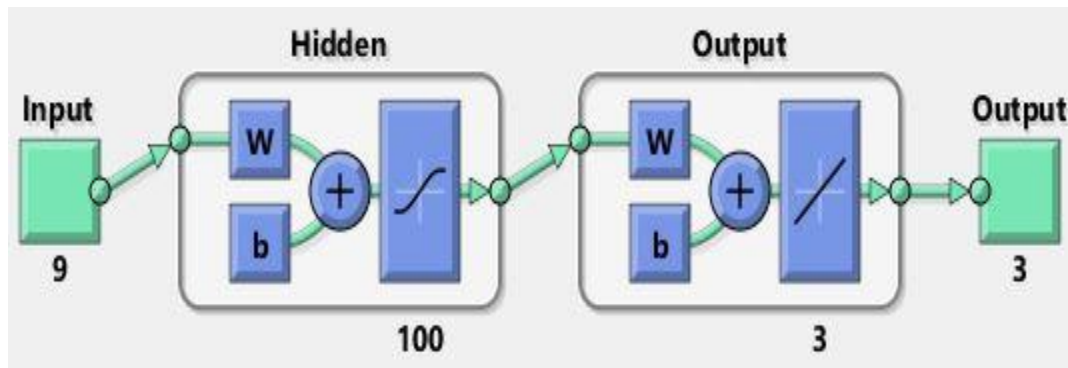


Figure 2: Layout of the Neural Net Fitting

The saved inputs and targets were uploaded in the Neural Net Fitting tool. Then the uploaded data patterns were divided into 70% as training data, 15% as validation data and 15% as checking data. The number of hidden neurons was selected accordingly in order to get more accuracy. Then the L-M algorithm is selected and trained with more number of iterations. The Mean Square Error for the best validation performance is obtained as shown the figure 3.

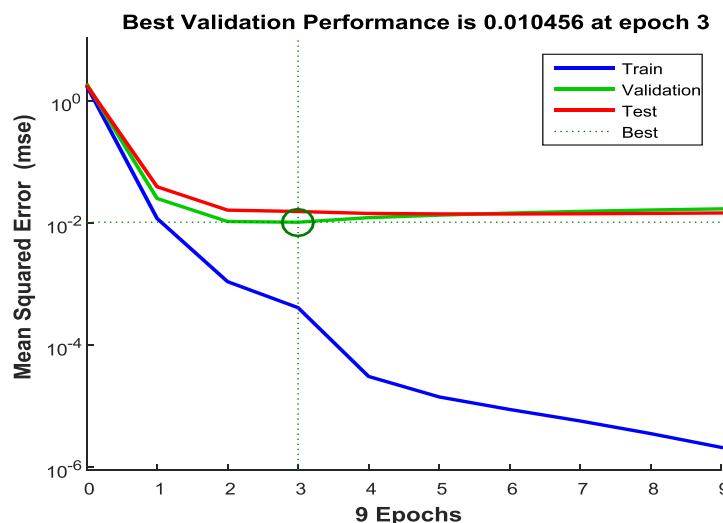


Figure 3: MSE for the Best validation performance

In the hidden neurons layer, the activation function is sigmoid function and in the output layer the function is linear function as shown in the figure 2. The mean square error for the best validation performance of the given data is 0.010456 at the epoch 3. The Value of R for the training, validation and testing data is shown separately as shown in the figure 4. The overall value of R for the given data is 93.74% which is in acceptable limit.

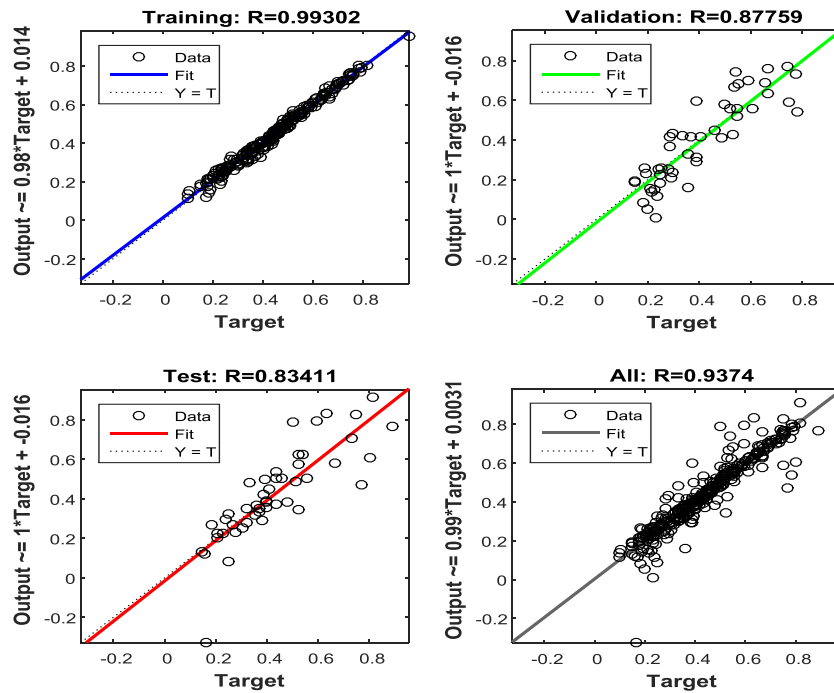


Figure 4: R Value for training, Validation and testing data

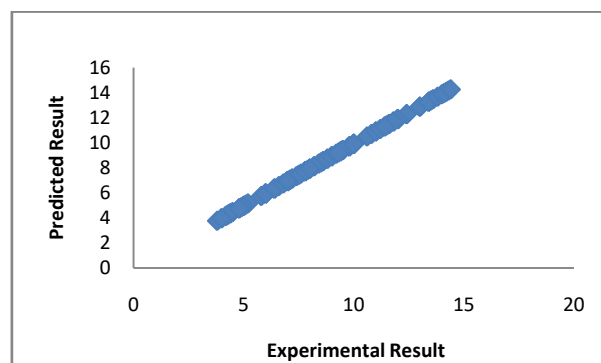
IV. Results and Discussions

The correlation of the predicted and experimental results was defined using the statistical tools like MAPE and R^2 . The MAPE and R^2 for the 3 different outputs are shown in the table 2.

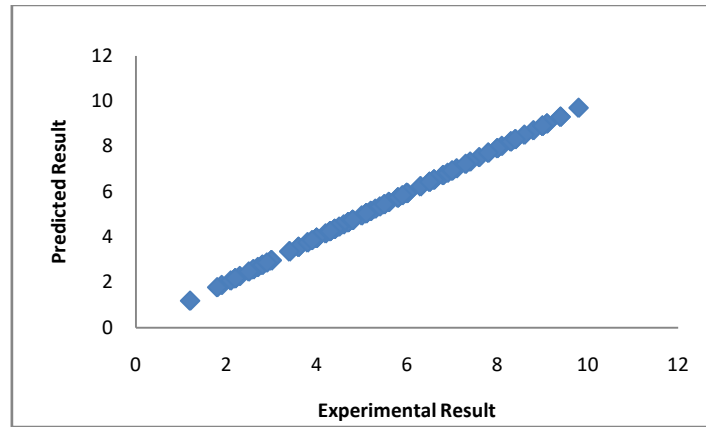
Table 2: MAPE and R^2 Values of outputs

Performance and Emission parameters	R^2	MAPE (%)
BTE	0.865	8.613
CO	0.879	10.259
HC	0.888	13.188

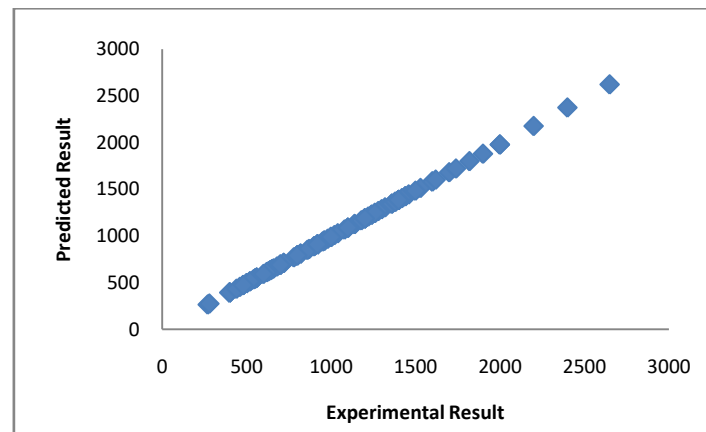
Since the value of the R^2 is above 0.85 for all the 3 outputs which reveals that there is a better correlation between the experimental and predicted results.



a) Correlation of Experimental Vs Predicted Result of BTE



b) Correlation of Experimental Vs Predicted Result of CO



c) Correlation of Experimental Vs Predicted Result of HC

Figure 5: Correlation of Experimental and predicted results of 3 outputs

By observing the figure 5, it is revealed that the experimental and predicted values are nearly equal for all the 3 outputs. Thus the ANN is successfully simulated the Engine model. If any untrained inputs are given to the trained algorithm, the outputs are obtained because of the linear behaviour of the correlation of experimental and predicted results of all the 3 outputs.

V. Conclusions

An artificial neural network (ANN) was developed and trained with the collected data of this research work. The results showed that the two layer feed-forward neural network with one hidden layer was sufficient enough in predicting 3 different outputs for 9 different inputs. It can be concluded that the high values of regression coefficients yielded when setting a regression line for predicted and measured datasets.

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