GSC Advanced Research and Reviews

eISSN: 2582-4597 CODEN (USA): GARRC2

Cross Ref DOI: 10.30574/gscarr

Journal homepage: https://gsconlinepress.com/journals/gscarr/

(RESEARCH ARTICLE)

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Creating a neural network-based model to predict the exhaust gas temperature of the internal combustion engine

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GSC Advanced Research and Reviews, 2024, 19(01), 079–085

Publication history: Received on 07 March 2024; revised on 15 April 2024; accepted on 18 April 2024

Article DOI: https://doi.org/10.30574/gscarr.2024.19.1.0147

Abstract

The regulation and improvement of the performance of internal combustion engines is a continual primary focus of research and development activities conducted within the automobile industry and other relevant sectors. To succeed in reaching this objective, it is necessary to have an accurate and complete model of these engines. However, due to internal combustion engines' complex and nonlinear nature, accurately replicating their behavior may be challenging and time-consuming. Neural networks are a potentially useful strategy for simulating these engines successfully since they offer a solution that strikes a healthy balance between speed and precision. This research investigates the process of building a model of an internal combustion engine by using not one but two separate kinds of neural networks: multilayer perceptrons and radial basis functions. These neural networks aim to simulate and make predictions about the temperature of the engine's exhaust gas. They are especially useful for modeling nonlinear systems because of their incredible convergence speed and excellent accuracy levels.

Keywords: Automotive Industry; Internal Combustion Engines; Neural Networks; Modeling; Performance Enhancement; Exhaust Gas Temperature

1. Introduction

Over the course of the next few years, one of the most major difficulties that the whole world has been presented with is the excessive use of fossil fuels and the generation of greenhouse gases. This has been one of the most critical challenges that the world has faced. The excessive use of fuel and the production of pollutants that are caused by internal combustion engines are the responsibility of these engines. The possibility exists that these kinds of engines are the cause of these issues. As a direct result of this, internal combustion engines that are less harmful to the environment and more efficient in terms of the amount of energy they use have been created. [1-5]. Before the oil crisis that occurred in the 1980s, the majority of people were just concerned with the movement of automobiles running smoothly and without any problems. This was prior to the disaster that occurred. No one paid any attention to the amount of pollution that was produced or the amount of petroleum that was used throughout the process even though it was a significant amount. Many people have come to the realization over the course of the last few years that one of the most critical difficulties that the world is now facing is the issue of air pollution. As a consequence of this knowledge, there has been a reduction in the amount of pollution that is produced by cars, and manufacturers of automobiles have made the management of pollution a primary concern in the manufacturing techniques that they use.

Reducing the quantity of fuel that is used and the amount of pollutants that are created may be accomplished via the management of the engine in a number of different methods, including modification [6-11]. In the event that you are in possession of a certain model of the engine, this procedure will be much less complicated, which will lead to a decrease

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in the amount of money that is necessary. It is possible that the model that was produced will act as a virtual laboratory and engine in place of the conventional testing and information gathering that is carried out in laboratories. This is something that is achievable. It is possible that this may be established as an alternative to the conventional methods of using labs. On top of that, you will have the opportunity to create the controller, in addition to any other alterations that are necessary in the software domain. Following that, you will be able to apply those changes to the model of your choosing and analyze the influence that those enhancements have upon the model. [12-15].

To have a model that is not only accurate but also has a rapid reaction time is something that is desired, but it is also something that is difficult to do effectively. Despite the fact that this is the case, there are challenges that are associated with this attempt. It is essential to take into consideration the fact that the dynamics of the engine are quite complicated and include nonlinear behavior. In the second place, the use of multidimensional coefficients in linearization methods is an urgent need. This is due to the fact that the dynamics of the engine include a wide range of situations that may be considered to be operational conditions [16-20].

However, the accuracy of the model and the speed with which it can simulate and do computations are two separate characteristics of any software model; hence, one must overlook the other to attain any of these qualities [21-23]. Neural networks, owing to their precision and speed of reaction, are an appealing choice for simulating internal combustion engines in all of the aforementioned circumstances [6, 24-30]. In order to train and construct a model, this inquiry included the utilization of a multilayer perceptron neural network. The ability of the neural network to represent internal combustion engines will be shown in this research.

2. Neural network training

2.1. Multilayer Perceptron Neural Network

The first kind of neural network considered for this engine's simulation was a multilayer perceptron network. This network may be used to simulate both static and dynamic systems effectively. Figure 8 presents a diagram of the network architecture considered for this model.

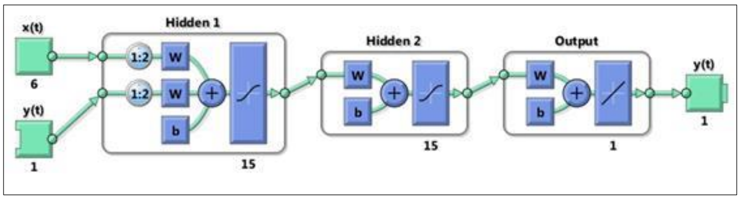

Figure 1 Network architecture used to model the Ricardo engine

Because of the dynamic nature of the system being researched, the output affects the inputs for the cycle that comes after it. The impacts of the system inputs may be seen in the cycle or cycles that come after the one to which they correspond [36-38]. The system inputs are not exclusive to the cycle to which they belong. To accomplish this goal, the inputs and the outputs have been given two delays each. This indicates that the inputs that correspond to that cycle, the two cycles that came before it, and the outputs of the two cycles that came before it are considered inputs in each cycle.

At the beginning of training a neural network, the data are partitioned into three distinct groups: training, verification, and evaluation. In the first stages, the network is educated using test data. The accuracy of the training process is assessed using validation data, and if the predictions are incorrect, the training process is repeated. If the predictions are accurate, the accuracy of the training process is improved. After the training has been completed, an evaluation of the accuracy of the network in the simulation is performed by feeding the reserved test data into the network and comparing the outputs of the network to the outputs that were really produced. The results of these examinations are shown in Figures 2 through 8.

Each of Figures 2 through 8 consists of four graphs: the actual outputs are represented in terms of the outputs caused by the network for the same inputs, the linear regression coefficient between these two categories is specified, and the line representing the intermediate equation is depicted in the upper right corner of the graph. These graphs can be found in each of Figures 2 through 8. These are the things that contribute to it. If the network's accuracy is 100 percent, then each point has to be situated on a line with a slope of one that runs through the starting point. In this case, the linear regression coefficient for the test data is 0.93882, which is extremely close to one, suggesting the high accuracy of the constructed network when applied to the test data. This is shown in the graph, and it can be seen that this coefficient is very close to one. The fact that this coefficient for all of the training and accessible data is 0.94564 and 0.94848, respectively, indicates that the network works extraordinarily well. Table 1 presents evidence of these values.

The actual outputs and network outputs for the same inputs are presented for test data, training data, and all data, respectively, in the top left graph of Figures 2 to 4. The suitable modeling accuracy for each of the three data categories is shown by the positioning of these graphs, which are displayed in these pictures.

Error scatter diagrams for the test, training, and complete data are shown in Figures 2 through 4 below, respectively. These figures show that the most significant amount of error dispersion happens close to zero and that the error frequency drops as the distance from zero grows. The average errors and the standard deviation are also provided above this graph, demonstrating that the modeling is correct. Table 1 has extensive information on each of these variables.

Error diagrams have been generated for testing, training, and all data in the bottom left diagram of Figures 2 to 4. These error diagrams are reasonable, given that the output values vary from 600 to 750. Above each of these plots, the average error, as well as the root mean squared error, are shown. Table 1 has all of these data for your perusal.

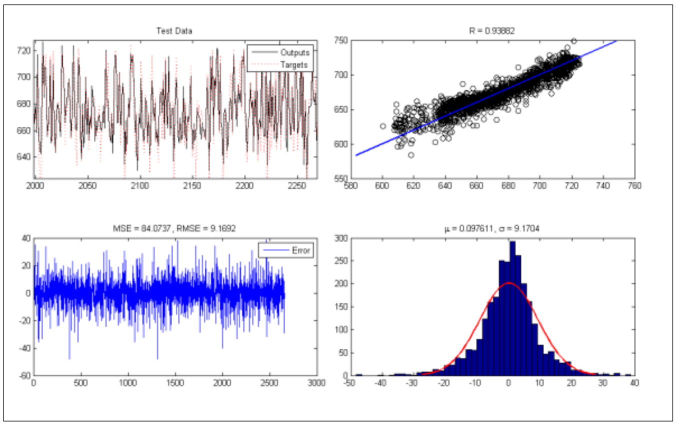

Figure 2 Comparison of the outputs caused by the network and the actual outputs belonging to the test data

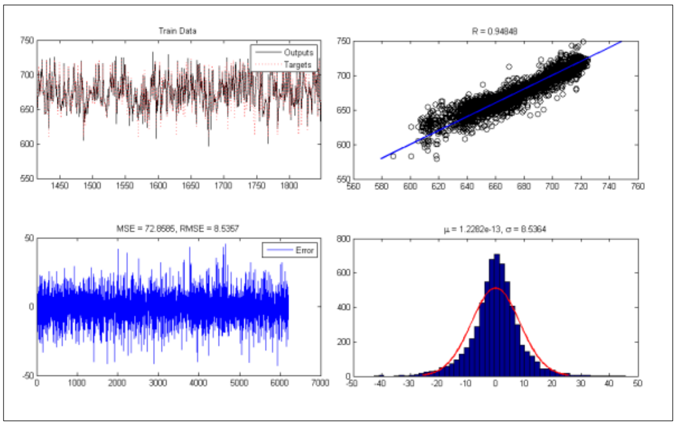

Figure 3 Comparison of the outputs caused by the network and the real outputs belonging to the training data

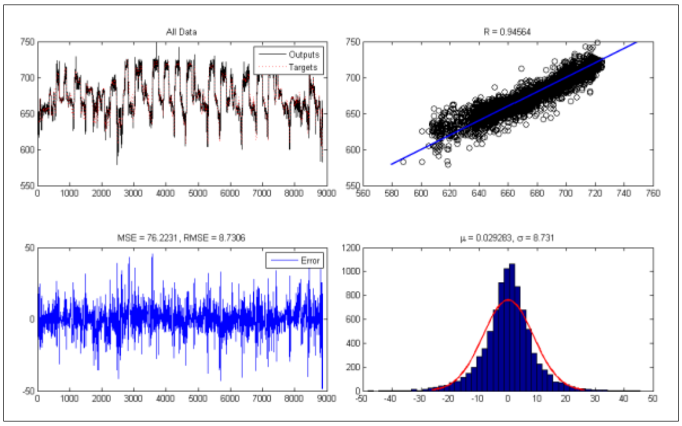

Figure 4 Comparison of the outputs caused by the network and the actual outputs of all the data

Figures 2 to 4 show that the multilayer perceptron neural network can model this system well.

Table 1 Modeling results

Data type	R	MSE	RMSE	μ	σ
Test	0.939	84.074	9.169	0.098	9.170
Education	0.948	72.858	8.536	1.228	8.536
All Data	0.946	76.223	8.731	0.029	8.731

2.2. Model Equations

RBF stands for the radiometric basis function. The consideration of coefficients allows for the approximation of nonlinear functions for the kernels of neural networks. The term "neural fuzzy networks" may also be used to refer to these networks. The square root of the mean error was the metric that needed to be minimized while assessing the performance of the network. The results of this network's training are shown in Figure 5, which can be seen here.

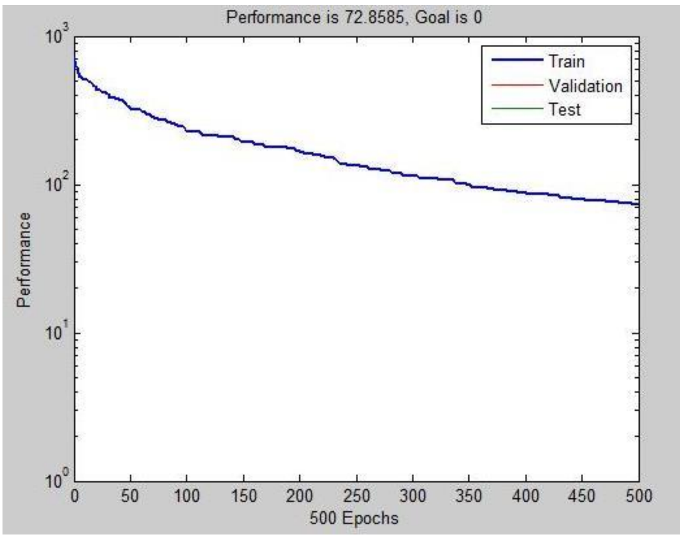

Figure 5 The result of modeling using radial basis functions neural network

Figure 5 demonstrates that after 500 iterations, the error value of this network is equivalent to that of the multilayer perceptron neural network, but its performance is somewhat more excellent. On the other hand, the amount of time necessary to train this network is noticeably more extended than the amount of time necessary to train a multilayer perceptron neural network, which suggests that a multilayer perceptron neural network is the preferable choice for this application.

3. Results and discussion

In light of the information shown so far, one may draw the conclusion that neural networks can be used to simulate internal combustion engines efficiently and that the resultant outputs can reliably anticipate the outputs that were originally intended.

The findings of two different multilayer perceptron neural networks and radial basis functions were compared to better understand how models operate. It was revealed that the outputs may be reliably calculated by employing both networks simultaneously. The training of a multilayer perceptron neural network, on the other hand, takes a lot less time. This network's use has become a lot more appealing as a consequence. A model of this kind may be used in the subsequent phases, during which a turbocharger or an exhaust catalyst for a vehicle might be designed. Conversely, this approach may estimate and utilize additional engine output variables for applications, including control or augmentation.

4. Conclusion

This research demonstrates that neural networks are capable of correctly replicating the behavior of internal combustion engines, which enables them to provide reliable predictions for a variety of engine factors. Two different types of neural networks, namely multilayer perceptron and radial basis functions were used in the computational modeling of the engines. Both networks demonstrated promising results, with the multilayer perceptron network displaying shorter training times than the other network. The study suggests that these models may be used in the design of components such as turbochargers or exhaust catalysts, as well as for applications linked to control or performance enhancement in internal combustion engines. Moreover, this research suggests that these models could be employed in the design of components. Neural networks provide a practical approach to accurately predicting and forecasting the performance of engines.

Compliance with ethical standards

Acknowledgments

This study did not receive funding from any government or private agency.

Disclosure of conflict of interest

Mahnaz Zameni: Methodology, investigation, formal analysis, visualization, writing–original draft; Mahdi Ahmadi: Methodology, investigation, formal analysis, writing–review and editing; Arash Talebi: Investigation, formal analysis, writing–review and editing.

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