CHAPTER 6

PREDICTION OF ENGINE PERFORMANCE AND EMISSIONS CHARACTERISTICS USING ANN

6.1 ARTIFICIAL NEURAL NETWORK

Manufacturers and application engineers usually want to know the performance of an engine operated with diesel with various fuels for the entire range of operating conditions. This requirement can be met either by conducting a comprehensive testing study or modeling the engine operation. Testing the engine under all possible operating conditions and fuel cases are both time consuming and expensive. As an alternative method, the performance and exhaust emissions of an engine can be modeled by using ANN. This new modeling technique can be applied to estimate desired output parameters when enough experimental data is provided. Therefore, ANN allows the modeling of physical phenomena in complex systems without requiring explicit mathematical representations. The use of ANN for modeling the operation of internal combustion engines is a more recent progress. Various authors (Kalogirou 2000, Pacheco-Vega et al 2001, Prieto et al 2001, Bechtler et al 2001, Chouai et al 2002, Sozen et al 2003, Arcaklioglu 2004, Ertunc and Hosoz 2006 and Hosoz and Ertunc 2006) investigated the performance of various thermal systems with the aid of ANN. This approach was used to predict the performance and exhaust emissions of internal combustion engines (Arcaklioglu and Celikten 2005, Canakci et al 2006, Sayin et al 2007) the specific fuel consumption and fuel air equivalence ratio of a diesel engine (Celik and Arcaklioglu 2005). Golcu et al (2005) reported the effects of valve timing in the spark-ignition engine on the engine performance and fuel economy by using ANN.
The steps for the ANN modeling design methodology are illustrated in Figure 6.1. ANN is an analytical method for simulating system performance. The method relies on experimental data that is used to train the ANN so that it can precisely predict the system performance at other conditions. This technique has found application in the situations where the simulation of complex system is required but only limited experimental data is available. ANN is a powerful, nonlinear tool and since many phenomena in industry have non-linear characteristics, ANN has been applied widely. The performance of the ANN based predictions is evaluated by regression analysis of the network outputs (predicted parameters) and the experimental values (Sayin et al 2007).

![Figure 6.1 ANN design methodology](image)

Figure 6.1 ANN design methodology
The error identified during learning process is called the root mean square error (RMSE) and is defined as

$$\text{RMSE} = \left( \frac{1}{n} \sum_{i=1}^{n} (a_i - p_i)^2 \right)^{\frac{1}{2}} \quad (6.1)$$

The correlation coefficient ($R^2$) and mean relative error (MRE) are used for characterizing the network performance. The correction coefficient can vary between -1 and +1, but $R$ values closer to +1 indicate a stronger positive linear relationship, while $R$ values closer to -1 indicate a stronger negative relationship.

The mean relative error, which shows the mean ratio between the error and the experimental values, is defined as

$$\text{MRE} (%) = \frac{1}{n} \sum_{i=1}^{n} \left| 100 \times \frac{(a_i - p_i)}{a_i} \right| \quad (6.2)$$

where $n$ is the number of the points in the data set, $a$ and $p$ are actual output and predicted output sets respectively (Sayin et al 2007).

An ANN model can accommodate multiple input variables to predict multiple output variables. It differs from conventional modeling approaches in its ability to learn about the system that can be modeled without prior knowledge of the process relationship. The prediction by a well-trained ANN is normally much faster than that of the conventional simulation programs or mathematical models as no lengthy iterative calculations are needed to solve differential equations by using numerical methods. But the selection of an appropriate neural network topology is important in terms of model accuracy and model simplicity. The network usually consists of an input layer, some
hidden layers and an output layer (Haykin 1994). If it is needed, input and output variables can be added or removed in the ANN. A popular algorithm is the back propagation which has different variants. Back propagation training algorithms such as gradient descent and gradient descent with momentum are often too slow for practical problems because they require small learning rates for stable learning. In addition, success in the algorithms depends on the user dependent parameters learning rate and momentum constant. This algorithm uses the supervised training technique in which the network weights and biases are initialized randomly at the beginning of the training phase. The error minimization process is achieved with a gradient descent rule. The number of hidden layers and neurons within each layer can be designed by the complexity of the problem and dataset.

6.2 MODELED WITH ANN

ANN model for the diesel engine with different blended fuels such as bioethanol-EEPO-diesel, bioethanol-n-butanol-diesel and bioethanol-MECSO-diesel blends was trained by using the data gathered in test runs. MAT LAB 7.2 neural network toolbox was used for training the network model in order to generate neural network modeling and analysis. 70% of the data was randomly assigned as the training set, which is given in the Table A6.1 to A6.3 of Appendix 6, while the remaining 30% of data, was used for testing the performance of the ANN predictions. Back propagation algorithm was chosen to calculate the weight values of network. The model was tested on different number of nodes in the hidden layer. The best learning capability and minimum error were found when the numbers of hidden nodes were chosen as 35, 33 and 31 for bioethanol-EEPO-diesel, bioethanol-n-butanol-diesel and bioethanol-MECSO-diesel blends respectively. The architecture of the ANN for the test engine is schematically shown in the Figure 6.2.
6.3 THE NETWORK TRAINING

The data taken for the training neural network was 25 set. The remaining set of 10 data was used to test the performance of the trained network as it is mentioned above. There were two input and six output parameters in the experimental tests. The input variables are different percentage of load and different percentage of blended blends. The outputs are brake thermal efficiency, CO, CO$_2$ and smoke in terms of percentages and HC and NO$_X$ in terms of ppm obtained. Therefore, the input layer consists of 2 neurons and the output layer has 6 neurons. The sigmoid function is chosen as the activation function for hidden layer and linear function is best selected for the output layer. The training errors were achieved $9.9 \times 10^{-7}$, $9.8 \times 10^{-6}$, $8.3 \times 10^{-6}$ with 1989 epochs, 1495 epochs, 290 epochs respectively for bioethanol-EEPO-diesel, bioethanol-n-butanol-diesel, bioethanol-MECSO-diesel blends respectively. The performances of training process were shown in the Figures 6.3 to 6.5. The simulink model for
predicating engine parameters is shown in the Figure 6.6. The computer program MATLAB 7.2, neural network toolbox is used for ANN design.

Figure 6.3  Performance graphics of tested ANN model for bioethanol-EEPO-diesel blends

Figure 6.4  Performance graphics of tested ANN model for bioethanol – n-butanol- diesel blends
Figure 6.5  Performance graphics of tested ANN model for bioethanol-MECSO- diesel blends

Figure 6.6 Simulink model for predicting engine parameters
6.4 TESTING THE ANN MODEL

6.4.1 Testing of bioethanol-EEPO-diesel blends

The ANN predicted versus experimental values of the brake thermal efficiency is shown in the Figure 6.7. For the brake thermal efficiency, the ANN yields a correlation coefficient of 0.998, root mean square error of 0.45% and mean relative error of 1.52%. The ANN predicted versus experimental values of HC emissions is shown in the Figure 6.8. For the HC emissions, the ANN yields a correlation coefficient of 0.993, root mean square error of 3.19ppm and mean relative error of 2.55%. The ANN predicted versus experimental values of CO emissions is shown in Figure 6.9. In prediction of CO emissions, the ANN results in a correlation coefficient of 0.975, root mean square error of 0.014% and mean relative error of 7.97%.

The ANN predicted versus experimental values of the CO$_2$ emissions is indicated in the Figure 6.10. The ANN predictions for the CO$_2$ emissions yield a correlation coefficient of 0.981, root mean square error of 0.149% and mean relative error of 2.48%. The ANN predicted versus experimental values of the NOx emissions are presented in the Figure 6.11. In prediction of NOx emissions, the ANN results in a correlation coefficient of 0.999, root mean square error of 5.13ppm and mean relative error of 1.12%. The ANN predicted versus experimental values of the smoke emissions is reported in Figure 6.12. For the smoke emissions, the ANN yields a correlation coefficient of 0.975, root mean square error of 2.55% and mean relative error of 5.62%.
Figure 6.7  ANN predicted versus experimental brake thermal efficiency values of bioethanol-EEPO-diesel blends

Figure 6.8  ANN predicted versus experimental HC values of bioethanol-EEPO-diesel blends
Figure 6.9 ANN predicted versus experimental CO values of bioethanol- EEPO-diesel blends

Figure 6.10 ANN predicted versus experimental CO\textsubscript{2} values of bioethanol- EEPO-diesel blends
Figure 6.11 ANN predicted versus experimental NOx values of bioethanol- EEPO-diesel blends

Figure 6.12 ANN predicted versus experimental smoke values of bioethanol- EEPO-diesel blends

Figure 6.13 compares the experimental and predicted brake thermal efficiency values for the test data. As shown in Figure 6.13, the experimental and predicted values are very close to each other. Figure 6.14 compares the
experimental and predicted HC emission values for the test data. As shown in Figure 6.14, the values predicted by ANN are generally larger than the experimental values. Figure 6.15 compares the experimental and predicted CO emission values for the test data. As shown in Figure 6.15, the values predicted by ANN approximately match the experimental values. Figure 6.16 compares the experimental and predicted CO$_2$ emission values for the test data. As shown in Figure 6.16, the values predicted by ANN are very close to the experimental values. Figure 6.17 compares the experimental and predicted NOx emission values for the test data. As shown in Figure 6.17, the experimental and predicted values are very close to each other. Figure 6.18 compares the experimental and predicted smoke emission values for the test data. As shown in Figure 6.18, the values predicted by ANN are generally larger than the experimental values. It is seen that the all test pattern consists of the results of 10 tests.

It was observed that the ANN model for bioethanol-EEPO-diesel blends can predict engine performance and exhaust emissions with a correlation coefficient in the range of 0.975 to 0.999, mean relative error values in the range of 1.52 to 7.97% and root mean square error is found to be very low.

![Figure 6.13 Comparisons of ANN predictions and experimental brake thermal efficiency values for bioethanol- EEPO-diesel blends](image)
Figure 6.14 Comparisons of ANN predictions and experimental HC values for bioethanol-EEPO-diesel blends

Figure 6.15 Comparisons of ANN predictions and experimental CO values for bioethanol-EEPO-diesel blends
Figure 6.16 Comparisons of ANN predictions and experimental CO\(_2\) values for bioethanol- EEPO-diesel blends

Figure 6.17 Comparisons of ANN predictions and experimental NOx values for bioethanol- EEPO-diesel blends
The ANN predicted versus experimental values of the brake thermal efficiency is shown in Figure 6.19. For the brake thermal efficiency, the ANN yields a correlation coefficient of 0.999, root mean square error of 0.467% and mean relative error of 1.834%. The ANN predicted versus experimental values of HC emissions is shown in Figure 6.20. For the HC emissions, the ANN yields a correlation coefficient of 0.994, root mean square error of 3.27ppm and mean relative error of 2.74%. The ANN predicted versus experimental values of CO emissions is shown in Figure 6.21. In prediction of CO emissions, the ANN results in a correlation coefficient of 0.981, root mean square error of 0.01129% and mean relative error of 6.75%.
The ANN predicted versus experimental values of the CO₂ emissions is indicated in Figure 6.22. The ANN predictions for the CO₂ emissions yield a correlation coefficient of 0.984, root mean square error of 0.158% and mean relative error of 3.265%. The ANN predicted versus experimental values of the NOx emissions are presented in Figure 6.23. In prediction of NOx emissions, the ANN results in a correlation coefficient of 0.999, root mean square error of 4.35ppm and mean relative error of 1%. The ANN predicted versus experimental values of the smoke emissions is reported in Figure 6.24. For the smoke emissions, the ANN yields a correlation coefficient of 0.993, root mean square error of 1.57% and mean relative error of 4.32%.

![Graph showing ANN predicted versus experimental brake thermal efficiency values of bioethanol-n-butanol-diesel blends](image.png)

**Figure 6.19**  ANN predicted versus experimental brake thermal efficiency values of bioethanol-n-butanol-diesel blends
Figure 6.20 ANN predicted versus experimental HC values of bioethanol- n-butanol-diesel blends

Figure 6.21 ANN predicted versus experimental CO values of bioethanol- n-butanol-diesel blends
Figure 6.22 ANN predicted versus experimental CO$_2$ values of bioethanol- n-butanol-diesel blends

Figure 6.23 ANN predicted versus experimental NOx values of bioethanol- n-butanol-diesel blends
Figure 6.24 ANN predicted versus experimental smoke values of ioethanol- n-butanol-diesel blends

Figure 6.25 compares the experimental and predicted brake thermal efficiency values for the test data. As shown in Figure 6.25, the experimental and predicted values are very close to each other. Figure 6.26 compares the experimental and predicted HC emission values for the test data. As shown in Figure 6.26, the experimental values are generally larger than the values predicted by ANN. Figure 6.27 compares the experimental and predicted CO emission values for the test data. As shown in Figure 6.27, the values predicted by ANN approximately match the experimental values. Figure 6.28 compares the experimental and predicted CO$_2$ emission values for the test data. As shown in Figure 6.28, the values predicted by ANN are close to the experimental values. Figure 6.29 compares the experimental and predicted NOx emission values for the test data. As shown in Figure 6.29, the experimental and predicted values are very close to each other. Figure 6.30 compares the experimental and predicted smoke emission values for the test data. As shown in Figure 6.30, the values predicted by ANN approximately match the experimental values. It is seen that all test patterns consist of the results of 10 tests.
It was observed that the ANN model for bioethanol-n-butanol-diesel blends can predict engine performance and exhaust emissions with a correlation coefficient in the range of 0.981 to 0.999, mean relative error values of 1% to 6.75% and root mean square error is found to be very low.

**Figure 6.25** Comparisons of ANN predictions and experimental brake thermal efficiency values for bioethanol-n-butanol-diesel blends

**Figure 6.26** Comparisons of ANN predictions and experimental HC values for bioethanol-n-butanol-diesel blends
Figure 6.27 Comparisons of ANN predictions and experimental CO values for bioethanol- n-butanol-diesel blends

Figure 6.28 Comparisons of ANN predictions and experimental CO$_2$ values for bioethanol- n-butanol-diesel blends
Figure 6.29 Comparisons of ANN predictions and experimental NOx values for bioethanol- n-butanol-diesel blends

Figure 6.30 Comparisons of ANN predictions and experimental Smoke values for bioethanol- n-butanol-diesel blends
6.4.3 Testing of bioethanol- MECSO -diesel blends

The ANN predicted versus experimental values of the brake thermal efficiency is shown in Figure 6.31. For the brake thermal efficiency, the ANN yields a correlation coefficient of 0.998, root mean square error of 0.74% and mean relative error of 2.917%. The ANN predicted versus experimental values of HC emissions is shown in Figure 6.32. For the HC emissions, the ANN yields a correlation coefficient of 0.975, root mean square error of 9.18ppm and mean relative error of 6.46%. The ANN predicted versus experimental values of CO emissions is shown in Figure 6.33. In prediction of CO emissions, the ANN results in a correlation coefficient of 0.988, root mean square error of 0.005% and mean relative error of 4.458%.

The ANN predicted versus experimental values of the CO$_2$ emissions is indicated in Figure 6.34. The ANN predictions for the CO$_2$ emissions yield a correlation coefficient of 0.986, root mean square error of 0.22% and mean relative error of 2.10%. The ANN predicted versus experimental values of the NOx emissions are presented in Figure 6.35. In prediction of NOx emissions, the ANN results in a correlation coefficient of 0.999, root mean square error of 7.4ppm and mean relative error of 1.308%. The ANN predicted versus experimental values of the smoke emissions is reported in Figure 6.36. For the smoke emissions, the ANN yields a correlation coefficient of 0.984, root mean square error of 2.28% and mean relative error of 5.6%.
Figure 6.31 ANN predicted versus experimental brake thermal efficiency values of bioethanol- MECSO -diesel blends

Figure 6.32 ANN predicted versus experimental HC values of bioethanol- MECSO-diesel blends
Figure 6.33 ANN predicted versus experimental CO values of bioethanol-MECSO-diesel blends

Figure 6.34 ANN predicted versus experimental CO\(_2\) values of bioethanol-MECSO-diesel blends
Figure 6.35 ANN predicted versus experimental NOx values of bioethanol-MECSO-diesel blends

Figure 6.36 ANN predicted versus experimental smoke values of bioethanol-MECSO-diesel blends

Figure 6.37 compares the experimental and predicted brake thermal efficiency values for the test data. As shown in Figure 6.37, the experimental and predicted values are very close to the each other. Figure 6.38 compares the
experimental and predicted HC emission values for the test data. As shown in Figure 6.38, the experimental values are very close to the values predicted by ANN. Figure 6.39 compares the experimental and predicted CO emission values for the test data. As shown in Figure 6.39, the experimental values are generally larger than the values predicted by ANN. Figure 6.40 compares the experimental and predicted CO$_2$ emission values for the test data. As shown in Figure 6.40, the values predicted by ANN are close to the experimental values. Figure 6.41 compares the experimental and predicted NOx emission values for the test data. As shown in Figure 6.41, the experimental and predicted values are very close to each other. Figure 6.42 compares the experimental and predicted smoke emission values for the test data. As shown in Figure 6.42, the values predicted by ANN are close to the experimental values. It is seen that the all test pattern consists of the results of 10 tests.

It was observed that the ANN model for bioethanol-MECSO-diesel blends can predict engine performance and exhaust emissions with a correlation coefficient in the range of 0.975 to 0.999, mean relative error values of 1.308% to 6.46% and root mean square error is found to be very low.

![Figure 6.37](image_url)  
**Figure 6.37** Comparisons of ANN predictions and experimental brake thermal efficiency values for bioethanol-MECSO-diesel blends
Figure 6.38 Comparisons of ANN predictions and experimental HC values for bioethanol-MECSO-diesel blends

Figure 6.39 Comparisons of ANN predictions and experimental CO values for bioethanol-MECSO-diesel blends
Figure 6.40 Comparisons of ANN predictions and experimental CO$_2$ values for bioethanol-MECSO-diesel blends

Figure 6.41 Comparisons of ANN predictions and experimental NOx values for bioethanol-MECSO-diesel blends
Therefore all the above blends, most of the predicted values fall with in the ± 10% deviation from the observed values. The above values are good correlation between the simulations from ANN and the measured data. The ANN models have proved to be a useful method for predicting the engine performance and emissions with reasonable accuracy by performing only a limited number of tests instead of a detailed experimental study, thus saving both engineering effort and funds for diesel engine.