POLİTEKNİK DERGİSİ

JOURNAL of POLYTECHNIC

ISSN: 1302-0900 (PRINT), ISSN: 2147-9429 (ONLINE)
URL: http://dergipark.org.tr/politeknik

Estimation of the COV_{IMEP} variation in a HCCI engine

Bir HCCI motorda COV_{IMEP} değişiminin tahmini

***Yazar(lar) (Author(s))**: Seyfi POLAT[1], Hamit SOLMAZ[2], Alper CALAM[3], Emre YILMAZ[4]*

ORCID[1]: 0000-0002-7196-3053

ORCID[2]: 0000-0003-0689-6824

ORCID[3]: 0000-0003-4125-2127

ORCID[4]: 0000-0002-5653-2079

Bu makaleye şu şekilde atıfta bulunabilirsiniz(To cite to this article): Polat S., Solmaz H., Calam A. ve Yılmaz E., "Estimation of the COV_{IMEP} variation in a HCCI engine", ***Politeknik Dergisi***, 23(3): 721-727, (2020).

Erişim linki (To link to this article): http://dergipark.org.tr/politeknik/archive

DOI: 10.2339/politeknik.567865

Estimation of the COVIMEP Variation in a HCCI Engine

Highlights

- *The variation of the COV_{IMEP} was tried to be predicted by using the ANN method*
- *Experimental data obtained for different boosted pressure and lambda values were used as input data*
- *The best performance was obtained at 37th iteration*
- *Total correlation factor was found as 0.97763*

Graphical Abstract

In this study, variation of the COV_{IMEP} was tried to be predicted by using the artificial neural network method for 4-stroke, 4-cylinder, direct injection and supercharged HCCI engine experimental data obtained by using n-heptane fuel at 60 °C intake air temperature, 1000 rpm engine speed at different boosted pressure. As a result of the study, it was seen that the stored data and the estimated COV_{IMEP} data were compatible.

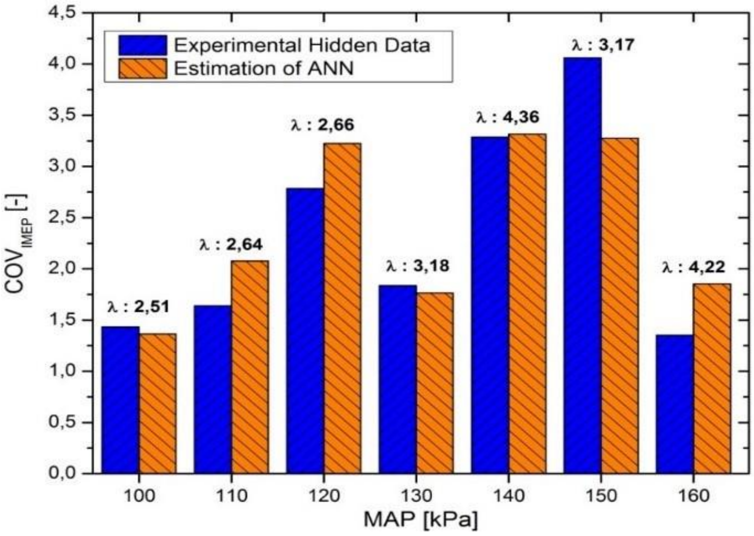


Figure. Comparison of ANN results with experimental data

Aim

COV_{IMEP}, which is an indicator of unstable operation in internal combustion engines, was estimated by ANN method.

Design & Methodology

The COV_{IMEP} estimation was performed with MATLAB ANN Toolbox using the experimental data obtained for seven different boosted pressure and different lambda values of HCCI engine.

Originality

COV_{IMEP} was used as target data 1000 iterations, 3 layers and 5 neurons were used in network structure and teaching, accuracy and testing procedures were conducted.

Findings

The best performance was obtained at 37th iteration with an average quadratic error of 0.0013026. Total correlation factor was found as 0.97763.

Conclusion

It is seen that the stored data and the estimated COV_{IMEP} data are in harmony.

Declaration of Ethical Standards

The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Estimation of the COV_{IMEP} Variation in a HCCI Engine

Araştırma Makalesi / Research Article

Seyfi POLAT[1*], Hamit SOLMAZ[2], Alper CALAM[3], Emre YILMAZ[4]

[1]Hitit University, Faculty of Engineering of Mechatronics Engineering, Çorum, Turkey
[2]Gazi University, Faculty of Technology of Automotive Engineering, Ankara, Turkey
[3]Gazi University, Technical Science Vocational High School of Machine and Metal Technology, Ankara, Turkey
[4]Hakkari University, Faculty of Engineering of Mechanical Engineering, Hakkari, Turkey

(Geliş/Received : 20.05.2019 ; Kabul/Accepted : 27.07.2019)

ABSTRACT

In this study, variation of the COV_{IMEP} was tried to be predicted by using the artificial neural network method for 4-stroke, 4-cylinder, direct injection and supercharged HCCI engine experimental data obtained by using n-heptane fuel at 60 ºC intake air temperature, 1000 rpm engine speed at different inlet air intake pressure. Intake air inlet pressure and lambda were used as input data in artificial neural network model. The COV_{IMEP} value was used as the target. Three layers and five neurons were used to construct the network using the Levenberg-Marquardt algorithm. Correlation between targets and outputs for teaching, accuracy and testing were obtained as 0.97989, 0.9504 and 0.91644, respectively. Total correlation factor was found as 0.96983. As a result of the study, it was seen that the stored data and the estimated COV_{IMEP} data were compatible.

Keywords: HCCI engine, low temperature combustion, artificial neural network.

Bir HCCI Motorda COV_{IMEP} Değişiminin Tahmini

ÖZ

Bu çalışmada, 4 zamanlı, 4 silindirli, direkt enjeksiyonlu ve süperşarjlı HCCI motorunda n-heptan yakıtı kullanılarak 60 ºC giriş sıcaklığında, 1000 rpm mtor hızında, farklı mme havası giriş basınçlarında elde edilen deneysel sonuçlar kullanılarak yapay sinir ağı metodu kullanılarak COV_{IMEP} değişimi tahmin edilmeye çalışılmıştır. Yapay sinir ağı modelinde giriş verisi olarak emme havası giriş basıncı ve lambda kullanılmıştır. COV_{IMEP} değeri hedef olarak belirlenmiştir. Üç katman ve beş nöron kullanılarak oluşturulan ağ yapısında Levenberg-Marquardt algoritması ile öğretme işlemi yapılmıştır. Öğretme, doğruluk ve test içi hedefler ile çıkışlar arasındaki kolerasyon faktörü sırası ile 0.97989, 0.9504 ve 0.91644 olarak elde edilmiştir. Toplam korelasyon faktörü ise 0.96983 olarak bulunmuştur. Yapılan çalışma sonucunda, saklanan veriler ile tahmin edilen COV_{IMEP} verilerinin uyum içerisinde olduğu görülmüştür.

Anahtar kelimeler: HCCI motoru, düşük sıcaklık yanması, yapay sinir ağı.

1. INTRODUCTION

Homogeneous charged compression ignition (HCCI) engines have advantages such as high thermal efficiency, very low NOx and PM emissions and low heat loss compared to conventional spark ignition (SI) and compression ignition (CI) engines. In HCCI engines, the air / fuel mixture prepared outside the cylinder is almost homogeneously taken into the cylinder and compressed. Combustion of the air / fuel mixture starts at the same time in all regions of the cylinder when the temperature reaches the ignition temperature. Since HCCI engines can operate in leaner homogeneous mixtures, NOx and PM emissions are simultaneously reduced as regional rich mixtures are not produced. However, the simultaneous combustion of the mixture in the whole cylinder causes a high pressure rise rate especially at high engine loads and this causes knocking. At low engine loads, misfiring problems occur due to the extremely lean mixture. HCCI engines cannot be used commercially yet because of these problems.

Researchers have tried to resolve these problems via increasing the intake air inlet temperature, increasing intake air inlet pressure, changing the compression ratio, changing valve timing, using exhaust gas recycle etc. Furthermore, since the physical and chemical features of the fuels used in HCCI engines affect the combustion stages directly, researchers also have conducted detailed studies by using fuels having different physical and chemical properties and tried to extent operation range of the HCCI engine [1-9].

One of the most important parameters used in HCCI engines for detecting misfire zones is COV_{IMEP} (coefficient of variation of indicated mean effective pressure) which expresses cycle to cycle variations in IMEP. Since the HCCI combustion starts with self-ignition in the cylinder, the combustion start angle cannot be controlled directly. The variations in instantaneous inlet air temperature, the remaining amount of exhaust gas in the cylinder and the temperature, cylinder wall and piston top temperature reveal a cycle to cycle variation in

**Sorumlu Yazar (Corresponding Author)*
e-posta : seyfipolat@hitit.edu.tr

cylinder pressure and IMEP. Variance differs rapidly, especially HCCI operation at misfiring regions of the engine. The variation in COV_{IMEP} can be examined to provide a more appropriate operating map for the misfire zone and to prevent the engine from running in these areas.

Experimental studies for HCCI engines are quite costly. Since the operation of the engine during the experiments is not completely stable, measurements cannot be taken at any desired range. Artificial neural networks are widely used for more precise evaluation of the data obtained from the tests. In addition, the software algorithm developed for engine control by determining engine operation range must determine the engine operation is progressing into the misfiring zone and intervene the engine before entering misfire zone. It is thought that artificial neural networks can be used for the software algorithm to predict the misfire zone in advance.

Solution methods based on only algorithm and mathematical approach are insufficient to solve complex problems. Therefore, artificial neural networks have been developed for use in solving complex problems [10]. Artificial Neural Networks is a parallel and distributed processor based on the human brain operating principle that simulates of the simple nervous system. Learning in artificial neural networks is accomplished by calculating the weights of synaptic connections between cells to achieve the desired target [11].

Ismail et al. developed an artificial neural network (ANN) model for light diesel engine using blends of conventional diesel and biodiesel fuels. In the study nine different engine output parameters such as carbon monoxide (CO), carbon dioxide (CO2), nitrogen monoxide (NO), unburned hydrocarbon (UHC), maximum pressure (Pmax), location of the maximum pressure (CAPmax), maximum heat release rate (HRRmax) and cumulative heat release rate were predicted in ANN model, engine speed, engine output torque, fuel mass flow rate and concentration rate of biodiesel in fuel blend were used as input parameters. In the study, it was found that the results obtained with the ANN method were compatible with the experimental data [12].

Rezai et al. have developed a model for the estimation of performance parameters in an HCCI engine by using artificial neural networks. In the study, indicated mean effective pressure (IMEP), thermal efficiency, in-cylinder pressure, cumulative heat release, nitrogen oxide (NOx), CO and total hydrocarbon (THC) were estimated. In order to estimate these seven different engine parameters, two separate ANN models, radial simple function (RBF) and feed forward (FF) were used. According to the results of the study, the performance parameters of the butanol and ethanol-fuelled HCCI engine were estimated with an error less than 4% in both models (RBF and FF). Since a lower number of neurons were used in the FF model, it was stated that a simpler network structure was obtained, but twice the learning time was required compared to the RBF model [13].

In this study, COV_{IMEP} variation was estimated with artificial neural network method by using the experimental data obtained at different intake air inlet pressures at 1000 rpm engine speed using n-heptane fuel in a 4-stroke, four-cylinder, direct injection and supercharged HCCI engine.

2. MATERIAL and METHOD

2.1.Experimental Setup

In the present study, 2.0 liter, 4 cylinder, four stroke, direct injection GM Ecotec gasoline engine was modified to be operated in HCCI mode. GM Ecotec gasoline engine has a compression ratio of 9.2 and provides 270 kW output power at engine speed of 6000 rpm. An external Eaton M62 model supercharger was used to increase the pressure of the air entering the cylinder, and this supercharger was driven by a 20 HP electric motor. An external fuel pump driven by an electric motor was used for the direct injection system. An air heater was fitted between the throttle body and the intake manifold to increase the intake air temperature. Engine load and speed were controlled by an AC dynamometer of 460 HP. A schematic view of the experimental setup is given in Figure 1.

HCCI engine was controlled with an interface and algorithm that was developed using dSPACE MicroAutoBox and RapidPro control modules. Instantaneous in-cylinder pressure data and crankshaft angle are recorded to the computer via the combustion analyzer device with 1 degree crank angle precision. In order to increase the accuracy of calculation in-cylinder pressure data of 100 consecutive cycles were recorded for each test point. The IMEP and COV_{IMEP} values for each test point were calculated by using the in-cylinder pressure data obtained from experiments.

By examining the differences between a numbers of consecutive cycles, it is determined whether the engine is running regularly or not. The performance stability of the engine can also be determined by examining the change of IMEP according to cyclical variations. The indicated mean effective pressure variance coefficient (COV-Coefficient of Variation) is widely used in the expression of cyclical variations of the internal combustion engines. In the literature, it was desired that the value of the coefficient of variance should not exceed 10% for the engine to work in a stable manner. This value was considered to be a critical value for HCCI combustion [4]. Variance coefficient in indicated mean effective pressure can be calculated by following equations;

$$COV_{imep} = \frac{\sigma_{imep}}{\bar{X}} \times 100 \qquad (1)$$

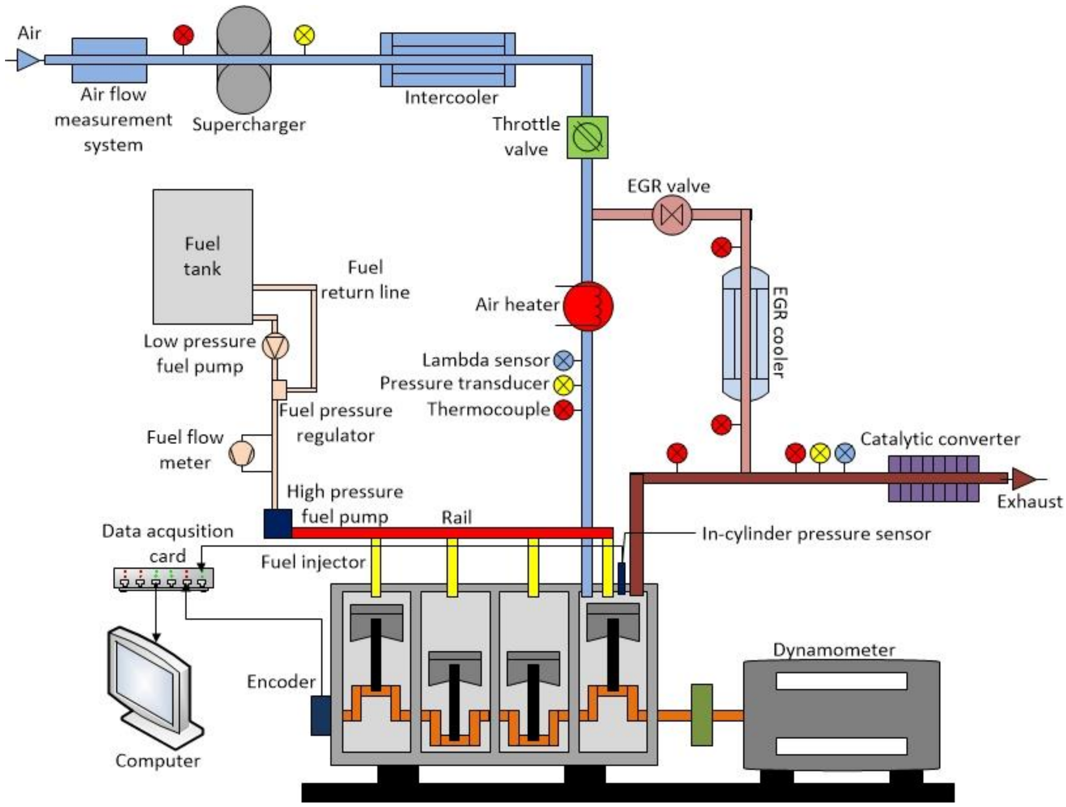


Figure 1. Schematic view of the experimental test setup

$$\bar{X} = \frac{\sum_{i=1}^{n} X_i}{n_{cycle}} \tag{2}$$

$$\sigma_{imep} = \sqrt{\frac{\sum_{i=1}^{n} \left(X_i - \bar{X} \right)^2}{n_{cycle}}} \tag{3}$$

Where, σ_{imep}, $\bar{X}$, X_i and n refers to standard deviation of IMEP values of 100 cycles, average IMEP of the 100 cycle, IMEP values of each cycle and cycle number respectively. In the present study experiments were conducted at engine speed of 1000 rpm, injection pressure of 100 bar, intake air temperature of 60 ºC, seven different intake air pressure of 100-110-120-130-140-150 ve 160 kPa with n-heptane which is a reference fuel.

2.2. Artificial Neural Network Method

There are many learning methods used in artificial neural networks. One of these methods is back propagation. Back propagation learning is one of the algorithms that used in multi-layer network. For the input data sent to the network, the output produced by the network is compared with the target. The difference between these two values gives the error value. The error found is distributed to the weight values of the network in the next iteration and it is aimed to decrease the error value at the end of the process [14]. Figure 2 shows the network structure created. Intake air inlet pressure and lambda were used as input data in artificial neural network model. The COV_{IMEP} value was used as the target.

Levenberg-Marquardt algorithm, which is derived from Newton's algorithms, performs parameter update processes with error vector and Jacobian matrix created for all inputs. The Levenberg-Marquardt algorithm uses system resources (memory, etc.) more than other algorithms. However, the training of the network takes place in a shorter time. Training ends when generalization stops healing [15-16]. In this study, Levenberg-Marquardt algorithm was used to teach experimental data to the ANN.

The COV_{IMEP} estimation was performed with MATLAB ANN Toolbox using the experimental data obtained for seven different intake air inlet pressure and different lambda values of HCCI engine. Experimental parameters and data were shown in Table 1. In order to test the accuracy of the artificial neural network model, one of the test data for each intake air pressures were hidden.

Figure 3 shows the variation of COVIMEP, which is calculated using the data obtained from the experiments, depending on the lambda and the intake air pressure.

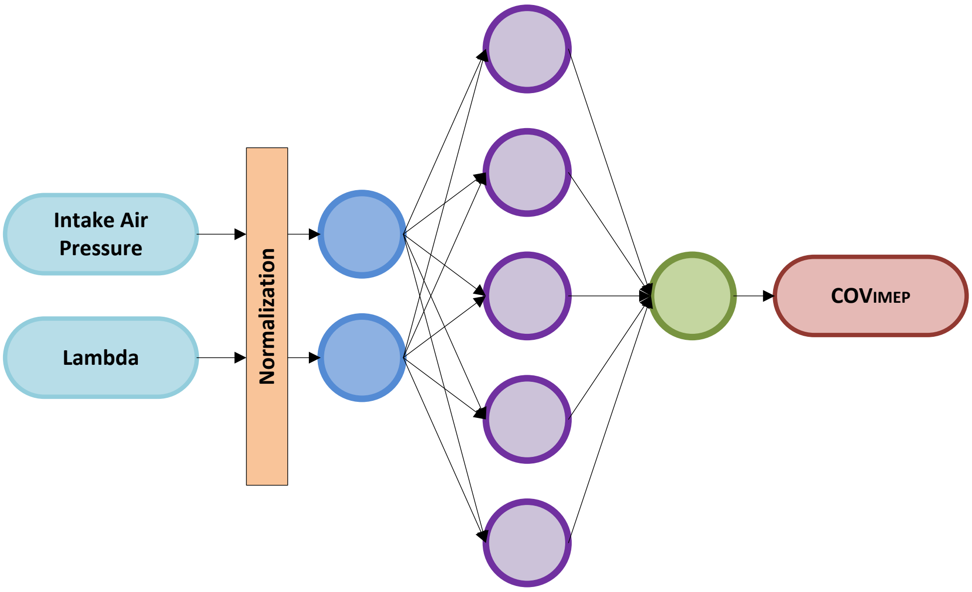
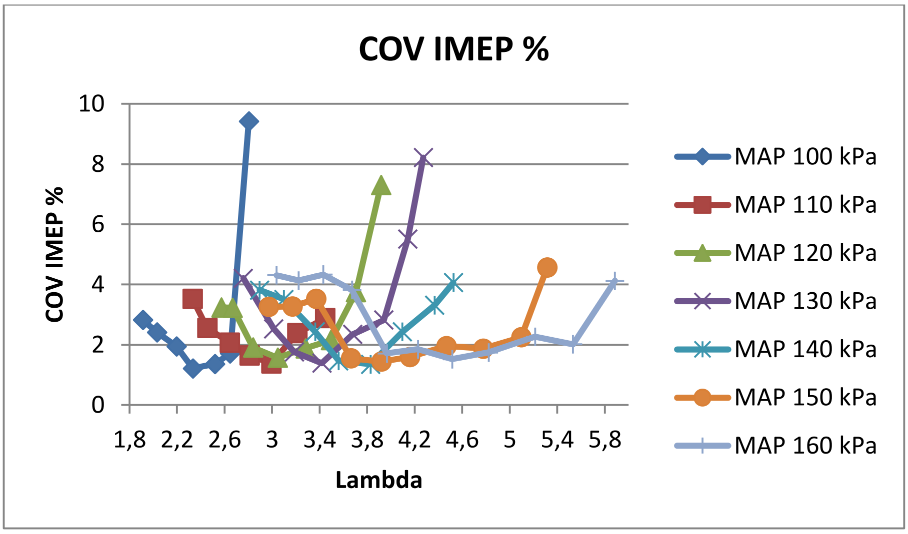


Figure 2. Structure of the artificial neural network

Table 1. Experimental data

	Teaching data	**Hidden data**
Intake air pressure [kPa]	**Lambda [-]**	**Lambda [-]**
100	1.91 - 2.03 - 2.20 - 2.33 - 2.65 - 2.80	2.52
110	2.33 - 2.45 - 2.81 - 2.99 - 3.21 - 3.45	2.64
120	2.57 - 2.84 - 3.05 - 3.28 - 3.49 - 3.71 - 3.92	2.67
130	2.76 - 3.01 - 3.42 - 3.68 - 3.94 - 4.14 - 4.27	3.19
140	2.89 - 3.10 - 3.36 - 3.56 - 3.83 - 4.10 - 4.52	4.37
150	2.97 - 3.37 - 3.67 - 3.92 - 4.16 - 4.47 - 4.78 - 5.10 - 5.31	3.17
160	3.04 - 3.22 - 3.43 - 3.67 - 3.97 - 4.51 - 4.82 - 5.21 - 5.53 - 5.88	4.23



Figrure 3. COV$_{IMEP}$ variation depending on lambda and intake air pressure

3. RESULTS AND DISCUSSION

In the present study, prediction of COV_{IMEP} variation due to inlet air pressure and lambda in a HCCI engine was conducted via ANN model using Levenberg-Marquardt teaching algorithm. Intake air pressure and lambda were used as input data and COV_{IMEP} was used as target data. The weights in the ANN were calculated using MATLAB ANN Toolbox for teaching, accuracy and test processes.

In this study, 52 of 59 of the values were taught to the network and 7 of them were stored to test the accuracy. In Figure 4 (a) upper graph shows the performance of neural networks due to the mean square error for teaching, accuracy and testing. A total of 1000 iterations were performed and the best performance was achieved with an average of 0.0013026 quadratic error in the 37th iteration.

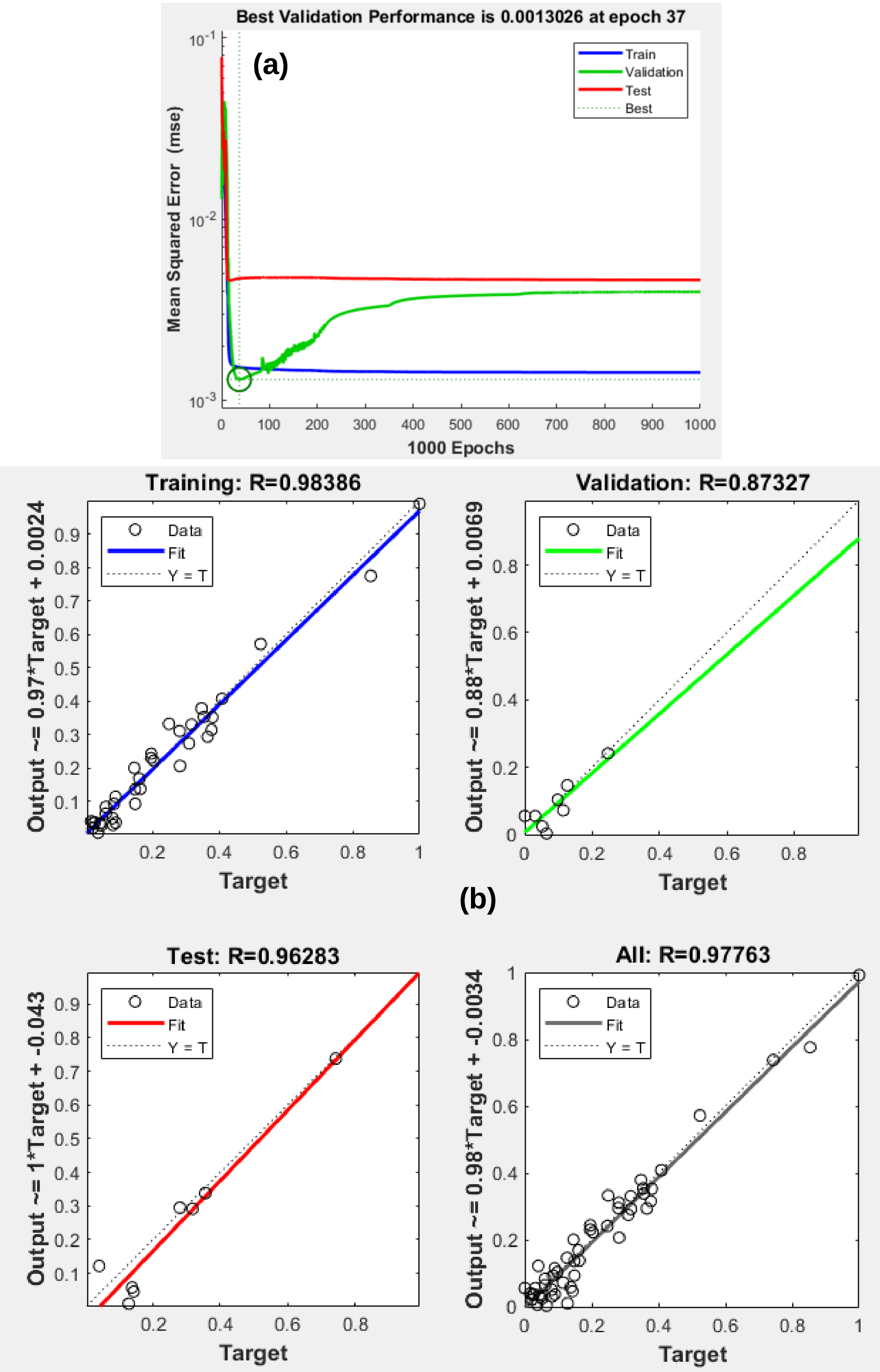


Figure 4. ANN performance due to mean quadratic error for teaching, accuracy and testing and correlation factors for teaching, accuracy and testing

Figure 4 (b) shows the regression analysis between the target values for the teaching, accuracy and testing and the artificial neural network output values. Correlation between targets and outputs for teaching, accuracy and testing was obtained as 0.98386, 0.87327 and 0.96283, respectively. Total correlation factor was found as 0.97763. It is also seen on Figure 4 that the accuracy of the ANN model applied in this study is high enough.

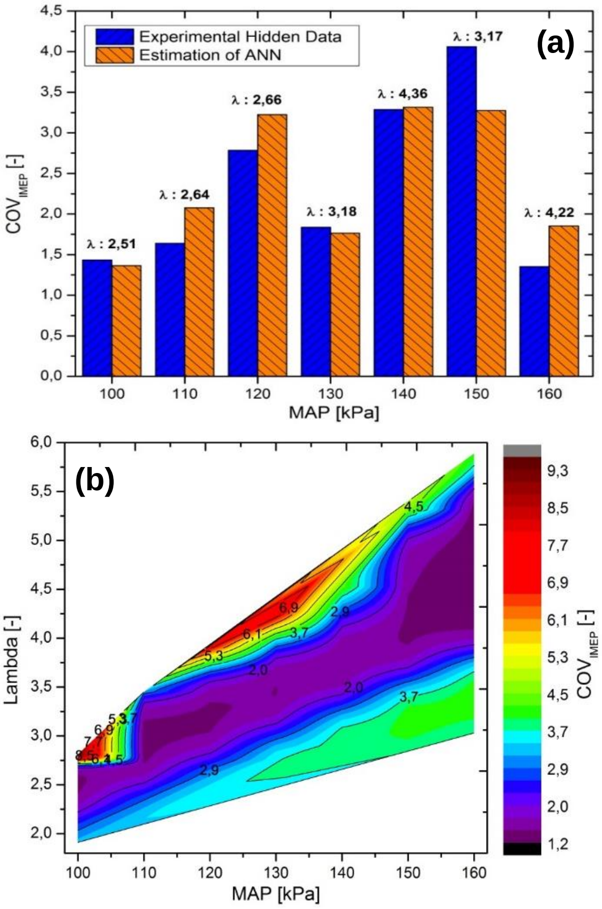


Figure 5. a) Comparison of ANN results with experimental data b) COVIMEP variations depending on lambda and intake air pressure with ANN

Figure 5 (a) shows the experimental COVIMEP data, which is not taught to the network of artificial neural networks, and the comparison with the results of predictions of ANN model at different intake air inlet pressures and different lambda values determined by the model. As a result of the comparison, it was seen that the hidden experimental data and the estimated COVIMEP data were compatible.

Figure 5 (b) shows the ANN results of COVIMEP variations depending on lambda and intake air pressure. The COVIMEP map was obtained the lambda values were changed to 0.01 at the different intake air pressures (100 kPa to 160 kPa) after the accuracy of the ANN model was tested. In the development of HCCI engines, it is very important to determine the limits of knock and misfire. The COVIMEP value exceeds 4 is one of the most important indicators of the operation of the HCCI engine in the knock or misfire zone. Thus, it is possible to estimate the knock and misfiring zones of the HCCI engine without experimenting using the developed ANN model.

6. CONCLUSION

In this study, by using the experimental data obtained at different intake air inlet pressures and 1000 rpm engine speed using n-heptane fuel in a 4-stroke, four-cylinder, direct injection and supercharged HCCI engine, COVIMEP values were estimated by using artificial neural network method. Experimental data obtained for seven different intake air pressure (from 100 kPa to 160 kPa with thee intervals of 10 kPa) and different lambda values were used as input data. COVIMEP was used as target data1000 iterations, 3 layers and 5 neurons were used in network structure and teaching, accuracy and testing procedures were conducted. The best performance was obtained at 37th iteration with an average quadratic error of 0.0013026. Total correlation factor was found as 0.97763. As a result of the study, it is seen that the stored data and the estimated COVIMEP data are in harmony.

REFERENCES

[1] Polat S., Özdilli Ö. and Çizmeci H., "An estimation of in-cylinder pressure based on lambda and engine speed in hcci engine using artificial neural networks", ***Fresenius Environmental Bulletin***, 28(4A): 3568-3576, (2019).

[2] Koten H., Yilmaz M. and Gul M.Z., "Effects of the injection parameters and compression ratio on the emissions of a heavy-duty diesel engine", ***International Journal of Vehicle Design***, 59(2/3): 147-163, (2012).

[3] Zhao H., "HCCI and CAI engines for the automotive industry", ***Woodhead Publishing Ltd.***, Cambridge England, (2007).

[4] Heywood J.B., "Internal combustion engine Fundamentals", ***McGraw- Hill***, New York, (1988).

[5] Hasan M.M., Rahman M.M. and Kadirgama K., "A review on homogeneous charge compression ignition engine performance using biodiesel-diesel blend as a fuel", ***International Journal of Automotive and Mechanical Engineering***, 11: 2199-2211, (2015).

[6] Hairuddin A.A., Wandel A.P. and Yusaf, T., "An introduction to a homogeneous charge compression ignition engine", ***Journal of Mechanical Engineering and Sciences***, 7: 1042-1052, (2014).

[7] Baumgarter C., "Mixture formation in internal combustion engines" ***Springer, Heat and Mass transfer series***, 253-286, (2006).

[8] Uyumaz A., "Investigation of the effects of valve lift in a homogenous charged compression ignition gasoline engine on combustion and performance***", Ph. D. Thesis, Gazi University***, 3-12, (2014).

[9] Polat S., "An investigation of the effects of operation parameters on combustion in a HCCI engine", ***Ph. D. Thesis, Gazi University***, 4-15, (2015).

[10] Khandelwal M. and Singh T.N., "Prediction of blast induced ground vibrations and frequency in opencast

mine: A neural network approach", ***Journal of Sound and Vibration***, 289(4-5): 711-725, (2006).

[11] Luger G.F., "Artifical intelligence: structures and strategies for complex problem solving", ***4th edition, Addison-Wesley***, (2002).

[12] Ismail H.M., Ng H.K., Queck C.W. and Gan S., "Artificial neural networks modelling of engine-out responses for a light-duty diesel engine fuelled with biodiesel blends", ***Applied Energy***, 92: 769-777, (2012).

[13] Rezaei J., Shahbakhti M., Bahri B. and Aziz A.A., "Performance prediction of HCCI engines with oxygenated fuels using artificial neural networks", ***Applied Energy***, 138: 460-473, (2015).

[14] Nabiyev V.V., "Yapay zeka", ***Seçkin Yayıncılık***, Ankara, 598, (2016).

[15] Marquardt D., "An algorithm for least-squares estimation of nonlinear parameters", ***SIAM Journal on Applied Mathematics***, 11(2): 431-441, (1963).

[16] Hagan M.T., and Menhaj M., "Training feed-forward networks with the Marquardt algorithm", ***IEEE Transactions on Neural Networks***, 5(6): 989-993, (1994).