An ANN approach to evaluate effect of injection timing, engine speed and load on a diesel engine cylinder pressure

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ABSTRACT: In this study, a back-propagation neural network model has been developed to predicting the cylinder pressure of a DI diesel engine. The inputs of the model were injection timing, crankshaft angle, engine speed, and engine load. An optimal design has been completed for the number of hidden layers, the number of hidden neurons, the activation function, and the goal errors in the back-propagation neural network model. After training, it was found that the R^2 values are closely 1 for the training and testing data. The results may easily be considered to be within the acceptable limits. Cylinder pressure has been predicted with the model, the effects of injection timing, crankshaft angle, engine speed and engine load on it have also been analyzed, and better results have been achieved. The relationship between input parameter and engine cylinder pressure can be determined by using the network. Therefore, the usage of ANNs may be highly recommended to predict the engine cylinder pressure instead of complex and time-consuming experimental studies.

Keywords: ANN, Cylinder pressure, Diesel engine, Prediction

INTRODUCTION

ANNs are good for some tasks. Specifically, they are good for tasks involving incomplete data sets, fuzzy or incomplete information, and for highly complex and ill-defined problems, where humans usually decide on an intuitional basis. They can learn from examples, and are able to deal with non-linear problems. Furthermore, they exhibit robustness and fault tolerance [Kalogirou, 2003].

The predictability of an ANN is a result of training with experimental data and validation with an independent set of data. The ANN has the ability to learn and improve its performance if new data are available [Oğuz, Sarıtas, & Baydan, 2010]. If there are enough experimental data, a well-trained ANN can be used as a predictive model for specific applications, such as internal combustion engines, in research and development. In several research papers, the researchers have used the ANN modeling technique on the internal combustion engine for related issues such as predicting engine exhaust emission, cylinder pressure reconstruction and engine fault diagnosis [Özener, Yüksek, & Özkan, 2012].

Deh kiani et al. [Deh Kiani, Ghobadian, Tavakoli, Nikbakht, & Najafi, 2010] studied BP ANN to predict engine brake power, output torque and exhaust emissions of the engine. The performance of the ANN was validated by comparing the prediction dataset with the experimental results. They found that the ANN provided the best accuracy in modeling the emission indices with correlation coefficient equal to 0.98, 0.96, 0.90 and 0.71 for CO, CO_2, HC and NO_x, and 0.99 and 0.96 for torque and brake power respectively. Also, stated that the artificial neural network offers the advantage of being fast, accurate and reliable in the prediction or approximation affairs, especially when numerical and mathematical methods fail.

Uzun [Uzun, 2012] used the ANN method to perform parametric studies to investigate the effect of engine speed, injection advance (IA), and engine load variation on brake specific fuel consumption (BSFC) in an engine equipped with or without a turbocharger. They choose MLP-type ANN with a sigmoid activation function for their analyses. They first experimented on the engine test bench and collected the data. They identified the ANN geometry using a trial and error method, and they used sum of squares error (SSE) to control the convergence of the network to the real outputs. The correlations obtained with the real output and the simulated output of the ANN were found to be reliable. After they completed the development of the reliable ANN model, they used this model for completing their comprehensive parametric analysis. Yuanwang et. al. [Yuanwang, Meilin, Dong, & Xiaobei, 2002] presented a neural network model that predicts the exhaust emissions from an engine using the total cetane number, base cetane number and cetane improver, total cetane number and total nitrogen content in the diesel fuel as neural network inputs. In addition, some other researcher used BP ANN algorithm to evaluating the engine parameters [Garg, Diwan, & Saxena, 2012; Ghobadian, Rahimi, Nikbakht, Najafi, & Yusaf, 2009; Soufi, Ghobadian, Najafi, Sabzimaleki, & Jaliliantabar, 2015; Yusaf, Buttsworth, Saleh, & Yousif, 2010]. The ANN prediction accuracy obtained was in an acceptable range.

In this study, a BP structured ANN was proposed to determine the cylinder pressure using a group of characteristic engine operating parameters as the ANN inputs.

Materials and methods

Experimental set up and measurements

Experimental research and necessary measurements of cylinder pressure curves were conducted on a test bench. The test engine and the experimental setup picture used for gathering data are shown in Figs.1.

Figure1. Engine test set-up and test instruments

The system for engine testing had four measurement chains for recording cylinder pressure, crankshaft angle, injection timing, engine speed and engine load. Pressure was measured by piezoelectric transducers. Measured values were recorded as a function of crankshaft rotation angle, expressed in degrees (°CA). The value of rotation angle was recorded by a rotary pulse transducer and the system of marking and synchronization of the crankshaft position. The injections time which applied were four injection timing (22, 27, 32, 37 and 42 °CA (crank angle) before TDC (Top dead center)) .The engine was operated under four load conditions 55%, 70%, 85% and 100% of full load. Also four engine speeds of 1200, 1350, 1500 and 1650 rpm have been used. The engine was fueled by diesel oil. Exactly 501 measurements were performed for each cycle of a four-stroke engine. The matrix of the test conditions is given in table 1.

Table1. Test matrix

Factors (parameters)	Levels (steps)				
	1	2	3	4	5
Engine speed (rpm)	1200	1350	1500	1650	-
Engine load torque (% of rated value)	55	70	85	100	-
Fuel injection timing (°CA btdc)	22	27	32	37	42

The engine used in this experiment was a single cylinder, 4 strokes stationary DI diesel engine. The technical specifications of the test engine are given in Table 2. The choice of this engine was guided by the fact that such small single cylinder DI diesels of about 0.5 liter capacity are used widely as stationary auxiliary power sources in urban areas to meet the peak power demand and also for powering agricultural machinery in rural areas.

Table2. Technical specifications of the test engine

Parameter	Specification
Brand	Kirloskar
Number of cylinders	one
Combustion system	Direct injection
Air intake system	Naturally aspirated
Output power	3.68 Kw
Speed	1200
Bore	80 mm
Stroke	110 mm
Compression ratio	16.5:1
Loading type	Electrical dynamometer
Rated engine speed	1500 rpm
Torque at rated speed and load	23.0 Nm

Instruments were used in this study were:

A. Instrumentation for regulating and monitoring engine operating and performance:
   1. Engine torque and speed
   2. Static injection timing
B. Instrumentation for measuring parameters concerning in cylinder process:
   1. Cylinder pressure
C. Equipment for data logging and analysis
   1. Triggering unit for starting data acquisition

Table 3 gives the brief specification of the main equipment.

Table3. Specifications of the instruments

Name of instrument	sensitivity	Range	Accuracy/Resolution	Make & Model

Quartz cylinder pressure transducer	15 pc/bar	0-250 bar	±1% up to 6 kHz	Kistler 6121A1, Switzerland
Eddy current dynamometer	-	-	-	Benz ECB 100, India
Speed indicator	-	4 digits	±1rpm	-
Load indicator	-	3.5 digits	1% const/10°c	-

Developing of ANN model

Network structure

The most popular learning algorithms are the backpropagation (BP) and its variants. The BP algorithm is one of the most powerful learning algorithms in neural networks. This algorithm was used in many of research conducted on engine parameters [Deh Kiani et al., 2010; Gölcü, Sekmen, Erduranlı, & Sahir Salman, 2005; Rahimi-Ajdadi & Abbaspour-Gilandeh, 2011; Yuanwang et al., 2002]. The training of all patterns of a training data set is called an epoch. BP training is a gradient descent algorithm. It tries to improve the performance of the neural network by reducing the total error by changing the weights along its gradient [Kalogirou, 2003].

BP networks are known for their ability to generalize well on a wide variety of problems. BP networks are a supervised type of networks, i.e. trained with both inputs and outputs. BP networks are used in a large number of working applications as they tend to generalize well. The first category of neural network architectures is the one where each layer connected to the immediately previous layer. Generally, three layers (input, hidden, and output layer) are sufficient for the majority of problems to be handled. Three layers BP network with standard connections is suitable for almost all problems. One, two or three hidden layers architecture can be used however, depending on the problem characteristics. Use of more than five layers in total generally offers no benefit and should be avoided [Kalogirou, 2003]. Thus, different topology of back propagation ANNs has been tested with 2 and 3 hidden layer.

The inputs correspond to the values of the input parameters used in a problem. The learning procedure in this network may be implemented by using the BP algorithm. In BP networks, the number of hidden neurons determines how well a problem can be learned. If too many are used, the network will tend to try to memorize the problem, and thus not generalize well later. If too few are used, the network will generalize well but may not have enough ‘power’ to learn the patterns well [Kalogirou, 2003]. So, the right numbers of hidden neurons were determined by trial and error [Uzun, 2012].

ANN consists of artificial neural cells (neurons). ANN has three main layers, namely, input, hidden and output layers. Neurons (processing elements) at input layer transfer data from external world to hidden layer [Çay, Çiçek, Kara, & Sağiroğlu, 2012]. The data in input layer do not process as the data in the other layers. In the hidden layer, outputs are produced using data from neurons in input layer and bias, and summation and activation functions. There can be more than one hidden layer. In this case, each hidden layer sends outputs to the following layer. In the output layer, the output of network is produced by processing data from hidden layer and sent to external world. The summation function calculates net input coming to a cell. For this reason, different functions are used. The most common one is to calculate the weighted sum.

Activation function provides a curvilinear match between input and output layers. In addition, it determines the output of the cell by processing net input to the cell. Selection of appropriate activation function significantly affects network performance. Recently, logistic sigmoid transfer function has been commonly used as an activation function in multilayer perception model, because it is a differentiable, continuous and non-linear function[Kröse, Krose, van der Smagt, & Smagt, 1996].

The Neural Networks Toolbox of MATLAB R2012a was used to form the ANN. The Tan-sigmoid transfer function was used in the hidden layer and output layer. Inputs of system determine the neuron number in the input layer of the network and its outputs determine the neuron number in the output layer of the network. Thus, input layer of network has four neurons and the output layer has one neurons. According to trial results, 10 neurons were used in hidden layer and obtained better predictions for cylinder pressure and is shown in Fig.2.

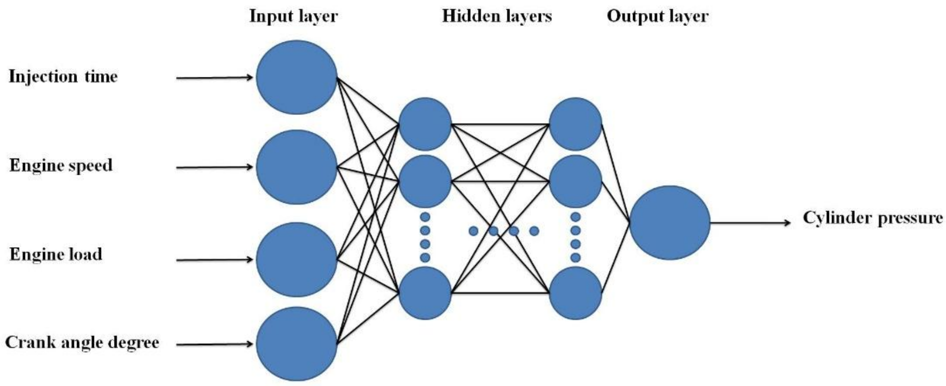

Figure2. architecture of created ANN

Learning algorithm

There are many learning algorithm in order to determine weights in ANN. One of the most common learning algorithms is back propagation. The back propagation method updates the weights in accordance with difference between available data and network output. Learning parameter used in

the method has a great importance in order to reach the optimal results. Learning parameter can be constant or dynamically updated in the model.

There are various training functions that have been applied by the previous studies such as Bayesian regularization, gradient descent with adaptive learning rule, gradient descent with momentum and adaptive learning rule, scaled conjugate gradient and LevenbergeMarquardt

[Çay et al., 2012]. But LevenbergeMarquardt was used widely in developing ANN to predict engine parameter and it shows the more capability to predict different parameter [Çay et al., 2012; Ghobadian et al., 2009; Rahimi-Ajdadi & Abbaspour-Gilandeh, 2011; Yap & Karri, 2012]. In order to acquire the closest output values to experimental results, the best learning algorithm and optimum number of neurons in hidden layer was determined. For this reason LM learning algorithms and different numbers of neurons in hidden layer were used in the built network structure for cylinder pressure. In consequence of trials, the best learning algorithm and network architecture for prediction of effective power became LM: 4-10-1 (Fig. 3). Determination of the best learning algorithm and optimal number of neurons for cylinder pressure is demonstrated in Table 4. The best learning algorithms and ANN architecture for other output parameters, cylinder pressure is given as LM:4-10-1.

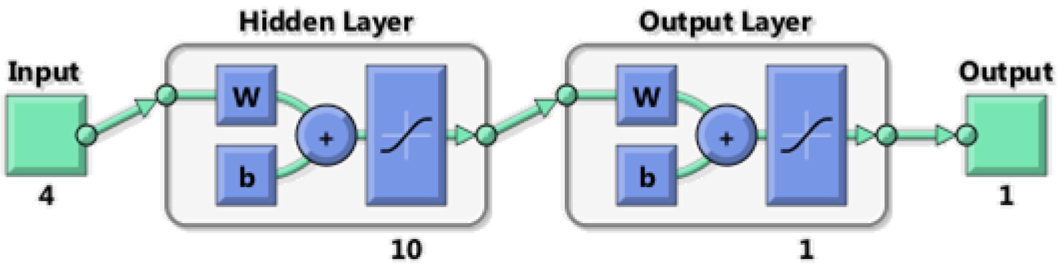

Figure3. The best learning algorithm and network

Normalization of input and output data

In back propagation model, scaling of inputs and outputs dramatically affects performance of ANN. As mentioned above, logistic sigmoid transfer function was used in this study. One of the characteristics of this function is that only a value between 0 and 1 can be produced. Input and output data sets are normalized before training and testing process. In ANN, normalization can be performed between 0 and 1[Arcaklioğlu & Çelıkten, 2005].

$$X_n=\frac{X_i-X_{min}}{X_{max}-X_{min}} \qquad \text{Eq.(1)}$$

Where X_i is actual data, X_n is normalized data, X_{min} is minimum of actual data and X_{max} maximum of actual data. In this study, the input and output values were normalized between 0 and 1 using equation 1.

Training and testing data

Three types of data files prepared: a training data file, a test data file and a validation data file. During training, the network was tested against the test file to determine accuracy and training stopped when the mean average error remains unchanged for a number of epochs. This is done in order to avoid overtraining, in which case, the network learns perfectly the training patterns but is unable to make predictions when an unknown training set is presented to it [Kalogirou, 2003].

Determination of percentages of training and testing data has an important role for building of ANN architecture. When the studies in literature are analyzed, it is revealed that different ratios for training and testing data are used 80%:20% [Mohammadhassani, Khalilarya, Solimanpur, & Dadvand, 2012], 75%:25% [Parlak, Islamoglu, Yasar, & Egrisogut, 2006], 70%:30% [Arumugam, Sriram, & Subramanian, 2012; Sayin, Ertunc, Hosoz, Kilicaslan, & Canakci, 2007; Yusaf et al., 2010], although, the percentage of training and testing data of 70%:30% are most in common. Thus, in this context, Approximately 39000 of the total experimental data was selected at random and was used for training purpose, while the 1080 values was reserved for testing, i.e. the ratio for training and testing data was selected as 70%:30%. The flowchart of determing the best ANN model to predict the cylinder pressure is shown in figure 4. The steps are given as follows:

1. In order to make the architecture of the BP neural network model simple, only two hidden layer will be used in it. The prediction accuracy of the network can be improved by choosing the proper number of hidden neurons.

2. When the tangential sigmoid function is selected as the activation function of the hidden layer, the BP neural network will have an improved prediction performance.

3. The proper goal error along with the initial weights and biases of the network can be chosen with the training samples training the model. By changing the number of the hidden neurons while training the model, the proper number of the hidden neurons can be selected by observing the training results of the model. According to the following three principles, the number of the hidden neurons can be selected: (1) the expected goal errors must be reached within the given training numbers. (2) The architecture of the network is not too complicated. (3) After training the network with the training samples, the network can reflect well the sample change law and have higher prediction accuracy. In Table 1if the number of the hidden neurons is too little, the network does not reach the expected goal error, or if the number of the hidden neurons is too many, the network is too complicated. Considering the architecture and prediction accuracy of the network, 10 hidden neurons can be selected.

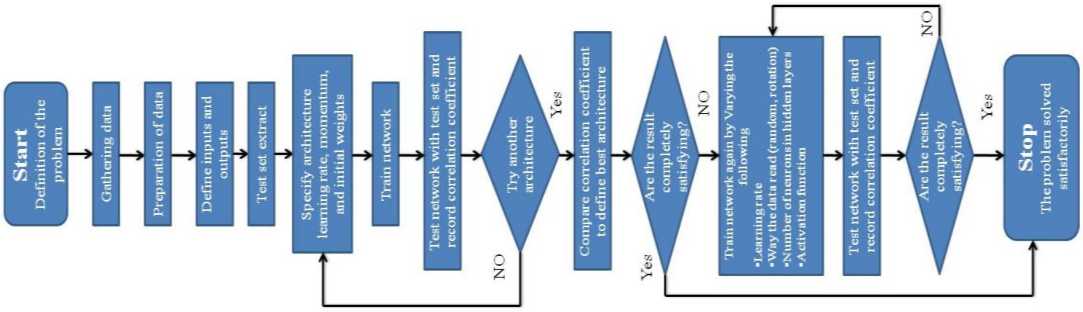

Figure4. the flowchart of determinig the best ANN model

Statistical evaluation of outputs

BP training algorithm is a ramp descent algorithm. The BP algorithm minimizes total error by changing the weights through its ramp and thus tries to improve the performance of the network.

The training of the network is stopped when the tested values of RMS stop decreasing and begin to increase. In order to understand whether an ANN is making good predictions, the testing data that has never been presented to the network, is used and the results are checked at this stage [Çay et al., 2012].

The performance of ANN model in testing sets is validated in terms of the common statistical measures; R2 (coefficient of determination which presents the degree of association between predicted and true values).

$$R^2=1-\frac{\sum_{i=1}^{N}(Yi_{obsereved}-Yi_{estimate})^2}{\sum_{i=1}^{N}(Yi_{estimate})^2} \qquad \text{Eq.(2)}$$

Where Yestimate is the estimated data, Yobserved is the observed data. These statistical measures provide information on the strength of linear relationship between the observed and the estimated values. If the model is “perfect”, SSE is zero and R2 is 1. If the model is a total failure, R^2 is zero.

Results and discussion

Prediction of engine pressure using ANN

The aim of using the ANN model, considered as a practical approach, is to test the ability to predict cylinder pressure. The network has four input parameters: injection timing, engine speed, engine load and crank angle.

Statistical values obtained for the network is given in Table 4. As shown in Table 4, it was shown that R2 are close to 1. Predictive ability of the network for cylinder pressure was found to be satisfactory.

Table4. Statistical data for the effective power using two different algorithms

Model topology	Number of neurons in hidden layers	Epochs		R2
4-2-1	10	81	$\begin{cases} TANSIG \\ TANSIG \end{cases}$	0.992
4-2-1	10	70	$\begin{cases} LOGSIG \\ LOGSIG \end{cases}$	0.154
4-2-1	10	45	$\begin{cases} PURELINE \\ PURELINE \end{cases}$	0.007
4-2-1	10	30	$\begin{cases} PURELINE \\ TANSIG \end{cases}$	0.009
4-2-1	10	490	$\begin{cases} PURELINE \\ LOGSIG \end{cases}$	4.39e-25
4-2-1	10	151	$\begin{cases} LOGSIG \\ PURELINE \end{cases}$	0.984
4-2-1	10	245	$\begin{cases} LOGSIG \\ TANSIG \end{cases}$	0.991
4-2-1	10	86	$\begin{cases} TANSIG \\ PURELINE \end{cases}$	0.990
4-2-1	10	138	$\begin{cases} TANSIG \\ LOGSIG \end{cases}$	0.155

After 81 training cycles the level of error was satisfactory and further cycles had no significant effect on error reduction. This can clearly be seen from Figure5.

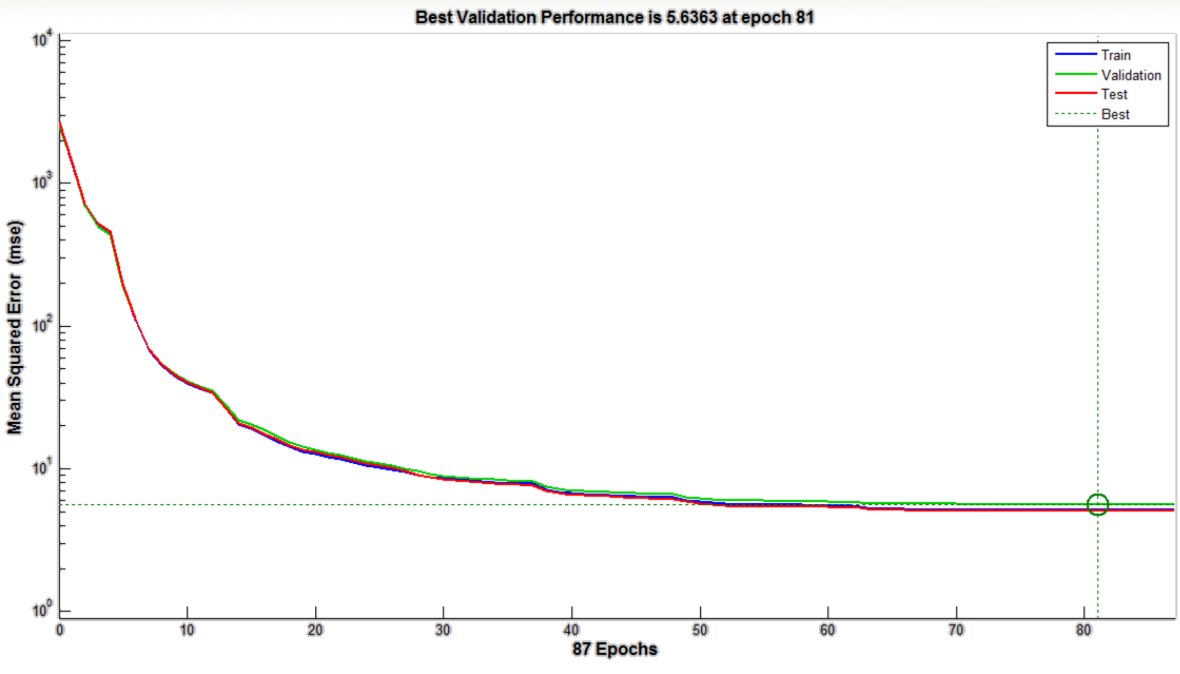

Figure5. Performance of proposed neural network configuration.

Matching of the experimental values and the values predicted by ANN for testing sets (Engine speed: 1650 rpm, advance: 42 deg, engine load: 100% load) was shown in Fig. 6. As shown in Fig. 6, predictive ability of the network was very good.

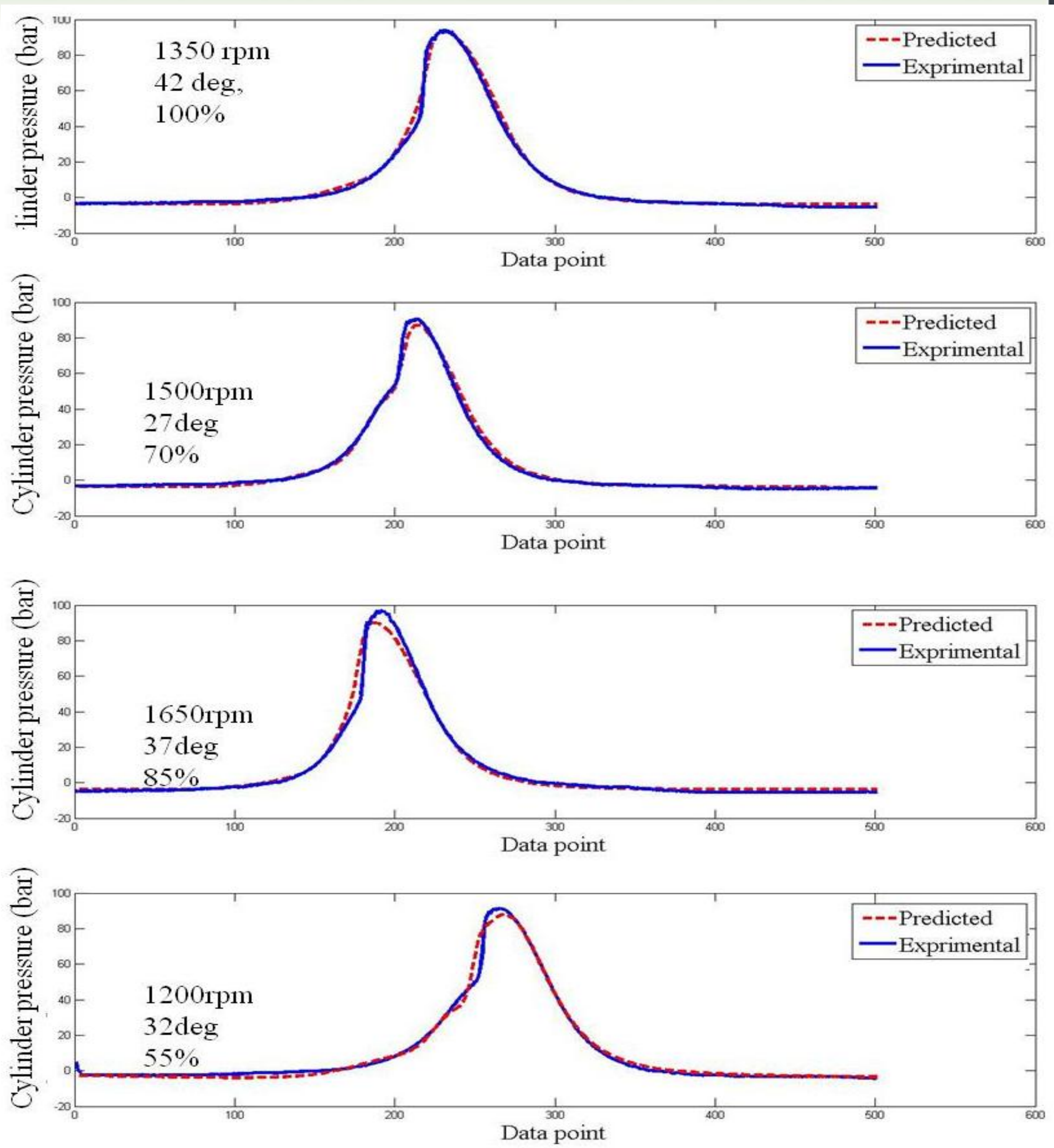

Figure 6. Matching of the experimental and ANN model values for testing sets of cylinder pressure

As it can be seen in figure 6, the created ANN model can predict the cylinder pressure very good except the harsh part of curve in top of the curve. Also, the ANN model ability in modeling of ignition delay part of curve and modeling the trend change of curve is not satisfying. It may be due to rapid oscillation in this part of curve, although the model performance in other part of curve is fairly good.

Conclusion

The applicability of ANNs has been investigated for the cylinder pressure. To train the network, Injection timing, Engine speed, engine load and crank angle are used as the input, while the outputs are cylinder pressure. This study deals with ANN modeling of an engine to predict the cylinder pressure. Using some of the experimental data for training, an ANN model based on standard back propagation algorithm for the engine was developed. Then, the performance of the ANN predictions were measured by comparing the predictions with the experimental results which were not used in the training process. Injection timing, Engine speed, engine load and crank angle were used as the input layer, while cylinder pressure was used as the output layer. After training, it was found that the R2 values are closely 1 for the training and testing data. The results may easily be considered to be within the acceptable limits. The relationship between input parameter and engine cylinder pressure can be determined by using the network. Therefore, the usage of ANNs may be highly recommended to predict the engine cylinder pressure instead of complex and time-consuming experimental studies. This study shows that, as an alternative to classical modeling [Soufi et al., 2015] techniques, the ANN approach can be used to accurately predict the problems of internal combustion engines. Moreover, as an alternative to classical modeling techniques, the ANN approach can be used to accurately predict the cylinder pressure of internal combustion engines.

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استفاده از روش ANN برای پیش بینی اثر زمان پاشش سوخت، سرعت موتور و بار روی موتور بر فشار درون سیلندر موتور دیزل

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چکیده

در این مطالعه، یک مدل شبکه عصبی پس انتشار برای پیش بینی فشار سیلندر یک موتور دیزل DI ارایه شده است. ورودی مدل زمان پاشش، زاویه میل لنگ، سرعت موتور و بار موتور بودند. تعداد لایه های پنهان، تعداد نورون پنهان، نوع تابع انتقال، و میزان خطای مجاز در مدل شبکه عصبی پس انتشار انتخاب گردید. پس از آموزش، مقدار R^2 برای داده های آموزش و آزمون نزدیک به ۱ به دست آمد.نتایج به دست آمده قابل قبول می باشد. با استفاده از این مدل ارایه شده فشار سیلندر بقابل پیشبینی می گردد. رابطه بین پارامترهای ورودی و فشار سیلندر موتور می تواند با استفاده از شبکه تعیین می شود. بنابراین، استفاده از شبکه های عصبی مصنوعی برای پیش بینی فشار سیلندر موتور به جای مطالعات پیچیده و وقت گیر تجربی بسیار توصیه می شود.